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par

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**Compter les galaxies infrarouges,
raconter leur histoire**

**Propriétés statistiques des galaxies infrarouges à grand
redshift et origine du fond extragalactique infrarouge**

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A mon grand père,

Résumé

Le fond extragalactique est le rayonnement relique issu de tous les processus de formation des structures dans l'Univers. Environ la moitié de ce fond, appelé fond infrarouge est émis dans l'intervalle 8-1000 μm , a un maximum d'émission autour de 150 μm , et est essentiellement dû aux processus de formation d'étoiles dans l'Univers. En effet, la luminosité infrarouge d'une galaxie est fortement liée à la formation d'étoiles en son sein. Pour bien comprendre l'origine du fond infrarouge, il faut donc également déterminer l'évolution des galaxies infrarouges.

Une mesure statistique relativement simple permettant de comprendre l'origine du fond infrarouge, mais également l'évolution des galaxies, consiste à compter les sources en fonction de leur flux. J'ai mesuré les comptages de sources infrarouges dans les données des télescopes spatiaux *Spitzer* et *Herschel*, ainsi que celles de l'expérience BLAST, en utilisant des méthodes variées. Les sources détectées individuellement dans les cartes *Spitzer* à 24 μm émettent la majeure partie du fond. En revanche, à plus grande longueur d'onde, la sensibilité et la résolution angulaire des instruments décroît. Les sources détectées n'expliquent alors plus qu'une petite partie du fond. L'analyse par empilement (ou *stacking*) permet de mesurer le flux moyen infrarouge lointain ou sub-millimétrique d'une population détectée uniquement dans l'infrarouge moyen. Cette technique fournit des limites inférieures contraignantes sur la valeur du fond à grande longueur d'onde, mais permet également de compter les sources trop faibles pour être détectées individuellement. Ces résultats sont confirmés grâce à l'analyse dite P(D), qui permet de déterminer les comptages directement à partir de l'histogramme d'une carte infrarouge.

Ces nouvelles contraintes permettent de préciser le scénario d'évolution des galaxies infrarouges. J'ai construit un modèle paramétrique d'évolution de ces objets permettant d'interpréter les comptages. Ce modèle reproduit de manière satisfaisant les propriétés statistiques de galaxies infrarouges de 15 μm à 1.1 mm. Il prédit que dans l'Univers jeune ($z > 2$), la formation d'étoile a eu lieu majoritairement dans des galaxies ultra-lumineuses en infrarouges ($L_{IR} > 10^{12} L_{\odot}$). Ces galaxies formaient des étoiles à un rythme très intense (plus de 100 $M_{\odot}/\text{ans}$) et n'ont que très peu d'équivalent dans l'Univers local. Depuis, le taux de formation d'étoiles a diminué d'un facteur 10, et la formation d'étoiles a aujourd'hui majoritairement lieu dans des galaxies semblables à la notre. Ce modèle d'évolution a par la suite été utilisé pour interpréter les fluctuations du fond infrarouge à grande longueur d'onde observées par BLAST, *Planck* et *Herschel*.

Abstract

The extragalactic background light is the relic emission of the process of structure formation in the Universe. About half of this background, called cosmic infrared background, is emitted in the 8-1000 microns interval, peaks near 150 microns, and is essentially due to the star formation processes in the Universe. In fact, the infrared luminosity of a galaxy is linked to the hosted star formation. It is thus necessary to determine the evolution of infrared galaxies to well understand the origin of the cosmic infrared background.

A rather simple statistical measurement, enabling to understand the origin of the cosmic infrared background, but also the evolution of the galaxies, consist in counting the sources as a function of their flux. I measured number counts of infrared galaxies using different methods in the data of the Spitzer and Herschel space telescopes, and of the BLAST experiment. The individually detected sources in the 24 microns Spitzer maps are responsible of the main part of the background. But, at larger wavelength, the sensitivity and the angular resolution of the instruments decreases, and the detected sources explain only a small part of the background. The stacking analysis enable to measure the mean far-infrared or sub-millimeter flux of a population detected only in the mid-infrared. This technique provides stringent lower limits on the level of the background, but also enables to count the sources which are too faint to be detected individually. These results are confirmed by the P(D) analysis, which determines the counts from the histogram of the infrared maps.

These new measurements constrain the evolution of the infrared galaxies. I built a parametric evolution model to interpret the source counts. This model well reproduces the statistical properties of the infrared galaxies between 15 and 1100 microns. It predicts that the star formation in the young Universe ($z > 2$) mainly happen in ultra-luminous infrared galaxies ($L_{IR} > 10^{12} L_{\odot}$). These galaxies formed stars very quickly (more than $100 M_{\odot}/\text{years}$), and have few equivalents in the local Universe. Nowadays, the star formation rate has decreased by a factor of ten, and the star formation mainly happen in galaxies like ours. This model has been used to interpret the fluctuations of the cosmic infrared background at large wavelength observed by BLAST, Planck, and Herschel.

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¹De toute façon, je sais que j'oublie plein de gens. Désolé !

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Introduction

L'astronomie vit aujourd'hui une époque formidable. Alors que notre horizon s'est limité, jusqu'au XX^{ième}, au système solaire, puis aux étoiles proches. Nous sommes aujourd'hui capables d'observer des milliards de galaxies, contenant elles-mêmes des milliards d'étoiles. De plus, par chance, la lumière voyage à une vitesse finie. En regardant loin dans l'espace, on regarde loin dans le passé. La vue perçante des grands télescopes permet alors de voir des objets toujours plus faibles et donc toujours plus éloignées, permettant ainsi de reconstituer l'histoire de l'Univers et des galaxies qu'il contient. Aujourd'hui, les observatoires terrestres et spatiaux réalisent des images de tout ou partie du ciel dans de nombreux domaines de longueur d'onde. Ces relevés quasi-industriels permettent de constituer des échantillons représentatifs de plusieurs millions de galaxies, jusqu'à des époques cosmiques reculées.

Chaque longueur d'onde fournit des informations différentes sur les propriétés physiques de galaxies. Les observations dans le domaine infrarouge lointain permettent ainsi de sonder l'émission de la poussière froide dans laquelle se forment les étoiles. A cause de l'opacité de l'atmosphère aux photons infrarouges, on ne peut observer que depuis l'espace. Ainsi, depuis le début des années 80, les télescopes infrarouges spatiaux se succèdent permettant de détecter des objets toujours plus faibles. Aujourd'hui, avec *Spitzer* et *Herschel*, il est enfin possible d'observer l'émission infrarouge des galaxies en train de former leurs étoiles dans l'Univers jeune, permettant de mieux comprendre les processus physiques régissant leur évolution.

Mon travail de thèse a consisté à étudier les propriétés statistiques des populations de galaxies infrarouges et leur évolution. Ces études ont permis de contraindre l'histoire de ces objets, et en particulier celle de la formation d'étoiles en leur sein. Les études réalisées précédemment montrent qu'il y a 7 milliards d'années, les étoiles se formaient à un rythme dix fois supérieur. Les observations *Herschel* permettent aujourd'hui de mesurer avec précision cette évolution du taux de formation d'étoiles. Par ailleurs, le rayonnement relique de toutes ces galaxies forme le fond cosmique infrarouge, détecté pour la première fois dans les données du satellite COBE. Cette émission fournit le budget total de photons émis par les processus de formation d'étoiles au cours de l'histoire de l'Univers. L'identification des galaxies responsables de ce fond est donc fondamentale pour comprendre

quand et comment se sont formées les étoiles dans l'Univers.

Dans le premier chapitre, je présenterai les piliers sur lesquels se fonde cette thèse (cadre cosmologique, formation et évolution des galaxies, fond infrarouge, observatoires infrarouges). Dans un second chapitre, je présenterai mon travail sur le comptages des sources infrarouges résolues et les problèmes statistiques qui y sont liés. Puis, dans le troisième chapitre, je montrerai comment, avec la méthode statistique de l'empilement, on peut sonder collectivement l'émission de galaxies faibles non-résolues. Dans le quatrième chapitre, je présenterai une méthode alternative à l'empilement, appelée analyse $P(D)$. Dans le cinquième chapitre, je traiterai des mesures et de l'origine du fond infrarouge. Dans le sixième chapitre, je décrirai le modèle d'évolution des galaxies infrarouges que j'ai développé, afin de reproduire les propriétés statistiques des galaxies et du fond infrarouge. Dans le septième chapitre, je montrerai comment ce modèle peut être utilisé pour interpréter les fluctuations du fond infrarouge. Enfin, je conclurai sur les travaux réalisés et énoncerai les perspectives liées aux thématiques de cette thèse.

Chapitre 1

Contexte

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1.1 Contexte cosmologique

1.1.1 Brève histoire de la cosmologie physique

La cosmologie est la science qui étudie l'Univers en tant que système physique. Elle apparaît au début du XX^{ième} siècle, avec la relativité générale d'Einstein (1916). Cette théorie lie la géométrie de l'Univers (l'espace-temps) et son évolution à son contenu. Elle permet de décrire des Univers en expansion ou en contraction. Cependant, Einstein ajouta une constante cosmologique dans ses équations afin qu'elles puissent décrire un Univers statique plus conforme aux conceptions de son époque.

Une dizaine d'années plus tard, une observation a révolutionné notre conception de l'Univers : Hubble (1929) découvre que les galaxies s'éloignent de nous à une vitesse proportionnelle à leur distance. Ceci suggère que l'Univers est en expansion. Lemaître (1931) montre que ce phénomène se décrit grâce à la relativité générale. De plus, quelques années plus tard, Alpher *et al.* (1948) montrent que l'abondance des différents noyaux atomiques dans l'Univers ne peut s'expliquer que par le passage de celui-ci par une phase chaude et dense, en accord avec le phénomène d'expansion. On parle de nucléosynthèse primordiale. Enfin, la relique du rayonnement de corps noir du jeune Univers chaud est détectée par Penzias et Wilson (1965) sous forme d'un fond cosmologique à 2,7 K. Ces trois observations (l'éloignement des galaxies, la nucléosynthèse primordiale et le fond cosmologique) sont aujourd'hui considérées comme les piliers de la théorie du *Big Bang*, qui décrit un Univers d'abord dense et chaud qui se refroidit ensuite au cours de son expansion.

Plus récemment, l'observation de supernovae lointaines a montré que l'expansion de l'Univers s'accélère (Riess *et al.* (1998)). Ce phénomène suggère l'action d'une énergie de nature inconnue : l'énergie noire. Les observations précises du fond cosmologique (COBE, WMAP...), des distances dans l'Univers (supernovae) et de la structuration des galaxies (grand relevés cosmologiques) permettent aujourd'hui de déterminer avec précision le contenu de l'Univers (Larson *et al.* (2010)) : 72% d'énergie noire, 23% de matière noire et seulement 5% de matière baryonique (ordinaire). Un des défis de la cosmologie dans les années futures sera de comprendre la nature de ces deux premières composantes.

1.1.2 Cadre formel

Cette partie s'inspire de l'article de Hogg (1999) et du cours de cosmologie de Yannick Mellier.

L'Univers relativiste

La cosmologie moderne est construite à partir de la théorie de la relativité générale, des équations d'Einstein et du principe cosmologique. Les deux premiers éléments relient la géométrie de l'espace temps à son contenu en matière-énergie. Le principe cosmologique postule quant à lui que l'Univers est homogène et isotrope.

On peut alors montrer que, dans ce cadre, la géométrie de l'univers est donnée par la métrique de Friedmann-Robertson-Walker (FRW) :

$$ds^2 = c^2 dt^2 - a(t)^2 \left(\frac{dr^2}{1 - kr^2} + r^2 d\theta^2 + r^2 \sin(\theta)^2 d\phi^2 \right) \quad (1.1)$$

où ds est un intervalle infinitésimal d'espace-temps, c la vitesse de la lumière, t le temps, $a(t)$ le facteur décrivant l'expansion de l'Univers, k la constante de courbure, et (r, θ, ϕ) les coordonnées spatiales en polaire. Les mesures du satellite WMAP (Wilkinson Microwave Anisotropy Probe) sont compatibles avec une courbure nulle ($k = -0.011 \pm 0.012$, Spergel *et al.* (2007)), que nous supposons par la suite.

L'équation d'Einstein, quant à elle, relie la géométrie de l'espace-temps à son contenu :

$$R_{\mu\nu} - \frac{1}{2} g_{\mu\nu} R + \Lambda g_{\mu\nu} = \frac{8\pi G}{c^4} T_{\mu\nu}, \quad (1.2)$$

où $R_{\mu\nu}$ est le tenseur de Ricci, R la courbure scalaire, $g_{\mu\nu}$ le tenseur décrivant la métrique, Λ la constante cosmologique, G la constante de gravitation et $T_{\mu\nu}$ le tenseur énergie impulsion. En combinant la métrique FRW (Eq. 1.1) et l'équation d'Einstein (Eq. 1.2), on obtient le système suivant :

$$\ddot{a} = -\frac{4\pi G}{3} \left(\rho + \frac{3P}{c^2} \right) + \frac{\Lambda c^2}{3} a \quad (1.3)$$

$$\dot{a}^2 = \frac{8\pi G}{3} \rho a^2 + \frac{\Lambda c^2}{3} a^2. \quad (1.4)$$

où ρ est la densité et P la pression. On a alors

$$\left(\frac{\dot{a}}{a} \right)^2 = \frac{8\pi G}{3} \rho + \frac{\Lambda c^2}{3}. \quad (1.5)$$

La densité ρ diminue avec l'expansion de l'Univers de la manière suivante :

$$\rho = \rho_0 \left(\frac{a(t_0)}{a(t)} \right)^3 \quad (1.6)$$

où ρ_0 est la densité de matière actuelle¹. On choisit les notations suivant :

$$\Omega_m = \frac{8\pi G}{3H_0^2} \rho_0 \approx 0.27 \quad (1.7)$$

$$\Omega_\Lambda = \frac{\Lambda c^2}{3H_0^2} \approx 0.73 \quad (1.8)$$

où H_0 est la constante de Hubble ($\approx 71 \text{ km.s}^{-1}.\text{Mpc}^{-1}$, Larson *et al.* (2010)). On obtient donc l'équation suivante :

$$\frac{\dot{a}}{a}(t) = H_0 \sqrt{\Omega_m \left(\frac{a(t_0)}{a(t)} \right)^3 + \Omega_\Lambda}. \quad (1.9)$$

Cette équation va nous servir de base pour calculer les distances dans l'Univers en expansion.

1.1.3 Les distances en cosmologie

Notion de décalage vers le rouge

Dans cette métrique, l'univers se dilate au cours du temps en suivant $a(t)$. La longueur d'onde d'un photon va donc varier entre son émission et sa réception. En effet, l'Eq. 1.1 implique que :

$$\lambda_e a(t_e) = \lambda_r a(t_0) \quad (1.10)$$

où t_e est la date de l'émission du photon, t_0 celle de sa réception, λ_e la longueur d'onde à l'émission, et λ_r celle à la réception.

La vitesse de la lumière étant finie, plus un objet est loin de l'observateur et plus il est vu dans le passé. Comme $a(t)$ est une fonction strictement croissante au cours du temps, plus les objets seront lointains et plus leur spectres seront décalés vers le rouge. Comme il y a bijection, le décalage vers le rouge (ou en anglais *redshift*), défini par

$$z = \frac{\lambda_r}{\lambda_e} - 1 = \frac{a(t_0)}{a(t_e)}, \quad (1.11)$$

¹ ρ ne prend ici en compte que la densité de matière. En effet, la densité de rayonnement varie en $(a(t_0)/a(t))^4$. Toutefois, cet effet n'est significatif que dans l'Univers très jeune (avant l'émission du fond cosmologique), et est totalement négligeable par la suite. L'énergie noire est, quant à elle, prise en compte par le second terme de l'Eq. 1.5.

peut donc permettre de désigner à la fois une époque et une distance.

La relation entre le *redshift* z_e et le temps de regard en arrière² t_{lb} à laquelle se situe l'objet observé peut se calculer simplement. D'après Eq. 1.9 et 1.11, on a :

$$dz = -\frac{\dot{a}(t)a(t_0)}{a^2(t)}dt = -\frac{\dot{a}(t)}{a(t)}\frac{a(t_0)}{a(t)}dt = H_0(1+z)\sqrt{(1+z)^3\Omega_m + \Omega_\Lambda}dt. \quad (1.12)$$

t_{lb} est le temps propre que va mettre un photon pour aller de la source à l'observateur. Grâce à l'Eq. 1.12, on obtient une expression simple le reliant à z_{obj} :

$$t_{lb} = \int_{t_e}^{t_0} dt = \int_0^{z_{obj}} \frac{1}{H_0(1+z)\sqrt{(1+z)^3\Omega_m + \Omega_\Lambda}} dz. \quad (1.13)$$

La Fig. 1.1 représente t_{lb} en fonction du *redshift*. On remarque que la relation entre t et z n'est pas linéaire. On note que t_{lb} tend vers 13.7 milliards d'années quand z tend vers l'infini. Ceci correspond au temps écoulé depuis que l'Univers a été infiniment dense ($a \rightarrow 0$). On parle improprement d'âge de l'Univers. En effet, la relativité générale cesse d'être valable pour a très petit, car la notion d'Univers infiniment dense n'a pas vraiment de sens physique.

Distances dans un Univers en expansion

Dans un Univers statique, la distance entre deux objets se définit très simplement. En revanche, dans un Univers en expansion, il existe plusieurs manières de définir la distance entre deux objets. Nous détaillons ici les différentes distances qui sont utilisées dans cette thèse.

La distance comobile (ou propre) est la distance instantanée mesurée à $t = t_0$. Les grandeurs comobiles sont très utiles car elles se conservent au cours de l'expansion. Par exemple, la distance comobile entre deux galaxies est constante au cours du temps si on néglige leurs mouvements propres. Cette distance, notée D_c , se calcule de la manière suivante :

$$D_c = \int_{t_e}^{t_0} c(1+z)dt. \quad (1.14)$$

où t_e est la date correspondant au *redshift* z et t_0 l'époque actuelle. $c \times dt$ est le petit élément de distance physique parcouru par un photon allant de la source à l'observateur à l'époque t . Sa longueur est aujourd'hui $c(1+z)dt$ du fait de l'expansion de l'Univers.

²Traduction en français du terme anglais *lookback time*, qui est bien plus élégant.

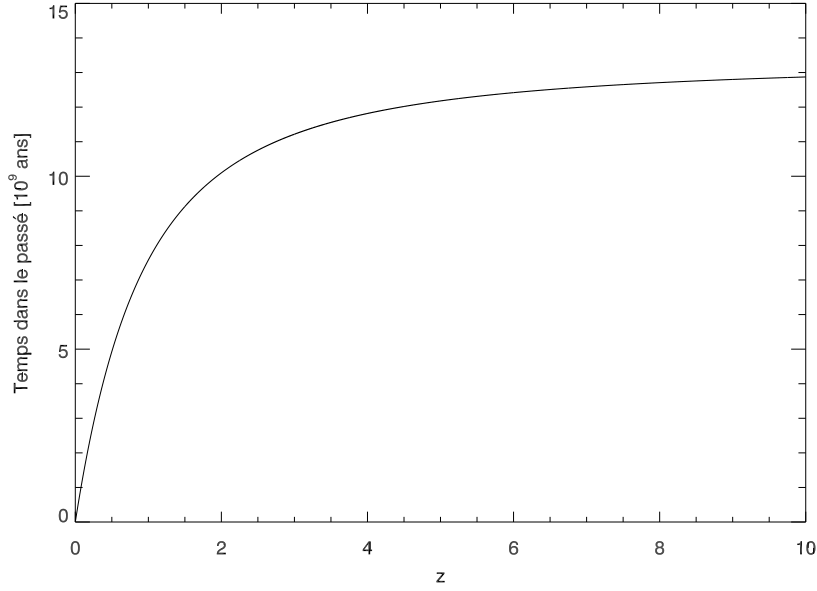


FIGURE 1.1 – Durée dans le passé à laquelle est vue un objet ayant un *redshift* z .

On peut alors appliquer un changement de variable de l'Eq. 1.12 dans l'Eq. 1.14 pour obtenir :

$$D_c = \int_0^z \frac{c}{H_0 E(z)} dz = \int_0^z \frac{c}{H_0 \sqrt{(1+z)^3 \Omega_m + \Omega_\Lambda}} dz. \quad (1.15)$$

On définit la distance diamètre angulaire D_A de façon à vérifier :

$$D_A = \frac{r_p}{\theta} \quad (1.16)$$

où r_p est la taille physique de l'objet considéré et θ le diamètre angulaire observé. Or, la taille comobile d'un objet de diamètre angulaire θ à une distance comobile D_c est simplement θD_c .³ Sa taille physique r_p est donc $\theta D_c (1+z)$. On en déduit

$$D_A = \frac{D_c}{1+z}. \quad (1.17)$$

La distance lumineuse D_L doit vérifier

$$S = \frac{L}{4\pi D_L^2} \quad (1.18)$$

³Ce n'est vrai que dans le cas où $k=0$.

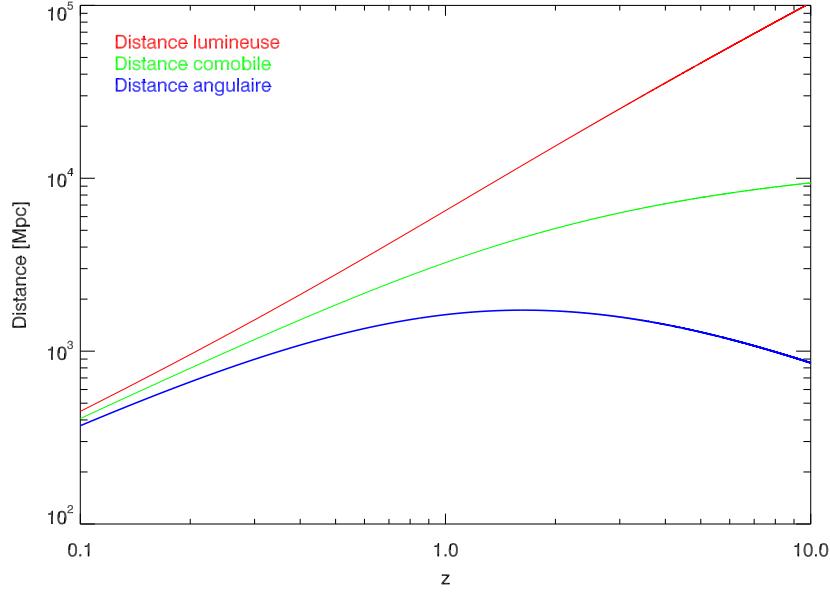


FIGURE 1.2 – Distances lumineuse (rouge), comobile (vert) et diamètre angulaire (bleu) en fonction du *redshift*.

où L est la luminosité, et S le flux. On peut relier cette distance à la distance comobile. L'énergie dE_e émise par une source de luminosité L pendant un instant dt_e vaut Ldt_e . A cause du décalage vers le rouge des photons, l'énergie reçue sera $dE_r = dE_e/(1+z)$.⁴ De même, le temps de réception dt_0 sera multiplié par $1+z$ ($dt_0 = dt_e(1+z)$). Or, l'énergie reçue peut aussi s'écrire

$$dE_r = 4\pi D_C^2 S dt_0, \quad (1.19)$$

d'où,

$$\frac{Ldt_e}{1+z} = 4\pi D_C^2 S dt_0 \quad (1.20)$$

puis,

$$S = \frac{L}{4\pi ((1+z)D_C)^2}. \quad (1.21)$$

En en déduit la relation entre la distance lumineuse et la distance angulaire :

$$D_L = (1+z)D_C. \quad (1.22)$$

Le Fig. 1.2 représente les différentes distances en fonction du *redshift*.

⁴Comme $E = hc/\lambda$, l'effet du décalage vers le rouge sur l'énergie est $E_r = E_e/(1+z)$.

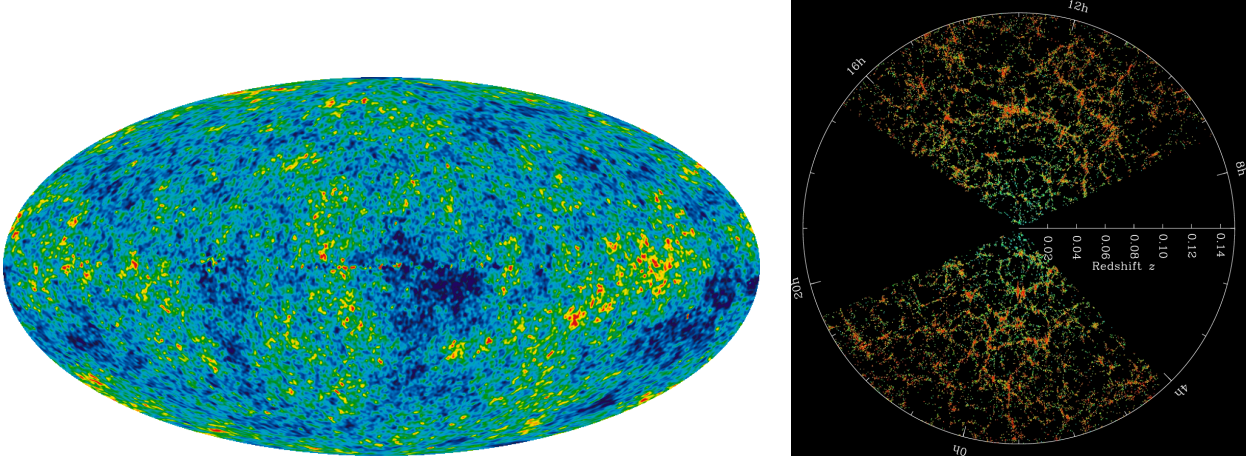


FIGURE 1.3 – A gauche : Anisotropie du fond cosmologique observée par le satellite WMAP (Jarosik *et al.* (2011)). A droite : Distribution spatiale des galaxies dans l’Univers local observé par le SDSS (Blanton et l’équipe SDSS).

Une autre grandeur intéressante pour l’étude des galaxies est le volume comobile sondé entre z et $z+dz$ pour un relevé d’angle solide $d\Omega$. La surface transverse comobile sondée est $((1+z)D_A)^2$. L’Eq. 1.15 donne la longueur comobile sondée sur la ligne de visée. On a donc

$$dV_C = \frac{c(1+z)^2 D_A^2}{H_0 \sqrt{\Omega_M(1+z)^3 + \Omega_\Lambda}} dz d\Omega. \quad (1.23)$$

L’avantage des volumes comobiles est qu’ils suivent l’expansion de l’Univers et que le nombre d’objets par unité de volume est donc conservé.

1.1.4 Formation des grandes structures

Les observations du fond cosmologique (voir Fig. 1.3) montrent que les hétérogénéités de densité dans l’Univers à $z=1100$ ne sont que de l’ordre de 10^{-5} (Smoot *et al.* (1991)). Bien que relativement homogène aux très grandes échelles (>1 Gpc, ce qui justifie les hypothèses effectuées dans la section précédente), l’Univers actuel est hétérogène aux autres échelles. En effet, la matière est distribuée sous forme de filaments séparés par des régions de faible densité (Bond *et al.* (1996)), voir aussi Fig. 1.3). Un défi de la cosmologie actuelle est d’expliquer avec précision comment on passe d’un Univers jeune quasi-homogène à un Univers fortement hétérogène et structuré aujourd’hui.

La formation des grandes structures de l’Univers (amas et super-amas de galaxies) est plutôt bien comprise. Sous l’effet de la gravitation, les surdensités de matière croissent progressivement pour former des halos denses. Ce processus est totalement dominé par

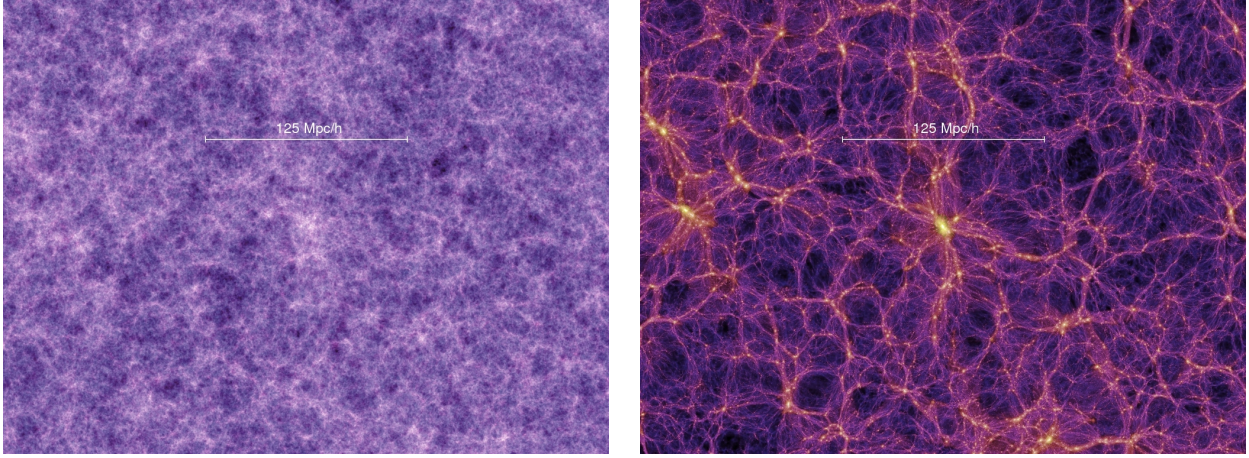


FIGURE 1.4 – Structuration de la matière noire dans l’Univers dans la simulation Millennium à $z = 18$ (gauche) et $z = 0$ (droite) (extrait de Springel *et al.* (2005)).

la matière noire, composée des particules massives n’étant sensibles qu’à la gravitation, qui représente 80% de la masse de matière dans l’Univers⁵. La croissance des perturbations peut se calculer de façon analytique dans le cas linéaire (Press et Schechter (1974)). Toutefois, aux petites échelles (< 10 Mpc) des comportements non-linéaires apparaissent, et il est alors nécessaire d’utiliser de lourdes simulations numériques. Ces grandes simulations de matière noire montrent comment les contrastes de densité augmentent au cours de l’histoire de l’Univers et comment la matière noire se structure en filaments (voire Fig. 1.4 et Springel *et al.* (2005)).

1.1.5 Formation des galaxies

La physique de la formation des galaxies est plus complexe, car elle fait appel à la physique des baryons. Il faut ainsi prendre en compte le refroidissement du gaz par rayonnement, la formation des étoiles, les champs magnétiques... Nous ferons ici un rapide historique de l’avancée de nos conceptions sur la formation des galaxies.

Le premier modèle de formation des galaxies est proposé par Eggen *et al.* (1962), qui prédisent qu’elles se sont formées par un effondrement gravitationnel monolithique du gaz. On parle de scénario *top-down*⁶. Cette théorie a été remise en cause par l’observation de galaxies satellites (Ibata *et al.* (1994)) et de fusions de galaxies massives (Schweizer

⁵En fait, les différents modèles de physique des particules décrivant la matière noire prédisent qu’elle peut interagir avec une très faible probabilité. Toutefois, de telles interactions n’ont jamais été détectées (Ahmed *et al.* (2011)).

⁶haut-bas

(1982)).

En 1978, Searle et Zinn (1978) proposent un scénario de fusion hiérarchique des halos de matière noire dans lesquels se forment les galaxies. Les galaxies massives sont ici le fruit d'un grand nombre de fusions d'objets peu massifs. On parle dans ce cas de scénario *bottom-up*⁷. Ce modèle est en très bon accord avec le comportement observé dans les simulations de matière noire. En revanche, il peine à expliquer le fait que des galaxies elliptiques massives soient observées à haut *redshift* (Zepf (1997)).

On ne peut plus, aujourd'hui, se contenter de ces modèles simples. La physique du gaz dans les halos de matière noire doit absolument être prise en compte. La formation d'étoiles a lieu quand le gaz contenu dans une galaxies parvient à se refroidir et à s'effondrer. Les processus de refroidissement sont fortement affectés par l'environnement intérieur et extérieur de la galaxie. Différents phénomènes en compétition favorisent, ou au contraire atténuent la formation d'étoiles dans les galaxies.

La formation rapide de galaxies massives à grand *redshift* pourrait par exemple s'expliquer par une alimentation en gaz froid allant des filaments vers les halos massifs (Kereš *et al.* (2005)). Ce gaz déjà refroidi permettrait de former très efficacement des étoiles. Une forte alimentation des halos massifs en gaz froid pourrait expliquer la formation très rapide de galaxies elliptiques massives à grand *redshift*.

La fusion de galaxies permet également de déclencher des sursauts de formation d'étoiles. En effet, la fusion provoque de fortes turbulences, qui favorise la formation de nuages de gaz moléculaires, et un fort et court épisode ($\sim 10^8$ ans) de formation d'étoiles. Il faut également noter que la fusion de deux galaxies spirales produit finalement une galaxie elliptique, pauvre en gaz et formant peu d'étoiles (Bournaud *et al.* (2011)). En effet, les fusions ont tendance à éjecter le gaz des galaxies, et les fortes émissions UV des étoiles formées par le sursaut de formation d'étoiles réchauffent le gaz et coupent à long terme la formation d'étoiles.

D'autres phénomènes de rétroaction importants sont dus aux noyaux actifs de galaxies (AGNs⁸). En effet, un trou noir alimenté par un fort flux de matière, chauffe et éjecte le gaz d'une galaxie. Ainsi, l'activité AGN a tendance à couper la formation d'étoiles dans une galaxie en la privant de gaz froid (Sijacki *et al.* (2007)). Il faut toutefois noter que dans certains cas très particuliers les AGNs peuvent favoriser la formation d'étoiles (Elbaz *et al.* (2009)).

⁷de bas en haut

⁸De l'anglais, *Active Galactic Nucleus*

1.2 Les galaxies infrarouges

Les propriétés d'émissions dans l'infrarouge moyen et lointain des galaxies sont liées à la formation d'étoiles en leur sein (Kennicutt (1998)). La mesure des propriétés des galaxies émettant dans l'infrarouge est donc fondamentale pour contraindre quantitativement les scénarios de formation d'étoiles. Nous allons, dans cette section, présenter la physique des galaxies infrarouges, ainsi que l'évolution de leur propriétés statistiques au cours de l'histoire de l'Univers.

1.2.1 Distribution spectrale d'énergie des galaxies

La distribution spectrale d'énergie (SED⁹) des galaxies présente une certaine diversité. La Fig. 1.5 représente quatre spectres de galaxies de l'ultraviolet (UV) jusqu'au domaine millimétrique. Ces SED présentent certains points communs, mais aussi des différences importantes.

Toutes les galaxies présentent une forte coupure à 91 nm, appelée coupure Lyman (Steidel *et al.* (1996)). Elle correspond à l'absorption des photons par l'hydrogène atomique au niveau quantique fondamental $n=1$. Une seconde coupure autour de $0.4 \mu\text{m}$, appelée coupure Balmer correspond quant à elle aux transitions à partir du niveau quantique $n=2$ (Baker et Menzel (1938)). Le spectre présente un maximum vers $1.6 \mu\text{m}$, dû au fait que l'émission stellaire est moins absorbée dans l'infrarouge (Sawicki (2002)). Au delà, le spectre est dominé par l'émission de la poussière interstellaire. Cette émission est caractérisée par des bandes d'émissions entre 8 et $20 \mu\text{m}$, ainsi que d'une émission thermique ayant un maximum proche de $100 \mu\text{m}$ (Desert *et al.* (1990)).

Il existe en revanche de fortes disparités dans le rapport entre optique et infrarouge. En effet, le rapport optique sur infrarouge est de l'ordre de 10 pour une galaxie elliptique, alors qu'il est de l'ordre de 0.1 pour une galaxie à flambée de formation d'étoiles (ou *starburst*). Cette forte différence s'explique par la nature différente de ces deux types d'objets. Une galaxie elliptique ne contient quasiment pas de gaz, et ne forme donc pas d'étoile. En revanche, une galaxie de type *starburst* contient beaucoup de gaz et forme plus de 5 masses solaires d'étoiles par ans. L'émission infrarouge des galaxies trace donc la formation d'étoiles en leur sein (Lagache *et al.* (2005)).

1.2.2 Origine physique des émissions infrarouges

Lorsque des étoiles sont formées, la distribution en masse de celles-ci est décrite par la fonction de masse initiale (IMF). La masse stellaire est dominée par des étoiles de faibles

⁹De l'anglais, *Spectral Energy Distribution*

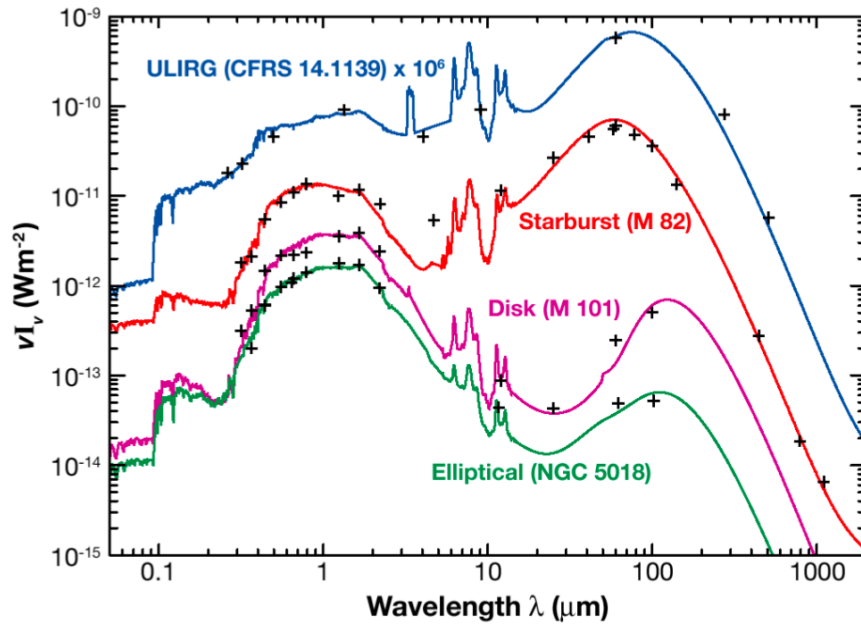


FIGURE 1.5 – Distributions spectrales d'énergie de différentes galaxies. Extrait de Lagache *et al.* (2005).

masses ayant une longue durée de vie (plusieurs milliards d'année). Ces étoiles sont en général assez froides et émettent dans le rouge et l'infrarouge proche. En revanche, comme la luminosité est proportionnelle à la masse à la puissance 3.6 (Salaris et Cassisi (2005)), l'émission totale est dans un premier temps dominée par les étoiles de fortes masses ayant une durée de vie courte (moins d'un milliards d'années). Ces étoiles émettent principalement dans l'UV et le bleu. Ainsi, une galaxie venant de former ses étoiles est bleue, puis rouge quand ses étoiles massives meurent (Bruzual et Charlot (2003)).

La SED d'une galaxie n'est toutefois pas la somme des SED de ses étoiles. En effet, le gaz et la poussière des galaxies absorbent le rayonnement des étoiles. Cette absorption est d'autant plus efficace que la longueur d'onde est courte (Mathis (1990)). Ainsi, la majeure partie de l'UV est absorbée, alors que les photons infrarouges s'échappent presque tous des galaxies. Les photons UV absorbés chauffent le milieu interstellaire qui va alors rayonner dans l'infrarouge moyen et lointain. Ce phénomène permet d'expliquer pourquoi l'infrarouge trace la formation d'étoiles. En effet, une galaxie formant beaucoup d'étoiles aura un grand nombre d'étoiles jeunes massives. Ces étoiles émettent principalement des photons UV, qui vont par la suite être transformés en photons infrarouges par les cocons de poussières dans lesquels se forment les étoiles (Kennicutt (1998)).

Il existe une relation empirique entre le taux de formation d'étoiles dans une galaxie

et sa luminosité bolométrique entre 8 et 1000 μm (appelée par la suite luminosité infrarouge) :

$$\frac{SFR}{1M_{\odot}/\text{ans}} = 1.7 \times 10^{-10} \frac{L_{IR}}{1L_{\odot}}, \quad (1.24)$$

où SFR^{10} est le taux de formation d'étoile et L_{IR} (Kennicutt (1998)). Cette relation a été calibrée à partir d'un échantillon de galaxies locales, en comparant différents estimateurs du taux de formation d'étoiles (continuum UV, $H\alpha$, OII). Il existe des incertitudes de l'ordre de 30% sur la calibration de cette relation.

La forme de la SED en infrarouge est expliquée par le modèle de Desert *et al.* (1990). Il considère trois composantes distinctes. Les PAHs¹¹ sont des cycles carbonés d'une taille de l'ordre du nanomètre. Du fait de leur petite taille, leur émission n'est pas thermique. Ils rayonnent dans des bandes d'émissions dans l'infrarouge moyen, correspondant à leur modes vibrationnels. Ce processus domine l'émission des galaxies entre 5 et 20 μm . Les VSGs¹² sont des petits grains carbonés de l'ordre de 10 μm . Ils ont une émission de type thermique. Néanmoins, du fait de leur taille modeste, leur chauffage par les photons UV est irrégulier à cause du bruit de Poisson. Leur température, et donc leur spectre d'émission, varie au cours du temps. Ils dominent la SED des galaxies entre 20 et 60 μm . Les BGs¹³ sont des grains silicatés amorphes ayant une taille comprise entre la dizaine et la centaine de microns. Ces grains sont à l'équilibre thermique avec le rayonnement à une température de l'ordre de 25 K. L'émission des grains est souvent modélisée par la loi suivante :

$$L_{\nu} = \nu^{\beta} B(\nu, T) \quad (1.25)$$

où L_{ν} est la densité de luminosité à une fréquence ν , β est un paramètre appelé émissivité, et $B(\nu, T)$ le spectre d'un corps noir de température T. La Fig. 1.6 illustre la contribution des différentes composantes au spectre infrarouge d'une galaxie. Cette loi simple, qui sera utilisée dans cette thèse, n'est toutefois qu'une approximation. D'une part, β peut varier en fonction de la fréquence (?). D'autre part, la température des grains varie d'un point à l'autre d'une galaxie. Il faudrait donc en toute rigueur utiliser une distribution de température.

Le mécanisme d'émission infrarouge des AGNs est relativement proche. Le chauffage UV de la poussière est ici dû au rayonnement thermique du disque d'accrétion à 10^5 K du trou noir central. L'environnement est assez différent de celui du milieu interstellaire, ce qui aboutit à une SED différente (Stern *et al.* (2005)). Il faut noter qu'il est fréquent que l'émission infrarouge d'une galaxie soit la somme d'une composante AGN et *starburst*

¹⁰De l'anglais, *Star Formation Rate*.

¹¹De l'anglais, *Polycyclic Aromatic Hydrocarbon*

¹²De l'anglais, *Very Small Grains*

¹³De l'anglais, *Big Grains*

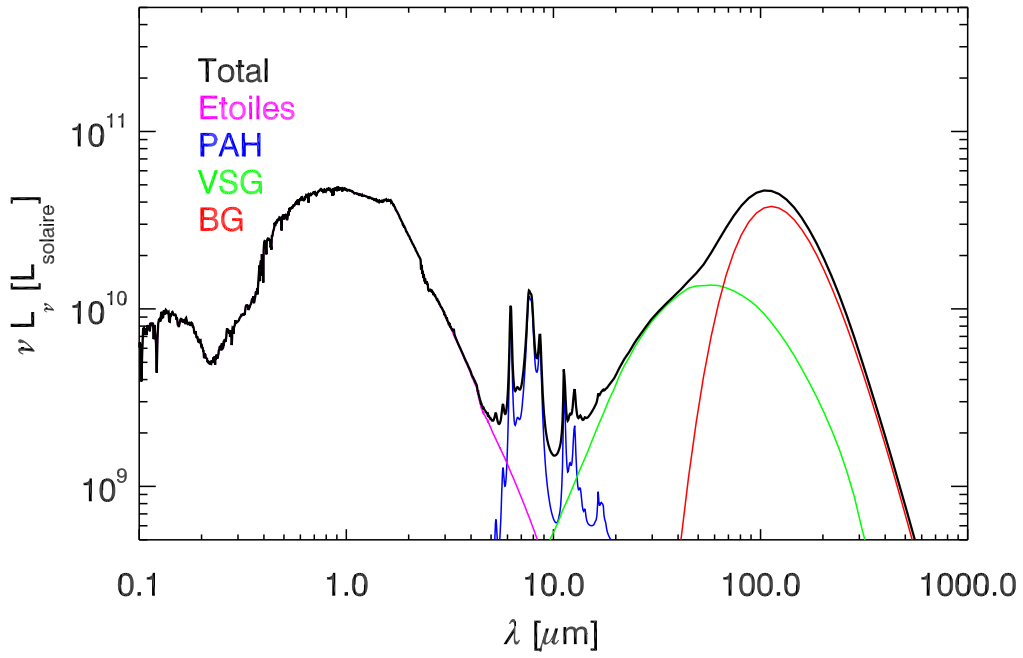


FIGURE 1.6 – Spectre d’une galaxie infrarouge typique. Les différentes composantes sont représentées en couleur. Ce spectre a été généré par *SpectrumMaker* et GALICS (voir rapport de stage de Morgane Cousin).

(e.g. Le Floc'h *et al.* (2007)).

1.2.3 Evolution des galaxies infrarouges

Dans l'Univers local, l'émission infrarouge des galaxies est dominée par des objets ayant une luminosité de l'ordre de $10^{10} L_{\odot}$ (Saunders *et al.* (1990)). Ces galaxies sont en majorité des galaxies spirales semblables à la notre. On qualifie par la suite de normales les galaxies ayant une luminosité infrarouge inférieure à $10^{11} L_{\odot}$. Bien qu'elles soient rares (environ 10% de la luminosité infrarouge totale à $z=0$ (Le Floc'h *et al.* (2005)), il existe dans l'Univers local des galaxies ayant une luminosité infrarouge supérieure. On parle alors de LIRGs¹⁴ ($10^{11} L_{\odot} < L_{IR} < 10^{12} L_{\odot}$). Ces objets sont en général le fruit d'interactions entre galaxies. Il existe une catégorie encore plus lumineuse appelée ULIRG¹⁵ ($10^{12} L_{\odot} < L_{IR} < 10^{13} L_{\odot}$). Ces objets sont en majorité dominés par l'émission infrarouge d'un AGN central, ou le fruit de fusions majeures (Imanishi (2009)).

Ces propriétés évoluent rapidement avec le *redshift*. On peut par exemple s'intéresser à l'évolution de la fonction de luminosité (LF¹⁶) infrarouge. Cette fonction décrit la distribution en luminosité des galaxies infrarouges. La Fig. 1.7 (gauche) montre cette fonction à différents *redshifts*. Entre $z=0$ et $z=1$, la fonction de luminosité se décale vers les fortes luminosités, sans évoluer en densité. Ceci indique que les galaxies étaient globalement plus lumineuses en infrarouge dans le passé. Après $z=1$, la luminosité continue d'augmenter, mais la densité commence à diminuer. A grand *redshift* ($z>2$), on constate la présence de quelques HyLIRG ($L_{IR} > 10^{13} L_{\odot}$). La nature des ULIRGs évolue également fortement avec le *redshift*. Alors que ces sources sont en majorité des AGNs dans l'Univers local, ce sont de très forts *starburst* à $z=2$ (Fadda *et al.* (2010)).

On peut s'intéresser également à l'évolution de la densité de luminosité infrarouge (voire Fig. 1.7 droite). Si on soustrait la contribution des AGNs, elle est proportionnelle au taux de formation d'étoiles (Kennicutt (1998)), augmente fortement entre $z=0$ et $z=1$, puis décroît légèrement avec le *redshift* (Caputi *et al.* (2007)). Alors que les galaxies normales dominent dans l'Univers local, les LIRGs dominent l'émission infrarouge à $z=1$. A $z=2$, les ULIRGs semblent dominer le fond. Néanmoins, les mesures sont encore peu précises. Cette évolution très rapide suggère que les conditions physiques typiques dans les galaxies formant des étoiles sont très différentes aujourd'hui et dans l'Univers jeune.

¹⁴Luminous Infrared Galaxies

¹⁵Ultra Luminous Infrared Galaxies

¹⁶De l'anglais, Luminosity Function

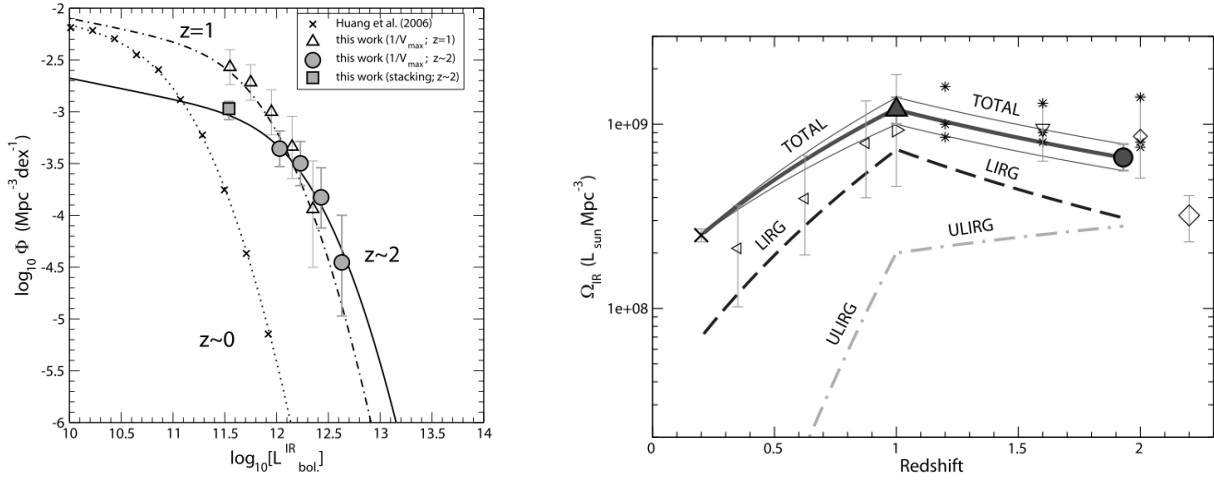


FIGURE 1.7 – (A gauche) Fonction de luminosité bolométrique infrarouge à $z=0$, $z=1$ et $z=2$ extraite de Caputi *et al.* (2007). (A Droite) Densité de luminosité bolométrique infrarouge en fonction du *redshift* extraite de Caputi *et al.* (2007).

1.2.4 Problématiques

L'évolution des galaxies infrarouges pose de nombreuses problématiques. Nous en citons ici quelques-unes.

- Le spectre des galaxies infrarouges évolue-t-il avec le *redshift* ?
- L'infrarouge est-il un bon estimateur du taux de formation d'étoile à grand *redshift* ?
- Comment les AGNs contribuent-ils à l'émission infrarouge des galaxies ? Comment cette contribution évolue-t-elle ?
- Comment évolue la formation d'étoiles à grand *redshift* ?
- Pourquoi la formation d'étoiles diminue-t-elle entre $z=1$ et $z=0$?
- Pourquoi les ULIRGs sont-elles aussi nombreuses à $z>2$?

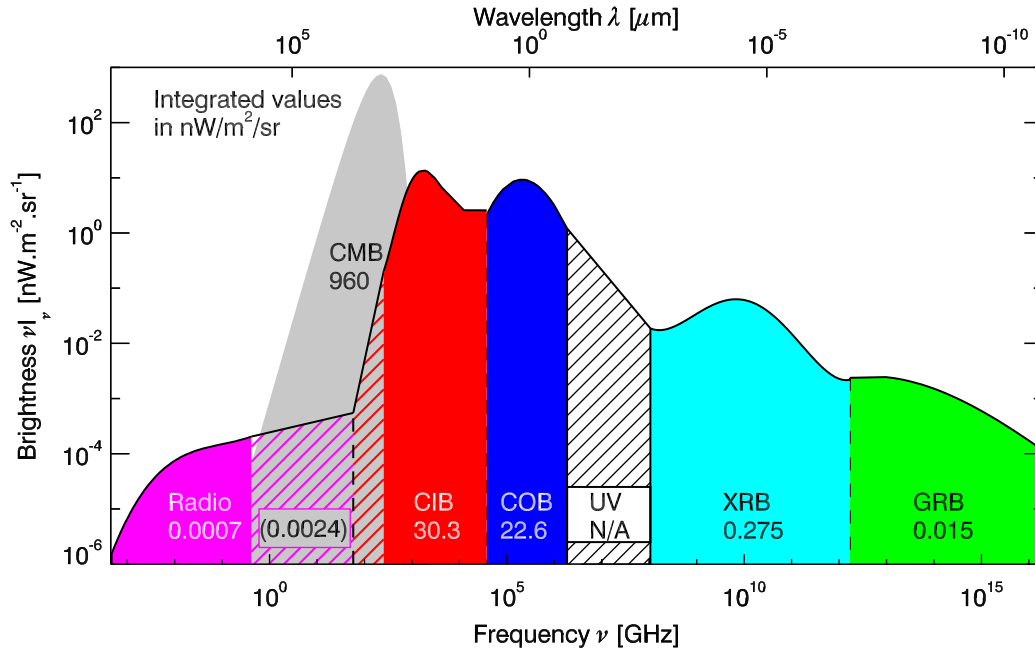


FIGURE 1.8 – Distribution spectrale d'énergie du fond de rayonnement extragalactique. Extrait de Dole et Béthermin en préparation.

1.3 Le fond extragalactique infrarouge

L'émission intégrée de toutes les galaxies infrarouges forme le fond extragalactique infrarouge. Sa distribution spectrale d'énergie donne le budget total de photons infrarouges émis par les processus de formation d'étoiles. Ses anisotropies nous renseignent sur la distribution spatiale des galaxies dans les halos de matière noire.

1.3.1 Le fond de rayonnement extragalactique

Le fond de rayonnement extragalactique (EBL¹⁷) est le rayonnement qui serait reçu par un observateur à l'extérieur de notre Galaxie. Ce rayonnement est la relique de tous les processus radiatifs ayant eu lieu dans l'Univers. La distribution spectrale d'énergie de ce fond est tracée Fig. 1.8. Elle comporte plusieurs composantes que nous allons traiter séparément.

¹⁷De l'anglais, *Extragalactic Background Light*

Fond cosmique micro-ondes

Le fond cosmique micro-onde (CMB¹⁸) est le rayonnement de corps noir émis par l'Univers jeune et chaud (3000 K à $z=1100$) lors du découplage matière-rayonnement. Ce rayonnement s'est aujourd'hui refroidi à 2.72548 ± 0.00057 K (Fixsen (2009)) à cause de l'expansion de l'Univers¹⁹. Le CMB représente 95% du fond extragalactique. Les fluctuations de températures sont de l'ordre de 10^{-5} .

Fond infrarouge

Le fond extragalactique infrarouge (CIB²⁰) se situe entre 8 et 1000 μm , et pique vers 150 μm . Il représente environ 2.5% de l'EBL (Dole *et al.* (2006)), et est essentiellement dû à l'émission de la poussière des galaxies formant des étoiles (Lagache *et al.* (2005)). Les poussières chauffées par les noyaux actifs de galaxies contribuent quand à elles à environ 15% du fond (Jauzac *et al.* (2011)). Ses fluctuations sont de l'ordre de 15% (Planck Collaboration *et al.* (2011)). L'origine de ce fond est une des problématiques principales de cette thèse.

Fond optique

Le fond optique (COB²¹) contient approximativement la même énergie que le fond infrarouge ($\sim 25 \text{ nW.m}^{-2}.\text{sr}^{-1}$, Dole *et al.* (2006)). Il s'étend de l'UV à l'infrarouge proche et est émis principalement par les étoiles, et est maximum autour de 1.5 μm (Keenan *et al.* (2010)). Dans l'infrarouge proche, une contribution non-négligeable pourrait être due aux étoiles de populations III (Fernandez *et al.* (2010)).

Fond X

Le fond X (CXB²²) ne représente qu'environ 0.5% de l'EBL hors CMB (Dole (2010)), est maximum autour de 30 keV, et émis principalement par les AGNs (Gilli *et al.* (2007)).

Fond γ

Le fond γ (CGRB²³) représente quant à lui 0.03% du fond extragalactique hors CMB (Dole (2010)), et présente un maximum pour une énergie de 1 MeV. Ce fond ne peut s'expliquer qu'en partie par l'émission des noyaux actifs de galaxies (Abdo *et al.* (2010)).

¹⁸De l'anglais, *Cosmic Microwave Background*

¹⁹On peut montrer le rayonnement d'un corps noir de température T à un *redshift* z est observée à une température $T/(1+z)$ aujourd'hui.

²⁰De l'anglais, *Cosmic Infrared Background*

²¹De l'anglais, *Cosmic Optical Background*

²²De l'anglais, *Cosmic X-ray Background*

²³De l'anglais, *Cosmic Gamma-ray Background*

Une contribution non-négligeable pourrait être dues aux galaxies à flambées de formation d'étoiles, dont les résidus de supernova émettent en γ (Fields *et al.* (2010), Makiya *et al.* (2011)).

Fond radio

Le fond radio (CRB²⁴) trace l'émission des sources radios dans l'Univers (de Zotti *et al.* (2005)). Il ne contient qu'un dix millionième du fond extragalactique total hors CMB (Dole (2010)).

1.3.2 Les mesures du fond infrarouge

Nous allons par la suite nous focaliser sur le fond infrarouge. Nous nous proposons ici de faire une synthèse des différentes méthodes de mesure. Cette revue se base sur l'article de conférence de Béthermin et Dole (2011).

Mesures absolues

Des mesures directes du fond infrarouge peuvent être réalisées grâce à des photomètres absolus. Ces mesures sont limitées par la précision de la modélisation et de la soustraction des avant-plans, qui sont l'émission zodiacale (Kelsall *et al.* (1998)) et les cirrus galactiques (Lagache *et al.* (2000)). La lumière zodiacale est l'émission thermique de la poussière interplanétaire. Autour de $20 \mu\text{m}$, elle domine d'un facteur 3 le fond infrarouge (Matsuura *et al.* (2010)). La précision de sa soustraction est la principale limite de ce type de mesure. Les cirrus galactiques sont, quant à eux, des nuages de poussières diffus dans notre Galaxie. Cette émission est de l'ordre de grandeur du CIB dans les régions peu contaminées. Leur soustraction peut s'effectuer grâce à l'information fournie par les données à 21 cm^{25} (Pénin *et al.* (2011b)). Une synthèse des mesures absolues est faite Table 1.1 et Fig. 1.9 (points en bleu).

Limites inférieures à partir des comptages de sources résolues

Dans l'infrarouge moyen, la sensibilité et la résolution angulaire des instruments permet de résoudre la majeure partie du fond infrarouge en sources individuelles. Leur émission totale fournit des limites inférieures robustes sur la valeur du fond. La fraction ainsi résolue est de l'ordre de 80% (Béthermin *et al.* (2010a)). Dans l'infrarouge lointain, la résolution angulaire des instruments est plus faible et la fraction du fond résolue en sources décroît (Dole *et al.* (2003)). Par exemple, *Herschel* ne résout que 15% du fond à $250 \mu\text{m}$

²⁴De l'anglais, *Cosmic Radio Background*

²⁵Cette raie correspond à une transition hyperfine de l'atome d'hydrogène.

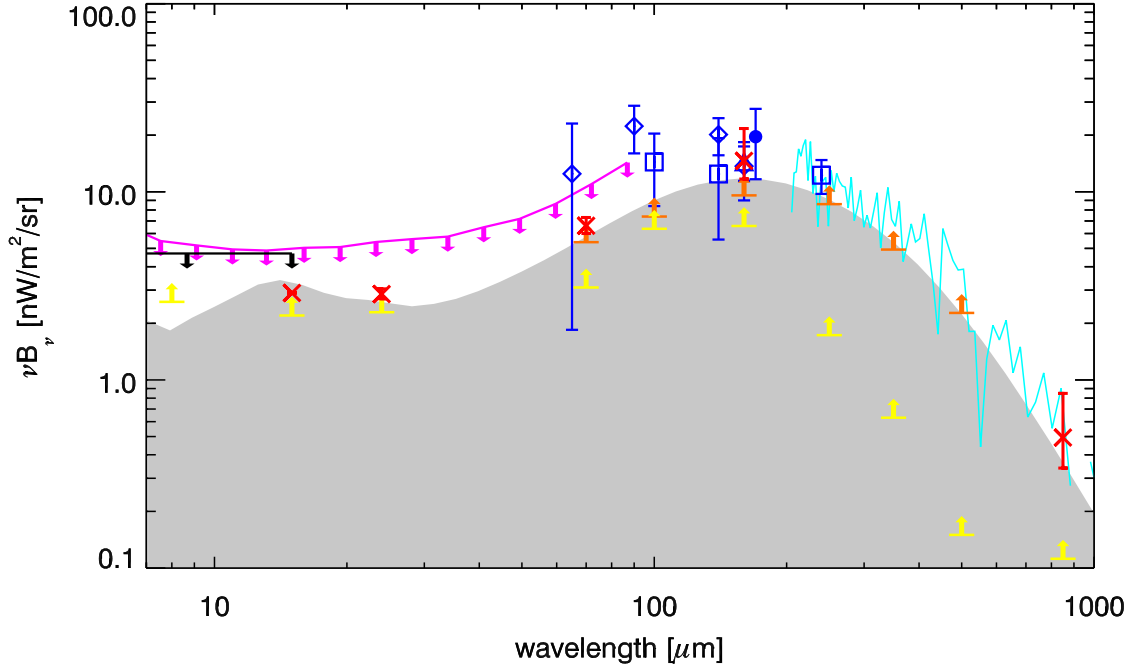


FIGURE 1.9 – SED du fond infrarouge. *Flèches jaunes* : Limites inférieures provenant des comptages de sources résolues à 8 μm (Fazio *et al.* (2004a)), 15 μm (Teplitz *et al.* (2010)), 24 μm , 70 μm (Béthermin *et al.* (2010a)), 100 μm , 160 μm (Berta *et al.* (2010)), 250 μm , 350 μm and 500 μm (Oliver *et al.* (2010)) et 850 μm (Coppin *et al.* (2006)). *Flèches oranges* : Limites inférieures provenant du stacking à 70 μm (Béthermin *et al.* (2010a)), 100 μm , 160 μm (Berta *et al.* (2010)), 250 μm , 350 μm and 500 μm (Marsden *et al.* (2009)). *Croix rouges* : Contribution totale extrapolée des galaxies au fond infrarouge à 15 μm (Teplitz *et al.* (2010)), 24 μm , 70 μm , 160 μm (Béthermin *et al.* (2010a)) et 850 μm (Zemcov *et al.* (2010)). *Carrés bleus* : Mesures absolue de DIRBE (Lagache *et al.* (2000)). *Losanges bleus* : Mesures absolues de AKARI (Matsuura *et al.* (2010)). *Triangle bleu* : Mesure absolue de MIPS à 160 μm (Pénin *et al.* (2011b)). *Rond bleu* : Mesure absolue avec ISOPHOT à 170 μm (Juvela *et al.* (2009)). *Ligne continue cyan* : Spectre du CIB obtenu avec FIRAS (Lagache *et al.* (2000)). *Flèches noires* : Limites supérieures provenant de l'opacité de l'Univers aux photons ayant une énergie de l'ordre du TeV (Renault *et al.* (2001)). *Flèches violette* : Autres limites supérieurs fourni par les hautes énergies (Mazin et Raue (2007)). *Zone grisée* : Fond infrarouge prédit par mon modèle (Béthermin *et al.* (2011)). Extrait de Béthermin et Dole (2011).

(Oliver *et al.* (2010)) malgré son miroir de 3.5 m de diamètre. Au-delà de 850 μm , l'atmosphère devient suffisamment transparent pour effectuer des mesures au sol avec des instruments de grands diamètres. Ceci permet de résoudre environ 20 à 30% du fond (Coppin *et al.* (2006)). Une synthèse de ces limites est réalisée Table 1.1 et Fig. 1.9 (points en jaune). Des comptages plus profonds peuvent être estimés grâce au lentillage gravitationnel provoqué par des amas de galaxies proches (Altieri *et al.* (2010), Zemcov *et al.* (2010)). Néanmoins, la correction des effets d'amplification de la lentille pour retrouver les comptages initiaux est difficile, et les champs utilisés sont très petits et donc soumis à une forte variance d'échantillon.

Limites inférieures par stacking

Dans l'intervalle 200-800 μm , les sources faibles responsables du fond infrarouge ne peuvent être résolues à cause de la résolution angulaire limitée des instruments actuels. Ces sources sont toutefois détectées par les relevés profonds à 24 μm . Leur signal collectif peut être mesuré à grande longueur d'onde grâce à la méthode de l'empilement (voir Chap. 3), qui fournit des limites inférieures très proches du fond total estimé. Cette méthode permet également d'estimer les comptages de galaxies en dessous du seuil de détection individuel. Les Table 1.1 et Fig. 1.9 (points en orange) synthétisent ces mesures. En extrapolant la pente des comptages à bas flux, on peut également produire une estimation de la contribution totale des galaxies au fond (Béthermin *et al.* (2010a), et points en rouge).

Limites supérieures grâce à l'opacité de l'Univers aux photons ayant une énergie de l'ordre du TeV

Deux photons peuvent interagir si l'énergie au centre de masse est suffisante pour produire une paire électron-positron. Les photons à hautes énergies peuvent donc être absorbés par collision avec ceux du fond infrarouge. Cette absorption est détectée sous forme d'une coupure dans le spectre à hautes énergies des blazars. Une analyse de ces coupures permet de produire des limites supérieures sur le fond infrarouge (Mazin et Raue (2007)). Une synthèse de ces limites est faite Table 1.1 et Fig. 1.9 (points en violet et noir).

1.3.3 Fond extragalactique et bilans d'énergie

Cette partie s'inspire en partie du cours de M2 de David Elbaz.

Energie rayonnée par les étoiles au cours de l'histoire de l'Univers

L'énergie rayonnée par les étoiles peut-être estimée à partir de la fraction d'hélium et de métaux produit au cours de l'histoire de l'Univers. Alors que la fraction en masse d'Hélium primordial est $Y_0 = 24.2 \pm 0.2\%$ (Izotov et Thuan (2004)), elle passe à $Y = 27.5\%$

Longueur d'onde μm	Référence	Niveau du CIB $\text{nW.m}^{-2}.\text{sr}^{-1}$	Instrument
Mesures absolues			
65	Matsuura et al. (2010)	$12.5 \pm 1.4 \pm 9.2$	AKARI
90	Matsuura et al. (2010)	$22.3 \pm 1.7 \pm 4.7$	AKARI
100	Lagache et al. (2000)	14.4 ± 6.0	DIRBE
140	Lagache et al. (2000)	12.4 ± 6.9	DIRBE
140	Matsuura et al. (2010)	$20.1 \pm 3.4 \pm 1.1$	AKARI
160	Matsuura et al. (2010)	$13.7 \pm 3.9 \pm 40.8$	AKARI
160	Pénin et al. (2011)	14.43 ± 3	<i>Spitzer</i> /MIPS
170	Juvela et al. (2009)	$19.6 \pm 5.8 \pm 5.5$	ISOPHOT
240	Lagache et al. (2000)	12.3 ± 2.5	DIRBE
200-1000	Lagache et al. (2000)	see figure	FIRAS
Limites inférieures obtenue grâce aux sources résolues			
8	Fazio et al. (2004)	2.6	<i>Spitzer</i> /IRAC
15	Teplitz et al. (2010)	2.2 ± 0.2	<i>Spitzer</i> /IRS
24	Béthermin et al. (2010)	2.29 ± 0.09	<i>Spitzer</i> /MIPS
70	Béthermin et al. (2010)	3.1 ± 0.2	<i>Spitzer</i> /MIPS
100	Berta et al. (2010)	6.33 ± 1.67	<i>Herschel</i> /PACS
160	Berta et al. (2010)	6.58 ± 1.62	<i>Herschel</i> /PACS
250	Oliver et al. (2010)	1.73 ± 0.33	<i>Herschel</i> /SPIRE
350	Oliver et al. (2010)	0.63 ± 0.18	<i>Herschel</i> /SPIRE
500	Oliver et al. (2010)	0.15 ± 0.07	<i>Herschel</i> /SPIRE
850	Coppin et al. (2008)	$0.11^{+0.05}_{-0.04}$	SCUBA
Limites inférieures obtenue grâce au stacking			
70	Béthermin et al. (2010)	5.4 ± 0.4	<i>Spitzer</i> /MIPS
100	Berta et al. (2010)	7.4 ± 0.5	<i>Herschel</i> /PACS
160	Berta et al. (2010)	9.6 ± 0.7	<i>Herschel</i> /PACS
250	Marsden et al. (2009)	8.6 ± 0.6	BLAST
350	Marsden et al. (2009)	4.9 ± 0.3	BLAST
500	Marsden et al. (2009)	2.3 ± 0.2	BLAST
Contribution totale extrapolée des galaxies au CIB			
24	Béthermin et al. (2010)	$2.86^{+0.19}_{-0.16}$	<i>Spitzer</i> /MIPS
70	Béthermin et al. (2010)	$6.6^{+0.7}_{-0.6}$	<i>Spitzer</i> /MIPS
160	Béthermin et al. (2010)	$14.6^{+7.1}_{-2.9}$	<i>Spitzer</i> /MIPS
850	Zemcov et al. (2010)	$0.34-0.85$	SCUBA
Limites supérieurs provenant des hautes énergies			
5-15	Renault et al. (2001)	4.7	CAT & HEGRA
1-90	Mazin&Raue (2007)	5-40	Collection of TeV data

TABLE 1.1 – Synthèse des mesures du fond infrarouge. Extrait de Béthermin et Dole (2011)

dans le système solaire (Pagel (1998)). On a donc $\Delta Y = 3.3\%$ d'hélium non primordial dans les galaxies. Alors qu'ils ne sont pas formés dans l'Univers primordial, les métaux²⁶ représentent $Z_{\odot} = 1.4\%$ dans le voisinage du système solaire (Przybilla *et al.* (2008)). La nucléosynthèse stellaire produit donc $\Delta Y/Z = 2.35$ masse d'hélium par masse de métal formé. On peut ensuite calculer l'énergie dégagée pour la formation d'un kg de métal :

$$\epsilon_{nucl} = \frac{\rho_{m\acute{e}tal}}{m_p} \left(E_{l,m\acute{e}tal} + \frac{\Delta Y}{Z} E_{l,He} \right) = \frac{\rho_{m\acute{e}tal}}{1 \text{ kg/m}^3} \times 1.4 \times 10^{28} \text{ MeV.m}^{-3} \quad (1.26)$$

$$= \frac{\rho_{m\acute{e}tal}}{1 \text{ kg/m}^3} \times 2.24 \times 10^{15} \text{ J.m}^{-3}, \quad (1.27)$$

où ϵ_{nucl} est la densité d'énergie due à la nucléosynthèse primordiale, ρ_b la masse volumique de métaux, m_p la masse du proton, Z la métallicité, et $E_{l,m\acute{e}tal}$ l'énergie de liaison par nucléon pour les métaux. On a pris $E_{l,He} = 7 \text{ MeV/nucléons}$, $E_{l,m\acute{e}tal} = 8 \text{ MeV/nucléons}$ ²⁷.

La densité de métaux n'est pas la même dans les galaxies elliptiques, spirales et le milieu inter-galactique. On suppose que la métallicité dans les galaxies spirales vaut $Z_d = Z_{\odot}$. Dans les galaxies elliptiques, on prend arbitrairement $Z_b = 2 \times Z_{\odot}$ (cette valeur est plus élevée car elles ont transformé tout leur gaz en étoiles). Quant à la métallicité intergalactique (qui devrait être plus faible que dans les galaxies), on la fixe arbitrairement à $Z_{ig} = 0.3 \times Z_{\odot}$. On prends également $\Omega_d = 0.00055$, $\Omega_b = 0.0015$, et $\Omega_{ig} = 0.04$ (Fukugita et Peebles (2004)). On a alors

$$\epsilon_{nucl} = Z_d \rho_d + Z_b \rho_b + Z_{ig} \rho_{ig} = 2.65 \times 10^{-30} \text{ kg.m}^{-3}, \quad (1.28)$$

où ρ_i est calculé grâce à la formule

$$\rho = \frac{3H_0^2}{8\pi G} \Omega_i. \quad (1.29)$$

On en déduit, grâce à Eq. 1.26, l'énergie rayonnée par la nucléosynthèse est $6.0 \times 10^{-15} \text{ J.m}^{-3}$.

Energie rayonnée par accréation dans les trous noirs super-massif

Les trous noirs super-massifs au centre des galaxies rayonnent également lorsqu'ils accrètent de la matière. La conversion masse-énergie a une efficacité de l'ordre de $\eta_{AGN} = 6\%$ pour un trou noir de Schwarzschild (1916). La densité de matière contenue dans les trous noirs super-massif est de l'ordre $\rho_{AGN} = 3.8 \times 10^{-32} \text{ kg.m}^{-3}$ (Fukugita et Peebles (2004)). On en déduit donc la densité d'énergie due aux noyaux actifs de galaxies :

$$\epsilon_{AGN} = \eta_{AGN} \rho_{AGN} = 2 \times 10^{-16} \text{ J.m}^{-3}. \quad (1.30)$$

²⁶Désigne en astrophysique tous les éléments plus lourd que l'hélium.

²⁷Valeur moyenne pour les différents métaux présents dans le système solaire.

La contribution des AGNs à la densité de rayonnement ne représente donc que 3.3% de la contribution stellaire, et est donc négligeable. Cette estimation peut être comparée avec les 6% de Dominguez *et al.* (2010).

Estimation du fond extragalactique

La densité d'énergie due aux processus stellaires et AGNs est donc $\epsilon_{tot} = 6.2 \times 10^{-15} \text{ J.m}^{-3}$. On peut en déduire le fond extragalactique (hors CMB) grâce à :

$$B = \frac{c}{4\pi} \epsilon_{tot} = 148 \text{ nW.m}^{-2}.\text{sr}^{-1}. \quad (1.31)$$

Cette valeur est élevée par rapport aux observations ($58.2 \text{ nW.m}^{-2}.\text{sr}^{-1}$ selon Dole (2010) et $68.2 \text{ nW.m}^{-2}.\text{sr}^{-1}$ selon Dominguez *et al.* (2010)). Toutefois, si on considère que le rayonnement a été émis à $z=1$ (voir par exemple ?) et Béthermin *et al.* (2011)), il faut alors diviser ce résultat par $(1+z)$. On obtient alors $\sim 74 \text{ nW.m}^{-2}.\text{sr}^{-1}$. Cette valeur est complètement compatible avec les observations étant donné les larges incertitudes sur le contenu en métaux de l'Univers.

Fond infrarouge et formation d'étoiles

Le fond infrarouge permet d'accéder à la masse d'étoiles formées au cours de l'histoire de l'Univers. Si on suppose le CIB émis à $z=1$, la densité d'énergie contenue dans le CIB est alors :

$$\epsilon_{CIB} = B_{CIB} \frac{4\pi(1+z)}{c} = 2.1 \times 10^{-15} \text{ J.m}^{-3}, \quad (1.32)$$

où B_{CIB} est l'émissivité du fond infrarouge prise à $25 \text{ nW.m}^{-2}.\text{sr}^{-1}$ (Dole *et al.* (2006), Béthermin *et al.* (2011)), et ϵ_{CIB} la densité d'énergie contenue dans le CIB.

La luminosité infrarouge peut être reliée au taux de formation d'étoiles grâce à la constante de Kennicutt (1998) : $K = 1.7 \times 10^{-10} \text{ M}_\odot.\text{yr}^{-1}.\text{L}_\odot^{-1} = 2.6 \times 10^{-14} \text{ kg.s}^{-1}.\text{W}^{-1}$. Elle peut également permettre de relier le fond infrarouge et la masse stellaire formée dans l'histoire de l'Univers :

$$\rho_{\star,form} = K \epsilon_{CIB} = 5.2 \times 10^{-29} \text{ kg.m}^{-3} = 7.7 \times 10^8 \text{ M}_\odot.\text{Mpc}^{-3}. \quad (1.33)$$

On a négligé dans ce calcul la contribution des AGNs. Cette valeur est supérieure avec l'estimation de la masse d'étoile dans l'Univers local ($\rho_\star = 1.9 \times 10^8 \text{ M}_\odot.\text{Mpc}^{-3}$, Fukugita et Peebles (2004)). Ceci montre qu'il y a donc eu nécessairement plusieurs générations d'étoiles dans l'Univers, et que le gaz des étoiles mortes a été recyclé. Si on suppose un taux de formation d'étoiles constant sur les 13 derniers milliards d'années, on trouve un taux de formation d'étoiles "moyen" de $0.06 \text{ M}_\odot.\text{ans}^{-1}.\text{Mpc}^{-3}$, en accord avec les observations (par exemple Rodighiero *et al.* (2009)) et les modèles d'évolution des galaxies (par exemple Le Borgne *et al.* (2009)).

Efficacité de la conversion masse-énergie dans les étoiles

On peut également calculer l'énergie rayonnée par masse d'étoile formée, e_* :

$$e_* = \frac{\epsilon_{tot}}{\rho_{*,form}} = 8 \times 10^{13} J.kg^{-1}, \quad (1.34)$$

où on a pris $\epsilon_{tot} = 4.2 \times 10^{-15} J.m^{-3}$ correspondant au fond extragalactique mesuré aujourd'hui ($50 \text{ nW.m}^{-2}.\text{sr}^{-1}$) et supposé émis à $z=1$. Ce qui correspond à une efficacité de conversion masse-énergie dans les étoiles de l'ordre de 8.8×10^{-4} . Ceci est en très bon accord avec l'efficacité de cette conversion par le Soleil, $\eta_\odot$:

$$\eta_\odot = \frac{L_\odot T_\odot}{M_\odot c^2} = 7 \times 10^{-4}, \quad (1.35)$$

où $T_\odot$ est la durée de vie du Soleil ($\sim 10^{10}$ ans).

1.3.4 Problématiques

De nombreuses problématiques scientifiques se posent à propos du fond infrarouge. Nous en avons sélectionné quelques-unes.

- Le CIB et le COB contiennent environ la même énergie. En revanche, le rapport optique sur infrarouge est de l'ordre de 3 dans l'Univers local (Soifer et Neugebauer (1991)). Les pics d'émission du COB et du CIB étant très éloigné ce pseudo-paradoxe ne peut s'expliquer que des effets de *redshift*. Ceci montre donc une forte évolution des propriétés des galaxies au cours de l'histoire de l'Univers. La compréhension de cette évolution est un enjeu majeur de ma thèse.
- Quelle est la contribution des AGNs au fond infrarouge et comment évolue-t-elle avec le *redshift* ?
- Les galaxies à flambées de formation d'étoile ont une contribution à la fois au fond infrarouge et γ . A quel points les deux fonds sont-ils liés (corrélations, distribution en *redshift*...) ?

1.4 Les observations infrarouges

Pour étudier les galaxies et le fond infrarouge, il est nécessaire d'utiliser des techniques spécifiques. Nous allons ici présenter les moyens observationnels à notre disposition.

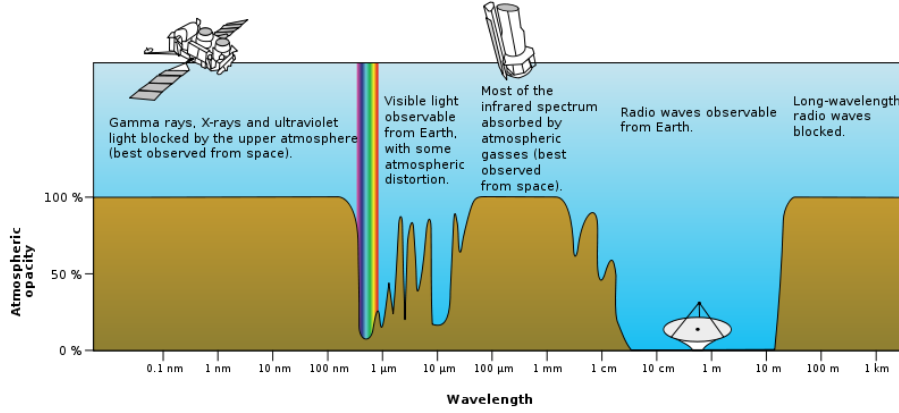


FIGURE 1.10 – Transmittance atmosphérique en fonction de la longueur d'onde (Crédit :NASA).

1.4.1 Spécificités des observations infrarouges

L'atmosphère est essentiellement opaque au rayonnement infrarouge. Ceci rend les observations au sol quasi-impossibles entre 3 et 450 μm de longueur d'onde (voir Fig. 1.10). Il est donc nécessaire de construire des télescopes infrarouges spatiaux.

La diffraction est également un problème dans l'infrarouge lointain. En effet, la résolution angulaire d'une télescope infrarouge vaut $\theta = \lambda/D$, λ étant la longueur d'onde d'observation, et D le diamètre du télescope. Pour avoir une résolution angulaire permettant de séparer les galaxies entre elles, il faut donc réaliser des miroirs spatialisables de grandes tailles.

Dans l'infrarouge moyen et lointain, l'émission thermique du miroir de diamètre D (et donc de surface $\pi D^2/4$) peut dominer l'émission des sources observées²⁸. Le rapport entre ces deux émissions dépend de la longueur d'onde et de la température du miroir. La puissance P_{source} , issue d'une source astrophysique ponctuelle de flux S , au foyer du télescope vaut :

$$P_{\text{source}} = F_{\nu} \Delta\nu \frac{\pi}{4} D^2, \quad (1.36)$$

où F_{ν} est le densité de flux de la source, et $\Delta\nu$ la largeur (en fréquence) du filtre utilisé. On considère par la suite un filtre large bande avec $\nu/\Delta\nu = 3$. La puissance due à l'émission thermique du miroir, P_{miroir} , vaut quant à elle :

$$P_{\text{miroir}} = B_{\nu}(\nu, T) \Delta\Omega \Delta\nu \frac{\pi}{4} D^2, \quad (1.37)$$

²⁸Ce calcul s'inspire de celui présenté par Hervé Aussel à l'école *Herschel* des cigales, organisée en Décembre 2009 à l'IAS et soutenue par l'ANR D-SIGALE.

où $B_\nu(\nu, T)$ est la luminance monochromatique d'un corps noir de température T , $\Delta\Omega$ est l'angle solide observé. On prend pour $\Delta\Omega$, l'angle solide correspondant à la taille de la tâche image de l'instrument :

$$\Delta\Omega = \frac{\pi}{4} \left(\frac{\lambda}{D} \right)^2. \quad (1.38)$$

Le bruit de photon de la source observée, σ_{source} , est :

$$\sigma_{sources} = \sqrt{N_{source}} = \sqrt{\frac{P_{source}\Delta t}{h\nu}} = \sqrt{\frac{F_\nu \Delta\nu \frac{\pi}{4} D^2 \Delta t}{h\nu}}, \quad (1.39)$$

où N_{source} est le nombre de photons reçus de la source, Δt est le temps d'intégration, et h la constante de Planck. De même, on a :

$$\sigma_{miroir} = \sqrt{N_{miroir}} = \sqrt{\frac{P_{miroir}\Delta t}{h\nu}} = \sqrt{\frac{B_\nu(\nu, T) \Delta\Omega \Delta\nu \frac{\pi}{4} D^2 \Delta t}{h\nu}}. \quad (1.40)$$

On peut également estimer le temps d'intégration nécessaire pour obtenir un rapport signal sur bruit de 5. On néglige ici, le bruit de photon des avant-plans (par exemple, l'émission zodiacale). On suppose également une électronique parfaite. Le rapport signal sur bruit est alors donné par :

$$S/N = \frac{N_{source}}{\sqrt{\sigma_{sources}^2 + \sigma_{miroir}^2}} = \frac{F_\nu}{\sqrt{F_\nu + B_\nu(\nu, T) \Delta\Omega}} \sqrt{\frac{\Delta\nu \frac{\pi}{4} D^2 \Delta t}{h\nu}} \quad (1.41)$$

La Fig. 1.11 montre le temps d'intégration nécessaire pour des sources de différents flux et un miroir de 0.85 cm (diamètre du miroir de *Spitzer*) à différentes températures. On remarque qu'au delà d'une longueur d'onde de $2 \mu\text{m}$, il n'est pas possible de réaliser des observations à température ambiante, car les temps d'intégration de sources faibles ($\sim 1 \mu\text{Jy}$) deviennent supérieurs à la dizaine d'heures. Pour un miroir à 100 K (ce qui est possible d'obtenir par refroidissement passif dans l'espace), on peut observer jusqu'à environ $5 \mu\text{m}$. Dans l'infrarouge lointain, on observe des sources de l'ordre du mJy. Dans cette gamme de longueur d'onde, un refroidissement à 5 K, permet d'être dominé par le bruit de photon jusqu'à $200 \mu\text{m}$. Toutefois, les valeurs fournies ici ne sont jamais atteintes, entre autres à cause de la lumière zodiacale qui domine largement l'émission des galaxies dans l'infrarouge moyen, et du bruit intrinsèque des détecteurs.

Les observations infrarouges sont donc difficiles à réaliser, car elles nécessitent l'utilisation de télescopes spatiaux de grands diamètres, refroidis à environ 5 K.

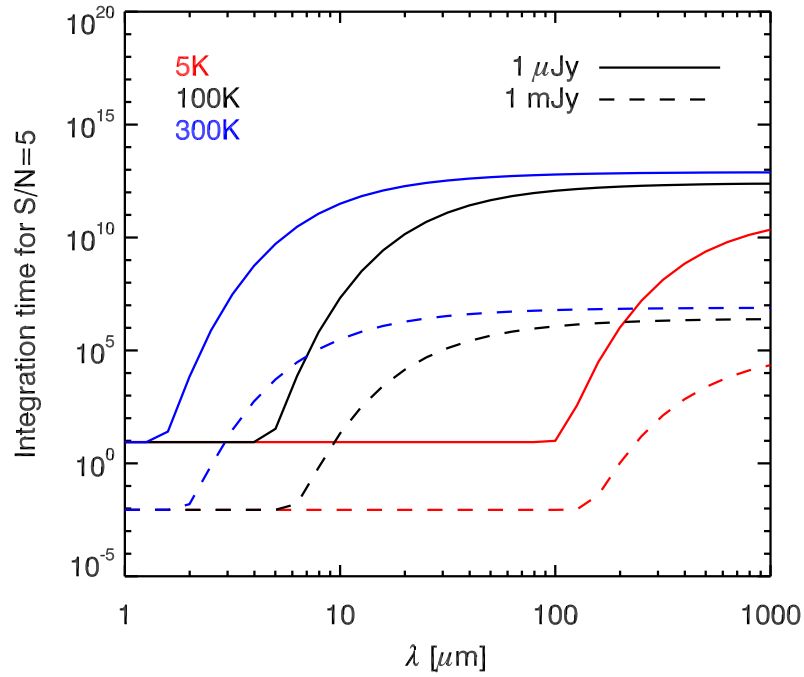


FIGURE 1.11 – Temps d'intégration nécessaire pour obtenir un rapport signal sur bruit de 5. On suppose que les seuls bruits sont les bruits de photons de la source et du miroir. Les lignes pleines correspondent à une source de $1 \mu\text{Jy}$, et les tirets à une source de 1 mJy . Les couleurs correspondent à des températures de miroir de 5 K (*rouge*), 100 K (*noir*) et 300 K (*bleu*).

1.4.2 Les grands précurseurs : IRAS et ISO

Le satellite IRAS (satellite astronomique infrarouge²⁹, Neugebauer *et al.* (1984)), construit par une collaboration entre les Etats-unis, le Royaume Uni et les Pays Bas, a été lancé en 1983 par la NASA³⁰. Ce télescope infrarouge d'un diamètre de 57 cm a effectué un relevé de 96% du ciel à 12, 25, 60 et 100 μm . Il était équipé d'un système de refroidissement à l'hélium superfluide (1,6 K) qui a fonctionné 10 mois. Ce télescope a permis de découvrir environ 75 000 galaxies infrarouges, mais aussi les cirrus galactiques (nuages de gaz diffus dans notre galaxie émettant dans l'infrarouge).

Le satellite ISO (Observatoire Spatial Infrarouge³¹, Kessler *et al.* (1996)), lancé en 1995, possédait un miroir de 70 cm par l'ESA³², était refroidi à l'hélium liquide, et observait entre 2 et 200 μm . Contrairement à IRAS qui observait tout le ciel, ISO réalisait des observations pointées. Il a permis de résoudre la majorité du fond infrarouge en sources individuelles à 15 μm (Elbaz *et al.* (1999)). En revanche, à cause de sa résolution angulaire limitée, il ne résolvait qu'une faible part du fond à plus grande longueur d'onde (Dole *et al.* (2001), Héraudeau *et al.* (2004)).

1.4.3 Spitzer

Spitzer (Werner *et al.* (2004)) est un télescope de la NASA, lancé en 2003. Il est placé en orbite héliocentrique avec un demi-grand-axe très légèrement supérieur à celui de la Terre, dont il s'éloigne lentement. Son miroir primaire, mesurant 85 cm de diamètre, est refroidi à 5.5 K. Il observe entre 3.6 et 160 μm , grâce aux instruments IRAC, IRS et MIPS. Le système de refroidissement s'est arrêté en 2009 rendant les observations impossibles au delà de 5 μm (voir Fig. 1.11).

L'instrument IRAC³³ (Fazio *et al.* (2004b)) est une caméra infrarouge observant à 3.6, 4.5, 5.8 and 8.0 μm . Chaque longueur d'onde est associée à un détecteur de 256×256 pixels, chaque pixel observant un angle de 1.2" sur le ciel. Les 4 canaux sont observés de manière simultanée grâce à des séparateurs dichroïques. La PSF (Fonction d'étalement de point³⁴) a une largeur à mi-hauteur de 1.66", 1.72", 1.88" et 1.98" à 3.6, 4.5, 5.8 et 8.0 μm , respectivement.

L'instrument MIPS³⁵ (Rieke *et al.* (2004)) est un photomètre imageur observant à 24,

²⁹En anglais, *InfraRed Astronomical Satellite*

³⁰*National Aeronautics and Space Administration.*

³¹*Infrared Space Observatory*

³²*European Space Agency.*

³³*InfraRed Array Camera*

³⁴*Point Spread Function*

³⁵*Multiband Imaging Photometer for Spitzer*

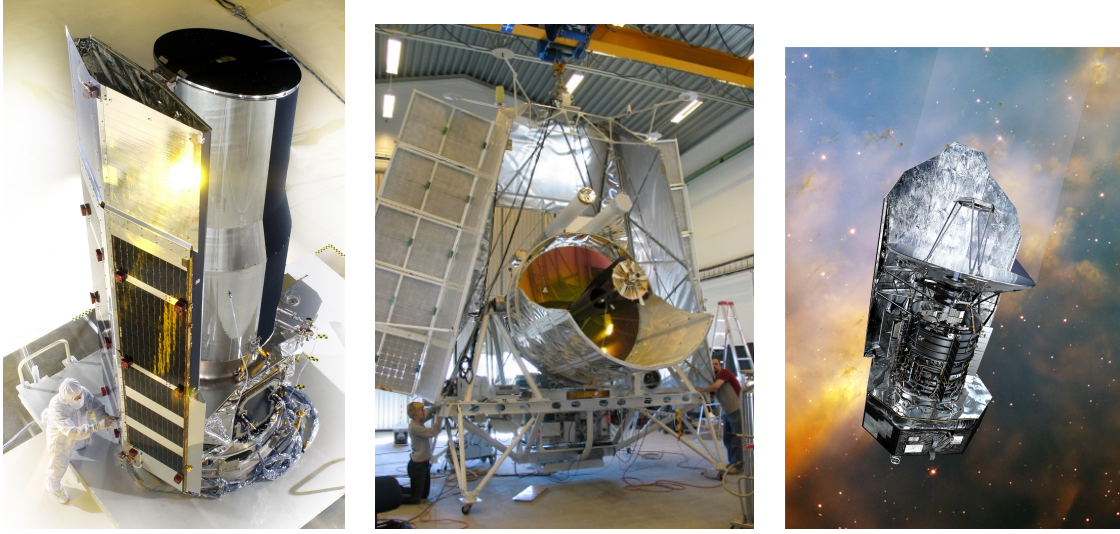


FIGURE 1.12 – De gauche à droite : le télescope spatial *Spitzer* (Crédit : NASA), le télescope porté par ballon BLAST (Crédit : Gaelen Marsden), le télescope spatial *Herschel* (Crédit : ESA).

70 et 160 μm . Les détecteurs possèdent 128×128 pixels de 2.5" projetés sur le ciel, 16×32 pixels de 9.8", et 2×20 pixels de 16", à 24, 70 et 160 μm , respectivement. La PSF a une largeur à mi-hauteur de, respectivement, 6.6", 18" et 40".

L'instrument IRS³⁶ Houck *et al.* (2004) est un spectrographe possédant deux modules de basse résolution ($R \sim 100$) et deux modules de haute résolution ($R \sim 600$). L'instrument possède également deux matrices permettant de réaliser des images à 15 et 22 μm , initialement prévues pour le centrage des sources. Elles ont également servi à réaliser des relevés photométriques à 15 μm (Teplitz *et al.* (2010)).

1.4.4 BLAST

L'expérience BLAST³⁷ (Pascale *et al.* (2008)) a pour but d'observer le ciel submillimétrique à 250, 350 et 500 μm . Il s'agit d'un télescope de 2 m de diamètre porté par un ballon stratosphérique. Il a volé en 2005 en Suède et en 2006 en Antarctique. Les détecteurs sont des matrices de bolomètres *spider web*³⁸ refroidis à l'hélium liquide, précurseurs de l'instrument SPIRE de *Herschel*. Sa PSF a une largeur à mi-hauteur de 36", 42" et 60" à 250, 350 et 500 μm , respectivement.

³⁶*InfraRed Spectrometer*

³⁷Balloon-borne Large-Aperture Submillimeter Telescope

³⁸Toile d'araignée

1.4.5 *Herschel*

Le télescope spatial européen *Herschel* (Pilbratt *et al.* (2010)) a été lancé avec succès en 2009 par l'ESA en même temps que *Planck* (voir section suivante). Il s'agit d'un télescope de 3.5 m de diamètre, placé au point de Lagrange 2³⁹. Grâce à une orientation dos au Soleil et la Terre, son miroir est refroidi passivement à 60 K. Il est équipé de 3 instruments : PACS, SPIRE et HIFI.

L'instrument PACS⁴⁰ (Poglitsch *et al.* (2010)) est capable de faire de la photométrie en bande large et de la spectroscopie basse résolution entre 55 et 210 μm . Ses bandes photométriques sont placées à 70, 100 et 160 μm . La largeur à mi-hauteur de la PSF est respectivement 5.2", 7.7" et 12". Une matrice de 32×16 bolomètres permet d'observer à 160 μm , en parallèle d'une autre matrice de 64×32 observant soit à 70, soit à 100 μm . La sensibilité de PACS est limitée par le bruit statistique des photons émis par le miroir.

L'instrument SPIRE⁴¹ (Griffin *et al.* (2010)) a les mêmes fonctions que SPIRE, mais dans le domaine sub-millimétrique de 200 à 650 μm . Les canaux du photomètre sont centrés autour de 250, 350 et 500 μm . Ces canaux sont équipés de matrices de bolomètres de respectivement 139, 88 et 43 éléments. Des bolomètres aveugles permettent de corriger les dérives en température de chaque matrice. La largeur à mi-hauteur de la PSF est, respectivement, 18", 25" et 37". Avec SPIRE, les observations de champs profonds sont très vite limitées par le phénomène de confusion dû à la faible résolution angulaire du télescope.

Herschel est également équipé du spectromètre hétérodyne de très haute résolution ($R \sim 10^7$) HIFI⁴² (de Graauw *et al.* (2010)). Malheureusement, à cause de sa sensibilité limitée, cet instrument ne peut observer que des objets très brillants et donc très proches.

³⁹Le point de Lagrange 2 est un point d'équilibre du système Terre-Soleil. Il est située à 1.5 millions de kilomètres de la Terre dans la direction opposée à celle du Soleil. Ainsi, le satellite voit le Soleil et la Terre alignés.

⁴⁰*Photoconductor Array Camera and Spectrometer*

⁴¹*Spectral and Photometric Imaging Receiver*

⁴²*Heterodyne Instrument for the Far-Infrared*

1.4.6 Les nouveaux observatoires spatiaux tout-le-ciel : AKARI, WISE, *Planck*

Des relevés tout-le-ciel ont également été réalisés dans l'infrarouge. En général, leur sensibilité ne permet pas de résoudre une partie significative du fond infrarouge. Ces observations sont en revanche cruciales pour les études sur l'Univers local et les fluctuations du fond.

Le satellite japonais *Akari*⁴³ (Ishihara *et al.* (2010)) a été lancé en 2006. Il a réalisé un relevé de tout le ciel dans de nombreuses bandes photométriques entre 6 et 180 μm . Des relevés profonds ont également été réalisés. Le satellite WISE⁴⁴, lancé par la NASA en décembre 2009, a réalisé également un relevé du ciel complet à 3.3, 4.7, 12 et 23 μm . Sa mission s'est achevée en septembre 2010, lorsque l'hydrogène solide du système de refroidissement a été entièrement consommé. Sa sensibilité est très supérieure à celle d'*Akari*.

Le satellite *Planck* (Tauber *et al.* (2010)), lancé en même temps que *Herschel*, réalise un relevé de tout le ciel du domaine sub-millimétrique au domaine radio. L'instrument HFI⁴⁵ (Lamarre *et al.* (2010)) observe à 350, 550, 840, 1380, 2100 et 3000 μm . Sa résolution inférieure à 3' ne permet de résoudre que les objets les plus brillants. En revanche, sa grande stabilité va permettre d'étudier avec une précision inégalée les fluctuations du fond infrarouge.

1.4.7 Télescopes sub-millimétriques et millimétriques au sol : JCMT, IRAM, APEX, SPT...

Au delà de 450 μm , il est possible d'observer depuis le sol dans les principales fenêtres atmosphériques (450 μm , 850 μm , 1.2 mm...). Les télescopes au sol ont de plus grands diamètres que leur homologue spatiaux. Néanmoins, la transmission atmosphérique est faible, et il est préférable d'observer dans des endroits secs en altitude. On peut citer entre autre le JCMT⁴⁶ à Hawaï, l'antenne de 30 m de l'IRAM⁴⁷ près de Grenade, APEX⁴⁸ et ACT⁴⁹ dans le désert de l'Atacama au Chili, et SPT⁵⁰ au Pôle sud.

⁴³Lumière en japonais

⁴⁴*Wide-Field Infrared Survey Explorer*

⁴⁵*High Frequency Instrument*

⁴⁶*James Clerk Maxwell Telescope*

⁴⁷Institut de Radioastronomie Millimétrique

⁴⁸*Atacama Pathfinder Experiment*

⁴⁹*Atacama Cosmology Telescope*

⁵⁰*South Pole Telescope*

Chapitre 2

Comptages de sources résolues

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2.1 Introduction

2.1.1 Pourquoi compter les sources infrarouges ?

On appelle comptages la distribution en flux des sources dans le ciel. Cette observable peut être mesurée à partir d'une simple carte infrarouge. Elle ne nécessite donc pas de rassembler des jeux de données hétérogènes, tel des *redshifts* ou des mesures photométriques issues d'autres bandes spectrales. Les effets de sélections peuvent ainsi être aisément interprétés par les modèles. Il est néanmoins nécessaire de corriger les biais dus à l'extraction des sources. Ce qui peut-être fait avec une très bonne précision. C'est pour cette raison que les comptages sont une contrainte massivement utilisée par les modèles d'évolution des galaxies.

2.1.2 Interprétation des comptages

Comptages intégraux et comptages différentiels

Les comptages de galaxies peuvent être exprimés en utilisant deux conventions différentes : comptages intégraux et comptages différentiels. Les comptages intégraux (notés $N(>S)$) correspondent au nombre de sources plus brillantes qu'un flux donné par unité d'angle solide. En général, $N(>S)$ est calculé pour une série de flux S . Cette convention a l'avantage de permettre de déterminer très rapidement le nombre de sources qu'il est possible de détecter en réalisant un relevé de sensibilité donnée et de taille donnée. Le gros désavantage des comptages intégraux est le fait que les points de mesures sont fortement corrélés. De plus, $N(>S)$ peut varier de plusieurs ordres de grandeur sur un même ordre de grandeur en flux. Ceci peut être problématique lors du tracé des courbes, et en particulier pour réaliser une comparaison fine entre observation et modèle.

Les comptages différentiels (noté $\frac{dN}{dS}$), correspondent au nombre de sources par unité d'angle solide et par intervalle de flux. Dans ce cas, les corrélations entre points sont plus faibles¹. Il est également possible de tracer $dN/dS \times S^{2.5}$ en fonction de S dans les graphiques afin de limiter le nombre d'ordres de grandeur à représenter en ordonnées.

Comptages dans un Univers euclidien sans évolution

Dans un Univers euclidien, infini et sans évolution, les comptages peuvent se calculer analytiquement. On considère ici une seule population de galaxies de luminosité L ayant une densité ρ_0 . Le nombre de sources plus brillantes que S_{max} est

$$N(> S_{max}) = \rho_0 V_{max}, \quad (2.1)$$

avec V_{max} le volume dans lequel les sources de flux S_{max} sont détectées. Calculons ce volume. La distance maximale à laquelle des sources sont vus est :

$$D_{max} = \sqrt{\frac{L}{4\pi S_{max}}}, \quad (2.2)$$

et donc,

$$V_{max} = \frac{4\pi}{3} \left(\frac{L}{4\pi S_{max}} \right)^{\frac{3}{2}}, \quad (2.3)$$

d'où,

$$N(> S_{max}) = \frac{\rho_0 L^{\frac{3}{2}} 6 \sqrt{\pi}^{-\frac{3}{2}}}{S_{max}}. \quad (2.4)$$

Ce comportement en $S^{-\frac{3}{2}}$ reste vrai dans un Univers contenant des galaxies de différentes luminosités, à condition que la fonction de luminosité LF n'évolue pas.

Les comptages différentiels sont donc donnés par

$$\frac{dN}{dS} = \frac{\rho_0 L^{\frac{3}{2}}}{4 \sqrt{\pi}} S^{-\frac{5}{2}}. \quad (2.5)$$

Si on multiplie les comptages différentiels par $S^{\frac{5}{2}}$, on obtient donc une constante. On trace souvent $dN/dS \times S^{2.5}$ pour pouvoir mesurer les écarts par rapport aux comptages euclidiens. On parle alors de comptages normalisés.

¹Elles sont même nulles si on suppose que les sources sont distribuées de manière poissonnienne.

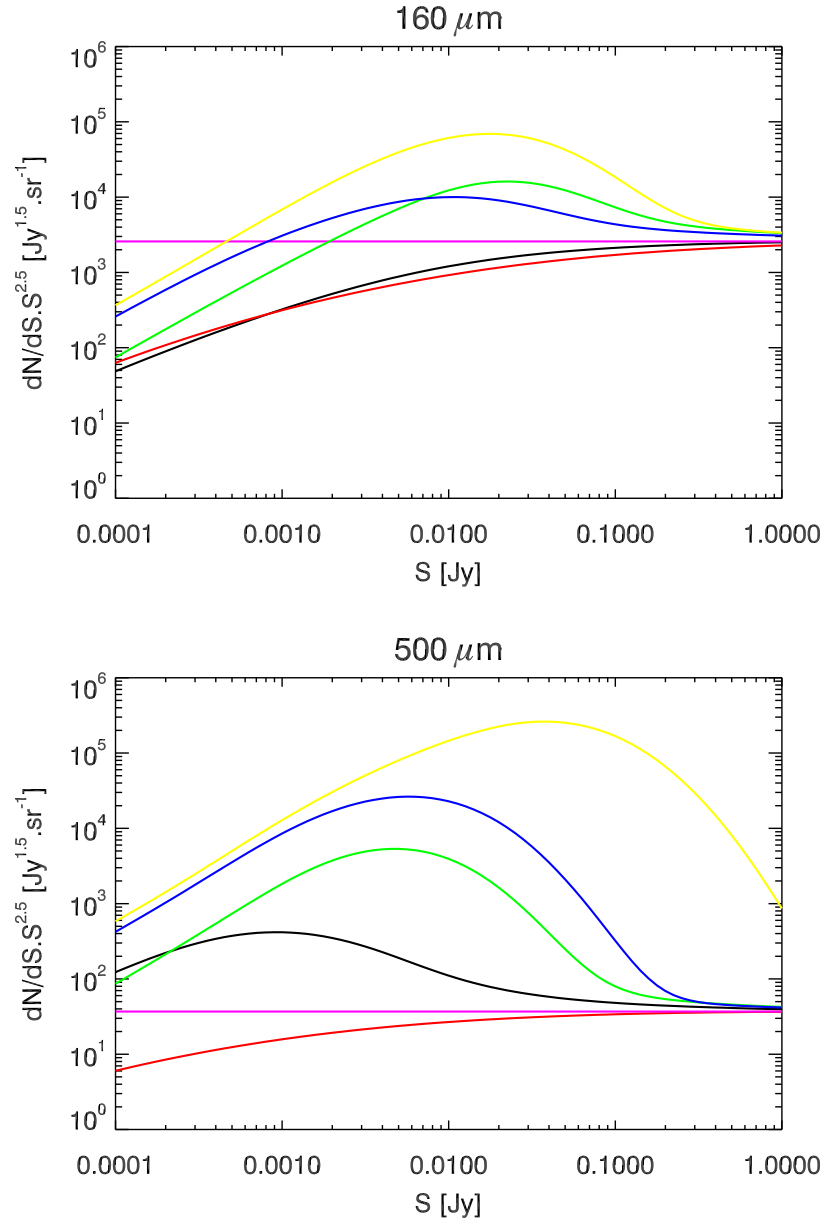


FIGURE 2.1 – Comptages différentiels normalisés à 160 (en haut) et 500 μm (en bas) prédits par le modèle Béthermin *et al.* (2011). Différentes situations sont représentées. En rouge : pas d'évolution, spectres des galaxies plats. En noir : pas d'évolution, spectres réalistes. En bleu : évolution de la luminosité des galaxies en $(1+z)^{2.5}$. En jaune : évolution de la luminosité des galaxies en $(1+z)^{3.5}$. En vert : évolution complexe en densité et luminosité utilisée par le modèle Béthermin *et al.* (2011). En violet : Univers euclidien sans évolution.

Comptages dans un Univers Λ CDM sans évolution

Le calcul précédent supposait que l'Univers était statique et sans expansion, mais, en réalité, l'Univers observable a un volume fini. La Fig. 2.1 montre les comptages à 160 et 500 μm prédits avec les outils présentés au Chap. 6 dans différents cas. La courbe violette correspond au cas du chapitre précédent, c'est à dire, un Univers euclidien, sans évolution. La courbe en rouge représente les comptages dans un Univers en expansion², mais où les spectres de galaxies sont supposés plats³. Les comptages de sources brillantes des deux modèles ($S > 1$ Jy) sont similaires. En effet, les sources brillantes se situent dans l'Univers proche, où les effets de l'expansion sont négligeables. En revanche, à bas flux, il y a moins de sources dans un Univers en expansion. Ce changement de pente des comptages à bas flux est obligatoire dans un Univers fini. En effet, si on intégrait des comptages euclidiens jusqu'à un flux nul, le fond total divergerait⁴.

La prise en compte de la SED réelle des sources infrarouges modifie les comptages à 500 μm , mais quasiment pas à 160 μm (voir courbe noire). Ceci s'explique par l'effet de K-correction, qui est le rapport entre la densité de luminosité d'un objet dans son référentiel propre et dans celui de l'observateur :

$$K(\nu, z) = \frac{L_{\nu(1+z)}}{L_{\nu}} \quad (2.6)$$

La Fig. 2.2 représente la K-correction pour différentes longueurs d'onde d'observation en fonction du *redshift*. Une K-correction grande devant 1 indique qu'une source est *boostée* par le décalage vers le rouge, c'est à dire qu'on la voit plus brillante qu'elle ne le serait dans un Univers euclidien à la même distance (lumineuse). La SED des galaxies infrarouges étant très pentue à grande longueur d'onde, la K-correction est donc très forte. Cet effet produit un excès dans les comptages autour de 10 mJy, qui correspond à des sources à haut *redshift*, vues proches de leur maximum d'émission. La K-correction étant faible à 160 μm , on n'y observe pas d'excès significatif.

Comptages dans un Univers Λ CDM avec évolution

On a jusqu'ici supposé que la distribution en luminosité des galaxies infrarouges ne changeait pas avec le *redshift*. Or, une évolution des populations infrarouges agit fortement

²On suppose une cosmologie Λ CDM avec les paramètres mesurés par WMAP 7 ans (Larson *et al.* (2010)).

³ $\nu L_{\nu} = \text{Constante}$

⁴Ceci est appelé paradoxe d'Olbers. En effet, au XIX^{me} siècle, les scientifiques pensaient que l'Univers était infini et sans évolution. Ceci conduisait au paradoxe d'un fond de rayonnement infini. On pensait alors que l'absorption des photons pouvait résoudre ce problème. En fait, la principale explication est bien sûr l'expansion de l'Univers et la finitude de la vitesse de la lumière (Wesson *et al.* (1987), Dole (2010)).

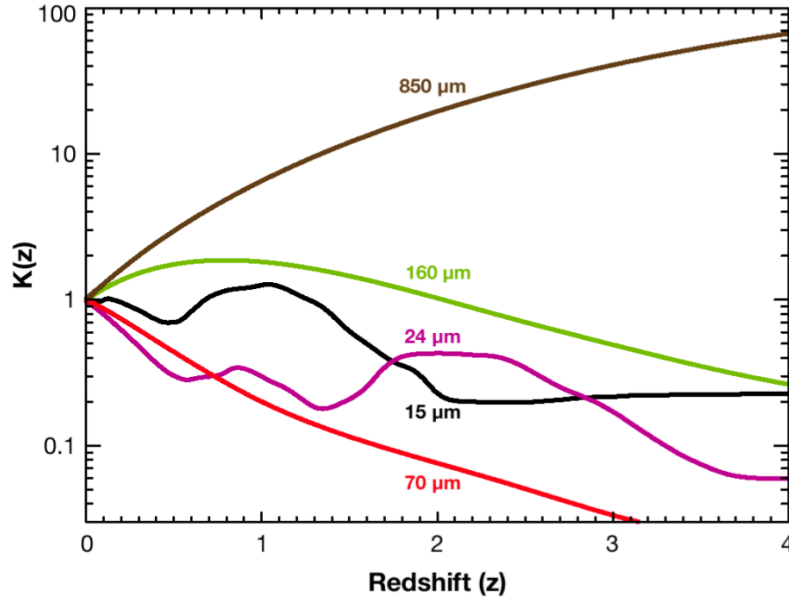


FIGURE 2.2 – K-correction pour différentes longueurs d’onde d’observation en fonction du *redshift* (extrait de Lagache *et al.* (2005)).

sur les comptages. On peut par exemple supposer une évolution simple où la luminosité de toutes les galaxies augmente comme $(1+z)^\alpha$. Le Fig. 2.1 représente les comptages pour une évolution en $(1+z)^{2.5}$ (en bleu) et en $(1+z)^{3.5}$ (en jaune). On constate que les comptages sont très sensibles à de telles évolutions. On remarque également que l’effet est assez différent en fonction de la longueur d’onde. En effet, à cause des effets de K-corrections, les comptages à $500\ \mu\text{m}$ sont plus sensibles aux grands *redshift*, où l’impact d’une évolution en $(1+z)^\alpha$ est plus fort. Cet effet montre que l’utilisation de comptages à différentes longueurs d’ondes peut lever certaines dégénérescences dans les scénarios d’évolution des galaxies.

En pratique, une évolution aussi simple ne permet pas de reproduire simultanément les comptages infrarouges à plusieurs longueurs d’ondes. Une évolution de la luminosité et de la densité des galaxies est souvent nécessaire. Les comptages prédits par le modèle Béthermin *et al.* (2011), qui utilise une évolution complexe de la fonction de luminosité, sont tracés en bleu. La démarche de construction d’un tel modèle sera expliquée Chap. 6.

2.2 Les relevés infrarouges

2.2.1 Choix des champs observés

Les comptages infrarouges peuvent être estimés à partir de la carte infrarouge d'une région du ciel. Il "suffit" alors d'estimer le nombre de sources par tranche de flux dans la carte et de le diviser par la surface. L'Univers étant isotrope, le champ choisi peut théoriquement se situer n'importe où dans le ciel. Toutefois, pour être représentative, les coordonnées de la région observée doivent être choisies de façon non biaisée. On ne peut pas, par exemple, utiliser un champ centré sur un super-amas de galaxies, qui contient un excès de sources par rapport à la moyenne. En pratique, le choix des champs à observer est guidé par ces deux éléments : présence de données ancillaires (comme des données optiques) et faible contamination par les avant-plans galactiques.

2.2.2 Observations

Le champ des télescopes infrarouges est souvent relativement petit (par exemple, $5' \times 5'$ pour MIPS à $24 \mu\text{m}$ ou $4' \times 8'$ pour SPIRE). Il n'est donc pas possible de construire une carte du ciel à partir d'une seule observation pointée. En général, le télescope balaye la région du ciel à observer de manière systématique. Chaque point est observé plusieurs fois, afin d'identifier dans les données des parasites tels que les impacts de rayons cosmiques sur les détecteurs. Ceci permet également de corriger une partie des effets dus au bruit basse fréquence des instruments.

2.2.3 Construction des cartes infrarouges

Les données fournies par le télescope sont les suivantes.

- Le signal reçu par chaque détecteur en fonction du temps. Ce signal peut être ou non déjà converti dans une unité de flux.
- La direction dans laquelle observe chaque détecteur en fonction du temps. En pratique, cette information est souvent fournie grâce au pointage d'un seul des détecteurs et d'un angle. Le pointage des autres détecteurs se déduit de la géométrie de la matrice de détecteurs.
- Dans certains cas (comme SPIRE), des bolomètres aveugles⁵ sont placés sur la matrice, afin de corriger les fluctuations de température de celle-ci.

⁵Ne captant pas le signal venu du ciel

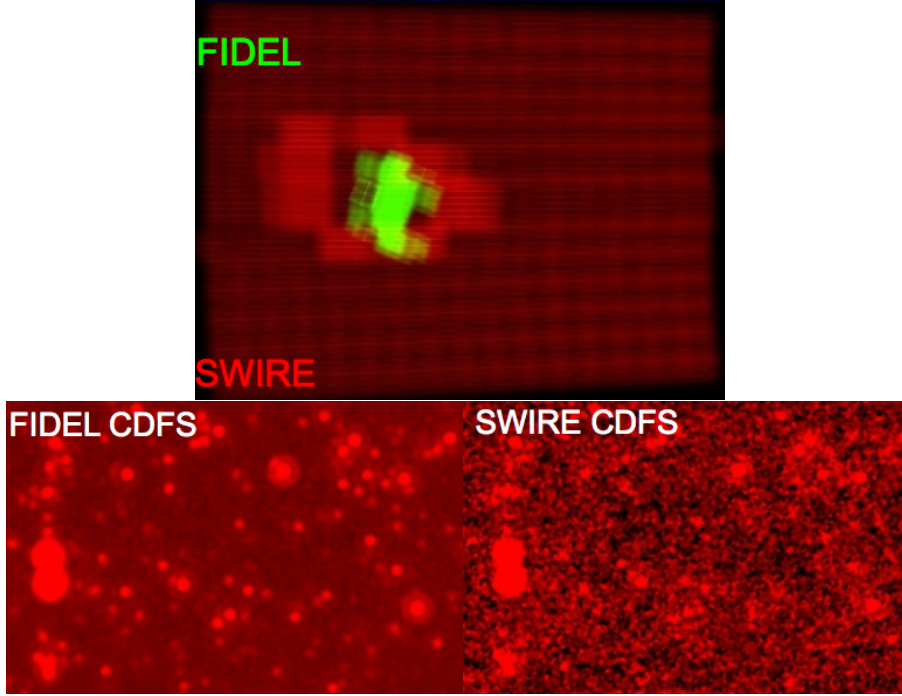


FIGURE 2.3 – Relevés *Spitzer* 24 μm larges et profonds dans le CDFS⁸. (En haut) Carte de couverture du relevé profond FIDEL (en vert) et du relevé large SWIRE (en rouge). (En bas) Image de la même zone du ciel vue par FIDEL (gauche) et SWIRE (droite).

Une première analyse permet de masquer ou corriger dans le signal temporel de chaque détecteur les zones affectées par des effets instrumentaux, comme par exemple les impacts de rayons cosmiques.

Des logiciels permettent de convertir ces informations en une carte de la région observée. La redondance peut être utilisée pour réduire les effets du bruit basse-fréquence des instruments. Le logiciel SANEPIC⁶(Patanchon *et al.* (2008)) réalise, par exemple, un traitement bayésien optimal du bruit corrélé pour produire les cartes BLAST. Toutefois, dans certains cas où le bruit basse fréquence est très fort, comme MIPS, il est soustrait par un filtrage médian multi-fenêtres des données (Gordon *et al.* (2007)).

2.2.4 Champs profonds et champs larges

En l'absence de corrélation, le bruit instrumental décroît comme $1/\sqrt{t_{int}}$, où t_{int} est le temps d'intégration sur un point donné du ciel. Pour détecter les sources les plus faibles,

⁶Signal and Noise Estimation Procedure Including Correlations

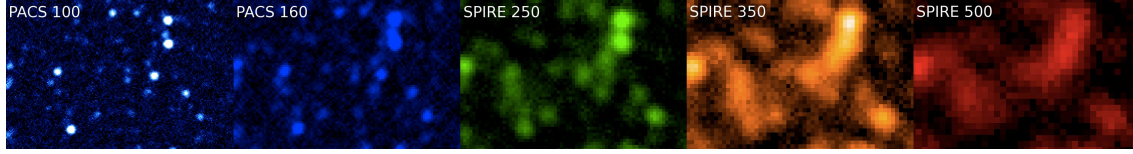


FIGURE 2.4 – Images de la même zone du ciel vue à différentes longueurs d’ondes par le satellite *Herschel* (données H-GOODS).

il est donc nécessaire d’utiliser des temps d’intégration très longs. On parlera alors de champs profonds. Il n’est donc en général pas possible d’obtenir ce genre d’images sur des grandes zones du ciel. Or, les petits champs ne contiennent que peu de sources brillantes. Pour obtenir un échantillon significatif de sources brillantes, il est donc également très utile de réaliser des observations peu profonde sur de larges régions du ciel. Les observations profondes et larges sont donc fortement complémentaires. La Fig. 2.3 illustre la différence entre champs profonds et larges. Il faut également noter que dans l’infrarouge le phénomène de confusion (voir la section suivante) limite fortement la profondeur des relevés. Certains flux faibles restent donc inaccessibles quelque soit le temps d’intégration.

2.3 Extraction des sources infrarouges

2.3.1 La problème de la confusion

A cause du phénomène de diffraction, la résolution angulaire d’un télescope de diamètre donné diminue quand la longueur d’onde augmente. A cause de cela, il est impossible d’extraire d’une carte même sans bruit instrumental les sources plus faibles qu’un certain flux, appelé limite de confusion. En effet, plus on considère des bas flux, et plus la densité de sources est grande. A partir d’un certain flux, il y a trop de sources par PSF, et elles deviennent impossibles à extraire. Ce phénomène limite fortement la possibilité d’étudier les sources faibles aux grandes longueurs d’ondes. La Fig. 2.4 illustre l’effet de la confusion dans le relevé profond *Herschel*-GOODS.

Il existe plusieurs critères permettant de définir le bruit de confusion. Le premier est un critère de densité. Il correspond au flux pour lequel la densité de source devient trop importante. Le choix de cette densité critique n’est pas trivial. On peut par exemple suivre l’approche de Dole *et al.* (2003). Le densité de sources limite N_{SDC} est atteinte quand il y a une probabilité P d’avoir une autre source dans un rayon $k \theta_{FWHM}$, où θ_{FWHM} est la largeur à mi-hauteur de la PSF. La probabilité P qu’une source tombe dans le rayon d’une autre source vaut :

$$P = 1 - e^{-\pi N k^2 \theta_{FWHM}^2}, \quad (2.7)$$

où N est la densité de sources. On en déduit :

$$N_{SDC} = -\frac{\log(1 - P)}{\pi k^2 \theta_{FWHM}^2}. \quad (2.8)$$

Dole *et al.* (2003) a proposé d'utiliser $P=0.1$ et $k=0.8$ en se basant sur des simulations. Ceci correspond à une densité d'environ 17 *beam*/source⁹.

Dans le cas où les comptages ont une forte pente, les fluctuations du fond dues aux sources faibles agissent comme un bruit. On parle alors de bruit de confusion. Ce bruit n'est pas gaussien. Le formalisme du $P(D)$ (voir Chap. 4) permet de calculer, à partir d'un modèle de comptages, l'histogramme d'une carte en l'absence de bruit instrumental. Cet histogramme présente une forme proche d'une gaussienne à bas flux et une queue de distribution en loi de puissance à haut flux due aux sources brillantes. Cette dernière rend non trivial la définition précise du bruit de confusion. Nous avons choisi le définir comme étant l'écart inter-quartile multiplié par 1.349, de manière à ce que dans le cas gaussien le bruit de confusion corresponde exactement à l'écart type. Le bruit de confusion prédit par le modèle Béthermin *et al.* (2011) (voir Chap. 6) est tracé Fig. 2.5 (graphique du haut). On remarque qu'il décroît fortement avec le diamètre de l'instrument.

Pour qu'une source soit résolue, il faut donc qu'elle soit plus brillante que le limite fixée par la densité, mais aussi le bruit de confusion à $5\text{-}\sigma$ ¹⁰. Le graphique du bas représente la fraction du CIB émise par les sources résolues. L'astérisque représente la longueur d'onde pour laquelle on change de régime. En effet, les courtes longueurs d'ondes sont limitées par la densité, et les grandes longueurs d'ondes par les fluctuations. On constate que *Spitzer* ne résout une fraction significative du CIB qu'en dessous de $70\text{ }\mu\text{m}$, alors que *Herschel* résout la majeure partie du CIB jusqu'à $160\text{ }\mu\text{m}$.

2.3.2 Détection

La première étape à réaliser lors d'une extraction de source est de déterminer leurs positions dans la carte. Il existe de nombreuses méthodes possibles. La plus simple consiste à chercher les pixels qui ont un rapport signal sur bruit supérieur à un certain seuil. Cette méthode est limitée car elle ne prend en compte qu'un seul pixel, alors que le flux d'une source s'étale sur plusieurs. Pour prendre cela en compte, on peut lisser la carte en la

⁹Le *beam* est la taille angulaire de la PSF. Il vaut $\Omega = \frac{\int \int PSF(\theta, \phi) d\theta d\phi}{\max(PSF)}$. Pour un profil gaussien ou de Airy, on a $\Omega \approx 1.1 \times \theta_{FWHM}^2$

¹⁰On peut descendre en dessous de $5\text{-}\sigma$, mais les biais d'extractions peuvent devenir importants

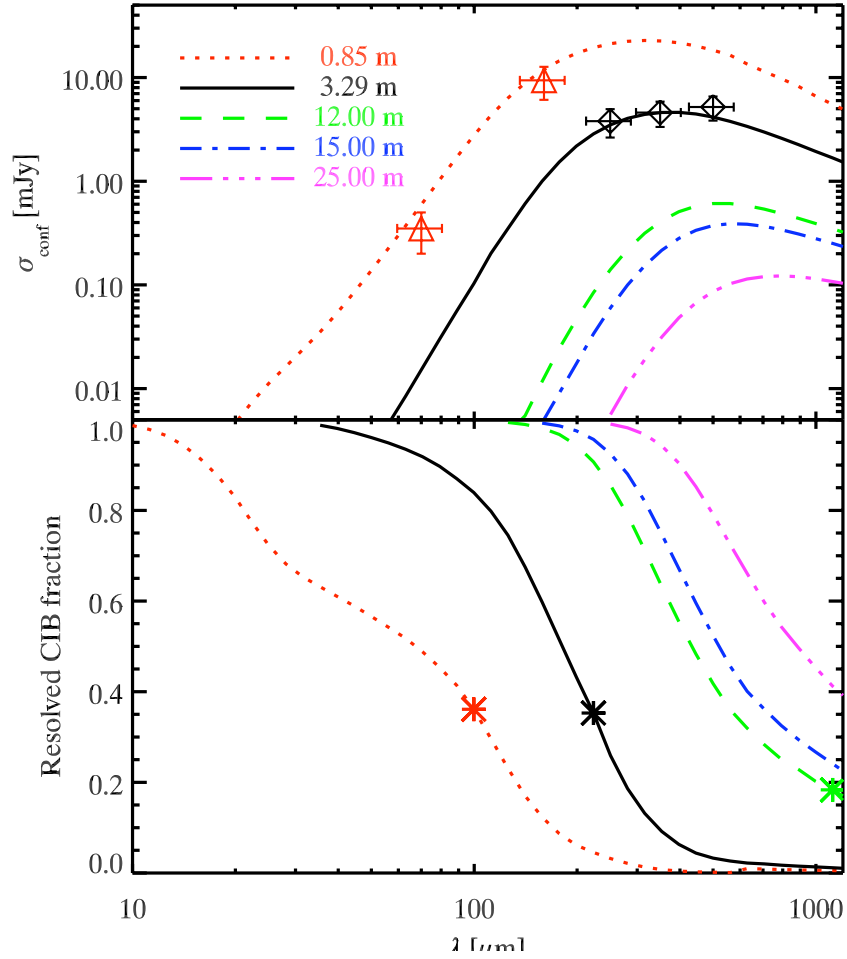


FIGURE 2.5 – (En haut) Bruit de confusion à 1σ en fonction de la longueur d’onde pour différents diamètres de télescopes. (En bas) Fraction du CIB résolue en fonction de la longueur d’onde pour différents diamètres de télescopes. L’astérisque marque le changement de régime de confusion. Extrait de Béthermin *et al.* (2011).

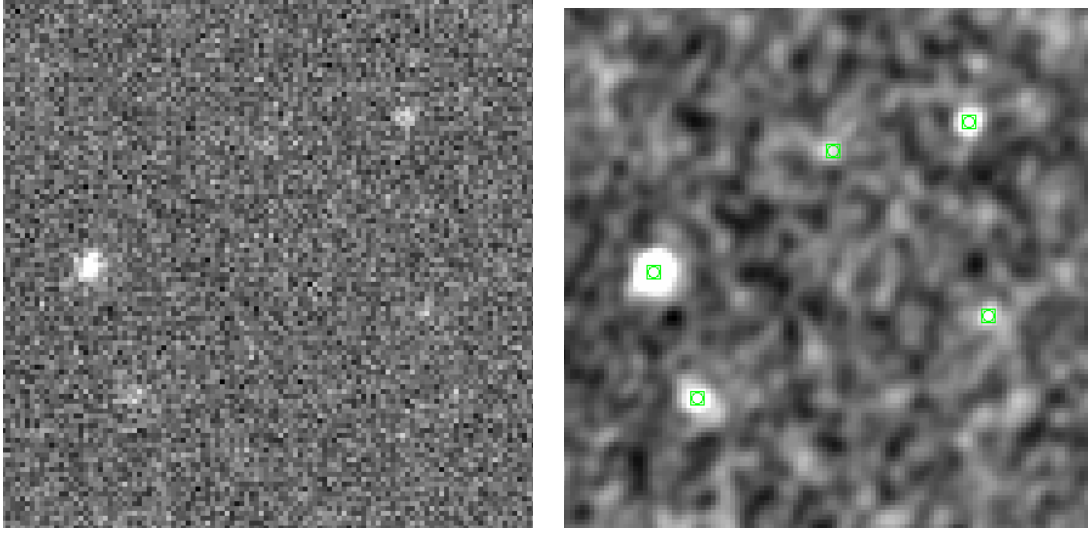


FIGURE 2.6 – (A gauche) Carte d’une région du ciel observée avec BLAST. (A droite) Même region, mais où la carte a été lissée par la PSF. Les carrés vers indiquent les détections à 5σ .

cross-corrélant avec la PSF. La carte lissée m_l est donc

$$m_l(i_0, j_0) = \sum_{i=-N}^{+N} \sum_{j=-N}^{+N} m(i_0 + i, j_0 + j) \times PSF(i, j), \quad (2.9)$$

avec $(m_l(i_0, j_0))$ le signal de la carte lissée aux coordonnées (i_0, j_0) , m le signal de la carte initiale. La carte de bruit correspondante n_l est donnée par

$$n_l(i_0, j_0) = \sqrt{\sum_{i=-N}^{+N} \sum_{j=-N}^{+N} n^2(i_0 + i, j_0 + j) \times PSF^2(i, j)}, \quad (2.10)$$

où n est la carte de bruit initiale. On en déduit la carte de signal sur bruit en divisant m_l par n_l . On détecte alors les maxima locaux dépassant le seuil demandé, typiquement entre 3 et 5. On peut montrer que cette méthode est optimale pour des sources isolées et un bruit gaussien non-corrélé (pour cela on utilise le formalisme présenté Sect. 2.3.4). La Fig. 2.6 illustre le fonctionnement de cette méthode. On voit clairement que les sources n’émergent que légèrement du bruit dans la carte initiale, alors qu’elles sont parfaitement visibles dans la carte lissée.

La routine `find` de DAOPHOT (Stetson (1987)) utilise une méthode quasi-similaire. Toutefois, la routine cross-correlle la carte par une gaussienne à la place de la PSF réelle. Les pics ne satisfaisant pas certains critères statistiques (symétrie centrale, moment d’ordre

3...) sont éliminés.

Lorsque la densité de source est forte, mais que les fluctuations du fond dues aux sources non résolues sont faibles (comme par exemple dans l'infrarouge proche et moyen), le principal défi est de séparer les paires de sources si proches que leurs PSFs se confondent. Le programme SExtractor (Bertin et Arnouts (1996)), grâce à une étude itérative des maxima locaux dans les cartes, est très efficace dans ces conditions.

Enfin, lorsque les fluctuations du fond sont fortes, comme c'est par exemple le cas pour BLAST, il est préférable d'utiliser une méthode séparant les fluctuations aux grandes échelles des sources (petites échelles). Cette analyse peut être faite par analyse en ondelettes, avec par exemple l'algorithme *atrou* (Starck *et al.* (1999)).

2.3.3 Photométrie d'ouverture

Un fois la position des sources connue, il est ensuite nécessaire de mesurer leur flux. La photométrie d'ouverture est une méthode simple de photométrie. Elle consiste à intégrer le flux reçu dans une ouverture circulaire centrée sur la source étudiée. Le niveau du fond sera estimé dans un anneau situé suffisamment loin de la source pour ne pas être trop contaminé par cette dernière, mais pas trop pour que l'estimation du fond reste fidèle. La Fig. 2.7 schématise le fonctionnement de cette méthode de photométrie.

Le flux mesuré dans l'ouverture n'est pas exactement le flux de la source. En effet, une partie non-négligeable de son flux est diffracté hors l'ouverture. En raison de la présence d'autres sources dans les cartes, il est en général impossible d'utiliser des ouvertures suffisamment grandes pour que ce problème soit négligeable. On peut néanmoins montrer que le flux initial s'obtient en appliquant un simple facteur multiplicatif, appelé correction d'ouverture. On considère une carte m contenant une unique source ponctuelle de flux S sur un fond C :

$$m(r, \theta) = S \times PSF(r, \theta) + C, \quad (2.11)$$

où $PSF(\theta, \phi)$ est la réponse instrumentale à une source de flux unité centrée sur l'origine des coordonnées. Le flux intégré sur l'ouverture de rayon a est

$$S_a = \int_{\theta=0}^{2\pi} \int_{r=0}^a S \times PSF(r, \theta) + C dr d\theta \quad (2.12)$$

$$= S \times \left[\int_{\theta=0}^{2\pi} \int_{r=0}^a PSF(r, \theta) dr d\theta \right] + A \times C \quad (2.13)$$

$$= S \cdot \alpha + A \cdot C, \quad (2.14)$$

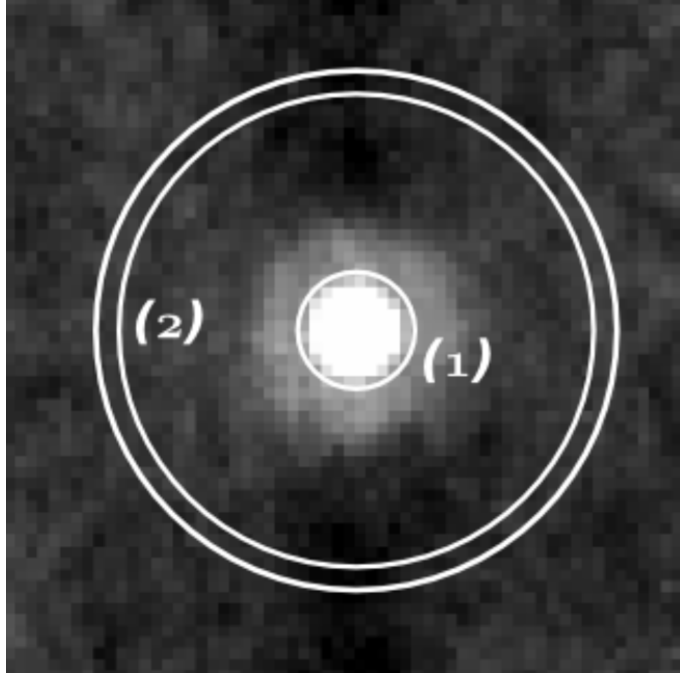


FIGURE 2.7 – Principe de la photométrie d'ouverture. (1) Ouverture circulaire. (2) Anneau d'estimation du fond de ciel. Extrait du rapport de stage de Morgane Cousin.

où A est l'aire de l'ouverture. On note $\alpha = \int_{\theta=0}^{2\pi} \int_{r=0}^{r_{ext}} PSF(r, \theta) dr d\theta$. Le signal provenant du fond dans l'ouverture est estimé à partir du signal dans l'anneau et du rapport des surfaces entre l'ouverture et l'anneau :

$$S_{a,fond} = \frac{A}{A_{anneau}} \int_{\theta=0}^{2\pi} \int_{r=r_{int}}^{r_{ext}} S \times PSF(r, \theta) + C dr d\theta \quad (2.15)$$

$$= S \times \left[\frac{A}{A_{anneau}} \int_{\theta=0}^{2\pi} \int_{r=r_{int}}^{r_{ext}} PSF(r, \theta) dr d\theta \right] + A \times C \quad (2.16)$$

$$= S \cdot \beta + A \cdot C, \quad (2.17)$$

où r_{int} et r_{ext} sont les rayons intérieurs et extérieurs de l'anneau, A l'aire de l'ouverture et A_{anneau} l'aire de l'anneau. On note $\beta = \int_{\theta=0}^{2\pi} \int_{r=r_{int}}^{r_{ext}} PSF(r, \theta) dr d\theta$. Le flux mesuré S_m est donc

$$S_m = S_a - S_{a,fond} = S \times (\alpha - \beta). \quad (2.18)$$

La correction d'ouverture est donc $1/(\alpha - \beta)$. En pratique, elle peut être estimée en mesurant l'inverse du flux d'une PSF unitaire¹¹, avec l'ouverture et l'anneau choisis.

¹¹Image d'une source de flux unité représenté dans les même unité que la carte sur laquelle on travaille.

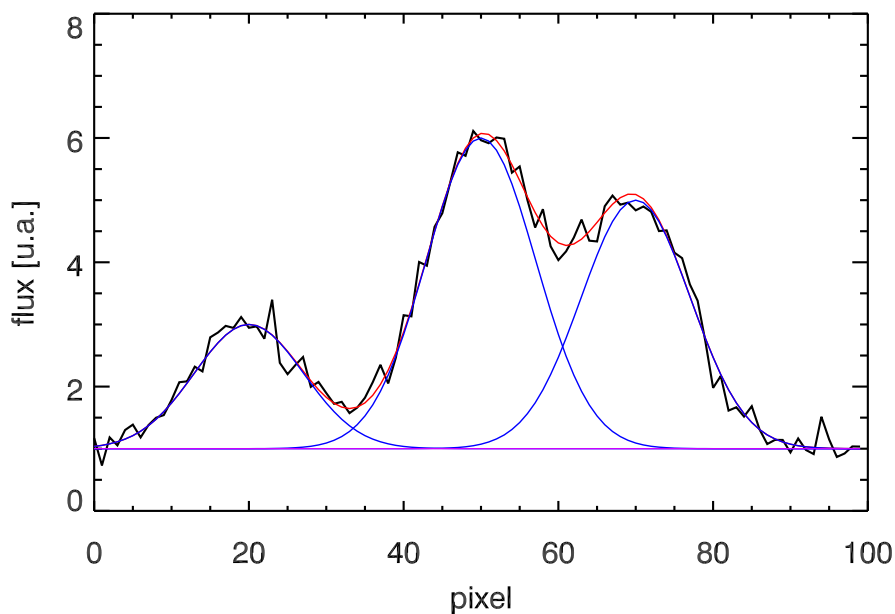


FIGURE 2.8 – Principe de la photométrie par ajustement de PSF. La courbe est une coupe d’une carte simulée où les sources sont supposées gaussiennes. La ligne en noir est le signal observé, la ligne en violet le fond, les lignes en bleu le profil des différentes sources, et enfin la ligne rouge le total des sources et du fond (sans bruit).

2.3.4 Photométrie par ajustement de PSF

Principe

La photométrie d’ouverture est une méthode très efficace lorsque les sources sont isolées. En revanche, elle l’est beaucoup moins lorsque la densité devient élevée. En effet, cette méthode ne permet pas de séparer le flux de deux sources proches dont les tâches de diffraction sont mélangées. Dans ce genre de cas, il est préférable d’utiliser des méthodes d’ajustement de PSF. Cette méthode consiste à ajuster un modèle contenant des sources et un fond. Les paramètres libres de ce modèle sont le flux des sources (et éventuellement leur position) et la valeur du fond. Les flux ajustés sont bien retrouvés même lorsque les sources sont mélangées. La Fig. 2.8 illustre le principe de cette méthode. Il existe de nombreuses routines d’ajustement de PSF, comme DAOPHOT/allstar (Stetson (1987)) ou Starfinder (Diolaiti *et al.* (2000)).

Développement mathématique

Sous certaines hypothèses, le PSF-fitting peut se résoudre à un problème relativement simple. On se place dans le cadre suivant :

- Les sources sont toutes ponctuelles et de positions connues ;
- Le bruit instrumental est gaussien et décorrélé.

La carte infrarouge considérée peut être décrite de la manière suivante :

$$m = \sum_{k=1}^{N_s} S_k \times PSF_{x_k, y_k} + \sigma + \mu, \quad (2.19)$$

où m est le tableau décrivant la carte, N_s le nombre de sources à ajuster, S_k le flux de la k -ième source, PSF_{x_k, y_k} est un tableau de la taille de la carte contenant une seule source de flux unité centrée sur la position (x_k, y_k) , σ un bruit gaussien, et μ un fond constant.

Le vecteur S est le vecteur contenant les S_k . La vraisemblance est alors donnée par :

$$L(m|S) = \prod_{pixels} C(n) \times \exp\left[-\frac{(m - \sum_{i=1}^{N_{sources}} PSF_{x_i, y_i} \times S_i - \mu)^2}{2n^2}\right], \quad (2.20)$$

où $C(n)$ est une constante de normalisation qui ne dépend que de n , la carte de bruit. Le logarithme de cette expression est donc :

$$-\log(L) = \sum_{pixels} \frac{(m - \sum_{i=1}^{N_{sources}} PSF_{x_i, y_i} \times S_i - \mu)^2}{2n^2} + \sum_{pixel} \log(C(n)). \quad (2.21)$$

La valeur de S maximisant la vraisemblance doit vérifier :

$$\forall S_k, \frac{\partial(-\log(L))}{\partial S_k} = 0 \quad \& \quad \frac{\partial(-\log(L))}{\partial \mu} = 0, \quad (2.22)$$

et par conséquent,

$$\forall S_k, \sum_{pixels} \frac{-PSF_{x_k, y_k} (m - \sum_{i=1}^{N_{sources}} PSF_{x_i, y_i} \times S_i - \mu)}{n^2} = 0. \quad (2.23)$$

$$\text{et } \sum_{pixels} \frac{m - \sum_{i=1}^{N_{sources}} PSF_{x_i, y_i} \times S_i - \mu}{n^2} = 0 \quad (2.24)$$

On peut réécrire cela de la façon suivante :

$$\forall S_k, \sum_{pixels} \frac{\mu \times PSF_{x_k, y_k}}{n^2} + \sum_{i=1}^{N_{sources}} S_i \times \sum_{pixels} \frac{PSF_{x_k, y_k} \times PSF_{x_i, y_i}}{n^2} = \sum_{pixels} \frac{PSF_{x_k, y_k} \times m}{n^2} \quad (2.25)$$

et

$$\sum_{pixels} \frac{\mu}{n^2} + \sum_{i=1}^{N_{sources}} S_i \times \sum_{pixels} \frac{PSF_{x_k, y_k}}{n^2} = \sum_{pixels} \frac{m}{n^2}. \quad (2.26)$$

Ceci est équivalent à une équation matricielle de taille $(N_{sources} + 1) \times (N_{sources} + 1)$:

$$A \cdot X = B \quad (2.27)$$

où X est un vecteur contenant $[S_1, S_1, ..., S_{N_{sources}}, \mu]$ et où A et B sont définies par :

$$\forall i \in [1, N_{sources}], \forall j \in [1, N_{sources}], A = (a_{ij}) = \sum_{pixels} \frac{PSF_{x_i, y_i} \times PSF_{x_j, y_j}}{n^2} \quad (2.28)$$

$$\forall i \in [1, N_{sources}], (a_{i(N_{sources}+1)}) = (a_{(N_{sources}+1)i}) = \sum_{pixels} \frac{PSF_{x_i, y_i}}{n^2} \quad (2.29)$$

$$(a_{(N_{sources}+1)(N_{sources}+1)}) = \sum_{pixels} \frac{1}{n^2} \quad (2.30)$$

$$\forall i \in [1, N_{sources}], B = (b_i) = \sum_{pixels} \frac{PSF_{x_i, y_i} \times m}{n^2} \quad (2.31)$$

$$B = (b_{N_{sources}+1}) = \sum_{pixels} \frac{m}{n^2} \quad (2.32)$$

La matrice A est symétrique et donc inversible. L'estimateur du maximum de vraisemblance est donc :

$$S = A^{-1}B. \quad (2.33)$$

L'ajustement simultané de N sources peut donc se réduire au problème de l'inversion d'une matrice $(N_{sources} + 1) \times (N_{sources} + 1)$.

On peut également estimer les erreurs. La matrice de Fisher de ce problème est :

$$F(S) = (f_{mn})(X) = -E\left(\frac{\partial^2 \log(L)}{\partial X_m \partial X_n} | X\right), \quad (2.34)$$

où $E(X|S)$ est l'espérance de la variable aléatoire X sachant S. On utilise alors les résultats de l'Eq. 2.26 :

$$\frac{\partial(\log(L))}{\partial S_n} = - \sum_{i=1}^{N_{sources}} S_i \times \sum_{pixels} \frac{PSF_{x_n, y_n} \times PSF_{x_i, y_i}}{n^2} + \sum_{pixels} \frac{PSF_{x_n, y_n} \times m}{n^2}, \quad (2.35)$$

puis,

$$\frac{\partial^2(\log(L))}{\partial S_m \partial S_n} = - \sum_{pixels} \frac{PSF_{x_n, y_n} \times PSF_{x_m, y_m}}{n^2} = (a_{nm}). \quad (2.36)$$

On peut aussi montrer que :

$$\frac{\partial^2(\log(L))}{\partial S_n \partial \mu} = (a_{n(N_{sources}+1)}) \quad \& \quad \frac{\partial^2(\log(L))}{\partial \mu \partial \mu} = (a_{(N_{sources}+1)(N_{sources}+1)}). \quad (2.37)$$

A est donc la matrice de Fisher du problème. Les variances sur les flux estimés sont donc les termes diagonaux de l'inverse de la matrice A, la matrice de covariance étant l'inverse de la matrice de Fisher.

$$Var(S_k) = (A^{-1})_{kk}. \quad (2.38)$$

C'est ce formalisme qui est utilisé par la routine FASTPHOT (Béthermin *et al.* (2010b)) que j'ai développé en collaboration avec Morgane Cousin lors son stage de Master 1. Elle a été optimisée pour être extrêmement rapide et s'applique au cas où les sources sont à une position connue (typiquement à partir d'observations à une plus courte longueur d'onde). La Fig. 2.10 montre une carte simulée du ciel et les résidus par rapport au modèle ajusté par FASTPHOT. On voit qu'il ne reste que du bruit instrumental, et que les sources même proches ont bien été extraites. FASTPHOT et sa documentation ont été mis en ligne publiquement sur le site web de groupe galaxies infrarouges de l'IAS (<http://www.ias.u-psud.fr/irgalaxies/downloads.php>).

2.3.5 Photométrie et filtrage des cartes

Dans le cas d'une source isolée et d'une carte à fond nul (ce qui est presque équivalent à une carte à moyenne nulle), A et B sont de simples nombres. On a alors

$$S = \frac{B}{A} = \frac{\sum_{pixels} \frac{PSF_{x_i, y_i} \times m}{n^2}}{\sum_{pixels} \frac{PSF_{x_i, y_i} \times PSF_{x_j, y_j}}{n^2}}. \quad (2.39)$$

Si on suppose également un bruit uniforme, le flux est estimé simplement par

$$S = \frac{B}{A} = \frac{\sum_{pixels} PSF_{x_i, y_i} \times m}{\sum_{pixels} PSF_{x_i, y_i} \times PSF_{x_j, y_j}}. \quad (2.40)$$

Dans une carte cross-corrélée par la PSF et normalisée en appliquant un facteur 1/A, le signal dans le pixel centré sur la source est donc exactement son flux estimé par PSF-fitting. Cette méthode est optimale au sens des moindres carrés dans le cas d'un bruit blanc, mais pas en présence de bruit de confusion où un autre filtrage peut être plus performant. De

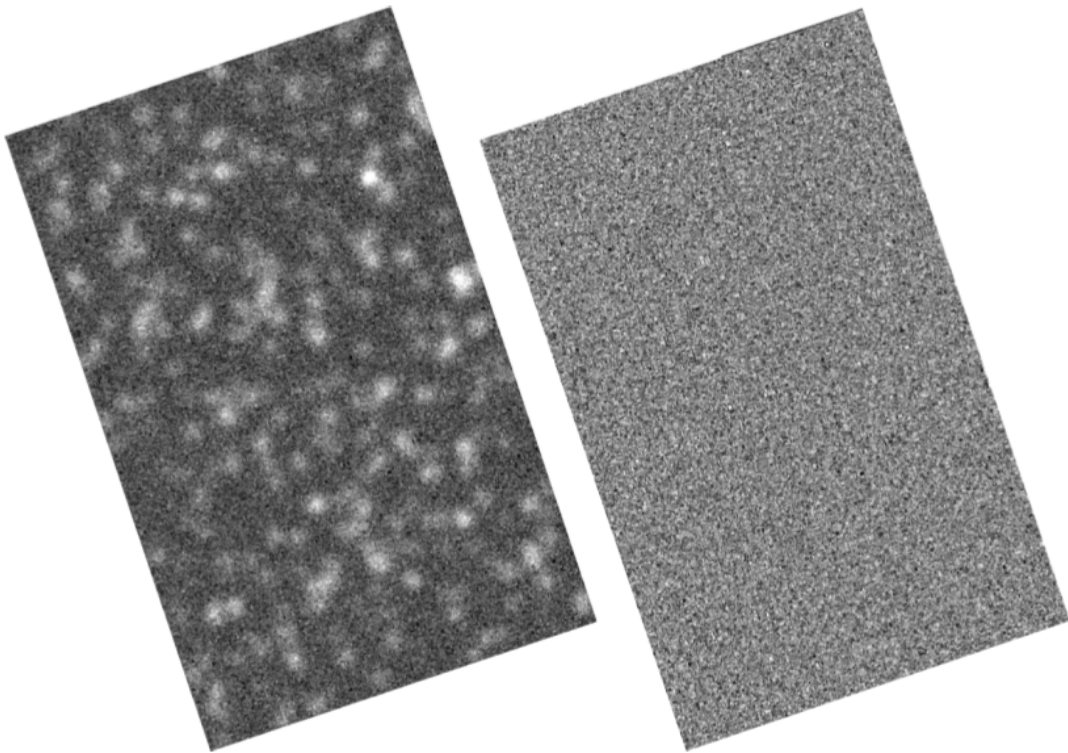


FIGURE 2.9 – (A gauche) Carte simulée. (A droite) Carte de résidus après utilisation de la routine d’ajustement de PSF FASTPHOT. Extrait du rapport de stage de M1 de Morgane Cousin.

façon plus générale, on peut obtenir une estimation du flux en lissant la carte avec un filtrage du type

$$m_l(i_0, j_0) = \frac{\sum_{i=-N}^{+N} \sum_{j=-N}^{+N} m(i_0 + i, j_0 + j) \times f(i, j)}{\sum_{pixels} f(i, j) \times PSF(i, j)}, \quad (2.41)$$

où m_l est la carte lissée, m la carte initiale, et f une fonction de deux variables. Dans la cas de l'ajustement de PSF, $f = PSF$. Pour la photométrie d'ouverture, f est à moyenne nulle, a une valeur uniforme positive dans l'ouverture centrale, et une valeur négative uniforme dans l'anneau d'estimation du fond. Cette propriété est fort commode pour estimer le bruit photométrique. En effet, il suffit d'estimer l'écart-type d'une carte lissée par la fonction f correspondant à la photométrie utilisée.

2.4 Estimation des comptages

2.4.1 Validation de l'extraction par méthode Monte-Carlo

L'efficacité de l'extraction de source et la précision de la photométrie doivent être évaluées pour produire des comptages fiables. Nous présentons ici une méthode basée sur l'injection de sources artificielles de flux connus dans les cartes. Le nombre de sources ne doit pas être trop grand pour que les sources injectées n'interfèrent pas entre elles. On extrait alors les sources de la nouvelle carte avec la même méthode d'extraction que pour la carte réelle. Puis, on recherche la présence des sources artificielles dans le nouveau catalogue. Leur présence dans le catalogue de sortie, leur position et leur flux mesuré permettent de qualifier la qualité de la méthode d'extraction. En général un grand nombre d'itérations est réalisé pour limiter les incertitudes statistiques. Il faut noter que cette méthode suppose que les sources sont distribuées de manière non-corrélée. Elle sera donc biaisée si les sources sont fortement regroupées.

2.4.2 Complétude

La complétude est la probabilité de retrouver une source dans le catalogue. Cette probabilité dépend bien entendu du flux de la source. En effet, il est bien plus difficile d'extraire une source faible qu'une source brillante. La complétude peut être estimée à partir des simulations Monte Carlo en calculant la fraction de sources artificielles retrouvées.

La fonction de complétude peut se calculer de façon analytique dans certains cas simples. Considérons le cas d'une carte lissée par la PSF, contenant des sources isolées et un bruit gaussien non-corrélé. Un pixel centré sur une source a la valeur du flux de cette

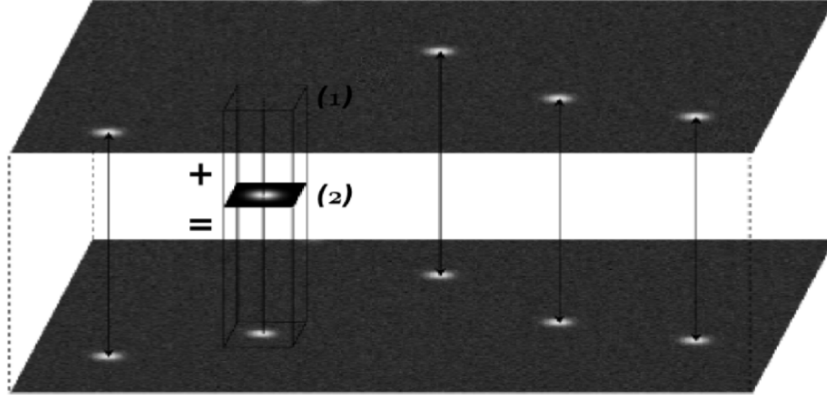


FIGURE 2.10 – Ajout d’une source artificielle Monte Carlo dans une carte infrarouge. Extrait du rapport de stage de M1 de Morgane Cousin.

source S_i , plus un bruit gaussien d’écart type σ . La densité de probabilité du signal S_{mes} dans ce pixel est donc

$$p(S_{mes}|S_i) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(S_{mes}-S_i)^2}{2\sigma^2}}. \quad (2.42)$$

Si on détecte les sources en utilisant un seuil de détection S_d , la probabilité que la source soit détectée est

$$P(S_{mes} > S_d|S_i) = \frac{1}{\sigma\sqrt{2\pi}} \int_{S_d}^{\infty} e^{-\frac{(S_{mes}-S_i)^2}{2\sigma^2}} dS_{mes} \quad (2.43)$$

$$= \frac{1 + \operatorname{erf}\left(\frac{S_i - S_d}{\sqrt{2}\sigma}\right)}{2}, \quad (2.44)$$

où erf est la fonction erreur¹². La Fig. 2.11 montre la fonction de complétude dans ce cas simple. En pratique, les sources voisines induisent un bruit non-gaussien (voir Chap. 4), et le calcul analytique devient alors beaucoup plus difficile.

2.4.3 Qualité de la photométrie

Les simulations Monte Carlo permettent également de déterminer la qualité de la photométrie. En effet, pour une série de sources injectées de même flux, on peut étudier la distribution des flux mesurés. On peut par exemple s’intéresser au flux moyen mesuré. Pour une extraction aveugle de sources de faibles flux, cette moyenne est supérieure au flux initial. Ce phénomène est appelé *flux boosting*.

¹²La fonction erreur est définie par $\operatorname{erf}(z) = \frac{2}{\sqrt{\pi}} \int_0^z e^{-\zeta^2} d\zeta$

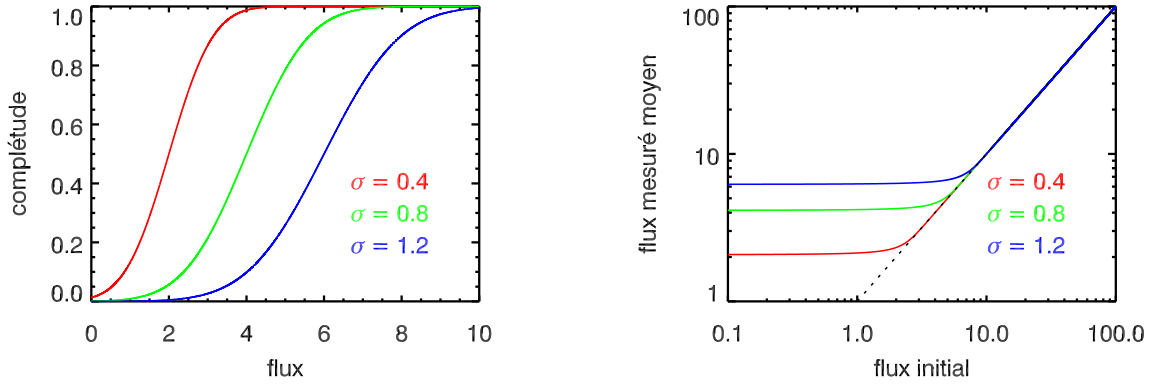


FIGURE 2.11 – (A gauche) Complétude en fonction du flux dans le cas simplifié présenté Sect. 2.4.2. Les différentes couleurs correspondent à différents niveaux de bruit (rouge : $\sigma = 0.4$, vert : $\sigma = 0.8$, et bleu : $\sigma = 1.2$). Le seuil de détection est fixé à 5σ et varie donc en fonction du niveau de bruit. (A droite) Flux moyen mesuré en fonction du flux initial.

Le phénomène de flux boosting peut être traité mathématiquement. L'espérance $\langle S_{mes} > S_d | S_i \rangle$ du flux mesuré pour un flux initial S_i et une coupure S_d vaut

$$\langle S_{mes} > S_d | S_i \rangle = \frac{\int_{S_d}^{\infty} S_{mes} \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(S_{mes}-S_i)^2}{2\sigma^2}} dS_{mes}}{P(S_{mes} > S_d | S_i)} \quad (2.45)$$

$$= \frac{\int_{\frac{S_d-S_i}{\sigma\sqrt{2}}}^{\infty} \left(\frac{S_{mes}\sigma\sqrt{2}}{\sqrt{\pi}} + \frac{S_i}{\sqrt{\pi}} \right) e^{-y^2} dy}{\frac{1+\text{erf}\left(\frac{S_i-S_d}{\sqrt{2}\sigma}\right)}{2}}, \quad (2.46)$$

où la deuxième expression est obtenue en faisant le changement de variable $y = (S_{mes} - S_i)/(\sigma\sqrt{2})$. Cette intégrale peut se calculer analytiquement¹³ :

$$\langle S_{mes} > S_d | S_i \rangle = \frac{S_i \frac{1+\text{erf}\left(\frac{S_i-S_d}{\sqrt{2}\sigma}\right)}{2} + \frac{\sigma}{\sqrt{2\pi}} e^{-\left(\frac{S_i-S_d}{\sqrt{2}\sigma}\right)^2}}{\frac{1+\text{erf}\left(\frac{S_i-S_d}{\sqrt{2}\sigma}\right)}{2}} \quad (2.47)$$

$$= S_i + \sqrt{\frac{2}{\pi}} \frac{\sigma e^{-\left(\frac{S_i-S_d}{\sqrt{2}\sigma}\right)^2}}{1+\text{erf}\left(\frac{S_i-S_d}{\sqrt{2}\sigma}\right)}. \quad (2.48)$$

On constate que la moyenne des valeurs retrouvées n'est pas S_i . Il existe un terme supplémentaire positif qui correspond au *flux boosting*. On remarque qu'à haut flux ($S_i - S_d \gg$

¹³En effet *Mathematica* donne $\int_x^{\infty} (ay + b)e^{-y^2} dy = \sqrt{\pi}b \frac{1-\text{erf}(x)}{2} + \frac{a}{2}e^{-x^2}$

σ), ce terme tend vers 0, et on n'a donc pas de biais ($\langle S_{mes} > S_c | S_i \rangle = S_i$). On peut aussi remarquer que dans le cas d'une extraction avec a priori (position des sources connue initialement), qui est équivalente à $S_d = -\infty$, on a également un biais nul. La Fig. 2.11 représente le flux moyen de sortie en fonction du flux initial. On remarque également qu'à bas flux ($S_i - S_d \ll \sigma$), on a $\langle S_{mes} > S_d | S_i \rangle \approx S_d$. En effet, seules les sources sur de forts pics de bruit vont être détectées. La partie de la distribution de probabilité supérieure à S_d décroissant rapidement, la moyenne sera donc approximativement S_d .

2.4.4 Estimation des comptages et correction des biais d'extractions

Dans le cas idéal d'un catalogue parfait, les comptages peuvent être estimés en comptant le nombre de sources par intervalle de flux et en divisant par la taille de celui-ci. Cette méthode simple souffre de biais dans la cas d'un catalogue réel. D'un part, l'incomplétude du catalogue fait sous-estimer les comptages à bas flux. D'autre part, le bruit photométrique a tendance à faire surestimer les comptages quand la pente des comptages est forte. En effet, même si le bruit photométrique est symétrique, dans un intervalle de flux mesuré donné, il y a plus de sources faibles de flux surestimé que de sources brillantes de flux sous-estimé. Ce phénomène est appelé biais d'Eddington (1913). La Fig. 2.12 illustre cet effet. En général, on applique un facteur correctif aux comptages déterminé grâce à une simulation. Cette simulation utilise les informations fournies par les injections de sources Monte Carlo. Elle nécessite également de supposer la forme des comptages initiaux.

2.4.5 Estimation des incertitudes sur les comptages

Les incertitudes sur les comptages sont souvent supposées poissonniennes. L'incertitude sur le nombre de sources dans un intervalle de flux est alors la racine du nombre de sources. En pratique, les écarts d'un champ à l'autre sont parfois largement supérieurs à cette estimation. On parle alors de variance cosmique. Elle vient du fait que les sources infrarouges sont distribuées de manière corrélée. Cette variance peut se calculer à partir de la fonction de corrélation angulaire à deux points.

La fonction de corrélation angulaire

La fonction de corrélation angulaire à deux points, w , permet de décrire la tendance des sources à se regrouper. Elle est définie par :

$$dP = \rho_0^2 (1 + w(\theta)) d\Omega_1 d\Omega_2, \quad (2.49)$$

où dP est la probabilité de trouver une galaxie dans un angle solide $d\Omega_1$ et une autre dans un angle solide $d\Omega_2$ séparés d'un angle θ . La Fig. 2.13 illustre cette définition. Lorsque

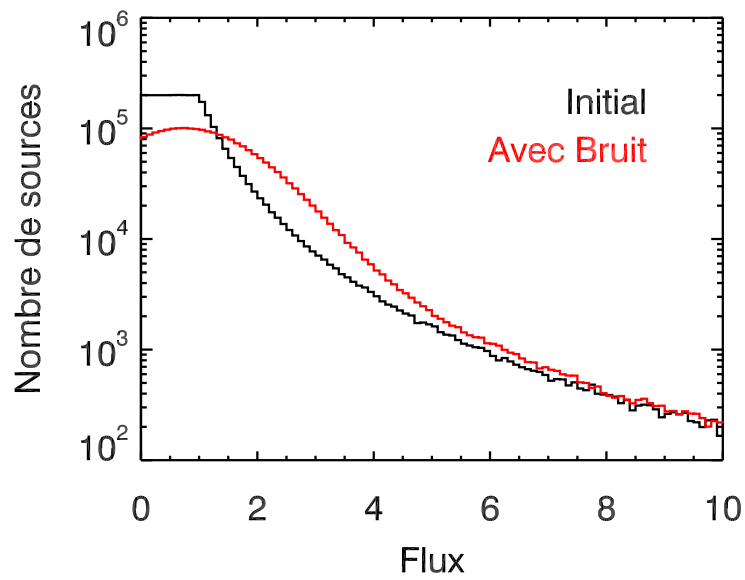
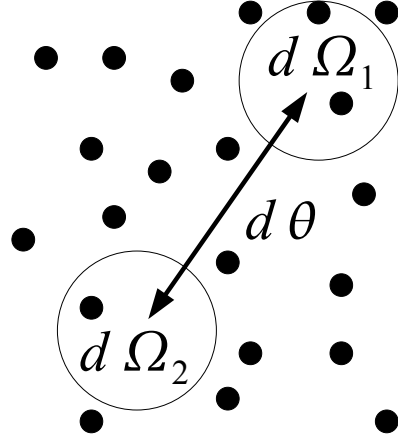


FIGURE 2.12 – Graphique illustrant le biais d'Eddington. Les comptages initiaux sont représentés en noir et les comptages finaux en rouge. Le bruit utilisé a un écart type de 1. Les comptages différentiels utilisés sont en $1/S^3$ pour $S > 1$, et constant pour $S < 1$ afin d'éviter une divergence en zéro.



Corrélation angulaire

FIGURE 2.13 – Schéma illustrant la définition de la fonction de corrélation angulaire à 2 points.

les galaxies sont distribuées de manière indépendante, w est nul. En revanche, quand elles ont tendance à se regrouper, cette fonction est positive. En général, elle décroît quand θ augmente en loi de puissance (par exemple, Waddington *et al.* (2007), Magliocchetti *et al.* (2008)) :

$$w(\theta) = \left(\frac{\theta}{\theta_0} \right)^{1-\gamma}, \quad (2.50)$$

avec $\gamma = 1.8$. Il y a souvent un excès de corrélation aux petites échelles dû au regroupement des sources dans un même halo de matière noire.

Incertitudes sur les comptages

La variance, σ_N sur le nombre de sources, N , est (Wall et Jenkins (2003)) :

$$\sigma_N = \sqrt{y \cdot \bar{N}^2 + \bar{N}}. \quad (2.51)$$

où $\bar{N}$ est la valeur moyenne de N et y est définie par :

$$y = \frac{\int \int_{champs} w(\theta) d\Omega_1 d\Omega_2}{\Omega^2}. \quad (2.52)$$

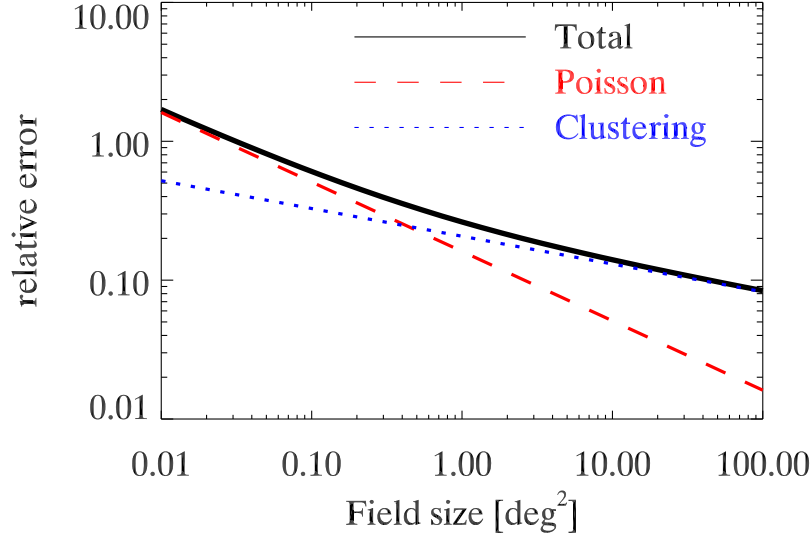


FIGURE 2.14 – Incertitudes relatives sur le nombre de sources en fonction de la taille du champs. Ce schéma, extrait de Béthermin *et al.* (2010a), représente le cas d’un intervalle de flux entre 80 et 120 mJy à 160 μm .

On remarque que dans le cas poissonien, on a $y=0$ et donc $\sigma_N = \sqrt{N}$.

L’incertitude sur le nombre de sources est donc piloté par deux termes combinés quadratiquement : un terme poissonien en $\sqrt{N}$ et un terme dû au regroupement des sources en $\sqrt{y} \times N$. N et y varient avec la taille du champ Ω : $N \propto \Omega$ et $y \propto \Omega^{(\gamma-1)/2}$ (Blake et Wall, 2002). On a donc deux régimes différents : $\sigma_N \propto \Omega^{-1/2}$ dans le cas poissonien, $\sigma_N \propto \Omega^{-(1-\gamma)/4}$ dans le cas dominé par le regroupement. La Fig. 2.14 représente ces différents régimes. On constate que pour les grands champs, la variance sur le nombre de sources n’est plus du tout poissonienne.

2.5 Résultats : comptages de sources avec MIPS à 24, 70 et 160 μm

Nous présentons ici un résumé des travaux publiés dans l’article Béthermin *et al.* (2010a).

2.5.1 Motivations

De nombreuses mesures des comptages ont été réalisées avec l'instrument MIPS, que ce soit avec le canal à 24 μm (Papovich *et al.* (2004), Chary *et al.* (2004), Marleau *et al.* (2004), Rodighiero *et al.* (2006), Shupe *et al.* (2008), Le Floc'h *et al.* (2009)) ou à 70 et 160 μm (Dole *et al.* (2004), Frayer *et al.* (2006a), Frayer *et al.* (2006b), Frayer *et al.* (2009)). Toutefois, chaque étude a été réalisée dans des champs différents et aucune ne combine l'ensemble des observations disponibles. De plus, à cause des mises à jour de la calibration, les différentes observations présentent des désaccords significatifs entre elles. Nous avons donc décidé de réaliser une analyse homogène des relevés FIDEL (relevés très profond), COSMOS (relevé large et profond) et SWIRE (relevés très larges), afin de produire des comptages homogénéisés. La Table 2.1 synthétise les champs utilisés. La grande quantité de données utilisées a permis de réduire au maximum les incertitudes statistiques, améliorant ainsi les contraintes sur les modèles d'évolution.

2.5.2 Méthodes

Extraction de sources et photométrie

A 24 μm , dans les champs profonds, l'extraction de sources est principalement limitée par la densité. Nous avons donc choisi d'utiliser le logiciel *SExtractor* (Bertin et Arnouts (1996)) pour son efficacité à séparer les sources voisines. En revanche, *SExtractor* ne permet pas de réaliser du *PSF-fitting*. Nous avons donc utilisé la routine *allstar* de DAOPHOT (Stetson (1987)) pour réaliser une photométrie. La PSF a été déterminée empiriquement avec les outils de DAOPHOT.

A 70 et 160 μm , les fluctuations du fond dues aux sources faibles rendent peu efficace *SExtractor*. Nous avons donc filtré la carte en ondelettes, puis détecté les pics. Les sources émergeant significativement des fluctuations étant relativement isolées, nous avons utilisé de la photométrie d'ouverture. Les corrections d'ouverture ont été calculées à partir de PSFs empiriques construites à l'aide de *Starfinder* (Diolaiti *et al.* (2000)).

Détermination des comptages

L'estimation des comptages requière une bonne connaissance des biais d'extraction. Ceux-ci ont été estimés par injection de sources Monte-Carlo (voir Sect. 2.4.1). Nous avons réalisé des simulations prenant en compte les effets de *flux-boosting* et de complétude pour estimer les corrections à appliquer aux comptages. Les incertitudes ont été estimées en utilisant la méthode présentée Sect. 2.4.5. A 24 μm , à haut flux, la contribution des étoiles est non négligeable. Elles ont été retirées du catalogue en utilisant un critère de couleur

Nom du champ	Taille du champs			Complétude à 80%		
	24 μm	70 μm	160 μm	24 μm	70 μm	160 μm
	deg^2			μJy	mJy	
FIDEL eCDFS	0.23	0.19	-	60.	4.6	-
FIDEL EGS	0.41	-	0.38	76.	-	45.
COSMOS	2.73	2.41	2.58	96.	7.9	46.
SWIRE LH	10.04	11.88	11.10	282.	25.4	92.
SWIRE EN1	9.98	9.98	9.30	261.	24.7	94.
SWIRE EN2	5.36	5.34	4.98	267.	26.0	90.
SWIRE ES1	7.45	7.43	6.71	411.	36.4	130.
SWIRE CDFS	8.42	8.28	7.87	281.	24.7	88.
SWIRE XMM	8.93	-	-	351.	-	-
Total	53.55	45.51	42.91			

TABLE 2.1 – Taille et profondeur (exprimé en terme de limite de complétude à 80%) des champs utilisés pour mesurer les comptages MIPS. Extrait de Béthermin *et al.* (2010a).

K-[24]<2 (Shupe *et al.* (2008)). Les données en bande K (2 μm) proviennent du relevé proche infrarouge 2MASS (Skrutskie *et al.* (2006)).

2.5.3 Résultats

Comptages à 24 μm

En combinant des champs profonds et larges, nous obtenons une mesure des comptages sur trois ordres de grandeur et demi en flux (de 35 μJy à 10 mJy). Nos points sont globalement en bon accord avec les mesures précédentes (c.f. Fig. 2.15). La grande quantité de données utilisées (>50 deg^2) permet de minimiser au maximum les incertitudes statistiques par rapport aux précédents travaux.

Les mesures sont également en bon accord avec le modèle de Le Borgne *et al.* (2009), à l'exception d'une légère sous-estimation ($\sim 10\%$) par rapport aux observations autour de 300 μJy . Le modèle de Lagache *et al.* (2004) est quant à lui en bon accord avec les observations en dessous de 100 μJy , mais tend à sous-estimer légèrement ($\sim 10\%$) les comptages à plus haut flux.

Comptages à 70 et 160 μm

A 70 μm , nos comptages vont de 4 mJy à 1 Jy. Ils sont en très bon accord avec les mesures précédentes de Dole *et al.* (2004) et Frayer *et al.* (2006a,b, 2009) (voire Fig. 2.16). Il y

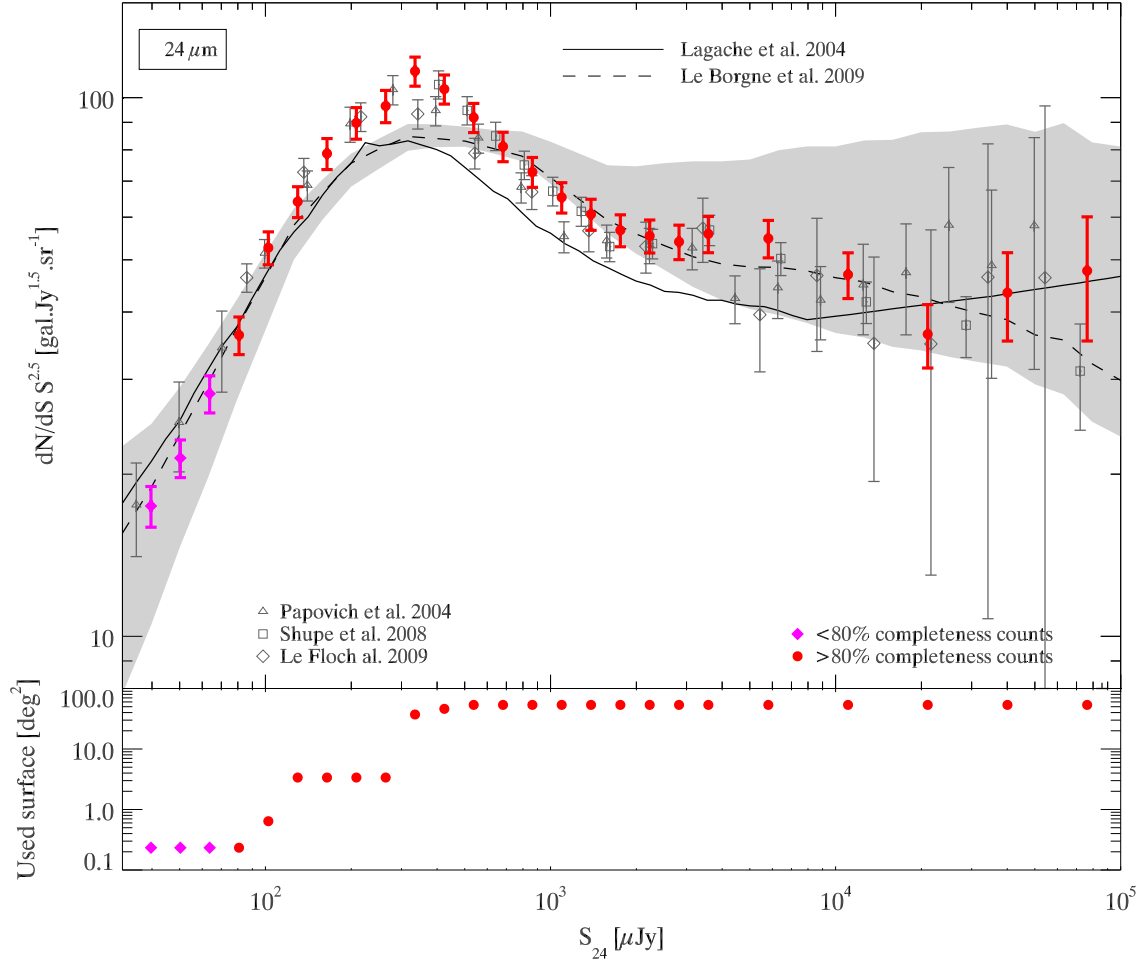


FIGURE 2.15 – Comptages différentiels à $24\ \mu\text{m}$. *Disques pleins rouges* : mesures réalisées avec plus de 80% de complétudes. *Losanges violets* : points entre 50 et 80% de complétudes. *Triangles ouverts gris* : mesures de Papovich *et al.* (2004). *Carrés ouverts gris* : mesures de Shupe *et al.* (2008). *Losanges ouverts gris* : mesures de Le Floch *et al.* (2009). *Ligne continue* : modèle de Lagache *et al.* (2004). *Ligne pointillée et zone grisée* : modèle de Le Borgne *et al.* (2009). Le panneau du bas indique la surface utilisée pour déterminer les comptages en fonction du flux. Extrait de Béthermin *et al.* (2010a).

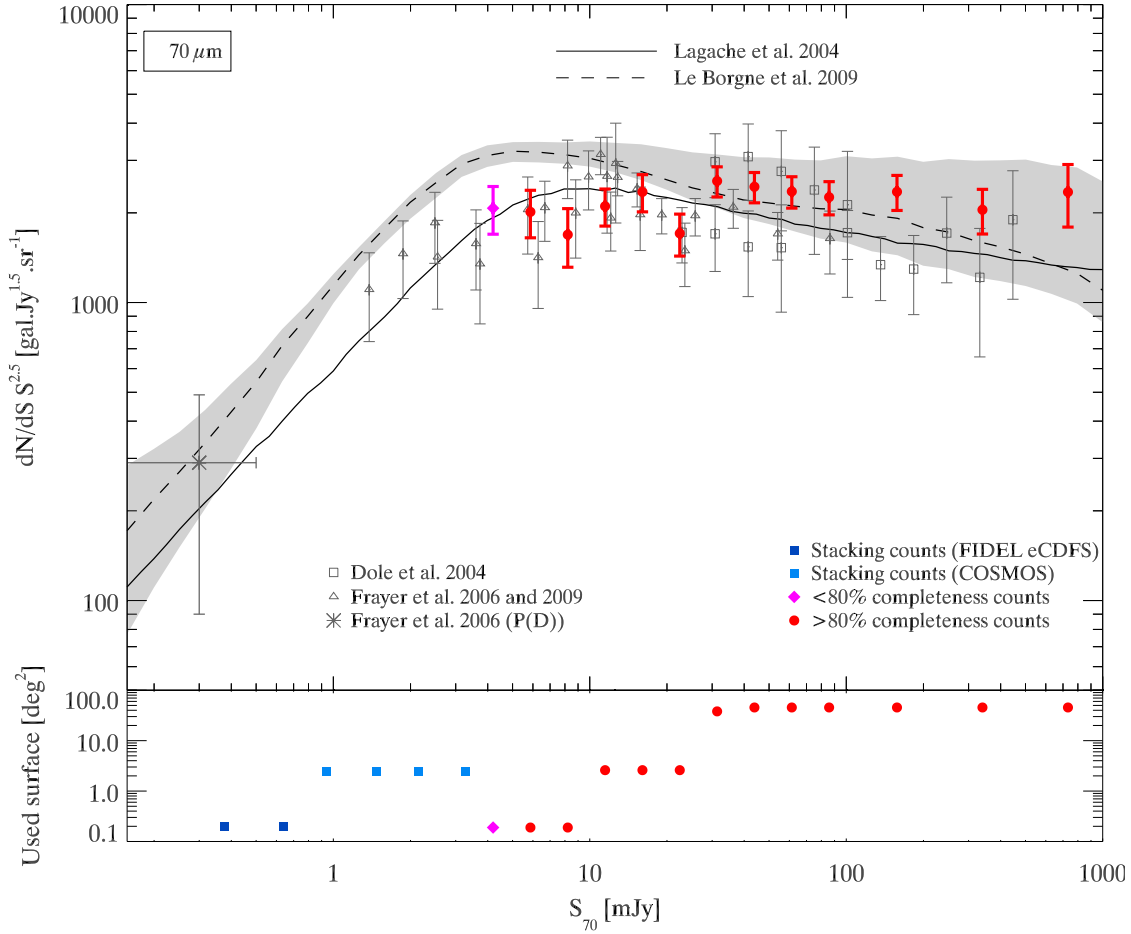


FIGURE 2.16 – Comptages différentiels à $70\ \mu\text{m}$. *Disques pleins rouges* : mesures réalisées avec plus de 80% de complétudes. *Losanges pleins violets* : points entre 50 et 80% de complétudes. *Triangles ouverts gris* : mesures de Frayer *et al.* (2006a), Frayer *et al.* (2006b) et Frayer *et al.* (2009). *Carrés ouverts gris* : mesures de Dole *et al.* (2004). *Astérisque grise* : mesures par analyse de fluctuations de Frayer *et al.* (2006b). *Ligne continue* : modèle de Lagache *et al.* (2004). *Ligne pointillée et zone grisée* : modèle de Le Borgne *et al.* (2009). Le panneau du bas indique la surface utilisée pour déterminer les comptages. Extrait de Béthermin *et al.* (2010a).

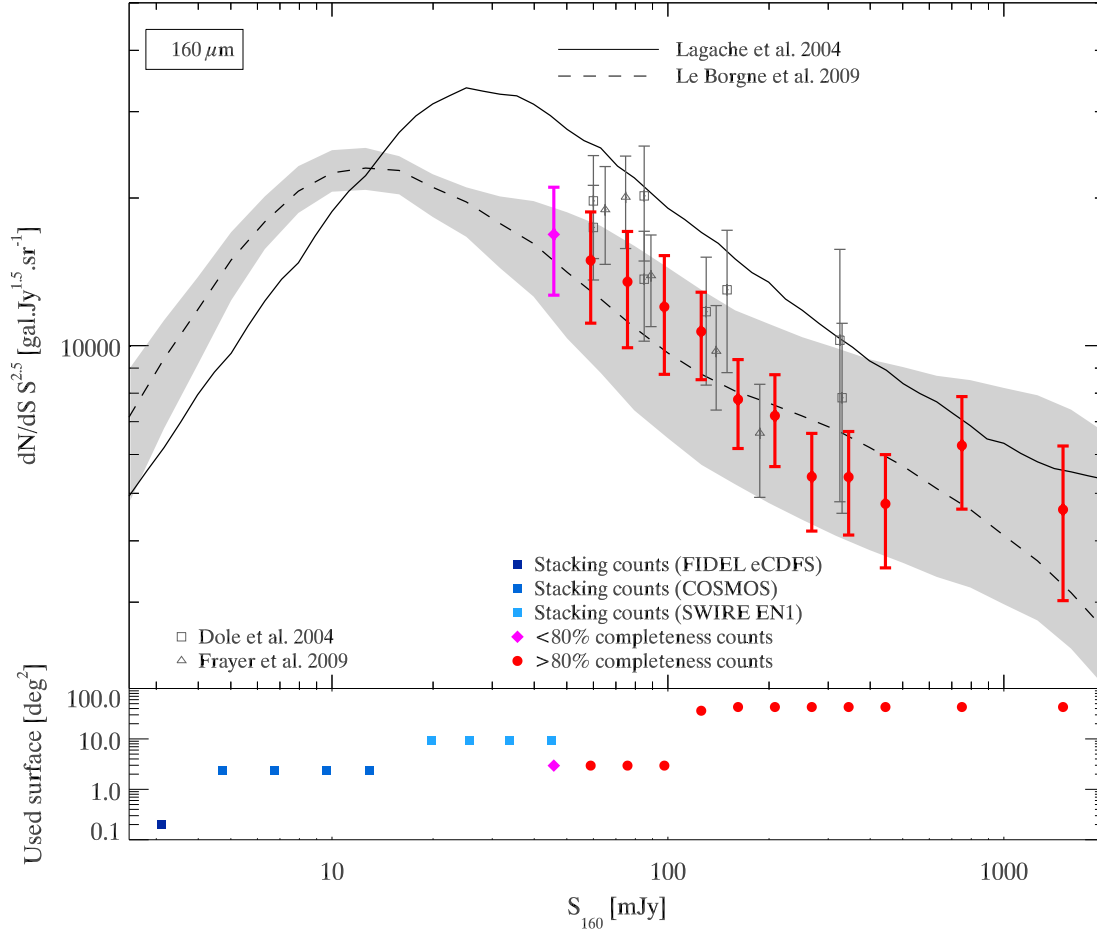


FIGURE 2.17 – Comptages différentiels à $160\ \mu\text{m}$. *Disques pleins rouges* : mesures réalisées avec plus de 80% de complétudes. *Losanges pleins violets* : points entre 50 et 80% de complétudes. *Triangles ouverts gris* : mesures de Frayer *et al.* (2006a), Frayer *et al.* (2006b) et Frayer *et al.* (2009). *Carrés ouverts gris* : mesures de Dole *et al.* (2004). *Ligne continue* : modèle de Lagache *et al.* (2004). *Ligne pointillée et zone grisée* : modèle de Le Borgne *et al.* (2009). Le panneau du bas indique la surface utilisée pour déterminer les comptages en fonction du flux. Extrait de Béthermin *et al.* (2010a).

a également un bon accord avec les modèles, à l'exception d'une légère ($\sim 25\%$) sous-estimation par le modèle de Lagache *et al.* (2004) au dessus de 50 mJy et une légère ($\sim 25\%$) surestimation par le modèle de Le Borgne *et al.* (2009) en dessous de 10 mJy. Nos comptages ne sont pas assez profonds pour que la coupure dans les comptages soit détectée.

A 160 μm , nous sommes capables de sonder les comptages de 40 mJy à 2 Jy. Nos mesures sont en bon accord avec Dole *et al.* (2004) et Frayer *et al.* (2006a, 2009) (voir Fig. 2.17). Le modèle de Lagache *et al.* (2004) sous-estime les comptages de 30%, alors que le modèle de Le Borgne *et al.* (2009) est en très bon accord. Nos comptages ne sont pas suffisamment profonds pour détecter le pic des comptages différentiels normalisés prédits par les modèles.

2.6 Résultats : comptages de sources avec BLAST à 250, 350 et 500 μm

Nous présentons ici un résumé des travaux publiés dans l'article Béthermin *et al.* (2010b).

2.6.1 Motivations

En mars 2009, l'équipe BLAST a rendu publiques ses observations du CDFS¹⁴ à 250, 350 et 500 μm (Devlin *et al.* (2009)). Elles comportent un champ large et peu profond de 10 deg^2 , au centre duquel se trouve une zone profonde d'environ 1 deg^2 . L'équipe BLAST a publié des comptages en utilisant uniquement une analyse P(D) (voir Chap. 4), en invoquant qu'il était impossible de construire des comptages fiables dans la confusion. Fort de l'expérience de MIPS à 160 μm , j'ai décidé de mesurer les comptages dans les données BLAST à partir d'une extraction de sources directe et d'une correction des différents biais d'extraction, afin de les comparer aux résultats obtenus par analyse P(D).

2.6.2 Extraction de sources aveugle

Dans un premier temps, nous avons réalisé une extraction aveugle des sources. On appelle aveugle une extraction qui se base sur une carte obtenue à partir d'observations à une seule longueur d'onde. Nous avons utilisé deux méthodes d'extraction différentes selon que l'on soit dans la zone centrale profonde, qui est limitée par la confusion, ou dans

¹⁴Chandra Deep Field South

	Complétude à 95%		Bruit instrumental		Bruit photométrique total		Bruit de confusion	
	mJy		mJy		mJy		mJy	
	large	profond	large	profond	large	profond	large	profond
250 μm	203	97	37.7	11.1	47.3	24.9	28.6	22.3
350 μm	161	83	31.6	9.3	35.8	20.3	16.8	18.0
500 μm	131	76	20.4	6.0	26.4	17.6	16.7	16.5

TABLE 2.2 – Limite de complétude à 95% et bruit photométrique aux différentes longueurs d’ondes. Le bruit instrumental est donné par la carte de bruit. Le bruit photométrique vient de l’injection de sources Monte Carlo. Le bruit de confusion est calculé avec $\sigma_{conf} = \sqrt{\sigma_{tot}^2 - \sigma_{instr}^2}$. Extrait de Béthermin *et al.* (2010b).

le reste de la carte, qui est limité par le bruit instrumental.

Dans la partie limitée par la confusion, nous avons utilisé la même méthode qu’à 160 μm avec *Spitzer*, à l’exception de la photométrie qui est réalisée avec FASTPHOT. Dans cette partie du champ, le bruit de confusion domine totalement le bruit instrumental à toutes les longueurs d’ondes. Le catalogue de source produit par l’équipe BLAST (Dye *et al.* (2009)) ne prenait pas en compte le bruit de confusion, ce qui explique en partie les problèmes qu’ils ont rencontrés dans la mesure des comptages à partir de leur catalogue. Le bruit photométrique à 1- σ est de l’ordre de 20 mJy dans les trois bandes. Ceci limite très fortement la possibilité de réaliser des comptages profonds. En effet, dans le cadre des fortes pentes de comptages du domaine sub-mm, les effets du bias d’Eddington et du *flux-boosting* sont très difficiles à corriger en dessous de 4- σ .

Dans le reste du champs, l’extraction de sources est limitée par le bruit instrumental. Nous avons donc utilisé la méthode présentée Sect. 2.3.2 et FASTPHOT.

2.6.3 Extraction de sources avec a priori

Il est possible d’extraire plus efficacement les sources en utilisant l’information fournie par les catalogues construits à d’autres longueurs d’ondes. Par exemple, la PSF de *Spitzer* à 24 μm a une largeur à mi-hauteur de 6.6" contre 32" à 250 μm avec BLAST. Le 24 μm fournit donc une information très précise sur la position des sources. Or, les modèles (Lagache *et al.* (2004), Le Borgne *et al.* (2009)) prédisent que les sources à 24 μm non détectées dans le relevé SWIRE ($S_{24} < 250 \mu\text{Jy}$) et détectables par BLAST à 3- σ représentent moins de 5% des sources BLAST. La position des sources à 24 μm est donc un a priori très utile pour l’extraction des sources.

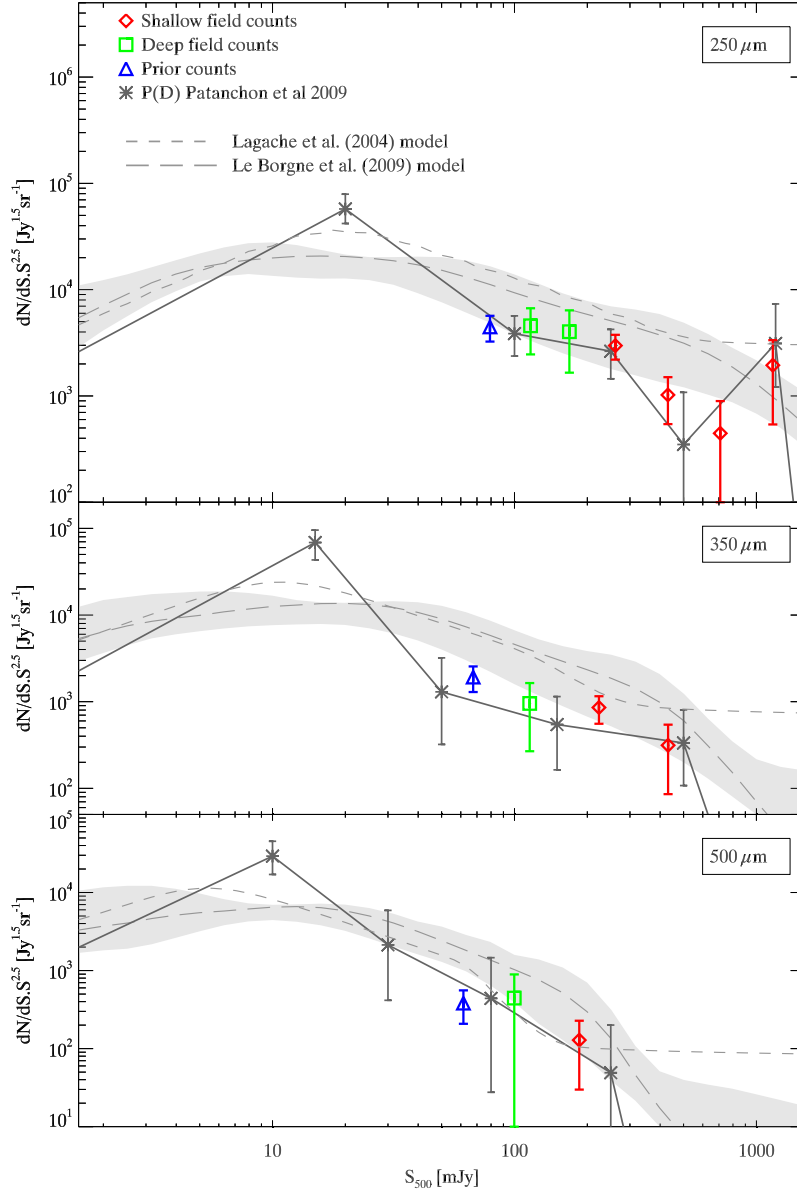


FIGURE 2.18 – Comptages à 250, 350 et 500 μm observés mesurés, dans les données BLAST. *Triangles bleus* : Comptages réalisés à partir d’une extraction de sources avec a priori. *Carrés verts* : Comptages de sources dans le champ profond. *Losanges rouges* : Comptages de sources dans le champ large. *Astérisques* : analyse P(D) de Patanchon *et al.* (2009). *Tirets courts* : modèle de Lagache *et al.* (2004). *Tirets long* : Modèle de Le Borgne *et al.* (2009). Extrait de Béthermin *et al.* (2010b). Extrait de Béthermin *et al.* (2010b).

Nous avons utilisé la routine de *PSF-fitting* FASTPHOT aux positions des sources $24\ \mu\text{m}$. La photométrie a été testée en injectant des sources artificielles dans le catalogue d’entrée et dans la carte. Le bruit photométrique est plus faible que pour une extraction aveugle (21.5 mJy contre 24.9 mJy à $250\ \mu\text{m}$). En effet, la connaissance de la position initiale des sources permet de mieux séparer le flux de sources proches l’une de l’autre. Enfin, il n’existe pas de phénomène de *flux-boosting*, car les sources sont extraites à une longueur d’onde différente de celle où la photométrie est réalisée. Il n’y a donc pas de biais vers les pics de bruit comme lors d’une extraction aveugle. Il faut toutefois corriger du biais d’Eddington, qui existent même en l’absence de *flux-boosting*. Pour cela, nous avons ajouté des erreurs photométriques gaussiennes à notre catalogue de sortie et comparé le nombre de sources présentes avant et après l’ajout de cette erreur dans le bins de flux utilisé. Nous avons trouvé des facteurs correctifs de 0.42, 0.35 et 0.21 à respectivement 250, 350 et $500\ \mu\text{m}$.

2.6.4 Discussion

Nos comptages sont en très bon accord avec l’analyse P(D) de Patanchon *et al.* (2009). Les barres d’erreurs (dont la validité a été testée sur des simulations) sont par ailleurs légèrement plus petites que celle obtenue par analyse P(D). Il faut toutefois noter que la contribution de ces comptages au fond ne résout que 2.3, 1.1 et 0.4% du fond mesuré par FIRAS (Lagache *et al.* (2000)) à respectivement 250, 350 et $500\ \mu\text{m}$. Cette méthode ne sonde qu’une petite partie des populations infrarouges. Le modèle de Lagache *et al.* (2004) sur-prédit les comptages d’un facteur 2. Ceci est probablement dû à un trop grand nombre de sources ultra-lumineuses à grand *redshift*. Le modèle de Le Borgne *et al.* (2009) est également légèrement trop haut.

2.7 Conclusion

Nous avons combiné une importante quantité de données publiques, afin de mesurer avec une précision inégalée les comptages extragalactiques dans les trois bandes de l’instrument MIPS. Nous avons également mesuré les comptages de sources brillantes dans les données BLAST en utilisant une extraction aveugle, mais aussi une extraction utilisant un a priori sur la position des sources provenant du $24\ \mu\text{m}$. Ces comptages sont en bon accord avec les mesures précédentes. En revanche, ni le modèle de Lagache *et al.* (2004), ni le modèle de Le Borgne *et al.* (2009) n’est capable de reproduire l’ensemble de ces comptages. Ces nouvelles mesures, à des longueurs d’ondes qui encadrent le pic du fond infrarouge, vont donc permettre de mettre à jour les modèles d’évolution des galaxies infrarouges. Aux grandes longueurs d’ondes, il faut toutefois noter que les méthodes d’ex-

traction de sources individuelles ne permettent de sonder que les populations les plus brillantes. Il est donc nécessaire d'utiliser d'autres méthodes pour sonder les populations plus faibles.

Chapitre 3

Comptages ultra-profonds par empilement

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Au delà de $70 \mu\text{m}$, il n'est possible ni avec *Spitzer*, ni avec BLAST, de sonder le pic des comptages différentiels normalisés (voir chapitre précédent). Or, sa position est une contrainte importante pour les modèles d'évolution. Dans cette partie, nous allons présenter une méthode permettant de sonder les populations plus faibles : l'empilement.

3.1 La méthode de l'empilement

3.1.1 Principe

A cause du phénomène de confusion, il n'est pas possible de détecter les sources faibles à grande longueur d'onde. En revanche, la position de ces sources est très bien connue grâce aux plus courtes longueurs d'ondes (c.f. Fig. 2.4). Si on mesure le flux S_{mes} d'une source non détectée à la longueur d'onde d'observation, mais dont la position est connue, on obtient :

$$S_{mes} = S + \sqrt{\sigma_{instr}^2 + \sigma_{conf}^2 + \sigma_{pop}^2} \times X \quad (3.1)$$

où S est le flux de la source, σ_{instr} le bruit instrumental, et σ_{conf} le bruit de confusion, σ_{pop} est la dispersion en flux de la population étudiée, et X une variable aléatoire gaussienne centrée réduite¹. On fait ici l'hypothèse que les bruits et la dispersion en flux sont gaussiens. Pour une source très faible, $S \ll \sigma_{instr}$ et σ_{conf} . Il est donc impossible de la détecter. En revanche, on peut mesurer le flux moyen d'une population. En effet, si on suppose que les bruits sont indépendants, le flux moyen mesuré, $\langle S \rangle_{mes}$, sera

$$\langle S \rangle_{mes} = \langle S \rangle + \frac{\sqrt{\sigma_{instr}^2 + \sigma_{conf}^2 + \sigma_{pop}^2}}{\sqrt{N}} X \quad (3.2)$$

où $\langle S \rangle$ est flux moyen de la population, et N le nombre de sources utilisées. Si N est assez grand ($N \gg \langle S \rangle^2 / (\sigma_{instr}^2 + \sigma_{conf}^2 + \sigma_{pop}^2)$), il est possible de détecter le signal collectif d'une population faible. En pratique, la dispersion en flux est le plus souvent de type log-normale. Toutefois, comme un grand nombre de sources est généralement utilisé, d'après le théorème central limite, les réalisations de la moyenne du terme de dispersion auront une distribution très proche d'une gaussienne d'écart type $\sigma_{pop} / \sqrt{N}$. La Fig. 3.1 illustre cet effet. L'histogramme de gauche montre la distribution en flux d'un échantillon de 1000 sources suivant une loi log-normale de moyenne unité et d'écart-type 0.48 (en linéaire, soit 0.2 dex).² L'histogramme de droite montre la distribution de la moyenne de

¹ X est donc tiré de manière aléatoire selon une distribution gaussienne de moyenne nulle et variance unité.

²La distribution log-normale n'étant définie que par deux paramètres, elle peut être caractérisée par sa moyenne et son écart type soit en linéaire soit en logarithme. On peut donc passer simplement d'une paire de paramètre à l'autre par une relation bijective.

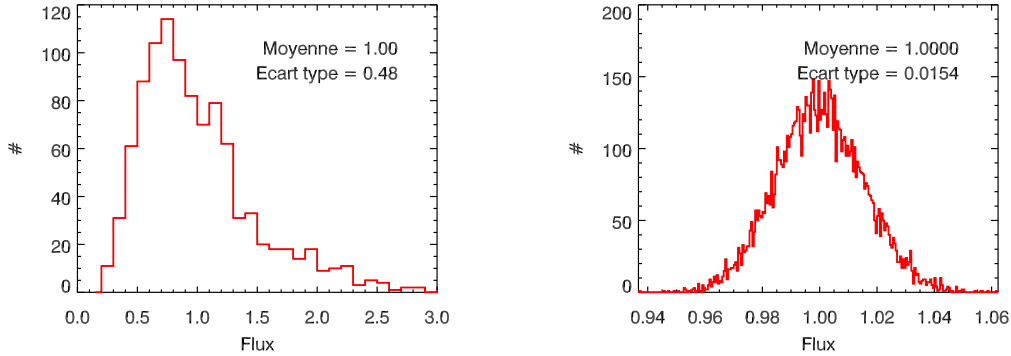


FIGURE 3.1 – A gauche : histogramme des flux d’un échantillon de 1000 sources suivant une loi log-normale de moyenne unité (en linéaire) et de dispersion 0.2 dex. A droite : histogramme de la moyenne de 10 000 de ces échantillons.

10 000 de ces échantillons. Comme prédit par le théorème central limite, la distribution des moyennes est à moyenne unité et d’écart-type $\sigma_{pop}/\sqrt{N}$ ($0.48/\sqrt{1000} = 0.015$).

En pratique, deux méthodes sont utilisables. La méthode de Dole *et al.* (2006) consiste à extraire de la carte des imagerie centrées sur les sources sélectionnées, puis de les empiler en faisant une moyenne (ou une somme) selon la propriété étudiée. Le résultat est une image avec au centre une source artificielle, dont le flux est la moyenne (ou la somme) des flux des sources étudiées (voir Fig. 3.2). Il suffit alors de mesurer le flux de cette source artificielle avec une technique de photométrie classique. Cette méthode a l’avantage de produire une image permettant de détecter d’éventuels artefacts, en revanche elle est relativement lente par rapport à la seconde méthode.

Cette seconde méthode a été proposée par Marsden *et al.* (2009). La carte est tout d’abord lissée par la PSF (voir Sect. 2.3.5) et mise à moyenne nulle, afin que le signal dans le pixel central d’une source contienne une estimation de son flux. On fait alors la moyenne (ou la somme) des pixels contenant une des sources étudiées. Cette méthode a l’avantage d’être extrêmement simple et rapide, en revanche, elle ne permet aucune visualisation.

En fait, ces deux méthodes sont quasiment similaires. En effet, le fond mesuré sur l’image résultant d’un empilement (méthode de Dole *et al.* (2006)) d’une carte à moyenne nulle est nul dans le cas poissonnien. De plus, utiliser du *PSF-fitting* sur l’image résultat (méthode de Dole *et al.* (2006)) est équivalent à lisser la carte avant d’empiler et de mesurer le flux dans le pixel central (méthode de Marsden *et al.* (2009)). En fait, ces méthodes diffèrent surtout du point de vue pratique : l’une est rapide, l’autre est visuelle.

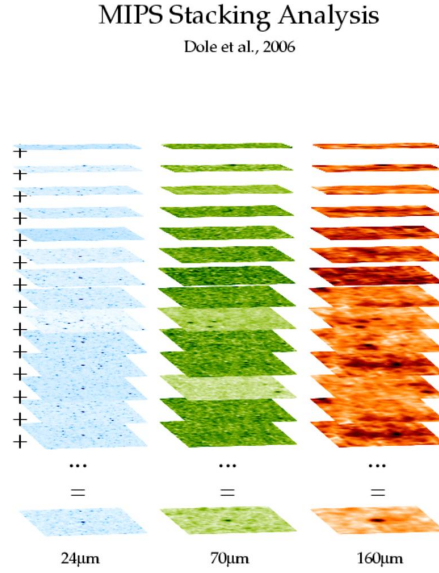


FIGURE 3.2 – Principe de l'analyse par empilement (crédits : Hervé Dole).

3.1.2 Estimation des erreurs

La méthode la plus basique permettant d'estimer les incertitudes consiste à mesurer le bruit photométrique (par exemple écart-type de la carte lissée pour la méthode de Marsden *et al.* (2009)) et de le diviser par $\sqrt{N}$. Néanmoins cette méthode ne prend pas en compte le fait que l'échantillon étudié n'a pas un flux homogène. Cette méthode ne fournit qu'une estimation du bruit photométrique σ_{phot} sur l'image empilée

$$\sigma_{phot} = \frac{\sqrt{\sigma_{instr}^2 + \sigma_{conf}^2}}{\sqrt{N}}. \quad (3.3)$$

L'incertitude totale peut être estimée en utilisant la méthode du *bootstrap*³. Cette méthode consiste à tirer N sources⁴ avec remise dans l'échantillon initial, où N est le nombre de source de l'échantillon initial. Une source peut donc être présente plusieurs fois dans

³Ce nom fait référence aux *aventures du baron Münchhausen* qui se maintient en l'air en tirant sur ses propres lacets (en anglais, *bootstrap*). En effet, la méthode du *bootstrap* détermine la variance d'échantillon à partir du seul échantillon disponible, ce qui peut faire penser à la technique de lévitation du baron.

⁴Si on veut mesurer l'incertitude sur le flux total d'une population, il est préférable d'utiliser n sources, avec n une variable aléatoire poissonnienne d'espérance N .

l'échantillon *bootstrap*. On réalise alors un nouvel empilement dont on conserve le résultat. Ce processus est réalisé un grand nombre de fois et on mesure l'écart-type des résultats obtenus. Ceci fournit une estimation de l'incertitude totale σ_{tot}

$$\sigma_{tot} = \frac{\sqrt{\sigma_{instr}^2 + \sigma_{conf}^2 + \sigma_{pop}^2}}{\sqrt{N}} \quad (3.4)$$

On remarque que, dans le cas gaussien (duquel on est très proche en vertu du théorème central limite), il est donc possible d'estimer la dispersion en flux de la population étudiée en utilisant :

$$\sigma_{pop} = \sqrt{N(\sigma_{tot}^2 - \sigma_{phot}^2)}. \quad (3.5)$$

L'empilement donne donc accès à la moyenne et à l'écart type des flux d'une population.

L'erreur sur l'incertitude fournie par la méthode du *bootstrap* dépend du nombre d'échantillons *bootstrap* utilisés et du nombre de sources présentes dans l'échantillon initial (voir Fig. 3.3). Pour un échantillon initial de N sources, l'erreur relative décroît avec le nombre d'échantillons *bootstrap* utilisés jusqu'à environ 3×N tirages, puis se stabilise. Utiliser plus de 3×N tirages n'améliore donc plus l'estimation de l'incertitude.

3.1.3 Librairie de programmes d'empilement de l'IAS

J'ai participé à la construction de la librairie de programmes destinés à l'empilement de l'IAS. Cette librairie a été développée en collaboration avec Nicolas Bavouzet, Alexandre Beelen et Hervé Dole. Elle est en téléchargement libre sur le site : <http://www.ias.u-psud.fr/irgalaxies/downloads.php>. J'ai en particulier écrit des programmes simples et facilement modifiables de photométrie et d'estimation des erreurs par la méthode du *bootstrap*. J'ai également développé le programme de test permettant de vérifier que la librairie est bien installée.

3.1.4 Empilement et distributions spatiales non-poissoniennes

En pratique, les sources étudiées ne sont pas distribuées de manière poissonnienne, mais ont tendance à se regrouper. Ce regroupement induit des biais dans les mesures réalisées par empilement. Les idées présentées ici sont reprises de la thèse de Nicolas Bavouzet et de Béthermin *et al.* (2010b). La méthode d'empilement utilisée est celle de Dole *et al.* (2006). On choisit de décrire le cas d'un empilement moyen. On suppose dans un premier temps que la carte initiale a une calibration absolue, c'est à dire que le signal nul correspond à une absence de source.

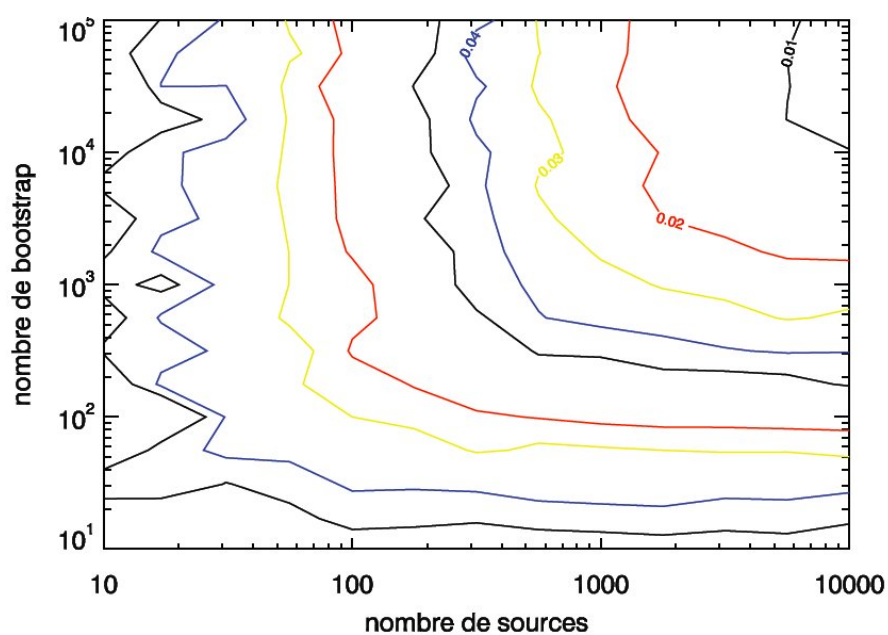


FIGURE 3.3 – Erreur relative sur l'incertitude déterminée par la méthode du *bootstrap* en fonction du nombre d'échantillons *bootstrap* générés. Les courbes de niveau représentent (de haut en bas) 1, 2, 3, 4, 5, 8, 10, 15 et 20%. Extrait du rapport de stage de Mathilde Jauzac.

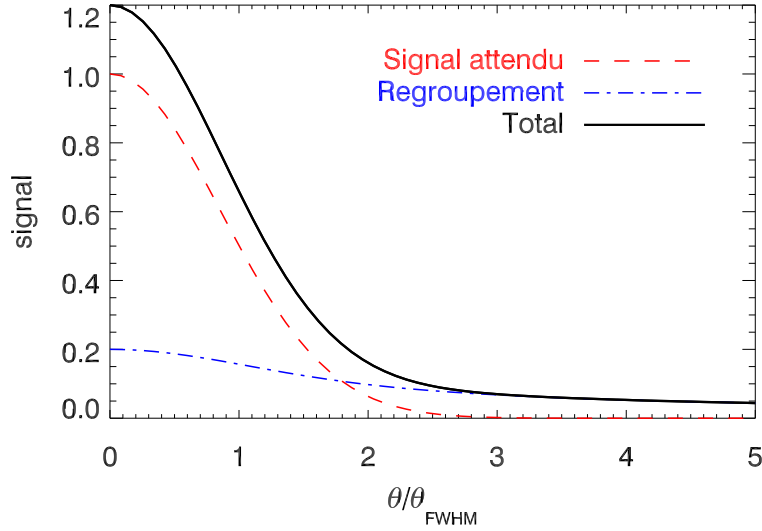


FIGURE 3.4 – Profil d'une image empilée affectée par le regroupement des sources. *Ligne continue noire* : Signal total (les unités sont arbitraires). *En rouge* : Signal attendu en l'absence de regroupement. *En bleu* : Signal dû au regroupement des sources (nous avons supposé $w(\theta) \propto \theta^{-0.8}$).

L'espérance de l'empilement d'une population distribuée de manière poissonnienne est

$$M(\theta) = \overline{S}_s \times PSF(\theta) + \int_0^\infty S \frac{dN}{dS} dS = \overline{S}_s \times PSF(\theta) + I_{CIB}, \quad (3.6)$$

où M est l'image résultant de l'empilement, θ la distance angulaire au centre de l'image, et $\overline{S}_s$ le flux moyen de la population étudiée. On peut remplacer le second terme (l'intégrale) par I_{CIB} , le niveau du fond infrarouge. Si on fait l'hypothèse simplificatrice que toutes les sources infrarouges, empilées ou non, ont la même fonction de corrélation angulaire $w(\theta)$, le résultat de l'empilement sera

$$M(\theta) = \overline{S}_s \times PSF(\theta) + I_{CIB} \times (1 + w(\theta)) * PSF(\theta). \quad (3.7)$$

En effet, à cause du regroupement des sources, il y a un excès de probabilité de trouver une source au voisinage d'une autre. Loin de la source, le signal mesuré est I_{CIB} . C'est également le moyenne de la carte. Si on utilise une carte à moyenne nulle ou si on soustrait le fond sur l'image empilée, on obtient donc

$$M(\theta) = \overline{S}_s \times PSF(\theta) + I_{CIB} \times w(\theta) * PSF(\theta). \quad (3.8)$$

Le premier terme correspond au résultat attendu et le second est un biais dû au regroupement des sources. La contribution relative du second terme sera d'autant plus grande

que la PSF est étendue. Cet effet sera donc plus important aux grandes longueurs d'ondes. La Fig. 3.4 représente la contribution des deux termes au profil de l'image finale. On remarque que la contribution relative due au regroupement est plus faible au centre de l'image. Dans un cas sans bruit, il est donc préférable de réaliser la photométrie en utilisant uniquement le pixel central de l'image empilée, ce qui est équivalent à utiliser la méthode de Marsden *et al.* (2009) sans lisser la carte par la PSF.

3.1.5 Estimation des biais dus au regroupement des sources

Nous allons ici présenter quelques méthodes permettant d'estimer le biais dû au regroupement des sources. Nous nous bornerons à traiter le cas de l'empilement de sources sélectionnées à $24\ \mu\text{m}$ dans l'infrarouge lointain.

Convolution de la carte à $24\ \mu\text{m}$

Si on fait l'approximation que la couleur entre l'infrarouge lointain et le $24\ \mu\text{m}$ est constante, on peut estimer l'effet du regroupement de manière simple. En effet, on empile dans un premier temps les sources à $24\ \mu\text{m}$. Puis on convolue la carte $24\ \mu\text{m}$ par la PSF dans l'infrarouge lointain, et on refait alors l'empilement. On compare enfin les deux résultats obtenus. L'excès observé dans le second cas est la contribution due au regroupement. Le rapport entre les deux mesures fournit un facteur correctif. Cette méthode fonctionne mal dans les bandes BLAST (et SPIRE), où la couleur des sources dépend fortement du *redshift*. Les simulations (Fernandez-Conde *et al.* (2008)) montrent que cette méthode surestime alors significativement les biais. Il est alors nécessaire d'utiliser d'autres méthodes.

Simulations à partir du catalogues $24\ \mu\text{m}$

Dans les champs profonds, on a parfois accès aux redshifts des sources $24\ \mu\text{m}$. Ceci permet d'estimer leur flux dans l'infrarouge en utilisant soit une couleur fournie par un premier empilement (par exemple par tranche de *redshift*), soit un modèle de SED. On peut donc construire une carte simulée en utilisant la position réelle des sources. Le biais de regroupement peut alors être estimé en comparant le flux mesuré par empilement avec le catalogue d'entrée. Cette méthode ignore en revanche la contribution des sources non-détectées à $24\ \mu\text{m}$, et ne sera donc fiable que dans les champs très profonds.

Ajustement de l'image empilée par un modèle de PSF et de contribution due au regroupement

Si la fonction de corrélation des sources empilée est bien mesurée, on peut réaliser un ajustement simultané de la PSF et d'un modèle de contamination causé par le regroupement des sources (c.f. Eq. 3.8 et la Fig. 3.4). Cette méthode ne peut marcher que dans le cas d'un très bon rapport signal sur bruit, sachant que les dégénérescences entre les deux contributions peuvent être fortes. Le fait que le résultat dépende du modèle de regroupement est également un des défauts de cette méthode. J'ai collaboré avec Sébastien Heinis à appliquer cette méthode à l'empilement des sources UV dans les données SPIRE. L'effet du regroupement y est de l'ordre de 10%.

Simulations basées sur des modèles

Il est également possible de produire une simulation plus ou moins réaliste prenant en compte le regroupement des sources. On peut alors mesurer exactement les biais en comparant le résultat de l'empilement au catalogue d'entrée de la simulation. L'énorme défaut de cette méthode est qu'elle nécessite d'avoir à la fois un modèle réaliste d'évolution des galaxies infrarouges (par exemple Béthermin *et al.* (2011)), et un modèle de distribution spatiale (par exemple Pénin *et al.* (2011a)). Or, pour l'instant, il y a peu de contraintes sur la distribution spatiale des sources faibles. Ce type de simulation semble donc être plus utile pour valider les méthodes basées sur les données uniquement qui ont été présentées précédemment.

3.1.6 Biais dus au catalogue d'entrée

L'incomplétude du catalogue d'entrée peut également biaiser le résultat d'un empilement. En effet, les logiciels d'extraction de sources ont tendance à plus facilement extraire les sources faibles dans les régions peu denses. Le catalogue d'entrée sera donc biaisé vers les régions de faible signal. Par conséquent, le fond au centre de l'image empilée est inférieur à la moyenne de la carte. Cet effet tend à faire sous-estimer le flux empilé. Pour éviter les problèmes, il vaut donc mieux empiler un catalogue quasi-complet. La Fig. 3.5, extraite de la thèse de Nicolas Bavouzet, illustre ce phénomène. Elle présente le résultat de l'empilement des sources IRAC à $3.6 \mu\text{m}$ avec $2 \mu\text{Jy} < S_{3.6} < 8 \mu\text{Jy}$ dans les cartes *Spitzer* à $24 \mu\text{m}$. Dans ce régime de flux à $3.6 \mu\text{m}$, le catalogue n'est pas complet ($< 90\%$ en dessous de $8 \mu\text{Jy}$). Pour les raisons invoquées précédemment, la source artificielle centrale se situe au milieu d'un trou dans le fond. La forme précise de ce trou peut être retrouvée à partir de simulations. En effet, on peut injecter des sources Monte Carlo dans la carte à $3.6 \mu\text{m}$ uniquement et n'empiler dans la carte grande longueur d'onde qu'aux positions où les sources ont été retrouvées. La figure de droite montre le résultat de ce processus.

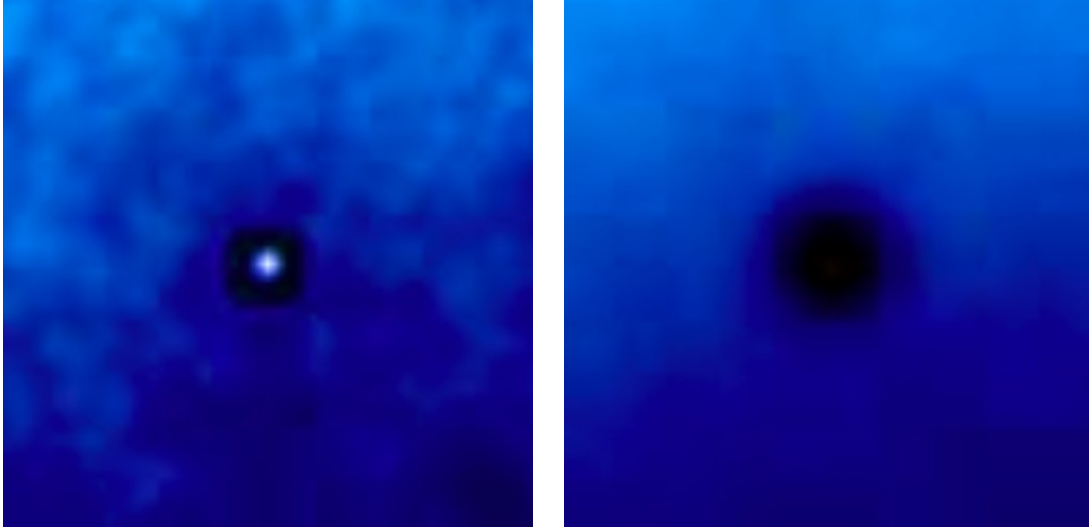


FIGURE 3.5 – Effet de l’incomplétude du catalogue d’entrée sur le résultat d’un empilement. *A gauche* : Résultat de l’empilement des sources IRAC à $3.6\ \mu\text{m}$ avec $2\ \mu\text{Jy} < S_{3.6} < 8\ \mu\text{Jy}$ dans les cartes *Spitzer* à $24\ \mu\text{m}$. *A droite* : Empilement des sources Monte Carlo retrouvées par SExtractor. Extrait de la thèse de Nicolas Bavouzet.

Cet effet d’incomplétude, qui a tendance à faire sous-estimer le flux, entre en compétition avec l’effet de regroupement des sources, qui tend à le faire sur-estimer.

3.1.7 Vers des méthodes avancées

Méthode de Kurczynski et Gawiser (2010)

Kurczynski et Gawiser (2010) ont proposé une méthode inspirée du *PSF-fitting* pour corriger des biais dus au regroupement des sources. Dans cette méthode, les sources sont séparées en plusieurs populations. Toutes les sources d’une population sont supposées avoir le même flux. Nous allons ici présenter le cas de 2 populations (une population cible et une population non-cible) présenté dans leur article. Cette méthode est construite pour être utilisée sur des cartes en Jy/beam ⁵. La somme des flux mesurés dans les pixels centrés sur les sources cibles est

$$\sum_{i=1}^{N_c} S_{i,c} = \sum_{i=1}^{N_c} \sum_{j=1}^N \delta_{j,c} \alpha_{ij} I_c + \sum_{i=1}^{N_c} \sum_{j=1}^N \delta_{j,nc} \alpha_{ij} I_{nc} + \sum_{i=1}^{N_c} n_{i,c}, \quad (3.9)$$

⁵Dans cette unité, le flux d’une source en Jansky est la valeur dans le pixel central de cette source, au bruit et aux effets de pixelisation près.

où N est le nombre de sources total, N_c le nombre de sources cibles, N_{nc} le nombre de sources non cibles, $S_{i,c}$ le flux à la position de la source cible i , $n_{i,c}$ est le bruit. α_{ij} est un coefficient inférieur à 1 qui donne la contribution de la source j au pixel centré sur la source i . Kurczynski et Gawiser (2010) supposent une PSF gaussienne, et ont donc $\alpha_{ij} = \exp(-r_{ij}/2\sigma^2)$, où r_{ij} est la distance entre les sources i et j , et σ un paramètre décrivant la largeur de la PSF. Enfin, $\delta_{j,c}$ est un paramètre qui vaut 1 si la source j est cible et 0 dans le cas contraire. De manière analogue, la somme des flux aux positions non cibles est

$$\sum_{i=1}^{N_{nc}} S_{i,nc} = \sum_{i=1}^{N_{nc}} \sum_{j=1}^N \delta_{j,c} \alpha_{ij} I_c + \sum_{i=1}^{N_{nc}} \sum_{j=1}^N \delta_{j,nc} \alpha_{ij} I_{nc} + \sum_{i=1}^{N_{nc}} n_{i,nc}. \quad (3.10)$$

Les seules inconnues de ce problème sont I_c et I_{nc} (sous hypothèse d'un bruit nul en moyenne). Le problème se réduit donc à l'inversion d'une matrice 2×2 . En revanche, l'hypothèse d'un unique flux pour chaque population est peu réaliste.

Méthode d'optimisation des couleurs

Je me suis inspiré de ce formalisme pour développer une nouvelle méthode basée sur la couleur des populations. Ici, c'est la couleur d'une population qui est supposée homogène et non son flux. Cette méthode se généralise également aux PSF non gaussiennes et utilise tous les pixels de la carte.

Soit N_{pop} populations de sources, chaque population a une couleur C_{AB} entre les bandes A (très profonde utilisée comme a priori) et B (bande confuse ou bruitée à analyser). La carte dans la bande B est

$$m_{B,ij} = \sum_{l=1}^{N_{sources}} P_{ij,x(l)y(l)} \cdot C_{AB,pop(l)} \cdot S_{A,l} + \sigma_{B,ij} + \mu, \quad (3.11)$$

où $m_{B,ij}$ est le signal dans le pixel (i,j) en bande B, $P_{ij,xy}$ le signal dans le pixel (i,j) issu d'une source de flux unité centrée sur les coordonnées (x,y) , $x(l)$ et $y(l)$ les coordonnées de la source l , $C_{AB,pop(l)}$ la couleur de la population à laquelle appartient la source l , $S_{A,l}$ le flux de la source en bande A, n_{ij} un bruit gaussien (supposé non-corrélé ici) et μ un fond constant. Pour simplifier nos équations, on note

$$n_{B,ij}^k = \sum_{sources\ l \in population\ k} P_{ij,x(l)y(l)} \cdot S_{A,l}. \quad (3.12)$$

n_B^k est donc la carte de la population k , avec la pixelisation et la PSF de la bande B, mais les flux de la bande A. Il suffit de multiplier cette carte par la couleur de A vers B de la population k pour obtenir sa contribution à la carte en bande B. Le but de cette méthode

est de trouver les couleurs qui reproduisent le mieux la carte B observée.

On recherche le maximum de vraisemblance des couleurs C_{AB} et de μ . L'opposé du logarithme de la fonction de vraisemblance est

$$-\log(L(m|C_{AB})) = \sum_{pixels} \frac{\left(\sum_{k=1}^{N_{pop}} C_{AB,k} \cdot n_{B,ij}^k + \mu - m_{B,i,j}\right)^2}{2\sigma_{B,ij}^2}. \quad (3.13)$$

Les couleurs qui minimisent L sont donc

$$\forall k, 0 = \frac{\partial(-\log(L))}{\partial C_{AB,k}} = \sum_{pixels} \frac{\left(n_{B,ij}^k (\sum_{l=1}^{N_{pop}} C_{AB,l} \cdot n_{B,ij}^l + \mu - m_{B,i,j})\right)}{\sigma_{ij}^2}, \quad (3.14)$$

et,

$$0 = \frac{\partial(-\log(L))}{\partial \mu} = \sum_{pixels} \frac{\left(\sum_{l=1}^{N_{pop}} C_{AB,l} \cdot n_{B,ij}^l + \mu - m_{B,i,j}\right)}{\sigma_{B,ij}^2}. \quad (3.15)$$

Ceci est équivalent à une équation matricielle $(N_{pop} + 1) \times (N_{pop} + 1)$.

$$A \cdot C = B, \quad (3.16)$$

$$\text{où } C = \begin{pmatrix} C_{AB,1} \\ \vdots \\ C_{AB,l} \\ \vdots \\ \mu \end{pmatrix}, B = \begin{pmatrix} \sum_{pixels} \frac{n_{B,ij}^1 m_{B,ij}}{\sigma_{B,ij}} \\ \vdots \\ \sum_{pixels} \frac{n_{B,ij}^l m_{B,ij}}{\sigma_{B,ij}} \\ \vdots \\ \sum_{pixels} \frac{m_{B,ij}}{\sigma_{B,ij}} \end{pmatrix} \text{ et } A = \begin{pmatrix} \sum_{pixels} \frac{n_{B,ij}^1 n_{B,ij}^1}{\sigma_{B,ij}} & \cdots & \sum_{pixels} \frac{n_{B,ij}^k n_{B,ij}^1}{\sigma_{B,ij}} & \cdots & \sum_{pixels} \frac{n_{B,ij}^1}{\sigma_{B,ij}} \\ \vdots & & \vdots & & \vdots \\ \sum_{pixels} \frac{n_{B,ij}^1 n_{B,ij}^l}{\sigma_{B,ij}} & \cdots & \sum_{pixels} \frac{n_{B,ij}^k n_{B,ij}^l}{\sigma_{B,ij}} & \cdots & \sum_{pixels} \frac{n_{B,ij}^l}{\sigma_{B,ij}} \\ \vdots & & \vdots & & \vdots \\ \sum_{pixels} \frac{n_{B,ij}^1}{\sigma_{B,ij}} & \cdots & \sum_{pixels} \frac{n_{B,ij}^k}{\sigma_{B,ij}} & \cdots & \sum_{pixels} \frac{1}{\sigma_{B,ij}} \end{pmatrix}$$

Cette méthode a été testée et validée dans un cas simple, où la couleur au sein d'une population a une dispersion nulle, et où le bruit est gaussien et non-corrélé. En revanche, des difficultés apparaissent quand les populations ne sont plus totalement homogènes, et quand on ajoute des fluctuations dues aux sources faibles non détectées à courte longueur d'onde. Dans ce cas, les résultats sont meilleurs que ceux obtenus par la méthode classique, mais les erreurs calculées à partir de la matrice de Fisher sont largement sous-estimées (un ordre de grandeur dans certains cas). De plus, il n'est pas possible, dans ce formalisme d'estimer les erreurs avec une méthode simple de type *bootstrap*. Une des pistes d'amélioration est d'intégrer dans le formalisme la dispersion en couleur et le bruit corrélé dû aux sources non présentes dans le catalogue d'entrée.

3.1.8 Compter les sources non résolues par empilement

A cause du phénomène de confusion (voire Chap. 2), il n'est pas possible d'extraire individuellement les sources responsables de la majeure partie du fond infrarouge lointain. En revanche, ces sources sont détectées entre autres à $24 \mu\text{m}$. Or, la méthode de l'empilement permet de mesurer la couleur moyenne des populations sélectionnées à $24 \mu\text{m}$. Il est donc possible de reconstruire indirectement les comptages de sources en dessous du seuil de confusion.

Si on suppose une dispersion en couleur nulle au sein d'une population, on peut facilement convertir les comptages 24 microns en comptages à plus grande longueur d'onde. En effet, en empilant les sources par tranches de flux à $24 \mu\text{m}$, on obtient :

$$\overline{S_{FIR}} = f(\overline{S_{24}}), \quad (3.17)$$

où $\overline{S_{FIR}}$ est le flux moyen de la population dans l'infrarouge lointain, $\overline{S_{24}}$ le flux moyen à $24 \mu\text{m}$, et f une fonction liant les deux quantités estimée par empilement. Si f est une fonction continue croissante, on peut alors estimer facilement les comptages infrarouges avec la relation :

$$\left. \frac{dN}{dS_{FIR}} \right|_{S_{FIR}=f(S_{24})} = \left. \frac{dN}{dS_{24}} \right|_{S_{24}} \left/ \left. \frac{dS_{FIR}}{dS_{24}} \right|_{S_{24}} \right. . \quad (3.18)$$

3.2 Résultats : comptages ultra-profonds à 70 et 160 microns avec MIPS

Nous présentons ici un résumé des travaux publiés dans l'article Béthermin *et al.* (2010a).

3.2.1 Motivation

Les comptages de sources résolues ne permettent pas de sonder la coupure à 70 et $160 \mu\text{m}$ (voir Chap. 2). Or, la position de cette coupure est importante à la fois pour contraindre l'évolution des populations infrarouges faibles, mais aussi pour estimer la contribution totale des galaxies au fond. Avant ce travail, un unique point à bas flux avait été estimé par Frayer *et al.* (2006b) à $70 \mu\text{m}$ avec une analyse de fluctuations, et rien n'avait été fait en dessous de 40 mJy à $160 \mu\text{m}$. Les méthodes de comptages par empilement sont donc essentielles pour avoir accès aux informations statistiques sur les populations faibles à grande longueur d'onde.

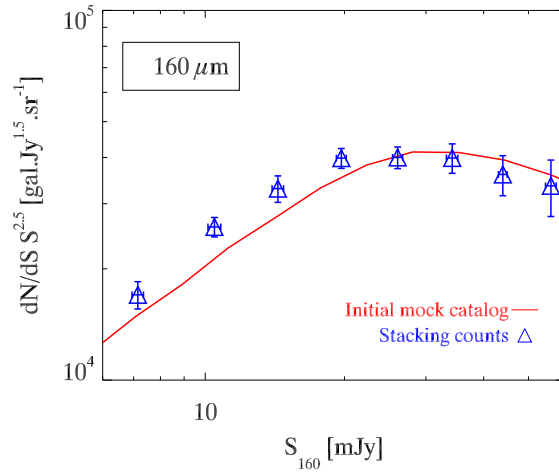


FIGURE 3.6 – Comptages déterminés par empilement à $160\ \mu\text{m}$ déterminés sur 20 simulations (en bleu), et comparaison avec les comptages initiaux (en rouge). Les barres d’erreurs représentent la dispersion des points d’une simulation à l’autre. Extrait de Béthermin *et al.* (2010a)

3.2.2 Méthode

J’ai utilisé la méthode présentée Sect. 3.1.8 pour estimer les comptages en dessous du seuil de confusion. La profondeur des catalogues à $24\ \mu\text{m}$ dépend des champs utilisés. Nous avons donc utilisé le champ FIDEL CDFS (très profond, mais peu étendu) pour sonder les bas flux, COSMOS (large et profond) pour sonder les flux intermédiaires, et SWIRE EN1 (très large, mais peu profond) pour sonder les populations plus brillantes. L’empilement est réalisé avec la librairie d’empilement de l’IAS, et la photométrie d’ouverture est réalisée avec les mêmes paramètres que l’extraction de sources directe.

Pour valider cette méthode de comptages par empilement, j’ai utilisé 20 simulations d’observations basées sur les travaux de Fernandez-Conde *et al.* (2008). Ces simulations contiennent du *clustering* et permettent de tester les effets de ce dernier sur le résultat final. J’ai alors appliqué la méthode de comptages par empilement à chacune des 20 simulations (Fig. 3.6). L’écart maximum entre l’entrée et la sortie est de l’ordre de 15% à $160\ \mu\text{m}$. Ces simulations permettent ainsi d’estimer les erreurs systématiques de cette méthode, dont entre autre le fait de négliger la dispersion en couleur. La comparaison a posteriori avec les comptages directs *Herschel*/PACS (Berta *et al.* (2010)) a confirmé l’efficacité de cette méthode.

3.2.3 Résultats

Comptages à 70 μm

L'empilement permet de sonder les comptages à 70 μm jusqu'à 0.38 mJy (voir Fig. 3.7). Ceci permet de descendre un ordre de grandeur en dessous de la limite de confusion. Ceci met en évidence une coupure autour de 10 mJy. Les points à haut flux ($1 \text{ mJy} < S < 3 \text{ mJy}$) sont en accord avec ceux obtenus par Frayer *et al.* (2006b) à partir d'un relevé ultra-profond dans GOODS-N. Les méthode d'empilement permettant de sonder de plus grands champs, nos barres d'erreurs sont plus petites d'un facteur 2 environ. Nous sommes également en accord avec le point déterminé par mesure du bruit de confusion, avec là encore des barres d'erreurs bien inférieures. Ces observations sont en bon accord avec le modèle de Lagache *et al.* (2004). Le modèle de Le Borgne *et al.* (2009) surestime très légèrement les comptages ($\sim 15\%$) dans le régime de flux sondé par l'empilement.

Comptages à 160 μm

A 160 μm , l'empilement sonde les comptages jusqu'à 3.1 mJy, soit là encore un ordre de grandeur sous la limite de confusion (voir Fig. 3.8). Ces comptages sont les premiers à sonder ce domaine de flux à 160 μm . Nous détectons pour la première fois le pic dans les comptages normalisés autour de 20 mJy, et un comportement en loi de puissance à bas flux ($dN/dS \propto S^{-1.61 \pm 0.21}$). Le modèle de Lagache *et al.* (2004) sur-estime les comptages de 30% au dessus de 10 mJy et est en très bon accord avec nos mesures à plus bas flux. Le modèle de Le Borgne *et al.* (2009) est en bon accord avec nos mesures à l'exception d'une sur-estimation des comptages à 1.5σ en dessous de 10 mJy.

3.3 Résultats : comptages ultra-profonds avec BLAST

Nous présentons ici un résumé des travaux publié dans l'article Béthermin *et al.* (2010b).

3.3.1 Motivations

Avant le lancement d'*Herschel*, très peu d'observations avaient été réalisées entre 200 et 600 μm . Quelques rares relevés avaient été réalisés, depuis le sol, dans de très petits champs fortement bruités. De plus, ces observations fournissent en général la valeur des comptages intégraux pour une seule coupure en flux, ce qui est peu contraignant pour les modèles. L'analyse P(D), réalisée par l'équipe BLAST (Patanchon *et al.* (2009)), n'utilise qu'un seul point à flux fixé dans la région du pic des comptages normalisés. L'analyse par

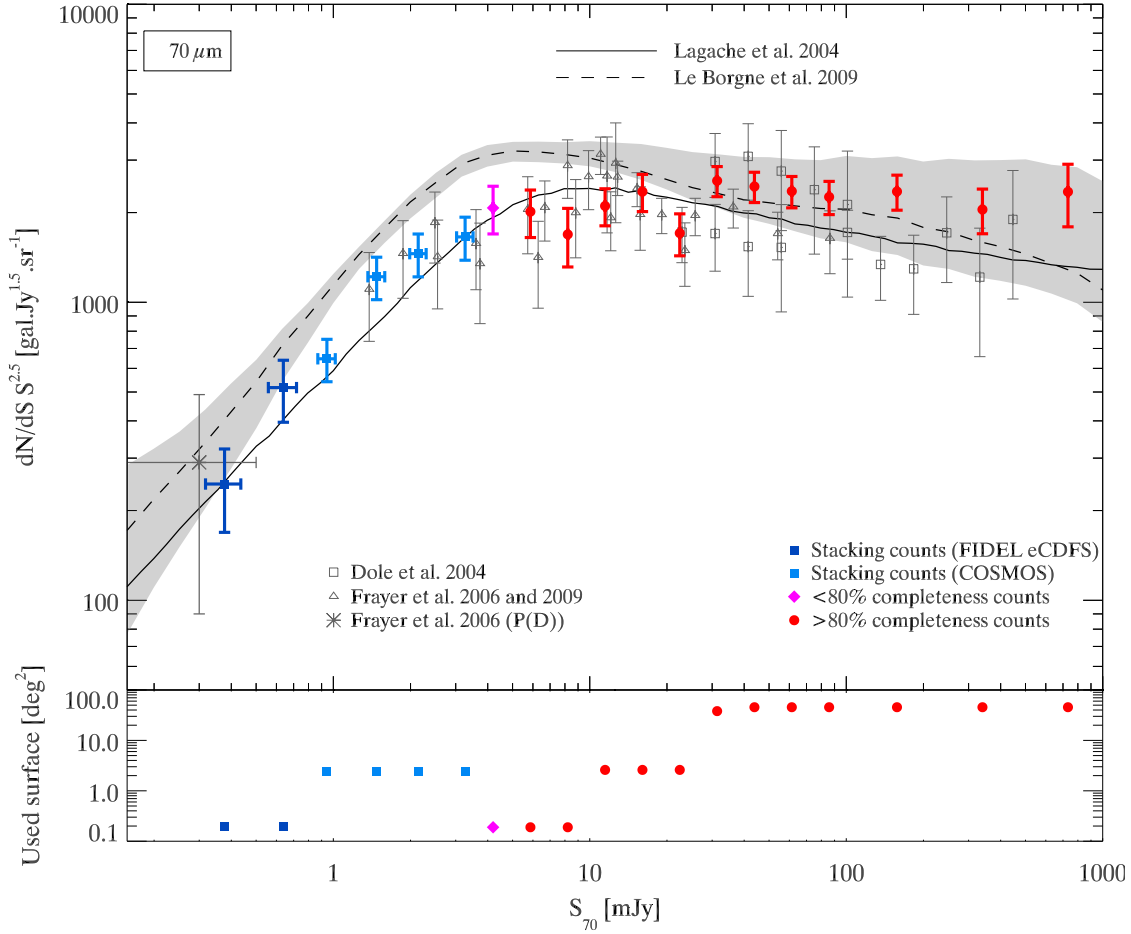


FIGURE 3.7 – Comptages différentiels à $70 \mu\text{m}$. *Disques pleins rouges* : mesures réalisées avec plus de 80% de complétudes. *Losanges violets* : points entre 50 et 80% de complétudes. *Carrés bleus* : Comptages mesurés par empilement dans FIDEL CDFS (bleu marine), COSMOS (bleu primaire) et SWIRE EN1 (bleu ciel). *Triangles ouverts gris* : mesures de Frayer et al. (2006a), Frayer et al. (2006b) et Frayer et al. (2009). *Carrés ouverts gris* : mesures de Dole et al. (2004). *Astérisque grise* : mesures par analyse de fluctuations de Frayer et al. (2006b). *Ligne continue* : modèle de Lagache et al. (2004). *Ligne pointillée et zone grisée* : modèle de Le Borgne et al. (2009). Le panneau du bas indique la surface utilisée pour déterminer les comptages en fonction du flux.

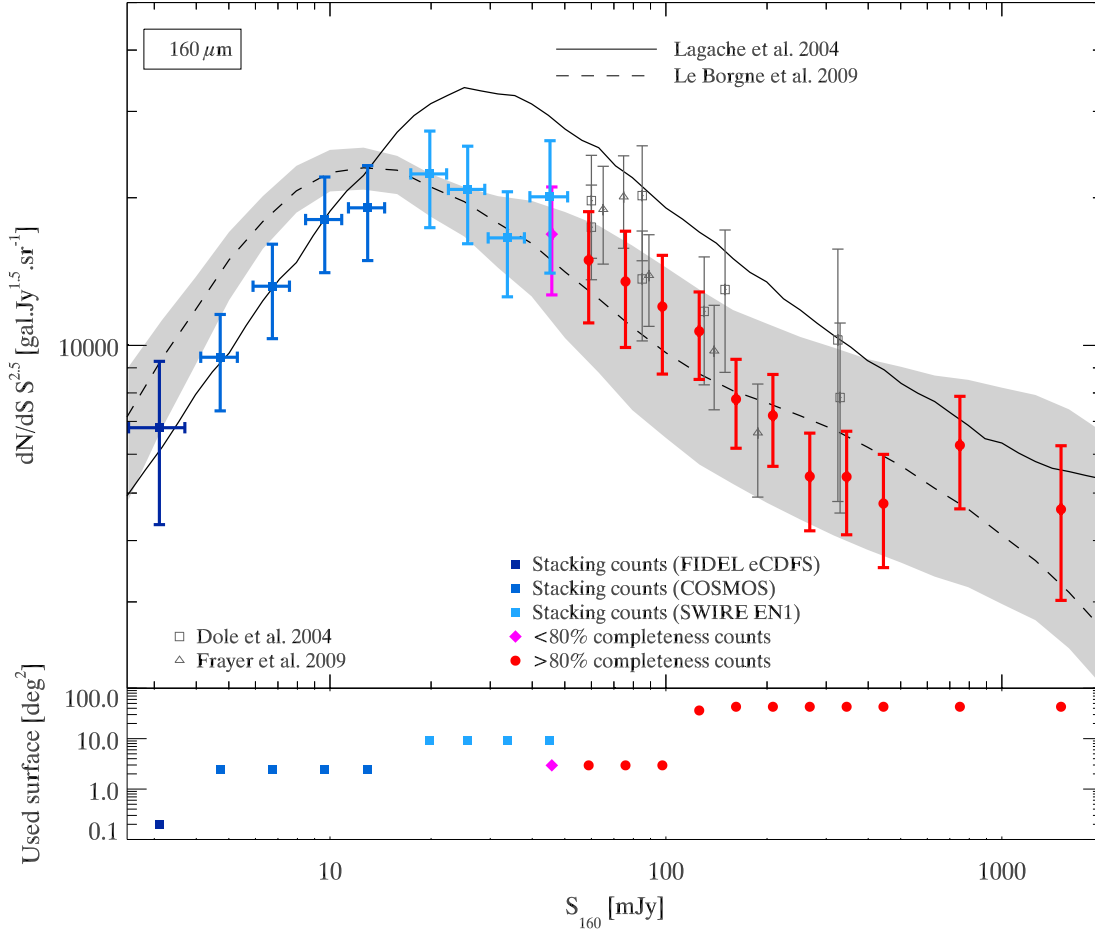


FIGURE 3.8 – Comptages différentiels à $160\ \mu\text{m}$. *Disques pleins rouges* : mesures réalisées avec plus de 80% de complétudes. *Losanges violets* : points entre 50 et 80% de complétudes. *Carrés bleus* : Comptages mesurés par empilement dans FIDEL CDFS (bleu marine), COSMOS (bleu primaire) et SWIRE EN1 (bleu ciel). *Triangles ouverts gris* : mesures de Frayer *et al.* (2006a), Frayer *et al.* (2006b) et Frayer *et al.* (2009). *Carrés ouverts gris* : mesures de Dole *et al.* (2004). *Ligne continue* : modèle de Lagache *et al.* (2004). *Ligne pointillée et zone grisée* : modèle de Le Borgne *et al.* (2009). Le panneau du bas indique la surface utilisée pour déterminer les comptages en fonction du flux.

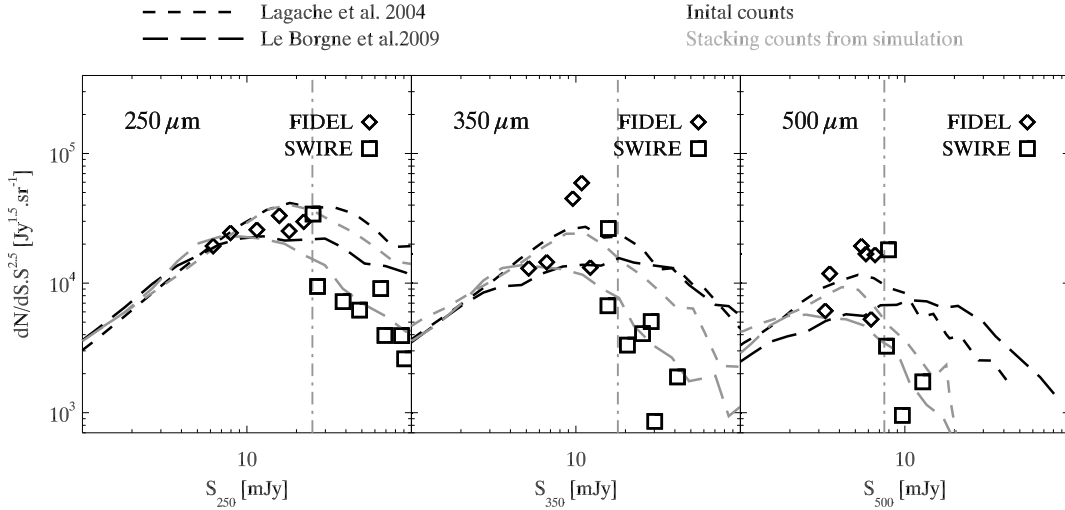


FIGURE 3.9 – Comptages dans les bandes BLAST venant des données (points FIDEL en losange et points SWIRE en carré) et des modèles (Lagache *et al.* (2004) en tirets courts et Le Borgne *et al.* (2009) en tirets longs). Les comptages initiaux des modèles sont en noir, et les comptages déterminés par empilement à partir de simulations basées sur les modèles sont en gris.

empilement permet d’avoir une confirmation indépendante et plus précise du comportement autour de ce pic.

3.3.2 Méthode

La méthode utilisée est similaire à celle de MIPS, à l’exception de la photométrie qui est réalisée par *PSF-fitting*. Les comptages à bas flux sont réalisés en utilisant mon catalogue à $24\ \mu\text{m}$ du relevé FIDEL (profond, mais couvrant uniquement la partie centrale du champ), et les comptages à plus haut flux sont réalisés à partir de mon catalogue du relevé SWIRE (couvrant presque tout le champs BLAST, mais peu profond). Toutefois, les simulations montrent que la méthode de comptage par empilement ne marche pas dans tous les régimes de flux. En effet, si la dispersion en couleur des sources infrarouges empilées est trop grande, les hypothèses utilisées deviennent fausses. La Fig. 3.9 montre comment notre méthode a tendance à sous-estimer les comptages au delà de 20 mJy. L’effet est observé à la fois dans les simulations et les comptages réels. Il est très prononcé à $500\ \mu\text{m}$, où les couleurs 500/24 des sources varient fortement en fonction de la température de poussière et du *redshift*. Pour cette raison, les comptages par empilement ont été coupés à haut flux. Les biais en dessous de cette coupure sont de l’ordre de 30% à $250\ \mu\text{m}$ et 50%

à 350 et 500 μm . Cette erreur systématique domine les incertitudes sur nos comptages.

Le fait que la méthode marche mal à haut flux, peut s'interpréter en terme de distribution en *redshift* (voir l'article Béthermin *et al.* (2010b) pour plus de détails). Par exemple, on peut comparer la distribution prédite par les modèles dans un bin de flux à 24 μm , et dans le bin de flux correspondant dans les bandes BLAST (les bornes du bin à 24 μm sont converties en utilisant la couleur moyenne des sources). Les distributions en *redshift* sont très proche à bas flux ($S < 10$ mJy), mais très différentes à haut flux ($S > 20$ mJy). Le faible rapport signal sur bruit de BLAST n'a pas permis de réaliser une analyse par tranche de *redshift*, en revanche cette analyse est réalisable avec *Herschel*. Toutefois, mes résultats ne sont pas encore assez solides pour être présentés dans cette thèse.

3.3.3 Résultats

La méthode de l'empilement permet de sonder les comptages jusqu'à environ 5 mJy. A 250 μm , nous obtenons 6 points, là où l'analyse P(D) de BLAST n'en possède qu'un seul. Ces points confirment que le pic des comptages se situe aux alentours de 10 mJy. Nos points sont inférieurs d'un facteur 2 à celui obtenu par analyse P(D). En fait, ceci est un biais dû à la paramétrisation des comptages choisie lors de cette analyse. Cet effet sera discuté en détail dans le Chap. 4. Nous sommes également en accord avec les observations au sol à 350 μm (Khan *et al.* (2007), Coppin *et al.* (2008)) et à 450 μm (Smail *et al.* (2002), Knudsen *et al.* (2006)), à l'exception de Borys *et al.* (2003) avec lequel nous sommes en désaccord de deux ordres de grandeurs. Dans l'article, nous avons mentionné le fait que leurs sources sont probablement des fausses détections. Les observations *Herschel* ont confirmé cela. Enfin, nous sommes en très bon accord avec les modèles de Lagache *et al.* (2004) et Le Borgne *et al.* (2009).

3.4 Conclusion

Dans ce chapitre, nous avons présenté la méthode de l'empilement. Cette méthode est extrêmement puissante pour étudier les populations faibles non-déteçtables aux grandes longueurs d'onde à cause du phénomène de confusion. Cette technique est aujourd'hui bien maîtrisée. Toutefois, des difficultés persistent lors de l'empilement de catalogues incomplets, ou de populations très corrélées à l'échelle de la PSF. Néanmoins, de nombreuses méthodes émergent pour estimer et corriger ces effets.

J'ai mis au point une méthode basée sur l'empilement et permettant de mesurer les comptages de sources en dessous de la limite de confusion. Cette méthode permet d'ex-

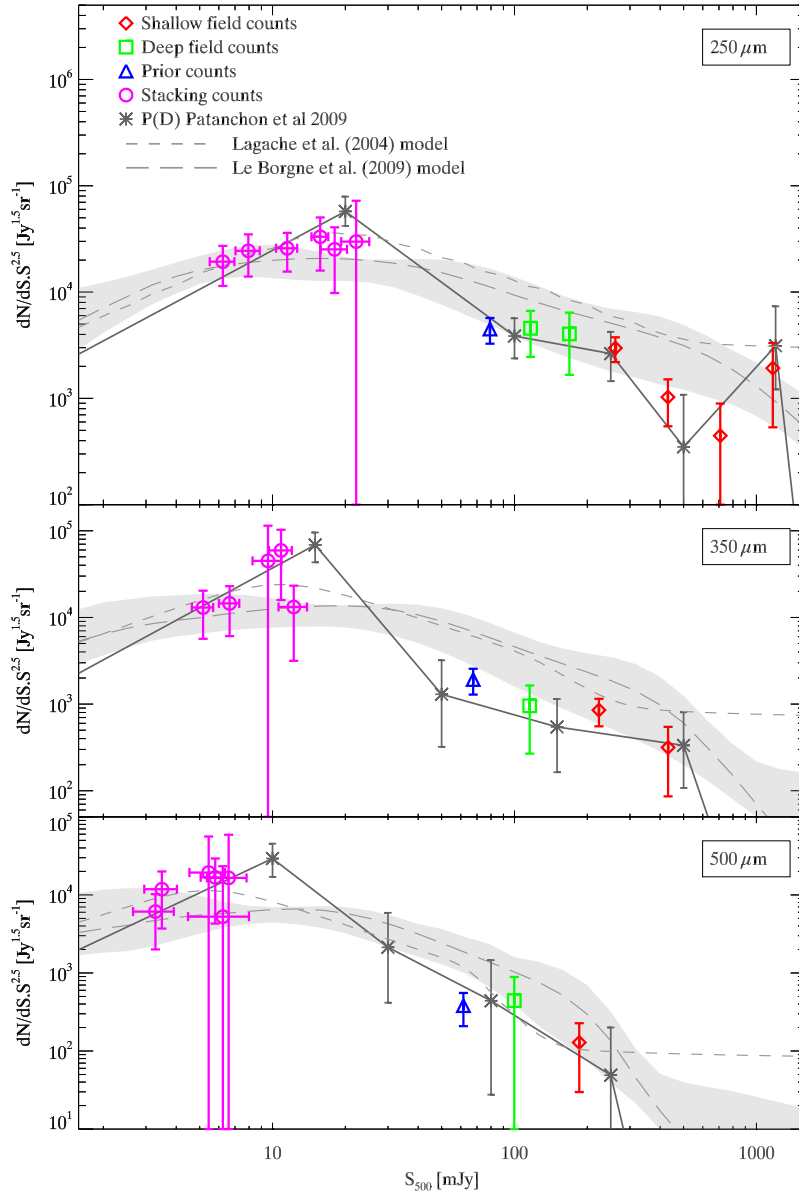


FIGURE 3.10 – Comptages à 250, 350 et 500 μm observés mesurés dans les données BLAST. *Triangles bleus* : Comptages réalisés à partir d’une extraction de source avec a priori. *Carrés verts* : Comptages de sources dans le champ profond. *Losanges rouges* : Comptages de sources dans le champ large. *Cercles violets* : Comptages par empilement. *Astérisques* : analyse P(D) de Patanchon *et al.* (2009). *Tirets courts* : modèle de Lagache *et al.* (2004). *Tirets long* : Modèle de Le Borgne *et al.* (2009).

plorer de nouvelles gammes de flux, et de détecter le pic des comptages différentiels normalisés de 70 à 500 μm . Ces points à bas flux vont permettre de mieux contraindre les émissions dans l'infrarouge lointain des galaxies faibles.

Chapitre 4

Analyse $P(D)$ des cartes SPIRE

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4.1 Présentation de l'analyse $P(D)$

4.1.1 Principe

Dans les chapitres précédents, nous avons vu qu'il est difficile d'étudier directement les sources les plus faibles à cause de la confusion. La méthode de l'empilement permet de sonder ces populations à condition d'avoir au préalable des informations venant d'autres longueurs d'onde. La méthode du $P(D)$ est complémentaire à l'empilement. En effet, elle se base uniquement sur l'histogramme d'une (ou plusieurs) cartes infrarouges, dont la forme dépend uniquement de la PSF, du bruit instrumental et des comptages¹. Dans le cas où la PSF et le bruit instrumental sont bien connus, il est possible de retrouver les comptages qui sont compatibles avec l'histogramme observé. Le principe est donc simple, mais la mise en application l'est beaucoup moins.

4.1.2 Quelques exemples illustratifs

La manière dont les comptages de sources sont liés à l'histogramme des pixels² d'une carte est non triviale (voire Sect. 4.2). La Fig. 4.1 illustre ce lien. Nous avons pris un modèle simple de comptages en $S^{-1.5}$ en dessous de 1 mJy et $S^{-3.5}$ au delà (en noir). On suppose également que les cartes sont à moyenne nulle³. On voit tout de suite qu'en dehors des hauts flux, les comptages et l'histogramme ont des comportements assez différents. En effet, une source affecte le signal dans plusieurs pixels, avec un effet qui décroît avec la distance entre la source et le pixel. De plus, il peut y avoir plusieurs sources faibles par pixel. C'est pour ces raisons que l'histogramme du flux des sources (les comptages) est assez différent de celui du signal dans les pixels.

La forme des comptages de sources affecte fortement l'histogramme d'une carte. Si on augmente le nombre de sources brillantes, en utilisant un comportement en $S^{-2.5}$ au delà de 10 mJy (courbe en bleu de la Fig. 4.1), la forme de l'histogramme est fortement affectée à haut flux ($D > 10$ mJy). En effet, plus de sources brillantes implique plus de pixels brillants. En revanche, le pic de l'histogramme est très peu affecté, car les ailes des sources brillantes, peu nombreuses, n'affectent que légèrement l'histogramme. Si on augmente le nombre de sources à bas flux, en utilisant un comportement en $S^{-2.5}$ en dessous de 1 mJy (courbe en rouge de la Fig. 4.1), on élargit le pic de la distribution, alors

¹En fait, les propriétés de regroupement des sources modifient également légèrement cet histogramme. Néanmoins, cet effet est souvent négligeable.

²On confondra ici l'histogramme des pixels avec la densité de probabilité du signal dans un pixel. En effet, l'histogramme moyen est exactement la densité de probabilité dans les pixels à une constante de normalisation près.

³Cette convention est souvent utilisée quand le niveau zéro du signal est inconnu. C'est le cas pour *Herchel* et la plupart des observations *Spitzer*

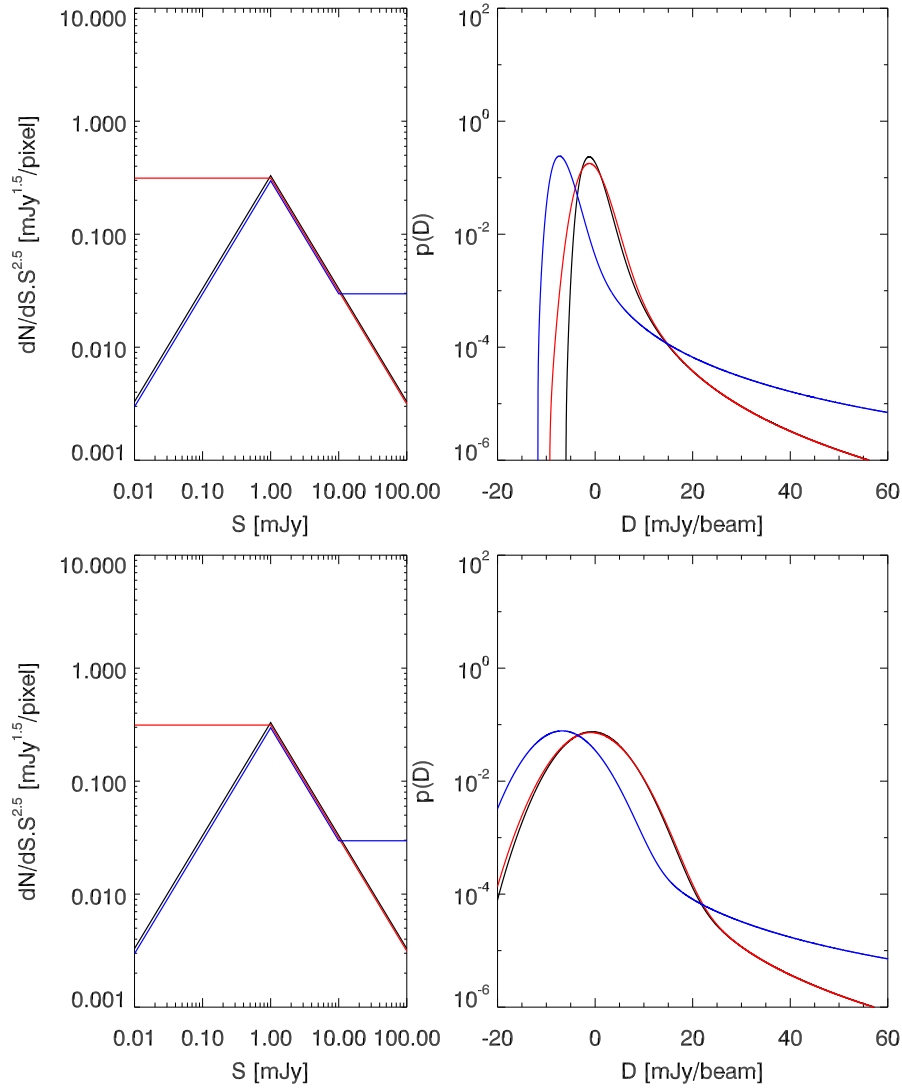


FIGURE 4.1 – Histogramme d’une carte infrarouge en fonction des comptages, avec une PSF gaussienne de 3 pixels de largeur à mi-hauteur et un bruit instrumental nul (en haut) et de 5 mJy (en bas). A gauche : Trois modèles de comptages différentiels normalisés en noir, rouge et bleu. A droite : Densité de probabilité du signal dans un pixel de la carte.

que les haut flux sont très peu affectés. Ces sources de flux faibles sont très nombreuses (plusieurs sources par *beam*), ne sont pas détectables individuellement dans les images, mais engendrent des fluctuations du fond. Si on augmente le nombre de sources faibles, ces fluctuations augmentent (comme $\sqrt{N}$ dans le cas simpliste où toutes les sources ont le même flux).

Cet exemple simple illustre les principes de base de l'analyse P(D). Les pixels brillants permettent de poser des contraintes sur les sources brillantes, alors que la largeur du pic à bas flux contraint les comptages de sources faibles. L'histogramme est très sensible aux comptages à haut flux, mais moins aux comptages à bas flux, plus difficiles à estimer. Enfin, un bruit instrumental important (graphique du bas) élargit l'histogramme et s'il est trop fort, peut empêcher de discriminer deux pentes de comptages à bas flux (courbes noire et rouge de la Fig. 4.1). Il est donc important pour bien contraindre les bas flux d'utiliser des observations très profondes.

4.1.3 Mise en oeuvre

Contrairement aux méthodes de comptages classiques pour lesquels on mesure simplement un nombre de sources par bin de flux, l'analyse P(D) nécessite de supposer une représentation paramétrique des comptages. On peut par exemple supposer une simple loi de puissance. Toutefois, ce type de fonction simple n'est pas représentatif des comptages réels, et le meilleur ajustement en loi de puissance peut être très différent de la réalité. Patanchon *et al.* (2009) a proposé d'utiliser une description paramétrique des comptages plus élaborée. Des noeuds sont placés à des flux fixés. La valeur des comptages différentiels (dN/dS) à chaque noeud est un paramètre libre, et sont reliés entre eux par des lois de puissances.

Les paramètres du modèle de comptages sont ajustés afin de reproduire les histogrammes observés. On peut par exemple utiliser une méthode MCMC (*Monte Carlo Markov Chain*, Chib et Greenberg (1995)) pour étudier précisément les dégénérescences entre paramètres et produire des intervalles de confiance réalistes. Cette technique consiste à explorer de manière semi-aléatoire l'espace de paramètres. A chaque pas, un déplacement aléatoire se fait dans l'espace des paramètres. La nouvelle position est conservée si la vraisemblance est meilleure qu'au pas précédent. Elle est conservée avec une probabilité $L(n)/L(n-1)$ (rapport entre la nouvelle et l'ancienne vraisemblance) dans le cas contraire. Pour une chaîne suffisamment longue (hypothèse d'ergodicité), les différentes réalisations ont la même distribution que la densité de probabilité a posteriori des paramètres du modèle de comptages. Cette propriété rend extrêmement commode la détermination des intervalles de confiance sur chacun des paramètres.

4.2 Le formalisme du $P(D)$

La densité de probabilité du signal dans un pixel peut se calculer analytiquement à partir des comptages, de la PSF et du bruit instrumental. Dans cette section, nous allons montrer comment ils sont reliés entre eux.

4.2.1 Cas d'une PSF ponctuelle

Le nombre de source par unité de flux et par unité d'angle solide est notée dN/dS , où S est le flux. On prendra la taille du pixel comme unité d'angle solide. Le nombre moyen $\bar{n}_k$ de sources observées dans un intervalle de flux k compris entre S_k et $S_k + \Delta S$ est

$$\bar{n}_k = \frac{dN}{dS} \Delta S. \quad (4.1)$$

Nous supposons que les sources sont non corrélées spatialement. Le nombre de sources observées dans une tranche de flux k (n_k) suit donc une loi de Poisson :

$$p_{n_k}(n_k) = \frac{\bar{n}_k^{n_k}}{n_k!} e^{-\bar{n}_k}. \quad (4.2)$$

Le flux total reçu par un pixel, D , vaut

$$D = \sum_k n_k S_k = \sum_k D_k, \quad (4.3)$$

où D_k est la contribution au flux total des sources dont le flux tombe dans le k -ième intervalle de flux. La densité de probabilité de D_k est

$$p_{D_k}(D_k) = \frac{1}{S_k} \times p_{n_k}(D_k/S_k). \quad (4.4)$$

Celle de D est donnée par (on peut démontrer que la densité de probabilité d'une somme de variable aléatoire est la convolution de leurs densité de probabilité)

$$p_D = \dots * p_{D_{k-1}} * p_{D_k} * p_{D_{k+1}} * \dots \quad (4.5)$$

Dans l'espace de Fourier, le produit de convolution devient une simple multiplication, et on a donc

$$\hat{p}_D = \otimes_{k=1}^{N_{bin}} \hat{p}_{D_k}, \quad (4.6)$$

où $\hat{p}$ est la transformée de Fourier de p (appelé aussi fonction caractéristique). On peut monter que

$$\hat{p}_{n_k}(\omega) = \exp(\bar{n}_k(e^{i\omega} - 1)), \quad (4.7)$$

puis,

$$\hat{p}_{D_k}(\omega) = \exp(\overline{n_k}(e^{i\omega S_k} - 1)). \quad (4.8)$$

En combinant les équations 4.1, 4.6 et 4.8, on trouve alors

$$\hat{p}_D(\omega) = \otimes_{k=1}^{N_{bin}} \exp(\overline{n_k}(e^{i\omega S_k} - 1)) = \exp\left(\sum_{k=1}^{N_{bin}} \frac{dN}{dS} \Delta S (e^{i\omega S_k} - 1)\right). \quad (4.9)$$

Puis, on passe à la limite continue :

$$\hat{p}_D(\omega) = \exp\left(\int_0^\infty \frac{dN}{dS} (e^{i\omega S} - 1) dS\right). \quad (4.10)$$

En appliquant la transformée de Fourier inverse, on obtient finalement

$$p_D(D) = \frac{1}{2\pi} \int_0^\infty \exp\left(\int_0^\infty \frac{dN}{dS} (e^{i\omega S} - 1) dS\right) e^{-i\omega D} d\omega. \quad (4.11)$$

4.2.2 Cas d'une PSF entendue positive

Lorsque la PSF n'est pas ponctuelle, une source n'a pas besoin d'être centrée sur un pixel pour contribuer au signal reçu par celui-ci. On note F le flux effectif vu par un pixel. Pour une source de flux S à une distance angulaire θ du pixel considéré, il vaut

$$F = S \times PSF(\theta), \quad (4.12)$$

où PSF est la réponse impulsionnelle de l'instrument. Le nombre de sources par unité de flux effectif et par pixel, n , est donné par

$$n(F) = \int \int \frac{dN}{dF} \Big|_F d\Omega. \quad (4.13)$$

Et l'équation 4.12 donne

$$\frac{dN}{dF} \Big|_F = \frac{dN}{dS} \Big|_{S=\frac{F}{PSF(\theta)}} \times \frac{dS}{dF} \Big|_{S=\frac{F}{PSF(\theta)}} = \frac{dN}{dS} \Big|_{S=\frac{F}{PSF(\theta)}} \times \frac{1}{PSF(\theta)}. \quad (4.14)$$

En combinant les équations 4.13 et 4.15, on trouve

$$n(F) = \int \int \frac{dN}{dS} \Big|_{S=\frac{F}{PSF(\theta)}} \times \frac{1}{PSF(\theta)} d\Omega. \quad (4.15)$$

La suite du calcul est similaire à celui de la section 4.2.1 en remplaçant dN/dS par n , et S par F . On obtient finalement

$$p_D(D) = \frac{1}{2\pi} \int_0^\infty \exp\left(\int_0^\infty n(F)(e^{i\omega F} - 1) dF\right) e^{-i\omega D} d\omega. \quad (4.16)$$

4.2.3 Effet du filtrage

Lors de la fabrication des cartes, un filtrage passe haut peut être appliqué. Une PSF prenant en compte ce filtrage peut posséder des parties négatives. Or, l'équation 4.15 n'est pas définie pour $PSF(\theta) = 0$. Par conséquent, il est nécessaire de séparer la contribution positive et la contribution négative de la PSF :

$$D = D_+ - D_- \quad (4.17)$$

La densité de probabilité de D sera donc

$$p_D(D) = P_{D_+}(D) * P_{D_-}(-D). \quad (4.18)$$

On définit alors

$$n_+(F) = \int \int_{PSF > 0} \frac{dN}{dS} \Big|_{S=\frac{F}{PSF_+(\theta)}} \times \frac{1}{PSF_+(\theta)} d\Omega, \quad (4.19)$$

et,

$$n_-(F) = \int \int_{PSF < 0} \frac{dN}{dS} \Big|_{S=\frac{F}{PSF_-(\theta)}} \times \frac{1}{PSF_-(\theta)} d\Omega, \quad (4.20)$$

où PSF_- est la valeur absolue des parties négatives de la PSF. On a alors la densité de probabilité de la contribution positive et négative (D_+ et D_-) au signal d'un pixel :

$$p_{D_+}(D_+) = \frac{1}{2\pi} \int_0^\infty \exp\left(\int_0^\infty n_+(F)(e^{i\omega F} - 1)dF\right) e^{-i\omega D_+} d\omega \quad (4.21)$$

puis,

$$p_{D_-}(D_-) = \frac{1}{2\pi} \int_0^\infty \exp\left(\int_0^\infty n_-(F)(e^{i\omega \times (-F)} - 1)dF\right) e^{-i\omega D_-} d\omega. \quad (4.22)$$

En combinant les relations 4.18, 4.21 et 4.22, et en utilisant les propriétés de la transformée de Fourier du produit de convolution, on obtient finalement

$$p_D(D) = \frac{1}{2\pi} \int_0^\infty \exp\left(\int_0^\infty n_+(F)(e^{i\omega F} - 1)dF\right) \times \exp\left(\int_0^\infty n_-(F)(e^{-i\omega F} - 1)dF\right) e^{-i\omega D} d\omega, \quad (4.23)$$

simplifiable en

$$p_D(D) = \frac{1}{2\pi} \int_0^\infty \exp\left(\int_0^\infty [n_+(F)e^{i\omega F} + n_-(F)e^{-i\omega F} - n_+(F) - n_-(F)]dF\right) e^{-i\omega D} d\omega. \quad (4.24)$$

4.2.4 Effet du bruit instrumental

Dans le cas d'une carte réelle, le bruit instrumental s'ajoute au signal dû aux galaxies. On supposera ici ce bruit gaussien :

$$p_B(B) = \text{normalisation} \times \exp\left(-\frac{B^2}{2\sigma^2}\right). \quad (4.25)$$

La transformée de Fourier d'une gaussienne étant une gaussienne, on a

$$\hat{p}_B(\omega) = \text{normalisation} \times \exp\left(-\frac{\omega^2 \sigma^2}{2}\right). \quad (4.26)$$

La densité de probabilité de $D_{gal+bruit}$ ($D_{gal+bruit} = D + B$) sera donc donnée par

$$p_{D_{gal+bruit}} = p_D * p_B, \quad (4.27)$$

soit dans l'espace de Fourier :

$$\hat{p}_{D_{gal+bruit}} = \hat{p}_D \times \hat{p}_B. \quad (4.28)$$

Finalement, en transformant le produit d'exponentielles en exponentielle d'une somme, on a

$$p_{D_{gal+bruit}}(D_{gal+bruit}) = \frac{1}{2\pi} \int_0^\infty \exp\left(\int_0^\infty [n_+(F)e^{i\omega F} + n_-(F)e^{-i\omega F} - n_+(F) - n_-(F)]dF - \frac{\omega^2 \sigma^2}{2}\right) e^{-i\omega D_{gal+bruit}} d\omega \quad (4.29)$$

4.2.5 Prise en compte d'une calibration relative

Les instruments de *Spitzer*, *Herschel* et BLAST font de la photométrie relative. Leur signal zéro est choisi arbitrairement. En général, on choisit le niveau zéro de manière à avoir une carte à moyenne nulle. On appelle μ la différence entre le zéro absolu (après soustraction des avant-plans zodiacaux et galactiques) et le zéro de la carte. La distribution $p_{D_{mes}}$, observée pour une calibration relative sera liée à p_D par

$$p_{D_{mes}}(D_{mes}) = p_D(D_{mes} + \mu), \quad (4.30)$$

soit dans l'espace de Fourier

$$\hat{p}_{D_{mes}}(\omega) = \hat{p}_D(\omega) \times e^{i\mu\omega}. \quad (4.31)$$

La densité de probabilité de D_{mes} peut donc se calculer en utilisant

$$p_{D_{mes}}(D_{mes}) = \frac{1}{2\pi} \int_0^\infty \exp\left(\int_0^\infty [n_+(F)e^{i\omega F} + n_-(F)e^{-i\omega F} - n_+(F) - n_-(F)]dF - \frac{\omega^2 \sigma^2}{2} + i\mu\omega\right) e^{-i\omega D_{mes}} d\omega. \quad (4.32)$$

4.2.6 Développement d'un code d'analyse P(D)

J'ai développé des outils en langage IDL permettant de réaliser une analyse P(D). Ces outils utilisent une paramétrisation des comptages similaire à celle de Patanchon *et al.* (2009). Toutefois, une option permet de relier les noeuds avec une *spline* à la place d'une

loi de puissance. Il est également possible de prendre en compte l'incertitude sur le bruit instrumental, en autorisant ce bruit à varier, mais en pénalisant les valeurs éloignées de la valeur mesurée. Un second terme additionnel peut être ajouté pour forcer un accord entre le modèle de comptages et le niveau du fond infrarouge mesuré par FIRAS. L'ajustement des paramètres est réalisé par méthode MCMC en utilisant l'algorithme Metropolis-Hastings. La loi de déplacement dans l'espace des paramètres est dans un premier temps choisie en calculant la matrice de Fisher du problème à une position initiale choisie manuellement (typiquement un modèle de comptages). Une première chaîne courte ($\sim 10\,000$ pas) est lancée. Sa matrice variance-covariance est calculée. La nouvelle loi de déplacement est la loi gaussienne ayant la même matrice variance-covariance. On lance alors une nouvelle chaîne plus longue. On vérifie la convergence de celle-ci en utilisant les critères de Dunkley *et al.* (2005), qui utilisent les spectres de puissance des réalisations des paramètres.

Le calcul rapide de la vraisemblance du modèle à chaque pas pilote totalement la vitesse du programme. J'ai écrit un programme rapide permettant de réaliser cette opération. La première étape consiste à calculer $n_+(F)$ et $n_-(F)$ (voir Eqs. 4.19 et 4.20). Pour gagner du temps, ces fonctions sont calculées sur une grille logarithmique. Un histogramme de la PSF est utilisée pour calculer l'intégrale, au lieu de sommer sur tous les pixels de la PSF. On interpole ensuite ces fonctions sur une grille régulière afin de calculer sa transformée de Fourier dans Eq. 4.23. On soustrait alors la moyenne du signal à la grille en D , afin d'obtenir une distribution à moyenne nulle. Puis, on intègre par la méthode des trapèzes la fonction $p(D)$ dans les bins de flux utilisés pour construire l'histogramme moyen des cartes analysées, afin d'en déduire la vraisemblance du modèle comptages testé (Patanchon *et al.* (2009))

$$\ln(L) = \sum_i (n_i \ln(p_i) - \ln(n_i!)) + \ln(N!), \quad (4.33)$$

où L est la vraisemblance, n_i le nombre de pixel de la carte dans le i -ième intervalle de flux, p_i est la valeur moyenne du nombre de pixels dans le même intervalle de flux, et N le nombre total de pixels.

4.3 Résultats : application aux données *Herschel*/SPIRE

Cette partie reprend les résultats que j'ai obtenus dans le cadre de la collaboration HerMES. Ces résultats ont été publiés dans Glenn *et al.* (2010). Ce résumé est centré sur ma contribution personnelle.

4.3.1 Motivations

L'analyse P(D) des données BLAST ne permettait pas de bien contraindre les comptages à bas flux. *Herschel*, grâce à une résolution angulaire et une sensibilité supérieure, permet d'obtenir des images d'une bien meilleure qualité. Lors de la phase de démonstration scientifique, quatre champs extragalactiques ont été observés par le programme HerMES⁴ (programme de temps garanti de l'instrument SPIRE) : GOODS-N (champs profond), Lockman-North (champs intermédiaire), FLS (champs large) et Lockman SWIRE (champs très large). La combinaison de champs larges et profonds fournit de fortes contraintes sur les sources faibles et brillantes, permettant de mesurer les comptages avec une précision et une profondeur inégalée, qui vont fortement contraindre les populations infrarouges à haut *redshift*.

4.3.2 Le problème de la paramétrisation des comptages

Le choix de la position des noeuds utilisés lors de l'analyse P(D) est le fruit d'un compromis entre deux effets. Si les noeuds sont trop éloignés les uns des autres, le modèle paramétrique ne peut pas reproduire fidèlement la forme complexe des comptages. En revanche, une trop grande proximité entre deux noeuds induit de fortes dégénérescences, et fait exploser les barres d'erreur.

On peut tester la pertinence d'un choix de noeuds en utilisant les comptages issus de modèles (Lagache *et al.* (2004), Le Borgne *et al.* (2009), Valiante *et al.* (2009)). On calcule les histogrammes attendus pour le modèle initial. Puis, on construit un second modèle de comptages en plaçant les noeuds exactement sur la courbe du modèle initial et en utilisant une interpolation entre les noeuds avec une loi de puissance ou une *spline*. Puis, on calcule la différence entre les histogrammes des deux modèles. Ces considérations nous ont montré qu'il est nécessaire d'utiliser environ 3 noeuds par décades, et qu'une interpolation *spline* est plus adéquate qu'une interpolation en loi de puissance. Néanmoins, aucune paramétrisation n'est parfaite, et la position d'un noeud ne peut en aucun cas être considérée comme une mesure des comptages à un flux précis. Les points P(D) ne doivent donc pas être ajustés tels quels par un modèle d'évolution.

4.3.3 Le problème du filtrage

Le formalisme du P(D) suppose que les sources sont distribuées de manière poissonnienne. En réalité, les sources infrarouges ont tendance à se regrouper (Lagache *et al.* (2007), Viero *et al.* (2009)). Ceci élargit le pic de l'histogramme. En effet, la largeur de ce

⁴*Herschel Multi-tiered Extragalactic Survey*

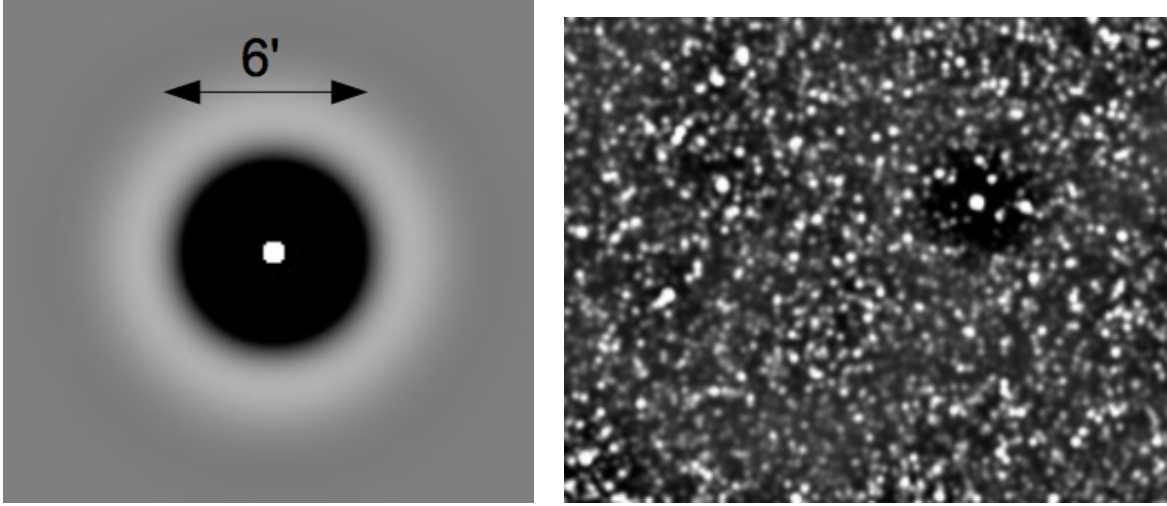


FIGURE 4.2 – (A gauche) : PSF après filtrage. (A droite) : carte simulée après filtrage.

pic est liée, en l'absence de bruit instrumental, au spectre de puissance du fond infrarouge (Takeuchi et Ishii (2004), Patanchon *et al.* (2009)) :

$$\sigma = \int \int P(k) \widetilde{PSF} d^2k, \quad (4.34)$$

où $P(k)$ est le spectre de puissance des cartes infrarouges et $\widetilde{PSF}$ la transformée de Fourier de la PSF. Lagache *et al.* (2007) sépare le spectre de puissance en plusieurs contributions : une contribution poissonnienne qui ne dépend pas de l'échelle, et une partie due au regroupement des sources qui domine au delà d'une dizaine d'arcminutes. La partie due au regroupement n'est pas prise en compte par le formalisme du $P(D)$. On peut par exemple comparer la variance entre sous-champs de 500×500 pixels dans Lockman SWIRE. La variance sur le nombre de sources dans un bin de flux est environ deux fois plus grande que pour une loi de Poisson. En revanche, elle est poissonnienne si on soustrait la moyenne de chaque sous-carte ou si on filtre les grandes échelles. Ceci confirme que les effets du regroupement sur l'histogramme agissent essentiellement aux grandes échelles.

Pour cette raison, nous avons filtré les échelles supérieures à 6 arcminutes dans les cartes et les PSFs. Ce filtrage permet également de réduire l'effet des cirrus qui dominent la puissance aux très grandes échelles (>30 arcmin). En pratique, ce filtrage est réalisé de la manière suivante. On calcule la transformée de Fourier de la carte $\tilde{m}$, où on a mis à zéro les pixels non observés. On construit un masque où les échelles supérieures à 6 arcminutes sont à 0 et les autres à 1, qu'on lisse avec un noyau gaussien de 1.8 arcmin. Ce lissage limite les oscillations autour des sources brillantes. On multiplie ensuite $\tilde{m}$ par ce masque lissé, et on réalise la transformée inverse. La Fig. 4.2 montre l'effet du filtrage sur la PSF et sur la carte. La PSF est peu modifiée aux petites échelles, mais présente de larges

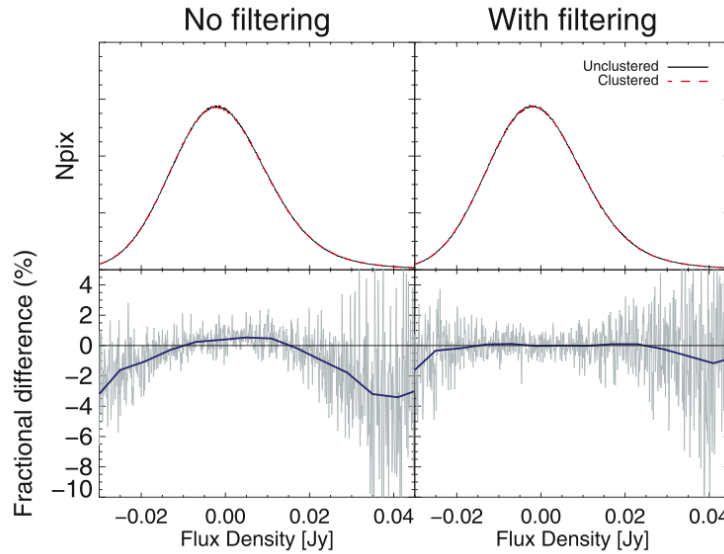


FIGURE 4.3 – (Panneaux du haut) Histogramme des pixels de cartes simulées du champ Lockman SWIRE avec (tirets rouges) et sans regroupement (ligne noire). (Panneaux du bas) : Différence entre les histogrammes avec et sans regroupement. (Panneaux de gauche) : Cartes non filtrées. (Panneaux de droite) : Cartes filtrées.

ailes négatives qui sont également visibles dans la carte. Notre filtrage étant parfaitement linéaire, il est pris en compte naturellement par le formalisme du $P(D)$, si on utilise une carte et une PSF filtrées de la même manière.

Nous avons validé cette méthode en comparant deux simulations avec et sans regroupement, basée sur les mêmes comptages (voire Fig. 4.3). L'écart entre les deux histogrammes est bien plus petit dans le cas où les grandes échelles ont été filtrées. J'ai par la suite réalisé des simulations avec regroupement des champs observés à partir du travail de Fernandez-Conde *et al.* (2008). J'ai alors appliqué mes outils d'analyse $P(D)$ et retrouvé des comptages en accord avec les comptages initiaux de la simulation. Ceci confirme l'efficacité de la méthodologie choisie.

Le filtrage des grandes échelles n'est pas le seul filtrage à tester. En effet, Patanchon *et al.* (2009) ont également lissé leur carte par la PSF, afin de réduire le bruit instrumental et améliorer la précision des comptages obtenus. Toutefois, les champs profonds SPIRE (GOODS-N et Lockman-N) sont peu affectés par le bruit instrumental. Dans ce cas, j'ai montré qu'il n'est pas nécessaire de lisser la carte par la PSF en utilisant une analyse de Fisher.

4.3.4 Résultats

Nous avons appliqué ces méthodes aux données de la phase de démonstration scientifique de l'instrument SPIRE. Nous avons fait le choix de n'utiliser que 3 champs extragalactiques sur 4. En effet, le champ FLS est contaminé par un cirrus. Son utilisation présentait donc des risques d'effets systématiques. De plus, ce champ peu profond et moins large que Lockman SWIRE n'améliore que très faiblement les contraintes sur les comptages. Nous avons donc ajusté simultanément les trois champs suivant : GOODS-N, Lockman-N et Lockman SWIRE.

Nous avons développé deux codes d'analyse distincts afin de s'assurer de la qualité de nos résultats : mon code IDL utilisant une interpolation spline entre les noeuds, et le code d'Alex Conley en C++ optimisé pour une interpolation en loi de puissance. Les deux codes ont fourni des résultats compatibles (voir Fig. 4.4). A l'exception du premier et du dernier noeud, tous les autres sont incompatibles avec zéro. Nous sommes donc en mesure de présenter une estimation robuste des comptages entre 2 mJy et 1 Jy⁵, sondant un domaine de flux jamais exploré à ces longueurs d'ondes. En effet, à cause de la confusion, les comptages résolus sont très difficiles à estimer en dessous de 20 mJy (Oliver *et al.* (2010)).

Ces résultats peuvent être comparés avec les mesures réalisées par BLAST (Fig. 4.4, panneau du haut). Les comptages que j'ai mesurés dans les données BLAST sont en bon accord avec l'analyse P(D) des données *Herschel*. En revanche, le pic des comptages différentiels normalisés de Patanchon *et al.* (2009) est trop haut. Ceci est probablement dû à un effet de paramétrisation. En effet, ils n'utilisent qu'un seul noeud entre 0.1 et 100 mJy, alors que les comptages évoluent rapidement dans cette région. On peut également comparer nos résultats aux comptages de sources résolues par *Herschel*. L'accord avec l'analyse de Oliver *et al.* (2010) des mêmes champs est très bon. Il y a également un bon accord avec les comptages H-ATLAS (16 deg²) de Clements *et al.* (2010). Enfin, nous avons comparé nos mesures avec une large collection de modèles. Aucun d'eux n'est en mesure de reproduire les comptages dans les trois bandes. Ceci montre à quel point l'analyse P(D) fournit des contraintes fortes sur l'évolution des galaxies infrarouges.

4.4 Conclusion

Dans ce chapitre, nous avons présenté le formalisme sur lequel se base la méthode du P(D). Cette méthode se révèle très puissante pour mesurer les comptages dans des régimes de confusion extrême. Contrairement à l'analyse par empilement, cette méthode ne

⁵La position des noeud étant arbitraire, la position du dernier noeuds bien contraint l'est tout autant. En revanche, différents tests nous ont montré qu'il est impossible de contraindre plus de deux noeuds en dessous de 5 mJy qui est le bruit de confusion à 1- σ de SPIRE.

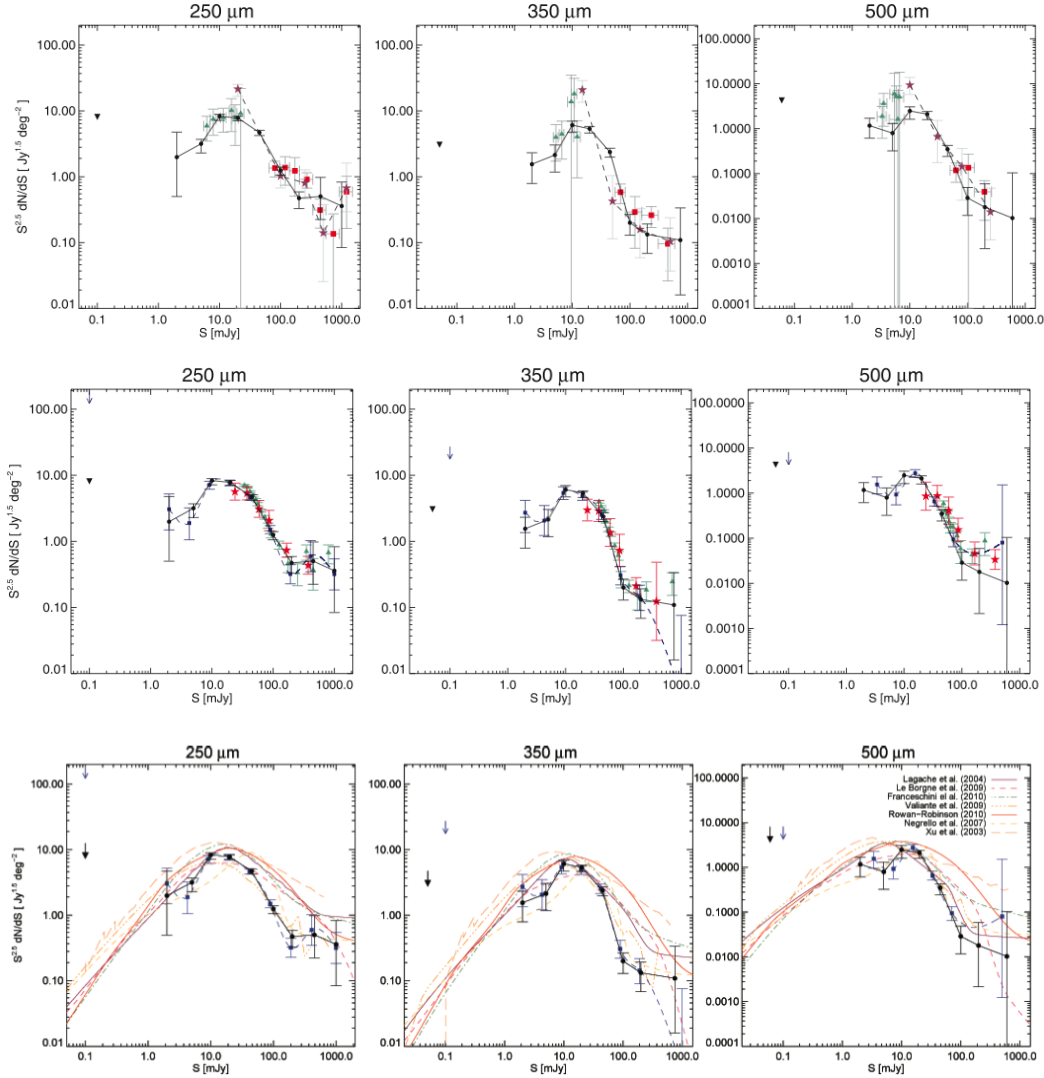


FIGURE 4.4 – Comptages diff  rentiels normalis  s    250, 350 et 500 μm . L’analyse P(D) des donn  es *Herschel* est en bleu (mon code) et en noir (code de Alex Conley). (Panneau du haut) : Comparaison avec les mesures BLAST : comptages r  solus en rouge, comptages par empilement en vert (B  thermin *et al.* (2010b)), et analyse P(D) en violet (Patanchon *et al.* (2009)). (Panneau du milieu) : Comparaison avec les comptages r  solus *Herschel* dans HerMES (Oliver *et al.* (2010) en rouge et dans H-ATLAS en vert (Clements *et al.* (2010))). (Panneau du bas) : Comparaison avec une collection de mod  les.

suppose aucun lien entre longueurs d'onde. Ceci permet de confirmer avec une méthode et des données différentes ce qui a été obtenu par empilement dans les données BLAST (voir Chap. 3). De plus, les points obtenus par analyse $P(D)$ des données SPIRE sont beaucoup plus contraignants pour les modèles que ce qui a été obtenu avec la méthode de l'empilement dans les données BLAST.

Toutefois, la mise en oeuvre d'une analyse $P(D)$ n'est pas triviale, et l'interprétation des résultats doit être faite avec précaution. Par exemple, le choix de la position des noeuds utilisés affecte fortement le résultat. Le pic des comptages différentiels normalisés trouvé par Patanchon *et al.* (2009) est ainsi trop haut d'un facteur 2. Le choix des noeuds utilisés pour réaliser l'analyse $P(D)$ des données HerMES cherche à limiter ce type d'effets, bien qu'un biais de paramétrisation soit inévitable. En fait, l'idéal serait d'ajuster directement les paramètres d'un modèle d'évolution sur l'histogramme des cartes.

4.5 Article : *HerMES : deep galaxy number counts from a $P(D)$ fluctuation analysis of SPIRE Science Demonstration Phase observations*

Un article synthétisant les travaux réalisés sur l'analyse $P(D)$ dans le cadre de la collaboration HerMES a été publié dans MNRAS.

HerMES: Deep Galaxy Number Counts from a $P(D)$ Fluctuation Analysis of SPIRE Science Demonstration Phase Observations

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ABSTRACT

Dusty, star forming galaxies contribute to a bright, currently unresolved cosmic far-infrared background. Deep *Herschel*-SPIRE images designed to detect and characterize the galaxies that comprise this background are highly confused, such that the bulk lies below the classical confusion limit. We analyze three fields from the HerMES programme in all three SPIRE bands (250, 350, and 500 μm); parameterized galaxy number count models are derived to a depth of ~ 2 mJy/beam, approximately 4 times the depth of previous analyses at these wavelengths, using a $P(D)$ (probability of deflection) approach for comparison to theoretical number count models. Our fits account for 64, 60, and 43 per cent of the far-infrared background in the three bands. The number counts are consistent with those based on individually detected SPIRE sources, but generally inconsistent with most galaxy number counts models, which generically overpredict the number of bright galaxies and are not as steep as the $P(D)$ -derived number counts. Clear evidence is found for a break in the slope of the differential number counts at low flux densities. Systematic effects in the $P(D)$ analysis are explored. We find that the effects of clustering have a small impact on the data, and the largest identified systematic error arises from uncertainties in the SPIRE beam.

Key words: Submillimeter Galaxies – Cosmology: Observations

1 INTRODUCTION

The cosmic far-infrared background (hereafter CFIRB) provides unique information on the history of energy injection in the Universe by both star formation and active galactic nuclei. First detected by the *COBE* satellite (Puget et al. 1996; Fixsen et al. 1998), the CFIRB contains a large amount of energy, indicating that the total luminosity from thermal dust emission is comparable to the integrated UV/optical energy output of galaxies (Guiderdoni et al. 1997).

Galaxy surveys, both from the ground (with SCUBA, LABOCA, Bolocam, AzTEC, and MAMBO at 850 μm , 870 μm , 1.1 mm, 1.1 mm, and 1.3 mm, respectively) and from space using *IRAS* (at 12, 25, 60 and 100 μm), *ISO* (at 15, 90, and 170 μm), and *Spitzer* (at 3.6 to 160 μm), found high number counts compared to non-evolving galaxy number counts models. This implied that strong evolution of the source populations must have occurred, challenging contemporary galaxy evolution models (Saunders 1990; Scott et al. 2002; Lagache et al. 2003). Deeper number counts test galaxy formation models more severely. By stacking *Spitzer* MIPS 24 μm sources, at least 80% of the CFIRB was resolved at 70 μm and 65% at 160 μm (Dole et al. 2006; Béthermin et al. 2010a). A small fraction (10-20%) has been resolved in the submillimeter in blind sky surveys from ground-based observatories, but it is possible to go deeper by taking advantage of gravitational lensing. At 850 μm this approach has resolved 60% or more of the background in small fields (Smail et al. 2002; Zemcov et al. 2010).

A $P(D)$ – probability of deflection – analysis of Bolocam observations of the Lockman Hole (Maloney et al. 2005) demonstrated that a fluctuation analysis can provide more stringent constraints on source number counts than those derived by extracting individual sources, for which the threshold must be set high enough to ensure a minority of false detections. $P(D)$ techniques were first developed for application to radio observations (Scheuer 1957), but have since been widely applied to other regimes. $P(D)$ was used to account for the majority of the X-ray background long prior to the availability of sufficiently deep imaging to resolve individual sources (Barcons 1994), to extend deep infrared counts

(Oliver et al. 1997), and in the sub-mm to SCUBA (Hughes et al. 1998), LABOCA (Weiß et al. 2009), and AzTEC (Scott et al. 2010) data. The depth of a $P(D)$ analysis is set by the flux density at which the number of sources per beam becomes large. The resulting contribution to the $P(D)$ becomes that of a Poissonian distribution with a large mean, which becomes difficult to distinguish from the nearly-Gaussian instrumental noise. An often-used rule of thumb for the maximum depth is one source per beam, but the precise limit depends on the survey area, the shape of the underlying counts, and how precisely the instrumental noise is known. In practice, for rapidly rising source counts at faint fluxes, this is considerably deeper than the limits for a source-extraction approach. Fluctuation analyses are well-suited to determination of source number counts in the case where the dynamic range of detected sources is not large because of confusion. Deep number counts are interesting because they allow us to measure the sources responsible for the bulk of the CFIRB, and because they probe intrinsically fainter galaxies which may have better matching counterparts in the local Universe.

Recently, a $P(D)$ analysis was performed on 250, 350, and 500 μm observations of a 10 deg² field (GOODS-S) with a 0.8 deg² deep inner region from the balloon-borne BLAST telescope, using duplicate SPIRE detector technology (Patanchon et al. 2009, hereafter P09). Differential number counts were estimated down to 20, 15, and 10 mJy in the three bands, respectively. Below these thresholds, upper limits were provided. Combined with 24 μm observations, Devlin et al. (2009) concluded that a large fraction ($> 1/2$) of the CFIRB comes from galaxies with $z > 1.2$. Also from BLAST observations, Marsden et al. (2009) concluded that 24 μm -selected galaxies can account for the entire CFIRB based on a stacking analysis. These results confirm that fluctuation and stacking analyses have substantial power in elucidating the sources of the CFIRB. Such techniques will also be necessary for SPIRE observations because galaxy models predict that at the confusion limit SPIRE is expected to resolve only a small fraction of the CFIRB (Lagache et al. 2003; Fernandez-Conde et al. 2008). A recent source extraction-based analysis of the SPIRE Science Demonstration Phase (SDP) data – the same data used in this paper – directly resolved 15, 10, and 6 per cent of the CFIRB at 250, 350, and 500 μm , respectively (Oliver et al. 2010). At shorter wavelengths, Berta (2010) directly

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resolved 52 and 45 per cent of the CFIRB at 100 and 160 μm using *Herschel*-PACS SDP data.

2 DATA

The observations used in this analysis were obtained with the SPIRE instrument (Griffin et al. 2010) on the *Herschel* Space Observatory (Pilbratt et al. 2010) as part of the HerMES programme¹ (Oliver et al. 2010, in prep) during the SDP. SPIRE observes simultaneously in three passbands: 250, 350 and 500 μm . The on-orbit beam sizes, including the effects of the scanning strategy, are 18.1, 25.2, and 36.6 arcseconds, respectively, with mean ellipticities of 7 - 12%. The calibration is based on observations of Neptune, and is described in Swinyard et al. (2010). Observations of five fields were obtained during SDP, but only three are used in this analysis: GOODS-N, Lockman-North, and Lockman-SWIRE. Their properties are summarized in table 1. The Lockman-North region are contained within the shallower Lockman-SWIRE field. The HerMES SDP fields omitted from this analysis are: FLS, which was left out because it is the same depth as the much-larger Lockman-SWIRE field and is significantly contaminated by infrared cirrus, and Abell 2218, because the strong lensing in this field complicates the interpretation of the background number counts.

The detector (bolometer) timelines were processed using the standard SPIRE pipeline, which detects cosmic rays and removes instrumental signatures and temperature drifts (Dowell et al. 2010). The maps were produced using the SMAP package (Levenson et al. 2010, in prep) using 1/3 beam-FWHM pixels (6, 8 1/3, and 12 arcsec); this is a compromise between adequately sampling the beam and maintaining even coverage over the map. Samples flagged as contaminated by cosmic-rays were excluded. Each map was masked to form an even-coverage region and was mean subtracted. In addition to the even-coverage mask, a small amount of additional masking was required, as there are five resolved sources in the Lockman-SWIRE field. These sources are relatively bright, but are not the brightest in the field. Since the $P(D)$ formalism is based on unresolved point sources, we mask these objects with a 2 arcmin circular mask, and then correct our final number counts using the measured flux of each excluded source. Our instrumental noise estimates are based on the technique of Nguyen et al. (2010), and are assumed to have 5% uncertainty, which represents only the uncertainty for a fixed calibration. The overall SPIRE calibration error is discussed in § 5.1. The resulting pixel flux density histograms are shown in figure 1.

Smoothing the maps by the beam (via cross-correlation) is beneficial for finding isolated point sources. For BLAST observations, Chapin et al. (2010) show that the standard point-source-optimized filter should be modified in the presence of confusion noise. However, there is no guarantee this will benefit a $P(D)$ analysis. Smoothing the map has the effect of broadening the effective beam, which decreases the depth that the $P(D)$ can probe, while also reducing (but correlating) the instrumental noise. We empirically determined if smoothing is beneficial for our analysis by fitting simulated data with and without smoothing and comparing the scatter in the recovered model parameters to the error estimates, and found that it helps for all but our deepest map (GOODS-N); note that our GOODS-N data are several times deeper (relative to the confusion noise) than the deepest BLAST observations. It is

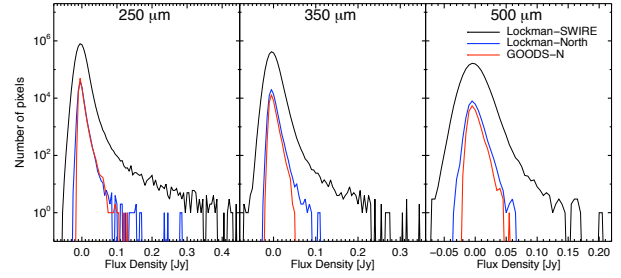


Figure 1. Histogram of pixel flux densities for the three fields considered in this paper in 5 mJy bins. The Lockman-SWIRE field is considerably shallower than the others, but it is the only field large enough to probe the bright end of the source distribution. The maps have been mean subtracted. The binning here is for display purposes and does not correspond to the binning used in the actual analysis, which is much finer. In all cases the pixel histograms show clear non-Gaussianity despite the Gaussian nature of the noise, indicating that a significant point-source contribution is present.

likely that some amount of spatial de-convolution would be beneficial for the GOODS-N field, but since this would significantly complicate the instrumental noise properties of our maps, and hence require extensive testing, we do not pursue de-convolution here, but do beam-smooth the two shallower fields. In addition, we have applied a 6 arcmin high-pass spatial filter to our maps to reduce the effects of clustering on our results. The motivation for this is discussed in § 3.3.

A $P(D)$ analysis is critically dependent on measurements of the effective beam (which includes the effects of the map making and reduction, as well as any smoothing applied). Our beam map is based on in-flight fine-scan (highly oversampled) observations of Neptune with a large number of repeats and small offsets between each scan. These observations allowed us to measure the beam with finer resolution than our data maps to properly match the SPIRE calibration (which is timestream rather than map based), and to build beam maps for the individual bolometers. We corrected these observations for the relative motion of Neptune during the scans using the HORIZONS² ephemeris computation service at the orbit of *Herschel*. The Neptune observations are deep enough that the third Airy ring is clearly detected for the array-averaged beams. As discussed later (§ 5.1), beam uncertainties are our largest identified systematic.

3 METHOD

We first describe the basic $P(D)$ framework, then discuss our particular implementations and the filtering we have applied to limit the effects of clustering.

3.1 Description of $P(D)$

If $dN/dS(S)$ is the differential number counts per solid angle and S the flux density, then the mean number density of sources per unit solid angle with observed flux densities between x and $x + dx$ is

$$R(x) dx = \int_{\Omega} \frac{dN}{dS} \left(\frac{x}{b} \right) b^{-1} d\Omega dx \quad (1)$$

¹ <http://www.hermes.sussex.ac.uk/>

² <http://ssd.jpl.nasa.gov/?horizons>

Table 1. HerMES SPIRE Science Demonstration Phase observations used in this paper

Field	Size deg ²	RA deg ²	Dec deg ²	Scan Rate arcsec/s	Repeats	σ_{250} mJy/beam	σ_{350} mJy/beam	σ_{500} mJy/beam
GOODS-N	0.29	189.23	62.24	30	30	1.77	1.59	1.89
Lockman-North	0.41	161.50	59.02	30	7	3.58	3.16	4.41
Lockman-SWIRE	13.6	162.0	58.11	60	2	9.47	8.47	11.99

The σ values for each band and field are the instrumental noise per pixel before any filtering or smoothing is applied. The confusion noise (the signal in this analysis) is ~ 6 mJy/beam in all bands (Nguyen et al. 2010).

where b is the beam function (not necessarily peak normalized). Ignoring clustering, the probability distribution of sources is Poissonian. The probability distribution function (pdf) for the observed flux in each sky area unit (usually a map pixel) is the convolution of the pdfs for each flux interval over all fluxes; this quantity is called the $P(D)$. Rewriting the above in terms of characteristic functions and denoting the inverse Fourier transform by F_{ω}^{-1} ,

$$P(D) = F_{\omega}^{-1} \left[\exp \left(\int_0^{\infty} R(x) \exp(i\omega x) dx - \int_0^{\infty} R(x) dx \right) \right]. \quad (2)$$

The mean of the $P(D)$ is

$$\mu = \int xR dx = \int b d\Omega \int S dN/dS(S) dS,$$

and the variance is

$$\sigma_p^2 = \int b^2 d\Omega \int S^2 dN/dS(S) dS.$$

For real observations, the instrumental noise contribution must also be included. Our observations are not sensitive to the mean flux in the maps. Therefore, it is useful to subtract off the mean of the $P(D)$ during construction. Only in the case of very simple models for dN/dS combined with trivial beams is it possible to compute $P(D)$ analytically – an example is given in Scheuer (1957), but even this is only valid for a restricted range of parameters. For an effective beam that is not strictly positive (due to filtering, for example), the $P(D)$ is the convolution of the individual $P(D)$ s for the positive beam and for the negative beam (P09). Azimuthally averaging the beam does not preserve the $P(D)$, so it is necessary to use the full 2D beam map.

The log likelihood ($\log \mathcal{L}$) of a dataset relative to a particular model is given (to within an irrelevant normalizing constant) by

$$\log \mathcal{L} = \sum_i \log P(D_i),$$

where D_i is the value of the i^{th} pixel. Usually it is more convenient to bin the data. As long as the individual bins are small compared to the width of the $P(D)$, the two formulations are practically equivalent. Then

$$\log \mathcal{L} = \sum_k h_k \log P(x_k), \quad (3)$$

where h_k is the number of pixels in the histogram bin centred at flux density x_k . The alternative of using the χ^2 as the fit statistic under-weights bins with a small number of pixels in them because the uncertainty in such a bin is not well modeled by $\sqrt{h_k}$, and is not recommended.

This treatment assumes that different pixels are uncorrelated, which is not true unless the beam is much smaller than a pixel. A source at one location will affect neighbouring values over an area about equal to the area of the beam. The result is that, if applied naively, fits based on the above likelihood will underestimate

the model errors. Properly treating this effect requires developing the $P(D)$ formalism in terms of multi-variate Poisson distributions, which is computationally infeasible. P09 recommend dividing the likelihood by the beam area in pixels ($\mathcal{L} \mapsto \mathcal{L}/A_b$) in order to correct for this effect, which amounts to approximately correcting the likelihood for the number of independent samples in the map. This is an ad hoc approach, but in the absence of a better alternative, we have adopted a similar method. However, based on Monte-Carlo simulations of synthetic data sets, we find that this correction factor is overly conservative, as discussed below.

Another approximation in the above treatment which is not valid for real data is that the sources are not Poisson distributed due to clustering. Our approach to this effect is described in § 3.3.

3.2 Implementation

We have developed two independent $P(D)$ analysis packages and checked them against each other. Given the large number of parameters and the non-linear nature of the problem, both make use of Markov Chain Monte Carlo (MCMC) methods. Overviews of MCMC methods can be found in MacKay (2002); Lewis & Bridle (2002); Dunkley et al. (2005). The important aspects of an MCMC implementation are the burn-in criterion and the proposal density. The burn-in criterion is the rule used to determine whether the fit has converged on the region of maximum likelihood. Once the fit has converged, subsequent steps are drawn from the posterior probability of the model given the data, and only these steps are used to measure the errors and values of the parameters. The proposal density is used to propose the next step in the Markov Chain from the current step. Any proposal density that can visit all valid parameters is correct, but a well chosen density can dramatically improve the efficiency of the fitting procedure.

The first code is written in IDL³ and the burn-in criterion is based on the power spectrum of the single chain (Dunkley et al. 2005). The first chain step within $\Delta \log \mathcal{L} = 2$ of the best-fit parameters is taken as the start of the converged sampling. A Fisher-matrix approximation to the $P(D)$ fit is used for the proposal density. This code interpolates in log space from a moderate number (~ 80) of flux densities to calculate the $P(D)$. The other code is written in C++, and is explicitly parallel. It uses the Gelman-Rubin criterion for burn-in (Gelman & Rubin 1992), which is based on computing the variance between chains and directly provides the point of convergence. This code does not use interpolation when computing the $P(D)$, but supports a more limited range of models. The proposal density is a multi-variate Gaussian estimated from the previous fit steps, and is frozen in at burn-in. We have checked these codes against each other on simulated data, and find good agreement.

³ Interactive Data Language: <http://www.itvis.com/ProductServices/IDL.aspx>

Our $P(D)$ methodology is almost identical to that described in P09 except as follows. First, P09 explicitly fit for the mean of pixel values in the map (μ). Since we can analytically predict the mean of the $P(D)$ for a given set of model parameters, we simply shift the mean to zero explicitly during construction. The input map is also mean-subtracted, and the uncertainty in this subtraction contributes negligibly to our error budget. Second, P09 fit to the instrument noise explicitly for each field except for the deepest section of their map. Instead, we marginalize over the noise for all fields in our full fits, but use the measurements of Nguyen et al. (2010) as a prior, assuming a Gaussian uncertainty of 5%. At low flux densities, the number of sources per beam is large, and hence the contribution to the $P(D)$ is almost Gaussian. Therefore, the values of dN/dS for the faintest flux densities probed and the noise level are nearly degenerate, and hence fixing the noise will tend to under-estimate the uncertainties in the model parameters at the faint end.

We have developed a simple simulation framework to test these codes and their sensitivity to various effects such as $1/f$ noise. As inputs we consider two types of catalogs that should be representative of the sub-mm sky: the P09 models, and the simulations of Fernandez-Conde et al. (2008). The fits to the P09 models are easier to compare with the inputs, but the Fernandez-Conde et al. (2008) models include clustering effects.

A fake sky is generated from the input catalogue, and scanned using the pointing information from the actual SPIRE observations. Different noise levels (white and $1/f$) can be specified. These data are then run through the same map-making pipeline as the real data. In addition to the simulated science data, we also simulate observations of Neptune using the same framework to determine the beams we use when fitting the simulated data. These simulations use simple Gaussian beams with FWHMs similar to those measured on-orbit, and account for characteristics of the data introduced by the mapping pipeline, but do not simulate errors in the lower-level SPIRE pipeline (pointing errors, crosstalk-corrections, etc.). We use them to quantify the effects of $1/f$ noise, uneven coverage, clustering, and smoothing by the beam on our maps. The SPIRE $1/f$ knee frequency is a few mHz, corresponding to a spatial scale of approximately 3 degrees for a scan speed of 30 arcseconds per second, and our map-making algorithm reduces this already small amount as discussed in Levenson et al. (2010, in prep). We find that the remaining amount, as well as the uneven coverage, introduces negligible bias in our fits, but that clustering can have measureable effects on our largest maps, as discussed in § 3.3.

In addition, we have determined the appropriate correction for pixel-pixel correlations using the same framework and a large number of simulated HerMES datasets. We find that the correct normalization factor varies with signal-to-noise ratio of the map, and whether it has been additionally smoothed with the beam. If the map is beam-smoothed, then the beam area factor is approximately correct, if slightly conservative for deeper fields; note that all of the maps in P09 were beam-smoothed. However, for deep, unsmoothed maps, this procedure clearly overestimates the uncertainties (by about a factor of 2 for GOODS-N). Rather than derive individual correction factors for each field, we have taken the more conservative approach of finding the largest correction factor (which therefore increases the uncertainties the most) for all of our fields, and applying it to all un-smoothed data. For the GOODS-N and Lockman-North observations, the correct normalization factor (without smoothing) is less than $A_b/3$. Because we do not have an exact formulation for this correction, we conservatively adopt $2A_b/5$. For the smoothed observations, we adopt the A_b normalization, also conservatively; this means that the two Lockman fields

have the same correction factors, but the (un-smoothed) GOODS-N field has a different one.

3.3 Filtering

Clustering will affect the $P(D)$ distribution in two ways. First, the presence of clustering implies sample variance effects, so that the SDP fields may not be representative of the all-sky number counts. Second, the fact that the underlying counts are not Poisson distributed would change the shape of the $P(D)$ distribution even if we were somehow lucky enough to select a precisely average region of sky. This effect can be modeled if all of the n -point statistics of the source distribution are known (Barcons 1992). The effect on the width of the $P(D)$ is discussed in Appendix A of P09, although clustering is not purely limited to changing the width of the distribution. Only the 2-point function has been measured for the population sampled by SPIRE, and even this is not known at the flux densities important for our results. The first issue is discussed in § 5.1, and the second here. There are two effects: clustering on small scales between individual SMGs, and clustering on larger scales between groups of SMGs.

The framework for the clustering contribution to the $P(D)$ is given in Barcons (1992); Takeuchi & Ishii (2004). The contribution to the n^{th} moment is proportional to $\int P_n(\mathbf{k}) \tilde{b}(\mathbf{k})^n d^2\mathbf{k}$, where $P_n(\mathbf{k})$ is the power spectrum of the n -point correlation function, and $\tilde{b}(\mathbf{k})$ is the Fourier transform of the beam. $\tilde{b}$ falls rapidly with $|\mathbf{k}|$ (e.g., an 18 arcsecond FWHM Gaussian beam has a $1/e$ value at $k = 1.2 \text{ arcmin}^{-1}$, and the higher powers fall off even more rapidly). Thus, small scale clustering, which is implied by the measurements of, e.g., Blain et al. (2004), is filtered out by the beam on scales of less than about one to two arcminutes in our data.

Generically, P_n falls rapidly with $|\mathbf{k}|$, suggesting that high-pass filtering the maps may mitigate large-scale clustering effects. In particular, in the far-IR the power spectrum of the two point correlation function (P_2) shows excess power above Poissonian noise at scales larger than $10'$ (Lagache et al. 2007; Viero et al. 2009; Cooray et al. 2010). In order to reduce ringing, our filter consists of a high-pass filter with a turn on at 6 arcmin convolved with a $\sigma = 1.8$ arcmin Gaussian. Only the Lockman-SWIRE field is large enough to be significantly affected because the other fields are not much larger than this scale. Since the benefit of $P(D)$ analyses is at faint flux densities where most of the CFIRB arises, and the shallow Lockman-SWIRE field has little constraining power here, our main scientific results are minimally affected by non-Poissonian clustering effects even if we ignore them. In fact, we find that the differences between fits to simulated data with and without clustering are well within the statistical errors even without filtering.

Analysis of simulated data from Fernandez-Conde et al. (2008), which has linear clustering based on the assumption that infrared galaxies are tracers of dark-matter fluctuations, shows that a high-pass filter is quite effective at removing clustering signal for this data set. We construct two sets of simulated maps: one with clustering, and another using the same catalogue but with clustering removed by randomizing the source positions. We then compare fits and pixel histograms for both maps. Because filtering will affect the $P(D)$ even in the absence of clustering, comparing these to unclustered, unfiltered maps is not useful. The fits recover the input model accurately in both cases, whereas if we do not filter dN/dS is slightly underestimated at low flux densities for the largest maps. Smaller maps show no evidence for bias. A pixel histogram from such a simulation is shown in figure 2. Such filtering is also effective at removing infrared cirrus, although we have not tested this

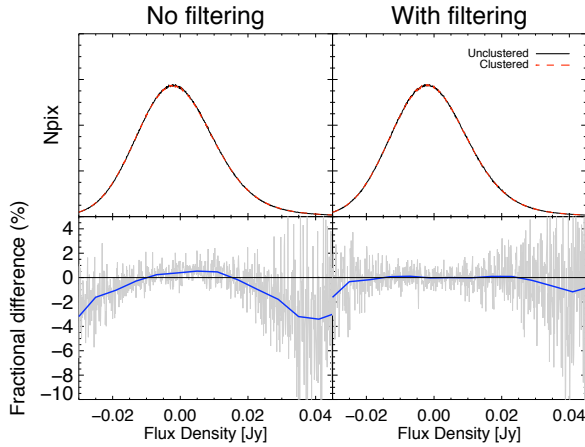


Figure 2. Comparison of the pixel histogram for simulated Lockman-SWIRE data with and without clustering, in the absence of high-pass filtering (left) and with a high-pass filter applied as described in the text (right). The top panel shows the resulting pixel histograms, and the bottom shows the fractional difference between the clustered and unclustered pixel histograms. The thick line in the bottom panel shows the average difference smoothed over a 3 mJy scale. Without filtering, there is a clear trend in the fractional difference, but with filtering the difference is consistent with zero for the bulk of the pixel fluxes. Even without filtering, the effect on the measured counts is smaller than the statistical errors.

explicitly in terms of the recovered fit parameters. However, it is possible that clustering signal on scales between one and six arcminutes could affect our results. This regime is currently not well characterized and thus we could not model it quantitatively in our analysis.

4 MODEL

The best approach for comparing a particular model to SPIRE data using $P(D)$ is to generate pixel histograms as a function of the model parameters and compare directly with our data. However, not all models have smoothly adjustable parameters, and furthermore, if the model is a poor fit to the data this may provide little insight as to at which flux densities the model disagrees with observations. Hence, we have followed P09 and fit simple, non-physical parametric models to our data. These models are defined by the values of the differential number counts dN/dS at a set of fixed flux densities (knots). Observationally we can never do more than place a lower limit on the total number of sources fainter than S , $N(<S)$ because we can never measure all the way down to zero flux density, but dN/dS is better behaved because it only depends on the number of sources in some small range. The actual fit parameters are $\log_{10} dN/dS$ at the knot positions. The differential number counts must become shallower than S^{-2} at low flux densities or else the contribution to the CFIRB diverges. However, this turn-over may lie below the flux densities probed by our data. Therefore, in order to avoid biasing our fits by excluding models which are too steep within the range of our measurements (i.e., would overpredict the CFIRB if integrated down to zero flux density), we assume that the number counts outside the largest and smallest knot are zero; the problem of choosing the limits is discussed below.

A $P(D)$ fit requires that the number counts model is continuous. Therefore, we must choose a method of interpolating between

the knots, and for a finite number of knots, the interpretation of our results depends on the interpolation method. We consider two methods of interpolation in this paper: first, as in P09, using power law extrapolation between each knot (these are multiply-broken power-law fits), and second, using a cubic spline in log-log space. The first code supports both methods, and the second only the former. We do not expect the fit parameters (i.e., dN/dS at the knot positions) of these models to be identical, since they have different meaning.

It is important to understand that the results of this paper are model fits. The fit results are not simply dN/dS at the flux densities of the knots, but instead are effectively integral constraints over some region surrounding each knot. Any excursion in the number counts that lies entirely between two knots will affect at least both neighboring knots, and likely others as well. The flux density range that each fit parameter is sensitive to depends on the interpolation scheme, with the spline response more local to the knot. Therefore, simply reading off the values predicted by a theoretical or empirical number counts model at the knot positions and comparing that with our fit parameters is wrong since they are *integral constraints* over a region surrounding the knot. This is also true for more traditional methods (i.e., simple number counts derived from individual galaxy detections) because of the importance of the de-boosting corrections for low signal-to-noise ratio detections. A preferable approach is to first find the best approximation to the differential counts of the theoretical (or empirical) number counts model chosen for comparison using either of our parametric models (for example, by fitting a multiply-broken power law to the dN/dS of the theoretical model giving equal weighting to all fluxes, not just the values at the knots) and comparing the parameters of that approximation to our results.

The highest and lowest knot positions must be chosen with some care because the differential number counts are assumed to be zero outside this range. Our criterion is based on examining the effects of cutting the number counts at a given level on a selection of galaxy evolution models from the literature. We compare the predicted $P(D)$ for each literature model truncated below a specified flux level with the $P(D)$ without truncation, and find that our data are not sensitive to a cut-off of less than 0.1 mJy at 250 μm . A similar analysis shows that truncating the fit above 1 Jy is also undetectable, with similar values for the other passbands. From simulations, we find that we can obtain good constraints if the second knot lies approximately at the 1σ instrumental noise. Because the number counts below our flux limit are unlikely to be well described by a single knot all the way down to 0.1 mJy, the fit value for this point should be treated with care; simulations indicate that this is not a problem for the 2 mJy knot. In order to avoid over-tuning our fits to represent literature models, we adopt approximately logarithmically spaced knots between these extremes. The choice of the number of knots is somewhat arbitrary. Neighboring knots are very strongly correlated, and as the number increases the correlations increase. We have tried to choose the number of knots to be as large as possible while keeping the correlations reasonably small.

5 RESULTS

We fit all three fields simultaneously, but each band independently. The uncertainty in the instrumental noise is modeled as a single multiplicative factor having a Gaussian prior with $\sigma = 5\%$. Note that we are making the assumption that the timestream instrumental noise is the same for all three fields as found in Nguyen et al.

Table 3. Differential Number Counts Constraints For a Multiply-Broken Power-Law Model with the FIRAS prior

250 μm		350 μm		500 μm	
Knot [mJy]	$\log_{10} dN/dS$ [deg $^{-2}$ Jy $^{-1}$]	Knot [mJy]	$\log_{10} dN/dS$ [deg $^{-2}$ Jy $^{-1}$]	Knot [mJy]	$\log_{10} dN/dS$ [deg $^{-2}$ Jy $^{-1}$]
0.1	< 9.38 (1 σ)	0.05	< 5.42 (1 σ)	0.05	< 4.37 (1 σ)
2	7.39 $^{+0.06}_{-0.17}$	2	7.87 $^{+0.08}_{-0.19}$	2	7.70 $^{+0.09}_{-0.21}$
5	5.83 $^{+0.15}_{-0.25}$	5	5.24 $^{+0.32}_{-0.56}$	5	5.50 $^{+0.29}_{-0.52}$
10	5.978 $^{+0.027}_{-0.071}$	10	5.87 $^{+0.05}_{-0.10}$	10	5.13 $^{+0.10}_{-0.21}$
20	5.13 $^{+0.02}_{-0.04}$	20	4.960 $^{+0.028}_{-0.067}$	20	4.686 $^{+0.039}_{-0.094}$
45	4.041 $^{+0.014}_{-0.034}$	45	3.744 $^{+0.026}_{-0.062}$	45	2.82 $^{+0.07}_{-0.15}$
100	2.591 $^{+0.027}_{-0.062}$	100	1.82 $^{+0.07}_{-0.16}$	100	1.10 $^{+0.19}_{-0.35}$
200	1.42 $^{+0.06}_{-0.14}$	200	0.81 $^{+0.16}_{-0.29}$	200	-0.08 $^{+0.54}_{-0.97}$
450	0.58 $^{+0.12}_{-0.22}$	750	-0.69 $^{+0.16}_{-0.29}$	600	-1.45 $^{+0.99}_{-2.01}$
1000	-0.44 $^{+0.32}_{-0.62}$				

Marginalized fit parameters for a multiply-broken power-law model from a joint analysis of all three fields including the FIRAS CFIRB prior of Fixsen et al. (1998). Quoted uncertainties are 68.3% confidence intervals, except for the first knot where 1 σ upper limits are given. The systematic uncertainties are the same as in table 2.

(2010). In addition to the SPIRE data, we also explore the effects of including the FIRAS CFIRB prior (Fixsen et al. 1998) by integrating SdN/dS for our model down to the lowest knot and adding a term to the likelihood that compares that value with the FIRAS measurement and its error. This assumes that the CFIRB is entirely due to discrete sources, and that flux densities outside the range of our model contribute only negligibly. We integrate the Fixsen et al. (1998) spectrum through the SPIRE passbands and adopt the relative errors given in Marsden et al. (2009). The uncertainty in the relative calibration between FIRAS and SPIRE significantly affects the utility of this prior.

The best fit multiply broken power-law fit is compared with the GOODS-N data in figure 3, and the parameters are given in tables 2 and 3, and for the spline interpolation fits in tables 4 and 5. The correlations between adjacent knots are large and negative⁴, with typical correlation coefficients of -0.5 to -0.8. The two models are compared with each other in figure 4. The two interpolating models (spline and multiply-broken power-law) produce very similar results. As discussed previously, these are model fits, not independent number counts, and since the parameterizations differ, directly comparing the values at the knot positions is not entirely correct. Nonetheless, the agreement is clear. Also, because the models were fit to the same data their results should not be coadded: they are both presented to demonstrate that similar results are obtained with using independent codes.

Since the agreement is so good, we express no preference of one model versus the other (multiply-broken power-law versus spline). However, we note that the spline model has a narrower flux density window function about each knot, and thus represents the differential number counts of the knot position slightly more accurately locally than the power-law model. For comparison to other number counts models, one can either (i) select the fits with the FIRAS prior, which assumes that the remaining portion of the CFIRB unaccounted for by our priorless fits is encompassed in the range

Table 5. Differential Number Counts Constraints For a Spline Model with the FIRAS prior

250 μm		350 μm		500 μm	
Knot [mJy]	$\log_{10} dN/dS$ [deg $^{-2}$ Jy $^{-1}$]	Knot [mJy]	$\log_{10} dN/dS$ [deg $^{-2}$ Jy $^{-1}$]	Knot [mJy]	$\log_{10} dN/dS$ [deg $^{-2}$ Jy $^{-1}$]
0.1	< 8.743 (1 σ)	0.05	< 7.63 (1 σ)	0.05	< 6.81 (1 σ)
2	7.281 $^{+0.067}_{-0.081}$	2	7.335 $^{+0.066}_{-0.077}$	3.4	6.578 $^{+0.064}_{-0.083}$
4.3	6.565 $^{+0.082}_{-0.094}$	4.3	6.26 $^{+0.23}_{-0.26}$	7.3	5.37 $^{+0.14}_{-0.22}$
9.1	5.817 $^{+0.049}_{-0.052}$	9.1	5.78 $^{+0.10}_{-0.11}$	15.5	4.91 $^{+0.090}_{-0.093}$
19.5	5.241 $^{+0.027}_{-0.028}$	19.5	4.983 $^{+0.058}_{-0.063}$	33.2	3.55 $^{+0.09}_{-0.10}$
41.8	4.023 $^{+0.033}_{-0.031}$	41.8	3.831 $^{+0.054}_{-0.055}$	71	1.82 $^{+0.15}_{-0.16}$
89.3	2.786 $^{+0.045}_{-0.049}$	89.3	2.13 $^{+0.10}_{-0.11}$	500	-0.63 $^{+1.11}_{-1.80}$
191	-0.08 $^{+0.26}_{-0.32}$	191	0.95 $^{+0.16}_{-0.18}$		
408	0.957 $^{+0.065}_{-0.075}$	1000	-2.12 $^{+1.06}_{-1.83}$		
1000	0.186 $^{+0.084}_{-0.088}$				

Marginalized fit parameters for a spline interpolation model from a joint analysis of all three fields including the FIRAS CFIRB prior of Fixsen et al. (1998). The systematic uncertainties are the same as in table 4.

between the upper limit on dN/dS at 0.1 mJy and the 2 mJy knot (at 250 μm) – this method is simpler; or (ii) select the fits without the CFIRB prior, in which case the prior should be applied independently. The latter does not require that the model share the same assumptions about the number counts at low flux densities as our fits.

Our fits are compared with other measurements in figures 5 and 6. Ignoring the lowest knot (where only an upper limit is available), our fits predict a CFIRB flux density of 0.54 ± 0.08 , 0.39 ± 0.06 , and 0.16 ± 0.03 MJy sr $^{-1}$ from all sources down to 2 mJy in the three bands; the dominant error in all cases is due to the 15 per cent calibration uncertainty of SPIRE. The contribution from each flux range is shown in figure 7. The CFIRB from Fixsen et al. (1998) integrated over the SPIRE bands is 0.85 ± 0.19 , 0.65 ± 0.19 , and 0.39 ± 0.10 MJy sr $^{-1}$, respectively, so our fits therefore account for 64 ± 16 , 60 ± 20 and 43 ± 12 percent in the SPIRE 250, 350, and 500 μm bands, respectively. We expect to resolve a smaller fraction of the CFIRB at longer wavelengths because the size of the SPIRE beam is proportional to wavelength, and hence the 500 μm band is more confused. Here the errors are dominated by the uncertainty in the FIRAS measurement. We find marginalized values for the instrumental noise that are 1.02, 1.1, and 1.01 times the values given in table 1 at 250, 350, and 500 μm , respectively, giving a χ^2 of 4.2 for 3 degrees of freedom. Hence, our instrumental noise values are consistent with the Nguyen et al. (2010) prior.

5.1 Systematic Effects

Our basic tool for estimating the importance of a particular systematic is to compute the $\Delta \log \mathcal{L}$ between the $P(D)$ with and without the effect for maps the same size and depth as our data. We use the P09 best fit model as a basis for this computation. Recall that a $\Delta \log \mathcal{L}$ of 0.5 corresponds roughly to a 1 σ statistical error.

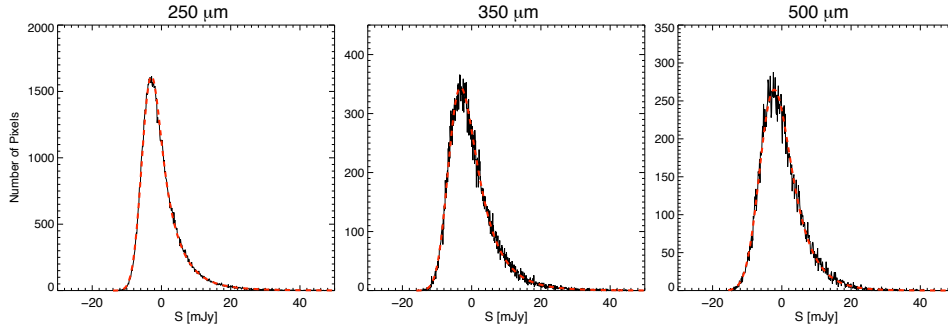
Because different parts of the map are sampled by different bolometers, and the beam shape varies across the bolometer array, the effective beam will vary over the map. We evaluated this effect by choosing 200 random pixels in our maps and computing the fractional contribution of each bolometer to each pixel. We

⁴ Covariance matrices are provided at <http://www.hermes.sussex.ac.uk/>

Table 2. Differential Number Count Constraints For a Multiply-Broken Power-Law Model

250 μm		350 μm		500 μm	
Knot [mJy]	$\log_{10} dN/dS$ [deg $^{-2}$ Jy $^{-1}$]	Knot [mJy]	$\log_{10} dN/dS$ [deg $^{-2}$ Jy $^{-1}$]	Knot [mJy]	$\log_{10} dN/dS$ [deg $^{-2}$ Jy $^{-1}$]
0.1	< 11.08 (1σ)	0.05	< 11.20 (1σ)	0.05	< 11.28 (1σ)
2	$7.05^{+0.33}_{-0.57} \pm 0.19$	2	$6.94^{+0.13}_{-0.27} \pm 0.11$	2	$6.82^{+0.11}_{-0.25} \pm 0.12$
5	$6.25^{+0.04}_{-0.13} \pm 0.05$	5	$6.08^{+0.13}_{-0.25} \pm 0.08$	5	$5.65^{+0.19}_{-0.38} \pm 0.09$
10	$5.919^{+0.028}_{-0.063} \pm 0.011$	10	$5.78^{+0.05}_{-0.11} \pm 0.04$	10	$5.39^{+0.09}_{-0.18} \pm 0.03$
20	$5.139^{+0.013}_{-0.035} \pm 0.025$	20	$4.976^{+0.026}_{-0.061} \pm 0.024$	20	$4.57^{+0.05}_{-0.12} \pm 0.03$
45	$4.038^{+0.015}_{-0.033} \pm 0.031$	45	$3.742^{+0.026}_{-0.061} \pm 0.051$	45	$2.91^{+0.07}_{-0.16} \pm 0.04$
100	$2.596^{+0.025}_{-0.058} \pm 0.044$	100	$1.80^{+0.07}_{-0.16} \pm 0.10$	100	$0.96^{+0.22}_{-0.38} \pm 0.06$
200	$1.42^{+0.05}_{-0.14} \pm 0.08$	200	$0.87^{+0.14}_{-0.28} \pm 0.08$	200	$0.00^{+0.51}_{-0.92} \pm 0.07$
450	$0.57^{+0.13}_{-0.24} \pm 0.26$	750	$-0.65^{+0.39}_{-0.78} \pm 0.30$	600	$-1.43^{+0.96}_{-2.09} \pm 0.29$
1000	$-0.45^{+0.31}_{-0.60} \pm 0.20$				

Marginalized fit parameters for a multiply-broken power-law model from a joint analysis of all three fields without using the FIRAS CFIRB prior. The quoted uncertainties are the 68.3% confidence intervals for the statistical error followed by the estimated systematic uncertainty, except for the first knot where the 1σ upper limit is given.

**Figure 3.** Comparison of the GOODS-N pixel histograms (solid lines) to the best fit model to all three fields (dashed lines) using the multiply-broken power law fit and not including the FIRAS prior.**Table 4.** Differential Number Counts Constraints For a Spline Model

250 μm		350 μm		500 μm	
Knot [mJy]	$\log_{10} dN/dS$ [deg $^{-2}$ Jy $^{-1}$]	Knot [mJy]	$\log_{10} dN/dS$ [deg $^{-2}$ Jy $^{-1}$]	Knot [mJy]	$\log_{10} dN/dS$ [deg $^{-2}$ Jy $^{-1}$]
0.1	< 10.29 (1σ)	0.05	< 11.43 (1σ)	0.05	< 10.91 (1σ)
2	$7.26^{+0.10}_{-0.17} \pm 0.19$	2	$7.18^{+0.15}_{-0.28} \pm 0.11$	3.4	$6.36^{+0.13}_{-0.18} \pm 0.10$
4.3	$6.54^{+0.10}_{-0.12} \pm 0.06$	4.3	$6.24^{+0.21}_{-0.21} \pm 0.09$	7.3	$5.31^{+0.19}_{-0.21} \pm 0.05$
9.1	$5.837^{+0.059}_{-0.056} \pm 0.013$	9.1	$5.831^{+0.081}_{-0.090} \pm 0.042$	15.5	$4.961^{+0.074}_{-0.085} \pm 0.029$
19.5	$5.230^{+0.029}_{-0.032} \pm 0.024$	19.5	$4.959^{+0.053}_{-0.061} \pm 0.025$	33.2	$3.511^{+0.094}_{-0.095} \pm 0.034$
41.8	$4.036^{+0.032}_{-0.036} \pm 0.030$	41.8	$3.849^{+0.051}_{-0.050} \pm 0.048$	71	$1.85^{+0.14}_{-0.16} \pm 0.063$
89.3	$2.802^{+0.045}_{-0.050} \pm 0.040$	89.3	$2.11^{+0.10}_{-0.11} \pm 0.076$	500	$-0.64^{+1.25}_{-1.80} \pm 0.028$
191	$0.20^{+0.24}_{-0.34} \pm 0.080$	191	$0.96^{+0.16}_{-0.19} \pm 0.075$		
408	$1.002^{+0.064}_{-0.068} \pm 0.26$	1000	$-2.34^{+1.82}_{-1.92} \pm 0.31$		
1000	$0.18^{+0.09}_{-0.10} \pm 0.20$				

Marginalized fit parameters for a spline model from a joint analysis of all three fields. Quoted uncertainties are as in table 2.

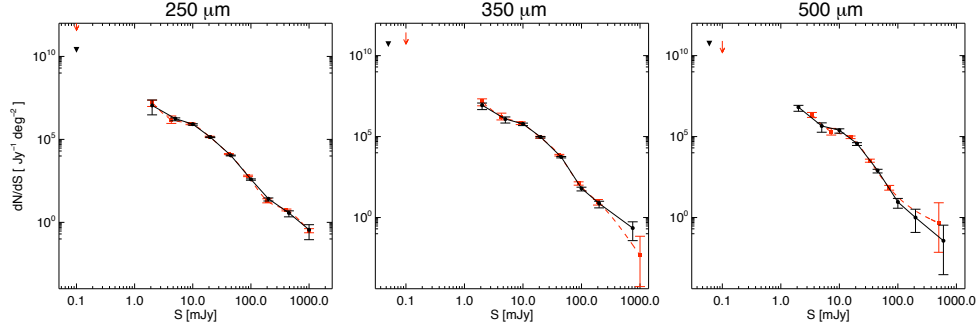


Figure 4. Comparison of the multiply-broken power-law (solid lines) and spline (dashed lines) $P(D)$ fits for the differential number counts to the three SDP fields simultaneously, without the FIRAS prior; 1σ upper limits are shown as arrows. For this comparison, only statistical errors are shown.

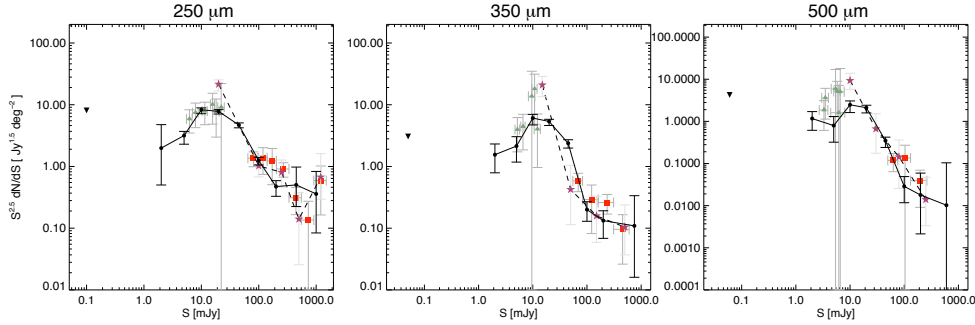


Figure 5. Comparison of Euclidean-normalized multiply-broken power law differential number counts fits (solid lines and circles) with previous balloon-based measurements from BLAST, not using the FIRAS prior. The BLAST $P(D)$ analysis (P09) is shown as dashed lines and stars, the stacking analysis of Béthermin et al. (2010b) as triangles and the source extraction analysis from the same reference as squares. Here the combined statistical and systematic errors are shown.

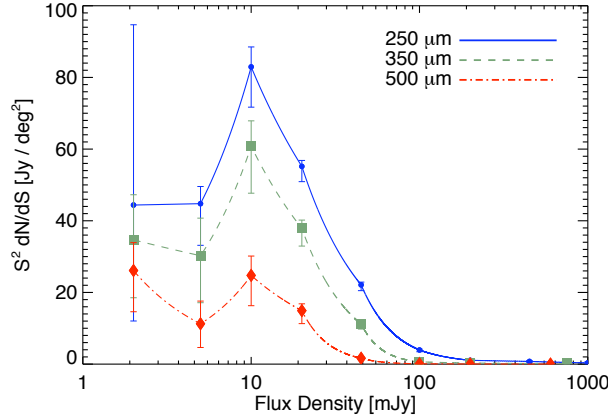


Figure 7. The contribution to the cosmic far-infrared background from each flux range for the multiply-broken power-law model versus the log of the flux density. The results for the spline interpolation model are almost identical. The integral of the curve over the log flux density is proportional to the total flux contribution in each band.

then built per-bolometer maps from our Neptune observations, and combined these to find the effective beam at each of these locations. The beam varies across the map in a complicated fashion because

even in our deepest map each pixel only samples a limited subset of bolometers. This produces significant variation in the $P(D)$ with position. In general, the $P(D)$ computed for the bolometer-averaged beam does not have to be the same as the $P(D)$ computed for each bolometer and then averaged across the array (which is the $P(D)$ of the entire map). To evaluate the importance of this variation, we compare the $P(D)$ for the average beam to the $P(D)$ computed for all 200 pixels and then averaged. The $\Delta \log \mathcal{L}$ of this comparison is < 0.01 , so for our analysis this is negligible.

Although we masked each map to exclude the low-coverage edges, the HerMES SDP observations were not dithered between repeats so there are significant variations in the number of measurements per pixel even within the high-coverage regions ($\sim 20\%$). This will introduce slight non-Gaussian tails to the instrument noise distribution. We simulated this effect in two ways. First, we generated random realizations of the instrument noise, including the uneven coverage, and compared the $P(D)$ using the resulting noise to the $P(D)$ assuming the noise is purely described by the average σ , and found negligible $\Delta \log \mathcal{L}$. Second, our end-to-end simulations (also including $1/f$ noise) implicitly include uneven coverage effects, and we found no bias in the recovered parameters. Future HerMES observations will include dithering, which will also have the benefit of improving the homogeneity of the beam.

Nguyen et al. (2010) explore the noise characteristics of the SDP maps by carrying out ‘Jack-Knife’ tests on the data. Their findings are generally consistent with the expected noise properties, but it is difficult to rule out some additional level of non-Gaussian

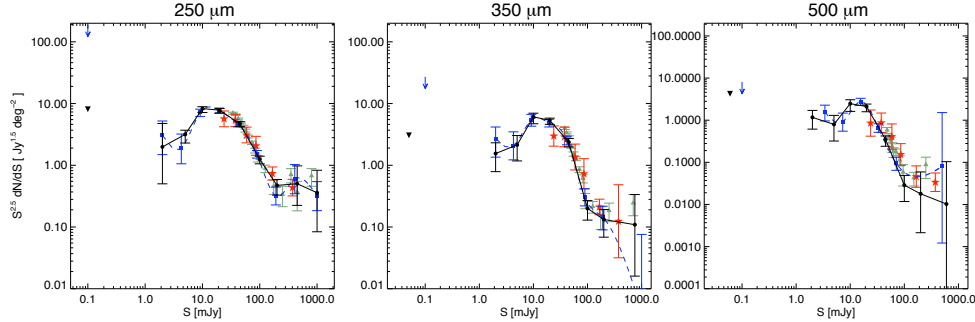


Figure 6. Comparison of Euclidean normalized SPIRE $P(D)$ differential number counts (solid lines/circles and dashed lines/squares for the multiply-broken power law and spline models, respectively, not using the FIRAS prior in both cases) with other SPIRE number counts: first, an analysis of the same data using source extraction techniques (Oliver et al. 2010, red stars), and second the H-ATLAS source extraction on an independent field (Clements et al. 2010, triangles). The errors are the combined statistical and systematic errors.

noise beyond the $1/f$ behavior we have simulated. Directly computing the effects of the Jack-Knife noise histograms on our model shows that any additional non-Gaussianity has negligible effects for the SDP data, down to our lowest constrained knot (2 mJy). This may not be true for future observations where the larger field sizes will reduce the statistical error considerably.

To test the sensitivity to the beam model, we use an alternative set of Neptune observations with a much smaller number of repeats and coarser sampling. Furthermore, the pointing of these observations is not corrected for the small offset between the *Herschel* and SPIRE clocks, and hence they suffer from pointing drift relative to the maps of the science fields⁵. The pipeline nominally corrects for this offset. However, to be conservative, we allow for the possibility that the pointing drift might not affect the beam maps in the same way as the science maps: we repeat the fits using the alternative beam, and use the difference in the results as an estimate of the beam systematic. This is the dominant identified systematic effect, with $\Delta\mathcal{L} \sim 0.3$. We take the differences between the recovered parameters between the two beams as the systematic error on each knot as given in tables 2 and 4. As our understanding of the SPIRE beams improves, it should be possible to decrease this error.

To further explore issues of pointing drift, we have constructed a simple drift model for the GOODS-N field using Jack-Knife comparisons. We then generate simulated maps with and without applying this model. Because the effect of the model is largely to twist successive observations relative to each other, this has very little effect on the $P(D)$, amounting to $\sim 0.1\sigma$ relative to the statistical errors.

While our results should represent the number counts in our fields quite well, sample variance means that they may not perfectly represent the number counts we would obtain with an infinitely large field. If we make the strong assumptions that the SPIRE clustering properties measured in Cooray et al. (2010) apply equally at all flux densities (and, in particular, to depths 10 times greater than they were measured), that the redshift distribution of our sources is independent of measured brightness, and that the source population peaks at $z = 1.5$, then a simple analytic computation suggests that sample variance could be a 20 per cent effect on the total number

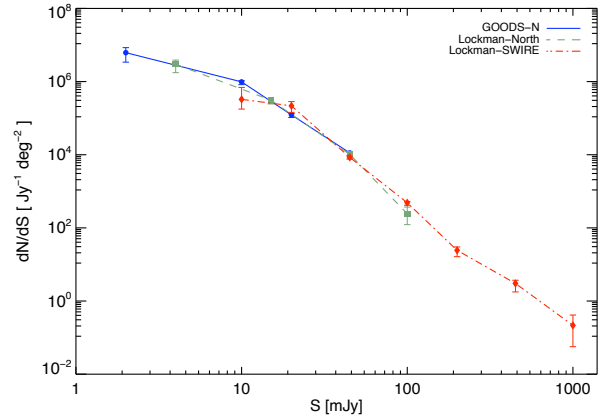


Figure 8. Comparison of 250 μm differential number counts derived from the three fields for the multiply-broken power-law model. Only statistical errors are shown and the FIRAS prior is not included.

counts in GOODS-N. More empirically, if we split the Lockman-SWIRE field into sub-regions there is evidence for variation in the pixel histogram from sub-field to sub-field. However, after applying our high-pass filter the variations are no longer statistically significant; that is, the difference between sub-fields lies in the mean rather than the shape of the histograms. Alternatively, mean subtracting each sub-field produces the same effect. This suggests that the fact that our measurements are not sensitive to the mean map values (and therefore are mean-subtracted) may provide some protection against sample variance effects. Since estimating the size of this effect is highly model dependent, we have not attempted to include this in our error budget. We do, however, fit the three fields independently at 250 μm and compare the results, although the different depths complicate this somewhat. For simplicity, we do not marginalize over the instrument noise in this fit, since the only purpose is to compare the three fields. This is shown in figure 8. Within the uncertainties, the fits are consistent. The post-SDP HerMES observations will allow sample variance effects to be better quantified.

We do not include the effects of the SPIRE calibration uncertainty ($\sim 15\%$ across all bands) in our error budget, except when using the CFIRB prior or computing the fraction of the FIRAS mea-

⁵ The SPIRE clock speed differs by a very small amount from the *Herschel* clock, resulting in a cumulative pointing drift with time in SPIRE maps. The magnitude of the effect is 0.7 arcseconds per hour, with rephasing occurring when “PCAL” internal calibrations are made.

surement accounted for by our model. However, any updates to the SPIRE calibration are easily incorporated into our results without refitting: if the flux scale is multiplied by a factor α the knot positions $K_i \mapsto \alpha K_i$ and the knot values decrease by $-\log_{10} \alpha$.

6 DISCUSSION

In general, our results agree well with those of P09, except for the faintest fluxes fully constrained by their analysis. For example, at $250 \mu\text{m}$ they find $\log_{10} dN/dS = 5.58^{+0.07}_{-0.11}$ at 20 mJy, while our result is $5.139^{+0.012}_{-0.033} \pm 0.025$. However, as discussed earlier, they did not marginalize over the instrumental noise for their deepest field, so their errors may be somewhat underestimated here. There is also some evidence from simulated data that the small number of knots and knot placement right at the break in the number counts may have biased this knot in the P09 analysis. We find good agreement with the stacking analysis of the BLAST data, but see some mild disagreement at higher fluxes for direct counts of the same data (B  thermin et al. 2010b) as shown in figure 5.

The deepest number counts available at these wavelengths are the result of a semi-traditional source extraction method on the same HerMES data set (Oliver et al. 2010). These are compared in figure 6. Where there is overlap, the agreement is good. A similar analysis was carried out using H-ATLAS SDP data by Clements et al. (2010); this is also shown. Unlike the HerMES source extraction and $P(D)$ analysis, the H-ATLAS counts are $250 \mu\text{m}$ -selected at all wavelengths, and hence may not entirely probe the same point source population. Nonetheless, again the agreement with the HerMES results is good.

A few features are worth noting. First, we clearly detect a break in the number counts around at 20 mJy in all bands at high significance. However, the SPIRE data alone do not detect the change in slope in dN/dS necessary to keep the CFIRB finite, as the differential counts continue to rise to the lowest limit of our analysis more steeply than S^{-2} . When the FIRAS prior is added, a break is present, but this mostly affects the lowest flux knot, for which we can only provide an upper limit (the effects on the other knots are mostly due to the strong correlations between knots; the FIRAS prior changes the structure of the correlations significantly at low flux densities). Second, there is possible weak ($\sim 1\sigma$) evidence for a ‘bump’ in the differential counts around 400 mJy at $250 \mu\text{m}$. There is no evidence at 350 and $500 \mu\text{m}$ around this flux density, but the error bars are large. However, this bump is present in the independent H-ATLAS field (Clements et al. 2010) at $250 \mu\text{m}$. The cause is unclear; lensing is an intriguing possibility, but we would expect the signature of lensing to be larger at $500 \mu\text{m}$ due to stronger negative K -correction effects (e.g. Negrello et al. 2007).

We can compare our model fits to the confusion noise estimates of Nguyen et al. (2010) measured using a different technique. The often-used criterion of one source per every n beams is difficult to use, since its translation into the effects on observations depends strongly on the underlying model (Takeuchi & Ishii 2004). Hence, we adopt the square root of the variance of the source contribution to the pixel distribution (σ_{conf}) as our measure. We find values of $6.5/6.4/6.1 \pm 0.2$ mJy in the three bands, slightly higher than the Nguyen et al. (2010) values, but by less than 2σ .

Our fits are compared with a selection of literature models in figure 9. No currently available model entirely fits our counts, especially when all three bands are considered. There is a general discrepancy in the galaxy number count models in that the theoret-

ical models generically overpredict the number of bright galaxies (in the several $\times 10$ to several $\times 100$ mJy range, limited at the upper end by uncertainties in the $P(D)$ number counts) compared to the number counts from the $P(D)$ analysis. The best match overall across all three SPIRE bands is given by the model of Valiante et al. (2009).

We interpret the discrepancy in the context of the theoretical models of Lagache et al. (2003) and Fernandez-Conde et al. (2008) (figure 9). In Figure 10 the redshifts and FIR luminosities of galaxies are plotted versus their observed flux densities for the Fernandez-Conde et al. (2008) simulations. The transitions from luminous to ultra-luminous infra-red galaxies (LIRGs to ULIRGs, at $10^{12} L_{\odot}$) with increasing observed flux densities occurs at approximately 12, 6, and 3 mJy, in the 250, 350, and $500 \mu\text{m}$ SPIRE bands, respectively. Thus, the discrepancy at the bright end likely results from the presence of too many ULIRGs in the theoretical models. It should be noted that the intrinsic luminosities of the underlying galaxy population that contribute to any given bin in observed flux density depend on the redshift distributions and spectral energy distributions; however, the very brightest galaxies are likely either intrinsically extremely luminous (ULIRGs or brighter), low redshift, or strongly lensed. There is a large dispersion in redshifts represented by galaxies in each observed flux density bin, with means in the range $z = 1 - 2$, with the average flux densities only mildly inversely correlated with redshifts (due to the negative K -correction).

In all three bands at and below 2 mJy, the $P(D)$ -derived number counts are consistent with the theoretical galaxy number count models. This is not surprising because: (i) the theoretical galaxy number count models are constrained not to overpredict the CFIRB, which arises, in large part, from numerous faint galaxies; and (ii) the upper limits of the lowest flux density knot in each band lies well above the theoretical number counts models.

Another more subtle feature also seems apparent in the measured counts. The results from both fitting methods – lending some confidence to their credence – have depressions at the third-lowest flux density knots with respect to the theoretical number count models at low-to-moderate significance (depending on the theoretical model), which are exclusively concave down in this range (a few mJy to a few times 10 mJy). The stacking analysis of B  thermin et al. (2010a) is not deep enough at 250 or $350 \mu\text{m}$ to verify this feature, although the turnover in $S^{2.5} dN/dS$ from the peak at approximately 10 mJy downward is clear at $250 \mu\text{m}$. At $500 \mu\text{m}$, the stacking analysis does not display the depression. This flux density range is approximately at the confusion limit (where the flux density is equal to the confusion noise, $\sigma_{\text{conf}} = 6$ mJy) and multiple galaxies contribute to the flux density in each beam. Thus, referring to the Fernandez-Conde et al. (2008) models (figure 10), this flux density range corresponds to the transition from ULIRGs to LIRGs, suggesting that LIRG number counts may also be overrepresented by the theoretical galaxy number counts models.

7 CONCLUSIONS

We have measured the differential galaxy number counts from *Herschel*-SPIRE Science Demonstration Phase HerMES observations at 250, 350, and $500 \mu\text{m}$ using $P(D)$ techniques and two simple parametric models. The number counts were measured down to 2 mJy, approximately a factor of 3 below the 1σ confusion noise. We find that 64 ± 14 per cent of the measured CFIRB is accounted for by point sources at $250 \mu\text{m}$, falling to 43 ± 12 per cent at $500 \mu\text{m}$. The errors on the fraction of the CFIRB accounted for by these

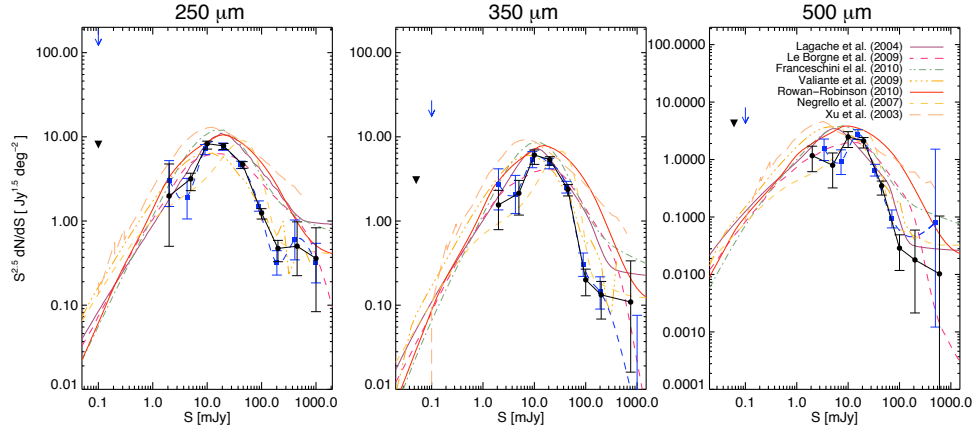


Figure 9. Comparison of our Euclidean normalized differential number counts fits (as in figure 6, and not using the FIRAS prior) to a selection of models from the literature. The error bars are the combined statistical and systematic errors.

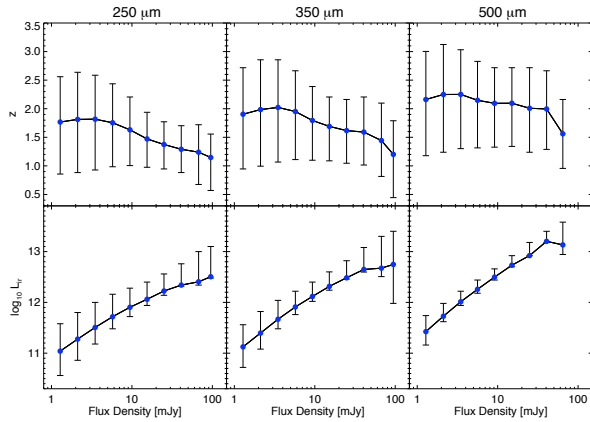


Figure 10. The intrinsic redshifts (upper panels) and infrared luminosities (lower panels) of galaxies as a function of the observed flux densities in the SPIRE 250, 350, and 500 μm bands (left, middle, and right panels, respectively) for the Lagache et al. models (Lagache et al. (2003); Fernandez-Conde et al. (2008)). The error bars give the interquartile range for each bin.

sources are now dominated by those of the FIRAS measurement. However, because of the remaining fraction not accounted for by our fits, this is still not a competitive method for measuring the total CFIRB. We find clear evidence of breaks in the slope of the differential number counts at approximately 10–20 mJy in all bands, which have been hinted at by previous analyses.

Where they overlap, our fits agree well with other *Herschel* results. Comparing with a selection of literature models, however, we find that no model entirely reproduces our observed number counts. As found by Oliver et al. (2010) and Clements et al. (2010), most published models significantly over-predict the number of bright sources at these wavelengths and have shallower slopes. We find somewhat better agreement at fainter fluxes, at or below the break, but the agreement is still not perfect.

Our main systematic uncertainties arise from our understanding of the SPIRE beams. We find that a high-pass filter is effective

in removing the signature of clustering from our counts, but in the future it may be preferable to attempt to directly marginalize over clustering using simple models.

These observations represent only ~ 60 hours of the 900 hours of observations that HerMES will ultimately obtain (although not all of these are with SPIRE). The final dataset will cover a wide range of depths and areas. This will significantly increase our ability to constrain dN/dS . Having a number of well-separated deep fields will also allow a direct measurement of sample variance.

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Chapitre 5

Le fond extragalactique infrarouge

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5.1 Contribution totale des galaxies infrarouges au fond extragalactique

Chap. 2, 3 et 4, nous avons déterminé par des méthodes variées les comptages de galaxies infrarouges à différentes longueurs d'onde infrarouges et sub-millimétriques. A partir de

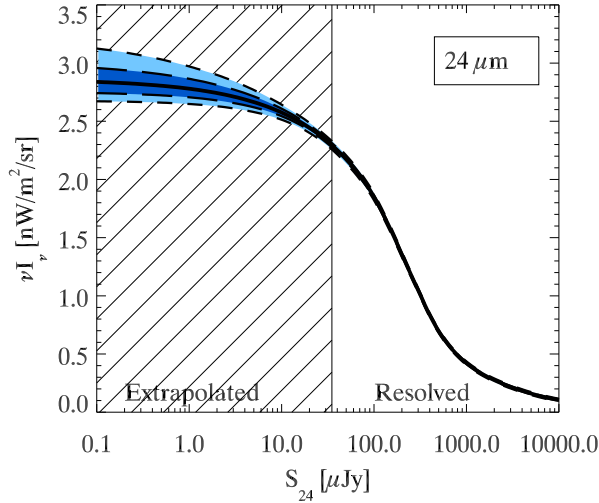


FIGURE 5.1 – Contribution cumulée au fond infrarouge à $24 \mu\text{m}$ en fonction du flux. Les deux zones colorées correspondent à 1 et 2- σ . Extrait de Béthermin *et al.* (2010a).

ceux-ci, il est facile d'estimer la contribution des sources infrarouges au fond infrarouge B :

$$B = \int S \frac{dN}{dS} dS. \quad (5.1)$$

Ceci fournit des limites inférieures sur le niveau du fond infrarouge qui peuvent être comparées avec les mesures absolues et les limites supérieures.

5.1.1 Fond infrarouge à $24 \mu\text{m}$

Des comptages profonds à $24 \mu\text{m}$ ont été estimés Sect. 2.5.3. On peut, à partir de cela, calculer grâce à l'Eq. 5.1 comment les sources contribuent au fond infrarouge à $24 \mu\text{m}$. La contribution des sources situées dans l'intervalle de flux étudié ($35 \mu\text{Jy} < S_{24} < 100 \text{ mJy}$) par nos comptages est $2.26 \pm 0.09 \text{ nW.m}^{-2}.\text{sr}^{-1}$. La contribution des sources plus brillantes que notre plus haut bin de flux est négligeable $0.032 \pm 0.003 \text{ nW.m}^{-2}.\text{sr}^{-1}$ (on extrapole ici un comportement euclidien). En revanche, la contribution des sources faibles ne l'est pas. A bas flux, les comptages ont un comportement en loi de puissance ($dN/dS \propto S^{-1.45 \pm 0.1}$). On peut alors extrapoler ce comportement jusqu'à flux nul pour estimer la contribution totale des galaxies au fond infrarouge : $2.86^{+0.19}_{-0.16} \text{ nW.m}^{-2}.\text{sr}^{-1}$. Les incertitudes sont réduites d'un facteur 5 environ par rapport aux estimations précédentes de Papovich *et al.* (2004) à partir des comptages *Spitzer* du temps garanti. Ces estimations sont également en accord avec les limites supérieures provenant de rayons gamma ($5 \text{ nW.m}^{-2}.\text{sr}^{-1}$, Mazin

et Raue (2007)). La Fig. 5.1 illustre la contribution cumulée des sources en fonction du flux.

Les sources résolues à $24\ \mu\text{m}$ expliquent donc 80% du fond total extrapolé. Si on considère que les galaxies sont la seule source d'émission du fond infrarouge à cette longueur d'onde, on peut donc considérer que le fond est quasiment résolu dans l'infrarouge moyen. Néanmoins, il n'existe pas de mesure absolue à cette longueur d'onde pour tester cette hypothèse. En effet, la lumière zodiacale domine de trois ordres de grandeur le fond extragalactique dans cette partie du spectre. Ces contributions pourraient être dues à une émission diffuse du milieu intergalactique (Montier et Giard (2005)) ou d'une contribution de sources ponctuelles très faibles telle que les étoiles de populations III (Raue *et al.* (2009)).

5.1.2 Fond infrarouge à 70 et 160 μm

La contribution des sources résolues à 70 ($S_{70} > 3.5\ \text{mJy}$) et 160 μm ($S_{160} > 40\ \text{mJy}$) au fond infrarouge est de $3.1 \pm 0.2\ \text{nW.m}^{-2}.\text{sr}^{-1}$ et $1.0 \pm 0.1\ \text{nW.m}^{-2}.\text{sr}^{-1}$, respectivement (calculé à partir des comptages présentés Sect. 2.5.3). Si on ajoute la contribution des sources sondées par la méthode de l'empilement (voir Sect. 3.2.3), on a alors $5.4 \pm 0.4\ \text{nW.m}^{-2}.\text{sr}^{-1}$ et $8.9 \pm 1.1\ \text{nW.m}^{-2}.\text{sr}^{-1}$, respectivement. L'empilement est donc crucial pour sonder les sources responsables du fond à 160 μm . De plus, les comptages par empilement permettent de déterminer la pente des comptages à bas flux, et d'extrapoler la contribution totale des galaxies au fond. On trouve alors une contribution totale de $6.6^{+0.7}_{-0.6}\ \text{nW.m}^{-2}.\text{sr}^{-1}$ et $14.6^{+7.1}_{-2.9}\ \text{nW.m}^{-2}.\text{sr}^{-1}$, respectivement. La Fig. 5.2 montre la contribution cumulée au fond dans ces deux bandes. Cette dernière valeur est en accord avec la mesure absolue de Pénin *et al.* (2011b) : $14.4 \pm 3\ \text{nW.m}^{-2}.\text{sr}^{-1}$. L'hypothèse d'un fond dû uniquement aux galaxies est donc compatible avec les observations actuelles. Néanmoins, les larges incertitudes de mesure laissent de la place pour d'éventuelles autres composantes non négligeables.

5.1.3 Fond infrarouge dans le domaine sub-millimétrique

Au delà de 200 μm , le niveau du fond infrarouge a été mesuré avec précision par FIRAS (Lagache *et al.* (2000)). Il est donc facile d'estimer la fraction du fond résolue par les différents comptages. La Fig. 5.3 présente la contribution au fond en fonction du flux de coupure des comptages. Les sources résolues par BLAST ne sont à l'origine que d'une infime partie du fond infrarouge à 250, 350 et 500 μm (2.3%, 1.1% et 0.4%, respectivement, Béthermin *et al.* (2010b)). Grâce à la meilleure résolution angulaire de SPIRE, Oliver *et al.* (2010) résolvent directement 15%, 10% et 6% du fond, respectivement. Pour aller plus

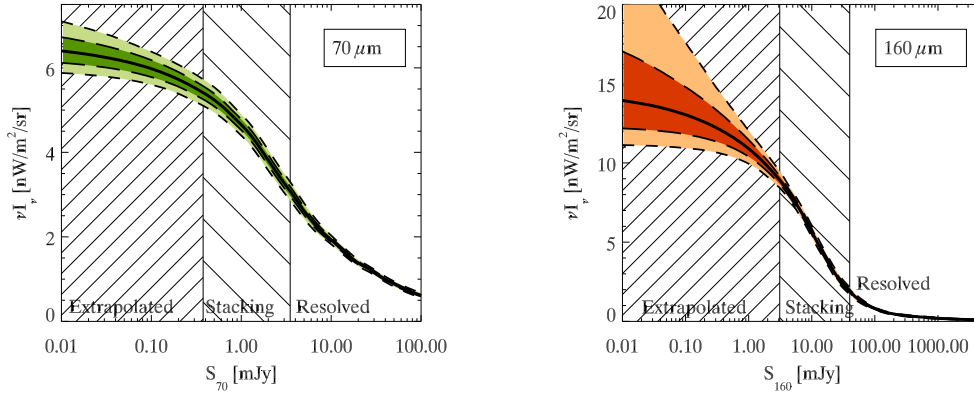


FIGURE 5.2 – Contribution cumulée au fond infrarouge à 70 (gauche) et 160 μm (droite) en fonction du flux. Les deux zones colorées correspondent à 1 et 2- σ . Extrait de Béthermin *et al.* (2010a).

loin, il faut faire appel à l'analyse par empilement des données BLAST, qui résout environ 50% du fond. Dans le cas de l'analyse P(D), on ne peut pas parler directement de fraction résolue. En effet, l'analyse P(D) analyse tout les régimes de flux simultanément. On peut également forcer le résultat à être en accord avec la mesure du fond total. Nous avons ici comparé le modèle spline avec a priori FIRAS aux autres estimations de la contribution différentielle au fond. Dans tout les cas, il y a un très bon accord entre le modèle P(D) et les autres mesures.

5.1.4 Conclusion

Les sources résolues par *Spitzer* et BLAST ne résolvent qu'une faible fraction du fond au delà de 70 μm . En revanche, la méthode de l'empilement permet en revanche de produire des comptages suffisamment profonds pour qu'ils suffisent à expliquer l'origine du fond infrarouge à 70 et 160 μm . A plus grande longueur d'onde, les données BLAST ne permettent pas de mesurer la pente des comptages à bas flux afin de l'extrapoler. Les données *Herschel* devraient permettre, dans un futur proche, de mesurer avec une bien meilleure précision les comptages dans ce domaine de longueur d'onde.

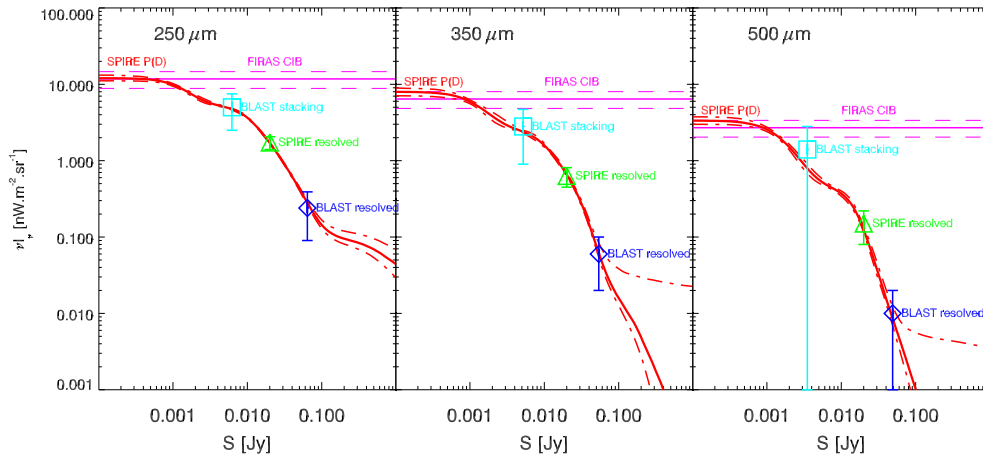


FIGURE 5.3 – Contribution cumulée au fond infrarouge à 250 (gauche), 350 (milieu) et 500 μm (droite) en fonction du flux. (Lignes violettes) : Niveau absolu du fond mesuré par FIRAS (Lagache *et al.* (2000)), et zone de confiance à 1σ . (Lignes rouges) : contribution des comptages P(D) SPIRE (modèle spline avec a priori FIRAS, Glenn *et al.* (2010)). (Losange bleu) : contribution des sources BLAST résolues (Béthermin *et al.* (2010b)). (Triangle vert) : contribution des sources SPIRE résolues (Oliver *et al.* (2010)). (Carré bleu ciel) : contribution des sources BLAST mesurée par empilement (Béthermin *et al.* (2010b)).

5.2 Contribution des sources détectées par *Spitzer* à $24\ \mu\text{m}$ au fond infrarouge et au taux formation d'étoiles en fonction du *redshift*

Les travaux présentés dans cette partie ont été réalisés en collaboration avec Joaquim Vieira et HerMES (programme de temps garanti SPIRE). Un article est en cours de préparation.

Dans certains champs profonds comme GOODS ou COSMOS, les sources infrarouges à $24\ \mu\text{m}$ peuvent être en général associées à des sources optiques dont le *redshift* est connu. On peut, par exemple, réaliser une extraction de sources en prenant la position des sources optiques comme *a priori* (Magnelli *et al.* (2009)). Il est également possible d'utiliser un catalogue infrarouge extrait en aveugle et de rechercher les sources optiques les plus proches pour réaliser l'identification (par exemple, Le Floc'h *et al.* (2009)). Pour les sources brillantes en optique, le *redshift* est estimé directement à partir du spectre haute résolution, en mesurant le décalage des raies. Dans ce cas la mesure est, en général, très précise. On parle alors de *redshifts* spectroscopiques. Dans la majorité des cas, le spectre des objets n'est pas accessible (manque de temps de télescope, objet trop faible en optique...). Il est alors possible d'estimer le *redshift* en ajustant des *templates* de SED aux points photométriques obtenus en bande large. Cette méthode permet d'associer un *redshift* à quasiment toutes les sources infrarouges détectées. Toutefois, ces *redshifts* "photométriques" sont beaucoup moins précis que les *redshifts* spectroscopiques ($\sigma_z \sim 10^{-3}$ pour les *redshifts* spectroscopiques de Lilly *et al.* (2007), contre $\sigma_z \sim 10^{-2}$ à 10^{-1} pour les *redshifts* photométriques de Ilbert *et al.* (2009)).

Dans les champs où le *redshift* de la quasi-totalité des sources $24\ \mu\text{m}$ est disponible, il est possible d'empiler toutes les sources $24\ \mu\text{m}$ d'une fine tranche de *redshift* afin de déterminer leur émission totale dans l'infrarouge lointain et le domaine sub-millimétrique. Ceci permet d'obtenir des contraintes fortes sur les modèles d'évolution, mais également de placer des limites inférieures sur le taux de formation d'étoiles à haut *redshift*. Ces mesures devraient également permettre d'améliorer le modèle d'absorption des rayons γ par le fond infrarouge.

5.2.1 Contribution des sources $24\ \mu\text{m}$ au fond infrarouge à plus grande longueur d'onde

La contribution différentielle des sources infrarouges au fond en fonction du *redshift*, dB/dz , se calcule en divisant la contribution d'une tranche de *redshift* ΔB par la taille Δz de celle-ci. Toutefois, il est impossible de mesurer directement la contribution totale

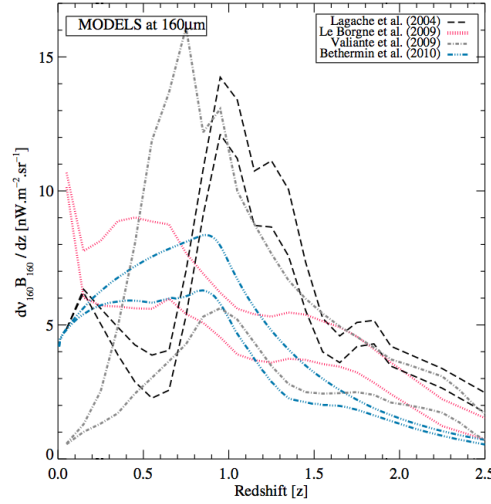


FIGURE 5.4 – Distribution en *redshift* du fond infrarouge à $160\ \mu\text{m}$ pour les modèles de Lagache *et al.* (2004) (en noir), Le Borgne *et al.* (2009) (en rouge), Valiante *et al.* (2009) (en gris) et de Béthermin *et al.* (2011) (en bleu). Pour chaque modèle deux courbes sont tracées : celle du bas correspond à la contribution des sources $S_{24} > 80\ \mu\text{Jy}$ et celle du haut au fond total. Cette figure est tirée de Jauzac *et al.* (2011).

d'une tranche, mais on peut estimer une limite inférieure sur celle-ci en sommant l'émission des sources résolues. Dans l'infrarouge lointain, seule une faible fraction du fond est résolue en sources. Une limite inférieure plus contraignante peut alors être estimée par empilement des sources détectées à $24\ \mu\text{m}$. La Fig. 5.4 compare la contribution différentielle totale au fond infrarouge et celle des sources détectées à $24\ \mu\text{m}$ uniquement pour différents modèles. Elle montre que les deux distributions ont des formes similaires, et que ces limites inférieures sont assez proches de la valeur totale (au plus 50 % inférieures au fond total, et souvent moins de 20% inférieures au total). Ces mesure permettent donc de contraindre fortement l'histoire du fond infrarouge.

J'ai collaboré à la première mesure de la contribution différentielle des sources détectées à $24\ \mu\text{m}$ au fond à 70 et $160\ \mu\text{m}$ par empilement de Jauzac *et al.* (2011). Cette mesure a été réalisée à partir des cartes *Spitzer* du champ COSMOS et du catalogue de sources à $24\ \mu\text{m}$ associé à leur *redshift* de Le Floch *et al.* (2009). J'ai ensuite réalisé cette même mesure dans le champ GOODS-N en utilisant à la fois les données MIPS, SPIRE et AzTEC, ainsi qu'un catalogue d'entrée (flux à $24\ \mu\text{m}$ et *redshift*) construit par Joaquim Vieira (Vieira *et al.*, en préparation). Cette mesure a été réalisée en utilisant la méthode d'empilement de Marsden *et al.* (2009) sans lissage préalable des cartes et la méthode du *bootstrap* pour déterminer les incertitudes de mesures. Le biais dû au regroupement est estimé à partir d'une simulation où la position des sources et leur flux $24\ \mu\text{m}$ sont les

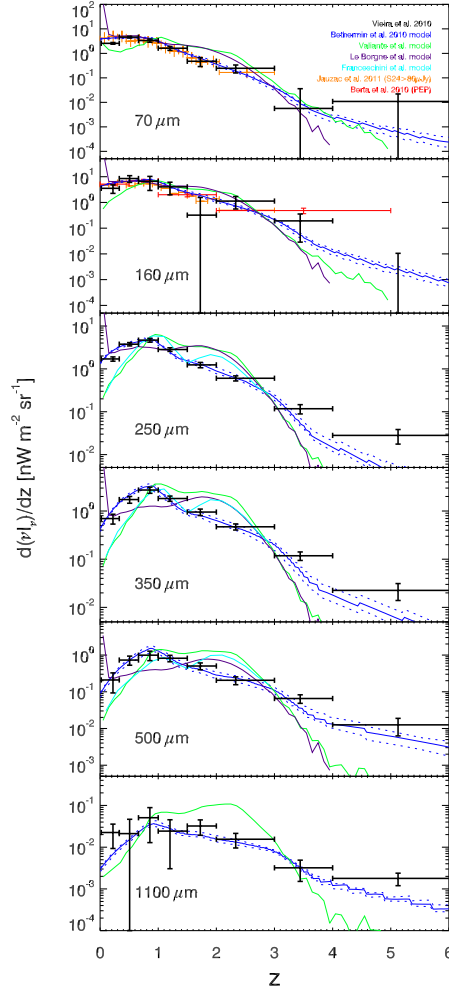


FIGURE 5.5 – Contribution différentielle des sources détectées à $24\ \mu\text{m}$ au fond infrarouge à 70 , 160 , 250 , 350 et $500\ \mu\text{m}$. *En noir* : résultat obtenu par empilement des sources $S_{24} > 40\ \mu\text{Jy}$ dans les cartes *Spitzer* (70 et $160\ \mu\text{m}$) et *Herschel* (250 , 350 et $500\ \mu\text{m}$) du champ GOODS-N. *En orange* : résultat obtenu par empilement des sources $S_{24} > 80\ \mu\text{Jy}$ dans les cartes *Spitzer* du champ COSMOS (Jauzac *et al.* (2011)). *En rouge* : Distribution des sources résolues par l'instrument PACS à $160\ \mu\text{m}$ (Berta *et al.* (2010)). Les lignes pleines représentent les modèles d'évolution de Béthermin *et al.* (2011) (bleu marine), Valiante *et al.* (2009) (vert), Le Borgne *et al.* (2009) (violet) et de Franceschini *et al.* (2010) (bleu ciel).

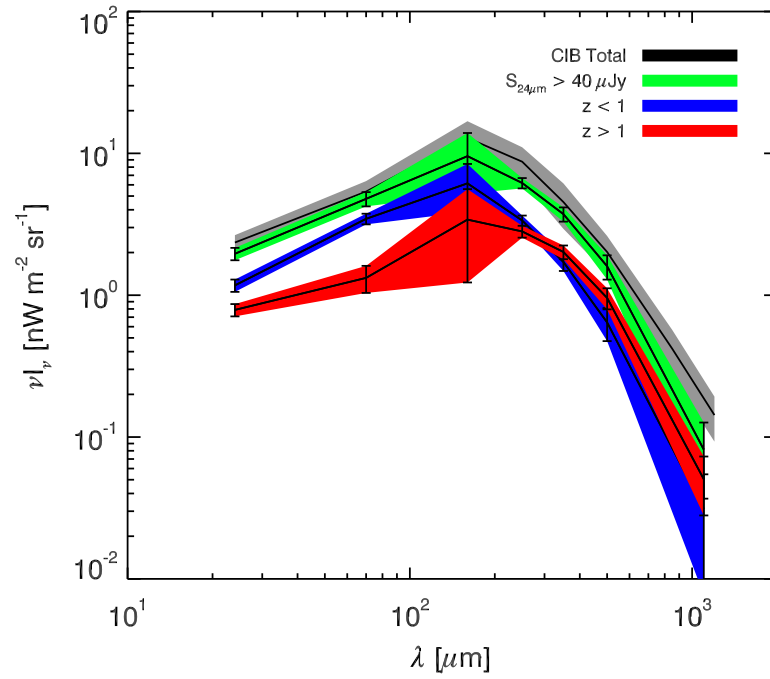


FIGURE 5.6 – Distribution spectrale d'énergie du fond infrarouge. *En noir* : fond total. *En vert* : contribution des sources à 24 μm . *En bleu* : contribution des sources à 24 μm à bas redshift ($z < 1.2$). *En rouge* : contribution des sources à 24 μm à bas redshift ($z > 1.2$)

mêmes que dans les cartes réelles et où le flux dans l'infrarouge lointain est déterminé en multipliant le flux $24\ \mu\text{m}$ par la couleur moyenne des sources dans la tranche de *redshift* associée. Nous avons estimé un biais de 7, 20, 6, 7, 11 et 11% à respectivement 70, 160, 250, 350, 500 et $1100\ \mu\text{m}$. La Fig. 5.5 montre les résultats obtenus. On observe une forte cassure à $z \sim 1$. De plus, comme attendu, la contribution relative des hauts (resp. bas) *redshift* augmente (resp. diminue) quand la longueur d'onde augmente. Ces observations sont également très discriminantes pour les modèles d'évolution : en effet, un seul modèle parvient à reproduire globalement ces observations. Il s'agit du modèle que j'ai développé pendant ma thèse, et qui est présenté Chap. 6.

On peut également étudier la SED du CIB en séparant haut ($z > 1.2$) et bas ($z < 1.2$) *redshift*. La Fig. 5.8 représente ces différentes contributions. L'estimation du fond total est issue de FIRAS (Lagache *et al.* (2000)) au delà de $250\ \mu\text{m}$. A plus courte longueur d'onde, nous utilisons ma valeur totale extrapolée à partir des comptages à $70\ \mu\text{m}$ (Béthermin *et al.* (2010a)), et la mesure absolue de Pénin *et al.* (2011b) à $160\ \mu\text{m}$. La contribution des sources détectées à $24\ \mu\text{m}$ ($S_{24} > 40\ \mu\text{Jy}$) est en bon accord avec les mesures de Dole *et al.* (2006) et mes propres mesures dans les bandes MIPS. En revanche, les valeurs dans les bandes SPIRE sont environ 20% inférieures à celle mesurée par Marsden *et al.* (2009). Cette différence s'explique, d'une part, par leur coupure du catalogue à $24\ \mu\text{m}$ à $20\ \mu\text{Jy}$ (avec les risques de biais que comporte l'utilisation d'un catalogue comportant de nombreuses fausses détections), et d'autre part par un *beam* deux fois plus large et donc un plus fort biais dû au regroupement. Nous avons également utilisé les données AzTEC à $1.1\ \text{mm}$ de Chapin *et al.* (2009b) pour prolonger la SED de l'EBL dans le domaine millimétrique. La séparation entre haut et bas *redshift* illustre le fait que plus on va à grande longueur d'onde et plus la contribution des grands *redshifts* est grande.

5.2.2 Distribution spectrale d'énergie moyenne de sources sélectionnées à $24\ \mu\text{m}$

Grâce à la méthode de l'empilement, il est possible de construire la SED moyenne dans l'infrarouge de galaxies sélectionnées à $24\ \mu\text{m}$, et qui ne sont pas détectables individuellement à grande longueur d'onde. La Fig. 5.7 montre la SED moyenne des sources $24\ \mu\text{m}$ séparées en différentes tranches de *redshift* ($z < 0.33$, $0.33 < z < 0.66$, $1 < z < 1.5$, $1.5 < z < 2$, $2 < z < 3$, $3 < z < 4$, $z > 4$). Nous avons estimé la luminosité infrarouge totale et la température de poussière en ajustant les mesures par le modèle suivant :

- Un corps noir modifié d'émissivité $\beta = 1.5$ fixée aux grandes longueurs d'onde ($\lambda > \lambda_c$),
- Un comportement en loi de puissance d'exposant fixé $\alpha = 1.8$ aux courtes longueurs d'onde ($\lambda < \lambda_c$),

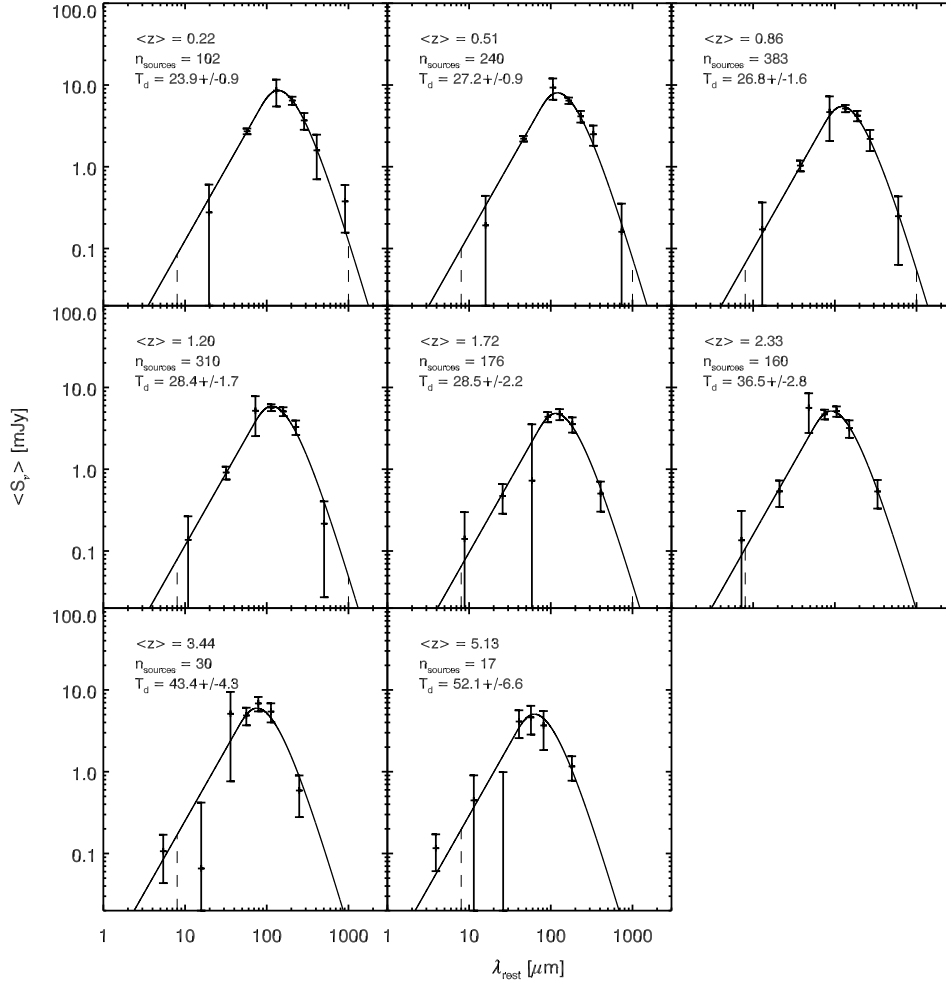


FIGURE 5.7 – Distribution spectrale d'énergie moyenne des galaxies sélectionnées à $24\ \mu\text{m}$ ($S_{24} > 40\ \mu\text{Jy}$) pour différentes tranches de *redshift* ($z < 0.33$, $0.33 < z < 0.66$, $1 < z < 1.5$, $1.5 < z < 2$, $2 < z < 3$, $3 < z < 4$, $z > 4$).

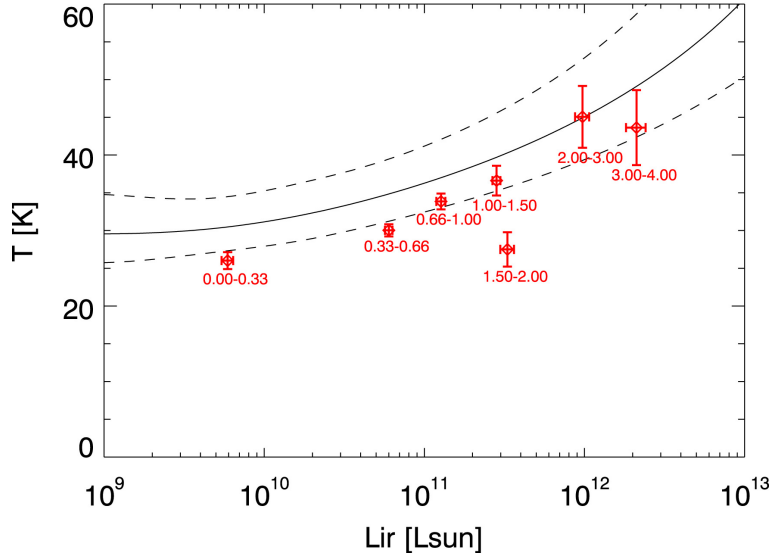


FIGURE 5.8 – Température en fonction de la luminosité des SED moyennes correspondant aux différentes tranches de *redshift* (cercles rouges), comparée avec la relation locale et sa dispersion mesurée par IRAS de Chapin *et al.* (2009a) (ligne continue et pointillée).

- On impose une continuité de la SED et de sa pente pour raccorder les deux parties. Cette condition fixe la valeur de λ_c .

En utilisant des *templates* de galaxies, nous avons montré que cette méthode simple permet de retrouver la luminosité infrarouge avec une précision de l'ordre de 10%, qui est bien inférieure aux erreurs statistiques. Les températures et luminosités moyennes trouvées suivent la relation locale entre luminosité et température mesurée par Chapin *et al.* (2009a). Ceci suggère donc une faible évolution de cette relation avec le *redshift*. Or, les températures des galaxies sélectionnées dans le domaine sub-millimétrique ont tendance à être plus froides que leurs analogues locaux. Le résultat trouvé par empilement suggère que ce phénomène est dû en partie à un biais de sélection.

5.2.3 Contribution des sources à $24 \mu\text{m}$ à la densité de luminosité infrarouge

A partir de la luminosité bolométrique infrarouge moyenne des sources $24 \mu\text{m}$ déterminée par empilement, il est possible de placer une limite inférieure sur la densité de luminosité infrarouge. Cette quantité est proportionnelle au taux de formation d'étoiles (Kennicutt (1998)), et est donc fondamentale pour comprendre l'histoire de la formation d'étoile. La méthode permettant de déterminer la densité de luminosité infrarouge dans une tranche de *redshift* consiste à calculer la luminosité totale produite par toutes les sources $24 \mu\text{m}$ du

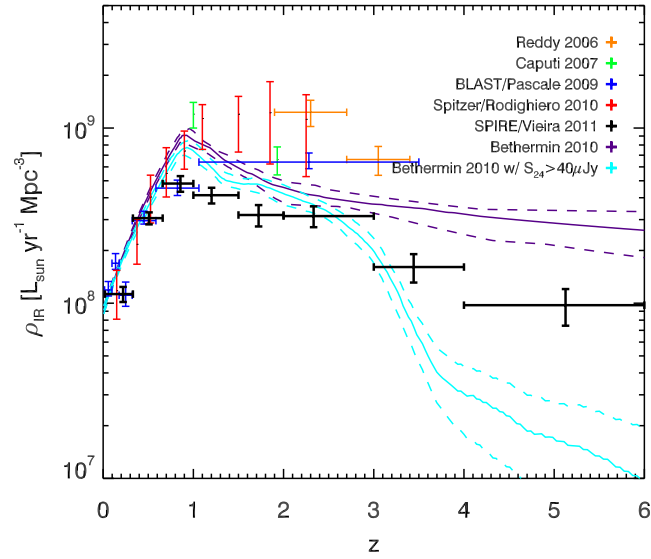


FIGURE 5.9 – Densité de luminosité infrarouge en fonction du *redshift*. *En noir* : contribution de toutes les sources $24 \mu\text{m}$. Il s'agit d'une limite inférieure à la densité de luminosité totale. *En violet* : mesure de Reddy *et al.* (2008) à partir de l'UV. *En vert* : mesure à partir de la LF de Caputi *et al.* (2007) à partir du $24 \mu\text{m}$ Spitzer. *En bleu* : limite inférieure à partir de l'empilement des sources $24 \mu\text{m}$ dans les données BLAST de Pascale *et al.* (2009). *En violet* : prédiction de la densité de luminosité infrarouge totale par le modèle de Béthermin *et al.* (2011). *En bleu ciel* : prédiction de la contribution des sources $24 \mu\text{m}$ par le même modèle.

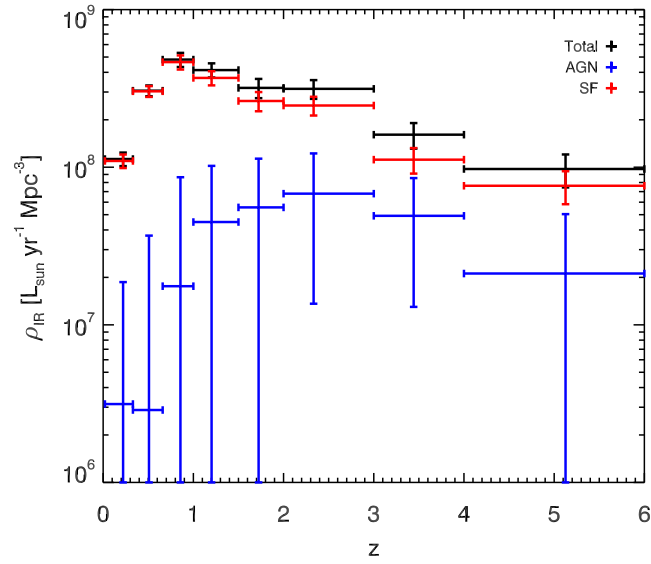


FIGURE 5.10 – Densité de luminosité infrarouge en fonction du *redshift*. *En noir* : Contribution de toutes les sources $24 \mu\text{m}$. *En rouge* : Contribution des sources $24 \mu\text{m}$ dominée par la formation d'étoiles. *En noir* : Contribution des sources $24 \mu\text{m}$ dominée par leur noyau actif.

champ, et à la diviser par le volume comobile associé

$$V_c = \frac{\Omega}{3} (D_C(z_{max})^3 - D_C(z_{min})^3), \quad (5.2)$$

où Ω est la taille du champ utilisé, $D_C(z_{max})$ la distance comobile correspondant au *redshift* maximum de la tranche, z_{min} correspondant au *redshift* minimal de la tranche.

La Fig. 5.9 montre les résultats obtenus, et les compare avec les mesures précédentes. Nos limites inférieures augmentent jusqu'à $z=1$, puis diminuent. Cette diminution est due à la fois au fait que le $24 \mu\text{m}$ ne permet pas d'accéder aux faibles luminosités à haut *redshift*, mais aussi très probablement à une décroissance de la densité de luminosité infrarouge avec le *redshift* pour $z > 1$. Nos limites inférieures sont très proches des valeurs totales mesurées jusqu'à $z=1$. Au delà, elle sont significativement inférieures, le $24 \mu\text{m}$ ne sondant que les objets les plus brillants. On peut également comparer ces mesures avec les prédictions du modèle de Béthermin *et al.* (2011). La ligne bleu ciel représente une prédiction prenant en compte la sélection à $24 \mu\text{m}$. L'accord est relativement bon, à l'exception d'une surestimation de 2σ à $z \sim 1$, et à $z > 3$. Il faut toutefois noter qu'au delà de $z=3$, le $24 \mu\text{m}$ observé ne sonde plus vraiment l'émission de la poussière, mais plutôt les vieilles populations stellaires qui ne sont pas modélisées avec précision. Nous avons également étudié la contribution des sources AGN, en les sélectionnant à partir de leur émission X. La Fig. 5.10 représente la contribution des sources AGNs et non-AGNs. On constate que cette contribution reste faible à tout *redshift*, et que la densité de luminosité infrarouge est donc toujours dominée par la formation d'étoiles.

5.2.4 Conclusion

Nous avons montré que l'empilement de sources sélectionnées en flux à $24 \mu\text{m}$ et en *redshift* fournit des contraintes très discriminantes sur l'évolution statistique des populations infrarouges. Ceci permet d'accéder à la distribution en *redshift* du fond infrarouge aux différentes longueurs d'onde, et ainsi de fournir de contraintes fortes sur le budget de photons que peuvent produire les processus de formation d'étoiles. Nos résultats indiquent que le taux de formation d'étoiles mesuré dans l'infrarouge augmente rapidement de $z=0$ à $z=1$. Le comportement à plus haut *redshift* semble plus stable, mais de grandes incertitudes sont encore présentes aujourd'hui, les populations de galaxies faibles ne pouvant pas être sondées, même par empilement.

5.3 Article : *Spitzer deep and wide legacy mid- and far-infrared number counts and lower limits of cosmic infrared background*

Les résultats présentés Chap. 2, 3 et 5 et concernant les comptages de sources et le CIB dans les bandes MIPS ont été publiés dans le journal *Astronomy&Astrophysics*.

Spitzer deep and wide legacy mid- and far-infrared number counts and lower limits of cosmic infrared background[★]

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ABSTRACT

Aims. We aim to place stronger lower limits on the cosmic infrared background (CIB) brightness at 24 μm , 70 μm and 160 μm and measure the extragalactic number counts at these wavelengths in a homogeneous way from various surveys.

Methods. Using *Spitzer* legacy data over 53.6 deg² of various depths, we build catalogs with the same extraction method at each wavelength. Completeness and photometric accuracy are estimated with Monte-Carlo simulations. Number count uncertainties are estimated with a counts-in-cells moment method to take galaxy clustering into account. Furthermore, we use a stacking analysis to estimate number counts of sources not detected at 70 μm and 160 μm . This method is validated by simulations. The integration of the number counts gives new CIB lower limits.

Results. Number counts reach 35 μJy , 3.5 mJy and 40 mJy at 24 μm , 70 μm , and 160 μm , respectively. We reach deeper flux densities of 0.38 mJy at 70, and 3.1 at 160 μm with a stacking analysis. We confirm the number count turnover at 24 μm and 70 μm , and observe it for the first time at 160 μm at about 20 mJy, together with a power-law behavior below 10 mJy. These mid- and far-infrared counts: 1) are homogeneously built by combining fields of different depths and sizes, providing a legacy over about three orders of magnitude in flux density; 2) are the deepest to date at 70 μm and 160 μm ; 3) agree with previously published results in the common measured flux density range; 4) globally agree with the Lagache et al. (2004) model, except at 160 μm , where the model slightly overestimates the counts around 20 and 200 mJy.

Conclusions. These counts are integrated to estimate new CIB firm lower limits of $2.29^{+0.09}_{-0.09}$ nW m⁻² sr⁻¹, $5.4^{+0.4}_{-0.4}$ nW m⁻² sr⁻¹, and $8.9^{+1.1}_{-1.1}$ nW m⁻² sr⁻¹ at 24 μm , 70 μm , and 160 μm , respectively, and extrapolated to give new estimates of the CIB due to galaxies of $2.86^{+0.19}_{-0.16}$ nW m⁻² sr⁻¹, $6.6^{+0.7}_{-0.6}$ nW m⁻² sr⁻¹, and $14.6^{+7.1}_{-2.9}$ nW m⁻² sr⁻¹, respectively. Products (point spread function, counts, CIB contributions, software) are publicly available for download at <http://www.ias.u-psud.fr/irgalaxies/>

Key words. cosmology: observations – diffuse radiation – galaxies: statistics – galaxies: evolution – galaxies: photometry – infrared: galaxies

1. Introduction

The extragalactic background light (EBL) is the relic emission of all processes of structure formation in the Universe. About half of this emission, called the Cosmic Infrared Background (CIB) is emitted in the 8–1000 μm range, and peaks around 150 μm . It is essentially due to the star formation (Puget et al. 1996; Fixsen et al. 1998; Hauser et al. 1998; Lagache et al. 1999; Gispert et al. 2000; Hauser & Dwek 2001; Kashlinsky 2005; Lagache et al. 2005).

The CIB spectral energy distribution (SED) is an important constraint for the infrared galaxies evolution models (e.g. Lagache et al. 2004; Franceschini et al. 2010; Le Borgne et al. 2009; Pearson & Khan 2009; Rowan-Robinson 2009; Valiante et al. 2009). It gives the budget of infrared emission since the first star. The distribution of the flux of sources responsible for this background is also a critical constraint. We propose to measure the level of the CIB and the flux distribution of the sources at 3 wavelengths (24 μm , 70 μm and 160 μm).

In the 1980's, the infrared astronomical satellite (IRAS) and COBE/DIRBE performed the first mid-infrared (MIR) and far-infrared (FIR) full-sky surveys. Nevertheless, the detected sources were responsible for a very small part of the CIB. Between 1995 and 1998, the ISO (infrared space observatory) performed deeper observations of infrared galaxies. Elbaz et al. (2002) resolved into the source more than half of the CIB at 15 μm . At larger wavelengths, the sensitivity and angular resolution was not sufficient to resolve the CIB (Dole et al. 2001).

The *Spitzer* space telescope (Werner et al. 2004), launched in 2003, has performed deep infrared observations on wide fields. The multiband imaging photometers for *Spitzer* (MIPS) (Rieke et al. 2004) mapped the sky at 24 μm , 70 μm and 160 μm . About 60% of the CIB was resolved at 24 μm (Papovich et al. 2004) and at 70 μm (Fayer et al. 2006). Because of confusion (Dole et al. 2003), only about 7% were resolved at 160 μm (Dole et al. 2004). Dole et al. (2006) managed to resolve most of the 70 μm and 160 μm by stacking 24 μm sources.

The cold mission of *Spitzer* is over, and lots of data are now public. We present extragalactic number counts built homogeneously by combining deep and wide fields. The large sky surface used significantly reduces uncertainties on number counts. In order to obtain very deep FIR number counts, we used a

[★] Counts and CIB contributions are only available in electronic form at the CDS via anonymous ftp to cdsarc.u-strasbg.fr (130.79.128.5) or via <http://cdsweb.u-strasbg.fr/cgi-bin/qcat?J/A+A/512/A78>

Table 1. Size, 80% completeness flux density, and calibration scaling factor (see Sect. 2.1) of the used fields.

Field name	Surface area			80% completeness flux			Scaling factor		
	24 μm	70 μm	160 μm	24 μm	70 μm	160 μm	24 μm	70 μm	160 μm
	deg ²			μJy			mJy		
FIDEL eCDFS	0.23	0.19	–	60.	4.6	–	1.0157	1	–
FIDEL EGS	0.41	–	0.38	76.	–	45.	1.0157	–	0.93
COSMOS	2.73	2.41	2.58	96.	7.9	46.	1	0.92	0.96
SWIRE LH	10.04	11.88	11.10	282.	25.4	92.	1.0509	1.10	0.93
SWIRE EN1	9.98	9.98	9.30	261.	24.7	94.	1.0509	1.10	0.93
SWIRE EN2	5.36	5.34	4.98	267.	26.0	90.	1.0509	1.10	0.98
SWIRE ES1	7.45	7.43	6.71	411.	36.4	130.	1.0509	1.10	0.98
SWIRE CDFS	8.42	8.28	7.87	281.	24.7	88.	1.0509	1.10	0.98
SWIRE XMM	8.93	–	–	351.	–	–	1.0509	–	–
Total	53.55	45.51	42.91						

Notes. Some fields are not used at all wavelengths.

stacking analysis and estimate the level of the CIB in the three MIPS bands with them.

2. Data, source extraction and photometry

2.1. Data

We took the public *Spitzer* mosaics¹ from different observation programs: the GOODS/FIDEL (PI: M. Dickinson), COSMOS (PI: D. Sanders) and SWIRE (PI: C. Lonsdale). We used only the central part of each field, which was defined by a cut of 50% of the median coverage for SWIRE fields and 80% for the other. The total area covers 53.6 deg², 45.5 deg², 42.9 deg² at 24 μm , 70 μm and 160 μm respectively. The surface of the deep fields (FIDEL, COSMOS) is about 3.5 deg². Some fields were not used at all wavelengths for different reasons: There is no public release of FIDEL CDFS data at 160 μm ; the pixels of the EGS 70 μm are not square; XMM is not observed at 70 and 160 μm . Table 1 summarises the field names, sizes and completenesses.

In 2006, new calibration factors were adopted for MIPS (Engelbracht et al. 2007; Gordon et al. 2007; Stansberry et al. 2007). The conversion factor from instrumental unit to MJy/sr is 0.0454 (resp. 702 and 41.7) at 24 μm (resp. 70 μm and 160 μm). The COSMOS GO3 and SWIRE (released 22 Dec. 2006) mosaics were generated with the new calibration. The FIDEL mosaics were obtained with other factors at 24 μm and 160 μm (resp. 0.0447 and 44.7). The 70 μm and 160 μm COSMOS mosaics were color corrected (see Sect. 2.3). Consequently we applied a scaling factor (see Table 1) before the source extraction to each mosaic to work on a homogeneous sample of maps (new calibration and no color correction).

2.2. Source extraction and photometry

The goal is to build homogeneous number counts with well-controlled systematics and high statistics. However, the fields present various sizes and depths. We thus employed a single extraction method at a given wavelength, allowing the heterogeneous datasets to combine in a coherent way.

2.2.1. Mid-IR/far-IR differences

The MIR (24 μm) and FIR (70 μm and 160 μm) maps have different properties: in the MIR, we observe lots of faint blended

sources; in the FIR, due to confusion (Dole et al. 2004), all these faint blended sources are only seen as background fluctuations. Consequently, we used different extraction and photometry methods for each wavelength. In the MIR, the priority is the deblending: accordingly we took the SExtractor (Bertin & Arnouts 1996) and PSF fitting. In the FIR, we used efficient methods with strong background fluctuations: wavelet filtering, threshold detection and aperture photometry.

2.2.2. Point spread function (PSF)

The 24 μm empirical PSF of each field is generated with the IRAF (image reduction and analysis facility²) DAOPHOT package (Stetson 1987) on the 30 brightest sources of each map. It is normalized in a 12 arcsec radius aperture. Aperture correction (1.19) is computed with the S Tiny Tim³ (Krist 2006) theoretical PSF for a constant νS_ν spectrum. The difference of correction between a $S_\nu = \nu^{-2}$ and a ν^2 spectrum is less than 2%. So, the hypothesis on the input spectrum is not critical for the PSF normalization.

At 70 μm and 160 μm , we built a single empirical PSF from the SWIRE fields. We used the Starfinder PSF extraction routine (Diolaiti et al. 2000), which median-stacks the brightest non-saturated sources (100 mJy < S_{70} < 10 Jy and 300 mJy < S_{160} < 1 Jy). Previously, fainter neighboring sources were subtracted with a first estimation of the PSF. At 70 μm (resp. 160 μm), the normalization is done in a 35 arcsec (resp. 80 arcsec) aperture, with a sky annulus between 75 arcsec and 125 arcsec (resp. 150 arcsec and 250 arcsec); the aperture correction was 1.21 (resp. 1.20). The theoretical signal in the sky annulus and the aperture correction were computed with the S Tiny Tim *Spitzer* PSF for a constant νS_ν spectrum. These parameters do not vary more than 5% with the spectrum of sources. Pixels that were affected by the temporal median filtering artifact, which was sometimes present around bright sources, were masked prior to these operations.

2.2.3. Source extraction and photometry

At 24 μm , we detected sources with SExtractor. We chose a Gaussian filter (gauss_5.0_9x9.conv) and a background filter of the size of 64 × 64 pixels. The detection and analysis thresholds were tuned for each field. We performed PSF fitting photometry

¹ from the Spitzer Science Center website: <http://data.spitzer.caltech.edu/popular/>

² <http://iraf.noao.edu/>

³ <http://ssc.spitzer.caltech.edu/archanaly/contributed/stinytim/>

with the DAOPHOT allstar routine. This routine is very efficient for blended sources flux measurement.

At $70\ \mu\text{m}$ and $160\ \mu\text{m}$, we applied the a-trou wavelet filtering (Starck et al. 1999) on the maps to remove the large scale fluctuations (10 pixels) on which we performed the source detection with a threshold algorithm (Dole et al. 2001, 2004). The threshold was tuned for each field. Photometry was done by aperture photometry on a non filtered map at the positions found on the wavelet filtered map. At $70\ \mu\text{m}$, we used 10 arcsec aperture radius and a 18 arcsec to 39 arcsec sky annulus. At $160\ \mu\text{m}$, we used an aperture of 20 arcsec and a 40 arcsec to 75 arcsec annulus. Aperture corrections were computed with the normalized empirical PSF: 3.22 at $70\ \mu\text{m}$ and 3.60 at $160\ \mu\text{m}$. In order to estimate the uncertainty on this correction, aperture corrections were computed using five PSF built on five different SWIRE fields. The uncertainty is 1.5% at $70\ \mu\text{m}$ and 4.5% at $160\ \mu\text{m}$.

2.3. Color correction

The MIPS calibration factors were calculated for a 10 000 K blackbody (MIPS Data Handbook 2007⁴). However, the galaxies SED are different and the MIPS photometric bands are large ($\lambda/\Delta\lambda \approx 3$). Thus, color corrections were needed. We used (like Shupe et al. (2008) and Frayer et al. (2009)) a constant νS_ν spectrum at $24\ \mu\text{m}$, $70\ \mu\text{m}$ and $160\ \mu\text{m}$. Consequently, all fluxes were divided by 0.961, 0.918 and 0.959 at $24\ \mu\text{m}$, $70\ \mu\text{m}$ and $160\ \mu\text{m}$ due to this color correction. Another possible convention is $\nu S_\nu \propto \nu^{-1}$. This convention is more relevant for the local sources at $160\ \mu\text{m}$, whose spectrum decreases quickly with wavelength. Nevertheless, the redshifted sources studied by stacking are seen at their peak of the cold dust emission, and their SED agrees better with the constant νS_ν convention. The difference of color correction between these two conventions is less than 2%, and this choice is thus not critical. We consequently chose the constant νS_ν convention to more easily compare our results with Shupe et al. (2008) and Frayer et al. (2009).

3. Catalog properties

3.1. Spurious sources

Our statistical analysis may suffer from spurious sources. We have to estimate how many false detections are present in a map and what their flux distribution is. To do so, we built a catalog with the flipped map. To build this flipped map, we multiplied the values of the pixels of the original map by a factor of -1 . Detection and photometry parameters were exactly the same as for normal catalogs. At $24\ \mu\text{m}$, there are few spurious sources ($<10\%$) in bins brighter than the 80% completeness limit flux density. At $70\ \mu\text{m}$ and $160\ \mu\text{m}$, fluctuations of the background due to unresolved faint sources are responsible for spurious detections. Nevertheless, the ratio between detected source numbers and fake source numbers stayed reasonable (below 0.2) down to the 80% completeness limit (see the example of FIDEL CDFS at $70\ \mu\text{m}$ in Fig. 1).

3.2. Completeness

The completeness is the probability to extract a source of a given flux. To estimate it, we added artificial sources (based on empirical PSF) on the initial map and looked for a detection in a 2 arcsec radius at $24\ \mu\text{m}$ around the initial position (8 arcsec

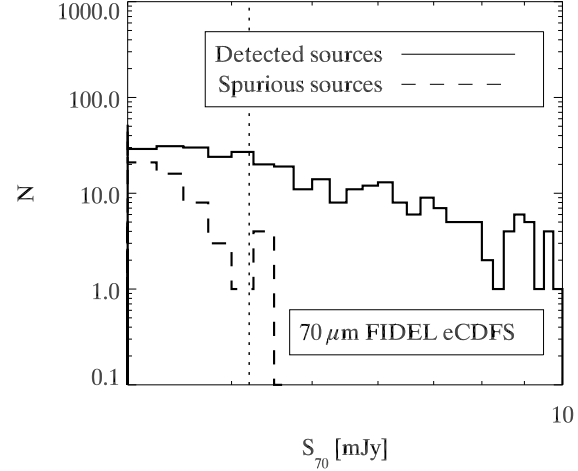


Fig. 1. Flux distribution of sources extracted from normal (solid line) and flipped (dash line) maps, at $70\ \mu\text{m}$ in FIDEL eCDFS. The vertical dashed line represents the 80% completeness flux density.

at $70\ \mu\text{m}$ and 16 arcsec at $160\ \mu\text{m}$). This operation was done for different fluxes with a Monte-Carlo simulation. We chose the number of artificial sources in each realization in a way that they have less than 1% probability to fall at a distance shorter than 2 PSF FWHM (full width at half maximum). The completeness is plotted in Fig. 2, and the 80% completeness level is reported in Table 1.

3.3. Photometric accuracy

The photometric accuracy was checked with the same Monte-Carlo simulation. For different input fluxes, we built histograms of measured fluxes and computed the median and scatter of these distributions. At lower fluxes, fluxes are overestimated and errors are larger. These informations were used to estimate the Eddington bias (see next section). The photometric accuracy at $70\ \mu\text{m}$ in FIDEL CDFS is plotted as an example in Fig. 3.

We also compared our catalogs with published catalogs. At $24\ \mu\text{m}$, we compared it with the GOODS CDFS catalog of Chary et al. (2004), and the COSMOS catalog of LeFloc'h et al. (2009). Their fluxes were multiplied by a corrective factor to be compatible with the $\nu S_\nu = \text{constant}$ convention. Sources were considered to be the same if they are separated by less than 2 arcsec. We computed the standard deviation of the distribution of the ratio between our and their catalogs. In a 80–120 μJy bin in the CDFS, we found a dispersion of 19%. In a 150–250 μJy bin in COSMOS, we found a scatter of 13%. The offset is +3% with COSMOS catalog and -1% with GOODS catalog. At 70 and $160\ \mu\text{m}$, we compared our catalogs with the COSMOS and SWIRE team ones. In all cases, the scatter is less than 15%, and the offset is less than 3%. At all wavelengths and for all fields, the offset is less than the calibration uncertainty.

3.4. Eddington bias

When sources become fainter, photometric errors increase. In addition, fainter sources are more numerous than brighter ones (in general $dN/dS \sim S^{-r}$). Consequently, the number of sources in faint bins are overestimated. This is the classical Eddington

⁴ <http://ssc.spitzer.caltech.edu/mips/dh/>

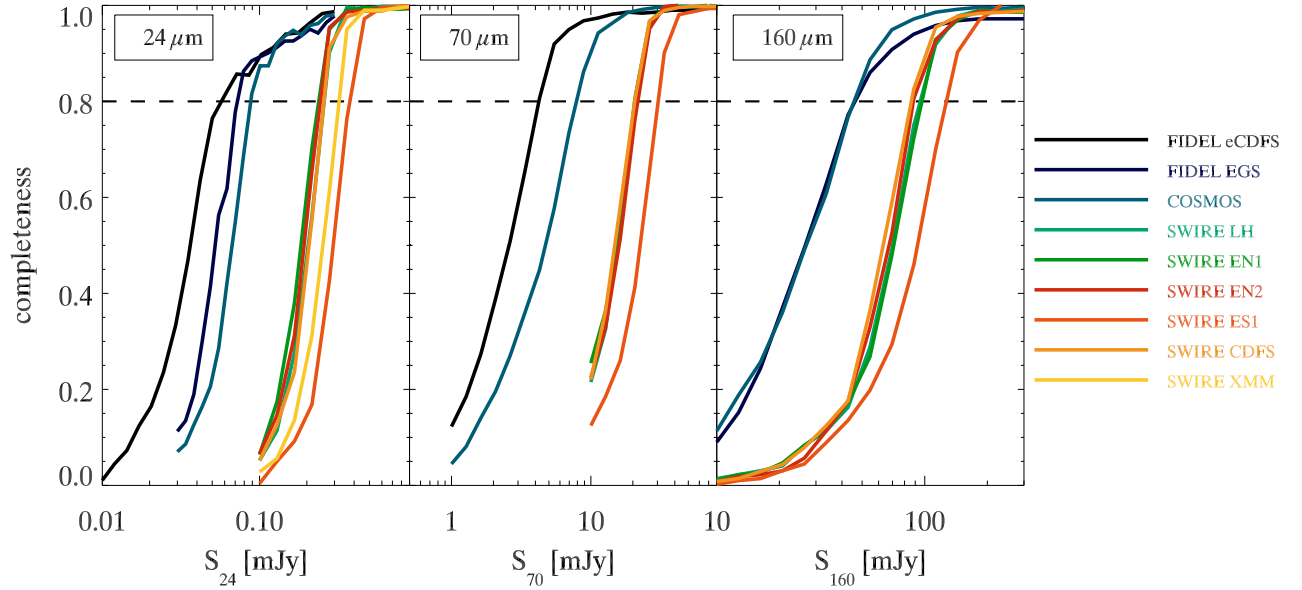


Fig. 2. Completeness at 24 μm (left), 70 μm (center), and 160 μm (right) as a function of the source flux for all fields. The dashed line represents 80% completeness.

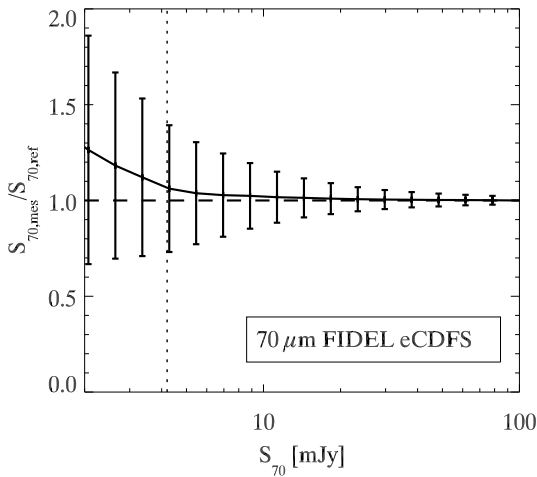


Fig. 3. Ratio between measured flux and input flux computed from Monte Carlo simulations at 70 μm in FIDEL eCDFS. Error bars represent 1σ dispersion. The vertical dashed line represents the 80% completeness flux density.

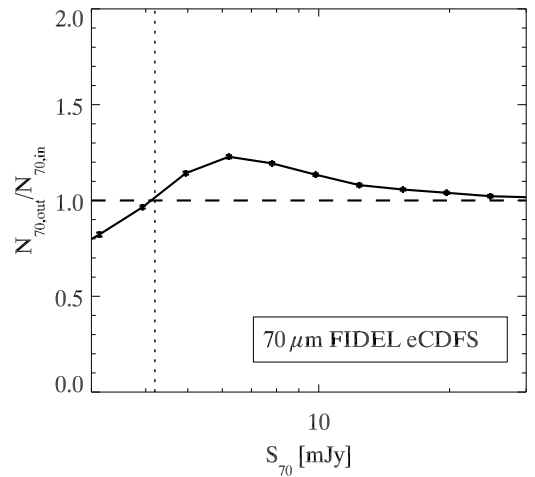


Fig. 4. Eddington bias: ratio between the number of detected sources and the number of input sources at 70 μm in FIDEL eCDFS. The vertical dashed line represents the 80% completeness flux density.

bias (Eddington 1913, 1940). The example of FIDEL CDFS at 70 μm is plotted in Fig. 4.

To correct for this effect at 70 μm and 160 μm , we estimated a correction factor for each flux bin. We generated an input flux catalog with a power-law distribution ($r = 1.6$ at 70 μm , $r = 3$ at 160 μm). We took into account completeness and photometric errors (coming from Monte-Carlo simulations) to generate a mock catalog. We then computed the ratio between the number of mock sources found in a bin and the number of input sources. This task was done for all fields. This correction is more important for large r (at 160 μm). At 24 μm , thanks to the PSF fitting, the photometric error is more reduced and symmetrical. Less faint sources are thus placed in brighter flux bins. Because of this property and the low r (about 1.45), this correction can be ignored for 24 μm counts.

4. Number counts

4.1. Removing stars from the catalogs

To compute extragalactic number counts at 24 μm , we removed the stars with the $K - [24] < 2$ color criterion and identification procedure following Shupe et al. (2008). The K band magnitudes were taken from the 2MASS catalog (Skrutskie et al. 2006). We ignored the star contribution at 70 μm and 160 μm , which is negligible ($< 1\%$ in all used flux density bins) according to the DIRBE Faint Count model (Arendt et al. 1998).

4.2. 24 μm number counts

We counted the number of extragalactic sources for each field and in each flux bin. We subtracted the number of spurious detections (performed on the flipped map). We divided by the

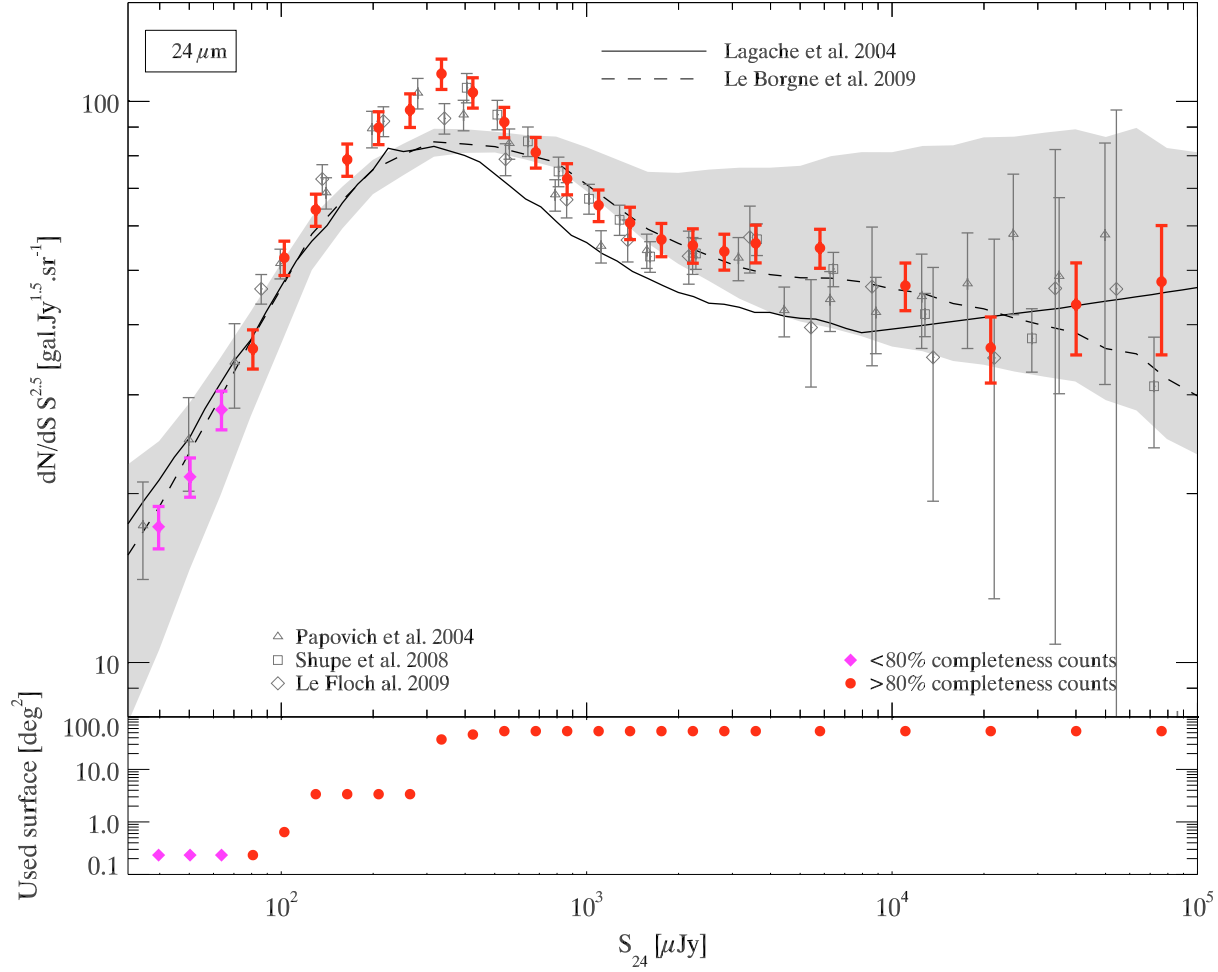


Fig. 5. Differential number counts at 24 μm . *Filled circle*: points obtained with $\geq 80\%$ completeness; *filled diamond*: points obtained with a 50% to 80% completeness; *open triangle*: Papovich et al. (2004) GTO number counts obtained with PSF fitting photometry; *open square*: Shupe et al. (2008) SWIRE number counts obtained with aperture photometry; *open diamond*: LeFloch et al. (2009) COSMOS number counts obtained with PSF fitting photometry; *continuous line*: Lagache et al. (2004) model; *dashed line and grey region*: Le Borgne et al. (2009) model and 90% confidence region. Error bars take into accounts clustering (see Sect. 4.5) and calibration uncertainties (Engelbracht et al. 2007).

completeness. As a next step, the counts of all fields were combined together with a mean weighted by field size. Actually, a weighting by the number of sources in each field overweighs the denser fields and biases the counts. Counts from a field were combined only if the lower end of the flux bin was larger then or equal to the 80% completeness. We thus reached 71 μJy (71 μJy to 90 μJy in the counts). However, to probe fainter flux densities, we used the data from the deepest field (FIDEL eCDFs) between a 50 and 80% completeness, allowing us to reach 35 μJy .

Our number counts are plotted in Fig. 5 and are written in Table 2. We also plot data from Papovich et al. (2004), Shupe et al. (2008) and LeFloch et al. (2009), and model predictions from Lagache et al. (2004) and Le Borgne et al. (2009). The Papovich et al. (2004) fluxes are multiplied by a factor 1.052 to take into account the update in the calibration, the color correction and the PSF. This correction of flux also implies a correction on number counts, according to:

$$\left(\frac{dN}{dS_f} S_f^{2.5}\right)_{S_f} = \left(c^{1.5} \frac{dN}{dS_i} S_i^{2.5}\right)_{cS_i}, \quad (1)$$

where S_i is the initial flux, S_f is the corrected flux and c the corrective factor ($S_f = cS_i$). A correction of the flux thus

corresponds to a shift in the abscissa (factor c) and in the ordinate (factor $c^{1.5}$). Papovich et al. (2004) do not subtract stars and thus overestimate counts above 10 mJy. We have a very good agreement with their work below 10 mJy. We also have a very good agreement with Shupe et al. (2008). The LeFloch et al. (2009) fluxes are multiplied by 1.05 to take into account a difference of the reference SED: 10 000 K versus constant νS_ν , and by another correction of 3% corresponding to the offset observed in Sect. 3.3. There is an excellent agreement with their work.

The Lagache et al. (2004)⁵ and Le Borgne et al. (2009)⁶ generally agree well with the data, in particular on the faint end below 100 μJy , and on the position of the peak around 300 μJy . However, the Lagache et al. (2004) model slightly underestimates (about 10%) the counts above 200 μJy . The Le Borgne et al. (2009) model is flatter than the data, and agrees reasonably well above 600 μJy .

⁵ Lagache et al. (2004) model used a ΛCDM cosmology with $\Omega_\Lambda = 0.73$, $\Omega_M = 0.27$ and $h = 0.71$.

⁶ Le Borgne et al. (2009) model used a ΛCDM cosmology with $\Omega_\Lambda = 0.7$, $\Omega_M = 0.3$ and $h = 0.7$.

Table 2. Differential number counts at 24 μm .

$\langle S \rangle$	$S_{\min}$	$S_{\max}$	$dN/dS \cdot S^{2.5}$	σ_{poisson}	$\sigma_{\text{clustering}}$	$\sigma_{\text{clus.+calib.}}$	Ω_{used}
	(in mJy)			(in $\text{gal Jy}^{1.5} \text{sr}^{-1}$)			deg^2
0.040	0.035	0.044	17.5	1.0	1.1	1.3	0.2
0.050	0.044	0.056	21.4	1.0	1.1	1.4	0.2
0.064	0.056	0.071	28.2	1.2	1.5	1.8	0.2
0.081	0.071	0.090	36.2	1.5	1.9	2.4	0.2
0.102	0.090	0.114	52.6	1.3	1.9	2.9	0.6
0.130	0.114	0.145	64.1	1.0	1.7	3.1	3.4
0.164	0.145	0.184	78.7	1.1	2.2	3.8	3.4
0.208	0.184	0.233	89.8	1.3	2.8	4.5	3.4
0.264	0.233	0.295	96.5	1.5	3.3	5.1	3.4
0.335	0.295	0.374	112.0	0.8	1.8	4.8	37.2
0.424	0.374	0.474	103.7	0.6	1.7	4.5	46.1
0.538	0.474	0.601	91.9	0.6	1.5	4.0	53.6
0.681	0.601	0.762	81.2	0.6	1.5	3.6	53.6
0.863	0.762	0.965	72.8	0.7	1.6	3.3	53.6
1.094	0.965	1.223	65.3	0.8	1.6	3.1	53.6
1.387	1.223	1.550	60.8	0.9	1.7	3.0	53.6
1.758	1.550	1.965	56.7	1.0	1.8	2.9	53.6
2.228	1.965	2.490	55.4	1.2	2.1	3.0	53.6
2.823	2.490	3.156	54.0	1.5	2.3	3.2	53.6
3.578	3.156	4.000	55.9	1.8	2.7	3.5	53.6
5.807	4.000	7.615	54.8	1.5	2.9	3.6	53.6
11.055	7.615	14.496	46.9	2.3	3.6	4.1	53.6
21.045	14.496	27.595	36.4	3.3	4.4	4.6	53.6
40.063	27.595	52.531	43.4	5.9	7.7	7.9	53.6
76.265	52.531	100.000	47.7	9.9	12.0	12.2	53.6

Notes. $\sigma_{\text{clustering}}$ is the uncertainty taking into account clustering (see Sect. 4.5). $\sigma_{\text{clus.+calib.}}$ takes into account both clustering and calibration (Engelbracht et al. 2007).

Table 3. Differential number counts at 70 μm .

$\langle S \rangle$	$S_{\min}$	$S_{\max}$	$dN/dS \cdot S^{2.5}$	σ_{poisson}	$\sigma_{\text{clustering}}$	$\sigma_{\text{clus.+calib.}}$	Ω_{used}
	(in mJy)			(in $\text{gal Jy}^{1.5} \text{sr}^{-1}$)			deg^2
4.197	3.500	4.894	2073.	264.	309.	342.	0.2
5.868	4.894	6.843	2015.	249.	298.	330.	0.2
8.206	6.843	9.569	1690.	289.	332.	353.	0.2
11.474	9.569	13.380	2105.	123.	202.	250.	2.6
16.044	13.380	18.708	2351.	148.	228.	281.	2.6
22.434	18.708	26.159	1706.	153.	208.	240.	2.6
31.369	26.159	36.578	2557.	69.	124.	218.	38.1
43.862	36.578	51.146	2446.	73.	123.	211.	45.5
61.331	51.146	71.517	2359.	90.	141.	217.	45.5
85.758	71.517	100.000	2257.	112.	164.	228.	45.5
157.720	100.000	215.440	2354.	121.	198.	257.	45.5
339.800	215.440	464.160	2048.	200.	276.	311.	45.5
732.080	464.160	1000.000	2349.	381.	500.	526.	45.5

Notes. $\sigma_{\text{clustering}}$ is the uncertainty taking into account clustering (see Sect. 4.5). $\sigma_{\text{clus.+calib.}}$ takes into account both clustering and calibration (Gordon et al. 2007).

4.3. 70 μm number counts

Counts in the flux density bins brighter than the 80% completeness limit were obtained in the same way as at 24 μm (Fig. 6 and Table 3). In addition, they were corrected from the Eddington bias (cf. Sect. 3.4). We reached about 4.9 mJy at 80% completeness (4.9 to 6.8 bin). We used CDFS below 80% completeness limit to probe fainter flux density level. We cut these counts at 3.5 mJy. At this flux density, the spurious rate reached 50%. We used a stacking analysis to probe fainter flux density levels (cf. Sect. 5).

We can see breaks in the counts around 10 mJy and 20 mJy. These breaks appear between points built with a different set of fields. Our counts agree with earlier works of Dole et al. (2004), Frayer et al. (2006) and Frayer et al. (2009). However, these works suppose only a Poissonian uncertainty, which underestimates the error bars (see Sect. 4.5). Our data also agree well with these works. The Lagache et al. (2004) model agrees well with our data. The Le Borgne et al. (2009) model gives a reasonable fit, despite an excess of about 30% between 3 mJy and 10 mJy.

Table 4. Differential number counts at 160 μm . $\sigma_{\text{clustering}}$ is the uncertainty taking into account clustering (see Sect. 4.5).

$\langle S \rangle$	S_{min}	S_{max}	$dN/dS.S^{2.5}$	σ_{poisson}	$\sigma_{\text{clustering}}$	$\sigma_{\text{clus.+calib.}}$	Ω_{used}
	(in mJy)			(in $\text{gal Jy}^{1.5} \text{sr}^{-1}$)			deg^2
45.747	40.000	51.493	16855.	1312.	2879.	3519.	3.0
58.891	51.493	66.289	14926.	1243.	2704.	3243.	3.0
75.813	66.289	85.336	13498.	1319.	2648.	3104.	3.0
97.596	85.336	109.860	12000.	1407.	2442.	2835.	3.0
125.640	109.860	141.420	10687.	457.	991.	1621.	36.2
161.740	141.420	182.060	7769.	425.	773.	1211.	42.9
208.210	182.060	234.370	7197.	472.	810.	1184.	42.9
268.040	234.370	301.710	5406.	487.	734.	979.	42.9
345.050	301.710	388.400	5397.	585.	843.	1063.	42.9
444.200	388.400	500.000	4759.	662.	891.	1059.	42.9
750.000	500.000	1000.000	6258.	685.	1158.	1380.	42.9
1500.000	1000.000	2000.000	4632.	989.	1379.	1487.	42.9

Notes. $\sigma_{\text{clus.+calib.}}$ takes into account both clustering and calibration (Stansberry et al. 2007).

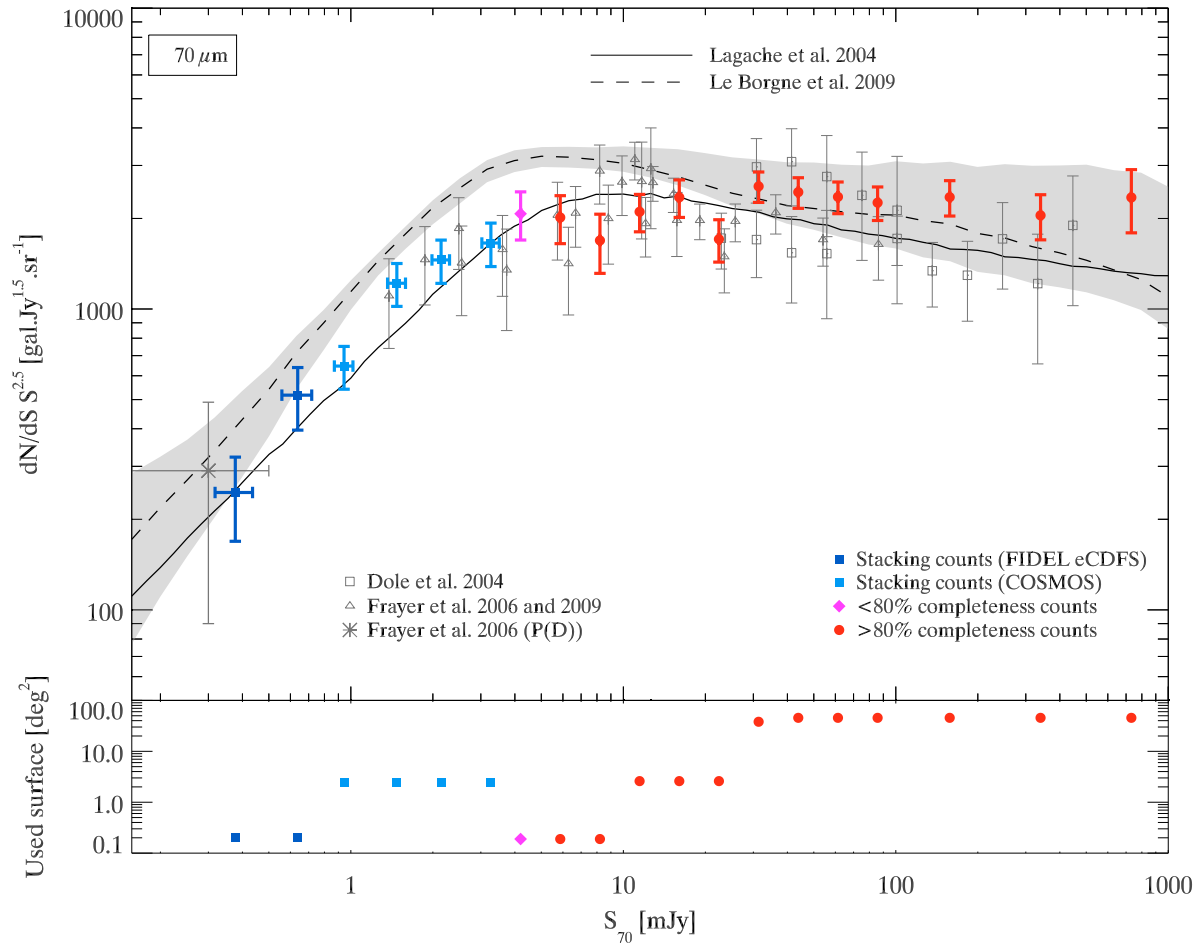


Fig. 6. Differential number counts at 70 μm . *Filled circle*: points obtained with $\geq 80\%$ completeness; *filled diamond*: points obtained with less than 50% spurious sources and less than 80% completeness; *filled square*: stacking number counts (clear: FIDEL eCDFS, dark: COSMOS); *open square*: Dole et al. (2004) number counts in CDFS, Bootes and Marano; *open triangle*: Frayer et al. (2006) in GOODS and Frayer et al. (2009) in COSMOS; *cross*: Frayer et al. (2006) deduced from background fluctuations; *continuous line*: Lagache et al. (2004) model; *dashed line and grey region*: Le Borgne et al. (2009) model and 90% confidence region. Error bars take into account clustering (see Sect. 4.5) and calibration uncertainties (Gordon et al. 2007).

4.4. 160 μm number counts

The 160 μm number counts were obtained exactly in the same way as at 70 μm . We used COSMOS and EGS to probe counts

below the 80% completeness limit. We reached 51 mJy at 80% completeness (51 mJy to 66 mJy bin) and 40 mJy for the 50% spurious rate cut (Fig. 7 and Table 4). We used a stacking analysis to probe fainter flux density levels (cf. Sect. 5).

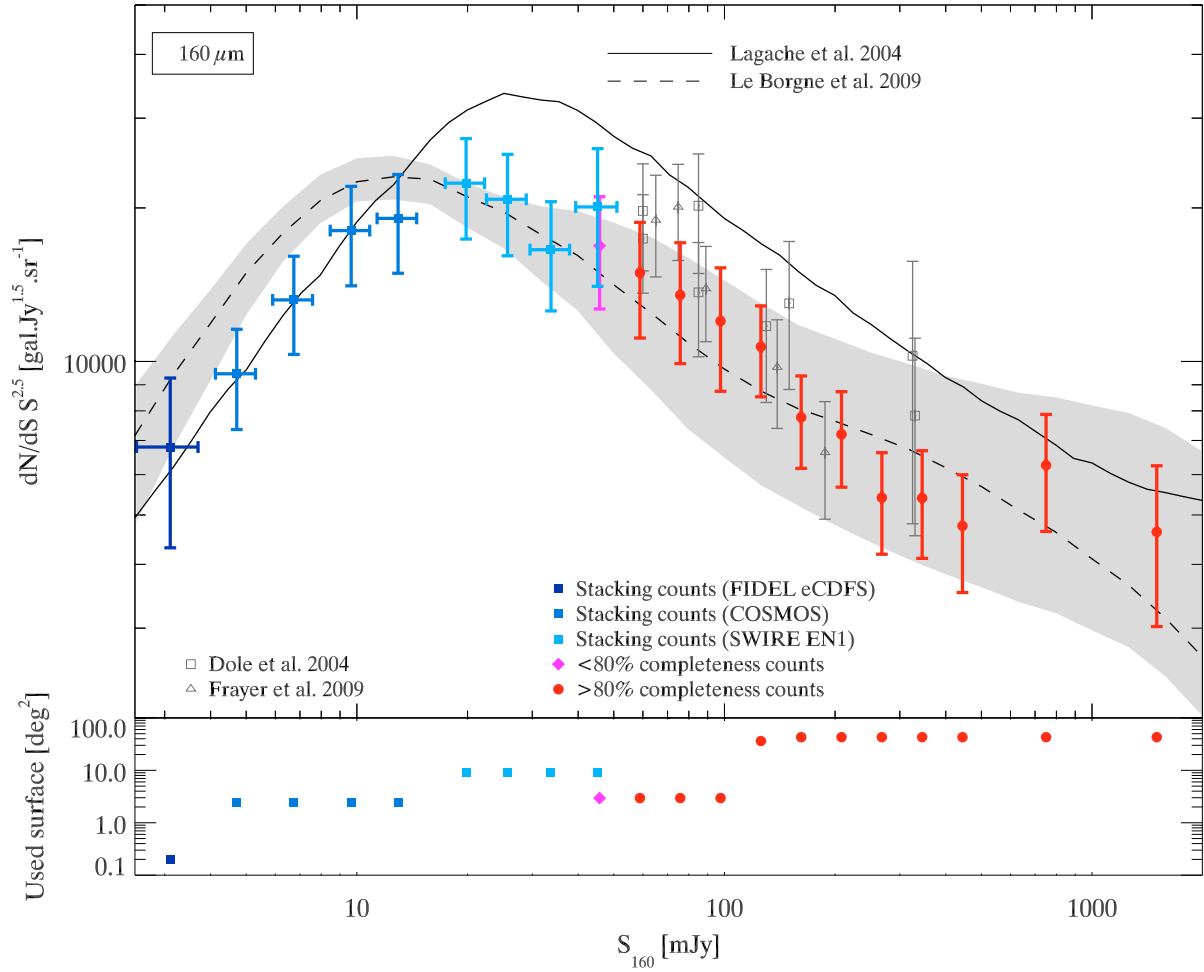


Fig. 7. Differential number counts at $160\ \mu\text{m}$. *Filled circle*: points obtained with $\geq 80\%$ completeness; *filled diamond*: points obtained with less than 50% spurious sources and less than 80% completeness; *filled square*: stacking number counts (clear: FIDEL/GTO CDFS, *middle*: COSMOS, dark: SWIRE EN1); *open square*: Dole et al. (2004) number counts in CDFS and Marano; *open triangle*: Frayer et al. (2009) in COSMOS; *continuous line*: Lagache et al. (2004) model; *dashed line and grey region*: Le Borgne et al. (2009) model and 90% confidence region. Error bars take into account clustering (see Sect. 4.5) and calibration uncertainties (Stansberry et al. 2007).

Our counts agree with the earlier works of Dole et al. (2004) and Frayer et al. (2009). We find like Frayer et al. (2009) that the Lagache et al. (2004) model overestimates the counts by about 30% above 50 mJy (see the discussion in Sect. 7.2). On the contrary, the Le Borgne et al. (2009) model underpredicts the counts by about 20% between 50 mJy and 150 mJy.

4.5. Uncertainties on number counts including clustering

Shupe et al. (2008) showed that the SWIRE field-to-field variance is significantly higher than the Poisson noise (by a factor of three in some flux bins). They estimated their uncertainties on number counts with a field bootstrap method. We used a more formal method to deal with this problem.

The uncertainties on the number counts are Poissonian only if sources are distributed uniformly. But, actually, the infrared galaxies are clustered. The uncertainties must thus be computed taking into account clustering. We first measured the source clustering as a function of the flux density with the counts-in-cells moments (c-in-c) method (Peebles 1980; Szapudi 1998; Blake & Wall 2002). We then computed the uncertainties knowing these

clustering properties of the sources, the source density in the flux density bins and the field shapes. The details are explained in the Appendix A.

This statistical uncertainty can be combined with the *Spitzer* calibration uncertainty (Engelbracht et al. 2007; Gordon et al. 2007; Stansberry et al. 2007) to compute the total uncertainty on differential number counts.

5. Deeper FIR number counts using a stacking analysis

5.1. Method

The number counts derived in Sect. 4 show that down to the 80% completeness limit, the source surface density is $24100\ \text{deg}^{-2}$, $1200\ \text{deg}^{-2}$, and $220\ \text{deg}^{-2}$ at 24, 70, and $160\ \mu\text{m}$, respectively, i.e. 20 times (resp. 110 times) higher at $24\ \mu\text{m}$ than at $70\ \mu\text{m}$ (resp. $160\ \mu\text{m}$). These differences can be explained by the angular resolution decreasing with increasing wavelength, thus increasing confusion, and the noise properties of the detectors. There are thus many $24\ \mu\text{m}$ sources without detected FIR

counterparts. If we want to probe deeper into the FIR number counts, we can take advantage of the information provided by the 24 μm data, namely the existence of infrared galaxies not necessarily detected in the FIR, and their positions.

We used a stacking analysis (Dole et al. 2006) to determine the FIR/MIR color as a function of the MIR flux. With this information, we can convert MIR counts into FIR counts. The stacking technique consists in piling up very faint far-infrared galaxies which are not detected individually, but are detected at 24 μm . For this purpose, it makes use of the 24 μm data prior to tracking their undetected counterpart at 70 μm and 160 μm , where most of the bolometric luminosity arises. This method was used by Dole et al. (2006), who managed to resolve the FIR CIB using 24 μm sources positions, as well many other authors (e.g Serjeant et al. (2004); Dye et al. (2006); Wang et al. (2006); Devlin et al. (2009); Dye et al. (2009); Marsden et al. (2009); Pascale et al. (2009)).

To derive the 70 μm or 160 μm versus 24 μm color, we stacked the FIR maps (cleaned of bright sources) at the positions of the 24 μm sources sorted by flux, and performed aperture photometry (same parameters as in Sect. 2). We thus get

$$\overline{S_{\text{FIR}}} = f(\overline{S_{24}}), \quad (2)$$

where $\overline{S_{\text{FIR}}}$ is the average flux density in the FIR of the population selected at 24 μm , $\overline{S_{24}}$ the average flux density at 24 microns, and f is the function linking both quantities. We derive f empirically using the S_{FIR} versus S_{24} relation obtained from stacking.

We checked that f is a smooth monotonic function, in agreement with the expectation that the color varies smoothly with the redshift and the galaxy emission properties. Assuming that the individual sources follow this relation exactly, the FIR number counts could be deduced from

$$\left. \frac{dN}{dS_{\text{FIR}}} \right|_{S_{\text{FIR}}=f(S_{24})} = \left. \frac{dN}{dS_{24}} \right|_{S_{24}} \left/ \frac{dS_{\text{FIR}}}{dS_{24}} \right|_{S_{24}}. \quad (3)$$

In practice, the two first terms are discrete. In addition, the last term is computed numerically in the same S_{24} bin, using the two neighboring flux density bins ($k-1$ and $k+1$). We finally get

$$\frac{dN}{dS_{\text{FIR}}}(\overline{S_{\text{FIR}}}) = \left(\frac{dN}{dS_{24}} \right)_k \left/ \frac{\overline{S_{\text{FIR},k+1}} - \overline{S_{\text{FIR},k-1}}}{\overline{S_{24,k+1}} - \overline{S_{24,k-1}}} \right|, \quad (4)$$

where $\langle S_{\text{FIR}} \rangle$ is measured by stacking. In reality, sources do not follow Eq. (2) exactly, but exhibit a scatter around this mean relation

$$S_{\text{FIR}} = f(S_{24}) + \sigma. \quad (5)$$

Our method is still valid under the condition $\frac{\sigma}{f} \ll 1$, and we verify its validity with simulations (see next section).

To obtain a better signal to noise ratio, we cleaned the resolved bright sources from the FIR maps prior to stacking. We used 8 S_{24} bins per decade. We stacked a source only if the coverage was more than half of the median coverage of the map. Uncertainties on the FIR mean flux were estimated with a bootstrap method. Furthermore, knowing the uncertainties on the 24 μm number counts and the mean S_{24} fluxes, we deduced the uncertainties on the FIR number counts according to Eq. (4).

At 70 μm , we used the FIDEL eCDFs (cleaned at $S_{70} > 10$ mJy) and the COSMOS (cleaned at $S_{70} > 50$ mJy) fields. At 160 μm , we used 160 μm the GTO CDFS (cleaned at $S_{160} > 60$ mJy), the COSMOS (cleaned at $S_{160} > 100$ mJy) and the SWIRE EN1 (no clean to probe the $S_{160} > 20$ mJy sources) fields.

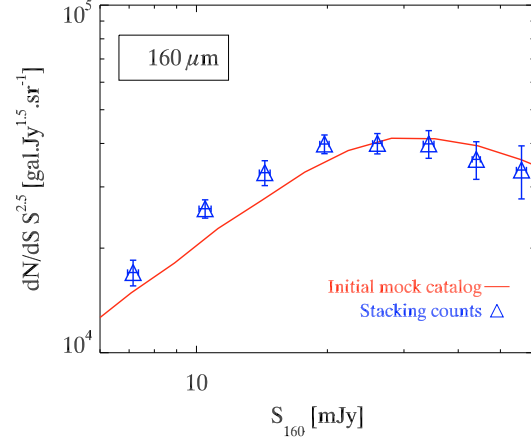


Fig. 8. Simulated number counts at 160 μm , computed from stacking counts (triangle) and from the input mock catalog (solid line). The good agreement (better than 15%) validates the stacking counts method (see Sect. 5.2). Twenty realizations of the 2.9 deg² field maps with about 870 000 mock sources each were used.

5.2. Validation on simulations

We used the Fernandez-Conde et al. (2008) simulations⁷ to validate our method. These simulations are based on the Lagache et al. (2004) model, and include galaxy clustering. We employed 20 simulated mock catalogs of a 2.9 deg² field each, containing about 870 000 mock sources each. The simulated maps have the same pixel size as the actual *Spitzer* mosaics (1.2'', 4'', and 8'' at 24 μm , 70 μm , and 160 μm , resp.) and are convolved with our empirical PSF. A constant standard deviation Gaussian noise was added. We applied the same method as for the real data to produce stacking number counts. At 160 μm , for bins below 15 mJy, we cleaned the sources brighter than 50 mJy. Figure 8 shows 160 μm number counts from the mock catalogs down to $S_{160} = 1$ mJy (diamond) and the number counts deduced from the stacking analysis described in the previous section (triangle). The error bars on the figure are the standard deviations of the 20 realization. There is a good agreement between the stacking counts and the classical counts (better than 15%). Nevertheless, we observed a systematic bias, intrinsic to the method, of about 10% in some flux density bins. We thus combined this 10% error with the statistical uncertainties to compute our error bars. We also validated the estimation of the statistical uncertainty in the stacking counts: we check that the dispersion of the counts obtained by stacking, coming from different realizations, was compatible with our estimation of statistical uncertainties. The results are the same at 70 μm .

5.3. Results

At 70 μm , the stacking number counts reach 0.38 mJy (see Fig. 6 and Table 5). The last stacking point is compatible with the Frayer et al. (2006) P(D) constraint. The stacking points also agree very well with the Lagache et al. (2004) model. The Le Borgne et al. (2009) model predicts slightly too many sources in 0.3 to 3 mJy range. The turnover around 3 mJy and the power law behavior of the faint counts ($S_{70} < 2$ mJy), observed by Frayer et al. (2006) are confirmed with a better accuracy.

At 160 μm , the stacking counts reach 3.1 mJy (see Fig. 7 and Table 6). We observed for the first time a turnover at about

⁷ Publicly available at <http://www.ias.u-psud.fr/irgalaxies/>

Table 5. Stacking extragalactic number counts at 70 μm .

$\langle S \rangle$ (in mJy)	$dN/dS \cdot S^{2.5}$ (in $\text{gal Jy}^{1.5} \text{sr}^{-1}$)	$\sigma_{\text{clus.}}$	$\sigma_{\text{clus.+calib.}}$	Field
0.38 ± 0.05	246.	72.	76.	FIDEL CDFS
0.64 ± 0.07	517.	109.	122.	FIDEL CDFS
0.94 ± 0.03	646.	80.	105.	COSMOS
1.48 ± 0.04	1218.	151.	198.	COSMOS
2.14 ± 0.05	1456.	183.	239.	COSMOS
3.27 ± 0.07	1657.	211.	273.	COSMOS

Notes. $\sigma_{\text{clus.}}$ is the uncertainty taking into account clustering (see Sect. 4.5). $\sigma_{\text{clus.+calib.}}$ takes into account both clustering and calibration (Gordon et al. 2007).

Table 6. Stacking extragalactic number counts at 160 μm .

$\langle S \rangle$ (in mJy)	$dN/dS \cdot S^{2.5}$ (in $\text{gal Jy}^{1.5} \text{sr}^{-1}$)	$\sigma_{\text{clus.}}$	$\sigma_{\text{clus.+calib.}}$	Field
3.11 ± 0.46	6795.	2163.	2485.	GTO CDFS
4.71 ± 0.16	9458.	1236.	2104.	COSMOS
6.74 ± 0.22	13203.	1627.	2880.	COSMOS
9.65 ± 0.26	18057.	2307.	3986.	COSMOS
12.95 ± 0.37	19075.	2388.	4182.	COSMOS
19.82 ± 0.48	22366.	2944.	4987.	SWIRE EN1
25.71 ± 0.81	20798.	2811.	4682.	SWIRE EN1
33.74 ± 0.98	16567.	2671.	4004.	SWIRE EN1
45.18 ± 2.08	20089.	4849.	6049.	SWIRE EN1

Notes. $\sigma_{\text{clus.}}$ is the uncertainty taking into account clustering (see Sect. 4.5). $\sigma_{\text{clus.+calib.}}$ takes into account both clustering and calibration (Stansberry et al. 2007).

20 mJy, and a power-law decrease at smaller flux densities. The stacking counts are lower than the Lagache et al. (2004) model around 20 mJy (about 30%). Below 15 mJy, the stacking counts agree with this model. The Le Borgne et al. (2009) model agree quite well with our points below 20 mJy. The results at 160 μm will be discussed in Sect. 7.2.

6. New lower limits and estimates of the CIB at 24 μm , 70 μm and 160 μm

6.1. 24 μm CIB: lower limit and estimate

By integrating the measured 24 μm number counts between 35 μJy and 0.1 Jy, we can estimate a lower value of the CIB at this wavelength. The counts were integrated with a trapeze method. We estimated the uncertainty on the integral by adding (on 10000 realisations) a random Gaussian error to each data point with the σ given by the count uncertainties taking into account clustering. We then added the 4% calibration error of the instrument (Engelbracht et al. 2007). We found $2.26^{+0.09}_{-0.09} \text{ nW m}^{-2} \text{ sr}^{-1}$. The very bright source counts ($S_{24} > 0.1 \text{ Jy}$) are supposed to be euclidian ($dN/dS = C_{\text{euc}} S^{2.5}$). We used the three brightest points to estimate C_{euc} . We found a contribution to the CIB of $0.032^{+0.003}_{-0.003} \text{ nW m}^{-2} \text{ sr}^{-1}$. Consequently, very bright sources extrapolation is not critical for the CIB estimation (1% of CIB). The contribution of $S_{24} > 35 \mu\text{Jy}$ is thus $2.29^{+0.09}_{-0.09} \text{ nW m}^{-2} \text{ sr}^{-1}$ (cf. Table 7).

We might have wanted to estimate the CIB value at 24 μm . To do so, we needed to extrapolate the number counts on the faint end. Below 100 μJy , the number counts exhibit a power-law behavior (Fig. 5). We assumed that this behavior (of the form

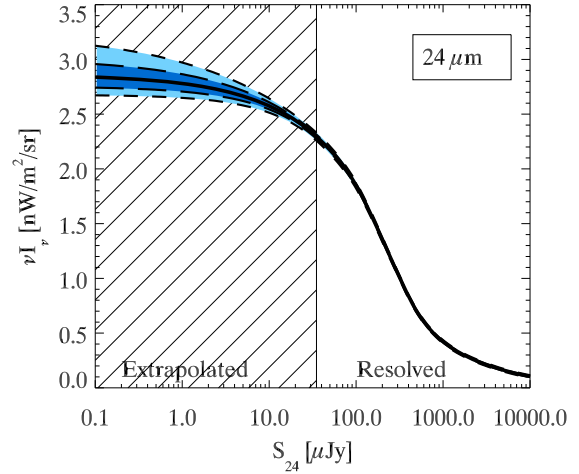


Fig. 9. Cumulative contribution to the surface brightness of the 24 μm CIB as a function of $S_{24 \mu\text{m}}$. The colored area represents the 68% and 95% confidence level. The shaded area represents the $S_{24} < 35 \mu\text{Jy}$ power-law extrapolation zone (see Sect. 6.1). The 4% calibration uncertainty is not represented. The table corresponding to this figure is available online at <http://www.ias.u-psud.fr/irgalaxies/>

Table 7. Summary of CIB results found in this article.

		24 μm	70 μm	160 μm
$S_{\text{cut,resolved}}$	mJy	0.035	3.50	40.0
$S_{\text{cut,stacking}}$		—	0.38	3.1
$\nu B_{\nu,\text{resolved}}$	$\text{nW m}^{-2} \text{sr}^{-1}$	$2.29^{+0.09}_{-0.09}$	$3.1^{+0.2}_{-0.2}$	$1.0^{+0.1}_{-0.1}$
$\nu B_{\nu,\text{resolved+stacking}}$		—	$5.4^{+0.4}_{-0.4}$	$8.9^{+1.1}_{-1.1}$
$\nu B_{\nu,\text{tot}}$		$2.86^{+0.19}_{-0.16}$	$6.6^{+0.7}_{-0.6}$	$14.6^{+7.1}_{-2.9}$

$dN/dS = C_{\text{faint}} S^r$) still holds below 35 μJy . r and C_{faint} are determined using the four faintest bins. We found $r = 1.45 \pm 0.10$ (compatible with 1.5 ± 0.1 of Papovich et al. 2004). Our new estimate of the CIB at 24 μm due to infrared galaxies is thus $2.86^{+0.19}_{-0.16} \text{ nW m}^{-2} \text{ sr}^{-1}$. The results are plotted in Fig. 9. We conclude that resolved sources down to $S_{24} = 35 \mu\text{Jy}$ account for 80% of the CIB at this wavelength.

6.2. 70 μm and 160 μm CIB: lower limit and estimate

At 70 μm and 160 μm , the integration of the number counts was done in the same way as at 24 μm , except for the stacking counts, which are correlated. To compute the uncertainties on the integral, we added (on 10000 realizations) a Gaussian error simultaneously to the three quantities and completely recomputed the associated stacking counts: 1- the mean density flux given by the stacking; 2- the 24 μm number counts; 3- the mean 24 μm flux density. At 70 μm , and 160 μm , the calibration uncertainty is 7% (Gordon et al. 2007) and 12% (Stansberry et al. 2007), respectively. We estimated the CIB surface brightness contribution of resolved sources ($S_{70} > 3.5 \text{ mJy}$ and $S_{160} > 40 \text{ mJy}$) of $3.1^{+0.2}_{-0.2} \text{ nW m}^{-2} \text{ sr}^{-1}$ and $1.0^{+0.1}_{-0.1} \text{ nW m}^{-2} \text{ sr}^{-1}$. The contribution of $S_{70} > 0.38 \text{ mJy}$ and $S_{160} > 3.1 \text{ mJy}$ is $5.4^{+0.4}_{-0.4} \text{ nW m}^{-2} \text{ sr}^{-1}$ and $8.9^{+1.1}_{-1.1} \text{ nW m}^{-2} \text{ sr}^{-1}$, respectively.

Below 2 mJy at 70 μm , and 10 mJy at 160 μm , the stacking counts are compatible with a power-law. Like at 24 μm , we assumed that this behavior can be extrapolated and determined the law with the five faintest bins at 70 μm , and the four faintest at 160 μm . We found a slope $r = 1.50 \pm 0.14$ at 70 μm , and

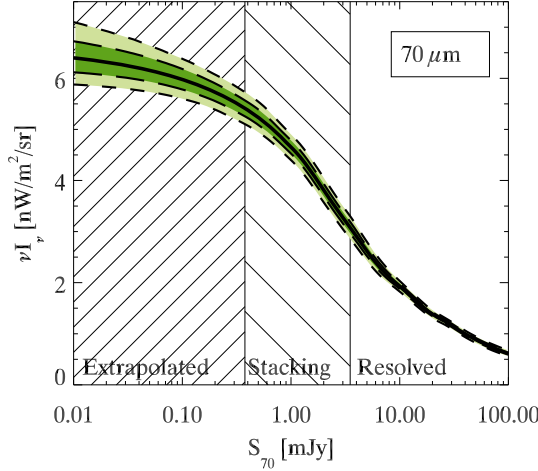


Fig. 10. Cumulative contribution to the surface brightness of the $70\ \mu\text{m}$ CIB as a function of $S_{70\ \mu\text{m}}$. The colored area represents the 68% and 95% confidence level. The shaded areas represent the $0.38 < S_{70} < 3.3$ mJy stacking counts zone and the $S_{70} < 0.38$ mJy power-law extrapolation zone (see Sect. 6.2). The 7% calibration uncertainty is not represented. The table corresponding to this figure is available online at <http://www.ias.u-psud.fr/irgalaxies/>

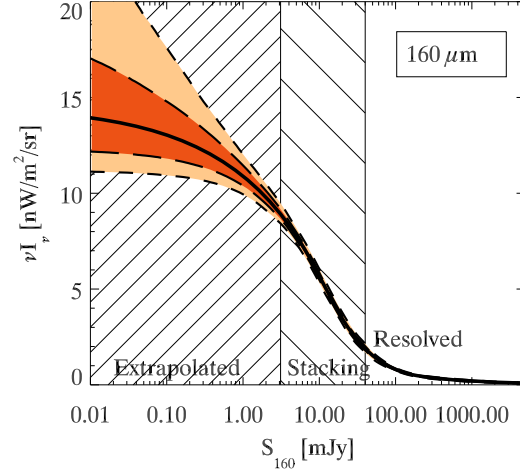


Fig. 11. Cumulative contribution to the surface brightness of the $160\ \mu\text{m}$ CIB as a function of $S_{160\ \mu\text{m}}$. The colored area represents the 68% and 95% confidence level. The shaded areas represent the $3.1 < S_{160} < 45$ mJy stacking counts zone and the $S_{160} < 3.1$ mJy power-law extrapolation zone (see Sect. 6.2). The 12% calibration uncertainty is not represented. The table corresponding to this figure is available online at <http://www.ias.u-psud.fr/irgalaxies/>

1.61 ± 0.21 at $160\ \mu\text{m}$. The slope of the number counts at $70\ \mu\text{m}$ is compatible with the Frayer et al. (2006) value (1.63 ± 0.34). The slope at $160\ \mu\text{m}$ is measured for the first time. Our new estimate of the CIB at $70\ \mu\text{m}$ and $160\ \mu\text{m}$ due to infrared galaxies is thus $6.6^{+0.7}_{-0.6}\ \text{nW m}^{-2}\ \text{sr}^{-1}$, and $14.6^{+7.1}_{-2.9}\ \text{nW m}^{-2}\ \text{sr}^{-1}$, respectively. We conclude that resolved and stacking-studied populations account for 82% and 62% of the CIB at $70\ \mu\text{m}$ and $160\ \mu\text{m}$, respectively. These results are summarized in Table 7, and Figs. 10 and 11.

7. Discussion

7.1. New lower limits of the CIB

The estimations of CIB based on number counts ignore a potential diffuse infrared emission like dust in galaxy clusters (Montier & Giard 2005). The extrapolation of the faint source counts supposes no low luminosity population, like population III stars or faint unseen galaxies. Accordingly, this type of measurement can provide in principle only a lower limit.

At $24\ \mu\text{m}$, Papovich et al. (2004) found $2.7^{+0.7}_{-1.1}\ \text{nW m}^{-2}\ \text{sr}^{-1}$ using the counts and the extrapolation of the faint source counts. We agree with this work and significantly reduced the uncertainties on this estimation. Dole et al. (2006) found a contribution of $1.93 \pm 0.23\ \text{nW m}^{-2}\ \text{sr}^{-1}$ for $S_{24} > 60\ \mu\text{Jy}$ sources (after dividing their results by 1.12 to correct an aperture error in their photometry at $24\ \mu\text{m}$). Our analysis gives $2.10 \pm 0.08\ \text{nW m}^{-2}\ \text{sr}^{-1}$ for a cut at $60\ \mu\text{Jy}$, which agrees very well. Rodighiero et al. (2006) gave a total value of $2.6\ \text{nW m}^{-2}\ \text{sr}^{-1}$, without any error bar. Chary et al. (2004) found $2.0 \pm 0.2\ \text{nW m}^{-2}\ \text{sr}^{-1}$, by integrating sources between 20 and $1000\ \mu\text{Jy}$ (we find 2.02 ± 0.10 for the same interval).

At $70\ \mu\text{m}$, using the number counts in the ultra deep GOODS-N and a P(D) analysis, Frayer et al. (2006) found a $S_{70} > 0.3\ \text{mJy}$ source contribution to the $70\ \mu\text{m}$ CIB of $5.5 \pm 1.1\ \text{nW m}^{-2}\ \text{sr}^{-1}$. Using the stacking counts, we found $5.5 \pm 0.4\ \text{nW m}^{-2}\ \text{sr}^{-1}$ for the same cut, in excellent agreement and with improved uncertainties. In Dole et al. (2006), the contribution at $70\ \mu\text{m}$ of the $S_{24} < 60\ \mu\text{Jy}$ sources was

computed with an extrapolation of the $24\ \mu\text{m}$ number counts and the $70/24$ color. They found $7.1 \pm 1.0\ \text{nW m}^{-2}\ \text{sr}^{-1}$, but the uncertainty on the extrapolation took only into account the uncertainty on the $70/24$ color and not the uncertainty on the extrapolated $24\ \mu\text{m}$ contribution, and was thus slightly underestimated. This is in agrees with our estimation.

At $160\ \mu\text{m}$ they found with the same method, $17.4 \pm 2.1\ \text{nW m}^{-2}\ \text{sr}^{-1}$ (a corrective factor of 1.3 was applied due to an error on the map pixel size). This estimation is a little bit higher than our estimation, and can be explained by a small contribution (of the order of 15%) of the source clustering (Bavouzet 2008).

Our results can also be compared with direct measurements made by absolute photometers. These methods are biased by the foreground modeling, but do not ignore the extended emission. Fixsen et al. (1998) found a CIB brightness of 13.7 ± 3.0 at $160\ \mu\text{m}$, in excellent agreement with our estimation ($14.6^{+7.1}_{-2.9}\ \text{nW m}^{-2}$). From the discussion in Dole et al. (2006) (Sect. 4.1), the Lagache et al. (2000) DIRBE WHAM (FIRAS calibration) estimation at $140\ \mu\text{m}$ and $240\ \mu\text{m}$ of $12\ \text{nW m}^{-2}\ \text{sr}^{-1}$ and $12.2\ \text{nW m}^{-2}\ \text{sr}^{-1}$ can be also compared with our value at $160\ \mu\text{m}$. A more recent work of Odegard et al. (2007) found 25.0 ± 6.9 and $13.6 \pm 2.5\ \text{nW m}^{-2}\ \text{sr}^{-1}$ at $140\ \mu\text{m}$ and $240\ \mu\text{m}$ respectively (resp. $15 \pm 5.9\ \text{nW m}^{-2}\ \text{sr}^{-1}$ and $12.7 \pm 1.6\ \text{nW m}^{-2}\ \text{sr}^{-1}$ with the FIRAS scale). Using ISOPHOT data, Juvela et al. (2009) give an estimation of the CIB surface brightness between $150\ \mu\text{m}$ and $180\ \mu\text{m}$ of $20.25 \pm 6.0 \pm 5.6\ \text{nW m}^{-2}\ \text{sr}^{-1}$.

The total brightness due to infrared galaxies at $160\ \mu\text{m}$ corresponds to the total CIB level at this wavelength. We thus have probably resolved the CIB at this wavelength. Nevertheless, the uncertainties are relatively large, and other minor CIB contributors cannot be excluded.

In addition, upper limits can be deduced indirectly from blazar high energy spectrum. Stecker & de Jager (1997) gave an upper limit of $4\ \text{nW m}^{-2}\ \text{sr}^{-1}$ at $20\ \mu\text{m}$ using Mkn 421. Renault et al. (2001) found an upper limit of $4.7\ \text{nW m}^{-2}\ \text{sr}^{-1}$ between 5 and $15\ \mu\text{m}$ with Mkn 501. This is consistent with our lower limit at $24\ \mu\text{m}$.

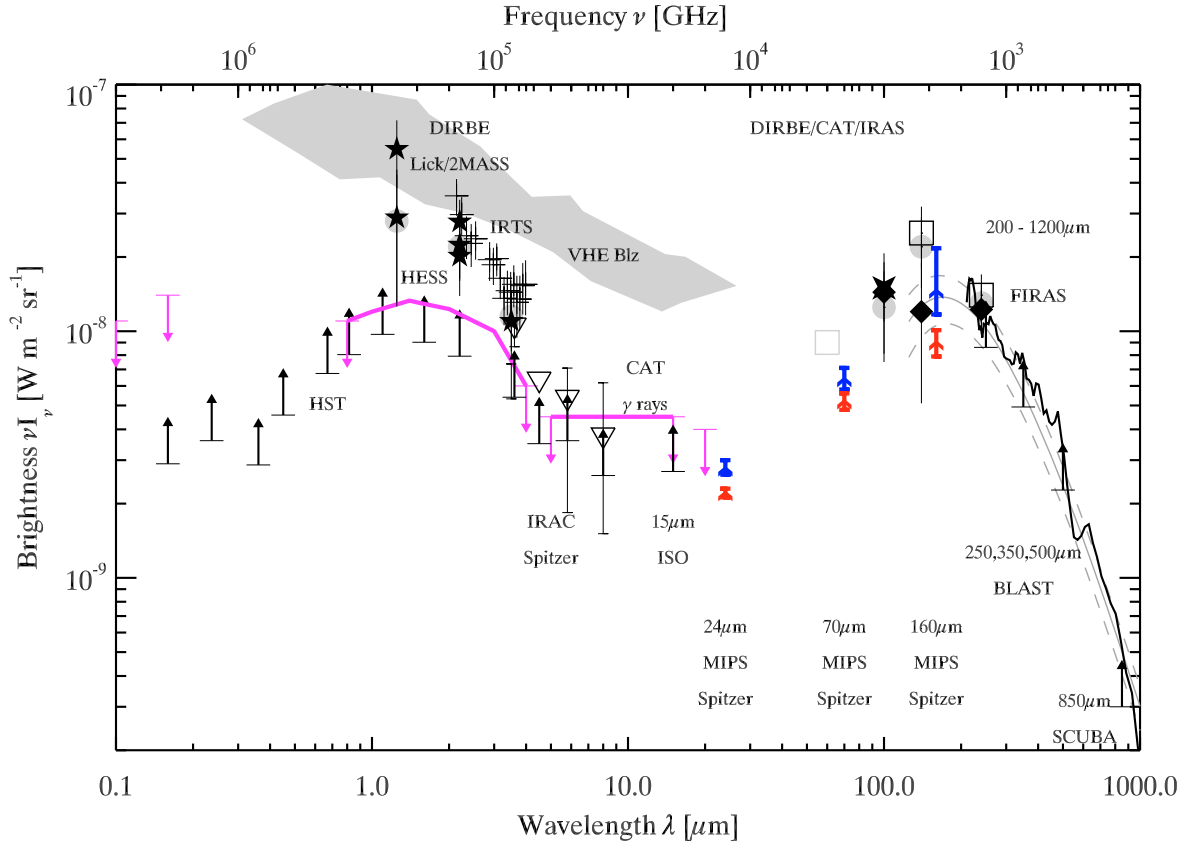


Fig. 12. Current measurement of the extragalactic background light spectral energy distribution from 100 nm to 1 mm, with the cosmic optical background (COB, $\lambda < 8 \mu\text{m}$) and cosmic infrared background (CIB, $\lambda > 8 \mu\text{m}$). Our new points at $24 \mu\text{m}$, $70 \mu\text{m}$ and $160 \mu\text{m}$ are plotted (triangle). Lower (red) triangles correspond to the CIB resolved with the number counts and stacking counts. Upper (blue) triangles correspond to the total extrapolated CIB due to infrared galaxies. BLAST lower limits at $250 \mu\text{m}$, $350 \mu\text{m}$ and $500 \mu\text{m}$ (Devlin et al. 2009; Marsden et al. 2009) are represented in black arrows. The FIRAS measurements of Fixsen et al. (1998) between $125 \mu\text{m}$ and $2000 \mu\text{m}$ are plotted with a grey solid line, and the $1-\sigma$ confidence region with a grey dashed line. Other points come from different authors (see Dole et al. (2006) for complete details). Old MIPS points are not plotted for clarity.

An update of the synthetic EBL SED of Dole et al. (2006) with the new BLAST (balloon-borne large-aperture submillimeter telescope) lower limits from Devlin et al. (2009) and our values is plotted in Fig. 12. The BLAST lower limits are obtained by stacking of the Spitzer $24 \mu\text{m}$ sources at $250 \mu\text{m}$, $350 \mu\text{m}$ and $500 \mu\text{m}$ (Devlin et al. 2009; Marsden et al. 2009).

7.2. $160 \mu\text{m}$ number counts

At most, we observed a 30% overestimation of the Lagache et al. (2004) model compared to the $160 \mu\text{m}$ number counts (Sect. 4.4 and 5.3 and Fig. 7), despite good fits at other wavelengths. This model uses mean SEDs of galaxies sorted into two populations (starburst and cold), whose luminosity functions evolve separately with the redshift. A possible explanation of the model excess is a slightly too high density of local cold galaxies. By decreasing the density of this local population a little, the model might be able to better fit the $160 \mu\text{m}$ number counts without significantly affecting other wavelengths, especially at $70 \mu\text{m}$ (more sensitive to warm dust rather than cold dust), and in the submillimetre range (more sensitive to redshifted cold dust at faint flux densities for wavelengths larger than $500 \mu\text{m}$).

The Le Borgne et al. (2009) model slightly overpredicts faint $160 \mu\text{m}$ sources, probably because of the presence of too many

galaxies at high redshift; this trend is also seen at $70 \mu\text{m}$. With our number counts as new constraints, their inversion should give more accurate parameters.

Herschel was successfully launched on May 14th, 2009 (together with *Planck*). It will observe infrared galaxies between $70 \mu\text{m}$ and $500 \mu\text{m}$ with an improved sensitivity. It will be possible to directly observe the cold dust spectrum of high- z ULIRG (ultra luminous infrared galaxy) and medium- z LIRG (luminous infrared galaxy). PACS (Photodetectors Array Camera and Spectrometer) will make photometric surveys in three bands centred on $70 \mu\text{m}$, $100 \mu\text{m}$ and $160 \mu\text{m}$. *Herschel* will allow us to resolve a significant fraction of the background at these wavelengths (Lagache et al. 2003; Le Borgne et al. 2009). SPIRE (spectral and photometric imaging receiver) will observe around $250 \mu\text{m}$, $350 \mu\text{m}$ and $500 \mu\text{m}$, and will be quickly confusion limited. In both cases, the stacking analysis will allow us to probe fainter flux density levels, as it is complementary to *Spitzer* and BLAST.

8. Conclusion

With a large sample of public *Spitzer* extragalactic maps, we built new deep, homogeneous, high-statistics number counts in three MIPS bands at $24 \mu\text{m}$, $70 \mu\text{m}$ and $160 \mu\text{m}$.

At 24 μm , the results agree with previous works. These counts are derived from the widest surface ever used at this wavelength (53.6 deg²). Using these counts, we give an accurate estimation of the galaxy contribution to the CIB at this wavelength ($2.86^{+0.19}_{-0.16} \text{ nW m}^{-2} \text{ sr}^{-1}$).

At 70 μm , we used the stacking method to determine the counts below the detection limit of individual sources, by reaching 0.38 mJy, allowing us to probe the faint flux density slope of differential number counts. With this information, we deduced the total contribution of galaxies to the CIB at this wavelength ($6.6^{+0.7}_{-0.6} \text{ nW m}^{-2} \text{ sr}^{-1}$).

At 160 μm , our counts reached 3 mJy with a stacking analysis. We exhibited for the first time the maximum in differential number counts around 20 mJy and the power-law behavior below 10 mJy. We deduced the total contribution of galaxies to the CIB at this wavelength ($14.6^{+7.1}_{-2.9} \text{ nW m}^{-2} \text{ sr}^{-1}$). *Herschel* will likely probe flux densities down to about 10 mJy at this wavelength (confusion limit, Le Borgne et al. (2009)).

The uncertainties on the number counts used in this work take carefully into account the galaxy clustering, which is measured with the “counts-in-cells” method.

We presented a method to build very deep number counts with the information provided by shorter wavelength data (MIPS 24 μm) and a stacking analysis. This tool could be used on *Herschel* SPIRE data with a PACS prior to probe fainter flux densities in the submillimetre range.

We publicly release on the website <http://www.ias.u-psud.fr/irgal/>, the following products: PSF, number counts and CIB contributions. We also release a stacking library software written in IDL.

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Appendix A: Uncertainties on number counts including clustering

A.1. Counts-in-cells moments

We consider a clustered population with a surface density ρ . The expected number of objects in a field of the size Ω is $\bar{N} = \rho\Omega$. In the Poissonian case, the standard deviation around this value is $\sqrt{\bar{N}}$. For a clustered distribution, the standard deviation σ_N is given by (Wall & Jenkins 2003)

$$\sigma_N = \sqrt{y \cdot \bar{N}^2 + \bar{N}}. \quad (\text{A.1})$$

The expected value of y is given by (Peebles 1980)

$$y = \frac{\int_{\text{field}} \int_{\text{field}} w(\theta) d\Omega_1 d\Omega_2}{\Omega^2}, \quad (\text{A.2})$$

where $w(\theta)$ is the angular two points auto correlation function of the sources.

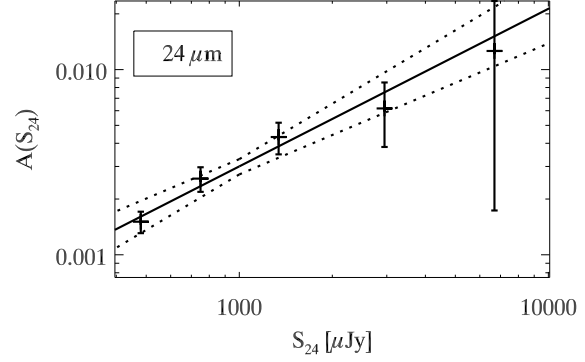


Fig. A.1. Amplitude of the auto correlation as a function of the flux density of the sources at 24 μm , and best power-law fit.

A.2. Measuring source clustering as a function of flux density

We assume the classical power law description $w(\theta) = A(S, \lambda)\theta^{1-\gamma}$ with an index $\gamma = 1.8$. So, y depends only on A and on the shape of the field:

$$y = A(S, \lambda) \frac{\int_{\text{field}} \int_{\text{field}} \theta^{1-\gamma} d\Omega_1 d\Omega_2}{\Omega^2}. \quad (\text{A.3})$$

The uncertainty on y is given by (Szapudi 1998):

$$\sigma_y = \sqrt{\frac{2}{N_{\text{cell}} \bar{N}^2}}. \quad (\text{A.4})$$

To measure $A(S, \lambda)$, we cut our fields in 30' $\times$ 30' square boxes, in which we count the number of sources and compute the variance in five, three and three flux density bins at 24 μm , 70 μm and 160 μm . We calculate the associate $A(S, \lambda)$ combining Eqs. (A.1) and (A.3)

$$A(S, \lambda) = \frac{\sigma_N^2 - \bar{N}}{\bar{N}^2} \times \frac{\Omega^2}{\int_{\text{field}} \int_{\text{field}} \theta^{1-\gamma} d\Omega_1 d\Omega_2}. \quad (\text{A.5})$$

The fit of $A(S_{24}, 24 \mu\text{m})$ versus S_{24} (see Fig. A.1) gives ($\chi^2 = 2.67$ for five points and two fitted parameters)

$$A(S, 24 \mu\text{m}) = (2.86 \pm 0.29) \times 10^{-3} \left(\frac{S}{1 \text{ mJy}} \right)^{0.90 \pm 0.15}. \quad (\text{A.6})$$

The measured exponent in A.6 of 0.90 ± 0.15 corresponds to $\gamma/2$, which is the expected value in the case of a flux-limited survey in an Euclidean universe filled with single luminosity sources. We fix this exponent to fit $A(S_{70}, 70 \mu\text{m})$ and $A(S_{160}, 160 \mu\text{m})$. We find $A(1 \text{ mJy}, 70 \mu\text{m}) = (0.25 \pm 0.08) \cdot 10^{-3}$ and $A(1 \text{ mJy}, 160 \mu\text{m}) = (0.3 \pm 0.03) \cdot 10^{-3}$.

A.3. Compute uncertainties due to clustering

With this model of $A(S, \lambda)$ and the field shape, we compute y (Eq. (A.3)). Assuming $\bar{N} = N$ (N to be the number of detected sources in a given field and flux density bin), we deduce $\sigma(N)$ from Eq. (A.1), and consequently the error bar on the number counts for a single field.

To compute the final uncertainty on the combined counts, we use the following relation

$$\sigma_{\text{comb}, \frac{dN}{dS}} = \frac{\sqrt{\sum_i \Omega_i^2 \sigma_{i, \frac{dN}{dS}}^2}}{\sum_i \Omega_i}, \quad (\text{A.7})$$

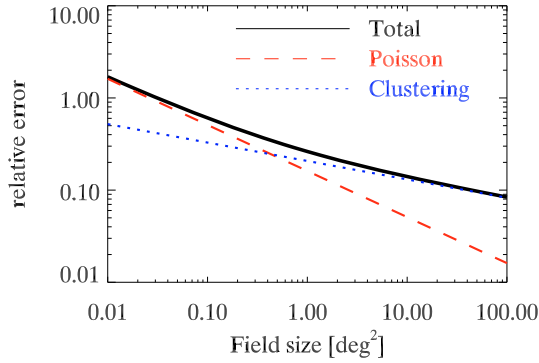


Fig. A.2. Relative error on the number count as a function of the field size. We have chosen $A = 0.019$ and $\rho = 38.5 \text{ deg}^{-2}$ (values for a 80–120 mJy flux density bin at $160 \mu\text{m}$). The field is a square.

where $\sigma_{\text{comb}, \frac{dN}{d\Omega}}$ is the uncertainty on the combined number counts, Ω_i the solid angle of the i th field, and $\sigma_{i, \frac{dN}{d\Omega}}$ the uncertainty on the number counts in the i th field (given by $\text{Var}(N)$, Eq. (A.1)).

A.4. Discussion about clustering and number count uncertainties

For a clustered distribution of sources, the uncertainties on the number counts are driven by two quadratically combined terms (Eq. (A.1)): a Poissonian term $\sqrt{N}$ and a clustering term $\sqrt{y} \cdot N$ (see Fig. A.2). We have $N \propto \Omega$ and $y \propto \Omega^{(\gamma-1)/2}$ (Blake & Wall 2002). When the uncertainty is dominated by the Poissonian term (small field), the relative uncertainty is thus proportional to $\sqrt{\Omega}^{-1/2}$. When the uncertainty is dominated by the clustering term (large field), the relative error is proportional to $\Omega^{(1-\gamma)/4}$ ($\Omega^{-0.2}$ for $\gamma = 1.8$).

Consequently uncertainties decrease very slowly in the clustering regime. Averaging many small independent fields gives more accurate counts than a big field covering the same surface. For example, in the clustering regime, if a field of 10 deg^2 has a relative uncertainty of 0.2, the relative uncertainty is $0.2/\sqrt{10} = 0.063$ for the mean of ten fields of this size, and $0.2 \times 10^{-0.2} = 0.126$ for a single field of 100 deg^2 . Consequently, if one studies the counts only, many small fields give better results than one very large field. But, this is not optimal if one studies the spatial properties of the galaxies, which requires large fields.

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5.4 Article : *Submillimeter number counts at 250 μm , 350 μm and 500 μm in BLAST data*

Les résultats présentés Chap. 2, 3 et 5 et concernant les comptages de sources et le CIB dans les bandes BLAST ont été publiés dans le journal *Astronomy&Astrophysics*.

Submillimeter number counts at 250 μm , 350 μm and 500 μm in BLAST data

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ABSTRACT

Context. The instrument BLAST (Balloon-borne Large-Aperture Submillimeter Telescope) performed the first deep and wide extragalactic survey at 250, 350 and 500 μm . The extragalactic number counts at these wavelengths are important constraints for modeling the evolution of infrared galaxies.

Aims. We estimate the extragalactic number counts in the BLAST data, which allow a comparison with the results of the P(D) analysis of Patanchon et al. (2009).

Methods. We use three methods to identify the submillimeter sources. 1) Blind extraction using an algorithm when the observed field is confusion-limited and another one when the observed field is instrumental-noise-limited. The photometry is computed with a new simple and quick point spread function (PSF) fitting routine (FASTPHOT). We use Monte-Carlo simulations (addition of artificial sources) to characterize the efficiency of this extraction, and correct the flux boosting and the Eddington bias. 2) Extraction using a prior. We use the *Spitzer* 24 μm galaxies as a prior to probe slightly fainter submillimeter flux densities. 3) A stacking analysis of the *Spitzer* 24 μm galaxies in the BLAST data to probe the peak of the differential submillimeter counts.

Results. With the blind extraction, we reach 97 mJy, 83 mJy and 76 mJy at 250 μm , 350 μm and 500 μm respectively with a 95% completeness. With the prior extraction, we reach 76 mJy, 63 mJy, 49 mJy at 250 μm , 350 μm and 500 μm respectively. With the stacking analysis, we reach 6.2 mJy, 5.2 mJy and 3.5 mJy at 250 μm , 350 μm and 500 μm respectively. The differential submillimeter number counts are derived, and start showing a turnover at flux densities decreasing with increasing wavelength.

Conclusions. There is a very good agreement with the P(D) analysis of Patanchon et al. (2009). At bright fluxes (>100 mJy), the Lagache et al. (2004) and Le Borgne et al. (2009) models slightly overestimate the observed counts, but the data agree very well near the peak of the differential number counts. Models predict that the galaxy populations probed at the peak are likely $z \sim 1.8$ ultra-luminous infrared galaxies.

Key words. cosmology: observations – galaxies: statistics – galaxies: evolution – galaxies: photometry – infrared: galaxies

1. Introduction

Galaxy number counts, a measurement of the source surface density as a function of flux density, are used to evaluate the global evolutionary photometric properties of a population observed at a given wavelength. These photometric properties mainly depend on the source redshift distribution, spectral energy distribution (SED), and luminosity distribution in a degenerate way for a given wavelength. Even though this is a rather simple tool, measurements of number counts at different observed wavelengths greatly help in constraining those degeneracies. Backward evolution models, among these Chary & Elbaz (2001); Lagache et al. (2004); Gruppioni et al. (2005); Franceschini et al. (2009); Le Borgne et al. (2009); Pearson & Khan (2009); Rowan-Robinson (2009); Valiante et al. (2009) are able to broadly reproduce (with different degrees of accuracy) the observed number counts from the near-infrared to the millimeter spectral ranges, in addition to other current constraints, like such as measured luminosity functions and the spectral energy distribution of the Cosmic Infrared Background (CIB) (Puget et al. 1996; Fixsen et al. 1998; Hauser et al. 1998; Lagache et al. 1999; Gispert et al. 2000; Hauser & Dwek 2001; Kashlinsky 2005; Lagache et al. 2005; Dole et al. 2006). In the details, however, the models disagree in some aspects like the relative evolution of luminous and ultra-luminous infrared

galaxies (LIRG and ULIRG) and their redshift distributions, or the mean temperature or colors of galaxies, as is shown for instance in LeFloc'h et al. (2009) from *Spitzer* 24 μm deep observations.

One key spectral range lacks valuable data to get accurate constraints as yet: the sub-millimeter range, between 160 μm and 850 μm , where some surveys were conducted on small areas. Fortunately this spectral domain is intensively studied with the BLAST balloon experiment (Devlin et al. 2009) and the *Herschel* and *Planck* space telescopes. This range, although it is beyond the maximum of the CIB's SED in wavelength, allows us to constrain the poorly-known cold component of galaxy SED at a redshift greater than a few tenths. Pioneering works have measured the local luminosity function (Dunne et al. 2000) and shown that most milli-Jansky sources lie at redshifts $z > 2$ (Ivion et al. 2002; Chapman et al. 2003a, 2005; Ivison et al. 2005; Pope et al. 2005, 2006). Other works showed that the galaxies SED selected in the submillimeter range (Benford et al. 1999; Chapman et al. 2003b; Sajina et al. 2003; Lewis et al. 2005; Beelen et al. 2006; Kovács et al. 2006; Sajina et al. 2006; Michałowski et al. 2010) can have typically warmer temperatures and higher luminosities than galaxies selected at other infrared wavelengths.

Data in the submillimeter wavelength with increased sensitivity are thus needed to match the depth of infrared surveys,

conducted by Spitzer in the mid- and far-infrared with the MIPS instrument (Rieke et al. 2004) at 24 μm , 70 μm and 160 μm (Chary et al. 2004; Marleau et al. 2004; Papovich et al. 2004; Dole et al. 2004; Frayer et al. 2006a,b; Rodighiero et al. 2006; Shupe et al. 2008; Frayer et al. 2009; LeFloc’h et al. 2009; Béthermin et al. 2010) as well as the near-infrared range with the IRAC instrument (Fazio et al. 2004b) between 3.6 μm and 8.0 μm (Fazio et al. 2004a; Franceschini et al. 2006; Sullivan et al. 2007; Barmby et al. 2008; Magdis et al. 2008; Ashby et al. 2009). Infrared surveys have allowed the resolution of the CIB by identifying the contributing sources – directly at 24 μm and 70 μm , or indirectly through stacking at 160 μm (Dole et al. 2006; Béthermin et al. 2010).

Although large surveys cannot solve by themselves all the unknowns about the submillimeter SED of galaxies, the constraints given by the number counts can greatly help in unveiling the statistical SED shape of submillimeter galaxies as well as the origin of the submillimeter background.

The instrument BLAST (Balloon-borne Large-Aperture Submillimeter Telescope, Pascale et al. 2008) performed the first wide and deep survey in the 250–500 μm range (Devlin et al. 2009) before the forthcoming *Herschel* results. Marsden et al. (2009) show that sources detected by *Spitzer* at 24 μm emit the main part of the submillimeter background. Khan et al. (2009) claimed that only 20% of the CIB is resolved by the sources brighter than 17 mJy at 350 μm . Patanchon et al. (2009) has performed a $P(D)$ fluctuation analysis to determine the counts at BLAST wavelength (250 μm , 350 μm and 500 μm). In this paper we propose another method to estimate the number counts at these wavelengths and compare the results with those of Patanchon et al. (2009).

2. Data

2.1. BLAST sub-millimeter public data in the Chandra Deep Field South (CDFS)

The BLAST holds a bolometer array, which is the precursor of the spectral and photometric imaging receiver (SPIRE) instrument on *Herschel*, at the focus of a 1.8 m diameter telescope. It observes at 250 μm , 350 μm and 500 μm , with a 36'', 42'' and 60'' beam, respectively (Truch et al. 2009).

An observation of the Chandra Deep Field South (CDFS) was performed during a long duration flight in Antarctica in 2006, and the data of the two surveys are now public: a 8.7 deg² shallow field and a 0.7 deg² confusion-limited (Dole et al. 2004) field in the center part of the first one. We use the non-beam-smoothed maps and associated point spread function (PSF) distributed on the BLAST website¹. The signal and noise maps were generated by the SANEPIC algorithm (Patanchon et al. 2008).

2.2. Spitzer 24 μm data in the CDFS

Several infrared observations were performed in the CDFS. The *Spitzer* Wide-Field InfraRed Extragalactic (SWIRE) survey overlaps the CDFS BLAST field at wavelengths between 3.6 μm and 160 μm . We used only the 24 μm band, which is 80% complete at 250 μJy . The completeness is defined as the probability to find a source of a given flux in a catalog. The Far-Infrared Deep Extragalactic Legacy (FIDEL) survey is deeper but narrower (about 0.25 deg²) than SWIRE and 80% complete

at 57 μJy at 24 μm . We used the Béthermin et al. (2010) catalogs constructed from these two surveys. These catalogs were extracted with SExtractor (Bertin & Arnouts 1996) and the photometry was performed with the allstar routine of the DAOPHOT package (Stetson 1987). The completeness of this catalog was characterized with Monte-Carlo simulations (artificial sources added on the initial map and extracted).

3. Blind source extraction and number counts

We started with a blind source extraction in the BLAST bands. Each wavelength was treated separately. For each wavelength we defined two masks: a shallow zone (about 8.2 deg²) covering the whole field except the noisier edge; and a deep zone (about 0.45 deg²) in the center of the confusion-limited area. We used different extraction methods in the shallow zone and the deep one, but the photometry and the corrections of the extraction bias were the same.

3.1. Detector noise-limited extraction (shallow zone)

In the shallow zone we used the non-smoothed map and the corresponding map of the standard deviation of the noise. The map was then cross-correlated by the PSF. The result of this cross-correlation is

$$m_{\text{conv}}(i_0, j_0) = \sum_{i=-N}^{+N} \sum_{j=-N}^{+N} m(i, j) \times \text{PSF}(i, j), \quad (1)$$

where $m_{\text{conv}}(i_0, j_0)$ is the flux density in the pixel (i_0, j_0) of the cross-correlated map, $m(i, j)$ the flux density in the pixel (i, j) of the map, and $\text{PSF}(i, j)$ the value of the normalized PSF in the pixel (i, j) (the center of the PSF is in the center of the pixel $(0, 0)$). The PSF size is $(2N + 1) \times (2N + 1)$ pixels. The standard deviation of the noise in the cross-correlated map is thus

$$n_{\text{conv}}(i_0, j_0) = \sqrt{\sum_{i=-N}^{+N} \sum_{j=-N}^{+N} n^2(i, j) \times \text{PSF}^2(i, j)}, \quad (2)$$

where n (n_{conv}) is the initial (cross-correlated) map of the standard deviation of the noise.

We found the pixels where $m_{\text{conv}}/n_{\text{conv}} > 3$ and kept the local maxima. The precise center of the detected sources was computed by a centroid algorithm. This low threshold caused lots of spurious detections, but helped to deblend the fluxes of 3 to 4-sigma sources and avoided to overestimate their fluxes. We could thus limit the flux boosting effect. A final cut in flux after the PSF fitting photometry eliminated the main part of these sources. We performed the extraction algorithm on the flipped map (initial map multiplied by a factor of -1) to check it. We found few spurious sources brighter than the final cut in flux determined in the Sect. 3.4. We found a spurious rate of 12%, 11% and 25% at 250 μm , 350 μm and 500 μm , respectively.

3.2. Confusion-limited extraction (deep zone)

In the confusion-limited zone we also used a non-smoothed map. In this region the noise is dominated by the confusion and not by the instrumental noise. Consequently, the method based on instrumental noise presented in the Sect. 3.1 is not relevant. We used an a trous wavelet filtering (Starck et al. 1999; Dole et al. 2001) to remove fluctuations at scales larger than 150''. Then we divided the resulting map by $\sigma_{\text{filtered map}}$, which is the standard

¹ <http://www.blastexperiment.info>

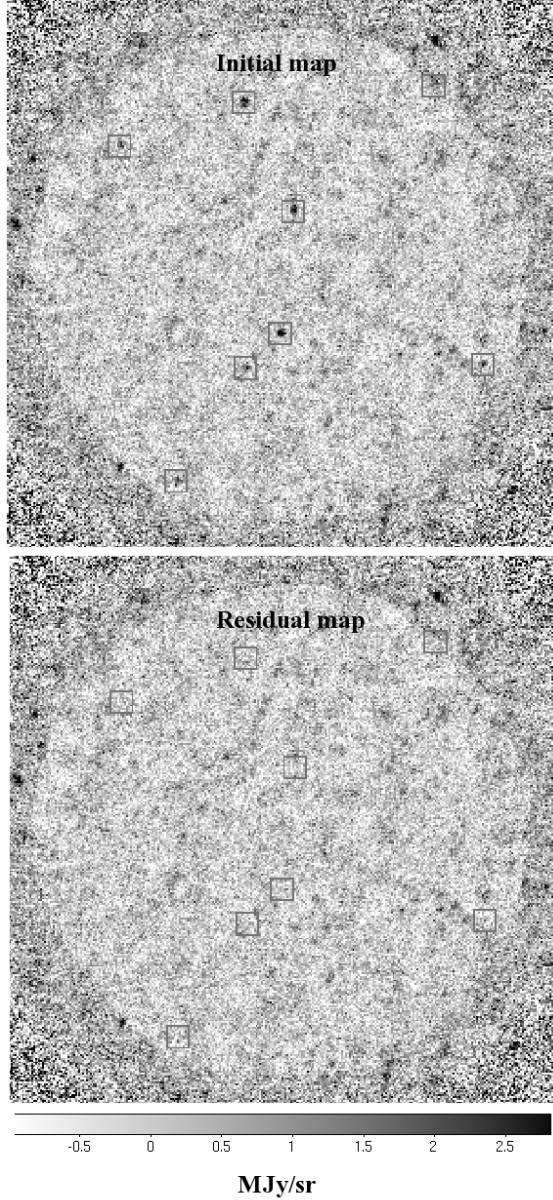


Fig. 1. Position of sources brighter than the 95% completeness flux at $250\ \mu\text{m}$ in deep zone. *Top*: initial map. *Bottom*: residual map. The area out of the mask are represented darker. These $1^\circ \times 1^\circ$ map are centered on the coordinates (RA, Dec) = (3h32min30s, $-27^\circ 50'$). The horizontal axis is aligned with the right ascension.

deviation of the pixel values on the filtered map in the working area. We finally kept local maxima with a signal greater than 3. The center of the sources was also determined by a centroid algorithm. The initial map and the cleaned map are shown in Fig. 1. When we flip the map, we find no spurious source brighter than the final cut in flux determined in Sect. 3.4.

3.3. A simple and quick PSF fitting routine: FASTPHOT

For both noise- and confusion-limited extraction, we apply the same quick and simple PSF fitting routine on the non-beam-smoothed map. This routine fits all the detected sources at the

same time and is consequently efficient for deblending (although no source was blended in this case; but source-blending will be an issue for an extraction using a prior, detailed in Sect. 4. We suppose that the noise is Gaussian and the position of sources is known. We then maximize the likelihood

$$L(m|S) = \prod_{\text{pixels}} C(n) \times \exp \left[-\frac{\left(m - \sum_{i=1}^{N_{\text{sources}}} \text{PSF}_{x_i, y_i} \times S_i \right)^2}{2n^2} \right], \quad (3)$$

where m and n are the map and the noise map. PSF_{x_i, y_i} is a unit-flux PSF centered at the position (x_i, y_i) , which are the coordinates of the i th source. These coordinates are not necessarily integers. $C(n)$ is a normalization constant and depends only of the value of the noise map. S is a vector containing the flux of the sources.

The value of S , which maximizes the likelihood, satisfies the following linear equation stating that the derivative of the likelihood logarithm equals zero

$$\forall i, 0 = \frac{\partial \log(L(m|S))}{\partial S_i} = A \cdot S + B, \quad (4)$$

where A is a matrix and B a vector defined by

$$A = (a_{ij}) = - \sum_{\text{pixels}} \frac{\text{PSF}_{x_i, y_i} \times \text{PSF}_{x_j, y_j}}{n^2} \quad (5)$$

$$B = (b_i) = \sum_{\text{pixels}} \frac{\text{PSF}_{x_i, y_i} \times \text{map}}{n^2}. \quad (6)$$

To perform this operation fast, we used a $70'' \times 70''$ (respectively $90'' \times 90''$ and $110'' \times 110''$) PSF at $250\ \mu\text{m}$ (respectively $350\ \mu\text{m}$ and $500\ \mu\text{m}$). This PSF, provided by the BLAST team, is the response for a unit-flux source and takes into account all the filtering effects. We used the conjugate gradient method to solve the Eq. (4) quickly.

This routine was tested with 200×200 pixels simulated maps containing 400 sources at a known positions with a beam of 10 pixels *FWHM*. The flux of all sources was perfectly recovered in the case where no noise was added. This routine (FASTPHOT) performs simultaneous PSF fitting photometry of 1000 sources in less than 1 s. It is publicly available².

3.4. Completeness and photometric accuracy

The completeness is the probability to detect a source of a given flux density. We measured it with a Monte-Carlo simulation. We added artificial point sources (based on PSF) on the initial map at random positions and performed the same source extraction and photometry algorithm as for the real data. A source was considered to be detected if there was a detection in a $20''$ radius around the center of the source. Table 1 gives the 95% completeness flux density (for which 95% of sources at this flux are detected) for different wavelengths and depths.

The photometric noise was estimated with the scatter of the recovered fluxes of artificial sources. We computed the standard deviation of the difference between input and output flux. This measurement includes instrumental and confusion noise ($\sigma_{\text{tot}} = \sqrt{\sigma_{\text{instr}}^2 + \sigma_{\text{conf}}^2}$). The results are given in Table 1. In the deep

² On the IAS website <http://www.ias.u-psud.fr/irgalaxies/>

Table 1. 95% completeness flux density and photometric noise for different depths at different wavelengths.

	95% completeness		Instrumental noise		Total photometric noise		Deduced confusion noise	
	mJy		mJy		mJy		mJy	
	Shallow	Deep	Shallow	Deep	Shallow	Deep	Shallow	Deep
250 μm	203	97	37.7	11.1	47.3	24.9	28.6	22.3
350 μm	161	83	31.6	9.3	35.8	20.3	16.8	18.0
500 μm	131	76	20.4	6.0	26.4	17.6	16.7	16.5

Notes. The instrumental noise is given by the noise map. The total photometric noise includes the instrumental and confusion noise and is determined by Monte-Carlo simulations. The confusion noise is computed with the formula $\sigma_{\text{conf}} = \sqrt{\sigma_{\text{tot}}^2 - \sigma_{\text{instr}}^2}$.

area, the photometric uncertainties are thus dominated by the confusion noise. The estimations of the confusion noise between the deep and shallow areas are consistent. It shows the accuracy and the consistency of our method.

Note that the uncertainties on flux densities in the [Dye et al. \(2009\)](#) catalog (based only on instrumental noise) are consequently largely underestimated in the confusion-limited area. Indeed, their 5σ detection threshold (based only on instrumental noise) at 500 μm in the deep zone corresponds to 1.76σ if we also include the confusion noise.

The faint flux densities are overestimated due to the classical flux boosting effect. This bias was measured for all bands for 60 flux densities between 10 mJy and 3 Jy with the results of the Monte-Carlo simulations. The measured fluxes were deboosted with this relation. We cut the catalogs at the 95% completeness flux, where the boosting factor is at the order of 10%. Below this cut, the boosting effect increases too quickly to be safely corrected. We also observed a little underestimation at high flux of 1%, 0.5% and 0.5% at 250 μm , 350 μm and 500 μm . It is due to FASTPHOT, which assumes that the position is perfectly known, which is not true, especially for a blind extraction.

3.5. Number counts

We computed number counts with catalogs corrected for boosting. For each flux density bin we subtracted the number of spurious detections estimated in the Sects. 3.1 and 3.2 to the number of detected sources and divided the number of sources by the size of the bin, the size of the field and the completeness.

We also applied a corrective factor for the Eddington bias. We assumed a distribution of flux densities in $dN/dS \propto S^{-r}$ with $r = 3 \pm 0.5$. This range of possible values for r was estimated considering the [Patanchon et al. \(2009\)](#) counts and the [Lagache et al. \(2004\)](#) and [Le Borgne et al. \(2009\)](#) model predictions. We then randomly kept sources with a probability given by the completeness and added a random Gaussian noise to simulate photometric noise. Finally we computed the ratio between the input and output number of sources in each bin. We applied a correction computed for $r = 3$ to each point. We estimated the uncertainty on this correction with the difference between corrections computed for $r = 2.5$ and $r = 3.5$. This uncertainty was quadratically combined with a Poissonian uncertainty (clustering effects are negligible due to the little number of sources in the map, see Appendix A).

The calibration uncertainty of BLAST is 10%, 12% and 13% at 250 μm , 350 μm and 500 μm respectively ([Truch et al. 2009](#)). This uncertainty is combined with other uncertainties on the counts. The results are plotted in Fig. 2 and given in Table 2 and interpreted in Sect. 6.

3.6. Validation

We used simulations to validate our method. We generated 50 mock catalogs based on the [Patanchon et al. \(2009\)](#) counts, and which covered 1 deg² each. These sources are spatially homogeneously distributed. We then generated the associated maps at 250 μm . We used the instrumental PSF, and added a Gaussian noise with the same standard deviation as in the deepest part of real map.

We performed an extraction of sources and computed the number counts with the method used in the confusion limited part of the field (Sect. 3.2). We then compared the output counts with the initial counts (Fig. 3). We used two flux density bins: 100–141 mJy and 141–200 mJy. We found no significant bias. The correlation between the two bins is 0.46. The neighbor points are thus not anti-correlated as in the [Patanchon et al. \(2009\)](#) P(D) analysis.

The same verification was done on 20 [Fernandez-Conde et al. \(2008\)](#) simulations (based on the [Lagache et al. 2004](#) model). These simulations include clustering. This model overestimates the number of the bright sources, and the confusion noise is thus stronger. The 95% completeness is then reach at 200 mJy. But there is also a very good agreement between input and output counts in bins brighter than 200 mJy. We found a correlation between two first bins of 0.27.

4. Source extraction using *Spitzer* 24 μm catalog as a prior

In addition to blind source extraction in the BLAST data (Sect. 3) we also performed a source extraction using a prior.

4.1. PSF fitting photometry at the position of the *Spitzer* 24 μm

The catalogs of infrared galaxies detected by *Spitzer* contain more sources than the BLAST catalog. The 24 μm *Spitzer* PSF has a Full Width at Half Maximum (*FWHM*) of 6.6". It is smaller than the BLAST PSF (36" at 250 μm). Consequently, the position of the *Spitzer* sources is known with sufficient accuracy when correlating with the BLAST data.

We applied the FASTPHOT routine (Sect. 3.3) at the positions of 24 μm sources. We used the [B  thermin et al. \(2010\)](#) SWIRE catalog cut at $S_{24} = 250 \mu\text{Jy}$ (80% completeness). In order to avoid software instabilities, we kept in our analysis only the brightest *Spitzer* source in a 20" radius area (corresponding to 2 BLAST pixels). The corresponding surface density is 0.38,

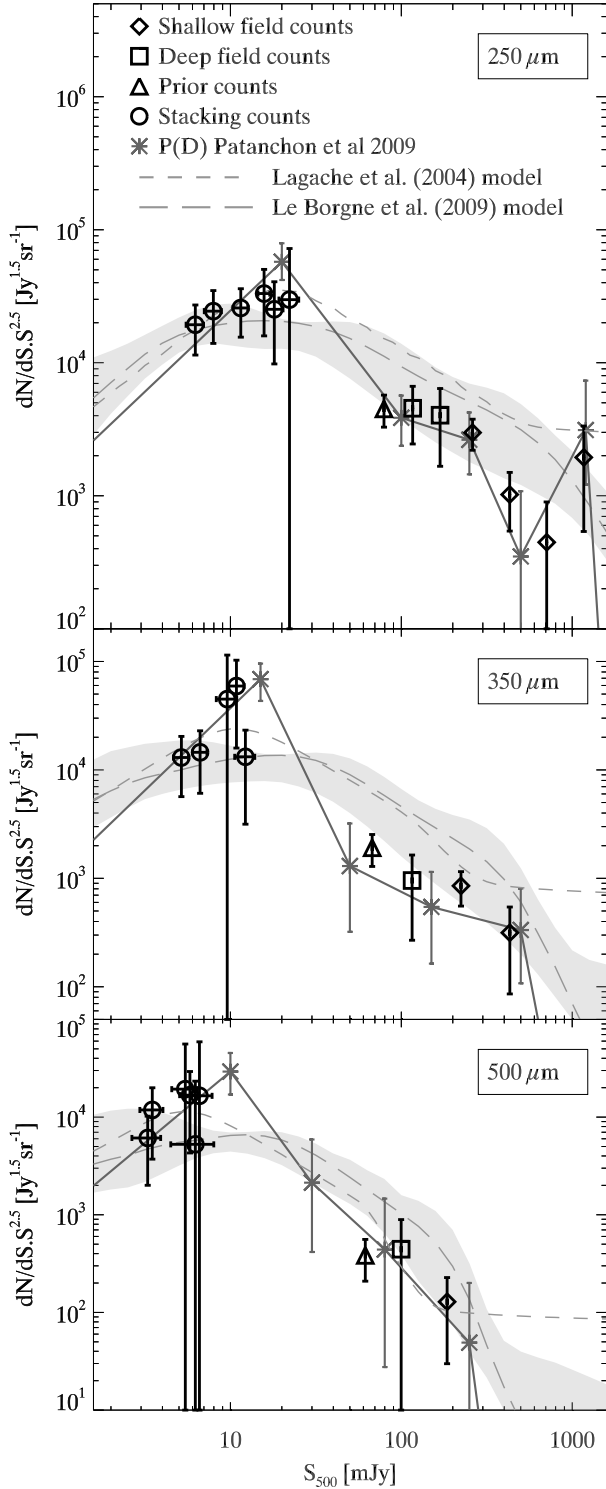


Fig. 2. Extragalactic number counts at 250 μm in the BLAST data. *Diamond*: counts deduced from the source catalog on the whole shallow field; *square*: counts deduced from the catalog of the deep part of the field; *triangle*: counts deduced from catalog of the deep part of the field with a 24 μm prior (this measurement gives only a lower limits to the counts); *cross*: counts computed with a stacking analysis; *grey asterisk*: counts computed with a P(D) analysis by Patanchon et al. (2009); *grey short dashed line*: Lagache et al. (2004) model prediction; *grey long dashed line and grey area*: Le Borgne et al. (2009) model prediction and 1- σ confidence area.

0.49 and 0.89 Spitzer source per beam³ at 250 μm , 350 μm and 500 μm , respectively.

This method works only if there is no astrometrical offset between the input 24 μm catalog and the BLAST map. We stacked the BLAST sub-map centered on the brightest sources of the SWIRE catalog and measured the centroid of the resulting artificial source. We found an offset of less than 1". It is negligible compared to the PSF FWHM (36" at 250 μm).

We worked only in the central region of the deep confusion-limited field (same mask as for blind extraction), where the photometric noise is low.

4.2. Relevance of using Spitzer 24 μm catalog as a prior

The S_{250}/S_{24} (S_{350}/S_{24} or S_{500}/S_{24}) color is not constant, and some sources with a high color ratio could have been missed in the prior catalog (especially high-redshift starbursts). We used the Lagache et al. (2004) and Le Borgne et al. (2009) models to estimate the fraction of sources missed. We selected the sources in the sub-mm flux density bin and computed the 24 μm flux density distribution (see Fig. 4). According to the Lagache et al. (2004) model, 99.6%, 96.4% and 96.9% of the sub-mm selected sources⁴ are brighter than $S_{24} = 250 \mu\text{Jy}$ for a selection at 250 μm , 350 μm and 500 μm , respectively. The Le Borgne et al. (2009) model gives 99.8%, 98.3% and 95.0%, respectively.

4.3. Photometric accuracy

The photometric accuracy was estimated with Monte-Carlo artificial sources. We added five sources of a given flux at random positions on the original map and add them to the 24 μm catalog. We then performed a PSF fitting and compared the input and output flux. We did this 100 times per tested flux for 10 flux densities (between 10 and 100 mJy). In this simulation we assumed that the position of the sources is exactly known. It is a reasonable hypothesis due to the 24 μm PSF FWHM (6.6") compared to the BLAST one (36" at 250 μm).

We did not detect any boosting effect for faint flux densities as expected in this case of detection using a prior. For a blind extraction there is a bias of selection toward sources located on peaks of (instrumental or confusion) noise. This is not the case for an extraction using a prior, for which the selection is performed at another wavelength.

The scatter of output flux densities is the same for all the input flux densities. We found a photometric noise σ_S of 21.5 mJy, 18.3 mJy and 16.6 mJy at 250 μm , 350 μm and 500 μm , respectively. It is slightly lower than for the blind extraction, for which the position of source is not initially known.

4.4. Estimation of the number counts

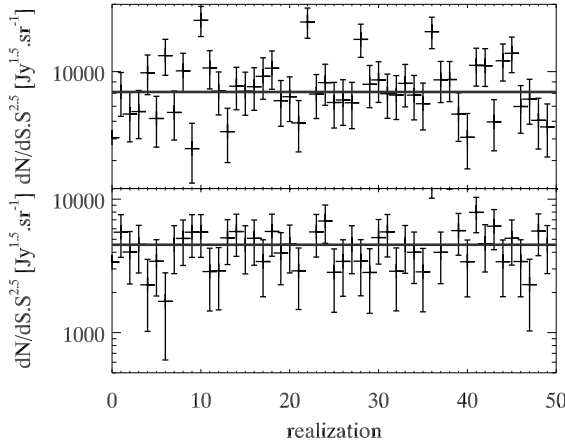
From the catalog described in Sect. 4.1 we give an estimation of the submillimeter number counts at flux densities fainter than reached by the blind-extracted catalog. We cut the prior catalog at $3\sigma_S$, corresponding to 64 mJy, 54 mJy and 49 mJy at 250 μm , 350 μm and 500 μm , respectively. We worked in a single flux density bin, which is defined to be between this value and the cut of the blind-extracted catalog⁴. There is no flux boosting effect, but we needed to correct the Eddington bias. The completeness

³ The beam solid angles are taken as 0.39 arcmin², 0.50 arcmin² and 0.92 arcmin² at 250 μm , 350 μm and 500 μm respectively.

⁴ The bins are defined as 64 to 97 at 250 μm , 54 to 83 at 350 μm and 49 to 76 at 500 μm .

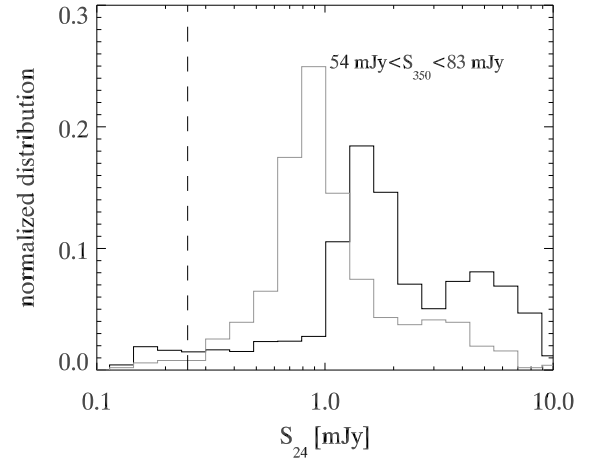
Table 2. Number counts deduced from source extraction. The not normalized counts can be obtained dividing the $S^{2.5} \cdot dN/dS$ column by the S_{mean} column.

Wavelength	S_{mean}	S_{min}	S_{max}	N_{sources}	$S^{2.5} \cdot dN/dS$	$\sigma_{S^{2.5} \cdot dN/dS}$	Method
μm	mJy			galaxies	gal $\text{Jy}^{1.5} \text{sr}^{-1}$		
250	79	64	97	26	4451	1203	Prior
250	116	97	140	5	4529	2090	Deep
250	168	140	203	3	4040	2377	Deep
250	261	203	336	34	2987	784	Shallow
250	430	336	552	5	1023	479	Shallow
250	708	552	910	1	445	449	Shallow
250	1168	910	1500	2	1939	1401	Shallow
350	67	54	83	17	1913	630	Prior
350	115	83	161	2	955	687	Deep
350	223	161	310	16	854	299	Shallow
350	431	310	600	2	314	228	Shallow
500	61	49	76	7	388	178	Prior
500	99	76	131	1	443	448	Deep
500	185	131	262	4	129	99	Shallow

**Fig. 3.** Number counts at 250 μm deduced from a blind extraction for 50 realizations of a simulation based on the Patanchon et al. (2009) counts. The horizontal solid line represents the input count value. The lower panel is the result of the 100–141 mJy bin, the upper panel is the 141–200 mJy bin.

could not be defined in the same way as for the blind extraction, because the selection was performed at another wavelength. We thus cannot suppose power-law counts, because the selection function is unknown and the distribution of the extracted sources cannot be computed.

The Eddington bias was estimated with another method. We took the sub-mm flux of each of the sources selected at 24 μm and computed how many sources lie in our count bin. We added a Gaussian noise σ_S to the flux of each source to simulate the photometric errors. We computed the number of sources in the counts bin for the new fluxes. We then compute the mean of the ratio between the input and output number of sources in the selected bin for 1000 realizations. The estimated ratios are 0.42, 0.35 and 0.21 at 250 μm , 350 μm and 500 μm , respectively. These low values indicate that on average the photometric noise introduces an excess of faint sources in our flux bin. This effect is strong because of the steep slope of the number counts, implying more fainter sources than brighter sources. The results are interpreted in the Sect. 6.

**Fig. 4.** Flux density distribution at 24 μm of the 54 mJy $< S_{350} < 83$ mJy sources. The Lagache et al. (2004) model is plotted in black and the Le Borgne et al. (2009) model is plotted in grey. The dashed line represents the cut of our catalog at 24 μm .

4.5. Sub-mm/24 color

In this part we work only on $S > 5\sigma_S$ sources of the catalog described in Sect. 4.1 to avoid bias due to the Eddington bias in our selection. At 250 μm , we have two sources verifying this criterion with a S_{250}/S_{24} color of 16 and 60. No sources are brighter than $5\sigma_S$ at larger wavelengths. For this cut in flux ($S_{250} > 5\sigma_S$), the Lagache et al. (2004) and Le Borgne et al. (2009) models predict a mean S_{250}/S_{24} color of 39 and 41, respectively. The two models predict a mean redshift of 0.8 for this selection, and the K -correction effect explains these high colors.

5. Non-resolved source counts by stacking analysis

5.1. Method

In order to probe the non-resolved source counts, we used same method as Béthermin et al. (2010), i.e. the stacking analysis applied to number counts (hereafter “stacking counts”). We first measured the mean flux at 250 μm , 350 μm or 500 μm as a function of the 24 μm flux ($\bar{S}_{250, 350 \text{ or } 500} = f(S_{24})$). This measurement was performed by stacking in several S_{24} bins. We used the

Table 3. Number counts deduced from stacking.

Wavelength	S	σ_S	$S^{2.5} \cdot dN/dS$	$\sigma_{S^{2.5} \cdot dN/dS}$
μm	mJy		gal Jy ^{1.5} sr ⁻¹	
250	6.2	0.7	19 313	7892
250	7.9	0.9	24 440	10 466
250	11.5	1.2	25 816	10 236
250	15.7	1.3	33 131	17 213
250	18.1	2.3	25 232	15 428
250	22.2	2.9	29 831	42 448
350	5.2	0.5	13007.	7343.
350	6.6	0.6	14519.	8434.
350	10.8	1.2	59314.	43418.
350	9.6	1.3	44944.	69505.
350	12.2	1.6	13200.	10044.
500	3.5	0.5	11842.	8134.
500	3.3	0.6	6115.	4112.
500	5.8	0.8	16789.	12498.
500	5.4	0.9	19338.	36659.
500	6.6	1.2	16526.	42476.
500	6.2	1.8	5263.	18087.

Notes. The not normalized counts can be obtained dividing the $S^{2.5} \cdot dN/dS$ column by the S column.

Béthermin et al. (2010) catalog at 24 μm of the FIDEL survey. It is deeper than the SWIRE one used in Sect. 4, but covers a smaller area (0.25 deg²). The photometry of stacked images was performed with the PSF fitting method (Sect. 3.3), and the uncertainties on the mean flux are computed with a bootstrap method (Bavouzet 2008). We then computed the counts in the sub-mm domain with the following formula:

$$\left. \frac{dN}{dS_{\text{submm}}} \right|_{S_{\text{submm}}=f(S_{24})} = \left. \frac{dN}{dS_{24}} \right|_{S_{24}} \left| \frac{dS_{\text{submm}}}{dS_{24}} \right|_{S_{24}}. \quad (7)$$

We show in Appendix B that the clustering effect can be neglected. The results are given in Table 3 and are plotted in Fig. 2.

5.2. Validity of the stacking analysis in the sub-mm range

There are 1.8, 2.4 and 4.5 $S_{24} > 70 \mu\text{Jy}$ sources per BLAST beam at 250 μm , 350 μm and 500 μm , respectively. We thus stacked several sources per beam. Béthermin et al. (2010) showed that the stacking analysis is valid at 160 μm in the *Spitzer* data, where the size of the beam is similar to the BLAST one.

To test the validity of the stacking analysis in the BLAST data from a *Spitzer* 24 μm catalog, we generated a simulation of a 0.25 deg² with a Gaussian noise at the same level as for the real map and with source clustering, following Fernandez-Conde et al. (2008). We stacked the 24 μm simulated sources per flux bin in the BLAST simulated maps. We measured the mean BLAST flux for each 24 μm bin with the same method as applied on the real data. At the same time we computed the mean sub-mm flux for the same selection from the mock catalog associated to the simulation. We finally compared the mean BLAST fluxes measured by stacking with those directly derived from the mock catalog to estimate the possible biases (see Fig. 5). The stacking measurements and expected values agree within the error bars. We notice a weak trend of overestimation of the stacked fluxes at low flux density ($S_{24} < 200 \mu\text{Jy}$) however, but it is still within the error bars. We can thus stack 24 μm *Spitzer* sources in the BLAST map.

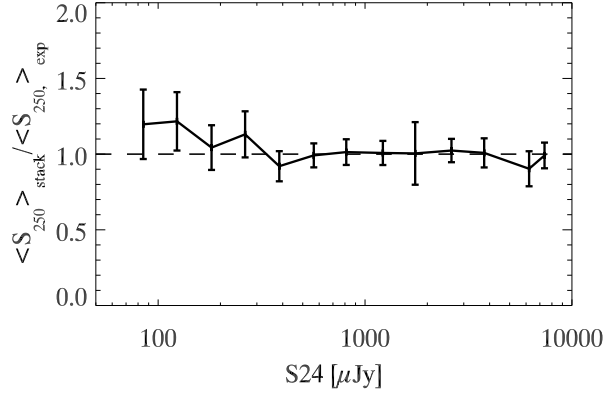


Fig. 5. Ratio between the mean flux density at 250 μm found by the stacking analysis and the expected flux for different S_{24} bins. It is based on a Fernandez-Conde et al. (2008) simulation of a 0.25 deg² field with a noise and PSF similar to the BLAST deep region.

5.3. Mean 24 μm to sub-mm color deduced by stacking analysis

The stacking analysis allowed to measure the mean 24 μm to sub-mm colors of undetected sub-mm galaxies. These colors depends on the SED of galaxies (or K -correction) and the redshift distribution in a degenerate way. The S_{submm}/S_{24} color and $dS_{\text{submm}}/dS_{24}$ as a function of S_{24} are plotted in Fig. 6.

The colors are higher for the fainter 24 μm flux ($S_{24} < 100 \mu\text{Jy}$). This behavior agrees with the model expectations: the faint sources at 24 μm lie at a higher mean redshift than the brighter ones. Due to the K -correction, the high-redshift sources have a brighter sub-mm/24 color than local ones.

The colors found by the stacking analysis are lower than those obtained by an extraction at 250 μm (Sect. 4.5). It is an effect of selection. The mid-infrared is less affected by the K -correction than the sub-mm, and a selection at this wavelength selects lower redshift objects. We thus see lower colors because of the position of the SED peak (around 100 μm rest-frame).

We also investigated the evolution of the derivative $dS_{\text{submm}}/dS_{24}$ as a function of S_{24} , which explicits how the observed sub-mm flux increases with the 24 μm flux densities. At high 24 μm flux densities ($S_{24} > 400 \mu\text{Jy}$) the derivative is almost constant and small (< 20 and compatible with zero), meaning that the observed sub-mm flux density does not vary much with S_{24} . For these flux bins we select only local sources and do not expect a strong evolution of the color. At fainter 24 μm flux densities the observed decrease can be explained by redshift and K -correction effects, as above.

The color in the faintest 24 μm flux density bin (70 to 102 μJy) is slightly fainter than in the neighboring points. It can be due to the slight incompleteness of the 24 μm catalog (about 15%), which varies spatially across the field: the sources close to the brightest sources at 24 μm are hardly extracted. The consequence is a bias to the lower surface density regions, leading to a slight underestimation of the stacked flux measurement.

5.4. Accuracy of the stacking counts method on BLAST with a *Spitzer* 24 μm prior

Béthermin et al. (2010) showed that the stacking counts could be biased: the color of sources can vary a lot as a function of the redshift. The assumption of a single color for a given S_{24}

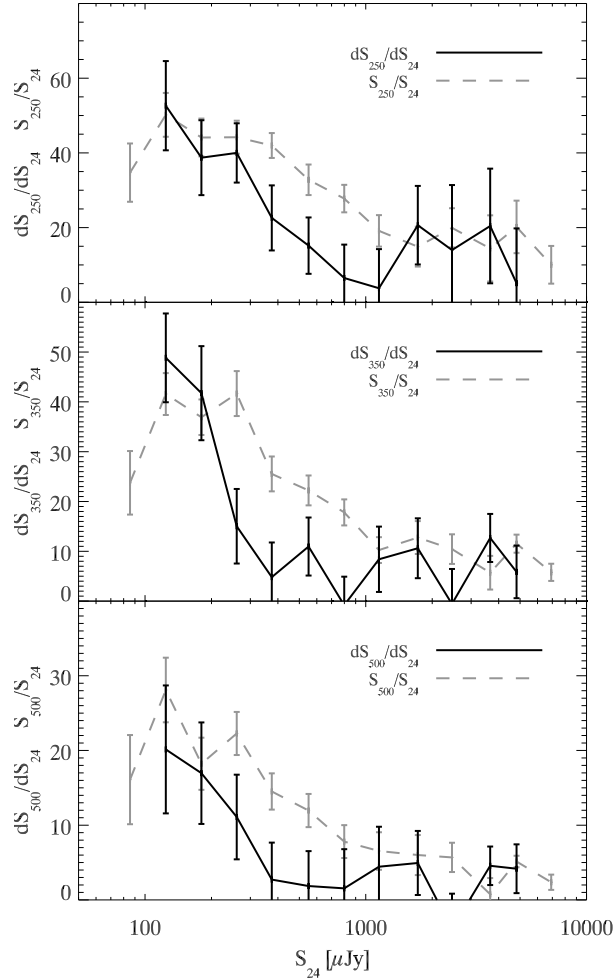


Fig. 6. Black solid line: $dS_{\text{submm}}/dS_{24}$ as a function of S_{24} . Grey dashed line: S_{submm}/S_{24} color as a function of S_{24} .

is not totally realistic and explains some biases. We used two simulated catalogs (containing for each source S_{24} , S_{250} , S_{350} and S_{500}) to estimate this effect: a first one based on the [Lagache et al. \(2004\)](#) model that covered $20 \times 2.9 \text{ deg}^2$ and a second one based on the [Le Borgne et al. \(2009\)](#) model and that covered 10 deg^2 . The large size of these simulations allows us to neglect cosmic variance.

In order to compute the stacking counts, we first computed the counts at $24 \mu\text{m}$ from the mock catalog. Then we computed the mean S_{250} , 350 or 500 flux density (directly in the catalog) in several S_{24} bins to simulate a stacking. We finally applied the Eq. (7) to compute stacking counts at the BLAST wavelengths.

The ratio between the stacking counts and the initial counts is plotted in Fig. 8 for the two mock catalogs. Between 1 mJy and 10 mJy we observe an oscillating bias. This bias is less than 30% at $250 \mu\text{m}$ and 50% at other wavelengths. When the flux becomes brighter than 25 mJy at $250 \mu\text{m}$ (18 mJy at $350 \mu\text{m}$ and 7.5 mJy at $500 \mu\text{m}$), we begin to strongly underestimate the counts. The analysis of real data also shows a very strong decrease in the counts around the same fluxes (see Fig. 7). Consequently, we cut our stacking analysis at these fluxes and we applied an additional uncertainty to the stacking counts of 30% at $250 \mu\text{m}$ (50% at $350 \mu\text{m}$ and $500 \mu\text{m}$).

Using the $24 \mu\text{m}$ observations as a prior to stack in the BLAST bands seems to give less accurate results than in the *Spitzer* MIPS bands. For a given S_{24} flux, the sub-mm emission can vary a lot as a function of the redshift. But the simulations shows that this method works for faint flux densities. It is due to the redshift selection which is similar for faint flux densities (see Fig. 9) and very different at higher flux densities (see Fig. 10). For example, $S_{24} \sim 100 \mu\text{Jy}$ sources are distributed around $z = 1.5$ with a broad dispersion in redshift. $S_{350} \sim 4 \text{ mJy}$ (based on averaged colors, 4 mJy at $350 \mu\text{m}$ corresponds to $S_{24} \sim 100 \mu\text{Jy}$) sources have quite a similar redshift distribution except an excess for $z > 2.6$. At higher flux densities (around 2 mJy at $24 \mu\text{m}$) the distribution is very different. The majority of the $24 \mu\text{m}$ -selected sources lies at $z < 1$ and the distribution of $350 \mu\text{m}$ -selected sources peaks at $z \sim 1.5$. Another possible explanation is that fainter sources lies near $z = 1$ and are thus selected at the $12 \mu\text{m}$ rest-frame, which is a very good estimator of the infrared bolometric luminosity according to [Spinoglio et al. \(1995\)](#).

In order to limit the scatter of the sub-mm/ 24 color, we tried to cut our sample into two redshift boxes following the [Devlin et al. \(2009\)](#) IRAC color criterion ($[3.6]-[4.5] = 0.068([5.8]-[8.0]) - 0.075$). But we had not enough signal in the stacked images to perform the analysis.

6. Interpretation

6.1. Contribution to the CIB

We integrated our counts assuming power-law behavior between our points. Our points are not independent (especially the stacking counts), and we thus combined errors linearly. The contribution of the individually detected sources ($S_{250} > 64 \text{ mJy}$, $S_{350} > 54 \text{ mJy}$, $S_{500} > 49 \text{ mJy}$) is then $0.24^{+0.18}_{-0.13} \text{ nW.m}^2.\text{sr}^{-1}$, $0.06^{+0.05}_{-0.04} \text{ nW.m}^2.\text{sr}^{-1}$ and $0.01^{+0.01}_{-0.01} \text{ nW.m}^2.\text{sr}^{-1}$ at $250 \mu\text{m}$, $350 \mu\text{m}$ and $500 \mu\text{m}$, respectively. Considering the total CIB level of [Fixsen et al. \(1998\)](#) (FIRAS absolute measurement), we resolved directly only 2.3%, 1.1% and 0.4% at $250 \mu\text{m}$, $350 \mu\text{m}$ and $500 \mu\text{m}$, respectively.

The populations probed by the stacking counts ($S_{250} > 6.2 \text{ mJy}$, $S_{350} > 5.2 \text{ mJy}$, $S_{500} > 3.5 \text{ mJy}$) emit $5.0^{+2.5}_{-2.6} \text{ nW m}^2 \text{ sr}^{-1}$, $2.8^{+1.8}_{-2.0} \text{ nW m}^2 \text{ sr}^{-1}$ and $1.4^{+2.1}_{-1.3} \text{ nW m}^2 \text{ sr}^{-1}$ at $250 \mu\text{m}$, $350 \mu\text{m}$ and $500 \mu\text{m}$, respectively. This corresponds to about 50% of the CIB at these three wavelengths.

6.2. Comparison with Patanchon et al. (2009)

The agreement between our resolved counts built from the catalogs and the P(D) analysis of [Patanchon et al. \(2009\)](#) is excellent (Fig. 2). We confirm the efficiency of the P(D) analysis to recover number counts without extracting sources. The stacking counts probe the flux densities between 6 mJy and 25 mJy at $250 \mu\text{m}$ (between 5 mJy and 13 mJy at $350 \mu\text{m}$ and 3 mJy and 7 mJy at $500 \mu\text{m}$). In this range there is only one P(D) point. At the three BLAST wavelengths the P(D) points agree with our stacking counts (Fig. 2). Our results thus confirm the measurement of [Patanchon et al. \(2009\)](#) and give a better sampling in flux.

6.3. Comparison with ground-based observations

We compared our results with sub-mm ground-based observations of SHARC. [Khan et al. \(2007\)](#) estimated a density of $S_{350} > 13 \text{ mJy}$ sources of $0.84^{+1.39}_{-0.61} \text{ arcmin}^{-2}$. For the same cut,

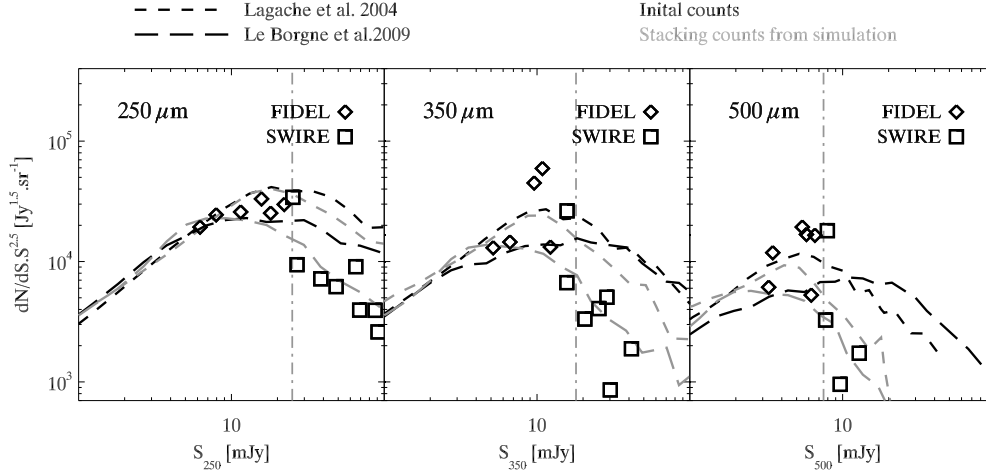


Fig. 7. Number counts at BLAST wavelengths coming from the data (points) and the models (lines). Short dashed line: initial (black) and stacking (grey) counts from the Lagache et al. (2004) mock catalog; long dashed line: initial (black) and stacking (grey) counts from Le Borgne et al. (2009); diamond: stacking counts built with the FIDEL catalog; square: stacking counts built with the SWIRE catalog; grey vertical dot-dash line: flux cut for stacking counts.

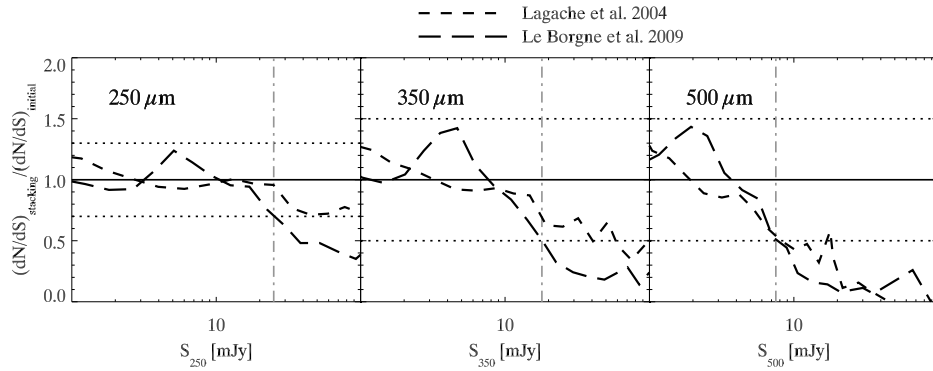


Fig. 8. Ratio between stacking counts and initial counts for two mock catalogs; short dashed line: Lagache et al. (2004) catalog; long dashed line: Le Borgne et al. (2009); grey vertical dot-dash line: flux cut for stacking counts; horizontal dot line: estimation of the uncertainty intrinsic to the stacking method.

we found $0.26 \pm 0.13 \text{ arcmin}^{-1}$, which agrees with their work. Our measurement ($175 \pm 75 \text{ sources deg}^{-2}$ brighter than 25 mJy) agrees also with that of Coppin et al. (2008) ones at the same wavelength ($200\text{--}500 \text{ sources deg}^{-2}$ brighter than 25 mJy).

We also compared our results at $500 \mu\text{m}$ with the SCUBA ones at $450 \mu\text{m}$. Borys et al. (2003) find $140^{+140}_{-90} \text{ gal deg}^{-2}$ for $S_{450} > 100 \text{ mJy}$. We found $1.2 \pm 1.0 \text{ gal deg}^{-2}$. We significantly disagree with them. Borys et al. (2003) claim 5 $4\text{-}\sigma$ detections in a 0.046 deg^2 field in the *Hubble* deep field north (HDFN). These five sources are brighter than 100 mJy. We find no source brighter than 100 mJy in a 0.45 deg^2 field at $350 \mu\text{m}$ nor at $500 \mu\text{m}$. The cosmic variance alone thus cannot explain this difference. A possible explanation is that they underestimated the noise level and their detections are dominated by spurious sources. It could also be due to a calibration shift (by more than a factor 2). The observation of the HDFN by *Herschel* will allow us to determine whether that these bright sources might be spurious detections.

We also compared our results with the estimations based on lensed sources at $450 \mu\text{m}$ with SCUBA (Smail et al. 2002; Knudsen et al. 2006). For example, Knudsen et al. (2006) find

$2000\text{--}50\,000 \text{ sources deg}^2$ brighter than 6 mJy. It agrees with our $3500^{+7700}_{-3400} \text{ sources deg}^2$.

6.4. Comparison with the Lagache et al. (2004) and Le Borgne et al. (2009) models

At $250 \mu\text{m}$ and $350 \mu\text{m}$ the measured resolved source counts are significantly lower (by about a factor of 2) than the Lagache et al. (2004) and Le Borgne et al. (2009) models. Nevertheless, our counts are within the confidence area of Le Borgne et al. (2009). The same effect (models overestimating the counts) was observed at $160 \mu\text{m}$ (Frayser et al. 2009; Béthermin et al. 2010). It indicates that the galaxies' SED or the luminosity functions used in both models might have to be revisited. At $500 \mu\text{m}$ our counts and both models agree very well, but our uncertainties are large, which renders any discrimination difficult.

Concerning the stacking counts, they agree very well with the two models. Nevertheless, our uncertainties are larger than 30%. We thus cannot check if the disagreement observed between the Lagache et al. (2004) model and the stacking counts at $160 \mu\text{m}$ (Béthermin et al. 2010) of 30% at $S_{160} = 20 \text{ mJy}$ still holds at $250 \mu\text{m}$.

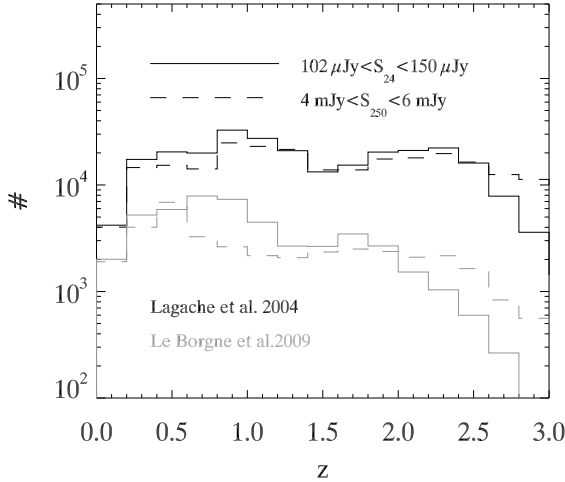


Fig. 9. Solid line: distribution in redshift of the sources with $102 \mu\text{Jy} < S_{24} < 150 \mu\text{Jy}$ for the mock catalogs generated with the Lagache et al. (2004) (black) and the Le Borgne et al. (2009) (grey) models; dashed line: distribution in redshift of the sources with $4 \text{ mJy} < S_{250} < 6 \text{ mJy}$ (determined using the mean 250/24 color).

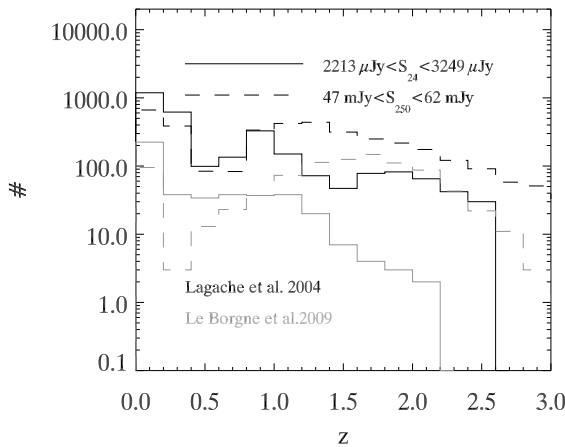


Fig. 10. Solid line: distribution in redshift of the sources with $2213 \mu\text{Jy} < S_{24} < 3249 \mu\text{Jy}$ for the mock catalogs generated with the Lagache et al. (2004) (black) and Le Borgne et al. (2009) (grey) models; dashed line: distribution in redshift of sources with $47 \text{ mJy} < S_{250} < 62 \text{ mJy}$ (determined using the mean 250/24 color).

6.5. Implications for the probed populations and the models

We showed that the two models nicely reproduce the sub-mm counts, especially below 100 mJy. We can thus use them to estimate which populations are constrained by our counts. For each flux density bin we computed the mean redshift of the selected galaxies in both models. We then used the SEDs given by the models at that mean redshift and at that flux bin and derived the infrared bolometric luminosity. The luminosities are shown in dashed lines in Fig. 11 for $350 \mu\text{m}$ as an example, and the redshift is given in solid lines.

The stacking counts reach 6.2 mJy, 5.3 mJy and 3.5 mJy at $250 \mu\text{m}$, $350 \mu\text{m}$ and $500 \mu\text{m}$, respectively. This corresponds to faint ULIRGs ($L_{\text{IR}} \approx 1.5 \times 10^{12} L_{\odot}$) around $z = 1.5$, 1.8 and 2.1 at $250 \mu\text{m}$, $350 \mu\text{m}$ and $500 \mu\text{m}$, respectively. Our measurements show that the predicted cold-dust emissions (between 100 μm

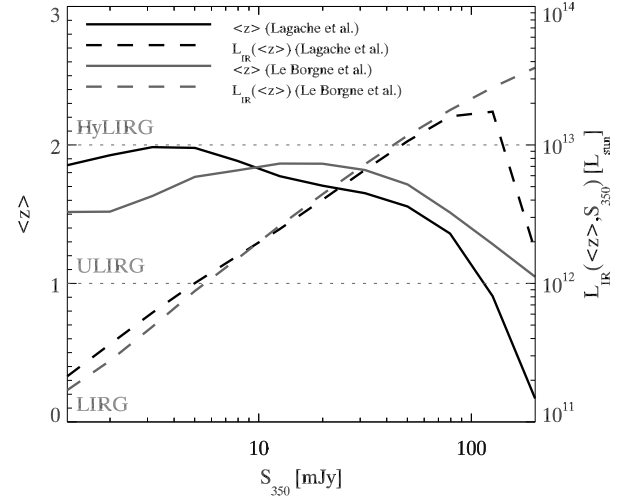


Fig. 11. Mean redshift (solid line) of sources for different fluxes at $350 \mu\text{m}$ for the Lagache et al. (2004) (black) and Le Borgne et al. (2009) (grey) models and corresponding infrared luminosity defined in Sect. 6.5 (dashed line).

and $200 \mu\text{m}$ rest frame) of this population in the models are believable.

At $250 \mu\text{m}$ and $350 \mu\text{m}$ the resolved sources ($S_{350} > 85 \text{ mJy}$) are essentially $z \sim 1$ ULIRGs ($L_{\text{IR}} > 10^{12} L_{\odot}$) and HyLIRGs ($L_{\text{IR}} > 10^{13} L_{\odot}$) according to the models. In Lagache et al. (2004) the local cold-dust sources contribute at very bright flux ($> 200 \text{ mJy}$). This population is not present in the Le Borgne et al. (2009) model. It explains the difference between the two models for fluxes brighter than 100 mJy at $350 \mu\text{m}$ (see Fig. 11). At $500 \mu\text{m}$, Lagache et al. (2004) predict that bright counts are dominated by local cold-dust populations and Le Borgne et al. (2009) that they are dominated by medium redshift HyLIRGs. Nevertheless, there is a disagreement with the observations for this flux density range, suggesting that there could be less HyLIRGs than predicted. But these models do not currently include any AGN contribution, which is small except at luminosities higher than $10^{12} L_{\odot}$ (Lacy et al. 2004; Daddi et al. 2007; Valiante et al. 2009).

7. Conclusion

Our analysis provides new stacking counts, which can be compared with the Patanchon et al. (2009) P(D) analysis. We have a good agreement between the different methods. Nevertheless, some methods are more efficient in a given flux range.

The blind extraction and the extraction using a prior give a better sampling in flux and slightly smaller error bars. The P(D) analysis uses only the pixel histogram and thus loses the information on the shape of the sources. The blind extraction is a very efficient method for extracting the sources, but lots of corrections must be applied carefully. When the confusion noise totally dominates the instrumental noise, the former must be determined accurately, and the catalog flux limit must take this noise (Dole et al. 2003) into account.

Estimating the counts from a catalog built using a prior is a good way to deal with the flux boosting effect. This method is based on assumptions however. We assume that all sources brighter than the flux cut at the studied wavelength are present in the catalog extracted using a prior. We also assume a flux

distribution at the studied wavelength for a selection at the prior wavelength to correct for the Eddington bias. Consequently an extraction using a prior must be used in a flux range where the blind extraction is too affected by the flux boosting to be accurately corrected.

P(D) analysis and stacking counts estimate the counts at flux densities below the detection limit. These methods have different advantages. The P(D) analysis fits all the fluxes at the same time, where the stacking analysis flux depth depends on the prior catalog's depth (24 μm *Spitzer* for example). But the P(D) analysis with a broken power-law model is dependent on the number and the positions of the flux nodes. The uncertainty due to the parameterization was not evaluated by Patanchon et al. (2009). The stacking counts on the other hand are affected by biases due to the color dispersion of the sources. The more the prior and stacked wavelength are correlated, the less biased are the counts. A way to overcome this bias would be to use a selection of sources (in redshift slices for example), which would reduce the color dispersion, and the induced bias; we did not use this approach here because of a low signal-to-noise ratio.

The stacking and P(D) analysis are both affected by the clustering in different ways. For the stacking analysis this effect depends on the size of the PSF. This effect is small for BLAST and will be smaller for SPIRE. The clustering broadens the pixel histogram. Patanchon et al. (2009) show that it is negligible for BLAST. Clustering will probably be an issue for SPIRE. The cirrus can also affect the P(D) analysis and broaden the peak. Patanchon et al. (2009) use a high-pass filtering that reduces the influence of these large scale structures.

The methods used in this paper will probably be useful to perform the analysis of the *Herschel* SPIRE data. The very high sensitivity and the large area covered will reduce the uncertainties and increase the depth of the resolved source counts. Nevertheless, according to the models (e.g. Le Borgne et al. (2009)), the data will also be quickly confusion-limited and it will be very hard to directly probe the break of the counts. The P(D) analysis of the deepest SPIRE fields will allow us to constrain a model with more flux nodes and to better sample the peak of the normalized differential number counts. The instrumental and confusion noise will be lower, and a stacking analysis per redshift slice will probably be possible. These analyses will give stringent constraints on the model of galaxies and finally on the evolution of the infrared galaxies.

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Appendix A: Effect of clustering on the uncertainties of number counts

Béthermin et al. (2010) showed how the clustering is linked with the uncertainties of the counts. We used the formalism of Béthermin et al. (2010) to estimate the effect of the clustering on our BLAST counts. There are few sources detected at 250 μm and the BLAST coverage is inhomogeneous. It is consequently very hard to estimate the clustering of the resolved population. We thus used the clustering measured at 160 μm by

Béthermin et al. (2010) and assumed a 250/160 color equal to unity. We then used the same method to compute the uncertainties. We then compare the uncertainties with and without clustering. Neglecting the clustering implies an underestimation of the uncertainties on the counts of 35% in the 203–336 mJy bin at 250 μm , and less than 20% in the other bins. We can thus suppose a Poissonian behavior, knowing that the Poisson approximation underestimates the error bars for the 203–336 mJy bin at 250 μm . Nevertheless, our model of clustering at 250 μm has strong assumptions (single 250/160 color, same clustering at 250 μm as measured at 160 μm), and it would be more conservative to update it with *Herschel* clustering measurements.

Appendix B: Effect of clustering on stacking

B.1. A formalism to link clustering and stacking

The clustering can bias the results of a stacking. We present a formalism based on Bavouzet (2008) work.

The expected results for mean stacking of an N non-clustered populations is

$$M(\theta) = \overline{S} \times PSF(\theta) + \int_0^\infty S \frac{dN}{dS} dS, \quad (\text{B.1})$$

where M is the map resulting from stacking, θ the distance to the center of the cutout image, $\overline{S}$ the mean flux of the stacked population. The integral is an approximation because the central source is treated in the first term. This approximation is totally justified in a strongly confused field where the number of sources is enormous. PSF is the instrumental response and is supposed to be invariant per rotation ($\theta = 0$ corresponds to the center of this PSF). $\frac{dN}{dS}$ is the number of the source per flux unit and per pixel. We assume an absolute calibration. The integral in the Eq. (B.1) is equal to the CIB brightness

$$I_{\text{CIB}} = \int_0^\infty S \frac{dN}{dS} dS. \quad (\text{B.2})$$

This term is constant for all pixels of the image and corresponds to a homogeneous background.

The stacked sources can actually be autocorrelated. The probability density to find a stacked source in a given pixel and another in a second pixel separated by an angle θ ($p(\theta)$) is linked with the angular autocorrelation function ($\omega(\theta)$) by

$$p(\theta) = \rho_s^2 (1 + \omega(\theta)), \quad (\text{B.3})$$

where ρ_s is the number density of the stacked source.

If we assume that there is no correlation with other populations, the results of the stacking of N autocorrelated sources is

$$M(\theta) = \overline{S}_s \times PSF(\theta) + I_{\text{CIB},s} (1 + \omega(\theta)) * PSF(\theta) + I_{\text{CIB},ns}, \quad (\text{B.4})$$

where $I_{\text{CIB},s}$ and $I_{\text{CIB},ns}$ is the CIB contribution of stacked and non-stacked sources. If we subtract the constant background of the image, we find

$$M(\theta) = \overline{S}_s \times PSF(\theta) + I_{\text{CIB},s} \times \omega(\theta) * PSF(\theta). \quad (\text{B.5})$$

The second term of this equation corresponds to an excess of flux due to clustering. This signal is stronger in the center of the stacked image. The central source appears thus brighter than expected, because of the contribution due to clustering.

The flux of the central stacked source computed by PSF-fitting photometry is

$$S_{\text{mes}} = \frac{\int \int M \times PSF d\Omega}{\int \int PSF^2 d\Omega} = \overline{S}_s + S_{\text{clus}}, \quad (\text{B.6})$$

where S_{clus} , the overestimation of flux due to clustering is given by

$$S_{\text{clus}} = I_{\text{CIB},s} \times \frac{\int \int ((\omega * PSF) \times PSF) d\Omega}{\int \int PSF^2 d\Omega}. \quad (\text{B.7})$$

Basically, the stronger the clustering, the larger the bias. In addition, the wider the PSF, the larger the overestimation. The stacked signal can be dominated by the clustering, if the angular resolution of the instrument is low compared to the surface density of the sources (like *Planck*, cf. [Fernandez-Conde et al. \(2010\)](#)) or if strongly clustered populations are stacked.

B.2. Estimation of the bias due to clustering

The estimation of S_{clus} with Eq. (B.7) requires particular hypotheses. The stacked population is $S_{24} > 70 \mu\text{Jy}$ sources detected by *Spitzer*. Their contribution to the CIB is $5.8 \text{ nW m}^{-2} \text{ sr}^{-1}$, $3.4 \text{ nW m}^{-2} \text{ sr}^{-1}$ and $1.4 \text{ nW m}^{-2} \text{ sr}^{-1}$ at $250 \mu\text{m}$, $350 \mu\text{m}$ and $500 \mu\text{m}$, respectively (estimated by direct stacking of all the sources). Following the clustering of $24 \mu\text{m}$ sources estimated by [Béthermin et al. \(2010\)](#), we suppose the following autocorrelation function:

$$\omega(\theta) = 2.3 \times 10^{-4} \times \left(\frac{\theta}{\text{deg}}\right)^{-0.8}. \quad (\text{B.8})$$

The excess of flux due to clustering (S_{clus}) is then 0.44 mJy , 0.35 mJy and 0.16 mJy at $250 \mu\text{m}$, $350 \mu\text{m}$ and $500 \mu\text{m}$, respectively. This is significantly lower than the bootstrap uncertainties on these fluxes. We can thus neglect the clustering.

B.3. Measurement of the angular correlation function by stacking

This new formalism provides a simple tool to measure the angular autocorrelation function (ACF) from a source catalog. This method uses a map called “density map”. One pixel of this map contains the number of sources centered on it. It is equivalent of a map of unit flux sources with the $PSF = \delta$ (Dirac distribution). The result of the stacking is thus

$$M(\theta) = \rho_s \times \delta(\theta) + \rho_s(1 + \omega(\theta)). \quad (\text{B.9})$$

The ACF can then be easily computed with

$$\forall \theta \neq 0, \omega(\theta) = \frac{M(\theta)}{\rho_s} - 1. \quad (\text{B.10})$$

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Chapitre 6

Modélisation empirique de l'évolution des galaxies infrarouges

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6.1 Introduction

La plupart des observables infrarouges (comptages, $N(z)$...) n'apportent pas une information directe sur l'évolution des galaxies. Par exemple, Sect. 2.1.2, nous avons vu comment celle-ci agit de manière non triviale sur les comptages de sources. Pour interpréter ces différentes observations, il est donc nécessaire de recourir à un modèle, qui peut se construire selon plusieurs approches. La première, dite semi-analytique, a pour but de retrouver l'évolution observée grâce à une modélisation purement physique. La seconde, dite *backward evolution*¹, est plus empirique et tente de reproduire finement les observations grâce à une évolution plus ou moins simple des propriétés statistiques des objets. J'ai développé au cours de ma thèse un modèle de type *backward evolution*.

6.1.1 Modèles semi-analytiques

Les modèles semi-analytiques se basent sur les grandes simulations d'effondrement de la matière noire (par exemple la simulation Millenium, Springel *et al.* (2005)). Elles partent des très faibles fluctuations de densité (de l'ordre de 10^{-5}) observées dans le fond cosmologique, et simulent la manière dont ces fluctuations croissent sous l'effet de la gravité pour former les halos de matière noire. Ceci fournit l'historique de la croissance par accretion et fusions éventuelles de tous les halos présents dans le volume d'Univers simulé. Des recettes semi-analytiques permettent alors de décrire l'effondrement et le refroidissement du gaz dans les halos, qui permet la formation d'étoiles. Ce mécanisme est piloté par le temps d'effondrement dynamique et le temps de refroidissement du milieu interstellaire.

Pour pouvoir comparer ces simulations aux données, il faut également simuler le spectre de chaque galaxie. La distribution en masse des étoiles créées à chaque pas de la simulation est donnée par la fonction de masse initiale (IMF²). On peut citer, entre autres, les IMFs de Salpeter (1955), Kroupa (2001) et Chabrier (2003). A chaque pas de la simulation, on calcule alors la distribution en masse et en âge des étoiles. La distribution spectrale d'énergie (SED) totale émise par les populations stellaires peut ainsi être déterminée en utilisant des *templates* comme ceux de Bruzual et Charlot (2003). On prend ensuite en compte l'extinction du spectre par la poussière. L'énergie ainsi absorbée est alors émise dans l'infrarouge.

Il existe de nombreux modèles semi-analytiques construits sur des hypothèses différentes, comme par exemple, Hatton *et al.* (2003), Somerville *et al.* (2008), ou Lacey *et al.* (2010). Aujourd'hui, ces modèles sont encore incapables de reproduire fidèlement les observations infrarouges sans modifier l'IMF. Les taux de formation d'étoiles sont trop

¹En français, évolution à rebours.

²De l'anglais, *Initial Mass Function*

faibles à haut *redshift* pour engendrer suffisamment d'ULIRGs à $z=2$. Les modèles utilisent en général une IMF modifiée avec plus d'étoiles massives que dans celle de Salpeter (1955) pour régler ce problème. En effet, si les étoiles sont plus massives, elles sont plus bleues. Leur lumière est donc plus absorbée, ce qui augmente mécaniquement la luminosité infrarouge pour un même taux de formation d'étoiles. Cette modification de l'IMF sans grande motivation physique n'est néanmoins pas très satisfaisante. Une meilleure prise en compte des courants de gaz froid le long des filaments de matière noire ou de la *clumpiness*³ pourrait permettre de régler ce problème.

6.1.2 Modèles *backward evolution*

L'approche dite *backward evolution* consiste à faire évoluer au cours du temps les propriétés statistiques des galaxies infrarouges comme la fonction de luminosité. Ces propriétés sont en général bien contraintes dans l'Univers local. Elles le sont beaucoup moins dans l'Univers lointain. Ces modèles partent donc en général des propriétés observées localement et les font évoluer avec le *redshift*, d'où le terme *backward evolution*.

Il existe de très nombreux modèles de type *backward evolution*. Chacun se construit sur des hypothèses assez différentes. Nous présentons ici une sélection de modèles récents.

Modèle de Lagache *et al.* (2003, 2004)

Le modèle de Lagache *et al.* (2003, 2004) utilise deux populations évoluant indépendamment pour reproduire les comptages de l'infrarouge moyen au domaine sub-millimétrique. Ces deux populations sont les galaxies passives froides et les galaxies à flambée de formation d'étoiles (*starburst*). Les distributions spectrales d'énergie des galaxies à flambée de formation d'étoiles évoluent avec la luminosité infrarouge : plus elles sont lumineuses et plus elles sont chaudes. Leur densité et leur luminosité caractéristiques évoluent très rapidement avec le *redshift*. Les SEDs des galaxies froides n'évoluent pas, quant à elles, en fonction de la luminosité. La LF de cette population évolue peu avec le *redshift*. Ces évolutions sont déterminées manuellement par essais successifs jusqu'à reproduire les observations.

³Ce mot difficile à traduire en français signifie que le gaz n'est pas réparti de manière uniforme, mais en paquets.

Modèle de Negrello *et al.* (2007)

Le modèle de Negrello *et al.* (2007) est construit de façon très différente. Il contient une population de galaxies sphéroïdales à haut *redshift* formant des étoiles à un rythme très soutenu. Leur évolution est décrite par le modèle physique de Granato *et al.* (2004). Une population de galaxies spirales formant leurs étoiles à un rythme plus modéré est ajouté de façon purement empirique afin d'ajuster les observations. Les radio-galaxies du modèle de Zotti *et al.* (2005) sont également ajoutées à ce modèle. Enfin, il contient une population de galaxies sphéroïdales amplifiée par effet de lentille gravitationnelle (Perrotta *et al.* (2002)). Ces sources lentillées ont un effet important sur les comptages de sources dans le domaine sub-millimétrique pour des flux de l'ordre de 100 mJy. La prise en compte de ce phénomène est une particularité importante de ce modèle.

Modèle de Le Borgne *et al.* (2009)

Le modèle de Le Borgne *et al.* (2009) est un modèle empirique basé sur une seule population, qui correspond à la bibliothèque de SED de Chary et Elbaz (2001). Cette bibliothèque évolue uniquement avec la luminosité infrarouge. L'originalité de ce modèle réside dans la façon dont est déterminée l'évolution des galaxies infrarouges. Il ne suppose pas une forme paramétrique particulière pour la fonction de luminosité, mais force la fonction de luminosité à évoluer lentement en fonction de la luminosité et du *redshift*. Les évolutions de la LF compatibles avec les comptages infrarouges sont déterminées de façon automatique.

Modèle de Valiante *et al.* (2009)

Le modèle de Valiante *et al.* (2009) utilise une stratégie assez différente. Il prend en compte les variations de température des grains et de contribution AGN entre galaxies. Il tire aléatoirement des *templates* de galaxies pour construire un catalogue simulé qui est ensuite utilisé pour prédire les différentes observables infrarouges. Les paramètres de ce modèle sont choisis manuellement afin reproduire de manière satisfaisante les observations. Les auteurs prétendent que la prise en compte des AGN est absolument nécessaire pour reproduire les comptages infrarouges.

Modèle de Franceschini *et al.* (2010)

Le modèle de Franceschini *et al.* (2010) utilise plusieurs populations ayant chacune sa propre évolution : spirales, AGNs, LIRGs et ULIRGs. L'évolution de chaque population est déterminée manuellement afin de reproduire au mieux les observations. Grâce à son

très grand nombre de paramètres libres, ce modèle est fréquemment revisité afin de toujours reproduire les observations.

6.1.3 Vers une nouvelle génération de modèles *backward evolution*

Des observations récentes mettent à mal les modèles cités précédemment. Deux observations à elles-seules éliminent l'ensemble des modèles pré-*Herschel*.

La première est la mesure des comptages observés avec SPIRE (Oliver *et al.* (2010)). A l'exception du modèle de Valiante *et al.* (2009) et Negrello *et al.* (2007), tous les modèles surestiment les comptages de sources à haut flux (c.f. Fig. 6.1 gauche). Le modèle de Negrello *et al.* (2007) surestime toutefois les comptages autour de 50 mJy. Seul le modèle de Valiante *et al.* (2009) est en bon accord avec cette observable.

Une autre mesure très discriminante a été réalisée. Il s'agit de la contribution des sources détectées à $24\ \mu\text{m}$ au fond infrarouge en fonction du *redshift* (c.f. Fig. 6.1 droite et Sect. 5.2.1). Le modèle de Valiante *et al.* (2009) est en complet désaccord avec cette mesure.

Aucun des modèles pré-*Herschel* n'a été donc en mesure de prédire ces nouvelles observables. Bien entendu, certains de ces modèles pourrait être légèrement modifiés pour mieux reproduire les nouvelles contraintes. Néanmoins, la modification permanente d'évolutions introduites "à la main" pour ajuster chaque nouvelle observation est-elle réellement satisfaisante ? De plus, nombre de ces modèles ont un très grand nombre de paramètres libres cachés (par exemple, plus de 40 pour le modèle Lagache *et al.* (2004)). La construction d'un modèle simple reproduisant la plupart des observations serait bien plus satisfaisante qu'une complexification d'un modèle ancien. C'est cette considération qui m'a poussé à construire un nouveau modèle paramétrique ajusté directement sur les observations.

Nous présentons ici un bref résumé du travail de modélisation que j'ai effectué. Le détail de ce travail est fourni dans l'article en fin de chapitre (Béthermin *et al.* (2011)).

6.2 Description du nouveau modèle

Ce nouveau modèle est purement paramétrique (13 paramètres libres). Il s'inspire du modèle de Lagache *et al.* (2004), mais limite grandement le nombre de paramètres à ajuster. Il n'utilise pas d'AGNs.

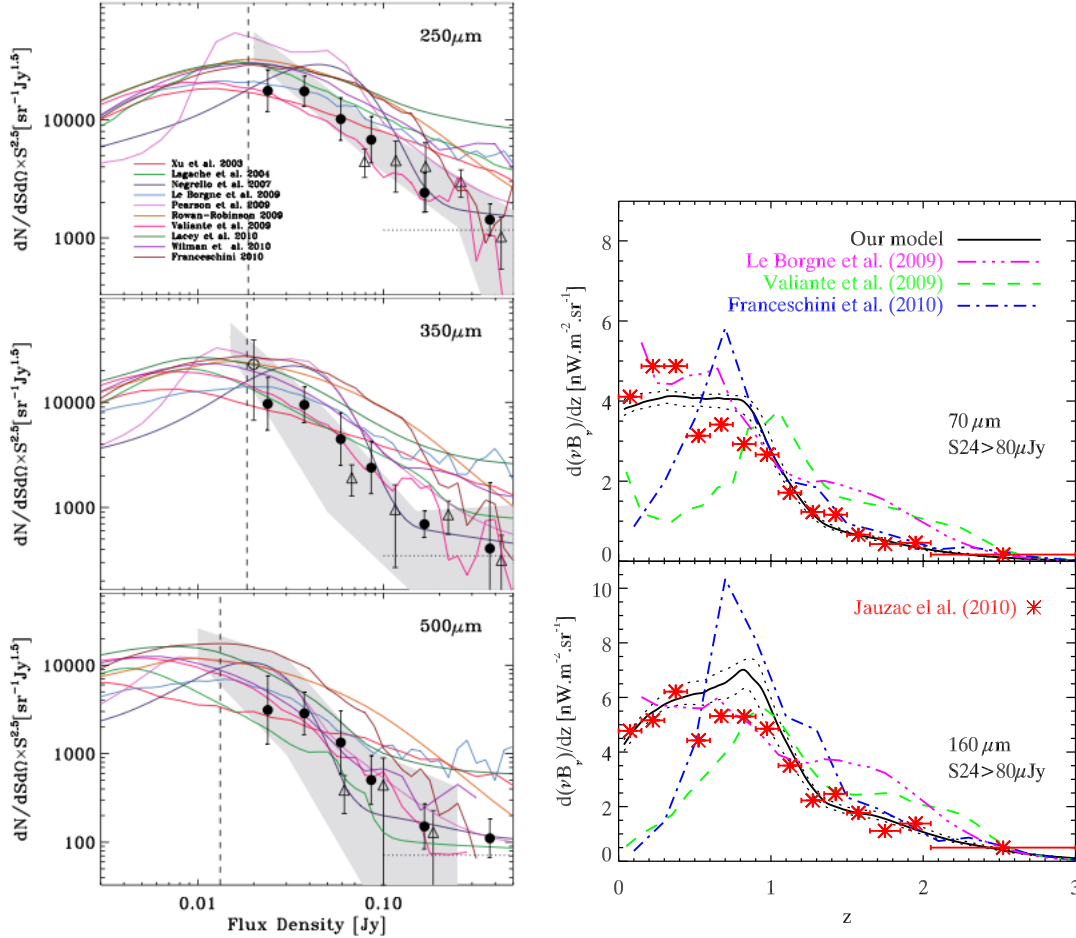


FIGURE 6.1 – (À gauche) Comptages extragalactiques à 250, 350 et 500 μm mesurés par Oliver *et al.* (2010) (cercles pleins), Béthermin *et al.* (2010b) (triangles ouverts), Khan *et al.* (2007) (cercles ouverts) et Patanchon *et al.* (2009) (zone grisée). Figure de Oliver *et al.* (2010). Les lignes colorées représentent différents modèles de galaxies. (À droite) Contribution des sources détectées à 24 μm au CIB en fonction du *redshift*. Les astérisques rouges correspondent aux mesures de Jauzac *et al.* (2011) par stacking. Les prédictions de différents modèles sont représentées : Le Borgne *et al.* (2009) (tirets-3 points violet), Valiante *et al.* (2009) (tirets verts), Franceschini *et al.* (2010) (tirets-points bleus) et Béthermin *et al.* (2011) (ligne pleine noire).

Les paramètres cosmologiques utilisés sont ceux du modèle Λ CDM ajusté sur les données WMAP 7 ans (Larson *et al.*, 2010). Nous avons donc $H_0 = 71 \text{ km.s}^{-1}.\text{Mpc}^{-1}$, $\Omega_\Lambda = 0.734$ and $\Omega_m = 0.266$.

6.2.1 Fonction de luminosité et son évolution

Nous utilisons dans ce modèle une fonction de luminosité (LF) infrarouge de la forme classique (Saunders *et al.*, 1990) :

$$\Phi(L_{IR}) = \Phi_\star \times \left(\frac{L_{IR}}{L_\star}\right)^{1-\alpha} \times \exp\left[-\frac{1}{2\sigma^2} \log_{10}^2\left(1 + \frac{L_{IR}}{L_\star}\right)\right] \quad (6.1)$$

où $\Phi(L_{IR})$ est le nombre de source par dex et par unité de volume comobile à une luminosité bolométrique infrarouge donnée L_{IR} donnée. $\Phi_\star$ et $L_\star$ caractérisent la densité et la luminosité caractéristiques à la coupure de la LF. α et σ régissent le comportement à basse et haute luminosité.

Pour reproduire les observations infrarouges, nous autorisons les paramètres de la fonction de luminosité à évoluer avec le *redshift*. Pour limiter le nombre de paramètres libres et également éviter de créer de fortes dégénérescences, nous fixons α et σ . L'évolution des autres paramètres est de la forme $L_\star \propto (1+z)^{r_L}$ et $\Phi_\star \propto (1+z)^{r_\Phi}$, un unique jeu de r_L et r_Φ ne pouvant permettre de reproduire les observations. Nous utilisons trois valeurs distinctes de r_L et r_Φ à bas (0 à z_{break}), moyen (z_{break} et 2) et haut *redshift* (plus de 2). z_{break} est un paramètre libre qui s'ajuste naturellement, en revanche nous fixons la second changement d'exposant à $z=2$, celui-ci n'apparaissant pas naturellement.

6.2.2 Distributions spectrales d'énergie

Pour construire ce modèle, nous utilisons les bibliothèques de distribution spectrale d'énergie de Lagache *et al.* (2004) (c.f. Sect. 6.1.2). Nous rappelons que cette bibliothèque contient deux familles : les galaxies foides passives (type spirale) et les galaxies à flambée de formation d'étoiles.

Les galaxies froides sont dominantes à faible luminosité infrarouge et les galaxies à flambées de formation d'étoiles le sont à forte luminosité. Nous avons choisi arbitrairement de décrire la fraction de galaxies à flambée de formation d'étoiles en fonction de la luminosité totale infrarouge L_{IR} de la manière suivante :

$$\frac{\Phi_{starburst}}{\Phi} = \frac{1 + th[\log_{10}(L_{IR}/L_{pop})/\sigma_{pop}]}{2} \quad (6.2)$$

où th est la fonction tangente hyperbolique. L_{pop} est la luminosité pour laquelle les contributions des deux populations sont égales. σ_{pop} caractérise la largeur de la transition entre les deux populations.

6.2.3 Effet des lentilles gravitationnelles sur les observables

En relativité générale, les fortes masses ont la faculté de courber les rayons lumineux. Les fortes concentrations de matière peuvent ainsi agir à la façon d’une lentille optique. On parle alors de lentilles gravitationnelles. Les halos des galaxies elliptiques massives proches peuvent amplifier le flux de galaxies lointaines (Perrotta *et al.*, 2001, 2002). Ce phénomène peut modifier significativement les comptages lorsque leur pente est forte. Pour prendre en compte ce phénomène dans le modèle nous utilisons un modèle simple supposant que les halos de matière noire sont des sphères isothermes, qui détermine comment les lentilles modifient les comptages.

6.3 Ajustement des observations

6.3.1 Sélection des données à ajuster

Une quantité colossale de mesures a été réalisée dans l’infrarouge : comptages, fonctions de luminosité, distribution en *redshift*, couleurs des sources... Néanmoins, ces différentes observations sont plus ou moins affectées par des biais d’analyse et/ou de sélection. Les comptages sont par nature peu biaisés, si les effets d’extraction sont bien corrigés. Néanmoins, de nombreux comptages publiés ne prennent pas en compte la variance cosmique. Ceci a guidé nos choix de comptages à ajuster. Nous avons également utilisé des fonctions de luminosité monochromatiques peu K-corrigées⁴ dans le but de mieux contraindre le modèle. Une discussion détaillée sur le choix des points à ajuster est faite dans Béthermin *et al.* (2011).

La liste des observations sélectionnées est la suivante :

- Comptages *Spitzer*/MIPS de Béthermin *et al.* (2010a) à 24, 70 et 160 μm ,
- Comptages *Herschel*/SPIRE de Oliver *et al.* (2010) à 250, 350 et 500 μm ,
- Comptages AzTEC de Austermann *et al.* (2010) and Scott *et al.* (2010) at 1.1 mm.
- Fonction de luminosité locale IRAS à 60 μm de Saunders *et al.* (1990)
- Fonction de luminosité locale *Spitzer* à 24 μm de Rodighiero *et al.* (2009),

⁴Typiquement LF à $\lambda_{rest}/(1+z)\mu\text{m}$ déterminée à partir de donnée à λ_{rest} .

- Fonction de luminosité *Spitzer* à 15 μm à $z=0.6$ de Rodighiero *et al.* (2009),
- Fonction de luminosité *Spitzer* à 12 μm à $z=1$ de Rodighiero *et al.* (2009),
- Fonction de luminosité *Spitzer* à 8 μm at $z=2$ de Caputi *et al.* (2007),
- Fond infrarouge mesuré avec FIRAS par Lagache *et al.* (1999).

6.3.2 Ajustement

La calibration des instruments infrarouges n'étant pas parfaite, il faut la prendre en compte lors de l'ajustement des données. Cette incertitude, dépendant de l'instrument et de la bande, varie entre 4% et 15% (Stansberry *et al.* (2007), Gordon *et al.* (2007), Engelbracht *et al.* (2007), Swinyard *et al.* (2010)). Une modification de la calibration translate tous les comptages en x et en y : $S' = \gamma S$ et $(S'^{2.5} dN/dS') = \gamma^{1.5} (S^{2.5} dN/dS)$, où γ est un facteur qui vaut 1 si la calibration est parfaite.

Nous supposons que les incertitudes de mesure et de calibration sont toutes gaussiennes et non-corrélées. La vraisemblance L est donc donnée par :

$$-\log(L(\theta)) = \sum_{k=1}^{N_{\text{points}}} \frac{(m_k - m_{\text{model},k}(\theta))^2}{2\sigma_m^2} + \sum_{b=1}^{N_{\text{band}}} \frac{(\gamma_b - 1)^2}{2\sigma_{\text{calib},b}^2} \quad (6.3)$$

où θ est le vecteur contenant les paramètres du modèle, m_k une mesure, $m_{\text{model},k}$ la prédiction du modèle pour la même mesure, σ_m l'incertitude sur cette mesure, γ_b le paramètre de calibration dans la bande b et $\sigma_{\text{calib},b}$ l'incertitude de calibration dans cette bande.

Le modèle contient un nombre important de paramètres à ajuster et la densité de probabilité *a posteriori* n'a aucune raison d'être gaussienne. Pour cette raison, j'ai choisi d'utiliser la méthode *Monte Carlo Markov Chain* (MCMC). Notre meilleur ajustement a un χ^2 de 177 pour 113 degrés de liberté. Cet ajustement est donc relativement bon.

6.4 Résultats

6.4.1 Comparaison avec les observations

Le modèle ajuste de façon satisfaisante notre sélection de comptages à 24, 70, 160, 250, 350, 500 et 1100 μm (voir une sélection Fig. 6.2). Il sous-estime néanmoins légèrement les comptages à 24 μm (environ 10%) autour de 300 μJy . Bien qu'en accord à $1-\sigma$ avec les points de Oliver *et al.* (2010) que nous avons ajustés, les comptages prédits par le modèle sont systématiquement plus bas que les mesures à 350 et 500 μm . Le désaccord avec les

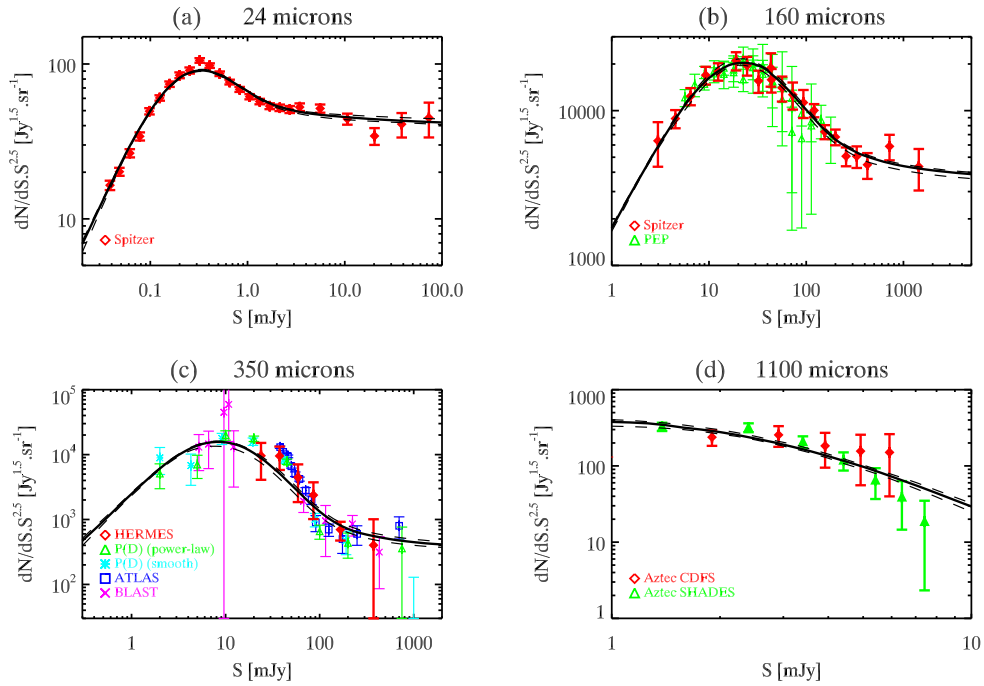


FIGURE 6.2 – Comptages infrarouge différentes longueurs d’onde comparées au modèle (ligne noire). (a) : Comptages à $24 \mu\text{m}$ de Béthermin *et al.* (2010a) (losanges rouges). (b) : Comptages à $160 \mu\text{m}$ de Béthermin *et al.* (2010a) (losanges rouges) et Berta *et al.* (2010) (triangles verts). (c) : Comptages à $350 \mu\text{m}$ de Béthermin *et al.* (2010b) (croix violettes), de Oliver *et al.* (2010) (losanges rouges), de Clements *et al.* (2010) (carrs bleus) et de Glenn *et al.* (2010) (triangles verts et astérisques bleues ciel). (d) : Comptages à 1.1 mm de Austermann *et al.* (2010) (losanges rouges) et de Scott *et al.* (2010) (triangles verts).

points de Clements *et al.* (2010) est plus grand. Toutefois, leurs points ne prennent pas en compte la variance cosmique. Les points $P(D)$ ne doivent pas, quant à eux, être directement comparés au modèle comme expliqué dans le Chap. 4. L'ajustement du modèle directement sur l'histogramme des pixels des cartes SPIRE pourrait permettre à moyen terme de bien mieux contraindre le modèle dans les bandes SPIRE.

Le modèle peut également être comparé avec les comptages à d'autres longueurs d'onde : 15, 60, 100 et 850 μm . Les points expérimentaux sont souvent en large désaccord entre eux. Néanmoins, le modèle passe dans le nuage de points à ces quatre longueurs d'onde. Nous avons également comparé nos comptages avec les comptages SPT de Vieira *et al.* (2009) à 1.4 mm. Notre modèle ne prend pas en compte les radio-galaxies (modélisées avec précision par le modèle de Zotti *et al.* (2005)). Toutefois, la couleur 1.4 mm/2 mm des sources synchrotrons est très différente des galaxies infrarouges. Nous avons donc comparé les prédictions du modèle avec les comptages de sources "poussiéreuses" rouges de Vieira *et al.* (2009). L'accord est très bon. Nous avons également un très bon accord avec les comptages de sources sans contrepartie IRAS à 60 μm . Le modèle prédit qu'une grande partie de ces sources sont des galaxies amplifiées par effet de lentille gravitationnelle.

La distribution en *redshift* des sources sélectionnées en flux infrarouge est une contrainte importante pour le modèle. Néanmoins, ces contraintes peuvent être biaisées par le processus d'identification des contreparties optiques. Nous avons comparé les prédictions du modèle avec les observations pour différentes sélections : $S_{24} > 80 \mu\text{Jy}$, $S_{24} > 300 \mu\text{Jy}$, $S_{250} > 40 \text{ mJy}$, $S_{350} > 30 \text{ mJy}$, $S_{500} > 20 \text{ mJy}$, $S_{850} > 3 \text{ mJy}$, $S_{1100} > 3 \text{ mJy}$. Pour les sélections à 24 μm , le modèle a tendance à surestimer le nombre de sources à bas *redshifts* ($z < 0.5$) et sous-estimer le nombre de sources à haut *redshifts* ($z > 2.5$) par rapport aux observations (Desai *et al.* (2008), Le Floc'h *et al.* (2009), Rodighiero *et al.* (2009)). Il y a un très bon accord avec les observations pour les sélections dans le domaine sub-millimétrique et millimétrique (Chapman *et al.* (2005); Chapin *et al.* (2009b, 2010)).

Les comptages prédits par le modèle permettent de calculer l'histogramme attendu des cartes BLAST. Ceci permet de tester la validité du modèle à bas flux. Il y a un très bon accord à 250 et 350 μm , en revanche le modèle prédit un pic légèrement trop étroit à 500 μm . Ce résultat est cohérent avec le fait que les comptages du modèle sont en dessous des observations 500 μm .

6.4.2 Histoire de la formation d'étoiles

Le modèle d'évolution permet de prédire la densité de luminosité bolométrique infrarouge ρ_{IR} , c'est-à-dire la puissance totale rayonnée en infrarouge par unité de volume comobile.

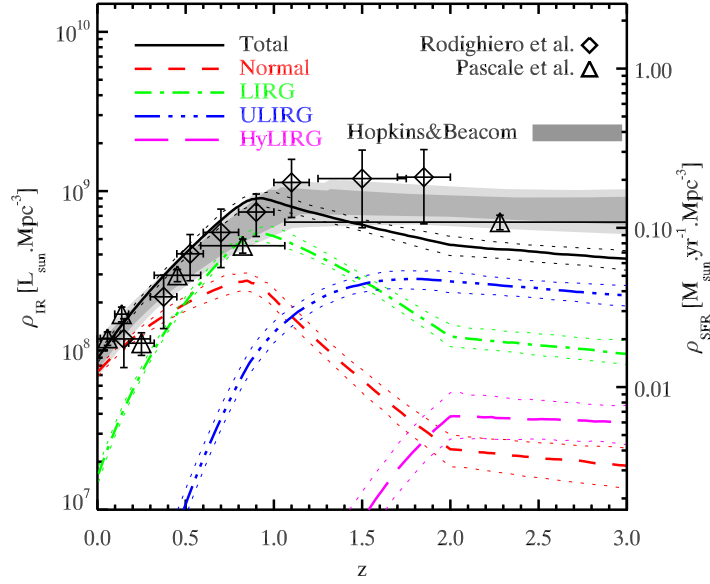


FIGURE 6.3 – Densité de luminosité infrarouge en fonction du *redshift* (en noir), et contribution des galaxies normales (rouge), des LIRGs (vert), ULIRG (bleu) et HyLIRG (violet). Comparaison avec les observations de Pascale *et al.* (2009), Rodighiero *et al.* (2009) et la compilation de Hopkins et Beacom (2006).

Cette grandeur peut être convertie en densité de formation d'étoiles grâce à la constante de Kennicutt qui vaut $1.7 \times 10^{-10} \text{ M}_\odot \cdot \text{yr}^{-1} \cdot \text{L}_\odot^{-1}$ (Kennicutt (1998)). La Fig. 6.3 représente l'évolution de ces deux quantités en fonction du *redshift*. On trouve que la densité de luminosité infrarouge (ainsi que la formation d'étoiles) augmente fortement jusqu'à $z \sim 1$. On passe ainsi de $10^8 \text{ L}_\odot \cdot \text{Mpc}^{-3}$ à $10^9 \text{ L}_\odot \cdot \text{Mpc}^{-3}$ entre l'Univers local et $z \sim 1$. La densité infrarouge décroît ensuite lentement avec le *redshift*. Cette évolution est en relatif accord avec les observations (Rodighiero *et al.* (2009), Pascale *et al.* (2009), Hopkins et Beacom (2006)).

Si on sépare les galaxies en différentes classes de luminosité, on constate que les galaxies normales dominent la densité infrarouge dans l'Univers local, alors qu'elle est dominée par les LIRGs à $z=1$ et les ULIRGs à $z=2$. Ceci montre que la formation d'étoiles a lieu dans des conditions physiques très différentes aujourd'hui et dans l'Univers jeune. Ceci pourrait s'expliquer par l'effondrement de gaz froid sur les halos les plus massifs à haut *redshift*.

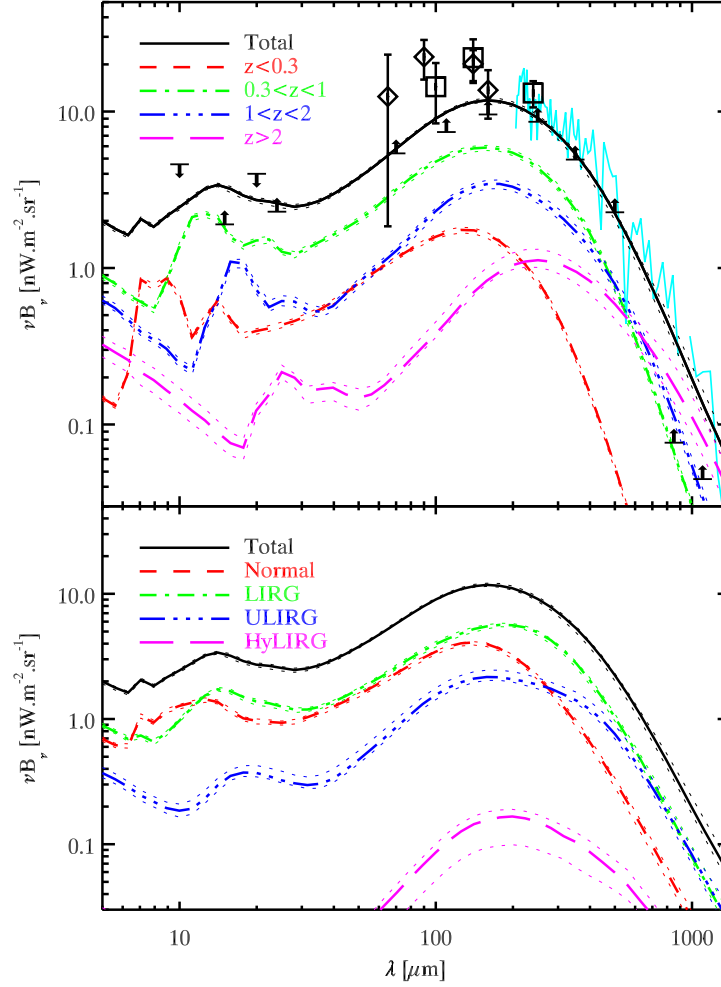


FIGURE 6.4 – Distribution spectrale d'énergie du fond infrarouge. Le fond total prédit par le modèle est en noir. (En haut) : Contribution des différentes tranches de *redshift* ($0 < z < 0.3$ en rouge, $0.3 < z < 1$ en vert, $1 < z < 2$ en bleu et $z > 2$ en violet). Les limites inférieures (comptages et/ou stacking) au fond sont représentées par des flèches vers le haut (Hopwood *et al.* (2010); Béthermin *et al.* (2010a); Berta *et al.* (2010); Marsden *et al.* (2009); Greve *et al.* (2009); Scott *et al.* (2010)). Les limites supérieures au fond (TeV) sont représentées par des flèches vers le bas (Stecker et de Jager (1997); Renault *et al.* (2001)). Les mesures absolues de DIRBE et *Akari* sont matérialisées par des carrés et des losanges, respectivement. Le spectre du fond infrarouge observé par FIRAS est en cyan (Lagache *et al.* (2000)). (En bas) : Contribution au fond des galaxies normales (rouge), des LIRGs (vert), des ULIRG (bleu) et des HyLIRG (violet).

6.4.3 Fond infrarouge

Le modèle peut également prédire la distribution spectrale d'énergie du fond infrarouge (voir Fig. 6.4). Le résultat est en bon accord avec les observations. On peut également séparer le fond infrarouge en tranches de *redshift*. On remarque qu'en dessous de $500\ \mu\text{m}$, la contribution dominante correspond à la tranche de *redshift* $0.3 < z < 1$. En revanche, aux plus grandes longueurs d'onde, le fond est émis en majorité par des sources à $z > 2$. En fait, plus on va vers les grandes longueurs d'onde, et plus on sonde les populations à haut *redshift*. Ceci est en accord avec les observations présentées Sect. 5.2.1

6.5 Conclusion

Nous avons montré dans ce chapitre qu'il est possible de reproduire avec succès les comptages infrarouges grâce à un modèle relativement simple. Ceci suggère que des modèles complexes utilisant un grand nombre de populations ne sont pas nécessaires pour reproduire les observations actuelles. Le nouveau modèle est le premier modèle d'évolution des galaxies infrarouges paramétriques, dont les paramètres sont déterminés par la méthode MCMC. Le même type de travail a été réalisé parallèlement⁵ par Marsden *et al.* (2010). Les évolutions de la densité de luminosité infrarouge prédites par les deux modèles sont très différentes, alors que ces deux modèles reproduisent tout deux les comptages. Ceci montre qu'à l'avenir l'utilisation de nouvelles observables (comme les distribution en *redshift*) va être nécessaire pour discriminer les modèles.

Ce travail de modélisation pose également des questions importantes sur les processus de formation d'étoiles à grand *redshift*. En effet, nous avons trouvé que les ULIRGs dominent la formation d'étoiles à $z=2$. Dans l'Univers local, ce type de sources ne peut être dû qu'à une fusion majeure. Dans l'Univers lointain, les ULIRGs pourraient avoir un mécanisme très différent, basé sur une accréation rapide de gaz froid. Ainsi, avec une approche globale, nous avons identifié une population d'objets surprenante. L'étude fine de leur physique devrait lever le voile sur la manière dont la majorité des étoiles se sont formées dans l'Univers jeune. Enfin, ce nouveau modèle permet de réaliser de nombreuses prédictions (limite de confusion, comptages...), qui devraient être très utiles pour préparer les relevés du futur. Elles sont également très utiles pour interpréter les récentes mesures des fluctuations du fond infrarouge, qui seront présentées au chapitre suivant.

⁵Pour la petite histoire, Gaelen Marsden et moi nous sommes rendu compte que nous travaillions tous les deux sur le même type de modèle un mois avant de soumettre nos articles. Nous nous sommes mis d'accord pour poster le même jour le papier sur astro-ph.

6.6 Article : *Modeling the evolution of the infrared galaxies : a backward evolution model.*

Mon travail de modélisation, résumé dans ce chapitre, a donné lieu à la publication dans le journal *Astronomy&Astrophysics*.

Modeling the evolution of infrared galaxies: a parametric backward evolution model

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ABSTRACT

Aims. We attempt to model the infrared galaxy evolution in as simple a way as possible and reproduce statistical properties such as the number counts between 15 μm and 1.1 mm, the luminosity functions, and the redshift distributions. We then use the fitted model to interpret observations from *Spitzer*, AKARI, BLAST, LABOCA, AzTEC, SPT, and *Herschel*, and make predictions for *Planck* and future experiments such as CCAT or SPICA.

Methods. This model uses an evolution in density and luminosity of the luminosity function parametrized by broken power-laws with two breaks at redshift ~ 0.9 and 2, and contains the two populations of the Lagache model: normal and starburst galaxies. We also take into account the effect of the strong lensing of high-redshift sub-millimeter galaxies. This effect is significant in the sub-mm and mm range near 50 mJy. It has 13 free parameters and eight additional calibration parameters. We fit the parameters to the IRAS, *Spitzer*, *Herschel*, and AzTEC measurements with a Monte Carlo Markov chain.

Results. The model adjusted to deep counts at key wavelengths reproduces the counts from mid-infrared to millimeter wavelengths, as well as the mid-infrared luminosity functions. We discuss the contribution to both the cosmic infrared background (CIB) and the infrared luminosity density of the different populations. We also estimate the effect of the lensing on the number counts, and discuss the discovery by the South Pole Telescope (SPT) of a very bright population lying at high redshift. We predict the contribution of the lensed sources to the *Planck* number counts, the confusion level for future missions using a $P(D)$ formalism, and the Universe opacity to TeV photons caused by the CIB. Material of the model (software, tables and predictions) is available online*.

Key words. diffuse radiation – galaxies: statistics – galaxies: evolution – galaxies: star formation – infrared: galaxies – submillimeter: galaxies

1. Introduction

The extragalactic background light (EBL) is the relic emission from galaxy formation and accretion processes since the recombination. The infrared ($8 \mu\text{m} < \lambda < 1000 \mu\text{m}$) part of this emission called the cosmic infrared background (CIB) was detected for the first time by Puget et al. (1996) and contains about half of the energy of the EBL (Dole et al. 2006; Béthermin et al. 2010a). Nevertheless, in the local universe, the optical/UV emissions is three times brighter than infrared/sub-millimeter ones (Soifer & Neugebauer 1991; Driver et al. 2008). This pseudo-paradox is explained by a strong evolution in the infrared galaxy properties.

The infrared luminosity density is dominated by normal galaxies ($L_{\text{IR,bolometric}} < 10^{11} L_{\odot}$) in the local Universe (Saunders et al. 1990). At higher redshift, it is dominated by luminous infrared galaxies (LIRG, $10^{11} L_{\odot} < L_{\text{IR,bolometric}} < 10^{12} L_{\odot}$) at $z = 1$ (Le Floc'h et al. 2005) and ultra-luminous infrared galaxies (ULIRG, $10^{12} L_{\odot} < L_{\text{IR,bolometric}} < 10^{13} L_{\odot}$) at $z = 2$ (Caputi et al. 2007). The infrared luminosity of these galaxies is correlated to the star formation rate (Kennicutt 1998). Thus, modeling this rapid evolution of the infrared galaxies is very important to understand the history of the star formation.

The physical models (such as Lacey et al. 2010; Wilman et al. 2010; Younger & Hopkins 2011, for the latest) use a physical approach based on semi-analytical recipes and dark matter numerical simulations. They use a limited set of physical parameters, but nowadays they poorly reproduce some basic observational constraints such as the infrared-galaxy number counts (Oliver et al. 2010).

The backward evolution models (like Lagache et al. 2004; Franceschini et al. 2010; Rowan-Robinson 2009; Valiante et al. 2009) use an evolution the luminosity function (LF) of the galaxies to reproduce empirically the galaxy counts, and other constraints. These models describe only the evolution and contain little physics. The parameters of these models were tuned manually to fit observational constraints. Le Borgne et al. (2009) used another approach and performed a non-parametric inversion of the counts to determine the LF. Nevertheless, this approach is complex, uses only one population of galaxy, and does not manage to reproduce the 160 μm number counts. An other fully-empirical approach was used by Domínguez et al. (2011). They fitted the SED from UV to mid-infrared of detected galaxies and extrapolated the far-infrared spectral energy distribution of these galaxies and the contribution of faint populations. Nevertheless, their model aims only to reproduce the CIB, although its ability to reproduce other constraints such as the number counts has not been tested.

* <http://www.ias.u-psud.fr/irgalaxies/>

The Balloon-borne Large-Aperture Submillimeter Telescope (BLAST) experiment (Pascale et al. 2008; Devlin et al. 2009) and the spectral and photometric imaging receiver (SPIRE) instrument (Griffin et al. 2010) onboard the *Herchel* space telescope (Pilbratt et al. 2010) performed recently new observations in the sub-mm at 250, 350, and 500 μm . In their current version, most of the models fail to reproduce the number counts measured at these wavelengths (Patanchon et al. 2009; Béthermin et al. 2010b; Clements et al. 2010; Oliver et al. 2010). The Valiante et al. (2009) model gives the best results, using a Monte Carlo approach (sources are randomly taken in libraries) to simulate the temperature scatter and the heterogeneity of the active galactic nucleus (AGN) populations, but this model strongly disagrees with the recent measurements of the redshift distribution of the CIB by Jauzac et al. (2011). It is thus necessary to develop new models that reproduce the recent far-infrared and sub-mm observations.

The discovery of very bright and high-redshift dusty galaxies by Vieira et al. (2010) with the South Pole Telescope (SPT) suggests that the contribution of high-redshift galaxies strongly lensed by dark matter halos of massive low-redshift galaxies on the bright sub-millimeter and millimeter counts is non-negligible. This contribution was discussed by Negrello et al. (2007) and observational evidence of this phenomenon was found by Negrello et al. (2010). We can also cite the simplified approach of Lima et al. (2010), who reproduced the AzTEC and SPT counts using a single population of galaxies with a Schechter LF at a single redshift and a lensing model. We can also cite Hezaveh & Holder (2010) on the effect of the lensing on the SPT counts, based on an advanced lensing model.

We present a new simple and parametric model based on Lagache et al. (2004) SED libraries, which reproduces the new observational constraints. The parameters of this model (13 free parameters and eight calibration parameters) were fitted from a large set of recent observations using a Monte Carlo Markov chain (MCMC) method, allowing us to study degeneracies between the parameters. This model also includes the effects of the strong lensing on the observations. We make predictions about the confusion limit for future missions, the high-energy opacity of the Universe, and the effects of strong lensing on the counts. This model is plugged into a halo model to study the spatial distribution of the infrared galaxies in a companion paper (Penin et al., in prep.). We note that another study also using MCMC methods was performed by Marsden et al. (2011) at the same time as ours.

We use the WMAP seven-years best-fit ΛCDM cosmology model (Larson et al. 2011) in this paper. We thus assume that $H_0 = 71 \text{ km s}^{-1} \text{ Mpc}^{-1}$, $\Omega_\Lambda = 0.734$, and $\Omega_m = 0.266$.

2. Approach

The backward evolution models are not based on physical parameters. Each model uses different evolving populations to reproduce the observational constraints. Some models (such as Franceschini et al. 2010; Rowan-Robinson 2009) use four galaxy populations evolving separately to reproduce the observations. Valiante et al. (2009) take randomly galaxy SEDs from a very large library of templates and claim that the contribution of the AGNs and the dispersion in the dust temperature of the galaxies must be taken into account to reproduce the observational constraints. Our approach is to keep the model as simple as possible, but to use advanced methods to constrain its free parameters. This new parametric model can be used as an input for halo modeling or $P(D)$ analysis for instance.

As we show, we need neither an AGN contribution nor a temperature dispersion to reproduce the current observational constraints. In the local Universe, the AGNs only dominate in the ULIRG regime (Imanishi 2009). Alexander et al. (2005) estimate an AGN contribution of 8% to the submillimeter galaxies (SMG). Fadda et al. (2010) showed that the proportion of AGN-dominated sources is rather small for LIRGs at $z \sim 1$ (5%) and ULIRGs around $z \sim 2$ (12%). Jauzac et al. (2011) demonstrated that the AGN contribution to the CIB is less than 10% at $z < 1.5$. These categories of luminosity dominate the infrared output at their redshift. The small contribution of AGNs to these categories explains why AGNs are not necessary to reproduce the mean statistical properties of the galaxies. Nevertheless, despite their small contribution to the infrared output, the AGNs play a central role in the physics of galaxies.

Our model takes into account the strong lensing of high-redshift galaxies by the dark matter halos of elliptical galaxies. According to the results of Sect. 7.3, the effect of the lensing on the counts we fitted is smaller than 10%. The model of lensing does not have free parameters. It is based on the WMAP seven-years best-fit cosmology and on some parameters taken at values given by the literature. The lensing is thus not useful to reproduce the current observations, but is necessary to make predictions at bright fluxes ($>100 \text{ mJy}$) in the sub-mm and mm range, where the effects of the lensing are large.

3. Description of the model

3.1. Basic formulae

The flux density S_ν at a frequency ν of a source lying at a redshift z is (Hogg 1999) is

$$S_\nu = \frac{(1+z)L_{(1+z)\nu}}{4\pi D_L^2(z)}, \quad (1)$$

where z is the redshift, D_L is the luminosity distance of the source, and $L_{(1+z)\nu}$ is the luminosity at a frequency $(1+z)\nu$. The comoving volume corresponding to a redshift slice between z and $z + dz$ and a unit solid angle is

$$\frac{dV}{dz} = D_H \frac{(1+z)^2 D_A^2}{\sqrt{\Omega_\Lambda + (1+z)^3 \Omega_m}}, \quad (2)$$

where D_H is the Hubble distance ($D_H = c/H_0$), D_A the angular distance to the redshift z , and Ω_m and Ω_Λ are the normalized energy density of the matter and the cosmological constant, respectively.

3.2. Bolometric luminosity function and its evolution

We assume that the luminosity function (LF) is a classical double-exponential function (Saunders et al. 1990)

$$\Phi(L_{\text{IR}}) = \Phi_* \times \left(\frac{L_{\text{IR}}}{L_*}\right)^{1-\alpha} \times \exp\left[-\frac{1}{2\sigma^2} \log_{10}^2\left(1 + \frac{L_{\text{IR}}}{L_*}\right)\right], \quad (3)$$

where $\Phi(L_{\text{IR}})$ is the number of sources per logarithm of luminosity and per comoving volume unit for an infrared bolometric luminosity L_{IR} , Φ_* is the normalization constant characterizing the density of sources, L_* is the characteristic luminosity at the break, and $1 - \alpha$ and $1 - \alpha - 1/\sigma^2/\ln^2(10)$ are the slope of the asymptotic power-law behavior at, respectively, low and high luminosity.

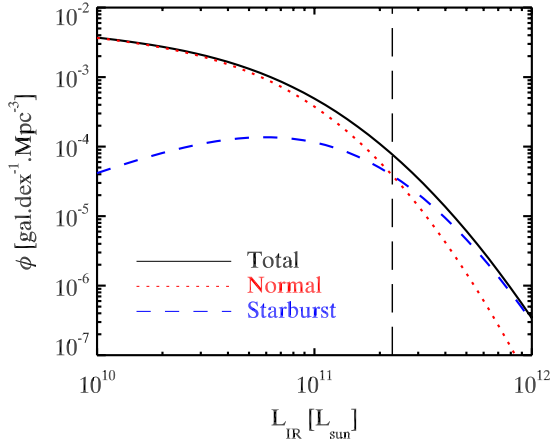


Fig. 1. Solid line: local infrared bolometric luminosity function from our best-fit model. Red dotted line: contribution of the normal galaxies. Blue dashed line: contribution of the starburst galaxies. Black vertical long dashed line: luminosity of the transition between the two populations (L_{pop}).

We assume a continuous evolution in luminosity and density of the luminosity function with the redshift of the form $L^* \propto (1+z)^{r_L}$ and $\Phi^* \propto (1+z)^{r_\Phi}$, where r_L and r_Φ are coefficients driving the evolution in luminosity and density, respectively. It is impossible to reproduce the evolution of the LF with constant r_L and r_Φ . We consequently authorize their value to change at some specific redshifts. The position of these breaks are the same for both r_L and r_Φ . The position of the first redshift break is a free parameter and converges to the same final value for initial values between 0 and 2. To avoid a divergence at high redshift, we also add a second break fixed at $z = 2$.

3.3. Spectral energy distribution (SED) of the galaxies

We use the [Lagache et al. \(2004\)](#) SED library. This library contains two populations: a starburst and a normal one. This library is parametrized only by the infrared bolometric luminosity (L_{IR}). There is no evolution of the SED with redshift. The normal population has that is a spectrum typical of a spiral galaxy. The SED of this population does not evolve with L_{IR} . In contrast, the starburst SED evolves with L_{IR} . The brighter the starburst galaxy, the hotter the dust.

The normal galaxies are dominant at low luminosity and the starburst at high luminosity. We thus chose arbitrarily a smooth function to describe the fraction of starburst galaxies as a function of the bolometric luminosity L_{IR}

$$\frac{\Phi_{\text{starburst}}}{\Phi} = \frac{1 + \text{th}[\log_{10}(L_{\text{IR}}/L_{\text{pop}})/\sigma_{\text{pop}}]}{2}, \quad (4)$$

where th is the hyperbolic tangent function, L_{pop} is the luminosity at which the number of normal and starburst galaxies are equal, and σ_{pop} characterizes the width of the transition between the two populations. At $L_{\text{IR}} = L_{\text{pop}}$, the fraction of starbursts is 50%. The fraction of starbursts is 88% at $L_{\text{IR}} = L_{\text{pop}} \times 10^{\sigma_{\text{pop}}}$, and 12% at $L_{\text{IR}} = L_{\text{pop}} \times 10^{-\sigma_{\text{pop}}}$. The contribution of the different populations to the local infrared bolometric LF is shown in Fig. 1.

3.4. Observables

The number counts at different wavelengths are an essential constraint of our model. The source extraction biases are in general accurately corrected for these observables. The counts are computed with the formula

$$\begin{aligned} \frac{dN}{dS_\nu d\Omega}(S_\nu) &= \sum_{\text{pop}} \int_0^\infty f_{\text{pop}}(L_{\text{IR}}) \frac{dN}{dL_{\text{IR}} dV} \bigg|_{L_{\text{IR}}(S_\nu, z, \text{pop})} \frac{dL_{\text{IR}}}{dS_\nu} \frac{dV}{dz d\Omega} dz \\ &= \sum_{\text{pop}} \int_0^\infty \frac{dN}{dS_\nu dz d\Omega} dz, \end{aligned} \quad (5)$$

where $dN/dS_\nu/d\Omega$ is the number of source per flux unit and per solid angle, $f_{\text{pop}}(L_{\text{IR}})$ is the fraction of the sources of a given galaxy population computed with Eq. (4), and $dN/dL_{\text{IR}}/dV$ is computed from Eq. (3) to be

$$\frac{dN}{dL_{\text{IR}} dV} = \frac{dN}{d\log_{10}(L_{\text{IR}}) L_{\text{IR}} \log(10) dV} = \frac{\Phi(L_{\text{IR}})}{L_{\text{IR}} \log(10)}, \quad (6)$$

where $L_{\text{IR}}(S_\nu, z, \text{pop})$ and dL_{IR}/dS_ν were computed on a grid in S_ν and z from the cosmology and the SED templates. These grids depend on neither the evolution of the LF nor the population mixing parameters. These grids are thus generated only once and saved to accelerate the computation of the counts. We note that with this method, it is very easy to change the SED templates and/or add other populations.

Other measurements help us to constrain our model. For example, the monochromatic luminosity Φ_{mono} function at a given redshift is

$$\Phi_{\text{mono}} = \sum_{\text{pop}} f_{\text{pop}}(L_{\text{IR}}(\nu L_\nu)) \phi(L_{\text{IR}}(\nu L_\nu)) \frac{d\log_{10}(L_{\text{IR}})}{d(\nu L_\nu)}. \quad (7)$$

We do not use the bolometric LFs, because they are biased by the choice of the assumed SED of the sources.

We can also compute the redshift distribution $N(z)$ for a selection in terms of flux $S_\nu > S_{\nu, \text{cut}}$ with

$$N(z, S_{\text{cut}}) = \int_{S_{\nu, \text{cut}}}^\infty \frac{dN}{dS_\nu dz} dS_\nu. \quad (8)$$

The extragalactic background due to the galaxies at a given wavelength is

$$B_\nu = \int_{z=0}^\infty \int_{S_\nu=0}^\infty S_\nu \frac{dN}{dS_\nu dz d\Omega} dS_\nu dz = \int_{S_\nu=0}^\infty S_\nu \frac{dN}{dS_\nu d\Omega} dS_\nu, \quad (9)$$

and can be compared to the measurements of the CIB.

The level of the non-correlated fluctuations (shot-noise) of the CIB can be easily computed from our model with the equation

$$P_{\text{SN}} = \int_0^{S_{\nu, \text{cut}}} S_\nu^2 \frac{dN}{dS_\nu d\Omega} dS_\nu, \quad (10)$$

where P_{SN} is the level of the non-correlated fluctuations and $S_{\nu, \text{cut}}$ the flux limit for the cleaning of the resolved sources.

3.5. Effect of the strong lensing on the counts

We use a simple strong-lensing model based on [Perrotta et al. \(2001, 2002\)](#), which assumes that the dark matter halos are singular isothermal spheres. The cross-section σ of a halo for a magnification μ larger than μ_{min} is

$$\sigma(\mu > \mu_{\text{min}}) = \frac{4\pi\alpha^2 D_{\text{A,ls}}}{\mu^2}, \quad (11)$$

where $D_{A,ls}$ is the angular-diameter distance between the lens and the source and α is given by

$$\alpha = 4\pi \frac{\sigma_v^2}{c^2}, \quad (12)$$

where c is the speed of light and σ_v the velocity dispersion in the halo, which depends on the cosmology, the redshift, and the mass of the halo.

The probability $P(\mu_{\min}, z_s)$ that a source at a redshift z_s is magnified by a factor greater than $\mu_{\min}$ is

$$P(\mu > \mu_{\min}, z_s) = \frac{(1 + z_s)^2}{4\pi D_c(z_s)} \int_0^\infty \int_0^\infty \frac{dN}{d(\log_{10}(M)) dV} \times \sigma(\mu > \mu_{\min}) \frac{dV}{dz} dM dz, \quad (13)$$

where z_s is the redshift of the source, D_c the comoving radial distance, $\frac{dN}{d(\log_{10}(M)) dV}$ is the halo mass function, and $\frac{dV}{dz}$ is the comoving volume associated with the redshift slice dz . We use the halo mass function of [Reed et al. \(2007\)](#).

The counts derived by our model take into account the fact that a small fraction of the sources are gravitationally magnified, i.e., the observed number counts taking into account the lensing $(dN/dS_\nu/d\Omega)_{\text{lensed}}$ are computed from initial counts $dS_\nu/dz/d\Omega$ with

$$\left(\frac{dN}{dS_\nu d\Omega} \right)_{\text{lensed}}(S_\nu) = \int_0^\infty \int_{\mu_{\min}}^{\mu_{\max}} \frac{dP}{d\mu}(z) \frac{1}{\mu} \frac{dN}{dS_\nu dz d\Omega} \left(\frac{S_\nu}{\mu}, z \right) d\mu dz. \quad (14)$$

In practice, this operation is performed by multiplying the vector containing the counts for a given redshift slice by a matrix describing the effects of lensing. This lensing matrix has diagonal coefficients values of around 1, and small ($<10^{-3}$) non-diagonal terms. These non-diagonal terms describe how the magnified faint sources affect the counts at brighter fluxes. The effect of the lensing on the monochromatic luminosity function was computed in the same way. We chose $\mu_{\min} = 2$, which corresponds to the limit of the validity of the strong-lensing hypothesis ([Perrotta et al. 2001](#)). The spatial extension of the lensed galaxies limits the maximum magnification. According to [Perrotta et al. \(2002\)](#), $\mu_{\max}$ is in the range 10–30. We chose to use $\mu_{\max} = 20$ in this paper. [Negrello et al. \(2007\)](#) used $\mu_{\min} = 2$ and $\mu_{\max} = 15$.

Figure 2 illustrates how number counts are affected by lensing. This figure is based on the number counts predicted by the model at 850 μm where the probability of magnification has been multiplied by a factor 10 to enhance the effect. The green dashed line represents contribution of the lensed sources. Owing to the magnification, the peak of this contribution is at higher flux than for non-lensed sources, and because of the small probability of lensing, the peak is lower than for non-lensed sources. This effect of the magnification on the counts become non-negligible when the slope of the counts is very steep, as in the sub-mm and mm domain.

4. Fitting the model parameters to the data

Our model has several free parameters. We attempted to use the minimum number of free parameters, which were determined by fitting the model to published measurements of the counts and LF. We used a Monte Carlo Markov chain (MCMC) to identify the best-fit parameters, their uncertainties, and their degeneracies. We do not fit the measured redshift distributions, because the cosmic variance and the selection effects are currently not accurately enough known.

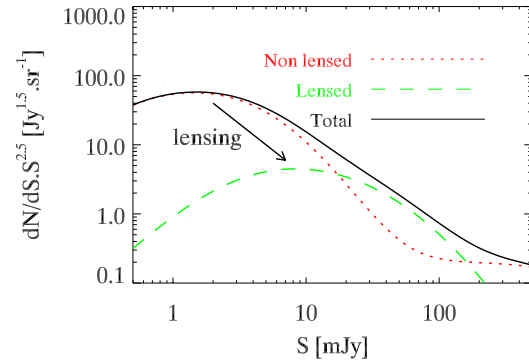


Fig. 2. Effect of the lensing on the number counts at 850 microns. The contribution of lensed sources is multiplied by ten to underline the effect of the lensing on the counts. Red dotted line: counts of non-lensed sources. Green dashed line: counts of lensed sources. Black solid line: total counts.

4.1. Data: extragalactic number counts

4.1.1. Data used for the fit

We chose to fit the following data:

- *Spitzer* MIPS counts of [Béthermin et al. \(2010a\)](#) at 24, 70, and 160 μm ;
- *Herschel* SPIRE [Oliver et al. \(2010\)](#) counts at 250, 350, and 500 μm ;
- AzTEC counts of [Austermann et al. \(2010\)](#) and [Scott et al. \(2010\)](#) at 1.1 mm.

4.1.2. Justification of our choice

We fit only the differential number counts since the integral counts are highly correlated and the correlation matrix is rarely estimated.

The number counts were measured at numerous bands between 15 μm and 1.1 mm. We chose a collection of points. We were guided by the reliability of the measurements and their error bars.

Number counts at 15 μm based on Infrared Space Observatory (ISO) data ([Elbaz et al. 1999](#); [Gruppioni et al. 2002](#)) and the AKARI data ([Pearson et al. 2010](#); [Hopwood et al. 2010](#)) differ by a factor of about 2, and their errors do not include the effects of cosmic variance. The results of these papers were not used for the fit. Nevertheless, we compared a posteriori these measurements to our own results to check for consistency in Sect. 5.4.

We fitted the *Spitzer* MIPS counts of [Béthermin et al. \(2010a\)](#) at 24, 70, and 160 μm . These points were measured from the data of FIDEL, COSMOS, and SWIRE legacy programs. The errors bars take into account the cosmic variance. These counts agree with the previous *Spitzer* measurements of [Papovich et al. \(2004\)](#), [Shupe et al. \(2008\)](#), [Le Floch et al. \(2009\)](#), and [Frayser et al. \(2009\)](#) and *Herschel* measurements of [Berta et al. \(2010\)](#) (in which the different fields were not combined).

At 250 μm , 350 μm , and 500 μm , we fitted the *Herschel* SPIRE counts of [Oliver et al. \(2010\)](#) which take into account the cosmic variance and the deboosting uncertainty. These counts agree with the BLAST measurements of [Patanchon et al. \(2009\)](#)

and Béthermin et al. (2010b) and the *Herschel* measurements of Clements et al. (2010). We chose Oliver et al. (2010) counts because *Herschel* data are points more accurate than BLAST ones and because Clements et al. (2010) counts use only Poissonian error bars, which could be largely underestimated. For instance, Béthermin et al. (2010a) estimate that the Poissonian uncertainties underestimate the real sample uncertainties by a factor three for counts around 100 mJy at 160 μm in a 10 deg² field.

We do not fit the 850 μm because of the large discrepancies between the Submillimeter Common-User Bolometer Array (SCUBA) observations (Coppin et al. 2006) and the Large APEX Bolometer CAmera (LABOCA) observations (Weiß et al. 2009). We discuss this problem in the Sect. 5.4.

We fitted the AzTEC measurements at 1.1 mm of Austermann et al. (2010) and Scott et al. (2010). The area covered by AzTEC is small compared to that covered by *Spitzer* and *Herschel*. We used two independent measurements of the AzTEC counts to increase the weight of the mm observations in our fit.

4.2. Data: monochromatic luminosity functions

4.2.1. Data used for the fit

We chose to fit the following data:

- InfraRed Astronomical Satellite (IRAS) local luminosity function at 60 μm of Saunders et al. (1990);
- *Spitzer* local luminosity function at 24 μm of Rodighiero et al. (2010);
- *Spitzer* luminosity function at 15 μm at $z = 0.6$ of Rodighiero et al. (2010);
- *Spitzer* luminosity function at 12 μm at $z = 1$ of Rodighiero et al. (2010);
- *Spitzer* luminosity function at 8 μm at $z = 2$ of Caputi et al. (2007).

4.2.2. Justification of our choice

We fitted some monochromatic luminosity functions. We chose only wavelengths and redshifts for which no K-corrections are needed. These observations strongly constrain the parameters driving the redshift evolutions of our model.

From the Rodighiero et al. (2010) LFs measured with the *Spitzer* data at 24 μm , we computed three non K-corrected LFs at $z = 0, 0.6$, and 1. We used their local LF at 24 μm . At $z = 0.6$ and 1, instead of directly using their results in their redshift bins, we combined their 15 μm LF at $z = 0.6$ (respectively, 12 μm LF at $z = 1$) in the $0.45 < z < 0.6$ and $0.6 < z < 0.8$ bins (respectively, $0.8 < z < 1.0$ and $1.0 < z < 1.4$) to obtain our version of the 15 μm LF at $z = 0.6$ (respectively, 12 μm LF at $z = 1$). The error in a point is the maximum of the combined statistical errors of the two bins and the difference between the measurements in the two bins. The second value is often larger because of the rapid evolution of the LF and the cosmic variance. We fitted only the points that do not suffer incompleteness to avoid possible biases. We also fitted the 8 μm at $z = 2$ of Caputi et al. (2007).

We also fitted the local LF at 60 μm determined from IRAS data (Saunders et al. 1990) to better constrain the faint-end slope of the local LF. Owing to the strong AGN contamination at 60 μm in the ULIRG regime, we did not fit the points brighter than $10^{11.5} L_\odot$ at 60 μm .

4.3. Data: CIB

The bulk of the CIB is not resolved at SPIRE wavelengths. We thus used the absolute measurement of the CIB level in SPIRE bands as a constraint of our model. We used the Lagache et al. (1999) measurement derived from the far-infrared absolute spectrophotometer (FIRAS) data: $11.7 \pm 2.9 \text{ nW m}^2 \text{ sr}^{-1}$ at 250 μm , $6.4 \pm 1.6 \text{ nW m}^2 \text{ sr}^{-1}$ at 350 μm , and $2.7 \pm 0.7 \text{ nW m}^2 \text{ sr}^{-1}$ at 500 μm . We assume that the CIB is only due to galaxies, thus neglect any possible extragalactic diffuse emission.

4.4. Calibration uncertainties

The calibration uncertainty is responsible for correlated uncertainties between points measured at a given wavelength with the same instrument. A change in the calibration globally modifies both the number counts and the LF. Assuming that the “good” calibration is obtained by multiplying the fluxes by a factor γ , the “good” normalized counts are obtained with $S_{\text{new}} = \gamma S$ and $(S_{\text{good}}^{2.5} dN/dS_{\text{good}}) = \gamma^{1.5} (S^{2.5} dN/dS)$. The effect on the LF in dex per volume unit is more simple. We just have to shift the luminosity in abscissa by a factor γ .

To our free parameters, we added a calibration parameter for each fitted band (see Table 2). We took into account the uncertainties in the calibration estimated by the instrumental team, in our fit (Stansberry et al. 2007; Gordon et al. 2007; Engelbracht et al. 2007; Swinyard et al. 2010; Scott et al. 2010).

4.5. Fitting method

To fit our points, we assumed that the uncertainties in both the measurements and calibrations are Gaussian and uncorrelated. The log-likelihood is then

$$-\log(L(\theta)) = \sum_{k=1}^{N_{\text{points}}} \frac{(m_k - m_{\text{model},k}(\theta))^2}{2\sigma_m^2} + \sum_{b=1}^{N_{\text{band}}} \frac{(\gamma_b - 1)^2}{2\sigma_{\text{calib},b}^2}, \quad (15)$$

where L is the likelihood, θ the parameters of the model, m_k a measurement, $m_{\text{model},k}$ the prediction of the model for the same measurement, σ_m the measurement uncertainty on it, γ_b the calibration parameter of the band b , and $\sigma_{\text{calib},b}$ the calibration uncertainty for this band.

We used a Monte Carlo Markov chain (MCMC) Metropolis-Hastings algorithm (Chib & Greenberg 1995; Dunkley et al. 2005) to fit our model. The method consists of a random walk in the parameter space. At each step, a random shift of the parameters is performed using a given fixed proposal density. The new step n is accepted with a probability of 1 if $L(\theta_n) > L(\theta_{n-1})$ or otherwise a probability $L(\theta_n)/L(\theta_{n-1})$. The distribution of the realization of the chain is asymptotically the same as the underlying probability density. This property is thus very convenient to determine the confidence area of the model parameters.

We used the Fisher matrix formalism to determine the proposal density of the chain from initial parameters values that had been set manually. The associated Fisher matrix is

$$F_{ij}(\theta) = \sum_{k=1}^{N_{\text{point}}} \frac{\partial m_{\text{model},k}}{\partial \theta_i} \frac{\partial m_{\text{model},k}}{\partial \theta_j} \frac{1}{2\sigma_m^2} \left(+ \frac{1}{2\sigma_{\text{calib},b}^2} \right), \quad (16)$$

where θ is a vector containing the model and calibration (γ_b) parameters. The term in brackets appears only for the diagonal terms corresponding to a calibration parameter. We performed a first short chain (10 000 steps) and computed a new proposal

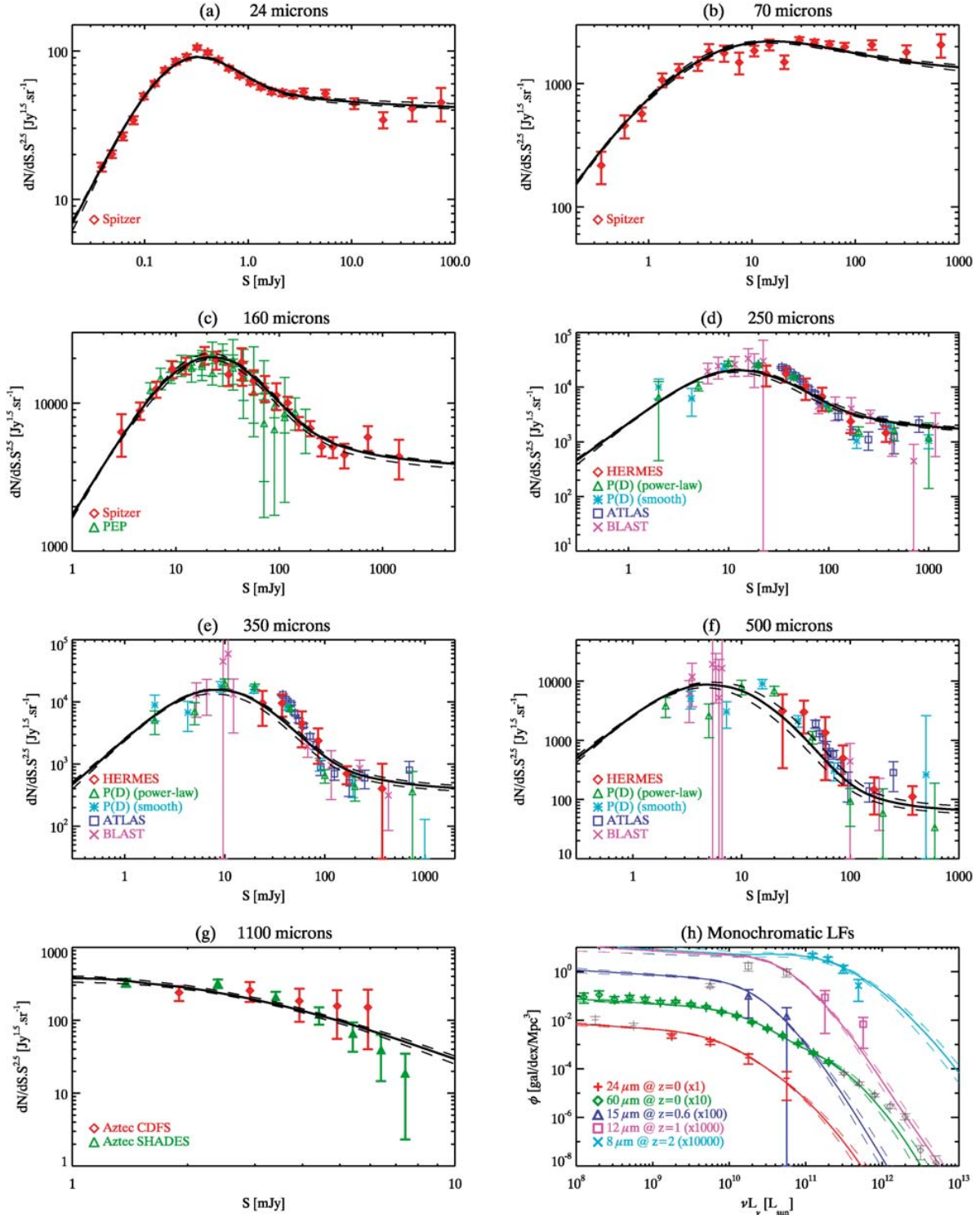


Fig. 3. a)–f) Differential extragalactic number counts used for the fit. h) Monochromatic LFs at different wavelengths and redshifts. a)–h) The fitted points are thicker. Black solid line: our best-fit model. Black dashed line: 1- σ range of the model. a)–c) Red diamonds: Béthermin et al. (2010a) Spitzer legacy number counts. c) Green triangles: Berta et al. (2010) Herschel/PEP number counts. d)–f) Red diamonds: Oliver et al. (2010) Herschel/Hermes number counts. Green triangles: Glenn et al. (2010) Herschel/Hermes $P(D)$ analysis. Clements et al. (2010) Herschel/ATLAS number counts. Purple cross: Béthermin et al. (2010b) BLAST number counts. g) Green triangles: Scott et al. (2010) AzTEC number counts in the CDFS field. Green triangles: Austermann et al. (2010) AzTEC number counts in the SHADES field. h) Red plus: Rodighiero et al. (2010) local 24 μ m LF (not fitted points in grey). Green diamonds: Saunders et al. (1990) local 60 μ m LF (shifted by a factor 10 on the y -axis; not fitted points in grey). Blue triangles: Rodighiero et al. (2010) 15 μ m LF at $z = 0.6$ (shifted by a factor 100 on the y -axis; not fitted points in grey). Purple squares: Rodighiero et al. (2010) 12 μ m LF at $z = 1$ (shifted by a factor 1000 on the y -axis; not fitted points in grey). Cyan crosses: Caputi et al. (2007) 8 μ m LF at $z = 2$ (shifted by a factor 10 000 on the y -axis).

Table 1. Parameters of our model fitted to our selection of infrared observations.

Parameter	Description	Value
α	Faint-end slope of the infrared bolometric LF	1.223 ± 0.044
σ	Parameter driving the bright-end slope of the LF	0.406 ± 0.019
$L_*(z=0) (\times 10^{10} L_\odot)$	Local characteristic luminosity of the LF	2.377 ± 0.363
$\phi_*(z=0) (\times 10^{-3} \text{ gal/dex/Mpc}^3)$	Local characteristic density of the LF	3.234 ± 0.266
$r_{L_*,Jz}$	Evolution of the characteristic luminosity between 0 and $z_{\text{break},1}$	2.931 ± 0.119
$r_{\phi_*,Jz}$	Evolution of the characteristic density between 0 and $z_{\text{break},1}$	0.774 ± 0.196
$z_{\text{break},1}$	Redshift of the first break	0.879 ± 0.052
$r_{L_*,mz}$	Evolution of the characteristic luminosity between $z_{\text{break},1}$ and $z_{\text{break},2}$	4.737 ± 0.301
$r_{\phi_*,mz}$	Evolution of the characteristic density of between $z_{\text{break},1}$ and $z_{\text{break},2}$	-6.246 ± 0.458
$z_{\text{break},2}$	Redshift of the second break	2.000 (fixed)
$r_{L_*,Jz}$	Evolution of the characteristic luminosity for $z > z_{\text{break},2}$	0.145 ± 0.460
$r_{\phi_*,Jz}$	Evolution of the characteristic density for $z > z_{\text{break},2}$	-0.919 ± 0.651
$L_{\text{pop}} (\times 10^{10} L_\odot)$	Luminosity of the transition between normal and starburst templates	23.677 ± 2.704
σ_{pop}	Width of the transition between normal and starburst templates	0.572 ± 0.056

Notes. The errors are derived from the MCMC analysis.

Table 2. Calibration parameters and 1- σ marginalized errors from our MCMC fit compared with calibration uncertainties given by the instrumental teams.

Instrument	Calibration parameter (γ_b)	Calib. uncertainty
MIPS 24 μm	1.00 ± 0.03	4%
MIPS 70 μm	1.06 ± 0.04	7%
MIPS 160 μm	0.96 ± 0.03	12%
SPIRE 250 μm	0.88 ± 0.05	15%
SPIRE 350 μm	0.97 ± 0.07	15%
SPIRE 500 μm	1.17 ± 0.1	15%
AzTEC 1.1 mm	0.98 ± 0.09	9%

density with the covariance matrix of the results. We then executed a second long chain of 300 000 steps. The final chain satisfies the [Dunkley et al. \(2005\)](#) criteria ($j^* > 20$ and $r < 0.01$).

5. Results of the fit

5.1. Quality of the fit

Our final best-fit model has a χ^2 ($\chi^2 = -2\log(L)$ because all errors are assumed to be Gaussian) of 177 for 113 degrees of freedom. Our fit is thus reasonably good. The parameters found with the fit are given in Table 1 (the uncertainties are computed from the MCMC). The calibration factor are compatible with the calibration uncertainties given by the instrumental teams with a χ^2 of 2.89 for seven points (see Table 2). The results are plotted in Fig. 3.

5.2. Comparison between the model and the observed counts used in the fit

The [Béthermin et al. \(2010a\)](#) points fit globally well, with some exceptions. Our model is lower by about 15% than two points around 300 μJy at 24 μm . These two points were produced combining data for the FIDEL, COSMOS and SWIRE fields. The SWIRE fields are shallow fields and the counts could be affected by the Eddington bias. We also observe a slight under-prediction of the bright ($S_{70} > 50 \text{ mJy}$) counts at 70 μm . We also plotted the [Berta et al. \(2010\)](#) counts at 160 μm measured using the photodetector array camera and spectrometer (PACS) on the *Herschel* satellite. These counts agree with [Béthermin et al. \(2010a\)](#) and our model.

Our model fits globally well the [Oliver et al. \(2010\)](#) and [Béthermin et al. \(2010b\)](#) counts, apart from a slight under-prediction of the counts between 30 mJy and 100 mJy at 500 μm . There is a mild disagreement with the [Clements et al. \(2010\)](#) counts, but their error bars do not take into account the cosmic variance and are thus underestimated. We also plotted the results of the $P(D)$ analysis of [Glenn et al. \(2010\)](#). These points and especially the error bars must be interpreted with caution (see the complete discussion in [Glenn et al. 2010](#)). We have plotted the knots of the smooth and power-law models, which globally agree with our model.

Our model agrees very well with the AzTEC counts of [Austermann et al. \(2010\)](#) and [Scott et al. \(2010\)](#). The contribution of the strong lensing objects to the AzTEC counts is weak (<10%, see Sect. 7.3).

5.3. Comparison between the model and the observed monochromatic LFs

Our model closely reproduces our collection of LFs ([Saunders et al. 1990](#); [Caputi et al. 2007](#); [Rodighiero et al. 2010](#)), apart from the brightest point of [Caputi et al. \(2007\)](#). In Fig. 3, we arbitrarily shifted the different LFs on the y -axis to obtain a clearer plot. Our model underestimates the 60 μm local LF in the ULIRG regime. It is expected because our model does not contain AGNs and confirms our choice of not fitting these points (Sect. 4.2).

5.4. Comparison between the model and the observed counts not used in the fit

We also compared our results with the counts at other wavelengths. They are plotted in Figs. 4 and 5. The 1- σ region of the model includes the γ_b uncertainty of AKARI at 15 μm (4%, [Ishihara et al. 2010](#)), PACS at 110 μm (about 10%, [Berta et al. 2010](#)), and LABOCA at 850 μm (8.5%, [Weiß et al. 2009](#)). The uncertainty in γ_b is about the same for LABOCA and SCUBA (~10%, [Scott et al. 2006](#)). The uncertainties in the model are larger at these non-fitted wavelengths because the correlations between the model and the calibration parameters are not taken into account by the fit.

At 15 μm , the [Elbaz et al. \(1999\)](#) counts from different fields are incompatible with each other, but our counts coincide with in the cloud of points. The [Gruppioni et al. \(2002\)](#)

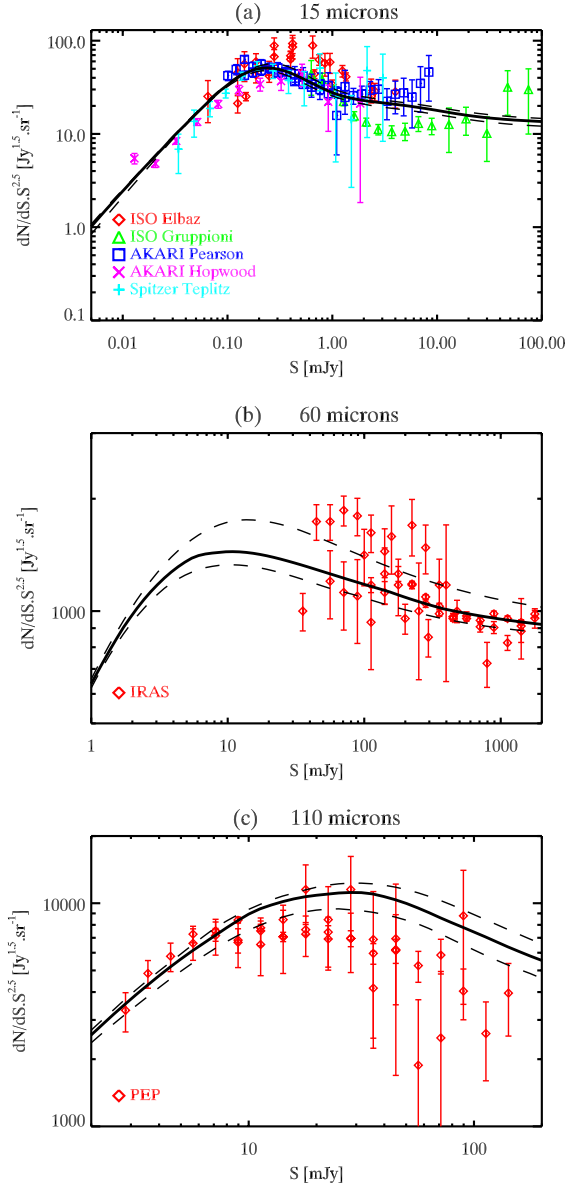


Fig. 4. a)–c) Differential extragalactic number counts not used for the fit. Black solid line: our best-fit model. Black dashed line: $1-\sigma$ range of the model. a) Red diamonds: Elbaz et al. (1999) ISO counts. Green triangle: Gruppioni et al. (2002) ISO counts. Blue squares: Pearson et al. (2010) AKARI counts. Purple cross: Hopwood et al. (2010) AKARI (lensed) counts. Cyan plus: Teplitz et al. (2011) *Spitzer*/IRS counts. b) Red diamonds: Hacking & Houck (1987), Lonsdale et al. (1990), Rowan-Robinson et al. (1990), Saunders et al. (1990), Gregorich et al. (1995) and Bertin et al. (1997) IRAS counts. c) Red diamonds: Berta et al. (2010) *Herschel*/PEP counts.

counts are significantly lower than our model and other works. We marginally agree with the Pearson et al. (2010) counts. The Hopwood et al. (2010) counts measured with AKARI in a field around Abell 2218 are lower than our model by about 25%. Nevertheless, their field is very narrow and their estimation may be affected by cosmic variance. Finally, we agree with the Teplitz et al. (2011) measurements performed with the infrared spectrograph (IRS) onboard the *Spitzer* space telescope.

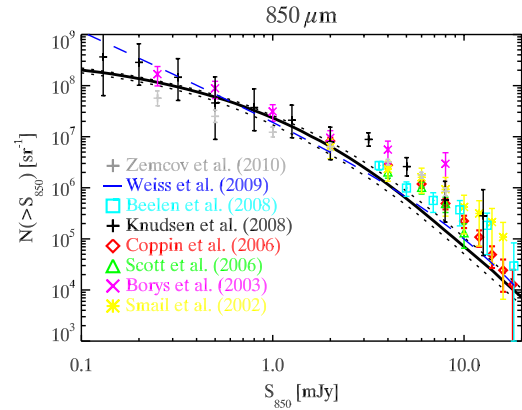


Fig. 5. Integral number counts at 850 μm . Black solid line: our best-fit model. Black dashed line: $1-\sigma$ range of the model. Grey plus: Zemcov et al. (2010) combined SCUBA lensed counts. Blue dashed line: Weiß et al. (2009) LABOCA $P(D)$ (Schechter model). Red diamonds: Coppin et al. (2006) SCUBA SHADES counts. Cyan square: (Beelen et al. 2008) LABOCA counts around the J2142-4423 Ly α protocluster. Black plus: Knudsen et al. (2008) combined SCUBA lensed counts; green triangles: Scott et al. (2006) revisited SCUBA counts. Purple cross: Borys et al. (2003) SCUBA HDFN counts. Yellow asterisks: Smail et al. (2002) lensed counts.

We compare our counts to Hacking & Houck (1987), Lonsdale et al. (1990), Rowan-Robinson et al. (1990), Saunders et al. (1990), Gregorich et al. (1995), and Bertin et al. (1997) at 60 μm from IRAS data. There are disagreements between the different observations and some error bars may be underestimated, but our model globally agrees with the cloud of points.

We can also compare the prediction of our model with the Berta et al. (2010) counts at 110 μm . Our model globally agrees with their work, although our model tends to be higher than their measurement near 100 mJy. Observations of several larger fields will help us to see whether this effect is an artifact or not.

At 850 μm , we closely agree with the $P(D)$ analysis of the LABOCA data of Weiß et al. (2009, see Fig. 5). However, the measurements performed with SCUBA (Borys et al. 2003; Scott et al. 2006; Coppin et al. 2006) and LABOCA (Beelen et al. 2008) are significantly higher than our model at 6 and 8 mJy. At low fluxes (<2 mJy), our model agrees very well with the measurement performed in lensed regions (Smail et al. 2002; Knudsen et al. 2008; Zemcov et al. 2010).

We also compare our model predictions with SPT measurements at 1.38 mm (Vieira et al. 2010). At this wavelength, the contribution of the synchrotron emission from the local radio galaxies to the counts is not negligible. Nevertheless, these sources can be separated from dusty galaxies by considering their spectrum. We thus compare our results with the counts of dusty sources. Vieira et al. (2010) measured counts for all the dusty sources and the dusty sources without IRAS 60 μm counterparts. Our model agrees with these two measurements. Figure 6 shows the counts of the non-IRAS dusty sources. The 7.2% calibration uncertainty of SPT is taken into account in the $1-\sigma$ region of the model.

5.5. Comparison with the observed redshift distributions

In Fig. 7, we compare our model predictions with observed redshift distributions. At 24 μm , our model overpredicts by about 20% the number of sources below $z = 1$ according to

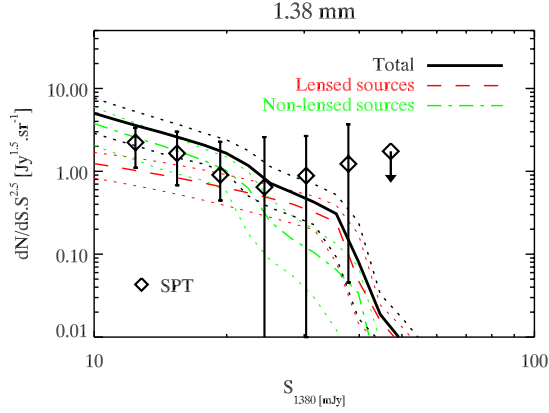


Fig. 6. Number counts at 1.38 mm of dusty sources without IRAS 60 μm counterpart. Black diamonds: Vieira et al. (2010) south pole telescope (SPT) measurements. Black solid line: total contribution of $S_{60} < 0.2$ Jy sources. Green dot-dashed line: contribution of the non-lensed sources. Red dashed line: contribution of the strongly-lensed sources. Dotted lines 1- σ contours.

Le Floch et al. (2009) observations for the selection $S_{24} > 80 \mu\text{Jy}$. Nevertheless, these authors excluded $i_{AB}^+ < 20$ galaxies and their number of sources at low redshift is thus underestimated. Our model also underpredicts the number of sources at $z > 3$. However, the redshifts of the $z > 2$ sources are only moderately accurate ($\sigma_z \approx 0.25$ for $i_{AB}^+ > 25$ at $z \sim 2$). Because of the steep slope of the redshift distribution, a significant number of sources measured near $z = 3.5$ could be sources lying around $z = 3$ with overestimated redshifts. If we convolve our model with a Gaussian error of $\sigma_z = 0.125z$ to simulate the redshift uncertainties, the model and the measurements agrees (Fig. 7). The Valiante et al. (2009) model poorly reproduces this observation. The Le Borgne et al. (2009) model agrees very well with the measurements, except at $z < 0.5$ and $z > 2.5$. The same observables was measured by Rodighiero et al. (2010). Their results agree with Le Floch et al. (2009), except at $z > 3$, where they are higher, perhaps because of a larger σ_z at high redshift.

We also compare the model with the redshift distribution of $S_{24} > 300 \mu\text{Jy}$ sources measured by Le Floch et al. (2009), Rodighiero et al. (2010), and Desai et al. (2008). These different measurements disagree below $z = 0.5$. This difference could be due to the removal of the brightest optical sources (see previous paragraph). Our model overestimates the number of sources at $z < 0.5$ by a factor of 2. There is rather close agreements between the model and the measurements between $z = 0.5$ and $z = 2.5$, apart from a small overestimation by Valiante et al. (2009) near $z = 2$. At higher redshifts, the measurements are significantly higher than the models for possibly two reasons: an effect of the redshift uncertainties and the absence of AGNs in our model.

We compare with the Chapin et al. (2011) redshift distributions of the BLAST isolated sources at 250 μm , 350 μm , and 500 μm . This selection of isolated sources does not allow us to determine the effective size of the field. We thus normalized our model and the measured counts to have $\int dN/dz dz = 1$. Our predicted redshift distribution globally fits the measurements, except at low z at 250 μm and 350 μm . This difference could be explained by the selection of isolated sources, which could miss sources in structures at low redshift. The other models (Le Borgne et al. 2009; Valiante et al. 2009) underpredict the number of sources at low z . Valiante et al. (2009) also slightly overpredicts the number of sources at $z \sim 1.5$.

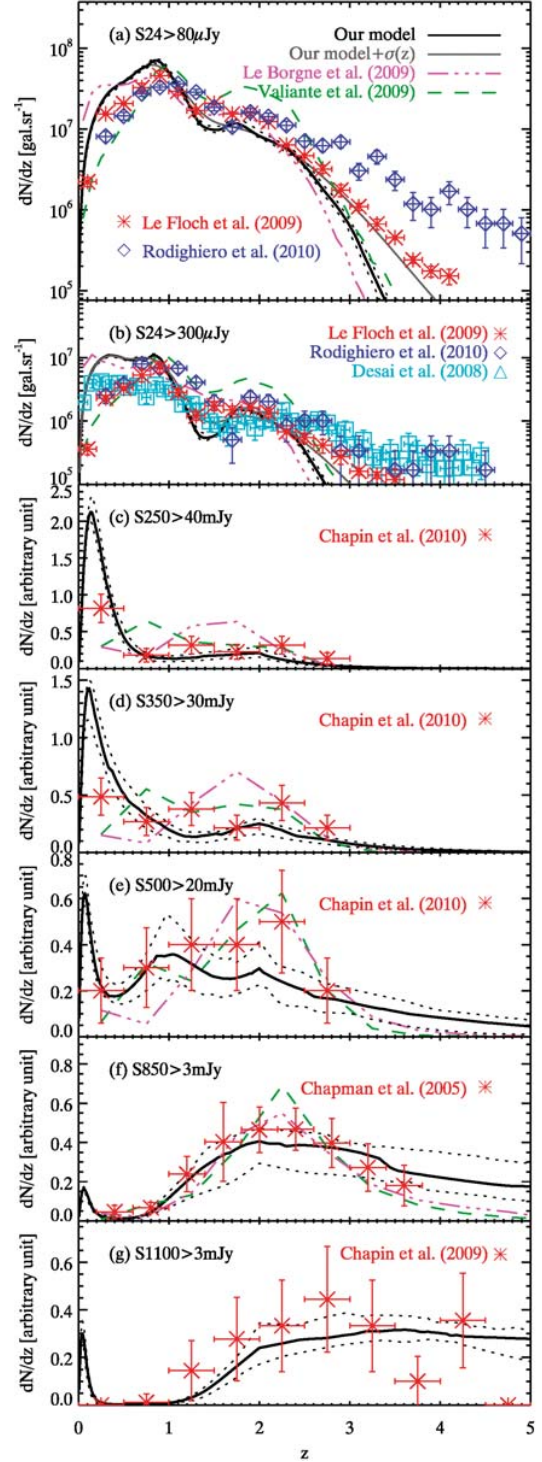


Fig. 7. Redshift distribution of the $S_{24} > 80 \mu\text{Jy}$ a), $S_{24} > 300 \mu\text{Jy}$ b), $S_{250} > 40 \text{ mJy}$ c), $S_{350} > 30 \text{ mJy}$ d), $S_{500} > 20 \text{ mJy}$ e), $S_{850} > 3 \text{ mJy}$ f), and $S_{1100} > 3 \text{ mJy}$ g) sources. These measurements are not fitted. Black solid line: our best-fit model. Black dotted line: 1- σ range of the model. Grey solid line: our best-fit model convolved by a Gaussian of $\sigma_z = 0.125z$. Purple three dot-dashed line: Le Borgne et al. (2009) model. Green dashed line: Valiante et al. (2009) model. Red asterisks: Le Floch et al. (2009) a), b), Chapin et al. (2011) c)–e), Chapman et al. (2005) f) and Chapin et al. (2009) g) measurements. Blue diamonds: Rodighiero et al. (2010) measurements a), b). Cyan squares: Desai et al. (2008) measurements b).

Table 3. Level of the non-correlated fluctuations of the CIB at different wavelengths and comparison with the predictions of the model.

Wavelength μm	Reference	S_{cut} mJy	$P_{\text{SN,mes}}$ $\text{Jy}^2 \text{sr}^{-1}$	$P_{\text{SN,model}}$ $\text{Jy}^2 \text{sr}^{-1}$	$\langle z_{\text{model}} \rangle$
60	Miville-Deschênes et al. (2002)	1000	1600 ± 300	2089 ± 386	0.20 ± 0.01
90	Matsuura et al. (2011)	20	360 ± 20	848 ± 71	0.79 ± 0.03
100	Miville-Deschênes et al. (2002)	700	5800 ± 1000	7364 ± 1232	0.38 ± 0.03
160	Lagache et al. (2007)	200	9848 ± 120	10834 ± 3124	0.73 ± 0.06
250	Viero et al. (2009)	500	11400 ± 1000	11585 ± 2079	0.81 ± 0.08
350	Viero et al. (2009)	400	6300 ± 500	5048 ± 1083	1.17 ± 0.12
500	Viero et al. (2009)	–	2700 ± 200	1677 ± 484	1.59 ± 0.21
1363	Hall et al. (2010)	15	17 ± 2	10 ± 3	4.07 ± 0.24

Notes. The uncertainties on the model predictions take into account the uncertainties on γ_b . The mean redshift $\langle z_{\text{model}} \rangle$ of the contribution to the fluctuations is a prediction of the model.

We compared the redshift distribution of the SCUBA sources at $850 \mu\text{m}$ with the prediction of our model. We used the selection-corrected measurements of Chapman et al. (2005) adopted by Marsden et al. (2011). All the models agree with this measurement.

We also compared the predictions of our model with the redshift distribution of the sources detected at 1.1 mm by AzTEC (Chapin et al. 2009). A significant fraction of the sources detected at this wavelength (10 over 28) are not identified, and the selection is not performed in term of flux, but signal-to-noise ratio. Consequently, the normalization of the redshift distribution is unknown. We thus use the same normalization than for the BLAST redshift distributions ($\int dN/dz dz = 1$). The behavior predicted by our model agrees well with the observations.

Jauzac et al. (2011) measured the contribution of the $S_{24} > 80 \mu\text{Jy}$ to the CIB at 70 and $160 \mu\text{m}$ as a function of the redshift. Their stacking analysis allows us to check the total far-infrared (FIR) emission of the faint sources not resolved at these wavelengths. Our model agrees well with their results, except near $z = 0.5$ (see Fig. 8), where their too low data points could come from a large-scale underdensity in the COSMOS field at this redshift. The Le Borgne et al. (2009) model overpredicts the contribution of the $24 \mu\text{m}$ sources at $z > 1$. The Valiante et al. (2009) model does not reproduce the trend of these measurements. Franceschini et al. (2010) underestimate the contribution of the local sources and overestimate the contribution of $z \sim 1$ sources.

5.6. Comparison with the measured Poisson fluctuations of the CIB

Table 3 summarizes the recent measurements of the non-correlated fluctuations of the CIB (P_{SN}) and the predictions of our model. We note that P_{SN} depends strongly on the $S_{\nu,\text{cut}}$, the flux density at which the resolved sources are cleaned. We agree with the measurements of Miville-Deschênes et al. (2002) at $60 \mu\text{m}$ and $100 \mu\text{m}$, Lagache et al. (2007) at $160 \mu\text{m}$, and Viero et al. (2009) at $250 \mu\text{m}$ and $350 \mu\text{m}$. We found a value 35% lower than Viero et al. (2009) at $500 \mu\text{m}$. This is consistent with the slight underestimation of the counts at $500 \mu\text{m}$ by our model. Our model is also about 40% lower than the SPT measurements at 1.36 mm (Hall et al. 2010), possibly because of a lack of faint sources at high redshift in our model. We also disagree with the results of Matsuura et al. (2011) at $90 \mu\text{m}$ within a factor of 2. Nevertheless, they cleaned all the detected sources without using a fixed cut in flux. We took their “mean” value of 20 mJy for the flux cut. The high sensitivity of the measurements to the flux cut could thus explain this difference (for instance, a decrease

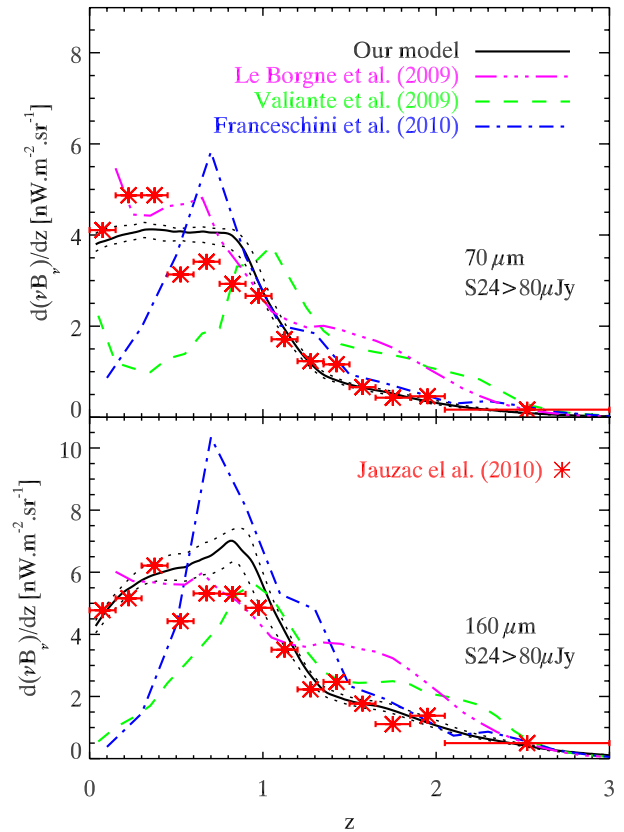


Fig. 8. Differential contribution of the $S_{24} > 80 \mu\text{Jy}$ sources to the CIB as a function of the redshift at $70 \mu\text{m}$ (upper panel) and $160 \mu\text{m}$ (lower panel). Red asterisks: measurement by stacking in the COSMOS field (Jauzac et al. 2011). Black solid line: our model ($1-\sigma$ limit in black dotted line). Purple three dot-dashed line: Le Borgne et al. (2009) model. Green dashed line: Valiante et al. (2009) model. Blue dot-dashed line: Franceschini et al. (2010) model.

in the flux cut by 25% leads to a decrease of the fluctuations of 19%).

We also computed the mean redshift at which the fluctuations are emitted with

$$\langle z \rangle = \frac{\int_0^\infty z \frac{dP_{\text{SN}}}{dz} dz}{\int_0^\infty \frac{dP_{\text{SN}}}{dz} dz}. \quad (17)$$

The results are written in Table 3. As expected, the mean redshift increases with the wavelength. Studying the long wavelengths is thus very useful for probing high redshift populations.

5.7. Comparison with the pixel histogram of the BLAST maps

The quality of our counts at low fluxes in the sub-mm range can be tested using a $P(D)$ analysis (Condon 1974; Patanchon et al. 2009; Glenn et al. 2010). Without instrumental noise, the probability density of the signal in a pixel of the map, $P(D)$, is given by

$$P(D) = \int_0^\infty \left[\exp \left(\int_0^\infty R(x) e^{i\omega x} dx - \int_0^\infty R(x) dx \right) \right] e^{-i\omega D} d\omega, \quad (18)$$

where $R(x)$ is defined by

$$R(x) = \int \frac{1}{b} \frac{dN}{dS_\nu} \left(\frac{x}{b} \right) d\Omega. \quad (19)$$

This probability distribution must be convolved with the distribution of the instrumental noise. We also subtract the mean of this distribution.

We tested our model by comparing with the deepest part of the observations of the CDFS by the BLAST team. We retained only the pixels in the map with a coverage larger than 90% of the maximum coverage. We smoothed the signal, noise, and beam map by a Gaussian kernel of the same full width at half maximum than the BLAST beam. This smoothing reduces the effect of the instrumental noise (Patanchon et al. 2009). Our model predictions and the BLAST pixel histograms at 250 μm , 350 μm , and 500 μm are shown in Fig. 9. The uncertainties in the model predictions take into account the BLAST calibration uncertainties (Truch et al. 2009). The model agrees rather well with the data. Nevertheless, the measured histogram is slightly broader than the predictions of the model, especially at 500 μm . It is consistent with the slight underestimation by our model of the counts at 500 μm (the higher the counts, the larger the histogram). The clustering of the galaxies (neglected in this analysis) tends to enlarge the histogram by about 10% and could also contribute to this disagreement (Takeuchi & Ishii 2004; Patanchon et al. 2009; Glenn et al. 2010). The Valiante et al. (2009) model reproduce the BLAST pixel histograms very well. Le Borgne et al. (2009) and Franceschini et al. (2010) overpredict the number of bright pixels at 250 μm and 350 μm ($S_\nu > 50$ mJy). It is consistent with these authors' overprediction of the counts at high flux (Oliver et al. 2010; Glenn et al. 2010).

5.8. Degeneracies between parameters

The Pearson correlation matrix of our model is given in Table 4. We found a very strong anti-correlations both between σ and $L_\star(z=0)$ (-0.90) and between $L_\star(z=0)$ and $\phi_\star(z=0)$ (-0.85). These classical strong correlations are due to the choice of the LF parametrisation. There are also very strong degeneracies between the evolution in density and luminosity of the LF: -0.81 between 0 and the first break; -0.67 between the two breaks; and -0.76 after the second break.

There are some slight degeneracies between the calibration factors. The *Spitzer* calibration parameters are correlated (0.68 between 24 μm and 70 μm , 0.73 between 24 μm and 160 μm , and 0.62 between 70 μm and 160 μm). The other correlations implying a calibration factor are between -0.6 and 0.6 .

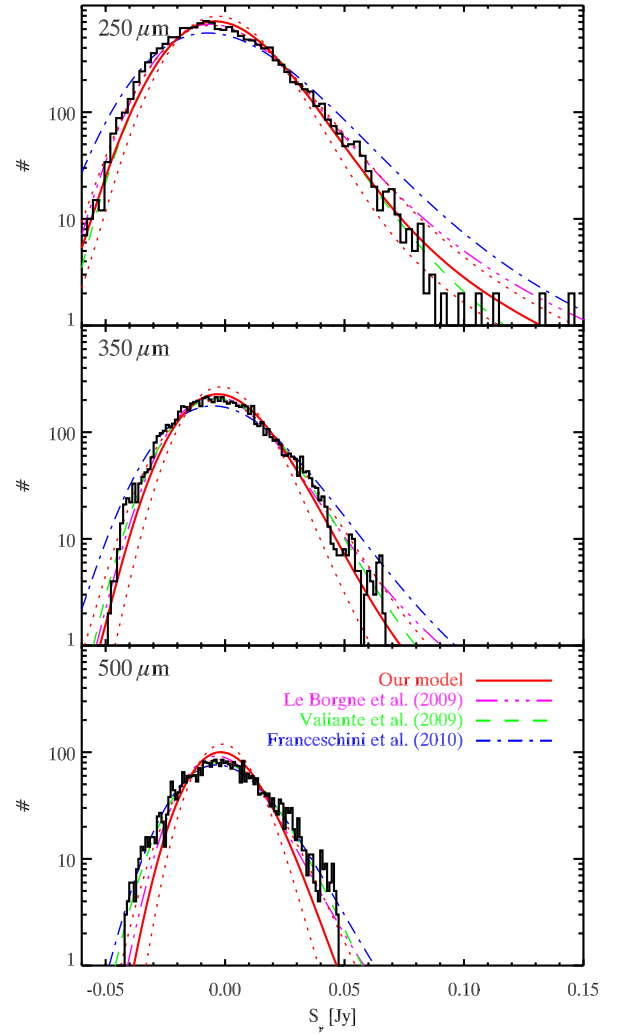


Fig. 9. Comparison with the BLAST pixel histogram at 250 μm (upper panel), 350 μm (middle panel) and 500 μm (lower panel). Black histogram: histogram of the values of the central part of the BLAST beam-smoothed map in Jy/beam. Red solid line: distribution predicted by our model using a $P(D)$ analysis. Our analysis does not include the clustering. Purple three dot-dashed line: Le Borgne et al. (2009) model. Green dashed line: Valiante et al. (2009) model. Blue dot-dashed line: Franceschini et al. (2010) model.

The marginalized probability distributions of each parameter and the 1, 2, and 3- σ confidence regions for each pair of parameters are plotted in Fig. 10. Some distributions are not Gaussian. It thus justifies the use of a MCMC algorithm.

6. Interpretation of the results

6.1. Evolution of the luminosity function

Our model uses a very strong evolution of the bolometric infrared luminosity function to reproduce the infrared observations. The characteristic luminosity ($L_\star$) has strongly decreased between $z = 2$ and now, by about a factor of 50 from $z = 2$ to 0. The characteristic density ($\phi_\star$) increases strongly between $z = 2$ and $z = 1$ and slightly decreases between $z = 1$ and now. At $z > 2$, the model is compatible with no evolution in luminosity

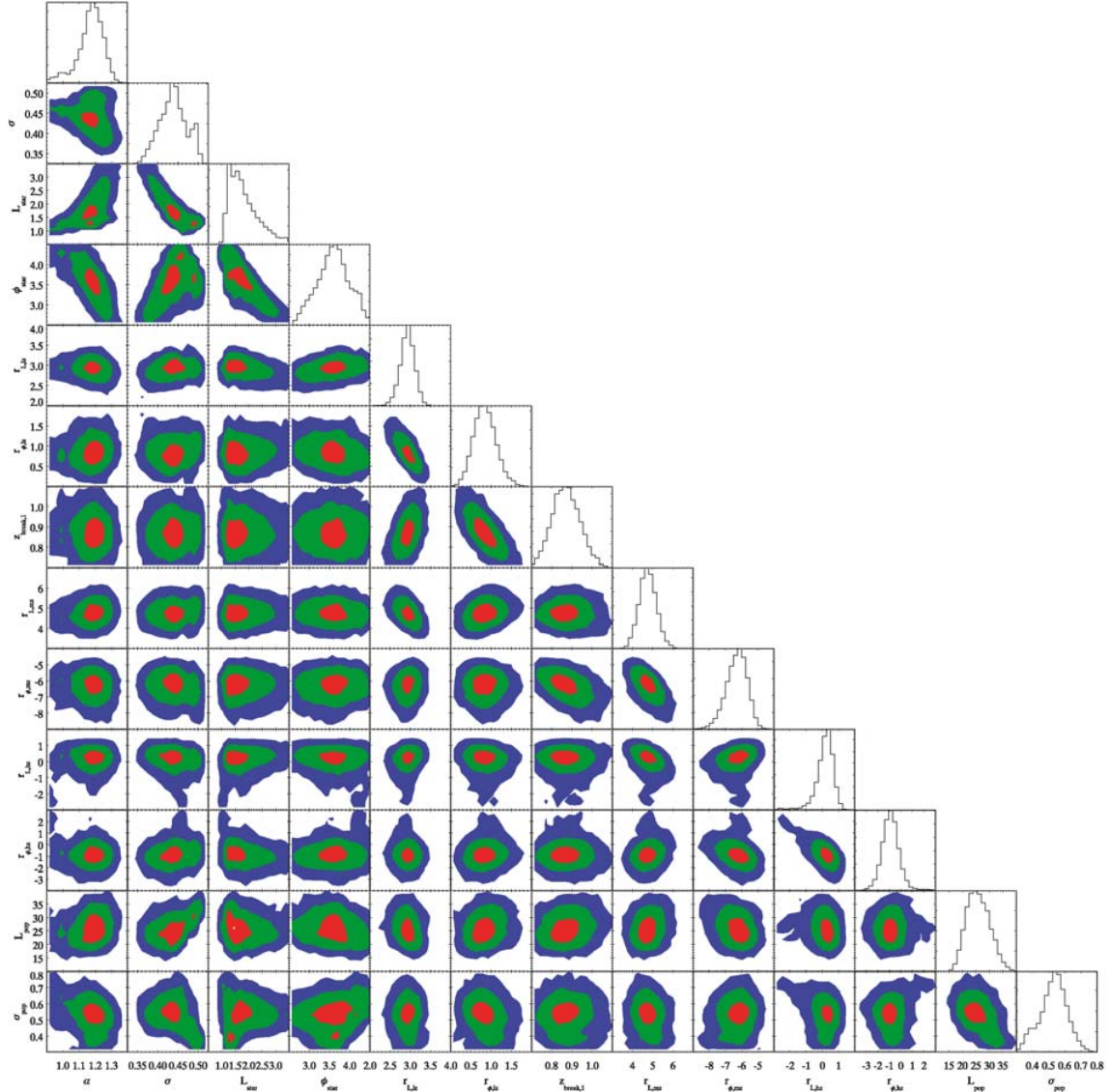


Fig. 10. Diagonal plots: marginalized probability distributions of each parameters deduced from the MCMC. Non-diagonal plots: 1- σ (red), 2- σ (green), and 3- σ (blue) regions for each pair of parameters). From left to right: α , σ , $L_\star$, $\phi_\star$, $r_{L_\star,jz}$, $r_{\phi_\star,jz}$, $z_{\text{break},1}$, $r_{L_\star,mz}$, $r_{\phi_\star,mz}$, $r_{L_\star,jz}$, $r_{\phi_\star,jz}$, L_{pop} , and σ_{pop} (cf. Table 1).

and a slight decrease in the density as redshift increases. The evolution of these two parameters are plotted in Fig. 11.

We compared our results with the measurements of Caputi et al. (2007) performed from MIPS 24 μm observations and the measurement of Magnelli et al. (2009) obtained using MIPS 70 μm observations. These two works used a stacking analysis to measure the faintest points. The evolutions of $L_\star$ and $\phi_\star$ only marginally agree with these two works. Nevertheless, they use different fixed values of σ and α and an extrapolation from the monochromatic luminosity to L_{IR} . These choices could imply some biases. We found as Caputi et al. (2007) a strong negative evolution in density between $z \sim 1$ and $z \sim 2$, these authors finding an evolution in $(1+z)^{-3.9 \pm 1.0}$ compared to our $(1+z)^{-6.2 \pm 0.5}$. Nevertheless, our value is probably biased by our non-smooth parametrization. This evolution is discussed in details by Caputi et al. (2007).

Reddy et al. (2008) claimed that $\alpha \sim 1.6$ at $z > 2$. However, we do not need to invoke an evolution of α and σ to reproduce

the observations. Nevertheless, the infrared measurements are not sufficiently deep to constrain accurately any evolution of α .

6.2. Evolution of the dust-obscured star formation rate

The bolometric infrared luminosity density (ρ_{IR}) can be deduced from the bolometric infrared LF. Our local value of ρ_{IR} ($(1.05 \pm 0.05) \times 10^8 L_\odot \text{ Mpc}^{-3}$) agrees with the Vaccari et al. (2010) measurements ($1.31^{+0.24}_{-0.21} \times 10^8 L_\odot \text{ Mpc}^{-3}$). We also agree well with higher redshift measurements of Rodighiero et al. (2010) and Pascale et al. (2009, see Fig. 12). The infrared luminosity density can be converted into star formation rate density (SFRD) using the conversion factor $1.7 \times 10^{-10} M_\odot \text{ yr}^{-1} L_\odot^{-1}$ (Kennicutt 1998). The SFRD derived from our model agrees rather well with the Hopkins & Beacom (2006) fit to the optical and infrared measurements.

We also determined the contribution of the different ranges of luminosity to the bolometric infrared luminosity density

Table 4. Pearson correlation matrix for our model.

	α	σ	$L_*(z=0)$	$\phi_*(z=0)$	$r_{L_*,Lz}$	$r_{\phi_*,Lz}$	$z_{\text{break},1}$	$r_{L_*,mz}$	$r_{\phi_*,mz}$	$r_{L_*,hz}$	$r_{\phi_*,hz}$	L_{pop}	σ_{pop}
α	1.00	-0.48	0.71	-0.75	0.02	-0.06	0.04	0.14	-0.16	-0.04	0.11	-0.02	0.05
σ	-0.48	1.00	-0.90	0.62	-0.03	0.15	-0.06	0.10	0.05	-0.20	0.12	0.48	-0.37
$L_*(z=0)$	0.71	-0.90	1.00	-0.85	-0.14	-0.03	0.07	0.00	-0.11	0.11	-0.04	-0.19	0.20
$\phi_*(z=0)$	-0.75	0.62	-0.85	1.00	0.22	-0.15	-0.05	0.04	0.08	-0.04	-0.09	-0.11	-0.01
$r_{L_*,Lz}$	0.02	-0.03	-0.14	0.22	1.00	-0.81	0.51	-0.44	0.10	0.14	-0.12	-0.27	0.13
$r_{\phi_*,Lz}$	-0.06	0.15	-0.03	-0.15	-0.81	1.00	-0.78	0.18	0.07	-0.08	0.13	0.18	-0.17
$z_{\text{break},1}$	0.04	-0.06	0.07	-0.05	0.51	-0.78	1.00	0.05	-0.51	-0.09	0.07	0.12	0.12
$r_{L_*,mz}$	0.14	0.10	0.00	0.04	-0.44	0.18	0.05	1.00	-0.67	-0.43	0.29	0.05	-0.09
$r_{\phi_*,mz}$	-0.16	0.05	-0.11	0.08	0.10	0.07	-0.51	-0.67	1.00	0.35	-0.41	-0.04	-0.07
$r_{L_*,hz}$	-0.04	-0.20	0.11	-0.04	0.14	-0.08	-0.09	-0.43	0.35	1.00	-0.76	-0.20	-0.26
$r_{\phi_*,hz}$	0.11	0.12	-0.04	-0.09	-0.12	0.13	0.07	0.29	-0.41	-0.76	1.00	0.11	0.18
L_{pop}	-0.02	0.48	-0.19	-0.11	-0.27	0.18	0.12	0.05	-0.04	-0.20	0.11	1.00	-0.39
σ_{pop}	0.05	-0.37	0.20	-0.01	0.13	-0.17	0.12	-0.09	-0.07	-0.26	0.18	-0.39	1.00

Notes. The part of the matrix concerning the calibration factors is not written to save space.

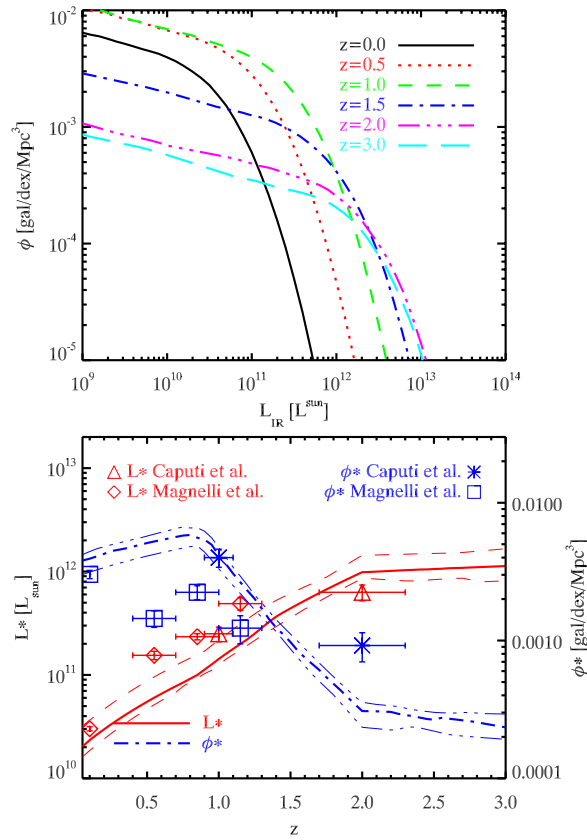


Fig. 11. Evolution of the bolometric infrared luminosity function with redshift. *Upper panel:* bolometric LF at $z=0$ (solid line), $z=0.5$ (dot line), $z=1$ (dashed line), $z=1.5$ (dot-dash line), $z=2$ (3-dot-dash line), and $z=3$ (long dashed line). *Lower panel:* Evolution of the L_* (red solid line) and ϕ_* (blue dot-dash line) parameter as a function of redshift and $1-\sigma$ confidence region. The measurement of L_* by Caputi et al. (2007) (triangles) using $24\ \mu\text{m}$ observations and Magnelli et al. (2009) (diamonds) using $70\ \mu\text{m}$ observations are plotted in red. The measurement of ϕ_* by Caputi et al. (2007) (cross) and Magnelli et al. (2009) (square) are in blue.

(normal: $L_{\text{IR}} < 10^{11} L_{\odot}$, LIRG: $10^{11} < L_{\text{IR}} < 10^{12} L_{\odot}$, ULIRG: $10^{12} < L_{\text{IR}} < 10^{13} L_{\odot}$, HyLIRG: $L_{\text{IR}} > 10^{13} L_{\odot}$). Between $z=0$ and 0.5 , the infrared luminosity density is dominated by normal galaxies ($L_{\text{IR}} < 10^{11} L_{\odot}$). Their contribution

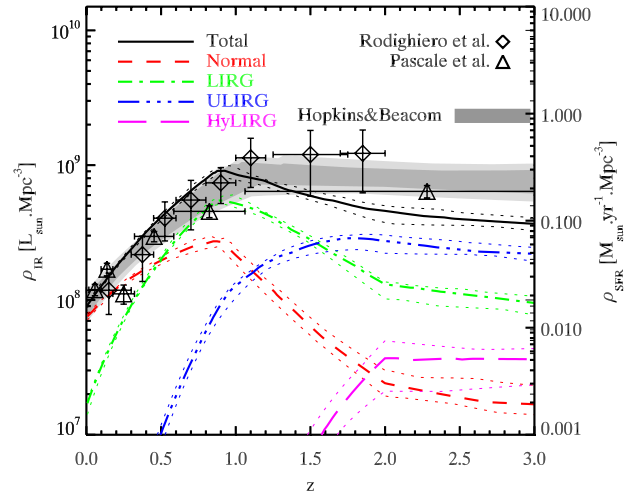


Fig. 12. Evolution of the bolometric infrared luminosity density (black solid line) as a function of the redshift. The contribution of normal galaxies ($L_{\text{IR}} < 10^{11} L_{\odot}$), LIRG ($10^{11} < L_{\text{IR}} < 10^{12} L_{\odot}$), ULIRG ($10^{12} < L_{\text{IR}} < 10^{13} L_{\odot}$), and HyLIRG ($L_{\text{IR}} > 10^{13} L_{\odot}$) are plotted with short-dashed, dot-dash, three-dot-dash, and long-dashed line respectively. The measurements of Rodighiero et al. (2010) using the MIPS $24\ \mu\text{m}$ data are plotted with diamonds and Pascale et al. (2009) ones using a BLAST stacking analysis with triangles. The Hopkins & Beacom (2006) fit to the optical and infrared measurement is plotted with a dark grey area ($1-\sigma$) and a light grey area ($3-\sigma$).

decreases slowly with redshift because of the evolution of the LF seen in Fig. 11. Between $z=0.5$ and 1.5 , the infrared output is dominated by the LIRG. At higher redshift, it is dominated by ULIRGs. The HyLIRGs never dominate and account for some percent at high redshift. A physical cutoff at very high luminosity would this not strongly change the infrared density evolution.

Following our model, the number of very bright objects ($>10^{12.5} L_{\odot}$) is maximal around $z=2$ (see Fig. 11). These objects could be very massive galaxies observed during their formation in the most massive dark matter halos. Among other analyses, the study of the spatial distribution of the galaxies will help us to confirm or exclude this scenario (Penin et al., in prep.).

Around $z=1$, the number of very bright objects is lower than at higher redshift, but the number of LIRGs is about one order of magnitude larger. From $z=1$ to now, the infrared output has decreased by about one order of magnitude. Our model describes

only this evolution and we need physical models to understand why, in contrast to today, the star formation at high redshift is dominated by a few very-quickly-star-forming galaxies, when the associated dark matter halos grew by hierarchical merging (Cole et al. 2000; Lanzoni et al. 2005). We also need to explain the decrease in the star formation since $z = 1$, the main candidates being the feedback of AGNs and starbursts (e.g. Baugh 2006) and/or the lack of gas.

6.3. CIB SED

The value of the CIB at different wavelengths predicted by the model is given in Table 5. We found a CIB integrated value (over the 8–1000 μm range) of $23.7 \pm 0.9 \text{ nW m}^{-2} \text{ sr}^{-1}$, which agrees with the 24–27.5 $\text{nW m}^{-2} \text{ sr}^{-1}$ range of Dole et al. (2006).

We compared the CIB spectrum found with our model with the measurements (see Fig. 13). Our model is always higher than the lower limit given by the stacking. The Marsden et al. (2009) limits are very stringent. Nevertheless, they could be overestimated because of the contamination due to clustering (Bavouzet 2008; Fernandez-Conde et al. 2010; Béthermin et al. 2010b). Our model is compatible with the upper limit given by the absorption of the TeV photons by photon-photon interaction with the CIB (see Sect. 7.2). We globally agree with the DIRBE/WHAM (Lagache et al. 2000) and AKARI (Matsuura et al. 2011) absolute measurement, except at 90 μm (AKARI) and 100 μm (DIRBE/WHAM) where the measurements are significantly higher than our model. These measurements need an accurate subtraction of both the zodiacal light and the galactic emissions and an accurate inter-calibration between DIRBE and FIRAS. A bad removal of the zodiacal light might explain this disagreement (Dole et al. 2006). At longer wavelengths, we closely agree with the FIRAS absolute measurements of Lagache et al. (2000).

We separated the contribution of the infrared galaxies to the CIB to four redshift slices, each slice corresponding to about a quarter of the age of the Universe (Fig. 13). Between 8 and 30 μm , we can see a widely varying behavior of each slice caused by the PAH emission bands. The total CIB is smoother. The $0 < z < 0.3$ slice dominates the spectrum only near 8 μm because of the strong PAH emission at this rest-frame wavelength. This slice, where the infrared luminosity density is at its lowest, has a minor contribution at the other wavelengths. The $0.3 < z < 1$ slice dominates the spectrum between 10 and 350 μm . The sub-mm and mm wavelengths are dominated by the sources lying at higher redshift ($z > 2$, see Lagache et al. 2005) because of the redshift effects that shift the peak of emission around rest-frame 80 μm in the sub-mm. The mean redshift of the contribution to the CIB is written in Table 5 and computed with

$$\langle z \rangle = \frac{\int_0^\infty z \frac{dB_\nu}{dz} dz}{\int_0^\infty \frac{dB_\nu}{dz} dz}. \quad (20)$$

We also separate the contribution of the different infrared luminosity classes. The normal galaxies and LIRGs dominate the background up to 250 μm , which is compatible these populations being dominant ones at low redshift. At longer wavelengths, the redshift effects tend to select high redshift sources, LIRGs and ULIRGs each being responsible for about half of the CIB. The HyLIRG have only a small contribution (<10%) including in the mm range (Fig. 13, bottom).

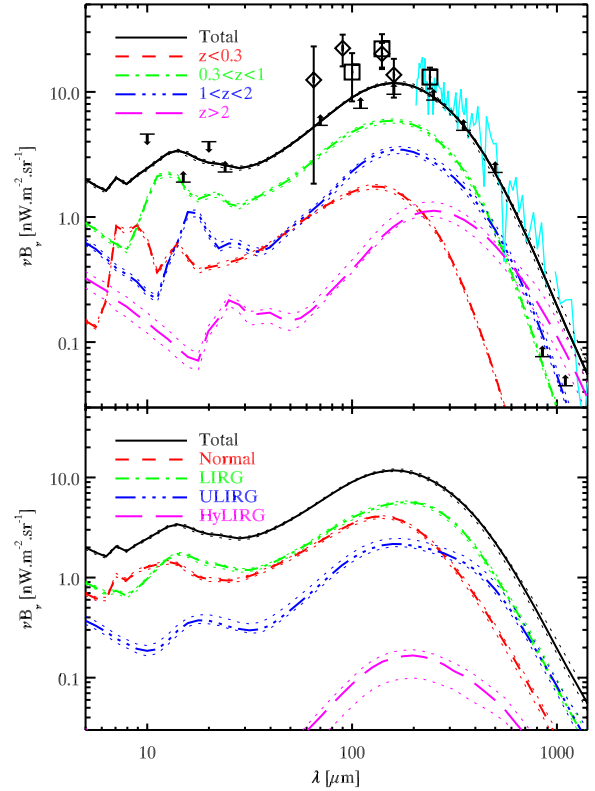


Fig. 13. Upper panel: contribution to the CIB per redshift slice. Black solid line: CIB spectrum predicted by the model. Red short-dashed line: contribution of the galaxies between $z = 0$ and 0.3. Green dot-dash line: same thing between $z = 0.3$ and 1. Blue three dot-dash line: same thing between $z = 1$ and 2. Purple long-dashed line: contribution of the galaxies at redshift higher than 2. Black arrows: lower limits coming from the number counts at 15 μm (Hopwood et al. 2010) and 24 μm (Béthermin et al. 2010a) and the stacking analysis at 70 μm (Béthermin et al. 2010a), 100 μm , 160 μm (Berta et al. 2010), 250 μm , 350 μm , 500 μm (Marsden et al. 2009), 850 μm (Greve et al. 2010), and 1.1 mm (Scott et al. 2010) and upper limits coming from absorption of the TeV photons of Stecker & de Jager (1997) at 20 μm and Renault et al. (2001) between 5 μm and 15 μm . Black diamonds: Matsuura et al. (2011) absolute measurements with AKARI. Black square: Lagache et al. (2000) absolute measurements with DIRBE/WHAM. Cyan line: Lagache et al. (2000) FIRAS measurement. Lower panel: contribution to the CIB of the normal galaxies (red short-dashed line), LIRGs (green dot-dash line), ULIRGs (blue three dot-dash line), HyLIRG (purple long-dashed line), and all the galaxies (black solid line).

7. Predictions

7.1. Confusion limit

The confusion limit can be defined in several ways. The radioastronomers classically use a source density criteria, where the confusion limit is the flux cut for which a critical density of sources is reached. The choice of this critical density is not trivial. We follow the approach of Dole et al. (2003). The source density limit N_{SDC} is reached when there is a probability P of having another source in a $k \theta_{\text{FWHM}}$ radius (where θ_{FWHM} is the full width at half maximum of the beam profile). Dole et al. (2003) show that

$$N_{\text{SDC}} = -\frac{\log(1-P)}{\pi k^2 \theta_{\text{FWHM}}^2}. \quad (21)$$

We chose $P = 0.1$ and $k = 0.8$ following Dole et al. (2003).

Table 5. Surface brightness of the CIB and mean redshift $\langle z \rangle$ of the contribution to the CIB at different wavelengths as predicted by the model.

Wavelength μm	CIB $\text{nW m}^{-2} \text{sr}^{-1}$	CIB MJy sr^{-1}	$\langle z \rangle$
15	$3.294^{+0.105}_{-0.128}$	$0.016^{+0.001}_{-0.001}$	$0.820^{+0.026}_{-0.018}$
24	$2.596^{+0.076}_{-0.139}$	$0.021^{+0.001}_{-0.001}$	$0.894^{+0.025}_{-0.029}$
70	$5.777^{+0.165}_{-0.067}$	$0.135^{+0.004}_{-0.002}$	$0.773^{+0.022}_{-0.021}$
100	$9.014^{+0.231}_{-0.125}$	$0.300^{+0.008}_{-0.004}$	$0.829^{+0.023}_{-0.024}$
160	$11.771^{+0.382}_{-0.318}$	$0.628^{+0.020}_{-0.017}$	$0.947^{+0.032}_{-0.019}$
250	$9.100^{+0.395}_{-0.382}$	$0.758^{+0.033}_{-0.032}$	$1.124^{+0.053}_{-0.021}$
350	$5.406^{+0.190}_{-0.417}$	$0.631^{+0.022}_{-0.049}$	$1.335^{+0.075}_{-0.060}$
500	$2.237^{+0.077}_{-0.217}$	$0.373^{+0.013}_{-0.036}$	$1.680^{+0.124}_{-0.122}$
850	$0.374^{+0.057}_{-0.042}$	$0.106^{+0.016}_{-0.012}$	$2.444^{+0.292}_{-0.192}$
1100	$0.139^{+0.031}_{-0.017}$	$0.051^{+0.011}_{-0.006}$	$2.833^{+0.341}_{-0.201}$

This source density criterion does not take into account the contributions of the sources fainter than the flux limit. We also estimated the photometric confusion noise based on the $P(D)$ analysis (see Sect. 5.7). The $P(D)$ distribution in the absence of instrumental noise is non-Gaussian and have a large tail at bright flux. Thus, the standard deviation is not a good estimator of the confusion noise. We chose to compute the interquartile interval of the $P(D)$ divided by 1.349. With this definition, the value of the confusion noise is exactly σ in the Gaussian case, and we are less sensitive to the bright outliers.

These two estimators can be computed from the counts predicted by our model. We assume that the sources are point-like. The confusion noise found for large telescopes at short wavelengths ($<8 \mu\text{m}$ for a 0.85 m-diameter telescope like *Spitzer* and $<35 \mu\text{m}$ for a 3.29 m-diameter telescope like *Herschel*) are thus underestimated. For this reason, we do not estimate the confusion levels for beams smaller than 2 arcsec.

Figure 14 (upper panel) represents the confusion noise, which agrees with the confusion noise measured by Frayer et al. (2009) and Nguyen et al. (2010) with *Spitzer*/MIPS and *Herschel*/SPIRE. Weiß et al. (2009) estimate that the confusion noise for a APEX/LABOCA map smoothed by the beam is 0.9 mJy/beam. We find 0.6 mJy/beam with the $P(D)$ approach.

We also compute the resolved fraction of the CIB by sources brighter than the confusion limit of Dole et al. (2003) (source density criterion) and the $5\text{-}\sigma_{\text{conf}}$ given by the $P(D)$. Figure 14 (lower panel) and Tables 6–10 summarize the results. The transition in the confusion regime between the source density limitation (short wavelengths) and the fluctuation limitation (long wavelengths) happens at $100 \mu\text{m}$ for *Spitzer*, $220 \mu\text{m}$ for *Herschel*, and $1120 \mu\text{m}$ for the JCMT (asterisks in the lower panel of Fig. 14). For larger antennas below 1.2 mm, the confusion is mainly due to the source density.

According to these results, at the confusion limit, *Herschel* can resolve 92%, 84%, 60%, 25.9%, 9.2%, and 3.3% of the CIB at $70 \mu\text{m}$, $100 \mu\text{m}$, $160 \mu\text{m}$, $250 \mu\text{m}$, $350 \mu\text{m}$, and $500 \mu\text{m}$, respectively. Nevertheless, owing to the blackbody emission of the telescope (about 60 K), very long integration times are needed to reach the confusion limit at short wavelengths. The confusion limit in PACS will only be reached in the ultra-deep region of the H-GOODS survey. The confusion limit will probably never be reached at $70 \mu\text{m}$. A telescope of the same size as *Herschel* and a cold (5K) mirror, such as SPICA, could resolve almost all the CIB from the mid-infrared to $100 \mu\text{m}$. A 25 m single-dish sub-mm telescope such as the Cornell Caltech Atacama telescope

Table 6. Confusion noise and resolved fraction of the CIB at different wavelengths for a 0.85 m telescope (*Spitzer* like).

λ μm	$5\sigma_{\text{conf},P(D)}$ mJy	CIB fraction ^a %	$S_{\text{conf,density}}$ mJy	CIB fraction ^b %
24	5.62×10^{-2}	83.1	7.51×10^{-2}	72.3
70	3.09×10^0	51.5	2.88×10^0	48.8
100	1.38×10^1	36.3	1.15×10^1	36.1
160	5.84×10^1	12.3	3.43×10^1	17.2
250	1.06×10^2	3.2	4.41×10^1	6.9
350	1.13×10^2	0.8	3.57×10^1	3.0
500	9.18×10^1	0.2	2.24×10^1	1.4
850	4.12×10^1	100.0	9.25×10^0	0.7
1100	2.76×10^1	100.0	6.25×10^0	0.5

Notes. ^(a) Fraction of the CIB resolved at $5\text{-}\sigma_{\text{conf}}$. ^(b) Fraction of the CIB resolved at the flux limit.

Table 7. Confusion noise and resolved fraction of the CIB at different wavelengths for a 3.29 m telescope (*Herschel* like).

λ μm	$5\sigma_{\text{conf},P(D)}$ mJy	CIB fraction ^a %	$S_{\text{conf,density}}$ mJy	CIB fraction ^b %
70	7.95×10^{-2}	96.4	1.20×10^{-1}	91.8
100	5.13×10^{-1}	90.8	7.75×10^{-1}	83.9
160	5.01×10^0	67.8	5.93×10^0	59.8
250	1.75×10^1	25.9	1.28×10^1	29.6
350	2.30×10^1	9.2	1.28×10^1	15.8
500	2.08×10^1	3.3	9.24×10^0	8.7
850	1.13×10^1	1.5	3.88×10^0	4.4
1100	8.40×10^0	1.2	2.66×10^0	3.5

Notes. ^(a) Fraction of the CIB resolved at $5\text{-}\sigma_{\text{conf}}$. ^(b) Fraction of the CIB resolved at the flux limit.

Table 8. Confusion noise and resolved fraction of the CIB at different wavelengths for a 12.00 m telescope (APEX like).

λ μm	$5\sigma_{\text{conf},P(D)}$ mJy	CIB fraction ^a %	$S_{\text{conf,density}}$ mJy	CIB fraction ^b %
160	5.86×10^{-2}	99.4	5.55×10^{-2}	98.2
250	7.06×10^{-1}	94.2	1.11×10^0	85.6
350	2.08×10^0	77.9	2.57×10^0	63.2
500	3.05×10^0	50.0	2.57×10^0	41.8
850	2.19×10^0	23.6	1.24×10^0	22.9
1100	1.74×10^0	18.4	8.74×10^{-1}	18.6

Notes. ^(a) Fraction of the CIB resolved at $5\text{-}\sigma_{\text{conf}}$. ^(b) Fraction of the CIB resolved at the flux limit.

Table 9. Confusion noise and resolved fraction of the CIB at different wavelengths for a 15.00 m telescope (JCMT like).

λ μm	$5\sigma_{\text{conf},P(D)}$ mJy	CIB fraction ^a %	$S_{\text{conf,density}}$ mJy	CIB fraction ^b %
160	2.34×10^{-2}	99.8	1.04×10^{-2}	99.3
250	3.01×10^{-1}	97.6	4.48×10^{-1}	92.5
350	1.08×10^0	88.6	1.55×10^0	74.7
500	1.87×10^0	66.6	1.86×10^0	52.4
850	1.55×10^0	33.8	9.70×10^{-1}	29.4
1100	1.26×10^0	26.7	6.89×10^{-1}	24.1

Notes. ^(a) Fraction of the CIB resolved at $5\text{-}\sigma_{\text{conf}}$. ^(b) Fraction of the CIB resolved at the flux limit.

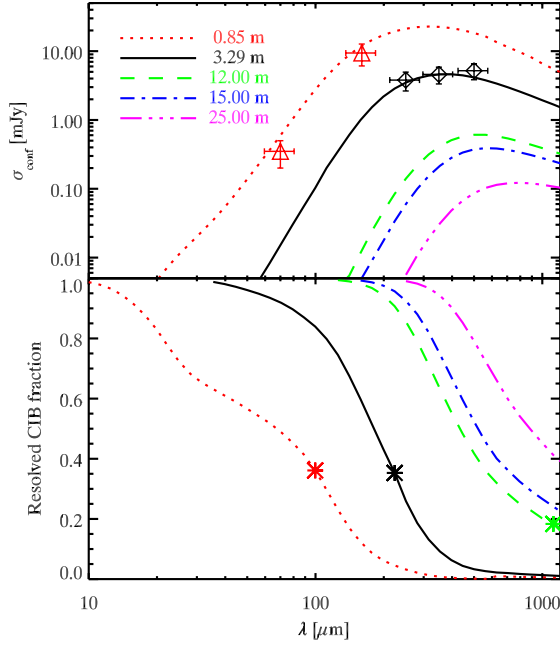


Fig. 14. *Upper panel:* 1- σ confusion noise as a function of the wavelength for different telescope diameters. We use the confusion noise given by the $P(D)$ method (see Sect. 7.1) for this plot. Red triangles: Frayer et al. (2009) *Spitzer*/MIPS confusion measurements. Black diamonds: Nguyen et al. (2010); *Herschel*/SPIRE confusion noise measurements ($5\text{-}\sigma_{\text{conf}}$ cut). *Lower panel:* resolved fraction of the CIB by sources brighter than $5\text{-}\sigma$ confusion noise (fluctuations) and the source density limit. *Both panel:* Red dotted line: telescope with a diameter of 0.85 m such as *Spitzer*. Black solid line: 3.29 m telescope such as *Herschel*. Green dashed line: 12 m telescope such as Atacama pathfinder experiment (APEX). Blue dot-dashed line: 15 m telescope such as the JCMT. Purple three dot-dashed line: 25 m such as the CCAT project. Asterisks: transition between the source density limitation (short wavelengths) and the fluctuation limitation (long wavelengths).

Table 10. Confusion noise and resolved fraction of the CIB at different wavelengths for a 25.00 m telescope (CCAT-like).

λ μm	$5\sigma_{\text{conf},P(D)}$ mJy	CIB fraction ^a %	$S_{\text{conf,density}}$ mJy	CIB fraction ^b %
250	2.81×10^{-2}	99.8	1.32×10^{-2}	99.1
350	1.57×10^{-1}	98.5	2.12×10^{-1}	94.2
500	4.31×10^{-1}	92.6	6.09×10^{-1}	79.1
850	5.99×10^{-1}	64.6	4.62×10^{-1}	49.7
1100	5.39×10^{-1}	53.1	3.46×10^{-1}	41.2

Notes. ^(a) Fraction of the CIB resolved at $5\text{-}\sigma_{\text{conf}}$. ^(b) Fraction of the CIB resolved at the flux limit.

(CCAT) project would be able to resolve more than 80% of the CIB up to 500 μm .

7.2. High energy opacity

The CIB photons can interact with TeV photons. The cross-section between a E_γ rest-frame high-energy photon and an infrared photon with a observer-frame wavelength λ_{IR}

interacting at a redshift z with an angle θ (and $\mu = \cos(\theta)$) is (Heitler 1954; Jauch & Rohrlich 1976)

$$\sigma_{\gamma\gamma}(E_\gamma, \lambda_{\text{IR}}, \mu, z) = H\left(1 - \frac{\epsilon_{\text{th}}}{\epsilon}\right) \frac{3\sigma_T}{16} (1 - \beta^2) \quad (22)$$

$$\times \left[2\beta(\beta^2 - 2) + (3 - \beta^4) \ln\left(\frac{1 + \beta}{1 - \beta}\right) \right] \quad (23)$$

with

$$\beta = \sqrt{1 - \frac{\epsilon_{\text{th}}}{\epsilon}}, \quad (24)$$

$$\epsilon_{\text{th}}(E_\gamma, \mu, z) = \frac{2(m_e c^2)^2}{E_\gamma(1 - \mu)(1 + z)}, \quad (25)$$

$$\epsilon(\lambda_{\text{IR}}, z) = \frac{hc(1 + z)}{\lambda_{\text{IR}}}, \quad (26)$$

where σ_T is the Thompson cross-section ($6.65 \times 10^{-29} \text{ m}^2$), m_e the mass of the electrons, and H the Heaviside step function ($H(x) = 1$ if $x > 0$ and 0 else).

The optical depth $\tau(E_\gamma, z_s)$ for a photon observed at energy E_γ and emitted at a redshift z_s can be easily computed (Dwek & Krennrich 2005; Younger & Hopkins 2011; Domínguez et al. 2011) with

$$\tau(E_\gamma, z_s) = \int_0^{z_s} dz \frac{D_H}{\sqrt{\Omega_\Lambda + (1 + z)^3 \Omega_m}} \times \int_{-1}^1 d\mu \frac{1 - \mu}{2} \int_{5\mu\text{m}}^\infty d\lambda_{\text{IR}} n_{\lambda_{\text{IR}}}(\lambda_{\text{IR}}, z) (1 + z)^2 \sigma_{\gamma\gamma}(E_\gamma, \lambda_{\text{IR}}, \mu, z), \quad (27)$$

where $n_{\lambda_{\text{IR}}}(\lambda_{\text{IR}}, z)$ is the comoving number density of photons emitted at a redshift greater than z between λ_{IR} and $\lambda_{\text{IR}} + d\lambda_{\text{IR}}$. The 5 μm cut corresponds to the limit of the validity of our model. The number density of photons is computed with

$$n_{\lambda_{\text{IR}}}(\lambda_{\text{IR}}, z) = \frac{4\pi}{hc\lambda_{\text{IR}}} (B_{\nu, \text{CIB}} + B_{\nu, \text{CMB}}), \quad (28)$$

where $B_{\nu, \text{CIB}}$ is the CIB given by our model and $B_{\nu, \text{CMB}}$ is the brightness of a blackbody at 2.725 K corresponding to the cosmic microwave background (Fixsen 2009). Our predicted opacities do not take into account the absorption by the cosmic optical background photons (COB, $\lambda < 5 \mu\text{m}$). Younger & Hopkins (2011) showed that the contribution of the COB to the opacity is negligible for energies higher than 5 TeV.

We can determine up to which redshift the opacity stays lower than 1. We can thus define an horizon as a function of the energy, called the Fazio-Stecker relation. We can see in Fig. 15 that the observed energy cutoff of low-redshift blazars (Mkn 501, Aharonian et al. 1999; Mkn 421, Aharonian et al. 2002; and BL Lac 1ES 1959+650, Aharonian et al. 2003) is compatible with this relation.

7.3. Effect of the strong lensing on the number counts

The strongly-lensed fraction is the ratio of the counts of lensed sources to the total observed counts. Because the slope of the counts varies a lot with the flux and wavelength, this fraction depends on the flux and the wavelength (see Fig. 16). The strongly lensed fraction is always smaller than 2% below 250 μm and is thus negligible. At longer wavelengths, we predict a maximum of the strongly lensed fraction near 100 mJy. At 500 μm , about 15% of the sources brighter than 100 mJy are lensed. This fraction increases to 40% near 1 mm.

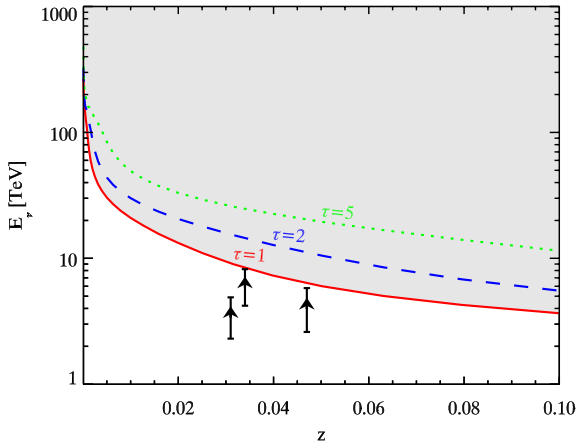


Fig. 15. Fazio-Stecker relation: energy at which the opacity reach a given τ as a function of redshift. This plot is done for $\tau = 1$ (red solid line), 2 (blue dashed line) and 5 (green dotted line). The data points are the cutoff energy of Mkn 501 (Aharonian et al. 1999), Mkn 421 (Aharonian et al. 2002) and Lac 1ES 1959+650 (Aharonian et al. 2003).

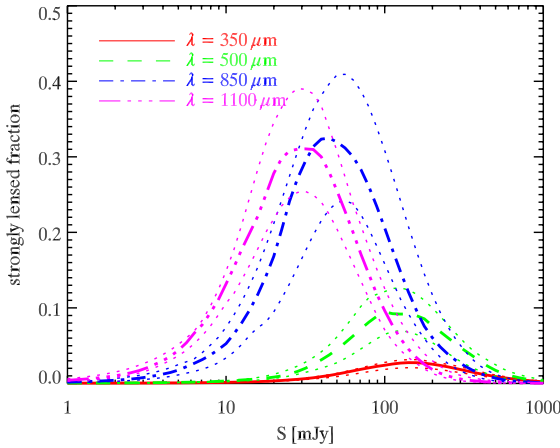


Fig. 16. Fraction of strongly lensed sources (magnification larger than 2) as a function of the flux at 350 μm (red solid line), at 500 μm (green dashed line), at 850 μm (blue dotted-dashed line) and at 1.1 mm (purple three-dot-dashed line). The dotted lines represent the 1- σ confidence area of our model.

Our results can be compared with those of the Negrello et al. (2007) model. The two models predict that the lensed fraction as a function of the flux is a bump around 100 mJy. However, the amplitude of this bump predicted by the two models is significantly different. For instance, the maximum of the lensed fraction at 500 μm is 15% for our model and 50% for the Negrello et al. (2007) model. The slope between 10 and 100 mJy is steeper in Negrello et al. (2007) model than in ours and is incompatible with the measurements (Clements et al. 2010; Oliver et al. 2010; Glenn et al. 2010). The steeper the slope, the larger the lensed fraction. This explains why the Negrello et al. (2007) model predicts larger lensed fraction than ours. The probability of a source being lensed increases with its redshift. The differences in the redshift distributions of the models could also explain some of the differences in the lensed fraction.

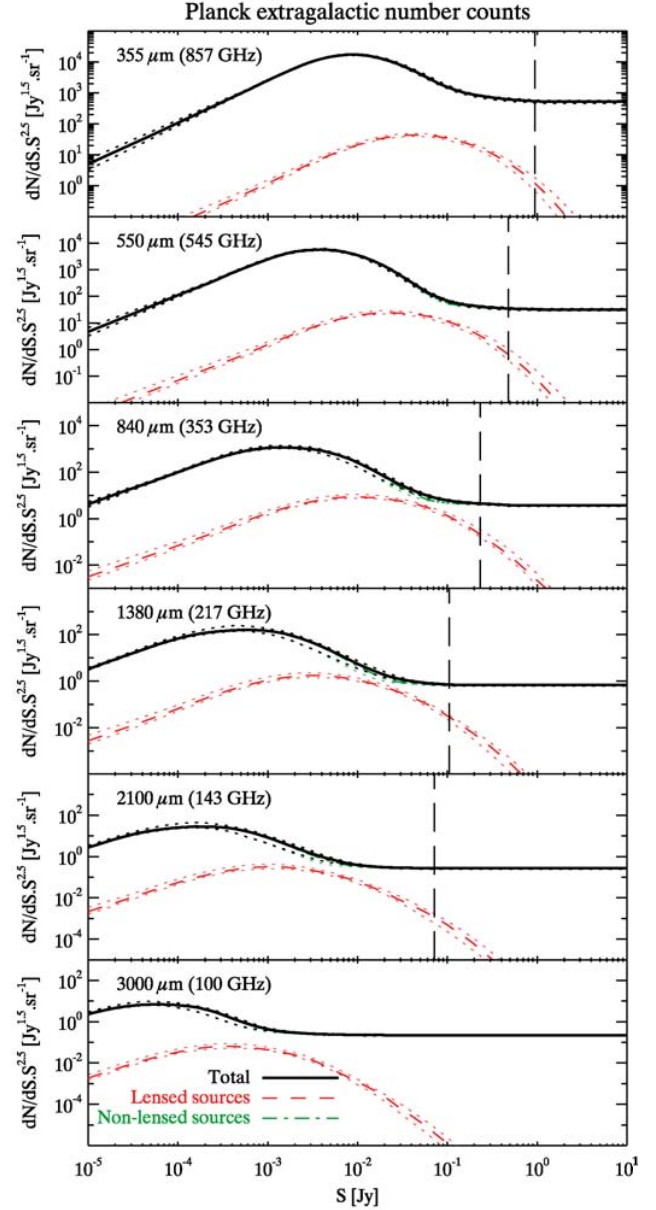


Fig. 17. Differential number counts in the *Planck* bands. These counts only take into account the individual star-forming galaxies. Black solid line: total contribution. Green dot-dashed line: contribution of the non-lensed sources. Red dashed line: contribution of the strongly-lensed sources. Dotted lines 1- σ contours. Vertical long-dashed line: 5- σ limits (confusion+instrumental) of Fernandez-Conde et al. (2008) for a bias of 1.5.

Figure 6 shows the respective contribution of the lensed and non-lensed sources to the SPT counts of dusty sources without IRAS 60 μm counterparts at 1.38 mm (Vieira et al. 2010). According to the model, these counts are dominated by strongly-lensed sources above 15 mJy. These bright sources are thus very likely to correspond to strongly-lensed sub-mm galaxies.

We predicted on the contribution of the strongly-lensed sources to the *Planck* number counts (see Fig. 17) using Fernandez-Conde et al. (2008) 5- σ limits, because they take into account the effect of the clustering on the confusion noise. This

effect is non-negligible because of the large beam of *Planck*. We found that the contribution of the lensed sources to the *Planck* counts is negligible in all the bands (a maximum of 0.47 galaxies sr^{-1} at $550 \mu\text{m}$). At high redshift, *Planck* will probably detect more small structures such as proto-clusters, than individual galaxies. *Planck* is thus not the best survey to find lensing candidates. Sub-mm surveys with a sensitivity near 100 mJy are more efficient. For instance, the *Herschel*-ATLAS survey should find 153 ± 26 and 411 ± 24 lensed sources with $S_{500} > 50$ mJy and $S_{350} > 50$ mJy, respectively, across 600 deg^2 .

8. Discussion

8.1. Comparison with other backward evolution models

The evolution of the infrared luminosity density predicted by our model can be compared with the predictions of other backward evolution models. We find, like Franceschini et al. (2010), a strong increase in ρ_{IR} from $z = 0$ to $z = 1$, a break around $z = 1$, and a decrease at higher redshift. In contrast, the Valiante et al. (2009) and Le Borgne et al. (2009) models predict a maximum of infrared luminosity density around $z = 2$.

In a similar way to Le Borgne et al. (2009) and Franceschini et al. (2010), we found that LIRGs dominate infrared luminosity density around $z = 1$ and that ULIRGs dominate at redshift higher than 1.5. We also found as Le Borgne et al. (2009) that normal galaxies dominates ρ_{IR} only up to $z \sim 0.5$.

Our model and the Valiante et al. (2009) one use a similar parametrization of the LF evolution. Both models found a very strong evolution in luminosity up to $z = 2$ ($(1+z)^{3.4}$ for the Valiante et al. (2009) model, which can be compared with $(1+z)^{2.9 \pm 0.1}$ from $z = 0$ to 0.87 ± 0.05 and $(1+z)^{4.7 \pm 0.3}$ from $z = 0.87 \pm 0.05$ to 2 for our model). At higher redshift, our model is compatible with no evolution and the Valiante et al. (2009) model predicts a slight decrease in $(1+z)^{-1}$. Concerning the evolution in density, both models predicts an increase from $z = 0$ to $z \approx 1$ (proportional to $(1+z)^2$ for the Valiante et al. (2009) model and $(1+z)^{0.8 \pm 0.2}$ for our model) and a decrease at higher redshift ($(1+z)^{-1.5}$ for the Valiante et al. (2009) model, $(1+z)^{-6.2 \pm 0.5}$ between $z = 0.87 \pm 0.5$ and $z = 2$ and $(1+z)^{-0.9 \pm 0.7}$ at $z > 2$ for our model). These two models thus agree on the global shape of the evolution of the LF, but disagree on the values of the coefficient driving it. There is in particular a large difference on the evolution density between $z \sim 1$ and $z \sim 2$. This difference could be explained by the different positions of the breaks. Nevertheless, the uncertainties on the Valiante et al. (2009) model are not estimated. It is thus difficult for us to draw any conclusion.

Valiante et al. (2009) and Franceschini et al. (2010) used AGNs to reproduce the infrared observations. Valiante et al. (2009) also used a temperature dispersion of the galaxies. Our model reproduce the same observations using neither AGNs nor temperature dispersion. This demonstrates that the AGN contribution and the temperature scatter cannot be accurately constrained by with this type of modeling.

8.2. Discriminating the models: smoking gun observations?

Although they use different galaxy populations and evolutions, the backward evolution models reproduce the number counts from the mid-IR to the mm domain in a reasonably good way. It is thus important to find new observables to discriminate between models.

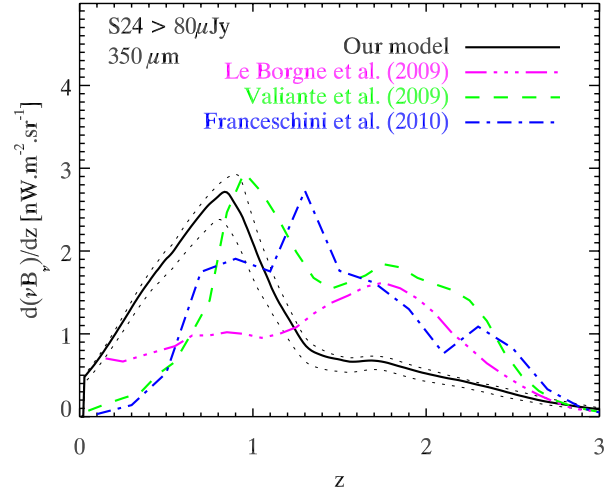


Fig. 18. Differential contribution of the $S_{24} > 80 \mu\text{Jy}$ sources to the CIB as a function of the redshift at $350 \mu\text{m}$. Black solid line: Our model ($1-\sigma$ limit in black dotted line). Purple three dot-dashed line: Le Borgne et al. (2009) model. Green dashed line: Valiante et al. (2009) model. Blue dot-dashed line: Franceschini et al. (2010) model.

The sub-mm redshift distributions of the bright sources are quite straightforward, but very discriminant observations. For instance, Fig. 7 shows a significant difference in the sub-mm redshift distributions predicted by the different models. The Chapin et al. (2011) measurements performed on one small field with a cut at high flux do not enable us to draw strong conclusions. *Herschel* will help us to increase the accuracy of the measured redshift distributions and estimate the cosmic variance in them. These constraints will be crucial for the next generation of models.

Jauzac et al. (2011) showed that the redshift distribution of the contribution of the 24 microns sources to CIB at 70 and $160 \mu\text{m}$ ($d(\nu B_\nu)/dz$) also provides a strong constraint. Figure 18 shows the $d(\nu B_\nu)/dz$ at $350 \mu\text{m}$. The different models make totally incompatible predictions in the sub-mm. An accurate measurement of $d(\nu B_\nu)/dz$ will thus be crucial for future models.

8.3. Limits of our model

Our model is a useful tool to make a first interpretation of the observations from the mid-infrared to the mm domain. Nevertheless, it is biased by some structural choice in its construction.

The choice of the parameters biases the results. For example, we have chosen the minimal number of parameters to reproduce the counts. If we had used more breaks in the evolution in both density and luminosity, the evolutions with redshift would have been smoother and the errors in the predictions would have been different. Our errors are just the statistical errors due to the determination of the parameter of a given model using the data. It does not include the uncertainty in our hypothesis about the evolution (such as α fixed) and the biases due to our choice of parameters (evolution in $(1+z)^r$ with breaks). For instance, the strong decrease in density between $z \sim 0.9$ and $z = 2$ is probably an artifact caused by our choice of parametrization. In addition, our model of lensing is very simple and should be improved in the future. Nevertheless, the contribution of the lensing in the fitted data is low and the bias is thus negligible.

The backward evolution models gives a very limited interpretation of the data. They provide only a description of the evolution of the statistical properties of the infrared galaxies. The physical processes explaining the strong evolution of these objects are ignored. A more complex physical approach is thus necessary to deeply understand the history of the infrared galaxies. Nevertheless, our model is very useful for providing a rapid interpretation of new observations and predictions for future missions.

8.4. Perspectives

Our models fit the current data when we employ rather simple hypotheses. Nevertheless, the increasing accuracy of infrared observations will probably help us to improve the model. Additional model updates will be possible in the future.

The α and σ parameters are fixed, but it may be necessary to incorporate an evolution of the shape of the LF with the redshift. A Fisher matrix analysis shows that the evolution of α at high redshift cannot be constrained without deeper observations in the sub-mm. An evolution of σ could be constrained, but is not necessary to reproduce the current data.

The evolution of the parameters is very simple in the current version and could be updated by using more breaks or a smoother functional form.

The observations of *Herschel* will help us to improve the SED used in our model, and maybe enable us to determine the SED evolution with redshift. The temperature of the big grains and its dispersion will be measured more accurately. Nevertheless, this dispersion must be modeled with a limited number of templates to allow us to use an MCMC approach. This will be one of the future challenges of including it in our model.

Nevertheless, each refinement increases the number of free parameters of the model. It is important to limit the number of new parameters in comparison with the number of measurements.

9. Summary

- Our new parametric backward evolution model has enabled us to reproduce the number counts from 15 μm to 1.1 mm, the monochromatic LF, and the redshift distributions.
- We have found that our model predicts a strong evolution in the LF characteristic luminosity up to $z = 2$ and a strong decrease in density from $z = 1$ to $z = 2$. We predict that the number of HyLIRG reaches a maximum around $z = 2$.
- We have found that normal galaxies, LIRGs, and ULIRGs dominates the infrared output at $z = 0$, $z = 1$, and $z = 2$, respectively. The HyLIRG accounts for a small fraction ($<10\%$) at all redshifts.
- We have reproduced the CIB spectrum and predicted the contributions per redshift and luminosity slice. We found that the mid- and far-infrared part of the CIB are mainly emitted by the normal galaxies and LIRG. The sub-mm part is mainly due to LIRGs and ULIRGs at high redshift in accordance with the sub-mm observations of deep fields. We estimated the total flux of the CIB total to be $23.7 \pm 0.9 \text{ nW m}^{-2} \text{ sr}^{-1}$.
- We estimated the fraction of lensed sources in the sub-mm as a function of the flux and wavelength. This contribution is low ($<10\%$) below 500 μm , but high (up to 50%) around 100 mJy in the mm domain.

- We predicted that the population of very bright dusty galaxies detected by SPT without an IRAS counterpart (Vieira et al. 2010) is essentially composed of lensed sub-mm galaxies. We have also predicted the contribution of the lensed sources to the *Planck* number counts.
- We predict the confusion limits for future missions like SPICA or CCAT.
- We estimated the opacity of the Universe to TeV photons.
- Material of the model (software, tables and predictions) is available online¹.

10. Conclusion

We have demonstrated that it is possible to reproduce the number counts from the mid-IR to the mm domain with a rather simple parametric model that is minimized automatically. Nevertheless, other automatically-tuned models reproduce these counts with different redshift distributions (Le Borgne et al. 2009; Marsden et al. 2011). This suggests that number counts alone are insufficient to uniquely constrain these models. Different observables are thus crucial to discriminate the different parametrizations proposed by the model builders. These constraints are the luminosity functions, the redshift distributions, $P(D)$, and the fluctuations. Future measurements of these quantities and their uncertainties have to be very robust to be used to constrain the next generation of models.

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¹ <http://www.ias.u-psud.fr/irgalaxies/>

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Chapitre 7

Modélisation des fluctuations du fond infrarouge

Sommaire

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7.1 Présentation

Le fond infrarouge n'est pas constant sur tout le ciel. En effet, bien que l'Univers soit homogène et isotrope, le nombre de galaxies infrarouges sur une ligne de visée varie à cause des fluctuations statistiques. Elles sont poissonniennes aux petites échelles, mais il existe également des fluctuations structurées aux grandes échelles suivant les grandes structures de l'Univers. Etudier les fluctuations du fond infrarouge fournit donc des informations sur la manière dont les galaxies infrarouges peuplent les halos de matière noire.

L'outil statistique le plus adapté pour étudier ces fluctuations est le spectre de puissance, $P(\vec{k})$, qui est le carré du module de la transformée de Fourier du signal étudié. L'Univers étant statistiquement isotrope¹, le spectre de puissance ne dépend donc pas de la direction de $\vec{k}$, mais juste de sa norme. On étudie donc en général la fonction à une dimension $P(|\vec{k}|)$, noté souvent simplement $P(k)$. Lorsqu'on étudie les grandes échelles, on ne peut plus considérer le ciel comme un plan. Dans ce cas, on utilise une décomposition sur la base des harmoniques sphériques à la place de celle de Fourier. L'équivalent du $P(k)$ dans cette base est noté C_l . Aux petites échelles, on a $P(k) = C_l$ pour $l = 2\pi k$. Ces deux conventions sont utilisées pour étudier les fluctuations du CIB.

7.2 Fluctuations non-corrélées

7.2.1 Niveau des fluctuations poissonniennes

Le niveau des fluctuations non-corrélées (ou poissonniennes) du fond infrarouge peut se calculer facilement à partir des comptages de sources. On considère un intervalle de flux $[S_k, S_k + \Delta S_k]$. Le nombre de sources par unité d'angle solide n_k comprises dans cet intervalle est

$$n_k = \frac{dN}{dS} \Delta S_k. \quad (7.1)$$

Dans le cas poissonien, la variance sur nombre de sources dans cet intervalle est donc

$$\sigma_{B_k}^2 = n_k \times S_k^2. \quad (7.2)$$

La contribution B_k de ces sources au fond vaut, quant à elle,

$$B_k = n_k \times S_k. \quad (7.3)$$

On en déduit la variance σ_B^2 sur la contribution totale au fond ($B = \sum_k B_k$)

$$\sigma_B^2 = \sum_k n_k S_k^2 = \frac{dN}{dS} S_k^2 \Delta S_k. \quad (7.4)$$

On peut alors passer à la limite intégrale :

$$\sigma_B^2 = \int_0^{S_c} \frac{dN}{dS} S^2 dS, \quad (7.5)$$

où S_c est le flux de coupure du nettoyage des sources brillantes. Ce nettoyage est nécessaire car l'intégrale ne converge pas en $+\infty$ dans le cas euclidien ($dN/dS \propto S^{-2.5}$). En

¹En pratique, à cause des grandes structures, il existe des surdensités dans l'Univers. Néanmoins, ces surdensités sont des fluctuations statistiques : tous les points ont la même distribution de probabilité *a priori*.

λ μm	Référence	S_{cut} mJy	$P_{SN,mes}$ $\text{Jy}^2.\text{sr}^{-1}$	$P_{SN,model}$ $\text{Jy}^2.\text{sr}^{-1}$	$\langle z_{mod} \rangle$
60	Miville-Deschênes <i>et al.</i> (2002)	1000	1600±300	2089±386	0.20±0.01
100	Miville-Deschênes <i>et al.</i> (2002)	700	5800±1000	7364±1232	0.38±0.03
160	Lagache <i>et al.</i> (2007)	200	9848±120	10834±3124	0.73±0.06
250	Viero <i>et al.</i> (2009)	500	11400±1000	11585±2079	0.81±0.08
250	Amblard et Hermes (2010)	50	6100±120	6726±1207	1.09±0.06
350	Viero <i>et al.</i> (2009)	400	6300±500	5048±1083	1.17±0.12
350	Amblard et Hermes (2010)	50	4600±70	4446±1320	1.32±0.11
500	Viero <i>et al.</i> (2009)	-	2700±200	1677±484	1.59±0.21
500	Amblard et Hermes (2010)	50	1800±80	1369±537	1.85±0.21
1363	Hall <i>et al.</i> (2010)	15	17±2	10±3	4.07±0.24

TABLE 7.1 – Niveau des fluctuations non corrélées du fond infrarouge et comparaison des mesures avec les prédictions du modèle de Béthermin *et al.* (2011). Les incertitudes sur les prédictions prennent en compte la calibration. Le *redshift* moyen $\langle z_{model} \rangle$ des fluctuations est celui prédit par le modèle. Extrait de Béthermin *et al.* (2011).

général, cette coupure est placée relativement basse (proche de la limite de complétude à 95%) pour fournir une meilleure contrainte sur les sources faibles.

Nous avons comparé les prédictions du modèle de Béthermin *et al.* (2011) (voir Chap. 6) avec les mesures des fluctuations poissonniennes. Il y a un très bon accord en dessous de $\lambda < 500\mu\text{m}$ (Miville-Deschênes *et al.* (2002); Lagache *et al.* (2007); Viero *et al.* (2009); Amblard et Hermes (2010)). Le modèle a tendance à légèrement sous-estimer (environ 30%) les fluctuations à plus grande longueur d'onde (Viero *et al.* (2009); Amblard et Hermes (2010); Hall *et al.* (2010)). On remarque également que les fluctuations à grande longueur d'onde sont dominées par les hauts *redshifts*. Les fluctuations dans le domaine millimétrique fournissent donc des contraintes très importantes sur les galaxies infrarouges à $z > 4$.

7.2.2 Niveau des fluctuations poissonniennes des spectres croisés

On peut de la même manière calculer le niveau poissonien (aux petites échelles) du spectre de puissance croisé entre deux bandes. On considère deux bandes A et B. Le nombre de sources n_{kl} dans une tranche de flux $[S_k, S_k + \Delta S_k]$ et de redshift $[z_l, z_l + \Delta z_l]$ est :

$$n_{kl} = \frac{dN}{dS dz} \Delta S_k \Delta z_l \quad (7.6)$$

Si on ne considère qu'une seule population de galaxies et une tranche de flux et *redshift* assez fine, la covariance entre les deux bandes $\sigma_{AB,kl}$ est

$$\sigma_{AB,kl} = n_{kl} S_{A,kl} S_{B,kl} = n_{kl} S_{A,kl}^2 C_{BA,kl}, \quad (7.7)$$

où $C_{BA,kl}$ est la couleur entre la bande B et la bande A pour une population dans l'intervalle considéré. Si on somme sur les deux populations et sur tous les intervalles, on obtient alors

$$\sigma_{AB} = \sum_{pop} \sum_k \sum_l n_{pop,kl} S_{A,kl}^2 C_{BA,pop,kl}, \quad (7.8)$$

où $n_{pop,kl}$ est le nombre de sources dans l'intervalle considéré appartenant à la population considérée, et $C_{BA,pop,kl}$ la couleur d'une source appartenant l'intervalle et la population sélectionnés. On peut alors passer à la limite intégrale pour obtenir :

$$\sigma_{AB} = \sum_{pop} \int_{S_A=0}^{\infty} \int_{z=0}^{\infty} H(S_A < S_{A,c}, C_{BA,pop} S_A < S_{B,c}) \frac{dN_{pop}}{dS dz} S_A^2 C_{BA,pop} dS_A dz, \quad (7.9)$$

où $H(P_1, P_2)$ vaut 1 lorsque P_1 et P_2 sont vraies, et 0 sinon. $S_{A,c}$ et $S_{B,c}$ sont les coupures en flux dans les bandes A et B. On peut également montrer que :

$$\sigma_{AB} = \int_{S_A=0}^{S_{A,c}} \int_{S_B=0}^{S_{B,c}} \frac{dN_{pop}}{dS_A dS_B} S_A S_B dS_A dS_B \quad (7.10)$$

Néanmoins, cette formule est moins pratique à utiliser ($dN/dS_A/dS_B$ n'est pas trivial à calculer contrairement $dN_{pop}/dS_A/dz$).

Le spectre de puissance croisé entre les cartes BLAST et ACT a été mesuré par Hajian *et al.* (2011). J'ai fourni grâce à mon modèle une prédiction des fluctuations poissonniennes croisées afin de les comparer aux observations. Le modèle est en relativement bon accord avec les niveaux poissonniens prédits (voire Fig. 7.1).

7.2.3 Fluctuations poissonniennes de la polarisation ?

La lumière émise par une galaxie infrarouge n'a aucune raison de ne pas être polarisée. La polarisation du fond infrarouge pourrait donc présenter des propriétés particulières. Elles peuvent être estimées par un modèle simple.

On note I l'intensité totale, I_x l'intensité polarisée selon x , et I_y l'intensité polarisée selon y . On introduit également $Q = I_x - I_y$ et $U = I_x^{45} - I_y^{45}$ (?), où I_x^{45} (resp. I_y^{45}) est l'intensité selon un axe à 45° avec l'axe x (resp. y). On appelle p la fraction de polarisation donnée par :

$$p = \sqrt{Q^2 + U^2} \times I. \quad (7.11)$$

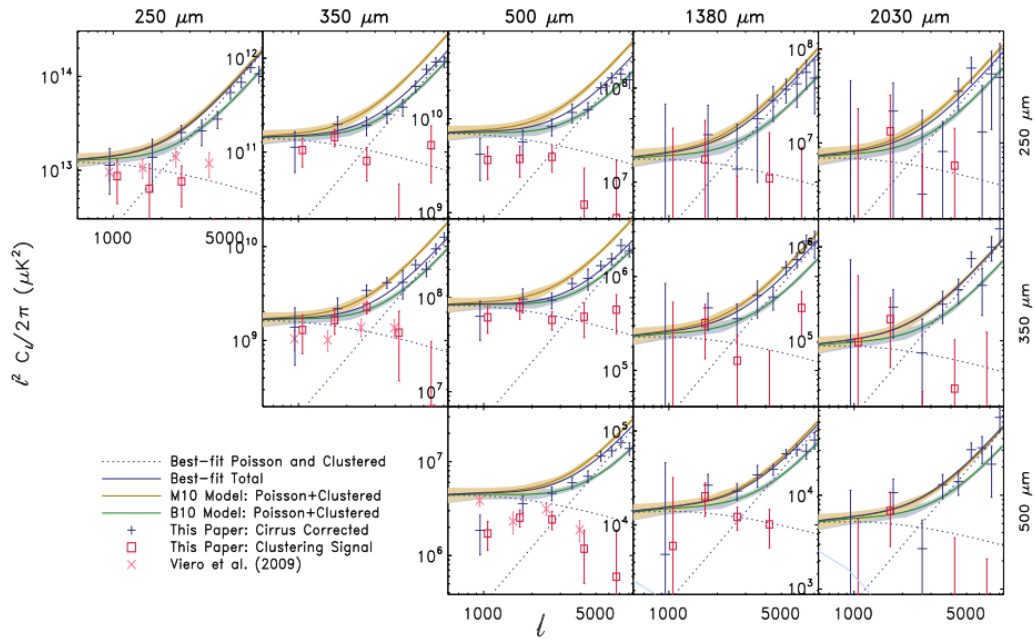


FIGURE 7.1 – Spectres de puissance croisés observés par BLAST et ACT (croix bleues). Le modèle de Béthermin *et al.* (2011) est en vert et celui de Marsden *et al.* (2010) est en doré. Extrait de Hajian *et al.* (2011).

Pour un objet dont la fraction de polarisation est p , les valeurs de Q et U sont :

$$Q = pI \cos(2\alpha) \quad (7.12)$$

$$U = pI \sin(2\alpha), \quad (7.13)$$

où α indique l'angle de polarisation. On supposera dans ce modèle que α est aléatoire (entre 0 et π), de densité de probabilité constante et indépendant d'une source à l'autre.

On peut montrer facilement que la polarisation moyenne du fond est nulle. On considère un intervalle de flux $[S_i, S_i + \Delta S_i]$ et d'angle de polarisation $[\alpha_j, \alpha_j + \Delta \alpha_j]$. Le contribution de cet intervalle à Q est

$$Q_{ij} = p S_i \cos(2\alpha_j) \frac{dN}{dS_i} \frac{\Delta \alpha_j}{\pi} \Delta S_i \quad (7.14)$$

Si on somme sur tous les intervalles et qu'on passe à la limite intégrale, on obtient :

$$Q = \int_0^{S_c} p S \frac{dN}{dS} dS \times \int_0^\pi \cos(2\alpha) \frac{d\alpha}{\pi} = 0 \quad (7.15)$$

Les galaxies n'ayant aucune raisons d'être alignées, le fond infrarouge a donc bien une polarisation à moyenne nulle.

En revanche, il peut exister des fluctuations statistiques en polarisation. En effet, dans l'hypothèse poissonnienne, la variance sur le nombre de sources dans un intervalle de flux et d'angle de polarisation est

$$\sigma_{n,ij}^2 = \frac{\Delta \alpha_j}{\pi} \frac{dN}{dS_i} \Delta S_i. \quad (7.16)$$

La variance sur la contribution à Q des sources dans cet intervalle est donc

$$\sigma_{Q,ij}^2 = \frac{\Delta \alpha_j}{\pi} \frac{dN}{dS_i} \Delta S_i \left(p S_i \cos(2\alpha_j) \right)^2. \quad (7.17)$$

La variance sur Q est alors

$$\sigma_{Q,tot}^2 = \sum_i \sum_j \frac{\Delta \alpha_j}{\pi} \frac{dN}{dS_i} \Delta S_i \left(p S_i \cos(2\alpha_j) \right)^2. \quad (7.18)$$

On peut passer à la limite intégrale :

$$\sigma_{Q,tot}^2 = \int_{\alpha=0}^\pi \int_{S=0}^{S_c} p^2 S^2 \cos^2(\alpha) \frac{dN}{dS} dS d\alpha \quad (7.19)$$

$$= \frac{p^2}{2} \int_{S=0}^{S_c} S^2 \frac{dN}{dS} dS = \frac{p^2}{2} \sigma_{I,tot}^2, \quad (7.20)$$

où $\sigma_{I,tot}^2$ est le niveau des fluctuations poissonniennes en intensité. Les fluctuations en polarisation ont donc $p^2/2$ fois plus faibles que les fluctuations en intensité. Si on suppose que p est de l'ordre de 1%, il y a donc plus de quatre ordres de grandeur entre les fluctuations en intensité et en polarisation. Ces dernières semblent donc être un phénomène indétectable aujourd'hui. Le satellite *Planck* devrait mesurer prochainement la polarisation de galaxies locales, permettant à l'avenir de mieux contraindre p et donc l'estimation du niveau de ces fluctuations polarisées.

7.3 Fluctuations corrélées

7.3.1 Modélisation

Le modèle présenté ici est publié dans Planck Collaboration *et al.* (2011) et Pénin *et al.* (2011a).

D'après Haiman et Knox (2000) et Knox *et al.* (2001), et dans le cadre de l'approximation de Limber (ciel plat), le spectre de puissance des fluctuations corrélées du fond infrarouge se calcule de la manière suivante :

$$C_l^{\lambda\lambda'} = \int \left(\frac{dD_c}{dz} \right) \left(\frac{1}{(1+z)D_c} \right)^2 \bar{j}_\nu(z) \bar{j}_{\nu'}(z) P_{gg}(k = l/\chi, z) dz, \quad (7.21)$$

où $C_l^{\lambda\lambda'}$ est le spectre de puissance croisé entre les longueurs d'onde λ et λ' , D_c la distance comobile correspondant au *redshift* z , $P_{gg}(k = l/\chi, z)$ est le spectre de puissance des galaxies à un *redshift* z^2 , et $\bar{j}_\nu(z)$ est l'émissivité moyenne des galaxies par unité de volume comobile. Les fluctuations corrélées dépendent donc de trois ingrédients : la cosmologie, la distribution spatiale des galaxies, et l'évolution des émissivités.

L'émissivité $\bar{j}_\nu(z)$ provient du modèle d'évolution des galaxies présenté Chap. 6 et se calcule de la manière suivante :

$$\bar{j}_\nu(z) = \frac{(1+z)}{dD_c/dz} \int_0^{S_{cut}} S \frac{d^2 N}{dS dz} dS. \quad (7.22)$$

Le partie corrélée du spectre de puissance du fond infrarouge dépend donc, comme sa partie poissonnienne, de l'évolution des galaxies. En revanche, seule la partie corrélée est affectée par la distribution spatiale des objets.

²On suppose ici implicitement que les galaxies lumineuses et peu lumineuses ont la même distribution spatiale.

La manière la plus simple d'estimer le spectre de puissance des galaxies est de supposer une relation de proportionnalité avec celui de la matière noire :

$$P_{gg}(k, z) = b_{lin}^2 P_{lin}(k, z) \quad (7.23)$$

où b_{lin} est un paramètre appelé le biais linéaire, et $P_{lin}(k, z)$ est le spectre de puissance de la matière noire calculé à partir de la théorie des perturbations linéaires. Ce modèle sera donc surtout valable aux grandes échelles.

Il est toutefois possible de décrire plus finement la distribution spatiale des galaxies grâce à un modèle de halo (Cooray et Sheth (2002)). Dans ce type de modèle, le spectre de puissance des galaxies est alors la somme de deux termes : un premier dû aux corrélations à l'intérieur d'un halo P_{1h} , et un second dû aux corrélations entre les galaxies de deux halos différents P_{2h} . Le terme 1-halo dépend du nombre de galaxies dans les halos, ainsi que du profil de densité, ces deux quantités dépendant de la masse du halo, M :

$$P_{1h}(k) = \int \frac{dN}{dM} \frac{\langle N_{gal}(N_{gal} - 1) \rangle}{\bar{n}_{gal}^2} u^2(k, M) dM, \quad (7.24)$$

où dN/dM est la fonction de masse des halos, N_{gal} est le nombre de galaxies, $\bar{n}_{gal}$ la densité moyenne de galaxies, et $u(k, M)$ est la transformée de Fourier normalisée du profil de densité d'un halo de masse M . On peut, par exemple, prendre un profil NFW (Navarro *et al.* (1997)). Le nombre de galaxies dans un halo, N_{gal} , peut quant à lui être décrit par un modèle du type de celui de Zheng *et al.* (2005) :

$$\langle N_{gal} \rangle = \langle N_{cen} \rangle + \langle N_{sat} \rangle. \quad (7.25)$$

N_{cen} est le nombre moyen de galaxie central dans un halo donné par :

$$\langle N_{cen} \rangle = \frac{1}{2} \left(1 + \operatorname{erf} \left(\frac{\log(M) - \log(M_{min})}{\sigma_{\log(M)}} \right) \right), \quad (7.26)$$

avec M_{min} la masse minimale typique d'un halo pour qu'il puisse contenir une galaxie centrale et $\sigma_{\log(M)}$ décrit la dispersion autour de cette valeur. N_{sat} est le nombre moyen de galaxies satellites donné par :

$$\langle N_{sat} \rangle = \frac{1}{2} \left(1 + \operatorname{erf} \left(\frac{\log(M) - \log(2M_{min})}{\sigma_{\log(M)}} \right) \right) \left(\frac{M}{M_{sat}} \right), \quad (7.27)$$

où M_{sat} et α décrivent comment le nombre de satellites augmente avec la masse. Le facteur 2 devant M_{min} est arbitraire et sert à éviter qu'un halo contienne une galaxie satellite et pas de galaxie centrale. La Fig. 7.2 montre comment ces deux quantités évoluent avec la masse du halo hôte.

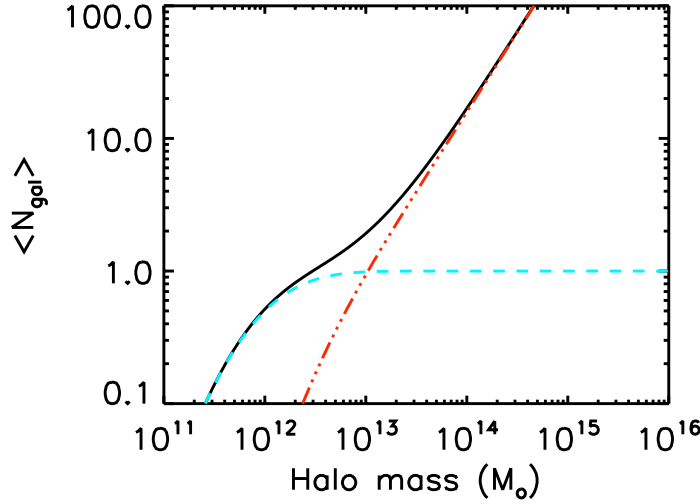


FIGURE 7.2 – Nombre moyen de galaxies dans un halo en fonction de sa masse. *Ligne noire* : nombre total de galaxies. *Tirets cyans* : nombre de galaxies centrales. *Tirets-2-points rouges* : nombre de galaxies satellites. Extrait de Pénin *et al.* (2011a)

Le terme 2-halo est, quant à lui, calculé de la manière suivante :

$$P_{2h} = P_{lin} \left(\int \frac{dN}{dM} b(M) \frac{\langle N_{gal} \rangle}{\bar{n}_{gal}} u(k, M) dM \right)^2, \quad (7.28)$$

où $b(M)$ est le bias linéaire des halos de masse M . Cette quantité provient d'un ajustement des résultats fournis par les simulations de matière noire (Tinker *et al.* (2010)).

J'ai participé à ce projet de modélisation en fournissant les $\bar{j}_v$ issus de mon modèle d'évolution (voir Chap. 6). En effet, les fluctuations corrélées sont très dépendantes du modèle d'évolution sous-jacent, et l'utilisation d'un modèle actualisé était fondamentale. Les Fig. 7.3 et 7.4 comparent les prédictions du modèle de Lagache *et al.* (2004) et de Béthermin *et al.* (2011) pour un même modèle de halos. On constate de forts écarts autour de $z=2$. L'effet sur le spectre de puissance peut atteindre un facteur 2. De plus, l'utilisation d'un modèle paramétrique permet d'étudier les dégénérescences entre les paramètres d'évolution et de halos (voir Pénin *et al.* (2011a) pour plus de détails).

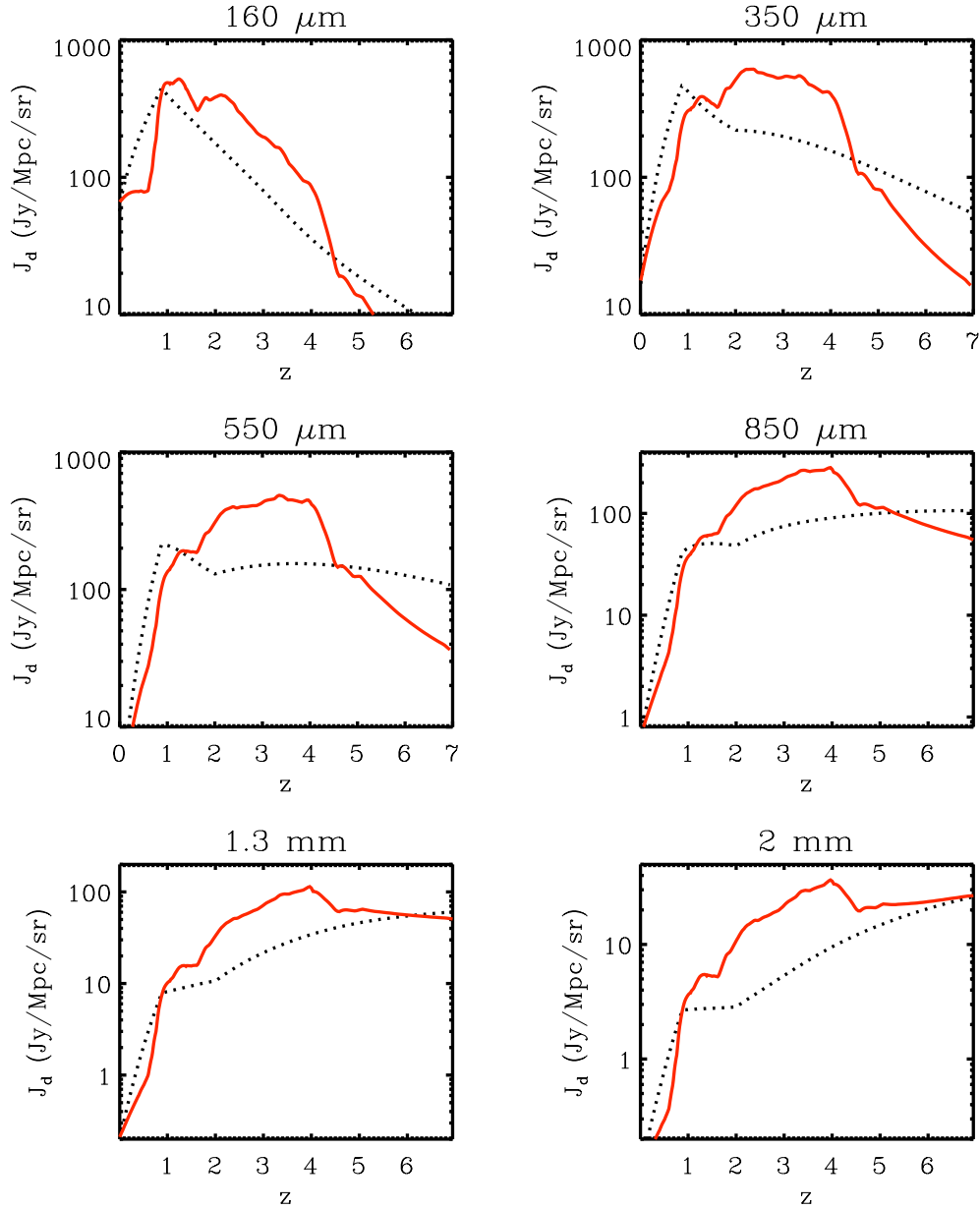


FIGURE 7.3 – Comparaison des émissivités prédites par les modèles de Lagache *et al.* (2004) (en rouge) et de Béthermin *et al.* (2011) (en noir). Extrait de Pénin *et al.* (2011a).

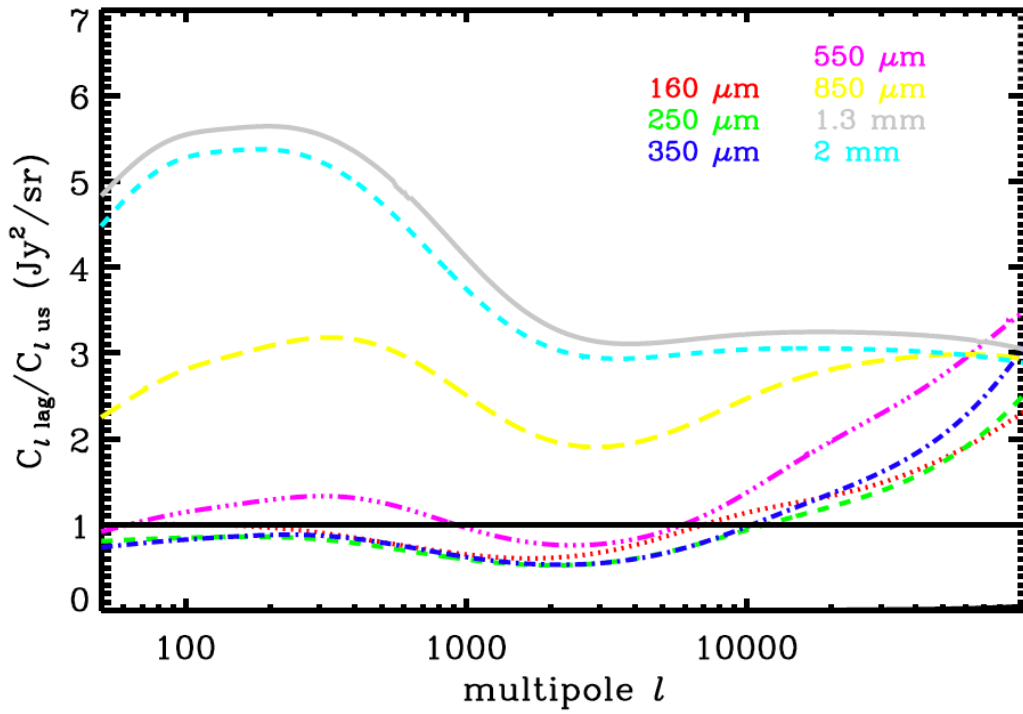


FIGURE 7.4 – Rapport entre les spectres de puissance prédits des fluctuations corrélées par les deux modèles d'évolution. Extrait de Pénin *et al.* (2011a).

7.3.2 Application

Ce modèle a été utilisé par la collaboration *Planck* pour interpréter les fluctuations du fond infrarouge. La Fig. 7.5 représente cette mesure et le meilleur ajustement de ces points. A cause de sa résolution angulaire limitée, *Planck* ne permet pas d'accéder aux petites échelles, et ainsi contraindre le niveau des fluctuations poissonniennes. Nous utilisons donc les niveaux de fluctuations prédites par notre modèle d'évolution. Chaque longueur d'onde est ajustée séparément. En effet, un modèle de halo unique ne parvient pas à reproduire le spectre de puissance observé à toutes les longueurs d'ondes. En revanche, l'ajustement de chaque bande individuellement est très bon. Chaque longueur d'onde est dominée par des *redshifts* différents (voir Chap. 5 et 6). Ceci suggère donc que les propriétés d'occupation des halos évoluent avec le *redshift*. Il est donc nécessaire de développer des modèles plus complexes pour interpréter avec finesse les résultats de *Planck*. Un second ajustement a été réalisé en laissant libre j_ν au-delà de $z=3.5$. Les dégénérescences sont trop importantes pour faire la moindre conclusion. Ceci montre qu'il n'est pas possible de contraindre à la fois le modèle de halos et l'évolution de l'émissivité avec le seul spectre de puissance. Il est donc important d'utiliser d'autres observables complémentaires pour lever ces dégénérescences.

7.4 Conclusion

Les fluctuations du fond infrarouge contiennent des informations importantes sur les populations faibles. Le niveau poissonien de ces fluctuations ne dépend que de l'évolution des galaxies, et pas de leur distribution spatiale. Ensuite, plus on va à grande longueur d'onde et plus on sonde des populations à grand *redshift*. Ce type de mesure semble par conséquent être une des manières les plus prometteuse de contraindre l'évolution des galaxies infrarouges à $z>4$. De plus, les fluctuations poissonniennes croisées fournissent des informations complémentaires sur la couleur des sources.

Les fluctuations corrélées, dominant aux plus grandes échelles (au delà de quelques arcmin), fournissent une information dégénérée sur l'évolution et la distribution spatiale des sources infrarouges. L'interprétation semble difficile, mais extrêmement prometteuse. En effet, les fluctuations corrélées dans le domaine millimétrique sondent la structuration spatiale des objets infrarouges à très grand *redshift*. Les fluctuations ont de grandes chances d'être dans la prochaine décennie une des observables phares de l'Univers infrarouge.

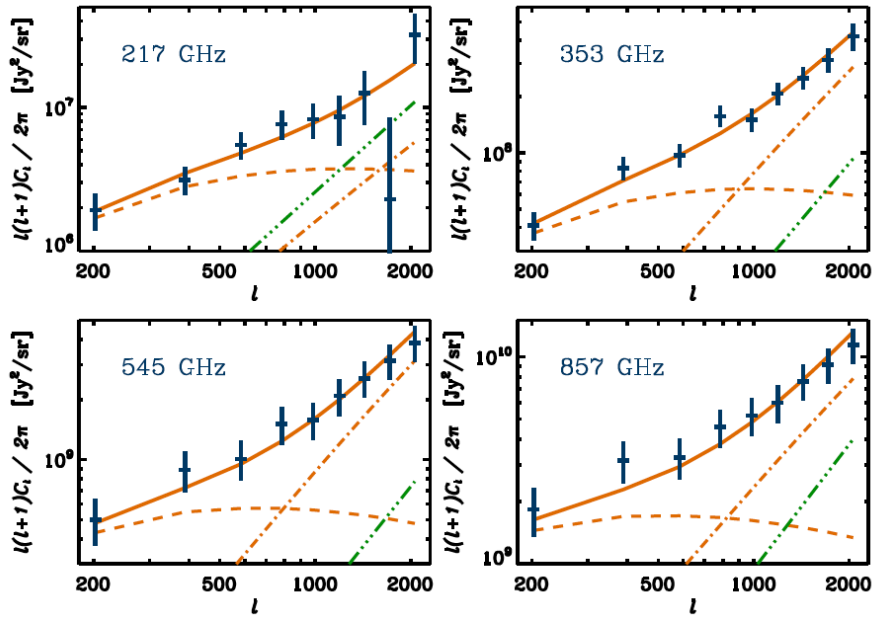


FIGURE 7.5 – Spectre de puissance des fluctuations du fond infrarouge mesuré par le satellite *Planck* (en bleu) et son ajustement par notre modèle (ligne continue jaune). Les contributions des termes poissonien (ligne tirets-3 points verte), 1-halo (ligne tirets-points jaune) et 2-halos (tirets jaune) sont également représentées. Extrait de Planck Collaboration *et al.* (2011)

7.5 Article : *Modeling the evolution of infrared galaxies : clustering of galaxies in the Cosmic Infrared Background*

Le modèle de fluctuations du fond infrarouge de l'IAS a fait l'objet d'un article soumis à *Astronomy&Astrophysics*.

Modeling the evolution of infrared galaxies : clustering of galaxies in the Cosmic Infrared Background

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ABSTRACT

Context. Star-forming galaxies are a highly biased tracer of the underlying dark matter density field. Their clustering can be studied through the cosmic infrared background anisotropies. These anisotropies have been measured from 100 μm to 2 mm in the last few years.

Aims. In this paper, we present a fully parametric model allowing a joint analysis of these recent observations.

Methods. In order to develop a coherent model at various wavelengths, we rely on two building blocks. The first one is a parametric model that describes the redshift evolution of the luminosity function of star-forming galaxies. It was introduced in Béthermin et al. (2011) and compares favorably to measured differential number counts and luminosity functions. The second one is a halo model based description of the clustering of galaxies. Starting from a fiducial model, we investigate parameter degeneracies using a Fisher analysis. We then discuss how halo of different mass and redshift, how LIRGs and ULIRGs, contribute to the CIB angular power spectra.

Results. From the Fisher analysis, we conclude that we cannot constrain the parameters of the model of evolution of galaxies using clustering data only. The use of combined data of C_ℓ , counts and luminosity functions improves slightly the constraints but does not remove any degeneracies. On the contrary, the measurement of the anisotropies allows us to set interesting constraints on the halo model parameters, even if some strong degeneracies remain. Using our fiducial model, we establish that the 1-halo and 2-halo terms are not sensitive to the same mass regime. We also illustrate how the 1-halo term can be misinterpreted with the Poisson noise term.

Conclusions. We present a new model of the clustering of infrared galaxies. Our framework allows a coherent and joint analysis of various probes of infrared galaxies : number counts, luminosity functions and clustering measurements. However such a model has a few limitations, as the parameters of the halo occupation suffer from strong degeneracies.

Key words. Infrared : galaxies - Cosmology : large scale structure of the Universe - galaxies :high redshift

1. Introduction

Infrared star-forming galaxies are mainly characterized by a very high star formation rate, tens or even hundreds times larger than that of the Milky Way, $\sim 10\text{--}100 M_\odot/\text{year}$ (Kennicutt 1998). The large number of young stars are embedded in dust that absorbs UV starlight and reemits it in the infrared (IR), from 5 μm to 1 mm. As a result, infrared star-forming galaxies emit most of their energy ($\sim 95\%$) in the IR. In the far IR ($\lambda > 200\mu\text{m}$) and sub-millimeter, observations are limited by confusion, small spatial scales are lost because of the poor angular resolution of the instruments. Thus we observe the Cosmic Infrared Background (CIB) (Puget et al. 1996; Fixsen et al. 1998) which is the contribution of infrared star-forming galaxies integrated over the age of the Universe, and its anisotropies. In the near and mid IR a large fraction of the CIB is resolved into sources whereas in the far IR only a few percents is. These fractions can be improved thanks to the use of statistical methods. For instance, at long wavelength, Oliver et al. (2010) directly resolved 15%, 10% and 6% of the CIB at 250, 350 and 500 μm in Herschel/SPIRE data whereas Papovich et al. (2004) resolved 70% of the CIB at 24 μm . Berta et al. (2010) resolved 45% and 52% of the CIB at 100 and 160 μm respectively by integrating number counts in Herschel/PACS data. Stacking 24 μm sources they increased

these fractions to 50% and 75% respectively. As a result, sources detected at 24 μm are the main sources of the CIB around its peak at $\sim 200 \mu\text{m}$. The CIB is dominated by objects that get more and more massive as the redshift increases from luminous IR galaxies (LIRGs) with $10^{11} L_\odot < L_{\text{IR}} < 10^{12} L_\odot$ at $0.8 < z < 1.2$ with intermediate mass, to extreme LIRGs with $10^{12} L_\odot < L_{\text{IR}} < 10^{14} L_\odot$ that dominate at $z > 2$ and with masses $> 10^{11} M_\odot$ (Caputi et al. 2006).

Magliocchetti et al. (2007) and Farrah et al. (2006) derived the two-point correlation function of Ultra LIRGs at $z \approx 1.6\text{--}2.7$ and $1.5 < z < 3$ respectively. They brought to light the very strong clustering of infrared star-forming galaxies and their embedment in very massive halos of $\approx 10^{13} M_\odot$. Cooray et al. (2010) computed the angular correlation function with Herschel/SPIRE data. They found that 250 μm sources are in DM halos with masses around $10^{12} M_\odot$ that lie at $z \sim 2.1$ whereas bright 500 μm sources are in more massive halos $\approx 10^{13} M_\odot$ at $z \sim 2.6$. More recently, Magliocchetti et al. (2011) derived the 3D correlation function of infrared sources using Herschel/PACS data up to a redshift of 3. They obtain that their galaxies lie in haloes with $> 10^{12.4} M_\odot$, value that is in agreement with previous studies. However the two-point correlation function is not easily computed using IR data because of confusion. As said before, confusion can be circumvented through the use of statistical

methods. Indeed, clustering can be measured in the correlated CIB anisotropies (CIBA). It has first been detected as an excess of signal at intermediate scales by Lagache et al. (2007) and Grossan & Smoot (2007) at $160\ \mu\text{m}$ in the Spitzer Multi-band Imaging Photometer (MIPS) data. These measurements have been followed by the detection in the Balloon-borne Large Aperture Sub-millimeter Telescope (BLAST) data at 250 , 350 and $500\ \mu\text{m}$ (Viero et al. 2009) and by that of the South Pole Telescope team (Hall et al. 2010) at 1.3 and $2\ \text{mm}$. More recently P nin et al. (2011) measured the clustering signal by removing accurately the cirrus contamination at 100 and $160\ \mu\text{m}$. The power spectrum of the CIBA has also been computed using Herschel/SPIRE at 250 , 350 and $500\ \mu\text{m}$ (Amblard et al. 2011), taking advantage of its angular resolution, and using Planck/HFI at 350 , 550 , $850\ \mu\text{m}$ and $1.3\ \text{mm}$ (Planck Collaboration et al. 2011) taking advantage of its sky coverage. Therefore, the clustering of infrared star-forming galaxies in the CIBA has been detected over a large range of wavelengths and angular scales. All these results have been analyzed in several ways, hardly comparable. As a first analysis, Lagache et al. (2007) derived the linear bias, the proportionality coefficient between the fluctuations of the dark matter (DM) density field and emissivities of galaxies. They found $b = 2.4 \pm 0.2$ and Viero et al. (2009) found $b = 3 \pm 0.3$ which implies that these galaxies are a highly biased tracer of DM. The difference between these two biases may be explained by the fact that at longer wavelength, higher redshift infrared star-forming galaxies are probed (Lagache et al. 2005; Fernandez-Conde et al. 2008) and thus are found to be more biased. New measurements needed more complex models. Viero et al. (2009), Amblard et al. (2011) and Planck Collaboration et al. (2011) introduced a halo occupation distribution for the study of CIBA. It describes the DM distribution and especially how galaxies are distributed in one DM halo. It appears that each wavelength must be fitted separately which indicates an evolution of the clustering with the redshift (Planck Collaboration et al. 2011). Most of the models determined the mass of the halos where infrared star-forming galaxies lie and thus where star formation occurs.

In the long term purpose of analysing all these new measurements in a consistent way, we present a new model of the clustering in CIBA. We use the halo model formalism (Cooray & Sheth (2002)) which has been often used in the last few years to predict and to interpret galaxy clustering. We link it to a recent model of infrared star-forming galaxies evolution that reproduces well number counts and luminosity functions (B thermin et al. 2011). This model of clustering has been successfully used to fit Planck data (Planck Collaboration et al. 2011).

The paper is organized as follows. We describe the model and its parameters in Sect. 2. We set a fiducial model inspired from Viero et al. (2009); Planck Collaboration et al. (2011); Amblard et al. (2011) and compute angular power spectra for several instruments with which we carry out a Fisher analysis in Sect. 4. Sect. 5 is dedicated to interpreting measurements such as the redshift and halo-masses contribution to the power spectrum, the linear bias, the influence of the mean emissivities and the contribution of LIRGs and ULIRGs to power spectra. We finally conclude in Sect. 6. Throughout this study we use the Wilkinson Microwave Anisotropy Probe 7-year Cosmology (Larson et al. 2011).

2. Why a new model?

As said previously several models of clustering in the Cosmic Infrared Background already exist so why constructing a new

one? There have been several measurements of the clustering and different models have been applied to analyze each measurement. Moreover their approaches are different which make comparison of the results difficult if not impossible. Thus one single model that ties together all available measurements is appealing, especially to analyze them simultaneously and search for an evolution of the clustering. Such a model requires three ingredients: a DM distribution, a relation between galaxies and DM halos and an evolution of infrared star-forming galaxies.

Lagache et al. (2007), Amblard & Cooray (2007) and Viero et al. (2009) used the model of galaxy evolution of Lagache et al. (2003). This model was the most up to date model at that time. It fitted well differential number counts and luminosity functions measurements from 24 to $850\ \mu\text{m}$ (IRAS, Spitzer/SCUBA). However it does not reproduce very well new measurements, especially differential number counts from Herschel. This is a phenomenological model in which the evolution of the luminosity function was tuned to reproduce the constraints available at that time. It over-predicts the luminosity density at high- z . Moreover, it does not reproduce very well the observed redshift distribution of the CIB (Jauzac et al. 2011). It predicts a peak at $z \sim 1$ that is not observed. The angular power spectra of CIBA strongly depend on the redshift distribution of the sources through the emissivities (see Sect. 3.2). Therefore, a ‘valid’ distribution in redshift is important and a more robust model in agreement with most recent measurements is needed.

Hall et al. (2010) used the galaxy templates from Lagache et al. (2003) in order to check a simple model with a ‘single SED’. This model has only a few parameters that can be changed easily and thus adapted to each of their wavelengths. They fixed the shape of the power spectrum and only changed its amplitude depending on the wavelength. Amblard & Cooray (2007) used the same model of infrared galaxies evolution : they used the luminosity function as a function of redshift at $350\ \mu\text{m}$ coming from Lagache et al. (2003) that they matched to conditional luminosity functions (CLFs). Other wavelengths are extrapolated from the $350\ \mu\text{m}$. Finally Amblard et al. 2011 avoid using any model of galaxies evolution by letting free the redshift distribution of the cumulative flux coming from the background faint galaxies in several redshift bins.

Concerning the distribution of DM, Viero et al. (2009) and Amblard et al. (2011) used the formalism of the halo model and the same halo occupation number whereas Lagache et al. (2007) and Hall et al. (2010) considered a linear power spectrum for dark matter. Amblard & Cooray (2007) also used the halo model formalism through CLFs. By integrating CLFs on the luminosity, the halo mass function is recovered. However this approach depends on too many parameters that cannot be constrained simultaneously.

In order to construct a new model, we link an up to date model of galaxies evolution to a recent version of the halo model. We use the model of evolution of galaxies of B thermin et al. (2011). It reproduces well Herschel measurements as well as older ones (from $15\ \mu\text{m}$ to $1.1\ \text{mm}$). It also very well reproduces the redshift distribution of the CIB of Jauzac et al. (2011). We use an updated version of the halo model of Viero et al. (2009), the halo occupation distribution (HOD) introduced by Tinker & Wetzel (2010). This HOD reproduces well the angular correlation function of optical galaxies, red (star-forming) and blue (quiescent) galaxies at $0.4 < z < 2$. Therefore we make a strong assumption here, assuming that this description would work on star-forming galaxies. Given the current lack of understanding of the details of the process of star-formation and its evolution with redshift, it is difficult to define what would be a better HOD prescription and

we therefore stay with this one. We study power spectra coming from our model for several wavelengths/instruments: 100 μm IRAS, 160 μm Spitzer/MIPS, 250, 350, 500 μm Herschel/SPIRE and 850 μm , 1.3 and 2mm Planck/HFI. A list of the available data of CIBA power spectra is given in table 2.

3. The model

3.1. The parametric model of star-forming galaxies evolution

To reproduce the angular power spectrum of the CIBA we need a model for the redshift evolution of star-forming galaxies. We use the model presented in B  thermin et al. (2011). It is a backward evolution model based on a parametrized luminosity function and on galaxies spectral energy distribution templates.

B  thermin et al. (2011) consider a luminosity function (LF) that behaves like a power law for $L \ll L^*$ and like a Gaussian for $L \gg L^*$ (Saunders et al. 1990) :

$$\Phi(L_{IR}) = \frac{dN(L_{IR})}{dV d \log_{10}(L_{IR})} \quad (1)$$

$$= \Phi^* \left(\frac{L_{IR}}{L^*(z)} \right)^{1-\alpha} \exp \left[-\frac{1}{2\sigma^2} \log_{10}^2 \left(1 + \frac{L_{IR}}{L^*(z)} \right) \right] \quad (2)$$

where $\Phi(L_{IR})$ is the number of galaxies with the infrared bolometric luminosity L_{IR} within the comoving volume dV and the bin $d \log_{10} L$. Φ^* is a normalization constant that fixes the density of sources. The low and high luminosity parts have different slopes, $1 - \alpha$ and $1 - \alpha - 1/\sigma^2 / \ln^2(10)$ respectively. L^* represents the luminosity at the break. The parameters that describe the luminosity function are listed in table 1.

The luminosity function evolves with the redshift through L^* and ϕ^* :

$$L^*(z) = L^*(z=0)(1+z)^{r_L} \quad (3)$$

$$\phi^*(z) = \phi^*(z=0)(1+z)^{r_\phi} \quad (4)$$

Exponents r_L and r_ϕ are not identical for all z . Two breaks are imposed to reproduce the evolution of the LF. The first one z_{break} is a free parameter and is found to be around 1. The second one is fixed at $z = 2$ to avoid divergence at high z . Between these two breaks, the values of r_L and r_ϕ change as shown on table 1.

B  thermin et al. (2011) used the SED library of Lagache et al. (2004). It contains two galaxy populations: star-forming and late-type galaxies. The latter emit half or less of their energy in the IR whereas the former emit more than 95 % of their energy in the IR. The fraction of each population depends on luminosity. Indeed, late-type dominate at low luminosity whereas star-forming dominate at high luminosity. For a given bolometric luminosity, the fraction of star-forming is :

$$f_{SF} = \frac{\Phi_{SF}}{\Phi} \quad (5)$$

$$= \frac{1 + \tanh[\sigma_{pop}(L) \log_{10}(L_{IR}/L_{pop})]}{2} \quad (6)$$

L_{pop} is the luminosity where $\Phi_{SF} = \Phi_{late-type}$ and σ_{pop} characterizes the width of the transition between the two populations. Differential number counts are then derived for each population and then summed. At flux S :

$$\frac{dN}{dS}(S) = \int_z \int_L f_{pop} \frac{dN_{pop}}{d \log_{10} L_{IR} dV} \frac{d \log_{10} L_{IR}}{dS} \frac{dV}{dz} dz \quad (7)$$

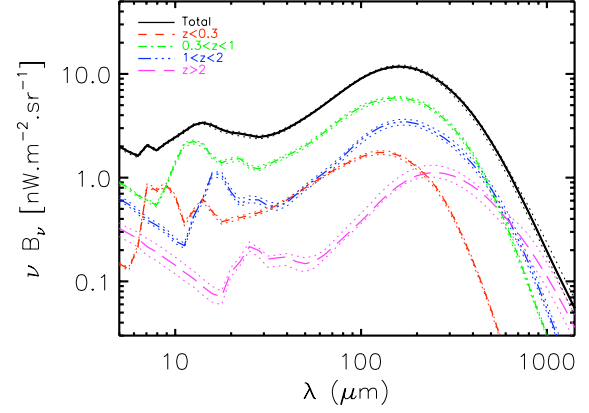


Fig. 1. CIB per redshift bins from the model of B  thermin et al. (2011). The high redshift contribution increases with the wavelength.

where dN/dS is the number of sources per flux unit in a unit solid angle and $pop = \text{late-type}$ or $pop = \text{star-forming}$.

The model of B  thermin et al. (2011) is described by thirteen free parameters. Best fit parameters and confidence areas are computed using Monte-Carlo Markov Chains on available and trustworthy differential number counts and luminosity functions at certain wavelengths. B  thermin et al. (2011) fitted number counts of Spitzer/MIPS at 24, 70 and 160 μm (B  thermin et al. 2010), those of Herschel/SPIRE at 250, 350 and 500 μm (Oliver et al. 2010) and those of Aztec at 1.1 mm (Austermann et al. 2010; Scott et al. 2010). A couple of luminosity functions at different redshifts are also fitted, the 8 μm one at $z = 2$ from Caputi et al. (2007), others derived from Rodighiero et al. 2009 (a local LF at 24 μm , a 15 μm one at $z = 0.6$ and a 12 μm LF at $z = 1$) and that at 60 μm at $z = 0$ from Saunders et al. (1990). Moreover, absolute measurements of the CIB are also used as a model constraint (Lagache et al. 1999). We do not describe and discuss all the fits here (for a full discussion see B  thermin et al. 2011). Using the best fit, this model also provides the redshift distribution of the CIB as shown on Fig. 1. We see that higher-redshifts contribution increases with wavelength : the redshift slice $0.3 < z < 1$ dominates up to 400 μm whereas in the sub-millimeter $z > 2$ dominates. This model provides a very good agreement with the CIB redshift distribution (Jauzac et al. 2011). We will study how these thirteen free parameters can be constrained with power spectra of the CIBA.

3.2. The angular power spectrum

According to Haiman & Knox (2000), Knox et al. (2001) and using the Limber approximation, the angular power spectrum of the anisotropies of the CIB at wavelengths λ and λ' is :

$$C_\ell^{\lambda\lambda'} = \int dz \frac{dr}{dz} \frac{a^2(z)}{d_A^2} \bar{j}_\lambda(z) \bar{j}_{\lambda'}(z) P_{ss}(k = \frac{\ell}{d_A}, z) \quad (8)$$

where ℓ is the multipole, r is the conformal distance from the observer, $a(z)$ the scale factor, d_A the comoving angular diameter distance, and $\bar{j}_\lambda(z)$ the mean emissivity per comoving unit volume at wavelength λ as a function of z . When $\lambda = \lambda'$ we recover the auto power spectrum. $P_{ss}(k)$ is the galaxy three dimensional power spectrum.

The emissivities are computed using the parametric luminosity functions following :

$$j_\nu(z) = \left(a \frac{d\chi}{dz} \right)^{-1} \int_L S(L_{IR}, z) \frac{dN}{dz d(\ln L_{IR})} d(\ln L_{IR}) \quad (9)$$

where $dN/dz d(\ln L)$ is the number of galaxies per redshift bin dz and per luminosity bin $d(\ln L)$ and S the flux. Each galaxy population (late-type and star-forming) emissivity are computed and summed to get the overall emissivity. Fig. 2 shows emissivities as a function of redshift. The two discontinuities at $z \sim 0.9$ and $z = 2$ are due to the breaks imposed by the parametrization of the model of galaxies. It is clear that as the wavelength increases, the contribution from the high redshift part increases. Emissivities are color corrected according to their instrument and wavelengths to give C_ℓ in Jy^2/sr (for the photometric convention $\nu I_\nu = \text{cst}$).

In the context of the halo model, $P_{ss}(k)$ is the sum of the clus-

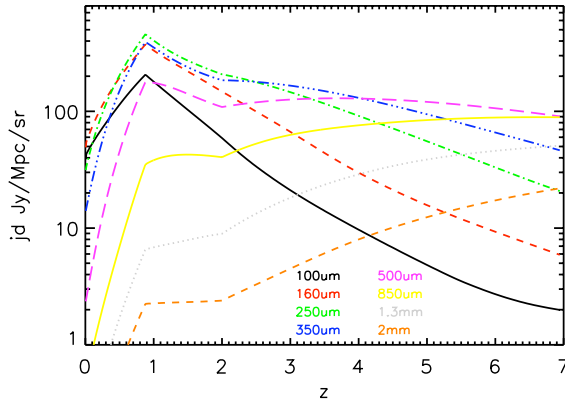


Fig. 2. Emissivities versus the redshift for different wavelengths. The contribution from high redshift increases with the wavelength.

tering in one single halo (1h) and in two different halos (2h):

$$P_{ss}(k) = P_{1h}(k) + P_{2h}(k) \quad (10)$$

where

$$P_{1h}(k) = \int_M \frac{dN}{dM} \frac{\langle N_{gal}(N_{gal} - 1) \rangle}{\bar{n}_{gal}^2} U(k, M)^p dM \quad (11)$$

$$P_{2h}(k) = P_{lin}(k) \left[\int_M \frac{dN}{dM} b(M) \frac{\langle N_{gal} \rangle}{\bar{n}_{gal}} U(k, M) dM \right]^2 \quad (12)$$

$$. \quad (13)$$

Here M is the halo mass, $P_{lin}(k)$ is the dark matter linear power spectrum (computed with the fit of Eisenstein & Hu 1998), $U(k, M)$ the normalized Fourier transform of the halo density profile that is assumed to be that of Navarro et al. (1996) truncated at the virial radius. $b(M)$ is the halo bias, $\langle N_{gal} \rangle$ the probability of having N_{gal} galaxies in a halo of mass M and we consider $p = 2$ (Cooray & Sheth 2002). The mean number density of galaxies $\bar{n}_{gal}$ is given by:

$$\bar{n}_{gal} = \int \frac{dN}{dM} \langle N_{gal} \rangle dM \quad (14)$$

where dN/dM is the halo mass function. We will use the universal form given by Tinker et al. (2008) as well as its redshift evolution. We use its associated halo bias (see Eq. A1 in Tinker et al. (2009)).

The halo occupation number introduces galaxies in the halos statistically. Recent data and simulations suggest a necessary distinction between the major galaxy that lies at the center of the halo and the satellite galaxies that populate the rest of the halo. Above a given mass threshold, most halos will host a central galaxy. Above a second higher mass threshold, they will also host satellite galaxies. N_{gal} can thus be written as :

$$\langle N_{gal} \rangle = \langle N_{cen} \rangle + \langle N_{sat} \rangle. \quad (15)$$

According to the prescription of Tinker & Wetzel (2010), the occupation function of central galaxies is:

$$\langle N_{cen} \rangle = \frac{1}{2} \left[1 + \text{erf} \left(\frac{\log M - \log M_{min}}{\sigma_{\log M}} \right) \right] \quad (16)$$

where M_{min} is the halo mass at which a halo has a 50 % probability of hosting a central galaxy. $\sigma_{\log M}$ controls the width of the transition between zero and one central galaxy. There is a smooth transition between low mass halos that do not contain bright enough galaxies to be seen in the data ($M \ll M_{min}$) and more massive ones that always contain a bright central galaxy. ($M \gg M_{min}$). The satellite occupation function is:

$$\langle N_{sat} \rangle = \frac{1}{2} \left[1 + \text{erf} \left(\frac{\log M - \log 2M_{min}}{\sigma_{\log M}} \right) \right] \left(\frac{M}{M_{sat}} \right)^{\alpha_{sat}} \quad (17)$$

It has a cut-off of the same form as the central occupation with a transition mass twice larger than that of the central to prevent halos which have a low probability of hosting a central galaxy to contain satellite galaxies. The number of satellite galaxies grows with a slope of α_{sat} . Both number of galaxies as well as their sum are plotted on Fig. 3.

With this model, the angular power spectrum of CIBA depends on only four halo model parameters α_{sat} , M_{min} , M_{sat} and $\sigma_{\log M}$. Cosmology is fixed at WMAP7 values. Our parameters are listed in Table 1 with their meaning and their fiducial values that we set in Sect. 4 .

The long term purpose of our model is to look for best fits of these parameters for Spitzer/MIPS, IRIS, Planck, Herschel and SPT data and study their evolution with wavelength. However it is beyond the scope of this paper. **Therefore we will not compare the data to the power spectra coming from our model.** Our first aim here is to study the parameter space and to investigate particularly the behaviour of the halo bias, the halo mass-contribution to the power spectrum and its redshift distribution. To do so we will consider a set of fiducial halo parameters identical at all wavelengths.

4. Power spectra and parameters degeneracies

In this section, we present the CIB power spectra computed with the model detailed in the previous section for several wavelengths in the far-IR and sumillimeter. We then study the degeneracies of the parameters, looking first at the galaxies model parameters and second at the HOD parameters.

4.1. Power spectra

Our fiducial model is set with the HOD parameters $\log M_{min} = 11.5$, $M_{sat} = 10M_{min}$ and $\alpha = 1.4$ at all wavelengths. These values are motivated by the parameters fit of

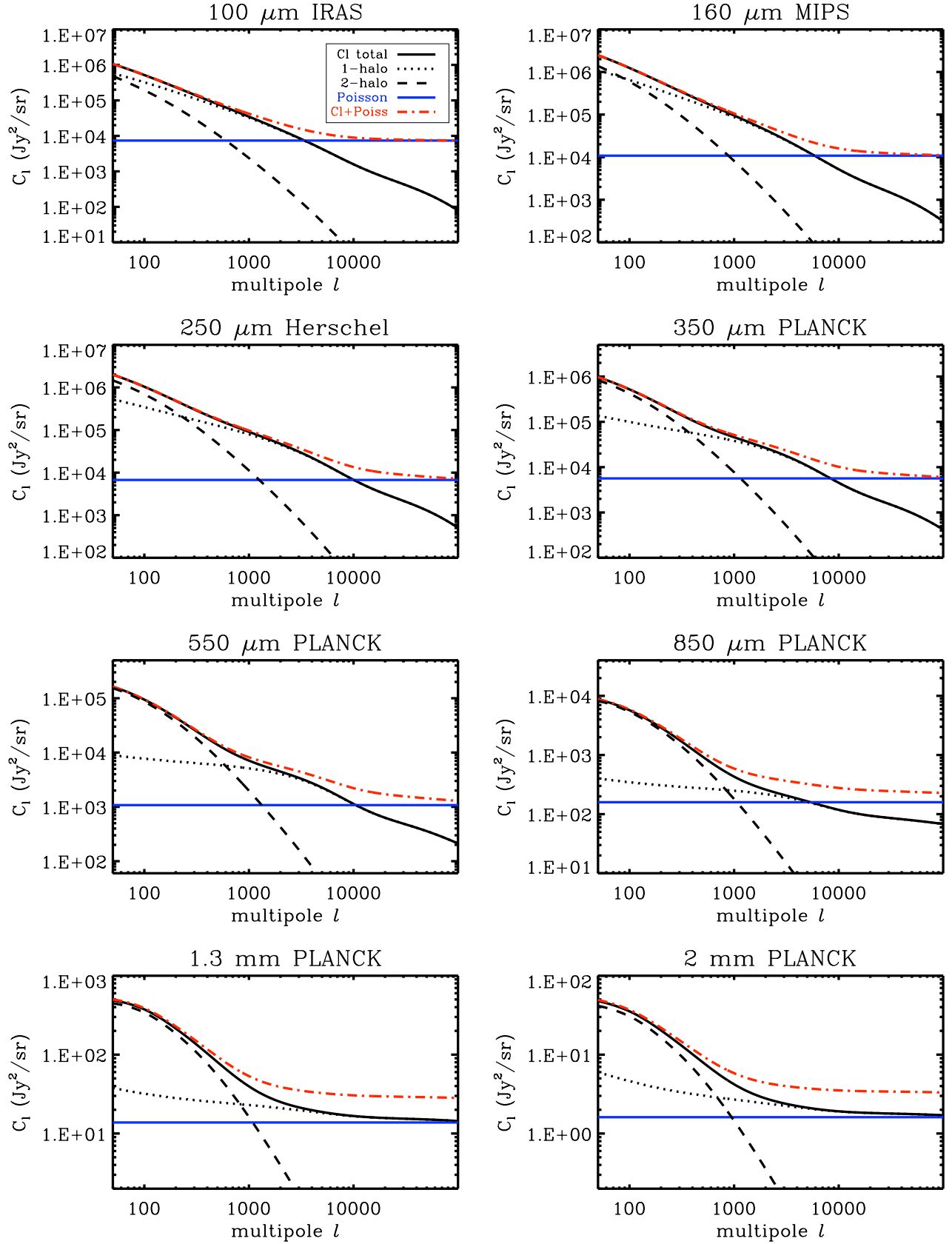


Fig. 4. CIB anisotropies power spectra at several wavelengths. The continuous black line shows the power spectra of the clustering. The dotted black line is the 1-halo term of the power spectrum and the dashed line is the 2-halo term. The blue horizontal line represents the shot noise level and the red dot-dashed curve is the total power spectrum. Titles of the plots give the reference for the shot noise level and the used bandpass filters.

parameter name	Description	Value
M_{min}	Minimal mass of a halo to have a central galaxy	$10^{11.5} M_{\odot}$
M_{sat}	Nomalisation mass for satellite galaxies	$10^{12.5} M_{\odot}$
α_{sat}	Slope of the number of satellite galaxies at high mass	1.4
σ_{logM}	Scatter in halo mass	0.748
α	Faint end slope of the IR bolometric LF	1.223
σ	Parameter driving the bright end slope	0.406
$L_{\star}(z=0)$	Local characteristic luminosity of the LF	$2.377 \times 10^{10} L_{\odot}$
$\phi_{\star}(z=0)$	Local characteristic density of the LF	$3.234 \times 10^{-3} \text{ gal/dex/Mpc}^3$
$r_{L_{\star},z}$	Evolution of the characteristic luminosity between 0 and z_{break}	2.931
$r_{\phi_{\star},z}$	Evolution of the characteristic density between 0 and z_{break}	0.774
z_{break}	Redshift of the first break	0.879
$r_{L_{\star},mz}$	Evolution of the characteristic luminosity between z_{break} and 2	4.737
$r_{\phi_{\star},mz}$	Evolution of the characteristic density between z_{break} and 2	-6.246
$r_{L_{\star},hz}$	Evolution of the characteristic luminosity for $z > 2$	0.145
$r_{\phi_{\star},hz}$	Evolution of the characteristic density for $z > 2$	-0.919
L_{pop}	Luminosity of the transition between normal and star-forming templates	23.677×10^{10}
σ_{pop}	Width of the transition between normal and star-forming templates	0.57

Table 1. Parameters of our model. The first part of the table lists the halo model parameters and the second part lists the parameters of the model of galaxies. The values of the latter are the mean ones of B  thermin et al. (2011).

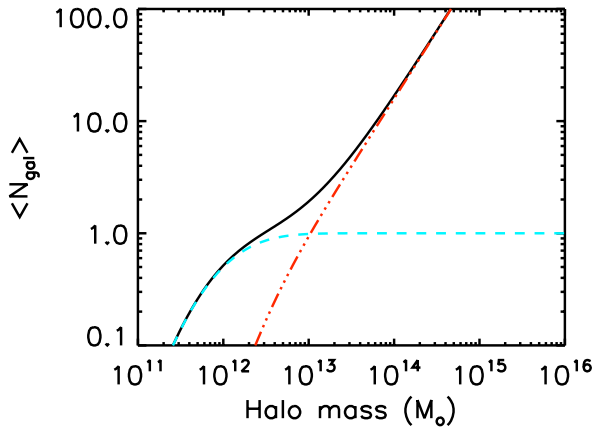


Fig. 3. Number of galaxies versus dark matter halo mass. The blue dashed line shows the central galaxies, the red dotted-dashed line shows satellite galaxies and the black continuous line shows the total. We use the parameters of our fiducial model (see Sect. 4), that is to say $\log M_{min} = 11.5$, $M_{sat} = 10M_{min}$ and $\alpha = 1.4$

Viero et al. (2009), Planck Collaboration et al. (2011), Amblard et al. (2011). As the halo parameters slightly depend on the wavelength (in reality but it is not the case here), the power spectra presented in this section may not be seen as an exact prediction but as a basis for a qualitative study. For this fiducial model, we present on Fig. 4 the power spectra for different experiments and selected wavelengths, from $100 \mu\text{m}$ to 2 mm.

The comparison to measurements also requires the introduction of a shot noise term due to the finite number of galaxies. We compute it using our galaxy evolution model (B  thermin et al. 2011).

$$C_{\ell} = C_{\ell,clus} + C_{\ell,shot} \quad (18)$$

where $C_{\ell,clus}$ is the power spectrum of the clustering and $C_{\ell,shot}$ is the shot noise. $C_{\ell,shot}$ depends on the flux cut applied to the

data when removing or masking the brightest sources. Typical flux cuts for different far-IR and sub-millimeter experiments are given in Tab. 2. On Fig. 4, we only show one shot noise level per wavelength corresponding to the instrument given in the plot titles, for purpose of clarity.

The contribution of the 1-halo (2-halo) corresponds to the dotted line (dashed line). The instrument noise is not shown here but it is often negligible, the CIB being measured with a very high S/N even at spatial scales close to the angular resolution. Looking at this plot, we see clearly that the interplay between 2h, 1h and shot noise terms will make the interpretation of measurements quite subtle. The contribution of the 1-halo term decreases with the wavelength which can prevent its measurement if the resolution of the instrument is low. For example, Planck with its 5 'angular resolution at high frequency, cannot measure directly the shot noise level and the 1-halo term can be easily misinterpreted as shot noise. Reversely, the 1-halo term dominates a large range of scales at 100 and $160 \mu\text{m}$ and thus can be measured accurately at these wavelengths.

High wavelengths probe higher redshifts than short ones and halos are relatively smaller at high redshifts compared to those in the local Universe as the latter had time to accrete more matter. Therefore the scale of the intersection between the 1- and 2-halo terms shifts towards higher ℓ as the wavelength increases. It goes from $\ell \sim 50$ at $100 \mu\text{m}$ to $\ell \sim 1000$ at 2 mm. Viero et al. (2009) also observed this trend. At $250 \mu\text{m}$ the crossing is at $k \sim 0.03 \text{ arcmin}^{-1}$ ($\ell \sim 648$) whereas it is at $k \sim 0.06 \text{ arcmin}^{-1}$ ($\ell \sim 1296$) at $500 \mu\text{m}$. The exact crossing point differs from ours because of the HOD parameterization.

4.2. Variation of power spectra with the galaxy-evolution model parameters

In order to do an overall study of how our model parameters can be constrained, i.e. to investigate how degenerated they are, we construct the Fisher matrix associated to the power spectra. We write the Fisher matrix for angular power spectrum measurements as:

$$F_{ij} = \sum_{\lambda} \sum_{\ell} \frac{1}{\sigma_{\ell}^2} \frac{\partial C_{\ell}^{\lambda}}{\partial \theta_i} \frac{\partial C_{\ell}^{\lambda}}{\partial \theta_j} \quad (19)$$

wavelength (μm)	Instrument	Reference	Flux Cut (mJy)	Shot noise level (Jy^2/sr)
100	IRIS	P�nin et al. (2011)	700	7364 ± 1232
160	Spitzer/MIPS	Lagache et al. (2007)	200	10834 ± 3124
250	Herschel/SPIRE	Amblard et al. (2011)	50	6715 ± 1458
350	Herschel/SPIRE	Amblard et al. (2011)	50	4362 ± 1250
350	Planck/HFI	Planck Collaboration et al. (2011)	710	5923 ± 367
500	Herschel/SPIRE	Amblard et al. (2011)	50	1156 ± 434
550	Planck/HFI	Planck Collaboration et al. (2011)	540	1150 ± 92
850	Planck/HFI	Planck Collaboration et al. (2011)	325	138 ± 22
1363	SPT	Hall et al. (2010)	6.4	11.9 ± 4.0
1363	ACT	Fowler & Atacama Cosmology Telescope Team (2010)	20	12.5 ± 3.9
1380	Planck/HFI	Planck Collaboration et al. (2011)	160	12.9 ± 2.9
2000	SPT	Hall et al. (2010)	6.4	1.73 ± 0.54
2000	ACT	Fowler & Atacama Cosmology Telescope Team (2010)	20	1.78 ± 0.60
2097	Planck/HFI		245	1.4 ± 0.3

Table 2. Shot noise levels in Jy^2/sr from B thermin et al. (2011) for available measurements of CIBA power spectra.

wavelength (μm)	Instrument	Jy^2/sr to $\mu\text{K}_{\text{CMB}}^2$
100	IRAS	9.59×10^{22}
160	Spitzer/MIPS	3.12×10^{11}
250	Herschel/SPIRE	1.34×10^3
350	Herschel/SPIRE	2.78×10^{-1}
350	Planck/HFI	2.00×10^{-1}
500	Herschel/SPIRE	7.45×10^{-4}
550	Planck/HFI	2.94×10^{-4}
850	Planck/HFI	1.20×10^{-5}
1380	SPT	4.39×10^{-6}
1380	Planck/HFI	4.32×10^{-6}
2000	SPT	6.10×10^{-6}
2097	Planck/HFI	7.31×10^{-6}

Table 3. Conversion factors from Jy^2/sr to $\mu\text{K}_{\text{CMB}}^2$. One should multiply the power spectrum in Jy^2/sr (with the convention $\nu I_\nu = \text{cst}$) by the coefficient to get $\mu\text{K}_{\text{CMB}}^2$.

where σ_ℓ are the errors on the measurements and they include both the cosmic variance and the instrumental noise at a multipole ℓ :

$$\sigma_\ell^2 = \left(C_\ell + \frac{N_\ell}{B_\ell^2} \right) \frac{2}{f_{\text{sky}}(2\ell + 1)} \quad (20)$$

where f_{sky} is the fraction of the sky we consider, N_ℓ is the level of the instrumental noise and B_ℓ^2 the power spectrum of the beam. To compute the Fisher matrices, we generate mock power spectra using our fiducial model and error bars derived following Eq. (20), from $100 \mu\text{m}$ to 1.3 mm . The range of multipoles is taken to be consistent with the available data. At 350 and $550 \mu\text{m}$, we assume combined power spectra for Planck and Herschel, and we thus extend Planck power spectra to the Herschel limit in multipole. We plot C_ℓ in Jy^2/sr . They can be converted in μK^2 using the coefficients given in Tab. 3.

The bottom left panel of Fig. 5 shows confidence ellipses (1σ in green and 2σ in black) coming from C_ℓ when trying to measure only the galaxy model parameters $r_{L^*,hz}$ and $r_{L^*,lz}$. Clearly, they are very poorly constrained. For instance $r_{L^*,hz} = 0.145 \pm 15.55$, or $r_{L^*,lz} = 2.93 \pm 20.0$. For reference, the constraints obtained using current number counts are $r_{L^*,hz} = 0.145 \pm 1.05$ and $r_{L^*,lz} = 2.93 \pm 0.27$, as shown on the top left panel of Fig. 5. The fact is that these parameters enter in the expression of the C_ℓ through the emissivities which are integrated on all redshifts, they are thus hard to measure from clustering measurements alone.

As a matter of fact, the lack of information in C_ℓ partially comes from the large number of parameters in the model of evolution of galaxies. To quickly quantify this we vary only a few of these parameters ($r_{L^*,lz}$, $r_{L^*,hz}$, z_{break} , $r_{\phi^*,lz}$ and $r_{\phi^*,hz}$) assuming that the others are perfectly known. Fixing all but these parameters corresponds to assuming that only the redshift evolution of the LF is unknown, clearly an unrealistic assumption. Not surprisingly, while some of the degeneracies remain in these reduced parameter space, on the whole, parameters are better constrained. For instance, we now obtain $r_{L^*,lz} = 2.93 \pm 0.10$ and $r_{L^*,hz} = 0.145 \pm 7.05$ which are about a two order of magnitude and a factor 2 improvement, respectively as compared to the numbers above.

In order to illustrate further this lack of information in C_ℓ s, we show how they change with only one parameter, $r_{L^*,lz}$. We make it vary by $\pm 2\sigma$ from its best fit (σ coming from B thermin et al. 2011). This parameter governs the evolution of the luminosity function for $0 < z < z_{\text{break}}$. A higher $r_{L^*,lz}$ means a faster increase of the luminosity, thus a higher value of $L^*(z = z_{\text{break}})$. The top panel of Fig. 6 shows the influence of this parameter on the counts at $160 \mu\text{m}$. A higher (smaller respectively) $r_{L^*,lz}$ implies higher (smaller) number counts thus more (less) galaxies on a large range of fluxes. This leads to a higher (smaller) emissivities as shows in the second and third panels of Fig. 6. This results in a modification of $\sim 20\%$ on the emissivities and from 15 to 35% on power spectra depending on the scale. The fact that this ratio is not constant is due to the fact that the ratio of the emissivities is not constant with redshift (3rd panel of Fig. 6). We can see that all power spectra are consistent within error bars and thus we can hardly discriminate between them. Therefore, it is hard to constrain the evolution model of galaxies using only power spectra.

More relevant data are required. We compare our confidence ellipses with those obtained with luminosity functions and number counts data. To do so we use the covariance matrix of B thermin et al. (2011). The error bars are in general much smaller and there are only a few degeneracies. For instance, as shown on the left panel of Fig. 5, $r_{L^*,hz}$ and $r_{\phi^*,hz}$ are still strongly degenerate but they are now much better constrained.

So far, we have investigated how galaxy evolution parameters are degenerated and constrained using LF/counts and C_ℓ separately. The next step is to look at the degeneracies when combining all these data. To do so, we add the two Fisher matrices coming from the counts/LF and the C_ℓ . The bottom panels of Fig. 5 show the confidence ellipses for $r_{L^*,hz}$, $r_{L^*,lz}$ and $r_{\phi^*,hz}$ using the combined data. Note that the axis scales are different. The con-

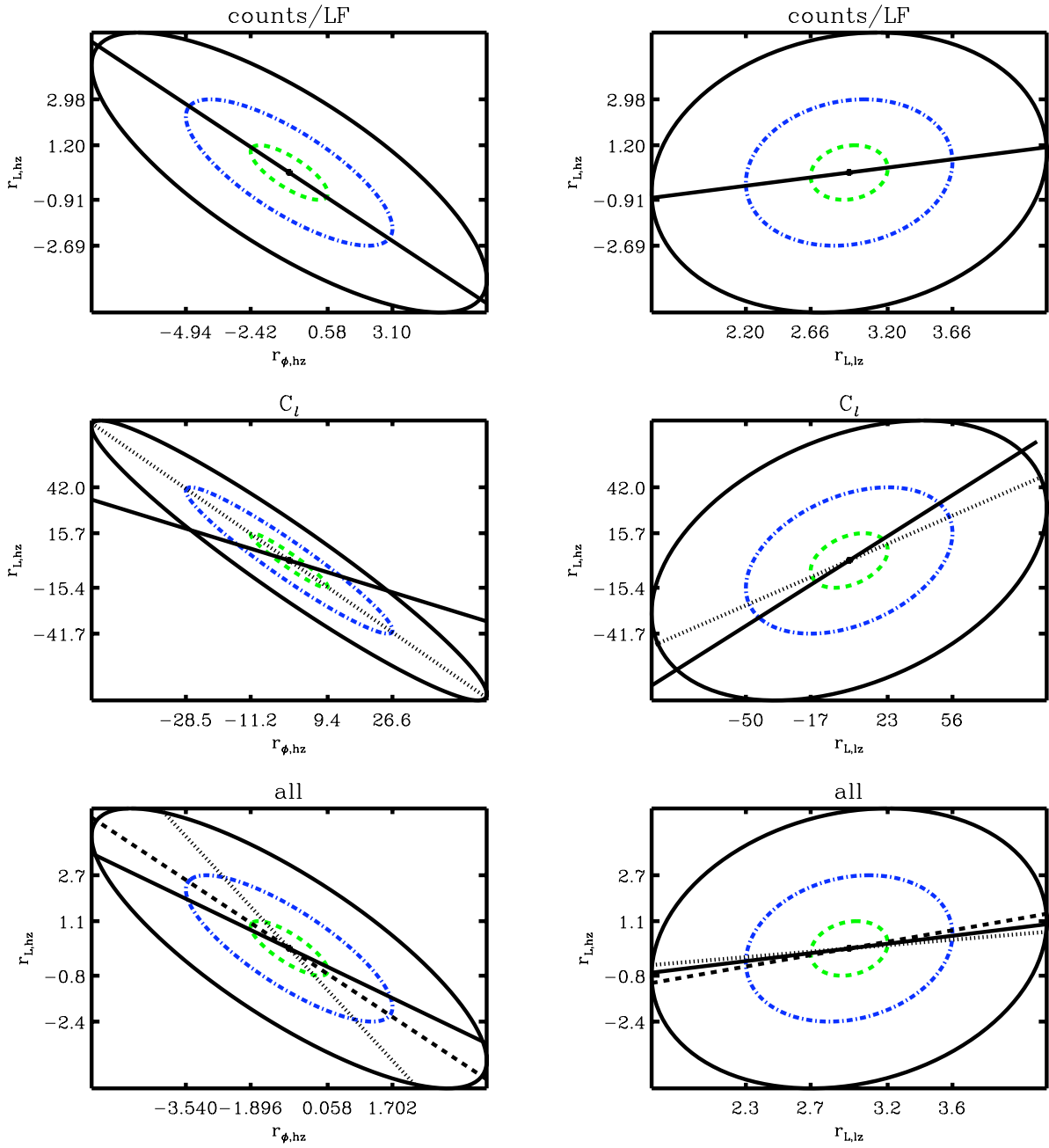


Fig. 5. 1σ (dashed green), 2σ (dash-dot blue), 3σ (black) likelihood contours of the galaxy evolution model parameters $r_{L^*,hz}$, $r_{L^*,lz}$ and $r_{\phi,hz}$. Top, Middle and Bottom panels show the contours computed using counts/LF data, C_ℓ data only, and combined counts/LF and C_ℓ data, respectively. The continuous line shows the direction of degeneracy using only counts/LF, the dotted line shows that using C_ℓ and the dashed line is that using all data. C_ℓ alone cannot constrain the galaxy-evolution model parameters and the combination of C_ℓ and counts/LF data do not change much the constraints. It slightly improves them.

tinuous/dashed/dotted lines on Fig. 5 indicate the degeneracy directions. They are different which illustrate the complementarity of the two data-sets and the constraints can be greatly improved. For example, the errors on $r_{\phi,hz}$ are decreased by a factor of 1.5 but the errors on $r_{L^*,hz}$ is not changing. However, this plot also clearly shows that overall, the number counts and LF measurements are much more powerful when looking at constraining the LF. However, C_ℓ can still constrain the global evolution of galax-

ies through their mean emissivities. A first attempt was made by Amblard et al. (2011) who did not use a model of galaxies to compute the emissivities but bin them in several redshift intervals and considered the values of the emissivities in these four bins as free parameters. They also required that the integrated source density is within the 68% confidence level ranges of the CIB obtained by FIRAS.

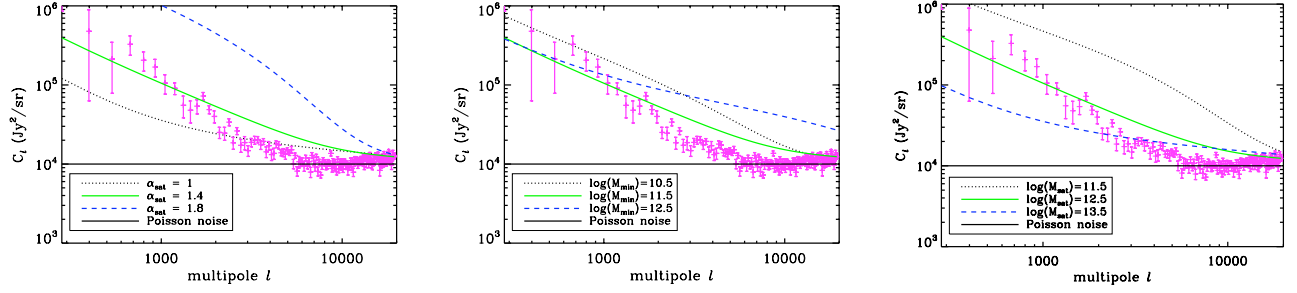


Fig. 7. CIBA power spectrum at $160\ \mu\text{m}$ obtained using several values of $\alpha_{\text{sat}}, M_{\text{min}}$ and M_{sat} . The level of the Poisson noise has also been added to the power spectra (black continuous line). Pink dots are the data from Lagache et al. (2007) at $160\ \mu\text{m}$. When fixed, the parameters are those of the fiducial model, $\alpha_{\text{sat}} = 1.4$, $M_{\text{min}} = 10^{11.5} M_{\odot}$ and $M_{\text{sat}} = 10^{12.5} M_{\odot}$. Left panel: The blue line is for $\alpha_{\text{sat}} = 1.8$, the green one for $\alpha_{\text{sat}} = 1.4$ and the black one for $\alpha_{\text{sat}} = 1$. Middle panel: The blue line is the clustering power spectrum for $M_{\text{min}} = 10^{12.5} M_{\odot}$, the green one for $M_{\text{min}} = 10^{11.5} M_{\odot}$ and the black one for $M_{\text{min}} = 10^{10.5} M_{\odot}$. Right panel: The blue line is for $M_{\text{sat}} = 10^{13.5} M_{\odot}$, the green one for $M_{\text{sat}} = 10^{12.5} M_{\odot}$ and the black one for $M_{\text{sat}} = 10^{11.5} M_{\odot}$. As expected, C_{ℓ} s strongly depend on the halo parameters. We can expect strong degeneracies between those parameters.

4.3. Halo occupation distribution parameters and their degeneracies

The shape of the clustering power spectra strongly depends on the HOD parameters as shown on Fig. 7. We vary M_{min} , M_{sat} and α_{sat} . Each panel shows the power spectrum at $160\ \mu\text{m}$ measured by Lagache et al. (2007) in addition to the ones coming from the model. In each plot we vary only one HOD parameter and hold the others fixed to the values of the fiducial model, $\alpha_{\text{sat}} = 1.4$, $M_{\text{min}} = 10^{11.5} M_{\odot}$ and $M_{\text{sat}} = 10^{12.5} M_{\odot}$. Both the shape and amplitude strongly vary. The fact that some similar changes are observed using different parameters suggest strong degeneracies. We compute the Fisher matrix as in Sect. 4.2 and likelihood contours at 1- and 2- σ are shown on Fig. 8. The error bars on $\sigma_{\log M}$ are very large, thus we fix its value to 0.65, following Tinker & Wetzel (2010) who studied the galaxy-clustering in optical surveys. Using C_{ℓ} only we are not able to constrain its value. M_{min} and M_{sat} happen to be highly degenerated in the direction $M_{\text{sat}} = 3.3 M_{\text{min}}$.

In previous works using optically selected galaxies, α is usually set to 1 (Gao et al. (2004)) and M_{min} and M_{sat} are the only parameters to be fitted to the data. Indeed, α is hardly constrained. For instance Tinker & Wetzel (2010) used the same halo distribution number on a sample of red and blue galaxies in the range $0.4 < z < 2$. They fitted well their correlation function fixing $\alpha = 1$ and letting free M_{min} and M_{sat} . But when they let α free in addition to the two others, they obtain unrealistic values for α (Tinker & Wetzel 2010). However, setting $\alpha = 1$ might not be appropriate for CIBA. The halo model is commonly used in galaxies catalogs that are not deeper than $z \sim 2$ and CIBA probe higher redshifts, especially at long wavelengths. Moreover optically-selected galaxies are not only star-forming galaxies, and there is no reason why optically-selected galaxies and star-forming galaxies should behave in the same way. Magliocchetti et al. (2008) used a similar form of the halo model to analyze the angular correlation function of $24\ \mu\text{m}$ sources at $0.6 < z < 1.2$ and $z \geq 1.6$. Using two halo density profiles (NFW and a steeper one $\rho \sim r^{-3}$), they derived $\alpha \sim 0.7$ for the steeper profile and $\alpha \sim 0.8$ for the NFW one. They get the same results for both sets of data. On the contrary, Cooray et al. (2010) computed the angular correlation function of sources detected at 250, 350 and $500\ \mu\text{m}$ in Herschel/SPIRE data. They used the same halo distribution as ours and get $\alpha = 1.3 \pm 0.4$, $\alpha < 1.8$ and $\alpha < 1.6$ at 250,

350 and $500\ \mu\text{m}$ respectively. Finally, the Planck Collaboration et al. (2011) derived values of α compatible with 1. The discrepancy with Magliocchetti et al. (2008) may be due to the different properties of the bright galaxies selected at $24\ \mu\text{m}$ and those that contribute to the CIBA at longer wavelengths. Here combining all CIBA measurements from $100\ \mu\text{m}$ to $1.3\ \text{mm}$ and low to high multipoles, α is well constrained and it is not strongly degenerated with other parameters. Note that values of $\alpha > 1$ implies that higher-mass halos contribute relatively more than smaller-mass ones compared to the halos in which lie optical galaxies such as those used by Tinker & Wetzel (2010).

In our analysis of the degeneracies of the halo parameters we have only considered a set of parameters identical for all wavelengths which is not the case in reality. It could thus be that the degeneracies depend on wavelength. We therefore checked that the degeneracies were not significantly changing when we compute the Fisher matrix with various set of parameters corresponding to the wavelength best-fit models.

The halo parameters cannot be constrained by counts or LF as they only intervene in the clustering of galaxies in the equation of the C_{ℓ} (see Eq. 8). Therefore we cannot carry a joint analysis of the degeneracies of the halo parameters using counts/LF and C_{ℓ} data all together. Note that in principle, we could extrapolate the number count measurements to constrain the total number of galaxies, which also depends on the HOD parameters, but this would be a difficult measurement as it would be strongly dependent on the flux cut, for example.

Emissivities are given by the model of galaxy evolution but we want to investigate the degeneracies if they are binned in redshift and their values considered as free parameters as in Amblard et al. (2011). They carried this analysis at redshift between 0 and 4. In order to be coherent with what has been done previously and to take advantage of our redshift range, from 0 to 7, we split the whole redshift range in four bins, $0 < z < 0.9$, $0.9 < z < 2$, $2 < z < 3.5$, $3.5 < z < 7$. For each bin i we take the mean value of the emissivity that we call b_{ji} with $i = \{1, 2, 3, 4\}$ and we compute the C_{ℓ} at $350\ \mu\text{m}$ (we assume a combined Planck and Herschel power spectrum) and the associated Fisher matrix. Confidence levels are given on Fig. 9. First we see that the halo occupation number degeneracies do not change much (see the previous paragraph) apart from the error bars which are much larger. M_{min} is still strongly degenerated with M_{sat} such as $M_{\text{sat}} = 2.7 M_{\text{min}}$. The direction of the degeneracy is roughly

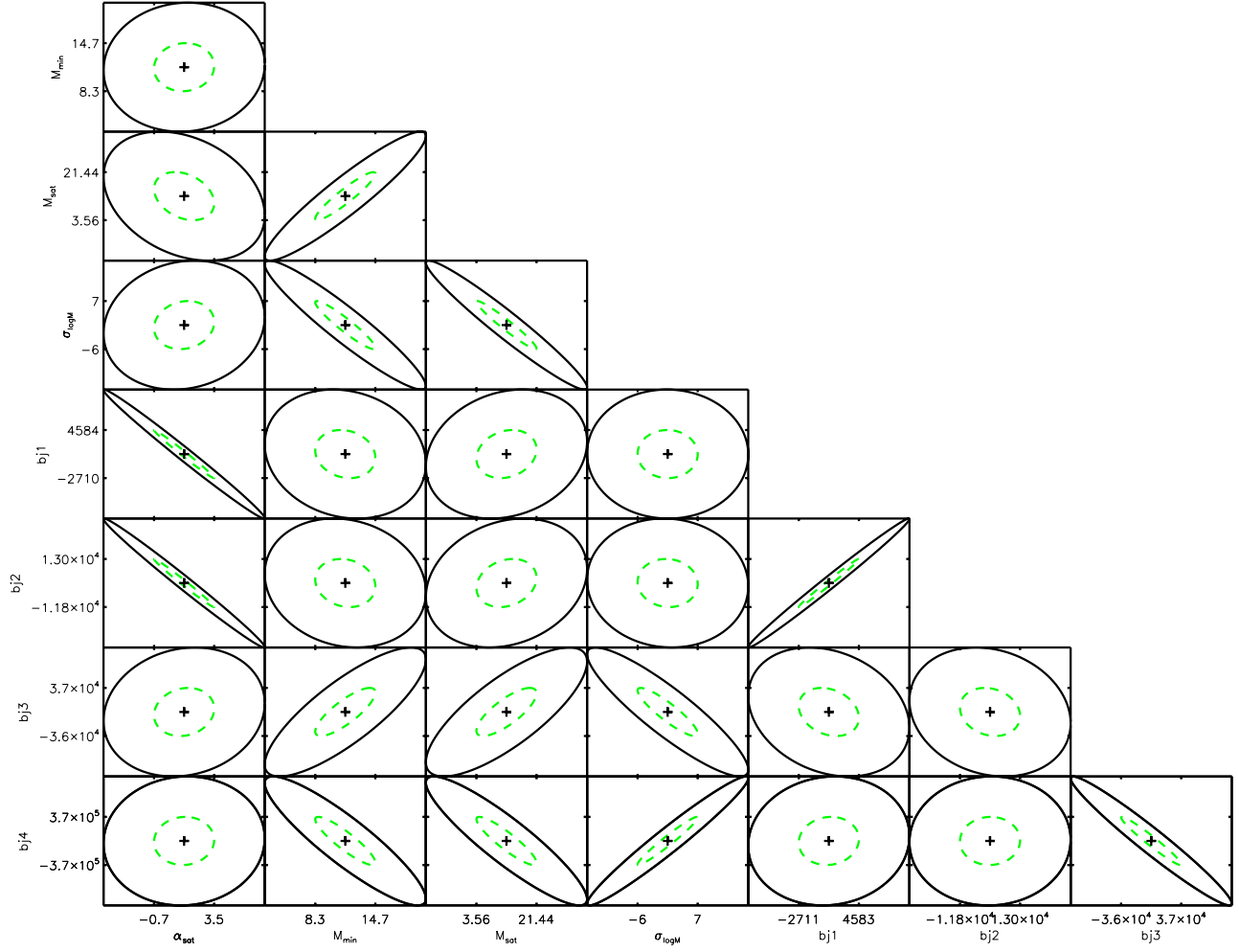


Fig. 9. 1σ (green) and 2σ (black) likelihood contours of the halo model parameters computed with mock data at $350\ \mu\text{m}$. Instead of using emissivities coming from the model of galaxies, we split C_ℓ in four redshift bins, on which we use the mean value of the emissivity on each bin $b_{j,i}$ that we consider as free parameters. The $b_{j,i}$ are hardly constrained with our data. α_{sat} is strongly degenerate with $b_{j,1}$ and $b_{j,2}$ which are the mean emissivities at low z . M_{min} , M_{sat} and $\sigma_{\log M}$ are degenerate with $b_{j,3}$ and $b_{j,4}$, the mean emissivities at high z .

the same as that derived using emissivities of the model as well as those of $\sigma_{\log M}$ and M_{sat} and M_{min} . Therefore, the degeneracy directions are all similar, using the emissivities or letting them free.

The degeneracies of the b_j with the halo parameters depend on the redshift. Indeed, α_{sat} is highly degenerated with $b_{j,1}$ ($0 < z < 0.9$) and $b_{j,2}$ ($0.9 < z < 2$) and not at all with $b_{j,3}$ ($2 < z < 3.5$) and $b_{j,4}$ ($3.5 < z < 7$). Therefore α_{sat} is constrained by $z > 2$ galaxies whereas the other halo parameters behave in the opposite way, they are not degenerate with $b_{j,1}$ and $b_{j,2}$ but with $b_{j,3}$ and $b_{j,4}$. This redshift dependency is emphasized by their own degeneracies. $b_{j,1}$ and $b_{j,2}$ are strongly correlated, the same is true for $b_{j,3}$ and $b_{j,4}$. The degeneracies using other wavelengths are only slightly different, we do not show them here. In general, the couples $(b_{j,1}, b_{j,2})$ and $(b_{j,3}, b_{j,4})$ are always strongly degenerate and the $b_{j,i}$ are degenerate with the halo parameters as shown on Fig. 9. Such a degeneracy dependence with the redshift has to be still understood.

In order to compare our results with those of Amblard et al.

(2011), we carry a similar analysis using their redshift bins, that is to say, $0 < z < 1$, $1 < z < 2$, $2 < z < 3$ and $3 < z < 4$. We observe the same behavior as described previously but different from their results. They used Monte Carlo Markov Chains to compute the degeneracies and usually the two dimensional probability distributions have two peaks (see their fig. S 13). Their S_i are equivalent to our $b_{j,i}$. S_1 is degenerate with the three others S_i , whereas there is no degeneracy between S_3 and S_4 . We do not discuss the degeneracy of the halo parameters with S_i as their parameterization of the halo occupation number slightly differ from ours.

Using $b_{j,i}$ and fitting them on the data avoids us to rely on a model of evolution of galaxies. However they are poorly constrained with the present data. Moreover the degeneracies between the $b_{j,i}$ and the halo parameters strongly depend on the halo parameterization used.

5. Interpreting measurements

Now that we have determined a model and the associated parameters degeneracies, we discuss their physical interpretation.

5.1. Redshift and halo-masses contribution to the power spectrum

The left panel of Fig. 15 shows the contribution to the C_ℓ by several redshift bins. As stated previously, the shorter the wavelength, the more important is the relative contribution from the low redshift. For example, while $z < 0.7$ contributes significantly at 100 and 160 μm , it becomes much less important in the millimeter range. Reversely, the high redshift bin ($z > 3$) is negligible at short wavelength but has an increasing contribution when the wavelength increases. The redshift distribution can change with the choice of the halo parameters as shown on Fig. 11. We have changed the values of α_{sat} on the left panels and that of M_{min} on the right panels (the change is in the 1σ error bars of the best fit found by Planck Collaboration et al. (2011)), the other parameters are those of the fiducial model. We recover the trend noticed above more or less emphasized.

Further, not only the redshift of the galaxies probed depends on the wavelength, but so does the mass of the halos in which they are embedded. Fig. 10 shows the contribution of mass and redshift to the 1- and 2-halo terms (at $\ell = 2002$ and $\ell = 100$ respectively) from 100 μm to 2 mm. High-mass halos ($M > 10^{13} M_\odot$) contribute the more to the 1-halo term from 100 μm to 2 mm at low redshift, and this dominant mass range stays constant with wavelength. More massive halos contain more galaxies than smaller ones therefore the galaxies contained in those halos contribute more to the angular power spectrum. This can be explained qualitatively in the following way. According to the mass function, at say $z = 0.5$, there are one thousand times more halos of $M = 10^{11} M_\odot/h$ than halos of mass $M = 10^{14} M_\odot/h$. According to the HOD, one out of one hundred $10^{11} M_\odot/h$ halo hosts a galaxy, whereas $M = 10^{14} M_\odot/h$ mass halos hosts on average 10 galaxies. Since the contribution to the 1-halo terms goes like N_{gal}^2 , more massive halos contribute relatively more to the 1-halo term. Note that this trend is less pronounced for the 2-halo term since it goes like N_{gal} . At all wavelengths, as the redshift increases, the dominant mass range decreases to $M \sim 10^{11-13} M_\odot$ as halos at higher redshifts are smaller than those at $z = 0$.

The 2-halo term does not exhibit the same behavior : at short wavelengths, halos in a large range of mass $10^{11} - 10^{15} M_\odot$ at low z contribute to the power spectrum. In parallel, intermediate masses contribute at higher z . As the wavelength increases, the relative contribution between high mass at low z and intermediate mass at high z becomes close to unity. It ends up in an equal contribution from high mass at low z and from intermediate mass at high z at 2 mm. Intermediate mass halos are more abundant which explains their high contribution. Both the 1 and 2-halo terms are sensitive to different mass regimes which evolve with the wavelength and thus with the redshift.

Magliocchetti et al. (2008) selected 24 μm sources at $1.5 < z < 3$ and deduced from their correlation function that they lie in $10^{13} M_\odot$ halos. Viero et al. (2009) found an $M_{\text{eff}} \sim 10^{13.2} M_\odot$ for unresolved galaxies at $z > 1$ at 250, 350 and 500 μm . Brodwin et al. (2008) derived the angular autocorrelation function of dust-obscured galaxies selected with a color criterion. They determined that they are in halos with an average mass of $10^{12.2} M_\odot$. Gilli et al. (2007) selected star forming galaxies at 24 μm , derived the projected correlation function and found

that LIRGs lie in halos $M > 3 \times 10^{13} M_\odot$. All these results are in agreement with ours. Overall, halos with masses such as $10^{12-13} M_\odot$ contribute the most to power spectra at all redshifts. However, we want to reemphasize here that these conclusions are model-dependent and depend on the particular emissivity model used, as discussed before. This is particularly true for the higher- z contribution, say $z > 2$.

5.2. Linear bias

Within our halo model we derive the linear bias as a function of the redshift following:

$$b_{\text{lin}}(k, z) = \sqrt{\frac{P_{\text{gg}}(k, z)}{P_{\text{lin}}(k, z)}} \quad (21)$$

where $P_{\text{gg}}(k, z)$ is the galaxy-galaxy power spectrum coming from our model, $P_{\text{lin}}(k, z)$ is the linear DM power spectrum and $b_{\text{lin}}(k, z)$ the linear bias.

We will call the effective bias coming from the HOD model, b_{HOD} . On large scale $u(k \rightarrow 0, M) \sim 1$, so the HOD bias from Eq. 13 is :

$$b_{\text{HOD}}(z) = \int dM \frac{dN}{dM} b(M) \frac{\langle N_{\text{gal}} \rangle}{\bar{n}_{\text{gal}}} \quad (22)$$

We plot in Fig. 12 the linear biases and the HOD bias for our fiducial model as a function of redshift for $k = 1 \text{ (Mpc/h)}^{-1}$ and $k = 10^{-2} \text{ (Mpc/h)}^{-1}$ where we also add current measurements detailed in Tab. 4. Note that in the linear regime, the HOD and linear biases are identical which is the case at $k = 10^{-2} \text{ (Mpc/h)}^{-1}$ but not at $k = 1 \text{ (Mpc/h)}^{-1}$. On small spatial scales, the $u(k \rightarrow 0, M) \sim 1$ is not true therefore it is strongly different from the linear bias for $k = 1$ as shown on Fig. 12.

For both scales, our linear biases as well as the HOD bias is not in agreement with measurements. Neither of them show the same trend as the data points. The measured linear biases as well as the HOD biases grow quicker towards higher values than the biases extracted from our model.

HOD bias measurements are from different HOD. Cooray et al. (2010) used the same halo occupation number to fit the correlation function and they found different parameters than ours. When using their parameters set, we do recover their results. The discrepancy could be explained by the fact that these measurements result from correlation function analysis, thus from resolved sources which is not the population we are studying here.

Concerning the linear bias determined with unresolved galaxies (Lagache et al. 2007; Viero et al. 2009), our linear bias is not in agreement with the measurements either. Indeed when using unresolved sources, the determination of the bias requires the use of emissivities, which are strongly model dependent (see Sect. 5.3) and it can affect the bias.

5.3. Influence of the mean emissivities

Previous models such as those of Lagache et al. (2007) and Viero et al. (2009) have used emissivities coming from Lagache et al. (2004). In Fig. 13, we plot the emissivity used in this paper as well as the Lagache et al. (2004) ones for reference. The peak at $z \sim 1$ in our emissivities is due to the parameterization of the LF. Despite the shapes of the emissivities of Lagache et al. (2004) and ours are different, they display similar trends. The relative

wavelength	kind of galaxies	reference	$\langle z \rangle$	b_{HOD}	b_{lin}
24	resolved	Magliocchetti et al. (2008)	0.79	1.70	
24	resolved	Magliocchetti et al. (2008)	2.02	6.17	
24	resolved	Brodwin et al. (2008)	2		3.1-5.3
24	resolved	Gilli et al. (2007)	0.75		1.3 $\pm$ 0.1
24	resolved	Gilli et al. (2007)	0.8		1.4 $\pm$ 0.1
24	resolved	Gilli et al. (2007)	1		1.8 $\pm$ 0.2
100	resolved	Saunders et al. (1992)	0		0.86
160	background	Lagache et al. (2007)	1		2.4 $\pm$ 0.2
250-350-500	background	Viero et al. (2009)	1.5	2.2 $\pm$ 0.2	3 $\pm$ 0.2
250	resolved	Cooray et al. (2010)	2.1 $^{+0.4}_{-0.4}$	2.9 $\pm$ 0.4	
350	resolved	Cooray et al. (2010)	2.3 $^{+0.4}_{-0.7}$	3.2 $\pm$ 0.5	
250	resolved	Cooray et al. (2010)	2.6 $^{+0.3}_{-0.7}$	3.6 $\pm$ 0.8	

Table 4. Linear and effective bias measurements. The third column gives the mean redshift of the galaxies probed and the last but one lists the HOD/effective bias values and the last one gives the linear bias.

contributions of high redshifts increases with wavelength while the contribution of low redshifts decreases. According to Jauzac et al. (2011), the model of Lagache et al. (2004) predicts too much power at high z . As the latter is forced to reproduce levels of the CIB and number counts, it does not predict enough power at low z . Therefore it predicts more galaxies at high z and less at low z . To illustrate how it influences our results, we show on Fig. 14 the ratios of the power spectra computed with our emissivities and those from Lagache et al. (2004). Up to 550 μ m the ratio is around 1 up to $\ell \sim 10000$ and it increases strongly at higher ℓ . At longer wavelength, the difference is much larger. It is in line with the over-prediction of power at high redshift of the model of Lagache et al. (2004). The same halo parameters have been used for this plot, however it is clear that when fitting the model to the data with both emissivities we will not find the same halo parameters.

As said previously the Lagache et al. (2004) model predicts too much power at high z , thus we need to compare the contribution in redshift to the C_ℓ . They are given on Fig. 15. In both cases we observe the same trend : high redshift contribute more and more as the wavelength increases. However, with Lagache et al. (2004) emissivities this evolution goes faster. For instance, at 250 μ m, the contribution of $1.5 < z < 3$ galaxies is of the same order of magnitude that those of $0.7 < z < 1.5$ whereas in our case the former is more than one order of magnitude inferior to the latter. As we go towards longer wavelengths, the two highest redshift bins have an increasing contribution, and both dominate the power spectrum at 850 μ m using Lagache et al. (2004) emissivities whereas using our emissivities $0.7 < z < 1.5$ galaxies contribute also strongly. At 1.3 and 2 mm both the highest redshift bins contribute the most but in our case, only the highest redshift bin dominate and the $1.5 < z < 3$ bin has a smaller contribution. Therefore the shape of the emissivities strongly influences our results, parameters determination and redshift distribution. The interpretation of clustering measurements is thus based on the use of a reliable model of evolution of galaxies.

5.4. Contribution of LIRGs and ULIRGs

Star-forming galaxies are split in several categories according to their luminosities. Normal, luminous infrared, and ultra luminous infrared galaxies have luminosities $L_{IR} < 10^{11} M_\odot$, $10^{11} M_\odot < L_{IR} < 10^{12} M_\odot$, $L_{IR} > 10^{12} M_\odot$, respectively. LIRGs dominate the infrared energy output at $z \sim 1$ and ULIRGs at $z \sim 2$ (P rez-Gonz lez et al. 2005; Le Floch et al. 2005; Caputi et al. 2007) therefore we look at their contribution to the C_ℓ and

to their evolution with the wavelength. To do so we split the emissivities in the following way :

$$\bar{j}_\lambda = \bar{j}_\lambda^{normal} + \bar{j}_\lambda^{LIRG} + \bar{j}_\lambda^{ULIRG} \quad (23)$$

and this contribution is squared in the C_ℓ . Therefore cross terms appear :

$$C_{\ell,total} = C_{\ell,Normal} + C_{\ell,LIRG} + C_{\ell,ULIRG} + 2(\times C_{\ell,Normal/LIRG} + 2C_{\ell,Normal/ULIRG} + C_{\ell,LIRG/ULIRG}) \quad (24)$$

We plot in Fig. 16 the contributions of normal, LIRGs and ULIRGs. Note that the sum of the three contributions does not make the total power spectrum because the cross terms are not shown.

Normal galaxies and LIRGs both dominate the power spectrum up to 550 μ m. The contribution of LIRGs increases slightly and finally dominates from 850 μ m to 2 mm. ULIRGs never clearly dominate the power spectrum at long wavelength, however their relative contribution increases at long wavelengths, from 850 μ m to 2 mm.

Therefore, we do recover what is expected from previous works. Normal galaxies dominate at low redshift, LIRGs at $z \sim 1$ and ULIRGs contribute in the same way as the others at high redshift and thus at long wavelengths.

6. Conclusion

We presented a new model of the clustering of star-forming galaxies in the Cosmic Infrared Background anisotropies. We interfaced a parametric model of star-forming galaxies evolution with a halo distribution approach. The model is fully parametric. Fixing the cosmology, it depends on the parameters of the model of galaxies and the HOD. We computed power spectra from 100 μ m to 2 mm for IRAS, Spitzer/MIPS, Herschel/SPIRE and Planck/HFI spectral bands. We showed how power spectra can depend on the parameters and we concluded that the parameters of the model of galaxies can hardly be constrained using C_ℓ only. Number counts and luminosity functions data are required. Fixing them at the mean values found by B thermin et al. (2011), we explored the HOD parameters constraints and degeneracies. The combination of C_ℓ and counts/LF data do not break the degeneracies but constraints are slightly improved. Some of the parameters are strongly degenerate, especially M_{min} and M_{sat} with $M_{sat} = xM_{min}$ with $x \sim 3$ where x is the direction of the degeneracy.

We have shown that the 1-halo term can be detected at all wavelengths and that galaxies at high redshift lie in smaller halos than

those at lower redshift. The level of the shot noise might not be reached with certain instruments such as Planck because of their angular resolution. However, this does not apply to the South Pole Telescope and to Herschel as they have a better angular resolution.

Using our fiducial model, we computed the halo mass and redshift contribution to the power spectra. Higher redshift galaxies contribute more at long wavelengths. Not surprisingly, the 1- and 2- halo terms do not have the same mass dependence. We found that high mass halos contribute the most to the 1 halo term whereas the 2-halo term is dominated by intermediate mass halos which are most numerous. Our model strongly depends on the emissivity given by the evolution model of galaxies, and we compare the resulting C_ℓ s with those obtained using the emissivities coming from Lagache et al. (2004). We have shown that the halo parameters strongly depend on the emissivities when data are fitted.

In order to avoid the use of a model of evolution of galaxies, we have split the redshift range in four bins and computed the C_ℓ using the mean emissivity on these four redshift bins as in Amblard et al. (2011). We considered these four parameters as free. They are not very well constrained, they cannot give any constraints on models of galaxies.

We investigate the contribution of LIRGs and ULIRGs to the power spectra and its evolution with the wavelength. Our results are in agreement with previous studies of normal galaxies, LIRGs and ULIRGs contribution to the CIB and to the luminosity functions. Normal galaxies dominate the power spectrum at low redshift. As the redshift increases, LIRGs dominate C_ℓ . Meanwhile, the contribution of ULIRGs keeps increasing up to 2 mm.

The main unknown in CIB anisotropies power spectrum measurements are the redshift distributions of CIB galaxies. The coming results from Planck and Herschel will enable a great leap in the understanding of the clustering of star-forming galaxies and its redshift evolution, measuring the cross power spectra between wavelengths. These new measurements will help to break some degeneracies and will allow to make more precise measurements of the star formation density at high redshift, and the characteristic mass of the dark matter halo at which the efficiency of the star formation is maximal.

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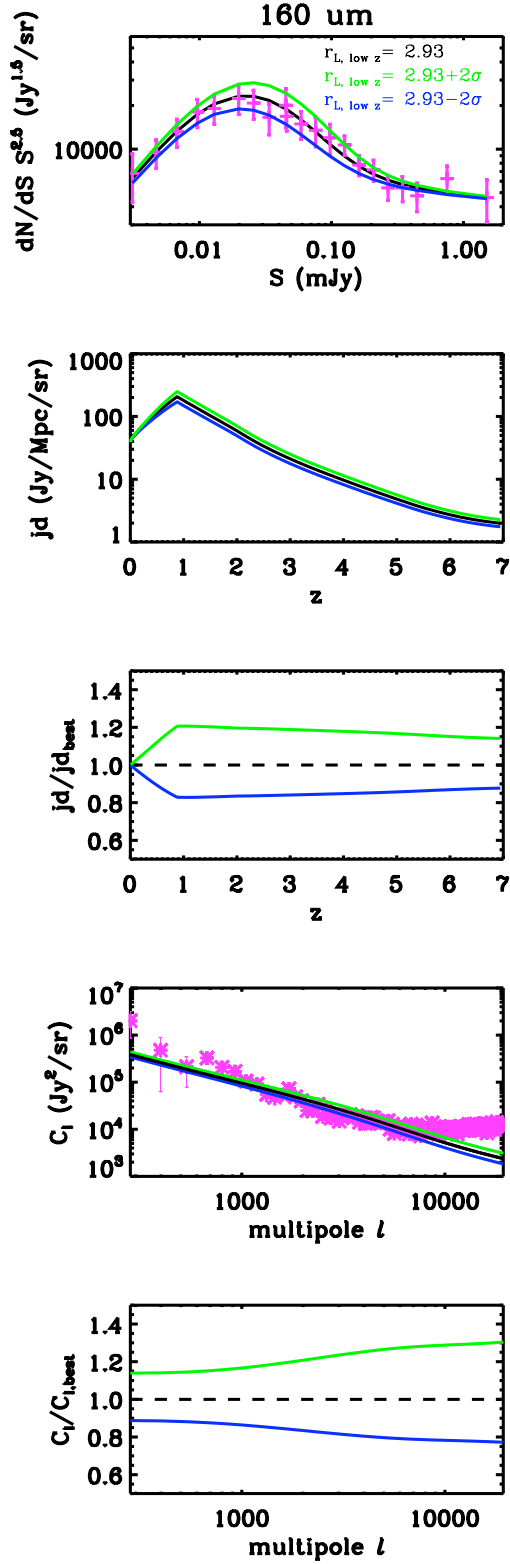


Fig. 6. Counts at $160 \mu\text{m}$, emissivities and clustering power spectrum for three values of $r_{L, \text{low } z}$, the best fit and the best fit $\pm 2\sigma$. Pink crosses are data, B thermin et al. (2010) for the counts and Lagache et al. (2007) for the power spectrum. Top panel : differential number counts at $160 \mu\text{m}$. 2nd panel : mean emissivities at $160 \mu\text{m}$. 3rd panel : ratio of the modified emissivities compared to the best fit one at $160 \mu\text{m}$. 4th panel : power spectra of the clustering at $160 \mu\text{m}$. Bottom panel : ratio of the modified power spectra compared to the best fit one at $160 \mu\text{m}$. A small change of $r_{L, \text{low } z}$ leads to a 20 % modification on the emissivities and on 15-35% on the C_ℓ .

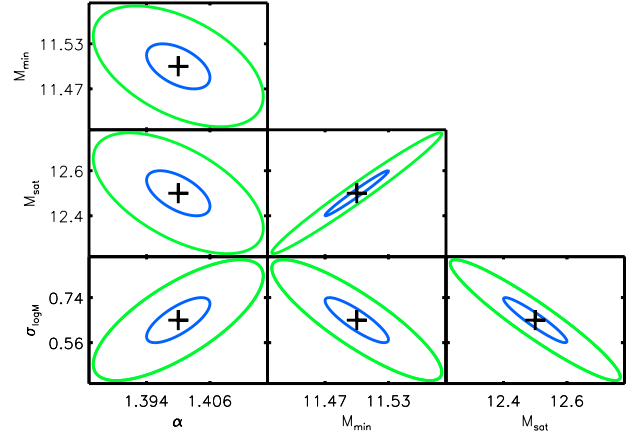


Fig. 8. 1σ (blue) and 2σ (green) likelihood contours of the halo model parameters computed with mock data from $100 \mu\text{m}$ to 1.3 mm .

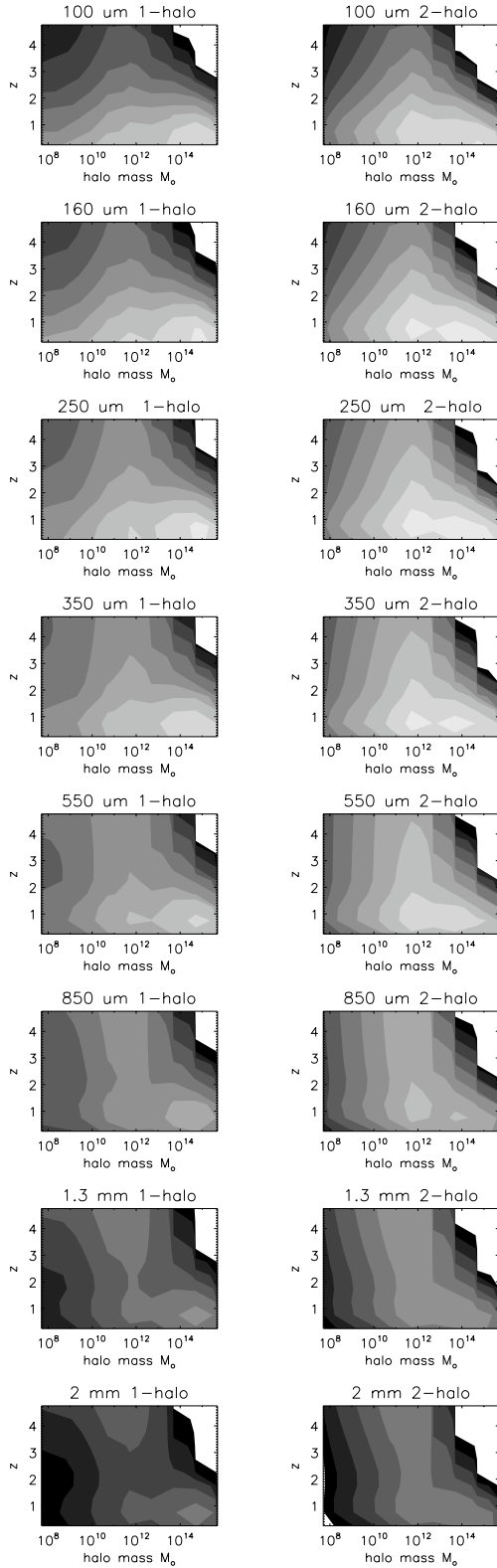


Fig. 10. Contribution of halo masses and redshift to the C_ℓ from $100\ \mu\text{m}$ to $2\ \text{mm}$. The first column shows the redshift and mass contribution to the 1-halo term ($\ell = 2002$) and the second column represents the same contributions to the 2-halo term ($\ell = 100$). The light grey corresponds to the highest contribution to the C_ℓ s. The step of the color range is logarithmic and the scale is the same for both columns. The 1-halo term is dominated by high masses at low z at all wavelength. At all wavelength, the 2-halo term is dominated by a large range of masses at low z and by intermediate masses at higher z . The 1- and 2-halo term are sensitive to different mass regimes. The former to high mass halos and the latter to intermediate mass halos.

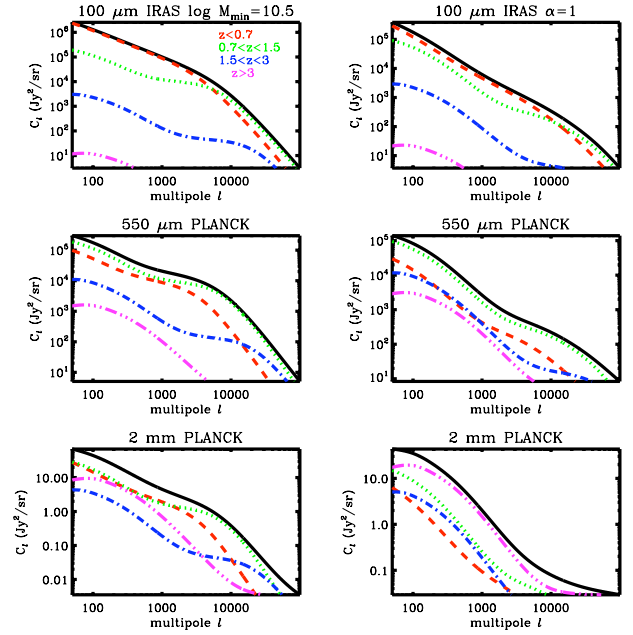


Fig. 11. Redshift distribution for several wavelengths for halo parameters different from the values of the fiducial model. The left panels are for $\log M_{\min} = 10.5$ instead of $\log M_{\min} = 11.5$ and the right panels are for $\alpha = 1$ instead of $\alpha_{\text{sat}} = 1.4$. The redshift distribution depends strongly on the chosen halo parameters although the same trend is observed: the low redshift dominate at short wavelengths, this contribution decreases with the wavelength and as the wavelength gets longer the contribution of high redshifts increases.

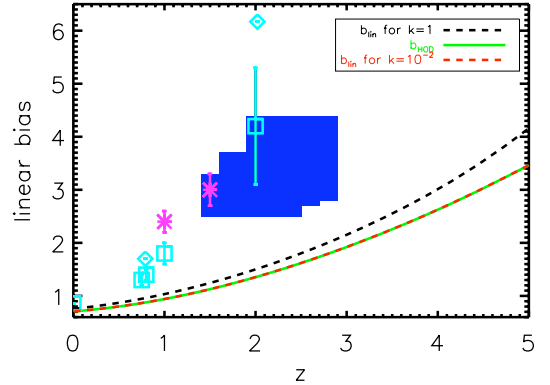


Fig. 12. Linear bias for several values of k (in $(\text{Mpc}/h)^{-1}$) and HOD bias. Light blue squares and diamonds bias values from resolved galaxies and pink crosses represent biases from unresolved galaxies measurements (see Table 4). The big blue squares represent the HOD biases coming from resolved galaxies from Cooray et al. (2010). Light blue diamonds and squares show HOD and linear biases, respectively.

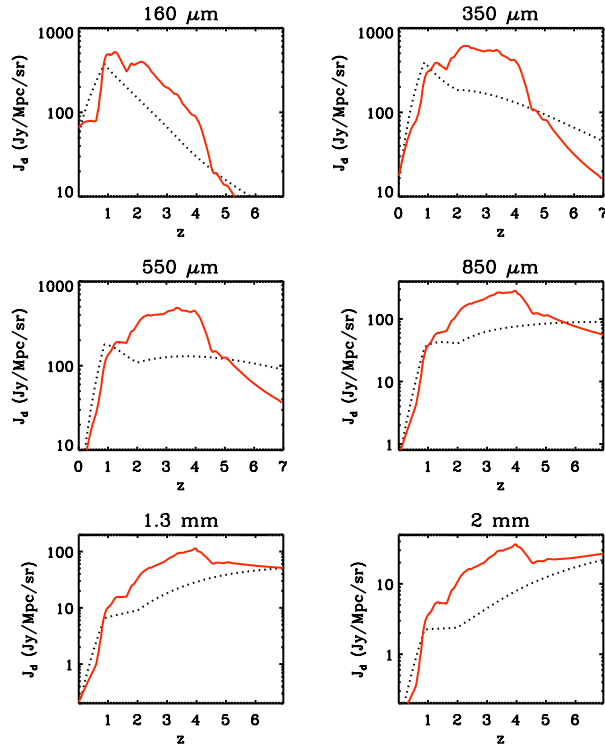


Fig. 13. Emissivities used by Viero et al. (2009) coming from Lagache et al. (2004) (red continuous line) and ours (black dotted line) coming from B thermin et al. (2011) at several wavelengths.

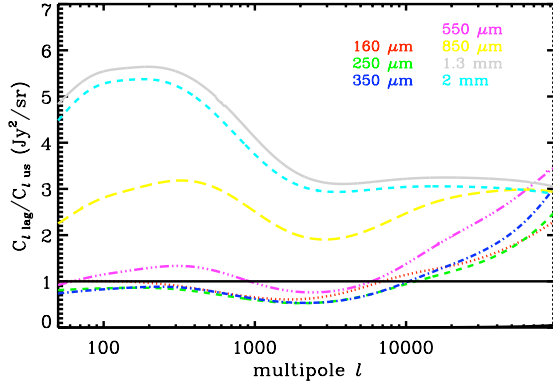


Fig. 14. Power spectra ratios computed using the emissivities of Lagache et al. (2004) ($C_{\ell,lag}$) and B thermin et al. (2011) ($C_{\ell,us}$), for several wavelengths.

Chapitre 8

Conclusion et perspectives

8.1 Conclusion

Dans la première moitié de cette thèse, nous avons exploré différentes méthodes de comptage des sources infrarouges. L'extraction directe des sources dans les cartes est la méthode la plus simple. Néanmoins, elle ne permet pas d'accéder aux galaxies de flux faibles dans l'infrarouge lointain à cause du phénomène de confusion. Pour aller plus loin, j'ai développé une méthode de comptages basée sur la technique de l'empilement. Cette méthode permet de descendre environ un ordre de grandeur en dessous de la limite de confusion dans les données MIPS à 70 et 160 μm (Béthermin *et al.* (2010a)) et BLAST à 250, 350 et 500 μm (Béthermin *et al.* (2010b)). L'efficacité de cette méthode a été confirmée a posteriori par les comptages PACS de Berta *et al.* (2010). Au delà de 200 μm , même *Herschel* ne résout qu'une faible fraction du fond infrarouge. Une confirmation des comptages en dessous du seuil de confusion par une autre méthode statistique est donc fort souhaitable. J'ai ainsi réalisé une analyse P(D) des cartes SPIRE (Glenn *et al.* (2010)). Les résultats obtenus confirment les résultats obtenus avec les données BLAST.

Ces comptages en dessous de la limite de confusion permettent de mieux contraindre l'évolution des populations faibles ou à grand *redshift*, mais également d'identifier les populations responsables du fond infrarouge. L'extrapolation à bas flux des comptages par empilement à 160 μm (Béthermin *et al.* (2010a)) permet de réaliser une estimation en parfait accord avec la mesure absolue de Pénin *et al.* (2011b). A plus grande longueur d'onde, les incertitudes sont plus larges. Il est donc difficile d'extrapoler le comportement à bas flux. La partie des comptages bien contraintes par l'analyse P(D) et les comptages par empilement explique néanmoins environ 50% du fond (Béthermin *et al.* (2010b), Glenn *et al.* (2010)). On peut également estimer la contribution au fond infrarouge lointain et sub-millimétrique des sources détectée à 24 μm en fonction du *redshift* (Jauzac *et al.* (2011), Vieira *et al.* (en préparation)). Ces mesures sont très discriminantes pour les modèles. Elles montrent également que plus on observe à grande longueur d'onde et plus le

fond est dominé par les hauts *redshifts*.

Les comptages de sources sont une contrainte simple à mesurer, mais difficile à interpréter. En effet, ils fournissent une information intégrée sur l'ensemble de l'histoire de l'Univers. Pour interpréter mes mesures, j'ai construit un modèle d'évolution des galaxies infrarouges. Ce modèle paramétrique, ajusté sur les comptages de sources, reproduit de manière satisfaisante la plupart des observables infrarouges. Il prédit une forte évolution en densité et en luminosité de la fonction de luminosité infrarouge. Le modèle suggère que la formation d'étoiles à haut *redshift* a lieu préférentiellement dans les ULIRGS, alors que cette population est négligeable dans l'Univers local. Ceci suggère une très forte évolution des conditions physiques dans les galaxies au cours de l'histoire de l'Univers. Enfin, ce modèle, couplé à un modèle de halo est utilisé pour interpréter les fluctuations du fond infrarouge observées par *Spitzer*, *Herschel* et *Planck*.

Au début de cette thèse, le fond infrarouge n'était résolu qu'en dessous de $160\ \mu\text{m}$, grâce à l'empilement des sources détectées à $24\ \mu\text{m}$ (Dole *et al.* (2006)). De plus, les mesures de sa distribution en *redshift* étaient encore totalement préliminaires. Aujourd'hui, le fond est résolu jusqu'à $1.1\ \text{mm}$ et sa distribution en *redshift* a été mesurée (Marsden *et al.* (2009), Béthermin *et al.* (2010b), Berta *et al.* (2010), Jauzac *et al.* (2011), Vieira *et al.* en prép.). Alors que le pic des comptages différentiels normalisés n'était détecté que jusqu'à $24\ \mu\text{m}$ (Papovich *et al.* (2004)), il est aujourd'hui observé dans tout le domaine infrarouge et sub-millimétrique (Patanchon *et al.* (2009), Béthermin *et al.* (2010a), Béthermin *et al.* (2010b), Glenn *et al.* (2010), Berta *et al.* (2010)). Ces dernières années ont également vu l'émergence de nouveaux modèles d'évolution des galaxies infrarouges ajustés automatiquement sur les données (Le Borgne *et al.* (2009), Béthermin *et al.* (2011), Marsden *et al.* (2010)), alors que les anciens modèles étaient ajustés "à la main". Ceci a permis d'étudier pour la première fois les dégénérescences entre les différentes évolutions possibles. Le modèle de Béthermin *et al.* (2011) reproduit très bien le niveau global, mais aussi la distribution en *redshift* du fond infrarouge (Jauzac *et al.* (2011), Vieira *et al.* en prép.). En trois ans, les connaissances sur le fond infrarouge ont donc fortement progressé, grâce à de nombreuses avancées concernant les observations et la modélisation.

8.2 Perspectives

Le travail réalisé au cours de cette thèse ouvre de nombreuses perspectives. L'analyse statistique de cartes *Herschel* n'est pas encore terminée. Pour l'instant, l'analyse P(D) ne permet pas de séparer les comptages en tranche de *redshift*. En revanche, ceci est possible avec la méthode de l'empilement, pourvu que des *redshifts* soient associés à chacune des sources $24\ \mu\text{m}$. Les données BLAST ne permettaient pas d'obtenir un signal suffisant pour

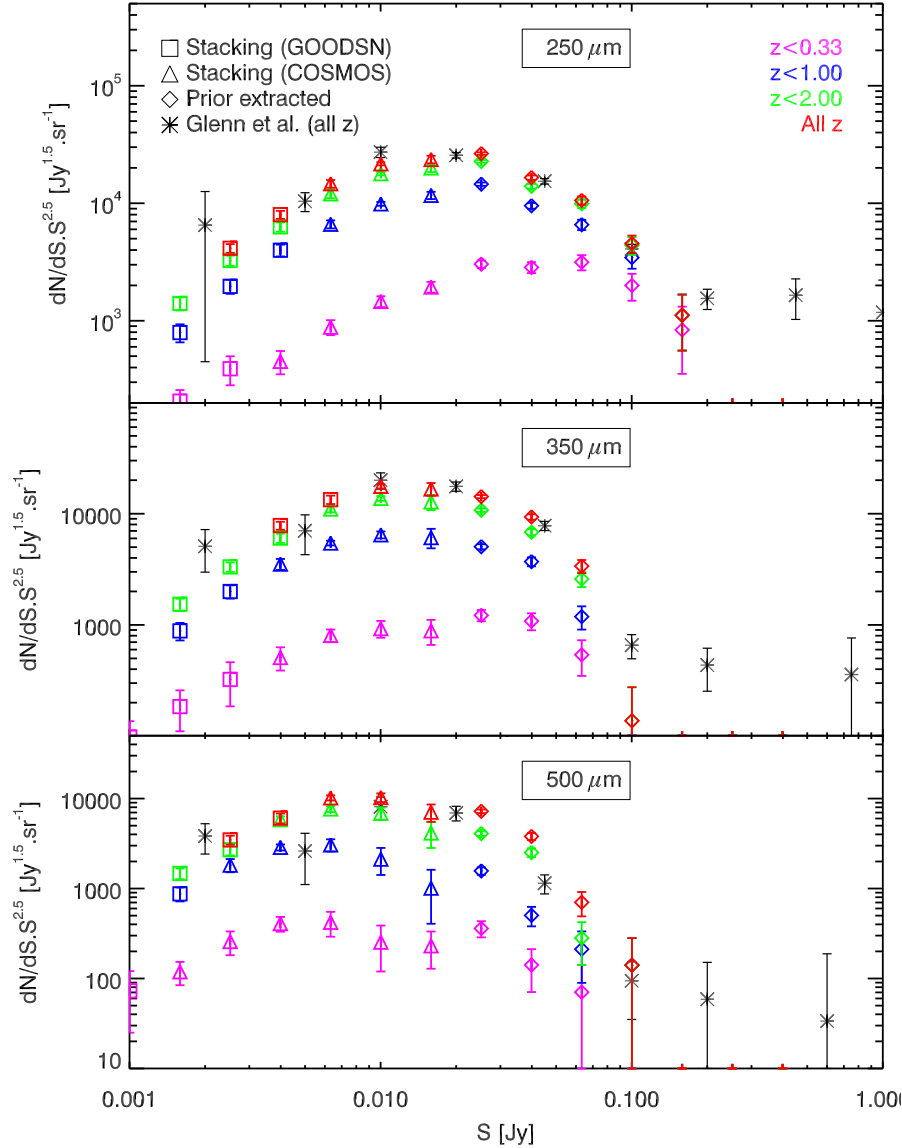


FIGURE 8.1 – Comptages de sources par tranches de *redshift* à 250 (haut), 350 (milieu) et 500 μm (bas). Les contributions de sources de *redshift* inférieur à 0.33, 1 et 2 sont représentés en violet, bleu et vert, respectivement. La contribution totale est en rouge. Les losanges correspondent aux comptages réalisés à partir d’une extraction de source avec a priori dans COSMOS. Les triangles et les carrés correspondent à des comptages par empilement dans COSMOS et GOODS-N, respectivement. Les astérisques représentent les comptages P(D) de Glenn *et al.* (2010).

ce type d'analyse. En revanche, les résultats préliminaires que j'ai obtenus avec SPIRE sont extrêmement encourageants (voir Fig 8.1). Ces analyses par empilement pourront être complétées par des analyses $P(D)$ multicolores, qui consiste à généraliser le $P(D)$ de une dimension (histogramme du signal du flux dans une seule bande) à N dimensions (histogramme à N dimensions du flux dans N bandes différentes). Le défi principal que pose cette méthode est le temps de calcul. Enfin, les mesures des niveaux de fluctuations poissonniennes croisées entre les bandes SPIRE, mais également entre SPIRE et ACT devraient fournir des contraintes supplémentaires sur l'évolution des galaxies à grand *redshift*.

Mon travail de modélisation a également de nombreuses perspectives d'amélioration. Pour l'instant, malgré sa relative simplicité, le modèle reproduit la plupart des observations infrarouges. Toutefois, il ne prend pas en compte la dispersion des températures de grains des galaxies. Il suppose également que les SEDs n'évoluent pas avec le *redshift*. L'analyse des données *Herschel* va permettre de construire de nouvelles bibliothèques de *templates*, qui pourront être utilisées par la nouvelle version du modèle. On peut également imaginer améliorer la manière dont la LF de chaque population est construite. Elbaz *et al.* (2011) ont trouvé une bimodalité dans les SEDs de galaxies infrarouges, avec une population sur la "séquence principale" et une autre de galaxies compactes à flambée de formation d'étoiles. La paramétrisation du modèle pourrait évoluer afin de mieux représenter l'évolution de ces deux populations, et leur importance relative sur l'histoire de la formation d'étoiles.

A long terme, les futurs instruments infrarouges devraient permettre de mieux sonder les populations faibles et à très haut *redshift*. ALMA¹ est un réseau d'antennes millimétriques et submillimétrique (66 à terme), situé à 5100 m d'altitude sur le plateau de Chajnantor. Sa sensibilité et sa résolution angulaire va permettre de résoudre² les galaxies infrarouges à grand *redshift*. Ceci va permettre de mieux comprendre la dynamique du gaz dans ces objets. En revanche, le faible champ de vue (moins d'une minute d'arc) ne permettra pas de réaliser des grands relevés en un temps raisonnable (ou tout du moins, pas à court terme). Le projet de télescope sub-millimétrique CCAT³ pourrait permettre réaliser cette tâche. Il s'agit d'un télescope de 25 m, situé à 5600 m d'altitude sur un sommet à proximité du site d'ALMA. L'aridité et l'altitude du site devrait permettre de réaliser des relevés à 350 et 450 μm , avec une résolution angulaire 7 fois supérieure à *Herschel*, réduisant ainsi fortement la confusion et permettant de résoudre les LIRGs à grand *redshift*.

¹De l'anglais, *Atacama Large Millimeter/submillimeter Array*

²Contrairement à l'usage qui en a été fait au cours de cette thèse, on entend ici par résoudre le fait que la source soit plus entendue que l'élément de résolution angulaire de l'instrument.

³Cornell Caltech Atacama Telescope

Les observatoires spatiaux auront également un grand rôle à jouer. La caméra MIRI⁴ sur le télescope spatial de 6.5 m de diamètre JWST⁵ va permettre de réaliser des relevés avec une bien meilleure sensibilité et résolution angulaire que *Spitzer* à 24 μm . Ceci devrait permettre d'observer les populations infrarouges faibles jusqu'à $z=2$ (au delà de $z=2$, le 24 μm observé ne sonde plus les émissions due à la poussière, mais celle des vieilles population stellaires). L'instrument SAFARI⁶ sur le télescope SPICA⁷ de 3.5 m refroidi à 5 K devrait, quant à lui permettre de réaliser de la spectro-imagerie entre 30 et 210 μm . Ceci permettra d'observer les PAHs des galaxies jusqu'à très grand redshift, et améliorer ainsi nos connaissance sur les mécanismes physiques qui régissent les galaxies infrarouges à grand *redshift*.

Ces trois années de thèse ont constitué une période extrêmement stimulante scientifiquement, mais l'avenir se présente tout aussi motivant !

⁴De l'anglais, *Mid-InfraRed Instrument*

⁵De l'anglais, *James Webb Space Telescope*

⁶De l'anglais, *Spica FAR-infrared Instrument*

⁷De l'anglais, *Space Infrared Telescope for Cosmology and Astrophysics*

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Annexe A

Autres articles

J'ai participé de manière ponctuelle à d'autres publications. Ces travaux n'étant pas centraux dans ma thèse, elles ont été mises en annexe.

A.1 Article : *The Herschel Multi-Tiered Extragalactic Survey : source extraction and cross-identifications in confusion-dominated SPIRE images*

J'ai participé à vérifier la qualité du catalogue XID (*cross-identification*) de HerMES en comparant les résultats obtenus avec ceux issus de la méthode utilisée dans Béthermin *et al.* (2010b) (sélection des sources par flux 24 microns et utilisation de FASTPHOT). J'ai également relu et commenté l'article.

The *Herschel* Multi-Tiered Extragalactic Survey: Source Extraction and Cross-Identifications in Confusion-Dominated SPIRE Images

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ABSTRACT

We present the cross-identification and source photometry techniques used to process *Herschel* SPIRE imaging taken as part of the *Herschel* Multi-Tiered Extragalactic Survey (HerMES). Cross-identifications are performed in map-space so as to minimise source blending effects. We make use of a combination of linear inversion and model selection techniques to produce reliable cross-identification catalogues based on *Spitzer* MIPS $24\,\mu\text{m}$ source positions. Testing on simulations and real *Herschel* observations show that this approach gives robust results for even the faintest sources ($S_{250} \sim 10\,\text{mJy}$). We apply our new technique to HerMES SPIRE observations taken as part of the science demonstration phase of *Herschel*. For our real SPIRE observations we show that, for bright unconfused sources, our flux density estimates are in good agreement with those produced via more traditional point source detection methods (SussExtractor; Savage & Oliver et al. 2006) by Smith et al. 2010. When compared to the measured number density of sources in the SPIRE bands, we show that our method allows the recovery of a larger fraction of faint sources than these traditional methods. However this completeness is heavily dependant on the relative depth of the existing $24\,\mu\text{m}$ catalogues and SPIRE imaging. Using our deepest multi-wavelength dataset in GOODS-N, we estimate that the use of shallow $24\,\mu\text{m}$ in our other fields introduces an incompleteness at faint levels of between 20–40 per cent at $250\,\mu\text{m}$.

Key words:**1 INTRODUCTION**

Measuring accurate flux densities for sources in astronomical images dominated by confusion noise is the greatest obstacle to scientific analysis of data from next generation telescopes at far-IR to radio wavelengths. Great advances in the sensitivity of instruments at these long wavelengths has meant that the blended signal from numerous, unresolved, faint sources now form a non-negligible fraction of the observed telescope background. Hence confusion noise, i.e. fluctuations in this background, is now the dominant source of noise in deep imaging.

This results in several complications in the analysis of low resolution, long wavelength, imaging. Firstly, confusion acts to increase the positional uncertainty of sources dramatically (e.g. Hogg 2001), making cross-identifications with other wavelengths problematic. Secondly, correlations between the confusing background and sources above the confusion limit result in, at best, flux boosting of detected sources above the confusion limit and, at worst, complex blends of correlated confusion noise, resulting in spurious sources (Scheuer & Ryle 1957, Condon 1974).

In recent history there have been two distinct approaches to dealing with these issues. Fairly traditional source detection methods, combined with probabilistic approaches for flux boosting and source identification have been used to good effect on sub-mm surveys performed with SCUBA (i.e. Lilly et al. 1999, Mortier et al. 2005, Pope et al. 2005., Ivison et al. 2007).

By comparison others have opted for a more statistical approach, choosing to ignore individual sources and look at the aggregate properties of sources via either stacking (Dole et al. 2006, Pascale et al. 2009, Marsden et al. 2010) or the map statistics themselves via the pixel intensity distribution, the so-called $P(D)$ (e.g. Patanchon et al. 2009).

Both approaches have advantages and disadvantages; working with individual sources allows the true variation of sub-mm galaxy properties and their correlations with other observables to be properly investigated. However, finding multi-wavelength identifications for individual sub-mm sources is usually difficult, and generally reliable identifications can be found for only a fraction of sources (Ivison et al. 2007; Roseboom et al. 2009). Statistical approaches have the advantage of using all the available data, and hence provide greater precision in the parameters of interest. However, interpretation of these statistically-derived quantities is sometimes complicated, and highly dependent on the choice of parameterisation.

Recently several authors have made use of an approach which arguably takes the best elements of the three techniques discussed above. By using a linear inversion technique to fit for the flux density of all known sources simultaneously, the ability to work on individual sources is retained, while the information in the map itself can be used to distinguish the contributions from each source. This approach has been used by Scott et al. (2002) to fit the flux densities of SCUBA $850\,\mu\text{m}$ sources in the $8\,\text{mJy}$ survey; Magnelli et al. (2009) to fit the *Spitzer* $24\,\mu\text{m}$ flux density of IRAC detected sources in GOODS-N; and also by Bethermin et al. (2010) and Chapin et al. (2010) to fit the BLAST and BLAST/LABOCA data, respectively, for $24\,\mu\text{m}$ detected sources in the extended *Chandra* Deep Field South (eCDFs). The key to this approach is its simplicity; the only assumptions are that all sources are unresolved by the telescope, and that the positions of all sources are known. If these assumptions hold, then in the limit of infinite signal-to-noise ratio in the image the resulting flux density measurements would be perfect, irrespective of source density.

Here we present a similar technique developed to fit the SPIRE band flux densities of $24\,\mu\text{m}$ sources in fields observed as part of the Science Demonstration Phase (SDP) of

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the *Herschel*¹ (Pilbratt et al. 2010) mission by the HerMES. The SPIRE instrument, its in-orbit performance, and its scientific capabilities are described by Griffin et al. (2010), and the SPIRE astronomical calibration methods and accuracy are outlined in Swinyard et al. (2010). Our technique is distinct from those discussed above as we include an additional model-selection stage to ensure that only input sources which are justified by the SPIRE data are retained. This stage helps to alleviate the problem of overfitting, i.e. fitting more sources than there are independent data points to constrain.

Section 2 describes the datasets used in this work, Section 3.1 presents the linear model used to describe the map. Section 4 discusses how model selection can be used to “tune” the input list of positions, while Sections 6 and 7 present and discuss the results obtained by implementing this technique on both simulated and observed *Herschel* datasets.

2 DATA

In this paper we make use of *Herschel* data from HerMES taken as part of the SDP of the *Herschel* mission. HerMES performed observations of 5 fields during SDP; these observations are described in Oliver et al. (2010a, 2010b) and summarised in Table 1.

SPIRE data are processed using the *Herschel* Interactive Processing Environment (HIPE). Details of the SPIRE data processing are described in Smith et al. (2010, in prep.), however we briefly summarise the main points here. SPIRE maps used in this paper make use of the naïve map-making algorithm, with no Wiener filtering applied. While the absolute astrometry of SPIRE imaging is accurate to ~ 2 arcsec we apply global corrections to the astrometry of the processed maps, based on stacking at the positions of known radio sources. After these corrections have been applied we expect our maps to have an overall astrometric accuracy of < 0.5 arcsec.

In addition source catalogues are produced using the Sussextractor algorithm in HIPE (Savage & Oliver 2006). Although we do not make use of these catalogues in the cross identification process, comparisons to them are made in Section 7. Throughout we refer to the HIPE processed data products by the moniker SCAT (SPIRE Catalogue) of which we use the latest v3 internal release.

Cross identifications are made between these data, and archival *Spitzer* IRAC and MIPS datasets. In the wide, shallow fields, Lockman SWIRE (LH-SWIRE) and FLS, we make use of the multi-wavelength catalogues described in Vaccari et al. (2010, in prep). In Lockman, these catalogues use the *Spitzer* SWIRE (Lonsdale et al. 2003) dataset as a starting point, specifically those sources detected by IRAC (at $3.6\mu\text{m}$ and/or $4.5\mu\text{m}$). Analogous catalogues are constructed in FLS, using the IRAC source catalogues of Lacy et al. (2005) and MIPS source catalogues of Fadda et al. (2006).

¹ *Herschel* is an ESA space observatory with science instruments provided by Principal Investigator consortia. It is open for proposals for observing time from the worldwide astronomical community.

In the deeper fields, archival ancillary data are provided by several previous projects. In GOODS-N we make use of the *Spitzer* IRAC and MIPS observations taken as part of the GOODS program, specifically the catalogue described in Magnelli et al. (2009), which measures the $24\mu\text{m}$ flux density using the position of IRAC sources as a prior.

In the Lockman North (LH-North) region we use reprocessed archival $24\mu\text{m}$ data from the GO program of Owen et al.

3 LINEAR FITTING METHOD

3.1 Basic Equations

Our data $\mathbf{d}$ is an image of dimensions $n_1 \times n_2 = M$ pixels. The pixels are located at discrete positions $(\mathbf{x}, \mathbf{y})$. Our model assumes this data to be formed by a number of point sources with known image coordinates, $(\mathbf{u}, \mathbf{v})$, and with unknown flux density, $\mathbf{f}$. If each source i makes a contribution to the data given by the point response function (PRF) $P(\mathbf{x} - u_i, \mathbf{y} - v_i)$ we can describe the flux density in a given pixel j as

$$d_j = \sum_i P(x_j - u_i, y_j - v_i) f_i + \delta_j \quad (1)$$

where δ_j is an additional noise contribution. Thus the entire image d can be described as:

$$\mathbf{d} = P(\Delta\mathbf{X}, \Delta\mathbf{Y})\mathbf{f} + \delta, \quad (2)$$

where $\Delta\mathbf{X}$ and $\Delta\mathbf{Y}$ define the offset between pixels and sources. This is a linear equation of the form

$$\mathbf{d} = \mathbf{A}\mathbf{f} + \delta. \quad (3)$$

Naturally our measures of the pixel intensities d will have an associated, and measurable, variance and possibly covariance between the pixels, which we define here as $\mathbf{N}_d = \langle \delta\delta^T \rangle$.

To derive the maximum likelihood solution, we write down the likelihood as the Gaussian probability function for the data given the flux densities:

$$\begin{aligned} \mathcal{L}(\hat{\mathbf{f}}) &= p(\mathbf{d}|\hat{\mathbf{f}}) \\ &\propto |\mathbf{N}_d|^{-1/2} \exp \left\{ -\frac{1}{2} (\mathbf{d} - \hat{\mathbf{d}})^T \mathbf{N}_d^{-1} (\mathbf{d} - \hat{\mathbf{d}}) \right\} \end{aligned}$$

where we define $\hat{\mathbf{d}}$ as the data resulting from a given set of flux densities $\hat{\mathbf{f}}$. Defining $\chi^2 = (\mathbf{d} - \hat{\mathbf{d}})^T \mathbf{N}_d^{-1} (\mathbf{d} - \hat{\mathbf{d}})$ we see that at the maximum of the likelihood we require χ^2 to be at a minimum. However it can be seen that $\hat{\mathbf{d}} = \mathbf{A}\hat{\mathbf{f}}$, so

$$\chi^2 = (\mathbf{d} - \mathbf{A}\hat{\mathbf{f}})^T \mathbf{N}_d^{-1} (\mathbf{d} - \mathbf{A}\hat{\mathbf{f}}).$$

Hence at the minimum

$$\begin{aligned} 0 &= \frac{\partial \chi^2}{\partial \hat{\mathbf{f}}} \\ &= \mathbf{A}^T \mathbf{N}_d^{-1} \mathbf{A} \hat{\mathbf{f}} - \mathbf{A}^T \mathbf{N}_d^{-1} \mathbf{d}, \end{aligned}$$

so the maximum likelihood solution can be written as

$$\hat{\mathbf{f}} = (\mathbf{A}^T \mathbf{N}_d^{-1} \mathbf{A})^{-1} \mathbf{A}^T \mathbf{N}_d^{-1} \mathbf{d}, \quad (4)$$

An equation which is familiar from maximum likelihood map-making for both sub-mm and CMB experiments (e.g. Tegmark 1997, Patanchon et al. 2008, Cantalupo et al. 2010).

Table 1. HerMES SDP Observations (Oliver et al. 2010a, 2010b). Size is approximate extent of region with uniform coverage. Repeats is total number of pairs of scans in both A and B directions. Sensitivity is that for a point source, ignoring confusion noise. S_{24} refers to existing MIPS observations in these fields.

Field Name	Size	RA deg	Dec deg	Repeats	S_{250} (mJy, 5σ)	S_{24} (μ Jy, 95 per cent completeness)
A2218	$9' \times 9'$	248.98	66.22	2	2.5	N/A
GOODS-N	$30' \times 30'$	189.23	62.24	30	4.	50
LH-North	$35' \times 35'$	161.50	59.02	7	8.	80
FLS	$155' \times 135'$	258.97	59.39	2	12.5	400
LH-SWIRE	$218' \times 218'$	162.00	58.11	2	23.	200

3.2 Estimating the errors

As this is a linear system the Fisher information matrix can be seen to be

$$\mathcal{I} = \mathbf{A}^T \mathbf{N}_d^{-1} \mathbf{A} \leq \mathbf{N}_f^{-1}, \quad (5)$$

which, by the Cramér-Rao inequality, is the inverse of the lower limit of the covariance matrix of the source flux densities ($\mathbf{N}_f$). Thus the covariance matrix is simply the inverse of the matrix $\mathbf{A}^T \mathbf{N}_d^{-1} \mathbf{A}$ in Equation 4. Intuitively this makes sense, if there are no overlaps between the sources then $\mathcal{I}$ would be a diagonal matrix with each entry corresponding to $\mathbf{PRF}^T \mathbf{N}_d^{-1} \mathbf{PRF}$ i.e. $\sum PRF_i^2 / \langle \delta_i^2 \rangle$, where $\langle \delta_i^2 \rangle$ is again the noise in a pixel i .

While we can solve Equation 4 for the flux densities f via some fast iterative method, to get the variances we must invert $\mathcal{I}$ by ‘brute-force’. However, the matrix is positive symmetric and highly optimised inversion codes for this class of matrix exist. Here we invert the $\mathcal{I}$ directly using LAPACK/BLAS routines.

One drawback to this approach is that we will always be limited to the lower limit of the covariance matrix, given the inequality presented in Equation 5. One alternative would be to use Monte Carlo Markov Chain (MCMC) methods to fully map the posterior probability distribution, allowing the true variance to be properly characterised, as will be discussed in Section 9

3.3 Background or other source terms

We can consider other additive model contributions to the signal in an obvious way, by including extra terms in Equation 2 and calculating the matrix $\mathbf{A}$ accordingly, with the vector $\mathbf{f}$ then representing all the model parameters. For example a constant flat background would be a single extra element in the vector $\mathbf{f}$ with a corresponding row of (1, 1, 1, ..., 1) in the matrix $\mathbf{A}$. More complicated model backgrounds with more parameters can be included by adding extra terms to $\mathbf{f}$ and $\mathbf{A}$. The ability to do this is particularly useful for our application to *Herschel* SPIRE imaging, as some astronomical flux is lost when removing the telescope background in the map making process for SPIRE imaging.

4 OPTIMISING THE INPUT LIST

The linear technique should return the optimal solution for a complete input list, containing the precise position of ev-

ery source contributing flux to the map. In practice we can never have a precise input list, because some sources will be missing due to flux density limits or masking in the ancillary data while some sources we include may in fact be spurious or emit no flux at the wavelength under investigation. A further complication is that most sub-mm facilities such as *Herschel* are not designed as absolute flux measuring devices; the mean level is lost when removing the telescope background. Hence the zero point of the map does not correspond to zero flux density, but rather an unknown mean level, and the faintest sources will appear as fluctuations about this point.

These issues become problematic at high source density, as degenerate solutions to the linear problem become more common. To highlight this consider the most extreme case, using deep optical catalogues as an input to *Herschel* SPIRE imaging. The number density of optical sources with $B < 28$ is roughly 10^6 deg^{-2} (Furusawa et al. 2008); given that the SPIRE beam size at $250 \mu\text{m}$ is $\sim 3 \times 10^{-5} \text{ deg}^2$ the expected number of optical sources per SPIRE beam is ~ 30 . Of course not all of these are going to be luminous at $250 \mu\text{m}$ so we need some way of culling those sources which are too faint to be present in our maps.

There are two clear approaches to reducing the input list. One method would be to consider properties of the input list, such as the probability of chance alignment given the number density of sources of that flux density (e.g. Downes et al. 1986, Lilly et al. 1999) or the likelihood that a particular source would be sub-mm luminous given its multi-wavelengths properties (e.g. Pope et al. 2006, Yun et al. 2008, Roseboom et al. 2009).

An alternative is to let the sub-mm data discriminate. The matrix $\mathbf{A}$ in Equation 4 is essentially a model we are trying to fit to the data, with the number of free parameters equal to the number of input sources. However we need to consider the possibility there may be a better model which needs fewer free parameters (sources) to sufficiently describe the data. The use of model selection techniques such as this is common and often rely on criteria such as the Bayesian information criterion (BIC; Schwartz 1978) or the Akaike information criterion (AIC; Akaike 1974).

Both approaches have advantages at different angular scales. The first approach, which tries to calculate the probability of a chance superposition, is heavily biased towards bright counterparts, and ignores any possible correlations in the clustering at different wavelengths. However the latter approach of letting the data discriminate will not give good results for heavily blended sources (i.e., source separ-

ation much less than the beam FWHM). Thus we want an approach which will incorporate the best elements of both techniques, as detailed in the following sections.

4.1 Segmenting the map

The biggest problem with implementing any model selection approach to source detection and extraction is that in a naïve implementation the number of calculations required is 2^N , where N is the number of sources to be considered. Given that a typical 1 deg^2 map may contain many thousands of sources, some cost saving measures must be introduced. The first step is to segment the map into isolated regions in which sources may contribute significantly, but not affect other sources outside it. For this step we can reuse the Fisher information matrix calculated in Equation 4, $\mathcal{I} = A^T N^{-1} A$. The non-diagonal elements of $\mathcal{I}$, i, j for $j \neq i$, describe the fractional contributions the source j makes to the noise-weighted, PRF convolved flux density in the map at the position of source i , i.e. $\sum_j \mathcal{I}_{i,j} f_j = m_i$, where m_i is the flux density in a PRF convolved map at the position of source i , weighted by the pixel noise. Thus we isolate regions of blended sources by taking sources to be paired if

$$\mathcal{I}_{i,j} m_j > 1,$$

i.e. if the flux density contributed by one source to another is greater than the 1σ pixel noise.

One problem with this approach is that it assumes we already know the flux densities of the sources in the map. However, given that we are only trying to segment the map, it should suffice to use some initial estimate of the flux densities f . Here we choose to simply use the PRF convolved flux density at the position of source i , irrespective of its neighbouring sources, i.e. $f_0 = A^T N^{-1} d / \mathcal{I}_{\text{diag}}$ where only the diagonal elements of $\mathcal{I}$ are considered. In this framework f_0 can be recognised as the upper limits to the flux densities. Chains of connected sources are identified by starting at one source, and going through all the elements of its row in $\mathcal{I}$, grouping the connected sources. After this first step iterations of this same process are repeated on all the sources in the group, until the group does not continue to grow in size.

4.2 Using model selection for source detection

Once the map has been segmented into groups we can use model selection to decide which sources in each group are justified by the data. However, the number of calculations to be performed is still 2^N , where N is now the group size. As discussed above, in heavily confused images the number density of input sources could be as high as 10 per beam element, resulting in a very large number of calculations to be performed. As an alternative we adopt an iterative ‘top-down’ approach in which we jackknife the input list i.e. consider all the models which have $N - 1$ sources, and select the best model. The process is then repeated with $N - 2, N - 3, \dots, N - s$ sources, until a better model cannot be found. Models are compared using the Akaike Information Criteria, corrected for finite sample sizes (AICc);

$$\text{AICc} = 2k - 2 \ln(\mathcal{L}) + \frac{2k(k+1)}{n-k-1},$$

Where k is the number of parameters, $\mathcal{L}$ is the likelihood, and n is the total number of data points used in the fit. While the BIC could have been used, here we choose the AIC as it penalises extra parameters less harshly than the BIC. Since our parameters are actual known sources (as opposed to simply free parameters in a model) we have good reason to believe they should be included unless there is evidence to the contrary. For our source fitting $-2 \ln(\mathcal{L}) = \chi^2$ model so the AICc becomes:

$$\text{AICc} = \chi^2 + 2k + \frac{2k(k+1)}{n-k-1},$$

where χ^2 is calculated on the fit to the map segment. Since we are fitting in source space, n here is the original number of sources considered and in the first step $k = n$.

4.3 Weighting the input list

A number of well-established probabilistic approaches exist for weighting identifications of low resolution, sub-mm sources. We require something more, because the traditional techniques require a source detection stage, which is absent from our methodology. What we wish to know is the likelihood that a particular input source is luminous (or more practically, detectable) in the sub-mm band of interest. One way to do this would be to consider the existing full multi-wavelength dataset for each input source, and predict the sub-mm flux density and its variance from the full range of plausible SEDs. While this would in principle return the best results, implementation of such an approach would be difficult and give mixed success due to the heterogeneous nature of most multi-wavelength data sets.

A simpler alternative is to weight the models by how likely they would be to appear by chance, i.e. what is the likelihood that a source is a random superposition? This approach is analogous to the ‘ p statistic’ analysis (Downes et al. 1986); however, in our implementation we do not have positions for our sub-mm sources and hence cannot work out the probability of finding a counterpart within a given search radius and separation.

Since the AIC offers a relative comparison of models, the absolute likelihood here is not important, thus we introduce a more naïve, but useful, estimate of the probability of a chance alignment. For a given source i we calculate the probability ϕ_i of finding a source in the input catalogue with flux density F greater than the source under consideration F_i within an area of one beam element $A = \pi \text{FWHM}^2 / 4 \ln 2$:

$$\phi_i = M_{F > F_i} A.$$

Where $M_{F > f_{\text{in}}}$ is the number density of sources present in the input list with $F > F_i$. We add this probability to the model selection stage and hence the AICc calculated for each model becomes;

$$\text{AICc} = \chi^2 + 2k + 2 \times \ln \left(\sum \phi_i \right) + \frac{2k(k+1)}{n-k-1}$$

where the $\sum \phi_i$ runs over all of the sources which are assigned zero flux density via the model testing or the fitting process itself.

5 THE HERMES CROSS-IDENTIFICATION ALGORITHM

As HerMES will identify $> 200,000$ sources in the *Herschel* SPIRE bands across all of our survey fields (Oliver et al. 2010a), we need an algorithmic, machine-based, approach to producing cross-identifications (XIDs) across the many data sets present in our fields. To achieve this we utilise an implementation of the method described above. One of the key features of HerMES is that all of the planned survey fields contain existing *Spitzer* data from a range of legacy surveys. More importantly the tiered nature of HerMES is well matched to the variable quality of the *Spitzer* data, in particular the MIPS $24\mu\text{m}$ observations. This is highlighted by comparing the S_{250} and S_{24} sensitivities in Table 1. With the exception of FLS, all of the SDP observations have a limiting S_{250}/S_{24} colour of ~ 100 . Using a compilation of pre-*Herschel* empirical models (Fernandez-Conde et al. 2008; Le Borgne et al. 2009; Franceschini et al., in prep; Pearson et al., in prep; Valiante et al. 2010; Xu et al. 2001) we estimate that 0.4–24 per cent of $S_{250} > 1$ mJy sources have $S_{250}/S_{24} > 100$, with the majority of these (up to 70 per cent) lying in the range $1.2 < z < 1.6$ where the $24\mu\text{m}$ band is coincident with the $10\mu\text{m}$ silicate feature present in strong absorption in typical starburst galaxies.

It is also clear from existing measurements of the cosmic IR background (CIRB) from BLAST (Devlin et al. 2009) that sources already detected at $24\mu\text{m}$ with *Spitzer* are the dominant contributor at these wavelengths. In particular, Pascale et al. (2009) show that greater than 90 per cent of the CIRB at BLAST/SPIRE wavelengths can be accounted for by $24\mu\text{m}$ sources with $S_{24} \geq 100\mu\text{Jy}$. Hence we can be confident that using the $24\mu\text{m}$ source lists as a model for the positions of sources in the SPIRE maps is appropriate. It is also worth considering that in the deepest fields (i.e. GOODS-N) the source density of $24\mu\text{m}$ sources is $\sim 24,000\text{ deg}^{-2}$, or ~ 2 SPIRE $250\mu\text{m}$ beam elements per source. Thus even recovering the SPIRE fluxes for the detected $24\mu\text{m}$ sources, involves going significantly beyond the confusion limit.

The full algorithm used to produce the XID catalogue for the SDP observations is described below. While it would be possible to include Gaussian priors on the SPIRE flux densities, at this stage we do not understand the SEDs of our SPIRE sources well enough to accurately predict the range of SPIRE flux densities from the existing *Spitzer* and short wavelength data (i.e. Rowan-Robinson et al. 2010). Hence only the simple non-negative flux density prior, $S_{\text{SPIRE}} \geq 0$, has been implemented. This is achieved by using the Bounded Variable Least Squares (BVLS) algorithm described by Stark & Parker (1995) to perform the matrix inversion.

It should be noted that this algorithm has been developed in parallel with the other data reduction techniques (i.e. Smith et al. 2010; Levenson et al. 2010) for use in the first SDP science papers from HerMES. Thus while this approach has proven to give the best performance under testing, it is clear that several aspects could be easily improved. However, to maintain consistency with the results presented in other HerMES SDP papers we only consider our original algorithm in the following. A description of problematic as-

pects of this approach, and how they may be improved in future applications, is presented in Section 9.

5.1 Step-by-step description of HerMES XID algorithm

For the $250\mu\text{m}$ band we follow these specific steps:

1) Produce input list from available $24\mu\text{m}$ source catalogues. Sources are considered if they are detected at 5σ in the MIPS $24\mu\text{m}$ imaging, and if they are above a given flux density limit: $20\mu\text{Jy}$ for GOODS-N, $50\mu\text{Jy}$ for LH-North, and $200\mu\text{Jy}$ for FLS and LH-SWIRE

2) Calculate the matrices needed for the inversion method using the input list, PRF model, and SPIRE $250\mu\text{m}$ map and variance (i.e. $\mathbf{A}$, $\mathbf{N}$ and $\mathbf{d}$ from Equation 4).

3) Generate the matrix $\mathcal{I} = \mathbf{A}^T \mathbf{N}^{-1} \mathbf{A}$ and $\mathbf{m} = \mathbf{A}^T \mathbf{N}^{-1} \mathbf{d}$.

4) Segment the map using information contained in $\mathcal{I}$ and $\mathbf{m}$. Segments are produced by weighing the contribution from source blending against the instrumental noise, as described in Section 4.1. In practice this method produces segments too large to be solved in a reasonable time, thus we add an extra factor, Δ_d , to the instrumental noise in quadrature. For the catalogues described here, $\Delta_d = 1$ mJy in all cases. Thus sources are segmented into groupings where no external sources contribute more than $(\sigma_{\text{inst}}^2 + \Delta_d^2)^{1/2}$ to any given source within the segment. In practice this extra term is thought to be less than the errors introduced by the unknown background (2–3 mJy), and the incompleteness of the input list, characterised by the surface brightness of sources undetected at $24\mu\text{m}$ (2–3 mJy/beam, predicted by FC08 mocks) and hence has a negligible effect on the quality of the output catalogues. A given source is allocated to exactly one segment, such that the algorithm returns a single estimate of the flux density for each input object. Typical segments are 10–50 sources in size for our deepest fields, with a maximum size of ~ 200 .

5) For each segment:

5.1) Build the smaller $\mathcal{I}'$ and $\mathbf{m}'$ for this segment from $\mathcal{I}$ and $\mathbf{m}$.

5.2) Build the noise weighted mini-map of the segment region $\mathbf{d}' = \mathbf{dN}^{-1}$.

5.2) Add a local flat background under the segment to $\mathcal{I}'$ and $\mathbf{m}'$. The response of the background is taken to be $1/M'_{\text{src}}$, where M'_{src} is the number of sources in the segment. It is necessary to fit this background to recover some of the astronomical flux lost to the telescope background in the map-making process. Note that we do not allow this parameter to be removed by the model selection stage.

5.3) Solve $\mathcal{I}' \mathbf{f}' = \mathbf{m}'$ for source flux densities $\mathbf{f}'$ using BVLS.

5.4) Calculate the initial χ^2 and AICc from the solution in 5.3 and mini-map $\mathbf{d}'$.

5.5) Iteratively search for the minimum AICc, starting with $i = 1$:

5.5.1) Fit the segment with all $M'_{\text{src}} - i$ combinations;

5.5.2) Measure χ^2 and AICc values for each combination;

5.5.3) From the set of $M'_{\text{src}} - i$ AICc values, identify the minimum;

5.5.4) If $\min[\text{AICc}(M'_{\text{src}} - i)] < \min[\text{AICc}(M'_{\text{src}} - i + 1)]$

then remove the source corresponding to that model from consideration, increment i , and go to step 5.5.1. Otherwise go to step 5.6.

5.6) Calculate the lower limit to the covariance matrix for the sources in this segment by directly inverting $\mathcal{I}'$ using LAPACK/BLAS routines. $\mathcal{I}'$ at this stage contains only the sources which have not been removed by the model selection stage (5.5).

5.7) Use the covariance matrix to find the maximum absolute value of the Pearson correlation coefficient² for sources in the segment. This can be used later to identify heavily blended sources which cannot be recovered by this method.

6) Write out the measured quantities (flux density, error, background for each segment, χ^2 and correlation).

5.2 Initial results from processing HerMES observations

The HerMES XID algorithm has been used to produce catalogues in each of the SDP fields, with the exception of Abell 2218. The typical fraction of sources removed by the model selection stage is 20–40 per cent, although this is strongly dependent on the depth of the 24 μm input list. Rare cases do occur where all sources are retained or only 1 source is retained in a segment. To illustrate this, in the GOODS-N field 47 per cent of input sources are rejected by the model selection. These sources have a median 24 μm flux density of 64 μJy while only 5 per cent have a 24 μm flux density greater than 150 μJy . By contrast, 21 per cent of the input sources in LH-SWIRE are rejected, with a median 24 μm flux density of 260 μJy and 5 per cent being greater than 700 μJy .

In order to achieve consistency between the 3 SPIRE bands we only carry out the model selection stage of the algorithm for the 250 μm band. An alternative approach, where all three SPIRE bands are treated independently, was initially considered, but found to give poor results. In particular the increase in beam size from 250 to 350 to 500 μm results in a decreased ability to deblend at long wavelengths and a preference to retain fewer sources. This naturally leads to inconsistencies between the measurements in the different bands. Thus it was decided to use the 250 μm results to determine which sources were indeed present at the SPIRE bands. One downfall of this approach is that some faint sources will be missed, where the observed-frame SED peaks longward of 250 μm . However, it was decided that these 250 μm faint sources would be too hard to recover reliably at this stage. Again we can use the pre-*Herschel* mock catalogues of Fernandez-Conde et al. (2008) to estimate the number of 350 and 500 μm sources missed by this requirement. Assuming a uniform sensitivity across the SPIRE bands, and the depth of the deepest field considered here (GOODS-N; 4 mJy), the number of sources the additional incompleteness due to requiring a detection at 250 μm is only 0.5 per cent. However it is clear that this estimate is highly dependant on the range of SEDs used in the Fernandez-Conde et al. models.

Ideally the model selection would be performed over

all three bands concurrently, such that evidence in any one band for a particular source would cause it to be preferred by the model. However, it was not possible to implement this approach in time for the SDP papers.

Of course even with these additions we are still limited to those sources which are detected at 24 μm . An additional step to find entirely new sources in the residual maps, using the AICc to determine their significance, would rectify this. Again it was not possible to implement such a feature in time for the SDP papers.

For the 350 and 500 μm bands only sources which are found to have $S_{250} > 1\sigma$ are considered. The flux densities for the 350 and 500 μm sources are then measured using steps 1–5.4 and 6 only.

XID catalogues have been produced in this way for the SDP fields described in Table 1. As an input to the algorithm we take the 24 μm source catalogues described in Section 2 and the known PRF. Testing on bright point sources has shown that the PRF can be adequately described as a 2D Gaussian with FWHM=18.15, 25.15 and 36.3 arcsec, for the 250, 350 and 500 μm bands, respectively.

While the input source list is defined by the 24 μm flux density limits, we use source positions from *Spitzer* IRAC 3.6 μm imaging where there is deep co-incident data and previous associations between the two data sets have been made. This occurs in all of our fields, with the exception of LH-North, and the wider area of HDF-N. The IRAC positional accuracy is typically ~ 0.2 arcsec (as opposed to ~ 1 arcsec for 24 μm) and hence using these eliminates any error in the flux density solutions introduced by astrometric errors.

The resulting HerMES XID catalogues contain the complete input 24 μm source catalogue, as well as any previously associated data sets at other wavelengths (see Vaccari et al. 2010, in prep.), as well as the best estimate of the SPIRE flux density for each 24 μm source passing our input selection criteria.

In addition to the flux density and error in each band for each input 24 μm source, the SPIRE component of the XID catalogues contain a number of extra columns describing diagnostics of the fitting process and local source confusion. These extra measures include:

- Maximum absolute value of the Pearson correlation coefficient calculated on the covariance matrix of the flux density solution (hereafter referred to as ρ).
- χ^2 of the source solution in the neighbourhood of source (7 pixel radius).
- The background level estimated in the fitting.
- The number of sources in the segment containing this source.
- The ID number of the segment.
- The PRF-smoothed flux density at the position of this source, ignoring contributions from neighbouring sources and the background.
- The number of 24 μm sources within a radius of the FWHM with greater than 50 per cent of the flux density of this source.
- The ‘purity’ of the SPIRE flux density, based on the ratio of this source’s 24 μm flux density to the 24 μm flux density smoothed with the SPIRE PRF at this position (see Brisbin et al. 2010).

² Pearson correlation coefficient is: $r = \text{cov}_{i,j} / \sigma_i \sigma_j$

The reason for including these extra columns is to enable samples of varying quality to be extracted from the XID catalogues based on differing scientific requirements. From an early assessment of the XID algorithm performance the recommended quality cuts for typical science applications were:

- $S_\lambda > 5 \times \Delta S_\lambda$;
- $\rho < 0.8$;
- $\chi^2 < 5$.

Given the more detailed analysis presented below, these cuts have proven to return very reliable samples, although possibly at the expense of completeness. Hence they represent fairly conservative guidelines for the use of the XID catalogues.

6 TESTING ON SIMULATIONS

To quantify the effectiveness of these new techniques we consider simulated SPIRE images. Here we consider two simulated cases: a ‘deep’ map, where $\sigma_{\text{conf}} \gg \sigma_{\text{inst}}$; and a ‘shallow’ map where $\sigma_{\text{inst}} \geq \sigma_{\text{conf}}$. In each case we simulate a $2.2^\circ \times 2.2^\circ$ patch of sky in all three SPIRE bands, taking the mock catalogues of Fernandez-Conde et al. (2008, henceforth FC08) as an input. While many mock catalogues exist at these wavelengths, the FC08 mocks were found to give the best match to the observed confusion noise and source colours in real SPIRE data. One key feature of the FC08 mock catalogues is that they incorporate a prescription for the clustering of sources (albeit flux and SED independent). This characteristic is of particular importance as the clustering introduces correlations between the resolved sources and the confusing background of the sort present in the real data. Additionally the FC08 mocks incorporate a semi-realistic range of SED types, and their evolution, based on a combination of detailed modelling of local sources, and constraints placed by pre-*Herschel* number counts at *Spitzer*, *ISO* and SCUBA wavelengths.

Simulated maps are produced from the positions and flux densities quoted in the mock catalogues by first making noise-free maps in each band, using the known SPIRE PRF parameters. Secondly, Gaussian noise and a flat background are added. To give the best possible correspondence to the real observations, this second step is repeated, varying the Gaussian noise and background, until the best match to the $P(D)$ in the observed SPIRE maps is found. For the deep scenario we match the observations in our GOODS-N observations, while for the shallow simulation we match to observations in LH-SWIRE. Given the confusion noise at SPIRE bands is known to be $\sim 5\text{--}7$ mJy (Nguyen et al. 2010, Smith et al. 2010), these scenarios represent the confusion-noise-dominated, and instrument-noise-dominated cases, respectively.

Figure 1 compares the $P(D)$ distributions for HerMES SPIRE observations in GOODS-N and LH-SWIRE to corresponding simulations. Table 2 lists the background and Gaussian noise added to each pixel in the simulated map in order to match the observations.

A mock $24\mu\text{m}$ input catalogue is produced by cutting the FC08 simulation at a level representative of the quality of the $24\mu\text{m}$ data in our observed fields: $S_{24} > 50\mu\text{Jy}$

Table 2. Details of simulation parameters

	Band (μm)	FWHM (arcsec)	Noise (mJy beam $^{-1}$)	Background (mJy beam $^{-1}$)
Deep	250	18.15	2.	6.5
Deep	350	25.15	1.1	10.9
Deep	500	36.3	2.7	14.7
Shallow	250	18.15	9.	7.1
Shallow	350	25.15	7.5	11.9
Shallow	500	36.3	11.1	15.7

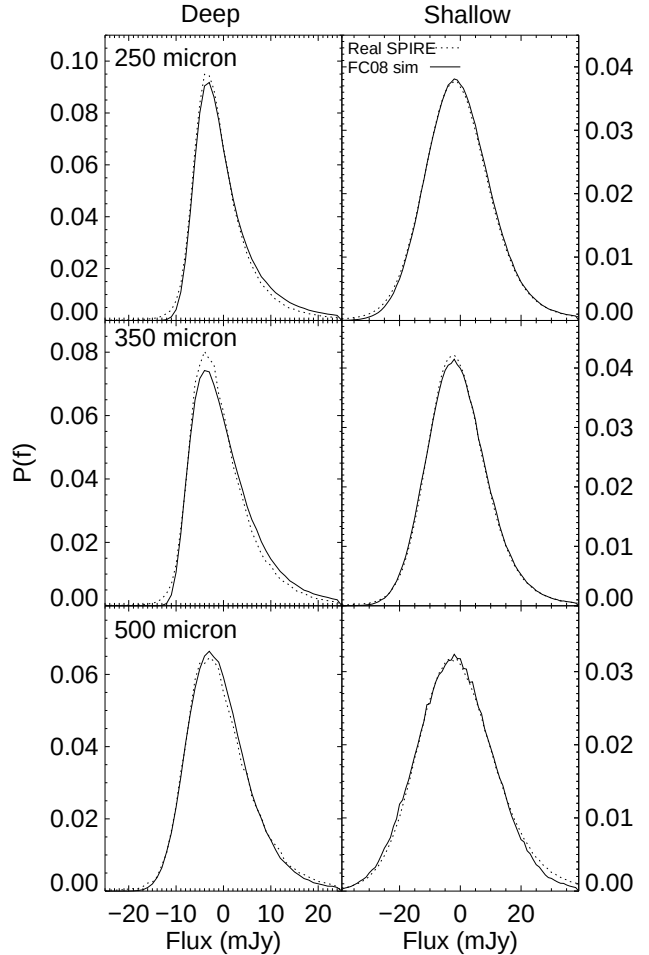


Figure 1. Normalised distribution of intensity values in each pixel ($P(D)$) for the SPIRE observations in GOODS-N (left; dashed), LH-SWIRE (right; dashed) and our deep and shallow simulated maps (left and right respectively; solid lines), based on Fernandez-Conde et al. (2008).

for the deep simulation, and $S_{24} > 200\mu\text{Jy}$ for the shallow simulation. In addition to these flux density limits some realistic limitations on source confusion in $24\mu\text{m}$ detected source lists are imposed. As the beam size of MIPS $24\mu\text{m}$ imaging is 6 arcsec very few sources appear with separations of < 3 arcsec, and those which do quite often turn out to be unreliable. Thus mock source pairs which are separated by less than half of the *Spitzer* MIPS $24\mu\text{m}$ beam (3 arcsec) are filtered, with preference given to the brighter source. Ad-

ditionally, sources within the Airy profile of bright $24\mu\text{m}$ sources are also removed. The first Airy ring of the MIPS $24\mu\text{m}$ PRF has a peak level of ~ 10 per cent of the peak of the PRF³. Hence we filter pairs of sources on the scale of 8 arcsec, with flux density ratios of greater than 10, again giving preference to the brighter source.

Simulated XID catalogues are produced using the HerMES XID algorithm outlined above (hereafter referred to as Method A). We compare our approach with two previously adopted XID methods for far-IR datasets using the same simulations: A catalogue-space method, using a combination of the Sussextractor algorithm and p -statistic matching (Method B), and a variant of existing linear inversion methods, based on that presented in Béthermin et al. (2010) (Method C). For method C we filter pairs in the $24\mu\text{m}$ input catalogue at separations of less than 20 arcsec, giving preference to the brighter source at $24\mu\text{m}$, as per Béthermin et al. (2010). In addition for method C we make use of a conjugate gradient method with no flux density priors to perform the inversion, as opposed to the BVLS method with a non-negative prior described above.

The performance of source extraction and cross-identification methods are typically characterised by two metrics: the completeness, i.e. the fraction of sources recovered at a given flux density; and the reliability or mis-ID rate. While the notion of completeness translates well to the methods presented here, reliability is not an intuitively useful quantity when performing XIDs in the map-space. We know (or assume) that all of our $24\mu\text{m}$ sources are reliable; the aim is solely to accurately measure their flux densities at other wavelengths. Thus the second metric by which we judge our XID methods is flux density accuracy.

In constructing the simulated catalogues for all three methods we need to make some XID and flux density quality cuts.

For the method A we select all sources from the output catalogues. Additionally we define a second sample using the $\chi^2 < 5$ and $\rho < 0.8$ selection thresholds described in Section 5. To emphasise the effect these additional cuts have on the completeness and flux density accuracy we denote the use of these additional quality cuts Method A'.

For method B we take all sources in the Sussextractor output lists and try to find matches in the mock $24\mu\text{m}$ catalogue within a search radius of 10 arcsec, 14 arcsec and 20 arcsec for the three SPIRE bands, respectively. For all sources within the search radius we calculate the p -statistic of the match using the formula of Downes et al. (1986), taking those with $p < 0.1$ to be possible counterparts. Cases are excluded where there are multiple counterparts with $p < 0.1$ for a single detected source.

For method C we take all sources in the output catalogue.

Figures 2 and 3 present the completeness and flux density accuracy for the three methods. In both Figures completeness is defined as the fraction of sources in the output catalogues recovered at 5σ significance and satisfying the above conditions, to the total number of sources in the original FC08 mocks. By contrast the flux density accuracy is measured across all recovered sources, irregardless of signif-

icance, although it should be noted that for a source to appear in the Sussextractor list it must be detected by that algorithm at $> 3\sigma$. A summary of the key statistics is also presented in Table 3. Both map-based methods (A and C) have higher completeness at faint flux densities at all wavelengths. It should be noted that for the method B it is the requirement that an ID be 'secure' that forces the completeness to be low. As shown in Smith et al. (2010), the completeness of the Sussextractor-alone catalogues is comparable to that achieved by the HerMES XID algorithm (method A). In the deep simulations, the $\rho < 0.8$ cut imposed in method A' has a similarly dramatic effect on completeness in the 350 and $500\mu\text{m}$ bands. This is primarily due to the lower resolution and $250\mu\text{m}$ -based input list used in the longer wavelength bands. As no model selection stage is performed on the 350 and $500\mu\text{m}$ images we are attempting to fit more sources than can be resolved in the map, leading to strong degeneracies between close pairs. This is understandable, as the typical separation between input sources to the 350 and $500\mu\text{m}$ map is 1.5 and 1 pixel (15 arcsec), respectively. It should be noted that similar degeneracies in the simple linear inversion are removed by the initial spatial filtering of the input list.

The completeness of the method A (and A') is not consistently better than the other methods; which can even be superior at bright flux densities in the long wavelength bands. However, the flux density accuracy of the HerMES XID algorithm is consistently better. This is most striking in the deep simulation, where the flux density accuracy of the method A, and in particular method A', is not only better, but has significantly fewer sources which have been boosted to erroneously high flux densities.

Another feature which is clear from Figures 2 and 3 is that the mean flux density error is always negative for the linear methods, i.e. method A and C systematically underestimate the flux density of sources. The mean $S_{\text{obs}} - S_{\text{true}}$ for each method and simulation is given in Table 3. The origin of these negative offsets can be attributed to fact the maps have a mean of zero, whereas we know that there is an unresolved background of sources contributing to each pixel (or beam) in the maps. For traditional source detection and extraction methods this is preferable, as fluctuations in the confusing background appear as quasi-symmetric noise about zero, and hence can be treated as another pseudo-Gaussian noise term.

However for our Method A and C the number density of our input list is much higher than could not be identified in the map blindly. Hence we are attempting to 'resolve' some of the confusing background, which is made up from the contributions of many faint unresolved sources, into source flux. This is why this feature does not appear in the results for Method B. While the local background fitting added to Method A goes some ways to alleviating this it is clear that this approach is not completely effective. The other two methods (B and C) do not consider any non-zero background. Simultaneously fitting a solid background under the entire map would almost certainly resolve this issue, however it is not computationally feasible to solve for more than a few hundred sources at once, and hence this is not currently possible. An alternative is to iteratively solve for the background, i.e. fit, and remove, all the known sources in the map (considering no background) and then calculate the

³ see <http://ssc.spitzer.caltech.edu/mips/mipsinstrumenthandbook>

Table 4. Best fit Gaussian parameters to the normalised flux density error distributions shown in Figure 4 and equivalent distributions for the shallow simulation. All measurements in units of the estimated error $\sigma_{\text{catalogue}}$

Deep Simulation						
	250 μm		350 μm		500 μm	
	mean	σ	mean	σ	mean	σ
Method A	-4.1	2.5	-4.6	4.8	-4.1	1.1
Method A'	-4.3	2.5	-5.2	5.1	-4.1	1
Method B	-5.3	5.5	-2.2	17	-0.5	6.
Method C	-8	4.1	-9.4	10.1	-4.2	4.4
Shallow Simulation						
Method A	-1.3	1.8	-1.6	1.8	-1.5	1.5
Method A'	-1.3	1.8	-1.6	1.8	-1.5	1.5
Method B	-1	1.9	-0.6	2.5	-0.3	1.6
Method C	-1.7	1.8	-1.8	2.1	-1.5	1.7

mean of the residual map. After one pass this will not give an accurate estimate of the true background, as the source flux densities will be underestimated and hence some flux will remain from known sources. However if we repeat this process a number of times, until the mean of the residual map converges, this will give an accurate estimate of the background due to unknown confusing sources. An approach similar to this will likely be used in the next iteration of the HerMES XID algorithm.

While high flux density accuracy and completeness are a key aim for any XID method, it is also vital that our proposed method return reliable estimates of the flux density error, as for real applications we will not have knowledge of the true flux density of our sources. In Figure 4 we show the distribution of observed flux density error (i.e. $S_{\text{obs}} - S_{\text{true}}$), normalised by the error estimated by the photometric pipeline for the deep simulation. The first obvious feature of these distributions, as previously discussed in reference to Figures 2 and 3, is that the peak in flux density error distribution is always negative. One side-effect of this systematic negative offset is that it makes the definition of the catastrophic failure rate problematic, if we simply take the number of sources which have $\text{abs}[S_{\text{obs}} - S_{\text{true}}]$, greater than $3\sigma_{\text{catalogue}}$ then a very large fraction of sources will be considered failures. Thus we take an alternative approach, as we ultimately want to treat our flux densities errors as Gaussian, it makes sense to fit the distributions shown in Figure 4 with a Gaussian, considering the amplitude, mean and sigma as free parameters. Table 4 describes the parameters of the best fit Gaussian to each of the distributions shown in Figure 4.

It is clear that for deep observations the quoted catalogue error from the HerMES XID method (Method A) underestimates the true error by a factor of at worst ~ 5 . This is consistent with the values quoted in Table 3, as the typical catalogue error estimated for the deep simulated catalogues is 0.9, 0.7 and 1.5 mJy for the 250, 350 and 500 μm bands, respectively. Fortunately the situation is much better once we reach the level of the shallow simulations, where the catalogue errors are consistently within a factor of 2 of the true error. The underlying reason for this discrepancy

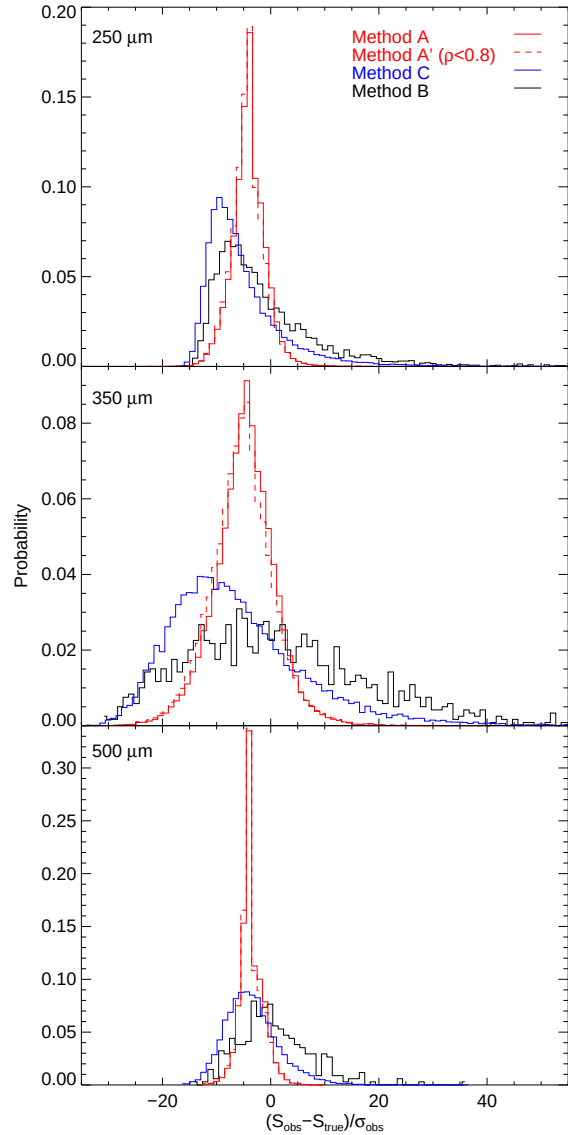


Figure 4. Distribution of observed flux density error, normalised by $\sigma_{\text{catalogue}}$, for the deep simulation.

between the true errors and those estimated from the data alone is not completely clear. One possible origin is erroneous fluctuations in the background, which could be eliminated by requiring a smooth background across the entire image, rather than fitting local backgrounds. Another factor will be the incompleteness of the input lists, due to the 24 μm flux limit. One puzzling feature is the large variation between the bands. It is worth noting that this variation is quite similar to the variation in input Gaussian noise to the simulations, as quoted in Table 2. This is suggestive of a hard limit to the flux density error, either from the factors listed above, or simply noise introduced from the deblending of confused faint sources.

One thing which is clear is that the other potential XID methods are significantly worse at accurately estimating the flux density error. While Method A shows a very Gaussian

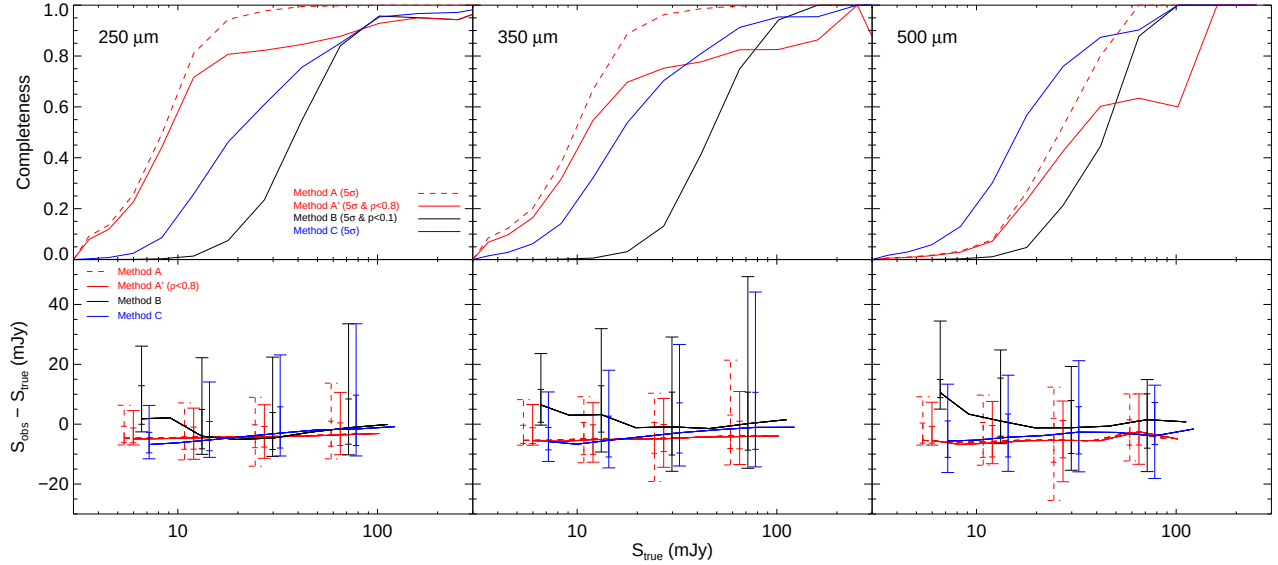


Figure 2. Deep simulation results for completeness (top) and flux density error (bottom). Completeness is for $5\sigma_{\text{catalogue}}$ sources only, while flux density error is measured for all objects in the resulting catalogues, regardless of significance. Results are shown for the three SPIRE bands; 250 μm (left), 350 μm (middle) and 500 μm (right) and the three XID algorithms considered: Method A (HerMES XID algorithm; red dashed line); Method A' (HerMES XID algorithm with $\rho < 0.8$ quality cut; red solid line); Method B (Sussex+ p -stat; black); Method C (simple linear inversion method; blue). Lines in bottom panel represent the median flux density error for each band/method, while the error bars are the 1σ and 3σ variation. Both map based, linear inversion methods (methods A and C) are seen to outperform the catalogue based method at faint flux densities. The low completeness of the HerMES XID algorithm at 350 and 500 μm can be attributed to the $\rho < 0.8$ cut.

Table 3. Summary of completeness and flux density accuracy for XID methods. In measuring the completeness we consider only sources which are detected at $5\sigma_{\text{catalogue}}$ and pass the quality control thresholds discussed in the text. For the flux density accuracy all sources which are returned by each method are considered. All values in mJy. Catastrophic failures are defined as those that are outside of the 3σ range of the best fit Gaussian to the distributions shown in Figure 4.

Deep Simulation, 24 $\mu\text{m} > 50\mu\text{Jy}$												
	$\langle S_{\text{obs}} - S_{\text{true}} \rangle$ (mJy)			RMS (3σ clipped; mJy)			Catastrophic failure rate (per cent)			Completeness ($S_{\lambda}[50 \text{ per cent}]; \text{mJy}$)		
	250 μm	350 μm	500 μm	250 μm	350 μm	500 μm	250 μm	350 μm	500 μm	250 μm	350 μm	500 μm
Method A (HerMES)	-3.1	-2.9	-1.8	4.9	5.4	6.5	2.4	2.2	9.6	10.8	9.8	26.3
Method A' (HerMES, $\rho < 0.8, \chi^2 < 5$)	-3.3	-3.1	-2.	4.65	4.9	6.8	2.9	2.1	12.9	11.2	11.3	33.3
Method B (SSX+ p -stat)	-0.7	1.4	1.7	7.5	9.8	9.1	9.6	2.1	1.5	39.6	47.7	44.7
Method C (Linear Inversion)	-4.3	-3.4	-3.4	6.3	6.8	7.8	9.5	3.7	2.0	20.3	16.8	16.4
Shallow Simulation, 24 $\mu\text{m} > 200\mu\text{Jy}$												
Method A (HerMES)	-3.8	-4.2	-2.4	10.1	10.8	14.5	2.2	2.5	2.2	24.5	26.4	38.4
Method A' (HerMES, $\rho < 0.8, \chi^2 < 5$)	-3.8	-4.3	-2.5	9.25	10.3	14.4	2.1.	2.5	2.1	24.5	26.5	38.6
Method B (SSX+ p -stat)	0.4	1.5	3.2	9.1	10.7	12.3	3.6	3.8	3.7	42.	46.8	53.
Method C (Linear Inversion)	-2.9	-4.2	-4.9	9.	10.7	15.8	2.1	4.4	2.1	28.7	27.4	34.5

distribution of normalised flux densities errors, the other methods have a long tail to very large values. To quantify this we define the catastrophic failure rate as the fraction of sources which appear at $\text{abs}[S_{\text{obs}} - S_{\text{true}}] > 3 \times \sigma_{\text{fit}}$, where σ_{fit} is the best fit value derived for a specific SPIRE band and method in Table 4. At 250 μm it is clear that Method A returns a highly Gaussian error distribution, with only ~ 2 per cent falling outside the $3\sigma_{\text{fit}}$ range. The other methods have a much higher catastrophic failure rate at 250 μm , approaching ~ 10 per cent. At the other SPIRE bands, the 350 μm distributions are well described by a Gaussian for all methods, but at 500 μm it appears that there are a signifi-

cant fraction of catastrophic failures produced by Method A. While these failures are still quite reliable compared to the very large errors returned by the other methods, it is worth commenting on this non-Gaussian element to the distribution. This is likely an artifact of the model selection being performed at 250 μm only, as high redshift 500 μm ‘peaking’ sources will appear faintly in the 250 μm maps and hence are likely to be missing from the input list at 250 μm . In these cases the 500 μm flux will be erroneously assigned to the neighbouring 250 μm bright source.

Interestingly the flux density errors for Method A and A' are in good agreement with the measured confusion noise

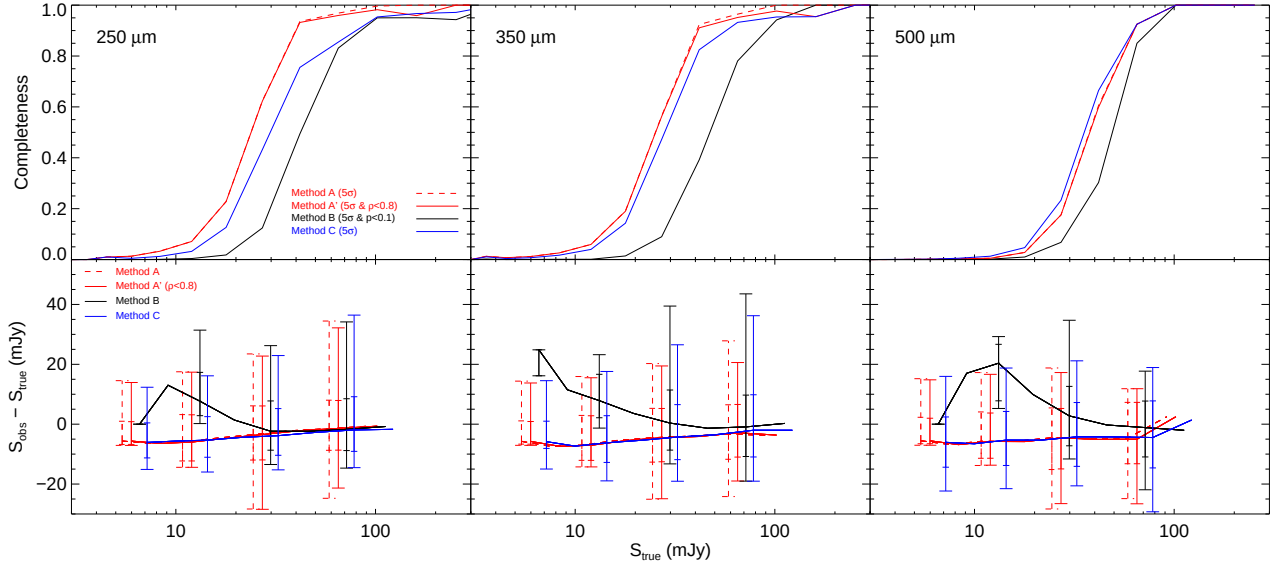


Figure 3. Shallow simulation results for completeness (top) and flux density error (bottom). Completeness is for $5\sigma_{\text{catalogue}}$ sources only, while flux density error is measured for all objects in the resulting catalogues, regardless of significance. Lines as per Figure 2. Again both map based, linear inversion methods (methods A and C) are seen to outperform the catalogue based method at faint flux densities.

limit from Nguyen et al. (2010). Thus it is clear that our method is able to probe flux densities close to, if not below, the confusion noise. This is particularly noteworthy when considering that the systematic negative offset in the flux densities, due to issues with the background fitting, is a large contributor to this noise.

As one of the key science goals of SPIRE surveys will be investigations of far-IR SEDs and their evolution, we need to understand not only the quality of the monochromatic SPIRE flux densities, but also any correlations between the bands. To investigate this in our simulated data set we look for correlated errors in the flux density accuracy of the deep simulation results.

Figure 5 shows the relationship between the flux density error ($S_{\text{obs}} - S_{\text{true}}$) in the three bands for the deep simulations. It is clear that the flux density errors show a strong linear correlation. Quantifying these correlations with the Pearson correlation coefficient (r) shows that the 250 to 350 μm and 350 to 500 μm flux density errors are strongly correlated ($r \sim 0.8$), while the 250 to 500 μm flux density errors show somewhat weaker correlations ($r = 0.5$). Performing similar tests on the shallow simulation and other XID methods gives similarly strong correlations.

Although the peculiarities of the XID algorithms could be partially responsible for these correlations, the underlying origin must be the effect of unknown, or poorly deblended, close neighbours. While our method is designed to optimally deblend sources in the input list, this can never be perfectly achieved without perfect input lists. Given this it is unlikely that modifications can be made to the XID algorithm to remove these correlations. One thing to note is that the correlations are dependent not only on the areal density of sources, but also on the far-IR colours. Since the FC08 mock skies include only a limited range of SED types and SED/flux density independent clustering it is reason-

able to assume that the amplitude of these correlations will be weaker in the real data.

Finally, while in the simulations described above the input positions here have no astrometric errors in real applications the input lists and SPIRE images will have errors on the order of $\sim 0.1 - 0.5$ arcsec. Thus it is worth considering the effects of astrometric distortions on our simulated dataset. To achieve this normally distributed random astrometric errors are added to the input positions and the XID process repeated. Here we only consider the HerMES XID algorithm (Method A). Figure 6 shows the result of adding errors on the scale of 0.1–10 arcsec to our input list. It can be seen that the accuracy of the flux density estimates is insensitive to astrometric errors of $< 1 - 2$ arcsec.

7 TESTING ON REAL DATA

While it is useful to assess the completeness and flux density accuracy of our method on totally artificial maps, we can also calculate these metrics for the real data by injection of mock sources into our observed maps. This has the advantage of reproducing the true noise properties of the data, as well as highlighting the confusion noise in the presence of angular clustering.

As our maps are already heavily affected by confusion, we only inject one source at a time into the map, and then run the XID source extraction algorithm, taking the input position of the mock source and the neighbouring 24 μm sources into account. For each SDP field we inject mock sources with flux densities in the range 3–200 mJy at random positions. Test positions outside of the 24 μm coverage are not considered. To maintain consistency with the properties of the real 24 μm input catalogues, test positions within 3 arcsec of an existing 24 μm source are also excluded, as was

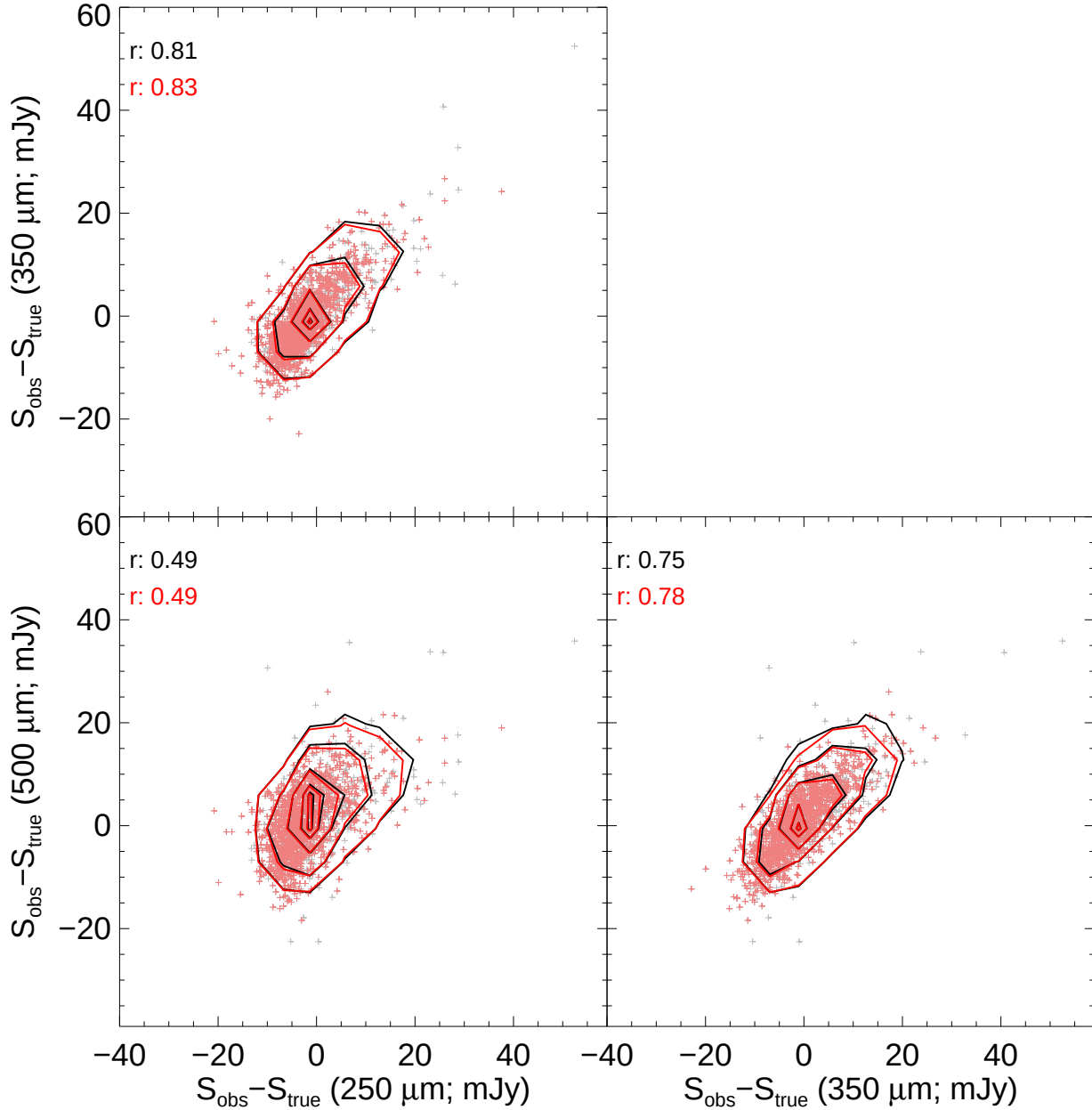


Figure 5. Correlations in the flux density errors found in the deep simulations. All 5σ sources are shown in grey (black contours), while those sources that also have $\rho < 0.8$ are shown in pink (red contours). The Pearson correlation coefficient (r) is quoted in the top left corner of each panel.

done with the fully artificial simulations. As a result the total number of test positions is ~ 3000 – 5000 per field, with 300–500 per test flux density. Figure 7 shows the completeness and flux accuracy determined by this method.

It can be seen that the completeness never reaches 100 per cent in any field. The values rise sharply from faint flux densities and then plateau at a quasi-constant value above a certain flux density level. This is due to the effect of the $\rho < 0.8$ criteria. Somewhat counter-intuitively, this is a bigger problem in the fields with deeper SPIRE/MIPS $24\mu\text{m}$ data.

The reason for this is simple; the input source density is much higher in the deep fields and, as we assume no prior on the SPIRE flux density, this affects all flux densities equally. If the $\rho < 0.8$ criteria is removed the residual ~ 20 – 50 per cent incompleteness in the deep fields is recovered, but at the expense of flux density accuracy. For sources with $\rho < 0.8$ in the GOODS-N field the 1σ flux density error is 4.24, 5.23 and 5.64 mJy for the 250, 350 and $500\mu\text{m}$ bands, respectively. For sources with $\rho > 0.8$ the comparable values are 6.3, 5.9, and 6.9 mJy, an increase of ~ 10 – 50 per cent.

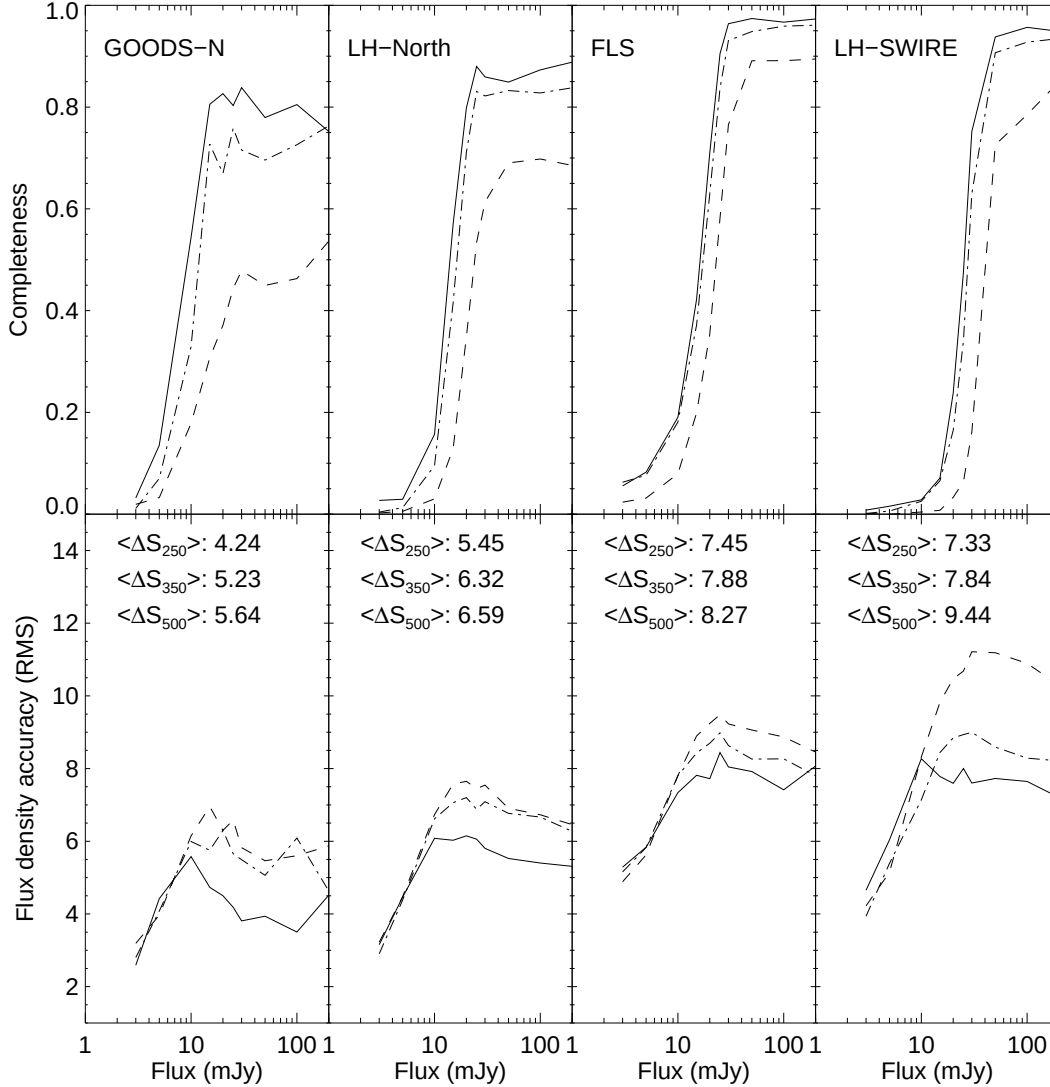


Figure 7. Completeness (top) and flux density accuracy (bottom) determined by injection of mock sources into our observed maps. The completeness is defined as the ratio of the number of sources recovered at $> 5\sigma$ and $\rho < 0.8$ to the number of input positions. Flux density accuracy is defined as the RMS of the input-output flux density. In calculating the recovered flux density accuracy all input positions recovered with $\rho < 0.8$ are considered. Sources are injected one at a time so as to avoid increasing the source confusion. In each panel the results for the $250\ \mu\text{m}$ (solid line), $350\ \mu\text{m}$ (dot-dashed line) and $500\ \mu\text{m}$ (dashed line) bands are shown. Mean flux density error for each band is shown in the top right corner of each of the lower panels.

Encouragingly, the completeness and flux density accuracy derived from source injection agrees reasonably well with the numbers for comparable simulations (Table 3). Two small exceptions to this are the completeness at $500\ \mu\text{m}$ in the deep simulation/GOODS-N and the error in the $500\ \mu\text{m}$ flux density in the shallow simulation/Lockman-SWIRE. In the first instance the observed completeness in the real maps is slightly lower than that found in the simulations. The origin of this is not clear, but it is likely caused by slight differences in the input list. The simulations use a hard $S_{24} > 50\ \mu\text{Jy}$ cut, while the real GOODS-N catalogue is cut at $S_{24} > 5\sigma$, which includes many sources fainter than

$S_{24} = 50\ \mu\text{Jy}$ and hence has a higher surface density, leading to more degenerate solutions. Another possible explanation is that real $500\ \mu\text{m}$ sources are more strongly clustered than those in the simulation. The second issue, the difference in the flux density error at $500\ \mu\text{m}$ between the shallow simulation and Lockman-SWIRE, likely originates from differences in how the 24 and $250\ \mu\text{m}$ selection affects the real and simulated datasets. Specifically, larger errors would be expected if the simulations predict a higher level of incompleteness at $500\ \mu\text{m}$ due to the 24 and/or $250\ \mu\text{m}$ selections. These problems aside the otherwise good agreement reinforces the

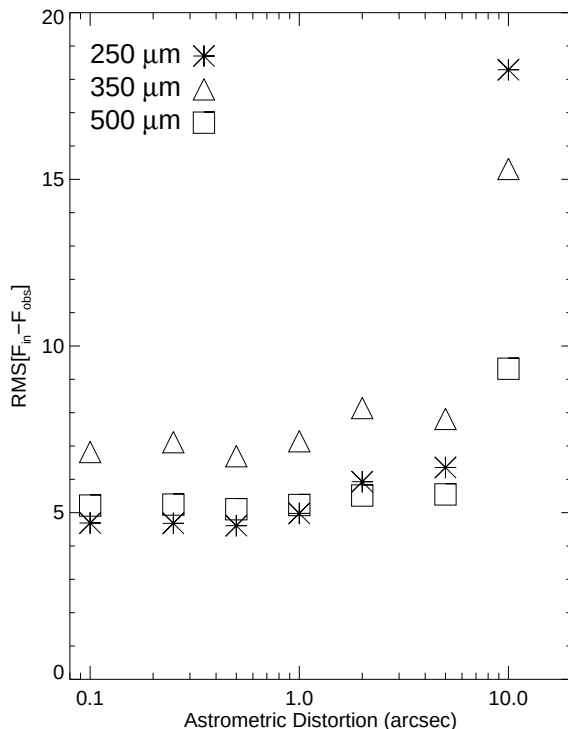


Figure 6. Effect of astrometric errors on the flux density accuracy of the HerMES XID algorithm (Method A). Gaussian distributed distortions are added to the input positions of the deep simulation described in Table 2. It can be seen that the accuracy of the flux density estimates is insensitive to astrometric errors of $< 1 - 2$ arcsec.

notion that our simulations are a realistic recreation of the *Herschel* data.

These results highlight the effectiveness of our method to recover faint sources in highly confused maps, Nguyen et al. (2010) estimate the confusion noise in SPIRE imaging to be 5.8, 6.3 and 6.8 mJy at 250, 350 and 500 μ m, respectively. It is clear that in our deepest fields, where instrumental noise is insignificant we are able to go significantly below this limit. Taking the 1σ flux density error quoted above for sources in GOODS-N with $\rho < 0.8$ it is clear our methods are able to reduce the effect of confusion noise by a factor of $\sim 20-30$ per cent.

To investigate possible systematics in our photometry we compare the XID catalogues to those generated using a combination of source detection and extraction, via *Sussextractor* and *p*-statistic methods (i.e. method B from Section 6), to match the resulting source lists with existing 24 μ m catalogues.

Sussextractor source lists are provided for each SPIRE band by SCAT (Smith et al. 2010). These source lists contain all SPIRE sources detected in the maps at a significance of greater than 3σ . The monochromatic SPIRE source lists are then matched to the same 24 μ m catalogues used as an input to XID algorithm. The matching is performed by finding potential counterparts within a search radius of 10 arcsec, 14 arcsec, and 20 arcsec for the 250, 350 and 500 μ m bands

respectively. For each of these potential IDs we calculate the *p*-statistic. The uncertainty of the SPIRE position is calculated using Equation B8 of Ivison et al. (2007). All IDs with $p < 0.1$ are considered. A complete sample is constructed by taking the best ID with $p < 0.1$ for each SPIRE source. Alternatively a ‘clean’ sample is constructed by taking only those cases where the separation is less than $0.6 \times \text{FWHM}$, and there is only one potential ID with $p < 0.1$.

Figure 8 compares the flux density estimates for sources in the LH-SWIRE, LH-North fields and GOODS-N from the XID catalogues and the SCAT+*p*-stat listings. Only those sources which are in common and are found at greater than 5σ in both catalogues are presented. The FLS field is omitted for clarity. While there is a large scatter between the two estimates for all sources, a good agreement can be seen for the ‘clean’ ones. The bulk of the sources which are discrepant between the two catalogues can be found above the one-to-one line in Figure 8, i.e. $S_{\text{XID}} < S_{\text{SCAT}}$. This is a natural consequence of the XID algorithm considering all known sources simultaneously, and thus deblending confused cases into their individual 24 μ m detected components.

As a final cross-check of the completeness estimates we compare the raw differential number density of sources found in both the XID and SCAT+*p*-stat catalogues to the best estimates of the source densities from Oliver et al. (2010b). Figure 9 shows the differential number density of sources in our XID and SCAT+*p*-stat catalogues, in the LH-SWIRE, FLS, and LH-North fields. GOODS-N observations are excluded as the number of sources detected is too small for this comparison to be useful. Encouragingly, at bright flux densities (i.e. > 50 mJy), both the XID and SCAT+*p*-stat catalogues show reasonable agreement with Oliver et al. (2010b), although cosmic variance introduces a large scatter at the highest flux densities. Both the XID and SCAT+*p*-stat are seen to be incomplete at faint flux densities, although in each band the XID catalogue is significantly more complete at flux densities $\sim 20-30$ mJy. Taking the Oliver et al. result to represent the total number of sources, Table 5 quotes the XID and SCAT+*p*-stat catalogue 50 per cent completeness levels. These values are in good overall agreement with the completeness estimates found via simulations and source injection.

8 THE EFFECT OF INCOMPLETE 24 μ m INPUT LISTS

We have shown that the use of existing 24 μ m source lists as a prior input to the source extraction process is beneficial in terms of flux density accuracy and completeness. However this methodology introduces a clear bias, in that we are restricted to only those sources which are sufficiently bright at both 24 μ m and SPIRE wavelengths.

One way to estimate this incompleteness is to again use the mock catalogues. Again turning to the FC08 mocks we can estimate the fraction of sources which would be present in our SPIRE images, but below the limit of the overlapping 24 μ m imaging. For the SPIRE bands we use the 50 per cent completeness limits quoted in Table 5, while for the 24 μ m flux density limit we use the values quoted in Table 1. As the GOODS-N field never reaches 50 per cent completeness we use the value from the deep simulation presented in Table

Table 5. Completeness estimates (50 per cent) for XID and SCAT+ p -stat catalogues for real observations of SDP fields. Completeness is estimated via both injection of sources into the map, and by comparing the number density of sources in the resulting catalogues to the best estimate of the true source density from Oliver et al. (2010b).

Field	S_{250} [50 per cent] (mJy)			S_{350} [50 per cent] (mJy)			S_{500} [50 per cent] (mJy)		
	Source Injection XID	Counts XID	Counts SCAT+ p -stat	Source Injection XID	Counts XID	Counts SCAT+ p -stat	Source Injection XID	Counts XID	Counts SCAT+ p -stat
GOODS-N	9.5	–	–	12.1	–	–	n/a	–	–
LH-North	14.1	13.3	26.7	16.4	23.8	30.5	24.1	23.6	31.5
FLS	16.4	21.6	23.3	17.5	21.6	23.3	23.2	22.9	25.5
LH-SWIRE	25.4	27.	36.4	27.8	26.7	35.6	42.	36.4	44.4

3. The fraction of sources missing due to the $24\mu\text{m}$ limit in the FC08 mock catalogues is given in Table 6

However relying on mock catalogues to describe this incompleteness is unsatisfactory, as it is very sensitive to the underlying SED distribution of sources, a known weakness of mock catalogues based on empirical fits to the observed monochromatic number density of sources.

In order to properly determine what additional incompleteness this introduces would require precise measurements of the bivariate number density, i.e. the areal number density of sources as a function of both $24\mu\text{m}$ and SPIRE flux density. While that analysis is beyond the scope of this work, we can roughly estimate the lower limit to this incompleteness in our fields by making use of the multi-tiered nature of HerMES. Specifically we can use our observations in GOODS-N, which contains both the deepest SPIRE imaging and deepest $24\mu\text{m}$ catalogues available, to determine the number of sources which would appear in the fields with shallower SPIRE data, if similar quality $24\mu\text{m}$ input catalogues were available.

Figure 10 shows the $24\mu\text{m}$ vs SPIRE band flux density for 5σ sources observed in GOODS-N, while Figure 11 shows our best estimate of the differential number density of SPIRE sources as a function of $24\mu\text{m}$ flux density derived from this data. The densities have been corrected for incompleteness in the $24\mu\text{m}$ input catalogue using the results presented in Magnelli et al. (2009). We do not correct for SPIRE incompleteness as we wish to estimate how many sources are missing from our catalogues due to solely the $24\mu\text{m}$ flux limits. GOODS-N sources which are 5σ in the relevant SPIRE band are considered, with no cut on ρ . To replicate the conditions found in our other fields we impose artificial SPIRE flux limits on the GOODS-N data. For each combination of SPIRE band and field we impose the 50 per cent completeness limit found via source injection quoted in Table 5. To find a robust estimate to the total number of sources missing from our shallower SPIRE observations we integrate Figure 11 from zero to the quoted $24\mu\text{m}$ limit given in Table 1. Below $S_{24} = 20\mu\text{Jy}$, or in cases where no sources are observed, we assume the differential density remains constant from zero to the last measured value. Table 6 summarises the results of these calculations. Given the very small area covered by GOODS-N, It should be noted that all of these values are subject to large uncertainties, especially at $500\mu\text{m}$ where the number of bright sources found in GOODS-N is very small.

Encouragingly in both the LH-SWIRE and LH-North

field at 250 and $350\mu\text{m}$ we appear to only be missing an additional ~ 20 per cent of sources due to the $24\mu\text{m}$ depth. The shallow nature of the $24\mu\text{m}$ imaging in FLS means we are missing a significant number of sources in this field, although the bulk of these will be at relatively faint fluxes (< 30 mJy). At $500\mu\text{m}$ all of the fields potentially suffer from a high degree of additional incompleteness due to the $24\mu\text{m}$ limits. This is understandable, as the strong negative k -correction with increasing redshift at $500\mu\text{m}$ should result in a population of high- z $500\mu\text{m}$ bright, $24\mu\text{m}$ faint sources which would not be found via the methodology presented here.

9 FUTURE WORK

As discussed in Section 5 the algorithm and catalogues described here represent the first attempt to produce robust XIDs for SPIRE sources, and hence many avenues for improvement are possible in terms of both flux density accuracy and completeness. Some clear improvements have already been discussed above. Specifically in these area:

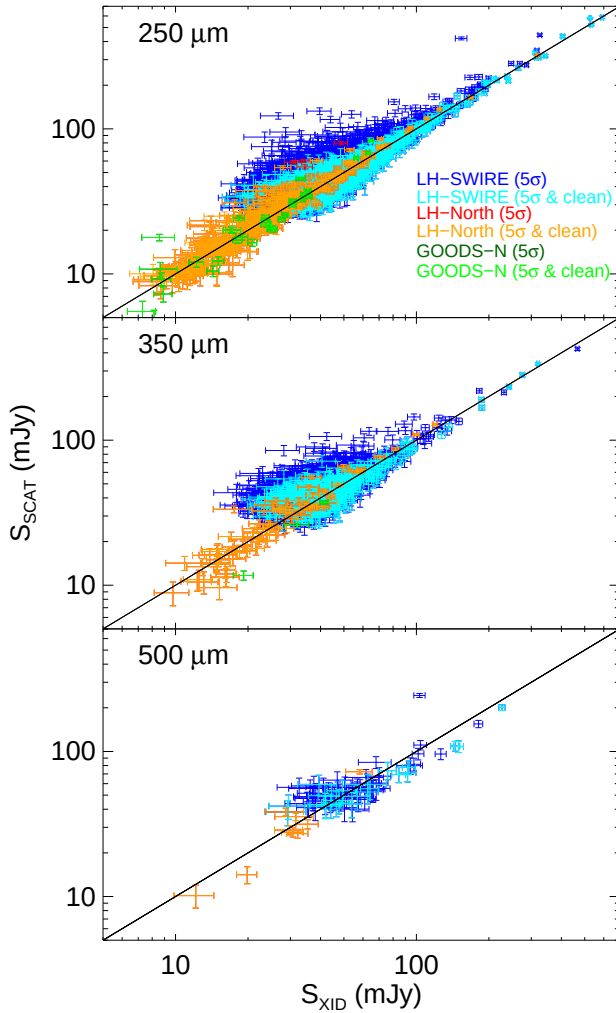
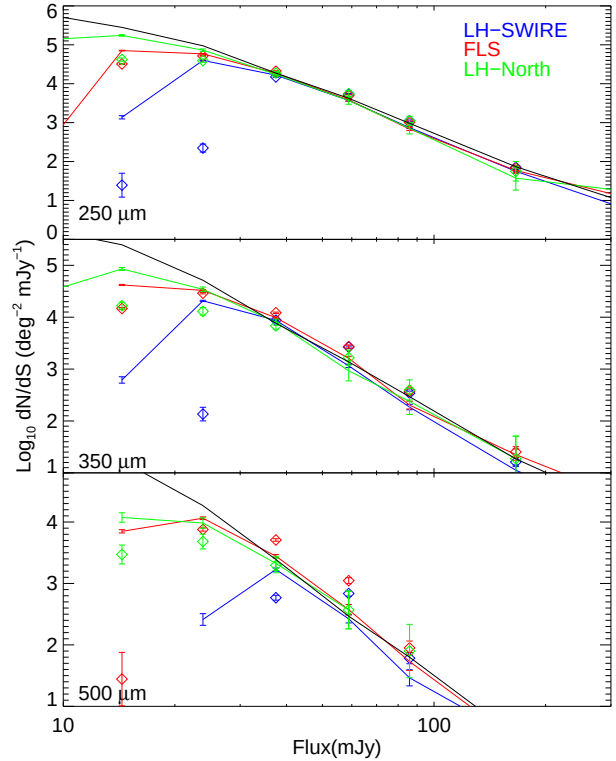
- Perform the model selection stage on all three SPIRE bands, and possibly other MIPS and PACS data, simultaneously.
- Introduce flux density priors based on SED fitting.
- Improve the process of background estimation and removal
- Use an iterative process to recover faint sources missing from our $24\mu\text{m}$ input list.
- Obtain accurate estimates of the true errors on our flux densities.

Of these the final one, accurate estimation of the errors, is arguably the most critical. It is clear from the accuracy metrics presented in Sections 6 and 7 that our flux density errors are underestimates of the true variance in our measurements. If the true variance, and covariance, of each flux density estimate could be obtained the use of crude ‘flags’ for selecting robust sources, such as the ρ , purity, and local $24\mu\text{m}$ source density, would no longer be necessary.

One way to more accurately estimate the flux density errors would be to make use of Monte-Carlo Markov Chain (MCMC) methods to perform the linear inversion. This would have many advantages: a MCMC approach would map out the true posterior probability density for not only the source flux density variances, but also the covariance.

Table 6. Upper limit to the incompleteness in our SDP fields due to $24\mu\text{m}$ flux limits, based on analysis of FC08 mock catalogues, and SDP observations of GOODS-N.

Field	$250\mu\text{m}$			$350\mu\text{m}$			$500\mu\text{m}$		
	N_{missing}	real per cent	mock per cent	N_{missing}	real per cent	mock per cent	N_{missing}	real per cent	mock per cent
GOODS-N	–	–	1	–	–	3	–	–	< 1
LH-North	80 ± 30	10 ± 4	1	60 ± 30	17 ± 7	3	10 ± 4	28 ± 12	1
FLS	2900 ± 1200	40 ± 16	50	2300 ± 900	50 ± 20	30	600 ± 200	60 ± 20	17
LH-SWIRE	2000 ± 1000	20 ± 10	2	800 ± 300	20 ± 10	5	300 ± 300	70 ± 70	7

**Figure 8.** Comparison of flux densities from XID catalogue to those from the SCAT SussExtractor-derived source catalogues in the Lockman Hole SWIRE, Lockman Hole North and GOODS-N fields. SCAT sources are matched to the $24\mu\text{m}$ sources via the p -statistic. Sources present in both catalogues at 5σ are presented, as well as a “clean” sample where $p < 0.1$, separation $< 0.6 \times \text{FWHM}_{\text{SPIRE}}$, and there are no alternative IDs with $p < 0.1$. XID fluxes are also required to have $\rho < 0.8$ and $\chi^2 < 5$. Good agreement can be seen between the XID and SCAT flux densities for “clean” sources. This suggests that any discrepancies between SCAT and XID are solely due to issues with source blending.**Figure 9.** Differential number density of sources in the XID catalogues and SCAT v3 release catalogues. The black line is the current best estimate of true source density from Oliver et al. (2010b). The solid lines are XID, open symbols are SCAT in all panels.

Additionally, a MCMC approach offers the natural inclusion of ‘non-linear’ prior knowledge on the solutions, such as smooth SED and background constraints. Preliminary testing of a hybrid MCMC method, which makes use of Hamiltonian dynamics to draw samples, on the simulated data presented in Section 6 has shown that for typical segment sizes containing < 100 sources, MCMC chains of length $\sim 10^6$ can robustly recover the true variance in the flux density estimates, although with some loss of precision in the flux density estimate. Further testing with this approach is needed to determine if MCMC based methods can return the best results in terms of both precision and robust error estimation.

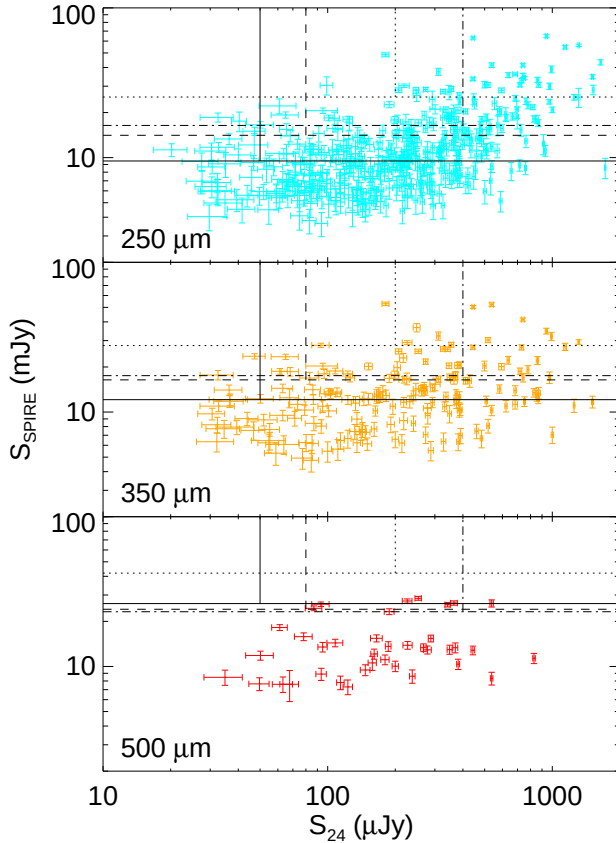


Figure 10. SPIRE vs. $24\mu\text{m}$ flux density for sources in GOODS-N. The vertical lines indicate the depth of $24\mu\text{m}$ imaging in each SDP field, while the horizontal lines indicate the 50 per cent completeness level of our SPIRE catalogues from the analysis presented in Section 7. Fields are: GOODS-N (solid), Lockman-North (dashed), FLS (dot-dashed), Lockman-SWIRE (dotted).

10 CONCLUSIONS

We have presented a new technique for producing associations between astronomical observations at different wavelengths. This method is optimised for use on *Herschel* SPIRE imaging in the presence of deep $24\mu\text{m}$ catalogues from *Spitzer*. This technique has been used to produce XID catalogues for the HerMES SDP fields. Thorough testing is performed on simulated and real data sets for both our new method, and two existing XID methods. Compared to a more traditional approach of source detection and catalogue-based cross identification, our map-based approach is found to give significantly greater accuracy in the flux density and recovers a much larger fraction of faint SPIRE sources. When compared to the Sussextractor derived source catalogues of Smith et al. (2010) we find good agreement between flux density estimates, for those sources considered to be ‘unconfused’. We find that the use of the $24\mu\text{m}$ prior input list can introduce an additional incompleteness which is strongly dependant on the relative depth of the existing $24\mu\text{m}$ data to our SPIRE data. From the combination of deep SPIRE and *Spitzer* $24\mu\text{m}$ observations in GOODS-N we estimate an incompleteness due to the $24\mu\text{m}$ limit in the

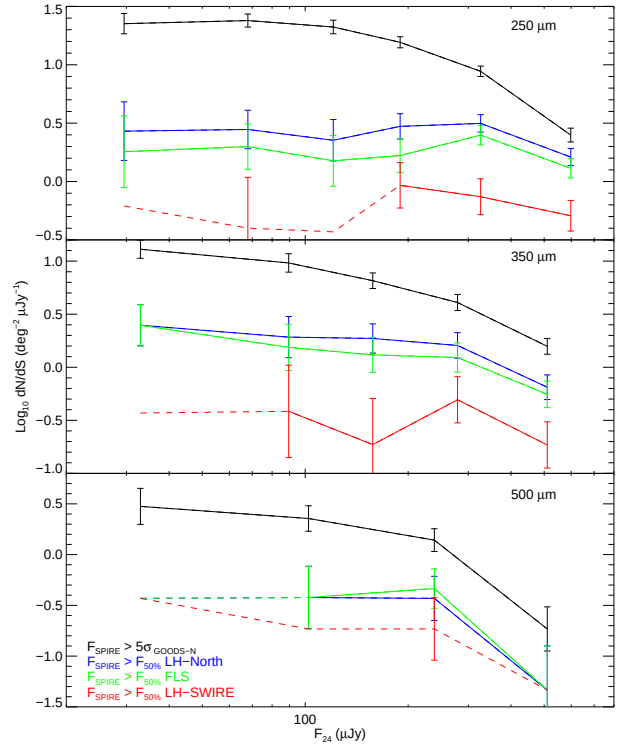


Figure 11. Differential number density of SPIRE sources in the GOODS-N field as a function of $24\mu\text{m}$ flux density. The curves have been corrected for incompleteness in the $24\mu\text{m}$ catalogue, but not the SPIRE incompleteness. The three panels show the results for the $250\mu\text{m}$ (top), $350\mu\text{m}$ (middle) and $500\mu\text{m}$ (bottom) band. The black line in each panel shows our best estimate of the differential number density of sources detected in the GOODS-N field as a function of $24\mu\text{m}$ flux density. The other lines show the effect of imposing the SPIRE 50 per cent completeness limit on the GOODS-N catalogue. The dashed line indicates the number density which would be quoted if one source was observed in that bin.

other SDP fields of ~ 20 per cent at $250\mu\text{m}$, increasing to ~ 40 per cent at $500\mu\text{m}$. However this incompleteness is dominated by the faintest SPIRE sources (i.e. less than $30\text{--}40\text{ mJy}$), and we can be confident our catalogues are complete at bright fluxes.

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A.2 Article : *The cosmic far-infrared background buildup since redshift 2 at 70 and 160 microns in the COSMOS and GOODS fields*

J'ai réalisé quelques contributions à ce papier :

- extraction et soustraction des sources résolues des cartes GOODS et COSMOS à 70 et 160 μm ,
- mesure des comptages à 24 μm dans les trois champs utilisés,
- photométrie et calibration,
- calcul des prédictions des différents modèles,
- relecture et commentaires.

The cosmic far-infrared background buildup since redshift 2 at 70 and 160 microns in the COSMOS and GOODS fields

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ABSTRACT

Context. The cosmic far-infrared background (CIB) at wavelengths around 160 μm corresponds to the peak intensity of the whole extragalactic background light, which is being measured with increasing accuracy. However, the build up of the CIB emission as a function of redshift is still not well known.

Aims. Our goal is to measure the CIB history at 70 μm and 160 μm at different redshifts, and provide constraints for infrared galaxy evolution models.

Methods. We used deep Spitzer 24 μm catalogs complete to about 80 μJy with spectroscopic and photometric redshift identifications, derived using the GOODS and COSMOS deep infrared surveys covering 2 square degrees total. After cleaning the Spitzer/MIPS 70 μm and 160 μm maps of detected sources, we stacked the far-IR images at the positions of the 24 μm sources in different redshift bins. We measured the contribution of each stacked source to the total 70 and 160 μm light, and compared with model predictions and far-IR measurements obtained for Herschel/PACS data of smaller fields.

Results. We detect components of the 70 and 160 μm backgrounds in different redshift bins up to $z \sim 2$. The contribution to the CIB reaches a maximum at $0.3 \leq z \leq 0.9$ at 160 μm (and $z \leq 0.5$ at 70 μm). A total of 81% (74%) of the 70 (160) μm background was emitted at $z < 1$. We estimate that the AGN contribution to the far-IR CIB is less than about 10% at $z < 1.5$. We provide a comprehensive view of the CIB buildup at 24, 70, 100 and 160 μm .

Conclusions. We find that IR galaxy models predicting a major contribution to the CIB from sources at $z < 1$ agree with our measurements, while our results exclude other models that predict a peak of the background at higher redshifts. The consistency of our results with those obtained by the direct study of Herschel far-IR data at 160 μm confirms that the stacking analysis method is a valid approach to estimate the components of the far-IR background using prior information about resolved mid-IR sources.

Key words. cosmology: observations – diffuse radiation – galaxies: evolution – galaxies: starburst – galaxies: active – infrared: diffuse background

1. Introduction

The extragalactic background light (EBL) is the relic emission of galaxy formation and evolution, i.e., produced by star formation and accretion processes (according to this definition, the cosmic microwave background due to recombination at redshift $z \sim 1100$ is not part of the EBL). The EBL spectrum peaks in the far-infrared (FIR), where it is commonly referred to as the cosmic infrared background (CIB) (Puget et al. 1996; Hauser et al. 1998; Hauser & Dwek 2001; Kashlinsky 2005; Dole et al. 2006). The EBL and the CIB encode the emission processes of structure formation, and can thus be used to constrain the photon budget of the cooling processes leading the baryons to fall within the dark matter halos and form galaxies. The measurements of the EBL level and structure bring thus one of the many useful constraints for the galaxy formation and evolution models.

The CIB spectral energy distribution is measured with increasing accuracy (for instance in the FIR and submillimetre regime: Puget et al. 1996; Aharonian et al. 2006; Dole et al. 2006; Béthermin et al. 2010a), but little is known about its

history, i.e., its buildup as a function of redshift. This missing information should help us to constrain galaxy evolution models, and more clearly understand the physics of blazars, whose high-energy photons interact with the CIB along the line of sight (e.g., Aharonian et al. 2007; Albert & Magic Collaboration 2008; Raue et al. 2009; Kneiske & Dole 2009).

The history of the CIB buildup can be derived by integrating the luminosity functions of galaxies as a function of redshift (neglecting other sources of diffuse emission and thus assuming that the CIB is due to galaxies). This is a very difficult task in practice, since high-redshift luminosity functions have not yet been measured at wavelengths close to the peak of the CIB (near 160 μm) but instead in the mid-infrared range (e.g. Le Floc'h et al. 2005; Caputi et al. 2007), or only in the local universe (Soifer & Neugebauer 1991; Takeuchi et al. 2006). This situation is about to change with the latest Spitzer surveys and the ongoing deeper Herschel surveys (Magnelli et al. 2009; Clements et al. 2010; Dye et al. 2010).

Two breakthroughs have been made by using COSMOS and GOODS surveys. Firstly, using about 30 000 Spitzer 24 μm

selected sources with accurate photometric redshifts (Ilbert et al. 2009), Le Floc'h et al. (2009) were able to measure the $24\ \mu\text{m}$ background buildup with redshift (e.g. their Figs. 7 to 9). They furthermore show that the redshift information is crucial when comparing data with the models, since it helps breaking degeneracies in the model parameters. Secondly, using the redshift identification of Herschel/PACS 100 and $160\ \mu\text{m}$ sources, Berta et al. (2010) were able to measure the CIB build up in four redshift bins, in the $140\ \text{arcmin}^2$ GOODS-N field (an area about 40 times smaller than used in this analysis).

In this paper, we measure the $70\ \mu\text{m}$ and $160\ \mu\text{m}$ CIB history since $z = 2$, by performing a stacking analysis of galaxies detected at $24\ \mu\text{m}$ (a good proxy for the $160\ \mu\text{m}$ CIB population, e.g. Dole et al. 2006; Bethermin et al. 2010a) in the Spitzer data of the GOODS and COSMOS fields¹. This approach complements over a large area the studies with Herschel in Berta et al. (2010) at 100 and $160\ \mu\text{m}$.

2. Data and sample

2.1. GOODS data

The data were acquired by the MIPS imaging photometer at $24\ \mu\text{m}$, $70\ \mu\text{m}$, and $160\ \mu\text{m}$ (Rieke et al. 2004) onboard the Spitzer infrared space telescope (Werner et al. 2004), and come from the GOODS team (Chary et al. 2004) and guaranteed time observations (Papovich et al. 2004; Dole et al. 2004) of the Chandra Deep Field South (CDFS) and the Hubble Deep Field North (HDFN). Papovich et al. (2004) extracted a catalog at $24\ \mu\text{m}$, with 80% completeness at $80\ \mu\text{Jy}$. We used a sample of 1349 galaxies with $24\ \mu\text{m}$ flux densities $S_{24} \geq 80\ \mu\text{Jy}$, located in the two GOODS fields, north and south, for a total area of $291\ \text{sq. arcmin}$ (Caputi et al. 2006; Caputi et al. 2007). The galaxies were completely identified, and redshifts were determined for all of them, with more than 45% of spectroscopic redshifts. Active galactic nuclei (AGNs) were distinguished from star-forming systems using X-ray data and near-infrared (3.6 to $8\ \mu\text{m}$) colors: we identified 136 AGNs among 1213 star-forming systems (Caputi et al. 2007). To determine the contribution of mid-infrared galaxies to the far-infrared background in redshift slices, we divided the $24\ \mu\text{m}$ sample into four redshift bins: $0 < z < 0.65$ with 317 sources (of which 9 AGNs); $0.65 < z < 1.3$ with 575 sources (45 AGNs); $1.3 < z < 2$ with 259 sources (38 AGNs); and $z > 2$ with 198 sources (44 AGNs). These bins were chosen to maximize the number of sources present in each bin, while keeping the Δz width constant.

2.2. COSMOS data

The Cosmic Evolution survey (COSMOS) data were acquired by MIPS at 24 , 70 , and $160\ \mu\text{m}$. The $24\ \mu\text{m}$ observations of the COSMOS field is part of two general observer programs (PI Sanders): G02 (PID 20070) carried out in January 2006, and G03 (PID 30143) carried out in 2007. We used a total net area of $1.93\ \text{square degrees}$. Le Floc'h et al. (2009) extracted a catalogue at $24\ \mu\text{m}$ and provided us with a sample of 32 840 galaxies found to have $24\ \mu\text{m}$ flux densities $S_{24} \geq 80\ \mu\text{Jy}$. The completeness limit is about 90% at this level. (Note that the survey sensitivities of the COSMOS and GOODS fields are similar at 24 , 70 , and $160\ \mu\text{m}$). The $24\ \mu\text{m}$ galaxies were completely identified, and redshifts were derived by Ilbert et al. (2009) and

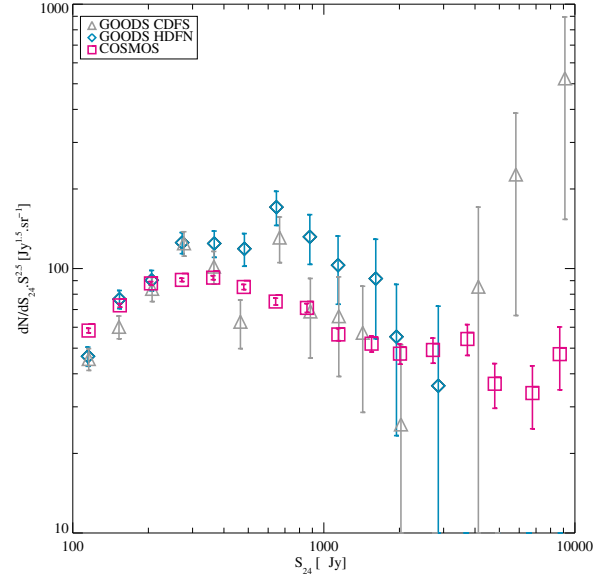


Fig. 1. Number counts at $24\ \mu\text{m}$ in the GOODS HDFN (blue diamond), GOODS CDFS (gray triangle), and COSMOS (pink square) fields. The errors bars used only account for Poisson statistics and not cosmic variance.

Salvato et al. (2009) for the optically and X-ray selected sources of the COSMOS field respectively. We used the Salvato et al. (2009) photometric redshift catalogue created using the Cappelluti et al. (2009) X-ray source catalogue, optically matched by Brusa et al. (2007) and Brusa et al. (2010), to identify the AGNs in the COSMOS field (Le Floc'h et al. 2009). We note that the X-ray flux limits used in the soft (0.5 – $2\ \text{keV}$), hard (2 – $10\ \text{keV}$), or ultra-hard (5 – $10\ \text{keV}$) bands are 5×10^{-16} , 3×10^{-15} , and $5 \times 10^{-15}\ \text{erg cm}^{-2}\ \text{s}^{-1}$, respectively (Cappelluti et al. 2007, 2009; Salvato et al. 2009). We complement this sample with sources found to have a power-law SED (Alonso-Herrero et al. 2006) in the redshift range $1.5 < z < 2.5$ using IRAC colors (at lower and higher redshifts, the colors can be contaminated by the PAH or stellar bumps) in the same way as for the GOODS sample. We obtained 1668 sources (1115 X-ray sources, 553 power-law sources) detected at $24\ \mu\text{m}$ and identified as AGNs for 31 172 star forming systems.

Since the COSMOS sample is larger than that of GOODS, we used 14 redshift bins, described in Table 1. The source statistics in these fields is summarized in Fig. 1, showing the number counts of the GOODS survey (CDFS and HDFN) as well as the COSMOS field, corrected for incompleteness. The errors bars used only include Poisson statistics, and not cosmic variance, and are thus likely underestimated. There is no evidence of a relative major over- or under-density, except maybe a slight overdensity in the HDFN around $1\ \text{mJy}$, which has a negligible contribution to the total background.

3. Analysis

3.1. Stacking analysis

To estimate the contribution of mid-infrared galaxies to the $70\ \mu\text{m}$ and $160\ \mu\text{m}$ background, we used a stacking analysis²

¹ Our results are available online at <http://www.ias.u-psud.fr/irgalaxies/>

² The IAS stacking library, written in IDL, is publicly available at <http://www.ias.u-psud.fr/irgalaxies>, cf. Bavouzet (2008) and Bethermin et al. (2010a).

Table 1. Number of 24 μm sources per redshift bins for the COSMOS field.

z bin	$0 < z < 0.15$	$0.15 < z < 0.3$	$0.3 < z < 0.45$	$0.45 < z < 0.6$	$0.6 < z < 0.75$	$0.75 < z < 0.9$	$0.9 < z < 1.05$
N_{tot}	2083	1559	2853	2201	3225	3590	3478
N_{AGNs}	34	32	74	48	88	110	123
z bin	$1.05 < z < 1.2$	$1.2 < z < 1.35$	$1.35 < z < 1.5$	$1.5 < z < 1.65$	$1.65 < z < 1.85$	$1.85 < z < 2.05$	$z > 2.05$
N_{tot}	2670	1401	2044	1311	1519	2073	2833
N_{AGNs}	83	76	55	225	232	200	288

Notes. N_{tot} is the total number of galaxies used in the stacks, and N_{AGNs} is the number of sources identified as AGNs that were used in the stacks to estimate the AGN contribution.

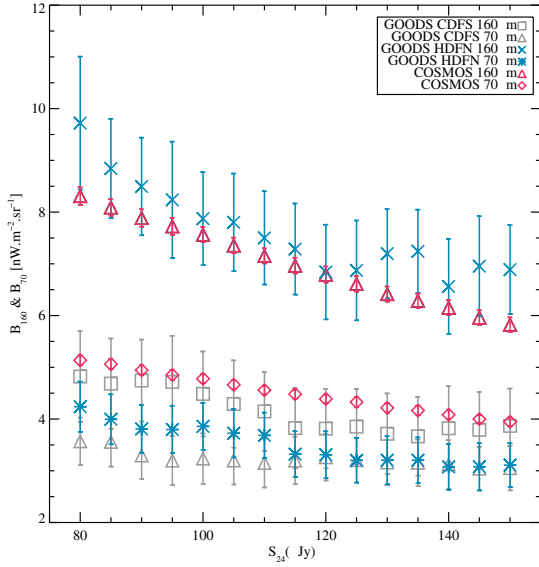


Fig. 2. Cumulative stacked brightness at 70 μm and 160 μm (in $\text{nW m}^{-2} \text{sr}^{-1}$) on the CLEANed maps, as a function of the 24 μm flux of our sample, regardless of the redshift. The 3 fields are represented at 160 and 70 μm : COSMOS, GOODS-N (HDFN), and GOODS-S (CDFs).

(Dole et al. 2006; Bethermin et al. 2010b). This method consisted of stacking the 70 and 160 μm maps at the location of the galaxies detected at 24 μm . The use of this method is justified for two reasons: 1) The 24 μm population is a good proxy for the 70 μm and 160 μm populations making up most of the CIB near its peak (Dole et al. 2006; Bethermin et al. 2010a). 2) Only a few sources are individually detected at FIR wavelengths and do not resolve much of the background (Dole et al. 2004; Frayer et al. 2006a; Frayer et al. 2006b; Dole et al. 2006; Frayer et al. 2009). We note that stacking may be affected by galaxy clustering, since the stacked image shows two dimensions the two point angular correlation function (Dole et al. 2006; Bavouzet 2008; Bethermin et al. 2010a). However, with the Spitzer and Herschel beams, the effects of clustering on the stacking are not important (less than 15%) (Bavouzet 2008; Fernandez-Conde et al. 2008, 2010).

We first stacked the 70 μm and the 160 μm MIPS data (CLEANed maps) as a function of the 24 μm flux, regardless of the redshift of the sources (Fig. 2). This allowed us to check the consistency of the procedure, since the total brightness measured for stacks down to $S_{24} = 80 \mu\text{Jy}$ should be equal to the sum of the brightnesses obtained in redshift slices, as well as identify possible biases. The stacks in the COSMOS and the two GOODS fields at 70 and 160 μm show strong dependencies on

the fields: while COSMOS and GOODS-N (HDFN) stacks are consistent within 20%, stacks in CDFS field have systematically fluxes lower than those of COSMOS by a factor of about 1.4–1.8. The higher quality statistics of the COSMOS field (surface area and number of sources) limits the impact of the variance caused by the large scale structure, and we attribute the systematically lower values of GOODS-S to this effect.

Prior to stacking the 24 μm catalog into redshift bins on the 70 μm and 160 μm maps, we used the algorithm (Hogbom 1974) to subtract the few resolved sources present in the far-infrared maps, to remove any bias in the resulting photometry of the stacked images. The stacking analysis presented on Fig. 2 was also done with the cleaned far-infrared maps. In the COSMOS field, we removed the sources brighter than 80 mJy and 20 mJy at 160 μm and 70 μm respectively, levels corresponding to 90 to 95% completeness and computed by Monte-Carlo simulations on the data themselves (Bethermin et al. 2010a). In both GOODS fields, we removed all the detected sources at 160 μm & 70 μm identified at 24 μm , which corresponds to removing all sources brighter than 19 mJy at 160 μm (5 sources in GOODS HDFN & 12 sources in GOODS CDFS) and 4.4 mJy at 70 μm (8 sources in GOODS HDFN & 17 sources in GOODS CDFS). These brightest source detections at 70 and 160 μm were individually identified at 24 μm without ambiguity, and the redshift of the 24 μm source is used. The flux densities of the removed detected sources were converted into brightnesses, and were added at the very end of the process to account for their CIB contribution (even if only a small fraction at far-IR wavelengths).

We estimated the AGN contribution to the CIB as a function of redshift using the identifications described in Sects. 2.1 and 2.2.

The stacking procedure was performed for each redshift bin independently, and the images of the stacks are presented in Figs. 3 and 4, for the GOODS and COSMOS fields, respectively, together with the measured signal-to-noise ratios (hereafter S/Ns).

In our approach, we:

- compute the brightness (in redshift bins) of the detected sources that are removed from the maps to create the cleaned maps;
- select galaxies at 24 μm (either all of them, only AGN, or only non-AGN) by redshift bins;
- stack at the positions of the selected galaxies in the 70 and 160 μm cleaned maps;
- perform photometry and bootstrap on those stacks;
- compute the uncertainty budget.

All measurements discussed in this section, i.e. number of stacked sources, resolved sources, AGN, and resulting brightnesses as a function of redshift, are summarized in Tables 2–5.

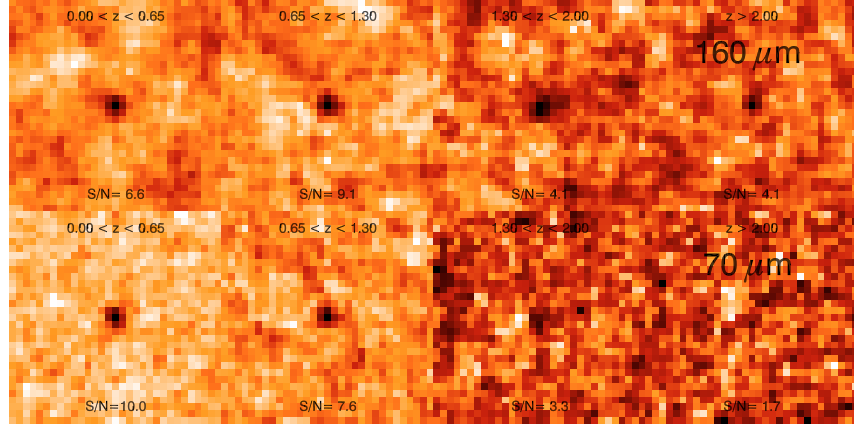


Fig. 3. Images of all the stacked galaxies in the 160 μm (top) and 70 μm (bottom) GOODS CLEANed maps by redshift bin (right to left): $0 < z < 0.65$, $0.65 < z < 1.3$, $1.3 < z < 2$, and $z > 2$. The signal-to-noise ratio (S/N) is indicated in each image. Note the detection in the two first redshift bins at both wavelengths. Images are 305×305 sq. arcsec. wide at 70 μm (with 9.85 arcsec pixel plate), and 496×496 sq. arcsec. at 160 μm (with 16 arcsec pixel plate). The PSF *FWHM* being 18 arcsec and 40 arcsec at 70 μm and 160 μm respectively, the PSF shown on these figures has about the same extent of 1.8 to 2.5 pixels at both wavelengths.

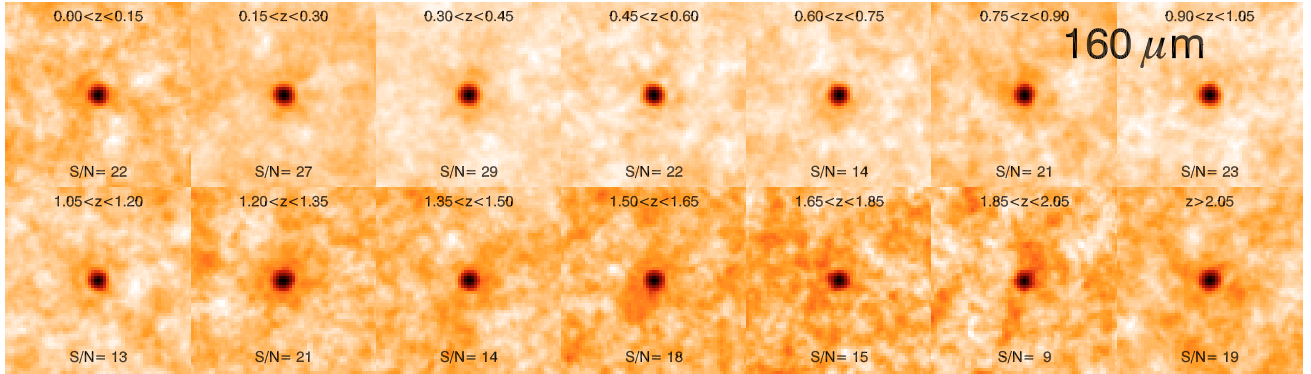


Fig. 4. Images of all the stacked galaxies in the 160 μm COSMOS CLEANed maps with 14 redshift bins (left to right and top to bottom). The S/N is indicated in each image. Note the clear detections in all redshift bins at both wavelengths. Images are 488×488 sq. arcsec at 160 μm (with 8 arcsec pixel plate). The PSF *FWHM* of 40 arcsec corresponds to 5 pixels in these images.

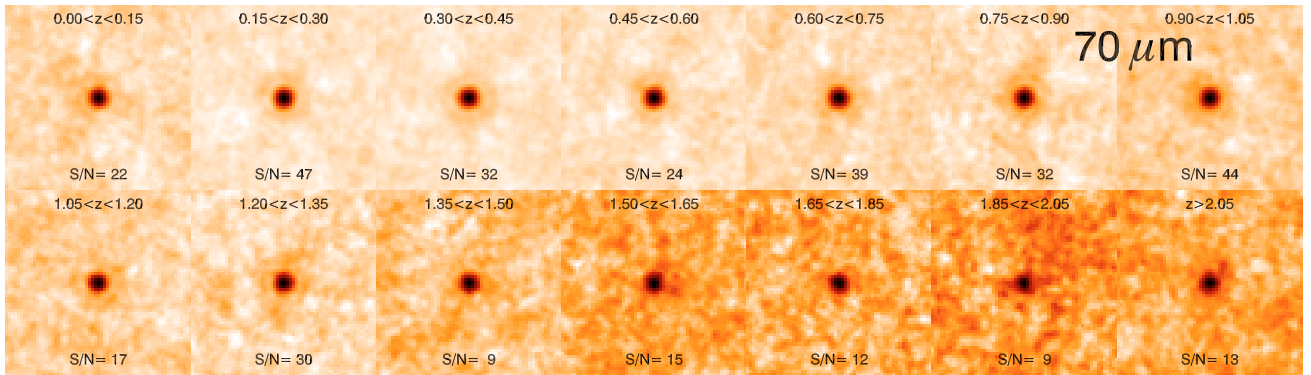


Fig. 5. Images of all the stacked galaxies in the 70 μm COSMOS CLEANed maps with 14 redshift bins. Images are 244×244 sq. arcsec wide at 70 μm (with 4 arcsec pixel plate). The PSF *FWHM* of 18 arcsec corresponds to 4.5 pixels in these images.

3.2. Photometry and uncertainty estimations

We performed aperture photometry on the stacked images with the following parameters at 160 μm : aperture radius of 25 arcsec, a sky annulus to estimate the background between 80 arcsec and 110 arcsec, and an aperture correction of 2.29. At 70 μm , the

respective parameters were: 18 arcsec, 50 arcsec and 70 arcsec, and 1.68. We have secure detections in all redshift bins at 160 μm and 70 μm , except in the two highest redshift bin ($z > 1.3$) in GOODS. The signal-to-noise ratio (hereafter S/N) is higher for COSMOS data than that of GOODS, because of the larger number of sources used (the number of sources used are reported in

Table 4. The CIB brightness by redshift range at 160 μm , in units of $\text{nW m}^{-2} \text{sr}^{-1}$, in the case of the COSMOS field.

	$0 < z < 0.15$	$0.15 < z < 0.3$	$0.3 < z < 0.45$	$0.45 < z < 0.6$	$0.6 < z < 0.75$	$0.75 < z < 0.9$	$0.9 < z < 1.05$
N_{stack}	2083	1559	2853	2201	3225	3590	3478
N_{sources}	56	40	18	9	11	12	6
N_{AGNs}	34	32	74	48	88	109	123
$B_{160\text{stack}}$	0.43 ± 0.04	0.56 ± 0.04	0.87 ± 0.05	0.63 ± 0.04	0.76 ± 0.07	0.75 ± 0.06	0.71 ± 0.06
$B_{160\text{sources}}$	0.3 ± 0.001	0.21 ± 0.002	0.07 ± 0.001	0.03 ± 0.001	0.034 ± 0.001	0.043 ± 0.001	0.021 ± 0.001
$B_{160\text{AGNs}}$	0.02 ± 0.006	0.01 ± 0.005	0.03 ± 0.01	0.02 ± 0.01	0.02 ± 0.01	0.01 ± 0.01	0.02 ± 0.01
$B_{160\text{tot}}$	0.72 ± 0.04	0.77 ± 0.04	0.93 ± 0.05	0.66 ± 0.04	0.8 ± 0.07	0.8 ± 0.06	0.73 ± 0.06
	$1.05 < z < 1.2$	$1.2 < z < 1.35$	$1.35 < z < 1.5$	$1.5 < z < 1.65$	$1.65 < z < 1.85$	$1.85 < z < 2.05$	$z > 2.05$
N_{stack}	2670	1401	2044	1311	1519	2073	2833
N_{sources}	2	0	2	2	0	1	2
N_{AGNs}	83	76	55	225	230	198	288
$B_{160\text{stack}}$	0.52 ± 0.05	0.33 ± 0.09	0.36 ± 0.04	0.26 ± 0.03	0.22 ± 0.02	0.27 ± 0.04	0.47 ± 0.04
$B_{160\text{sources}}$	0.005 ± 0.0003	–	0.006 ± 0.0003	0.006 ± 0.0003	–	0.003 ± 0.0001	0.007 ± 0.0003
$B_{160\text{AGNs}}$	0.02 ± 0.01	0.02 ± 0.01	0.01 ± 0.008	0.04 ± 0.03	0.04 ± 0.03	0.05 ± 0.03	0.04 ± 0.03
$B_{160\text{tot}}$	0.53 ± 0.05	0.33 ± 0.09	0.37 ± 0.04	0.27 ± 0.03	0.22 ± 0.02	0.28 ± 0.04	0.47 ± 0.04

Notes. The subscript “stack” refers to the measurement of the signal on the cleaned and stacked image; “sources” to the individually detected sources; “AGN” to the sources identified as AGN by [Salvato et al. \(2009\)](#). The total number of sources used in this analysis is thus $N_{\text{stack}} + N_{\text{sources}}$.

Table 5. The CIB brightness by redshift range at 70 μm , in units of $\text{nW m}^{-2} \text{sr}^{-1}$, in the COSMOS field.

	$0 < z < 0.15$	$0.15 < z < 0.3$	$0.3 < z < 0.45$	$0.45 < z < 0.6$	$0.6 < z < 0.75$	$0.75 < z < 0.9$	$0.9 < z < 1.05$
N_{stack}	2083	1559	2853	2202	3225	3590	3478
N_{sources}	77	82	48	23	13	11	3
N_{AGNs}	34	32	74	48	88	110	123
$B_{70\text{stack}}$	0.31 ± 0.03	0.39 ± 0.02	0.6 ± 0.03	0.42 ± 0.03	0.47 ± 0.03	0.41 ± 0.03	0.39 ± 0.03
$B_{70\text{sources}}$	0.31 ± 0.001	0.34 ± 0.001	0.13 ± 0.0005	0.05 ± 0.0003	0.04 ± 0.0003	0.027 ± 0.0003	0.008 ± 0.0001
$B_{70\text{AGNs}}$	0.011 ± 0.004	0.008 ± 0.003	0.015 ± 0.006	0.009 ± 0.003	0.016 ± 0.005	0.015 ± 0.007	0.015 ± 0.008
$B_{70\text{tot}}$	0.62 ± 0.03	0.73 ± 0.02	0.73 ± 0.03	0.47 ± 0.03	0.51 ± 0.03	0.44 ± 0.03	0.4 ± 0.03
	$1.05 < z < 1.2$	$1.2 < z < 1.35$	$1.35 < z < 1.5$	$1.5 < z < 1.65$	$1.65 < z < 1.85$	$1.85 < z < 2.05$	$z > 2.05$
N_{stack}	2670	1401	2044	1311	1519	2073	2833
N_{sources}	2	1	2	0	0	0	0
N_{AGNs}	83	76	55	225	232	200	288
$B_{70\text{stack}}$	0.25 ± 0.02	0.18 ± 0.01	0.17 ± 0.02	0.1 ± 0.01	0.09 ± 0.02	0.09 ± 0.02	0.16 ± 0.02
$B_{70\text{sources}}$	0.004 ± 0.0001	0.002 ± 0.0001	0.003 ± 0.0001	–	–	–	–
$B_{70\text{AGNs}}$	0.14 ± 0.007	0.011 ± 0.005	0.006 ± 0.004	0.28 ± 0.012	0.026 ± 0.015	0.022 ± 0.01	0.029 ± 0.018
$B_{70\text{tot}}$	0.26 ± 0.02	0.18 ± 0.01	0.17 ± 0.02	0.1 ± 0.01	0.09 ± 0.02	0.09 ± 0.02	0.15 ± 0.02

Notes. Terms are defined in the caption of Table 4.

Table 2. The CIB brightness by redshift range at 160 μm , in units of $\text{nW m}^{-2} \text{sr}^{-1}$, in the case of the GOODS fields.

	$0 < z < 0.65$	$0.65 < z < 1.3$	$1.3 < z < 2$	$z > 2$
N_{stack}	317	573	258	198
N_{sources}	10	11	3	2
N_{AGNs}	9	45	38	44
$B_{160\text{stack}}$	2.18 ± 0.45	2.39 ± 0.54	1.13 ± 0.35	0.78 ± 0.27
$B_{160\text{sources}}$	0.57 ± 0.18	0.34 ± 0.11	0.06 ± 0.04	0.07 ± 0.05
$B_{160\text{AGNs}}$	0.04 ± 0.07	0.17 ± 0.25	0.32 ± 0.22	0.20 ± 0.19
$B_{160\text{tot}}$	2.75 ± 0.46	2.73 ± 0.54	1.19 ± 0.35	0.85 ± 0.27

Notes. The subscript “stack” refers to the measurement of the signal on the cleaned and stacked image; “sources” to the individually detected sources; “AGN” to the sources identified as AGN by [Caputi et al. \(2006\)](#). The total number of sources used in this analysis is thus $N_{\text{stack}} + N_{\text{sources}}$.

Table 3. The CIB brightness by redshift range at 70 μm , in units of $\text{nW m}^{-2} \text{sr}^{-1}$, in the GOODS fields.

	$0 < z < 0.65$	$0.65 < z < 1.3$	$1.3 < z < 2$	$z > 2$
N_{stack}	317	575	259	198
N_{sources}	19	5	1	0
N_{AGNs}	9	45	38	44
$B_{70\text{stack}}$	1.29 ± 0.22	1.25 ± 0.28	0.35 ± 0.15	0.15 ± 0.12
$B_{70\text{sources}}$	0.77 ± 0.18	0.14 ± 0.07	0.01 ± 0.015	–
$B_{70\text{AGNs}}$	0.05 ± 0.03	0.1 ± 0.12	0.11 ± 0.08	0.11 ± 0.12
$B_{70\text{tot}}$	2.06 ± 0.24	1.4 ± 0.28	0.36 ± 0.15	0.15 ± 0.12

Notes. Terms are defined in the caption of Table 2.

Tables 2 to 5). In our analysis, we thus considered the redshifts bins $0 < z < 1.3$ in GOODS and $0 < z < 2.5$ in COSMOS.

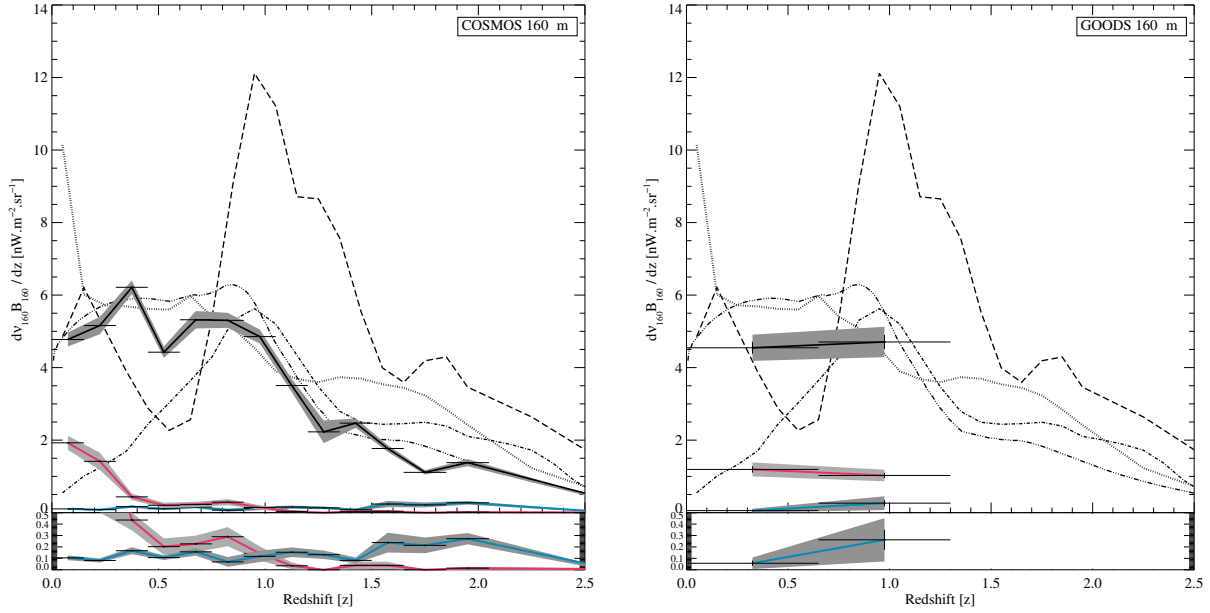


Fig. 6. Differential $160\ \mu\text{m}$ background brightness $dv_{160}B_{160}/dz$ as a function of redshift, in units of $\text{nW m}^{-2}\text{sr}^{-1}$, in the COSMOS field (*left*) and GOODS field (*right*). The lower part of the plot shows a linear zoom between 0 and $0.5\ \text{nW m}^{-2}\text{sr}^{-1}$ to show more clearly the trend of cleaned sources and AGNs. Black solid lines: total contribution of infrared galaxies. Solid red lines: contribution from resolved sources only. Solid blue line: contribution from AGN only. Dashed line: Lagache et al. (2004) model, with $S_{24} > 80\ \mu\text{Jy}$ cut. Dotted line: Le Borgne et al. (2009) model, with $S_{24} > 80\ \mu\text{Jy}$ cut. Dot-dash line: Valiante et al. (2009). Dot-dot-dot-dash line: Bethermin et al. (2010c) model, with $S_{24} > 80\ \mu\text{Jy}$ cut. Models are presented and discussed in Sect. 4.5 and Fig. 10.

The error bars correspond to three quadratically summed terms: (1-) the photometry uncertainty, (2-) the Poisson noise coming from the number of stacked sources, and (3-) a bootstrap analysis.

The bootstrap analysis involved repeating the stacking process N_b times (usually $N_b = 5000$ and $N_b = 14\,000$ for GOODS and COSMOS data respectively) of a new sample composed of randomly selected sources from our original sample, keeping the total number of sources constant (Bavouzet 2008); this means that some stacked positions might be present zero, or multiple times in each realization. The bootstrap error bars correspond to the standard deviation in the distribution of the photometry measured for these N_b realizations. We note that the S/N of the detections in the stacked images (only photometric) is higher than the value quoted in this paper, since we added the Poisson and bootstrap terms to estimate the final error bar, which takes into account the dispersion in the underlying sample. The final error bar is thus larger than just the photometric noise estimate. The error bars for the AGN samples were determined using a smaller number of bootstrap iterations, $N_b = 100$ and $N_b = 2000$ for GOODS and COSMOS, respectively.

The variance due to large-scale structure (also known as cosmic variance) and field-to-field variations are a systematic component of the noise, which is difficult to estimate at this stage. The Poisson noise, used here, provides a strict lower limit of the cosmic variance.

3.3. Measurements

By adding the brightnesses derived by the stacking analysis of $24\ \mu\text{m}$ sources with $S_{24} \geq 80\ \mu\text{Jy}$ and by the few detected far-infrared sources, we measured

$$\begin{aligned} B_{160\text{tot-GOODS}} &= 7.53 \pm 0.52\ \text{nW m}^{-2}\text{sr}^{-1} \text{ at } 160\ \mu\text{m}, \\ B_{70\text{tot-GOODS}} &= 3.97 \pm 0.17\ \text{nW m}^{-2}\text{sr}^{-1} \text{ at } 70\ \mu\text{m} \\ \text{and } B_{160\text{tot-COSMOS}} &= 7.88 \pm 0.19\ \text{nW m}^{-2}\text{sr}^{-1} \text{ at } 160\ \mu\text{m}, \\ B_{70\text{tot-COSMOS}} &= 4.95 \pm 0.08\ \text{nW m}^{-2}\text{sr}^{-1} \text{ at } 70\ \mu\text{m} \end{aligned}$$

(see also the summary in Table 6).

If we compare these brightnesses with the models from Lagache et al. (2004), Le Borgne et al. (2009), and Bethermin et al. (2010c) (cf. Sect. 4.5 and Table 6) applying the same selection of using the $24\ \mu\text{m}$ sources with $S_{24} \geq 80\ \mu\text{Jy}$, we find that we can resolve between 66% and 89% of the $160\ \mu\text{m}$ background, and between 75% and 98% of the $70\ \mu\text{m}$ background.

Using only the post-Herschel model in hand (Bethermin et al. 2010c), our data indicate that we can resolve in COSMOS data 90% at $160\ \mu\text{m}$ and 98% at $70\ \mu\text{m}$ of the background we should detect by applying the selection at $24\ \mu\text{m}$. Our selection introduces an incompleteness in the CIB estimate corresponding to the fainter $24\ \mu\text{m}$ sources ($S_{24} < 80\ \mu\text{Jy}$), omitted from our analysis; this omission implies that we resolve 68% of the total $160\ \mu\text{m}$ background and 81% of the total $70\ \mu\text{m}$ background in COSMOS (see Sect. 4.5 for the details). For comparison, Berta et al. (2010) identified about 50% of the $100\ \mu\text{m}$ and $160\ \mu\text{m}$ backgrounds with individual sources, and account between 50% and 75% of the background when stacking at the positions of $24\ \mu\text{m}$ galaxies, as we do.

4. Discussion

We now present both the measurements and models in the form of $\frac{d(\nu B_\nu)}{dz}$ versus redshift z , where νB_ν is the CIB brightness in $\text{nW m}^{-2}\text{sr}^{-1}$, λ is the wavelength ($70\ \mu\text{m}$ or $160\ \mu\text{m}$), and ν is the corresponding frequency. This representation has the advantage of being independent of the redshift binning, thus allowing

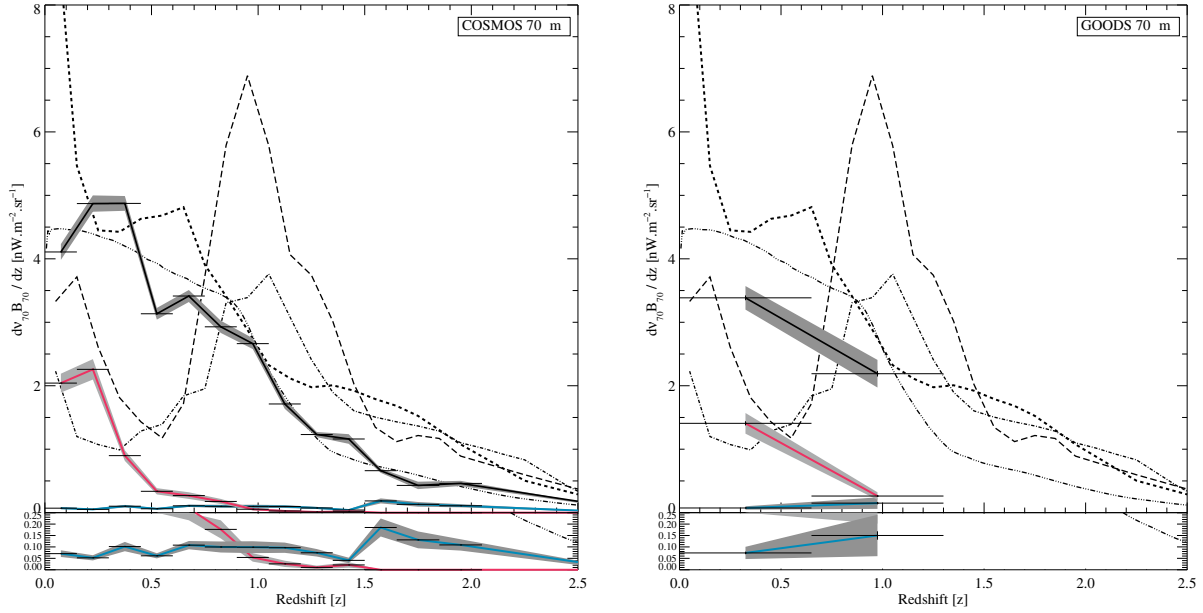


Fig. 7. Differential 70 μm background brightness $dv_{70} B_{70}/dz$ as a function of redshift, in units of $\text{nW m}^{-2} \text{sr}^{-1}$, in the COSMOS field (*left*) and GOODS field (*right*). The lower part of the plot shows a linear zoom between 0 and $0.25 \text{ nW m}^{-2} \text{sr}^{-1}$ to show more clearly the trend of cleaned sources and AGNs. Black solid lines: total contribution of infrared galaxies. Solid red lines: contribution from resolved sources only. Solid blue line: contribution from AGN only. Dashed line: Lagache et al. (2004) model, with $S_{24} > 80 \mu\text{Jy}$ cut. Dotted line: Le Borgne et al. (2009) model, with $S_{24} > 80 \mu\text{Jy}$ cut. Dot-dash line: Valiante et al. (2009). Dot-dot-dot-dash line: Bethérmin et al. (2010c) model, with $S_{24} > 80 \mu\text{Jy}$ cut. Models are presented and discussed in Sect. 4.5 and Fig. 10.

a direct comparison between datasets and models sampled in different ways into redshift bins. We discuss data and models with the prior selection of $S_{24} > 80 \mu\text{Jy}$, and show (Sect. 4.5) that our conclusions for $z < 1.5$, i.e., where most of the FIR background originates, are no different with this prior selection than when including fainter galaxies.

4.1. The 160 μm background: its history since $z = 2$

The distribution of the 160 μm CIB measured brightness as a function of redshift (Fig. 6) shows a plateau between redshifts 0.3 and 0.9 in both the COSMOS and GOODS fields, followed by a decrease at higher redshift. The small dip at $z = 0.5$ in COSMOS is not significant, since it disappears when the size of the redshift bin is increased ($\Delta z = 0.3$ instead of 0.15) and is probably caused by a structure in the COSMOS field. The GOODS field exhibits the same trend in redshift.

The contribution from resolved sources reaches a maximum at $z < 0.3$ and strongly decreases toward higher redshift, in agreement with the identifications of Frayer et al. (2006a). The AGN contribution is rather constant with redshift; the relative contribution of AGN thus increases with redshift. Assuming that the COSMOS field is representative of the whole CIB population, we find that 33% of the 160 μm background is accounted for at redshifts $0 < z < 0.5$, 41% for $0.5 < z < 1$, 17% for $1 < z < 1.5$, and 9% for $1.5 < z < 2$. Our results are consistent with Berta et al. (2010), who analyzed a deep sample in the GOODS-N field at 160 μm with PACS/Herschel. Most of the far-infrared sources are resolved by Herschel, and the stacks of 24 μm sources provide slightly more depth. Their peak at $z = 1$ is more pronounced than in our analysis.

The Lagache et al. (2004), Le Borgne et al. (2009), Valiante et al. (2009), and Bethérmin et al. (2010c) models are

Table 6. The total CIB brightness at 160 μm & 70 μm for the GOODS & COSMOS fields, in units of $\text{nW m}^{-2} \text{sr}^{-1}$.

	160 μm	70 μm
$B_{\text{tot-GOODS}}$	7.53 ± 0.84	3.97 ± 0.41
$B_{\text{tot-COSMOS}}$	7.88 ± 0.19	4.95 ± 0.08
$B_{\text{Bethérmin}}$	9.0 ± 1.1	5.2 ± 0.4
$B_{\text{BethérminCIBestimate}}$	$14.6^{+7.1}_{-2.9}$	$6.4^{+0.7}_{-0.6}$
$B_{\text{modelLagache}} (S_{24} > 80 \mu\text{Jy})$	11.91	5.73
$B_{\text{modelLagache}}$	14.87	6.78
$B_{\text{modelLeBorgne}} (S_{24} > 80 \mu\text{Jy})$	9.54	6.65
$B_{\text{modelLeBorgne}}$	13.57	8.54
$B_{\text{modelValiante}} (S_{24} > 80 \mu\text{Jy})$	6.84	4.27
$B_{\text{modelValiante}}$	16.70	6.98
$B_{\text{modelBethérmin}} (S_{24} > 80 \mu\text{Jy})$	8.82	5.02
$B_{\text{modelBethérmin}}$	11.66	6.09

Notes. Lines 1 & 2: our estimates; line 3: Bethérmin et al. (2010a) CIB measured value using number counts integration; line 4: Bethérmin et al. (2010a) CIB value with extrapolation of the number counts in power-law; line 5: Lagache et al. (2004) CIB model value with the constraint: $S_{24} > 80 \mu\text{Jy}$; line 6: Lagache et al. (2004) CIB model value of the total background; line 7: Le Borgne et al. (2009) CIB model value with the constraint: $S_{24} > 80 \mu\text{Jy}$; line 8: Le Borgne et al. (2009) CIB model value of the total background; line 9: Valiante et al. (2009) CIB model value with the constraint: $S_{24} > 80 \mu\text{Jy}$; line 10: Valiante et al. (2009) CIB model value of the total background; line 11: Bethérmin et al. (2010c) CIB model value with the constraint: $S_{24} > 80 \mu\text{Jy}$; line 12: Bethérmin et al. (2010c) CIB model value of the total background.

overplotted to our measurements on Fig. 6, after applying the same selection of $S_{24} \geq 80 \mu\text{Jy}$ as applied on the data. Pre-Herschel models predict different redshift distributions for

$dv_{160}B_{160}/dz$. The Lagache et al. (2004) models peaks at $z \sim 1$ and disagrees with our data. Our data are in closer qualitative agreement with the Le Borgne et al. (2009) model (except for $z < 0.3$), but no model is capable of reproducing the $z > 1$ tail. The problem of the discrepancy between our data and the Le Borgne et al. (2009) model at $z < 0.3$ might be twofold: our data is of lower statistical quality at very low redshift due to the relatively small sky area covered, and the model might be overpredicting low- z galaxies because of the lack of a cold component in the galaxy SED used. The model of Bethermin et al. (2010c) provides a close fit to our data in the low, intermediate, and high redshift ranges, most likely because it is based on a optimal minimization between the model and the most recent Spitzer and Herschel data, and already takes into account the FIR and submm statistical properties of galaxies (see Sect. 4.5).

4.2. The 70 μm background: its history since $z=2$

The distribution of the measured 70 μm CIB measured brightness as a function of redshift (Fig. 7) clearly indicates that the greatest contribution is from sources at $z < 0.5$ in COSMOS, in agreement with the GOODS measurements. The peak contribution at 70 μm occurs at lower redshift than at 160 μm , which is expected as a consequence of the K-correction (the effect of the redshifted shape of the galaxy spectra). This difference is also seen between 100 μm and 160 μm in the PACS/Herschel data by Berta et al. (2010). The dip at $z \sim 0.5$ is most likely caused by cosmic variance, because it is not seen in the GOODS field and disappears when we use broader redshift bins. This dip does not affect our conclusions about the 70 μm background emission with redshift.

The contribution from resolved sources reaches a maximum at $0.15 < z < 0.3$ and strongly decreases at higher redshift, in agreement with the identifications of Frayer et al. (2006a). The AGN contribution remains almost constant with redshift. Assuming that the COSMOS field is representative of the whole CIB population, we conclude that 43% of the 70 μm background is accounted for at redshifts $0 < z < 0.5$, 38% for $0.5 < z < 1$, 13% for $1 < z < 1.5$, and 5% for $1.5 < z < 2$. Those results agree with those of Pascale et al. (2009).

The Lagache et al. (2004) model predicts that the CIB at 70 μm reaches a maximum at around $z = 1$, which is not seen in the data presented here. The Le Borgne et al. (2009) model predicts a peak at lower redshift ($z \leq 0.5$) and a strong contribution at $z \sim 0$, neither of which seen in the data; otherwise, the decrease at $z > 0.5$ has a shape comparable to the data, despite there being a larger high-redshift tail. The post-Herschel Bethermin et al. (2010c) model closely agrees with the observed evolution in both COSMOS and GOODS (Fig. 7).

4.3. Role of AGN

The AGN contribution in each redshift bin is shown in Figs. 7 and 6, as the lower blue area. The estimate of this contribution can be considered as a “best effort” estimate, because of the difficulty in identifying the origin of the far-infrared emission (star formation or AGN). Our AGN identification relies on X-ray detections and IRAC colors (Caputi et al. 2006; Salvato et al. 2009), but the far-infrared emission is not necessarily physically linked to the AGN (Le Flocc’h et al. 2007).

Our analysis indicates that the absolute contribution of AGN to the CIB at 70 μm and 160 μm is almost constant with redshift. Figure 8 shows the relative contribution to the CIB, which

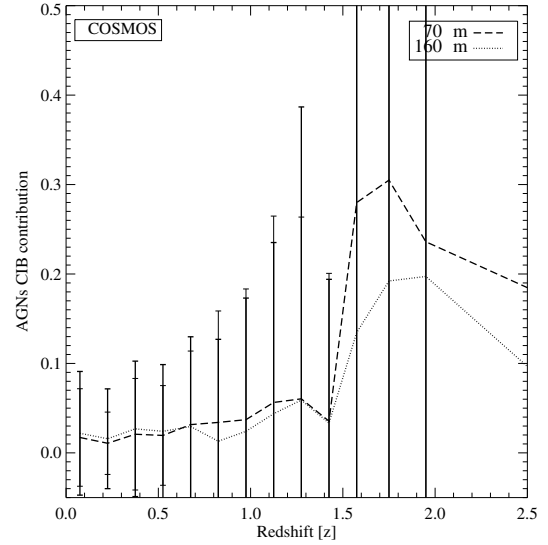


Fig. 8. The relative contribution of identified AGN to the 70 μm and 160 μm CIB as a function of redshift, for the selection at 24 μm given by $S_{24} > 80 \mu\text{Jy}$.

is obtained by dividing the AGN contribution by the total CIB contribution. Because of the smaller contribution of higher redshift sources to the CIB, the AGN fraction contribution to the CIB increases with redshift, from about $3 \pm 10\%$ for $0 < z < 1.5$, and possibly up to 15–25% for $z > 1.5$, but our large error bars do not allow any meaningful estimate. We thus can only state that the relative AGN contribution is smaller than about 10% at $z < 1.5$. Our results agree with Daddi et al. (2007), who predict that the AGN contribution should not exceed about 7% up to a redshift of unity.

AGNs are understood to play a central role in terms of physical processes driving galaxy evolution and regulating star formation by means of feedback (e.g. Magorrian et al. 1998; Ferrarese & Merritt 2000; Bower et al. 2006; Hopkins et al. 2006; Cattaneo et al. 2009; Hopkins et al. 2010). However, our work confirms that, in terms of total energy contributions to the CIB, the AGNs play a minor role. This conclusion agrees with the identifications of Frayer et al. (2006a) and the analysis of Valiante et al. (2009), which demonstrates (their Fig. 19) that fewer than 10% of the sources with $S_{24} > 80 \mu\text{Jy}$ (i.e. the sources constituting the CIB at 24 to 160 μm , see Dole et al. 2006) are affected by a significant AGN contribution.

4.4. The 24, 70, 100, and 160 μm backgrounds

The mid- and far-infrared background buildup at 24, 70, 100, and 160 μm as a function of redshift is presented in Fig. 9 and is available online³. The 24 μm data from Le Flocc’h et al. (2009) were normalized to $2.86 \text{ nW m}^{-2} \text{ sr}^{-1}$ (Bethermin et al. 2010a), the data at 100 μm are from Berta et al. (2010), but the data at 70 and 160 μm come from this work. At wavelengths longer than 60 μm , the observed build-up sequence has an increasing contribution between $z \sim 0.5$ and $z \sim 1$ with increasing wavelength. This behavior is expected because of the redshifted peak in the galaxy spectral energy distributions, or k-correction (e.g. Lagache et al. 2004; Lagache et al. 2005). The 24 μm distribution

³ <http://www.ias.u-psud.fr/irgalaxies/>

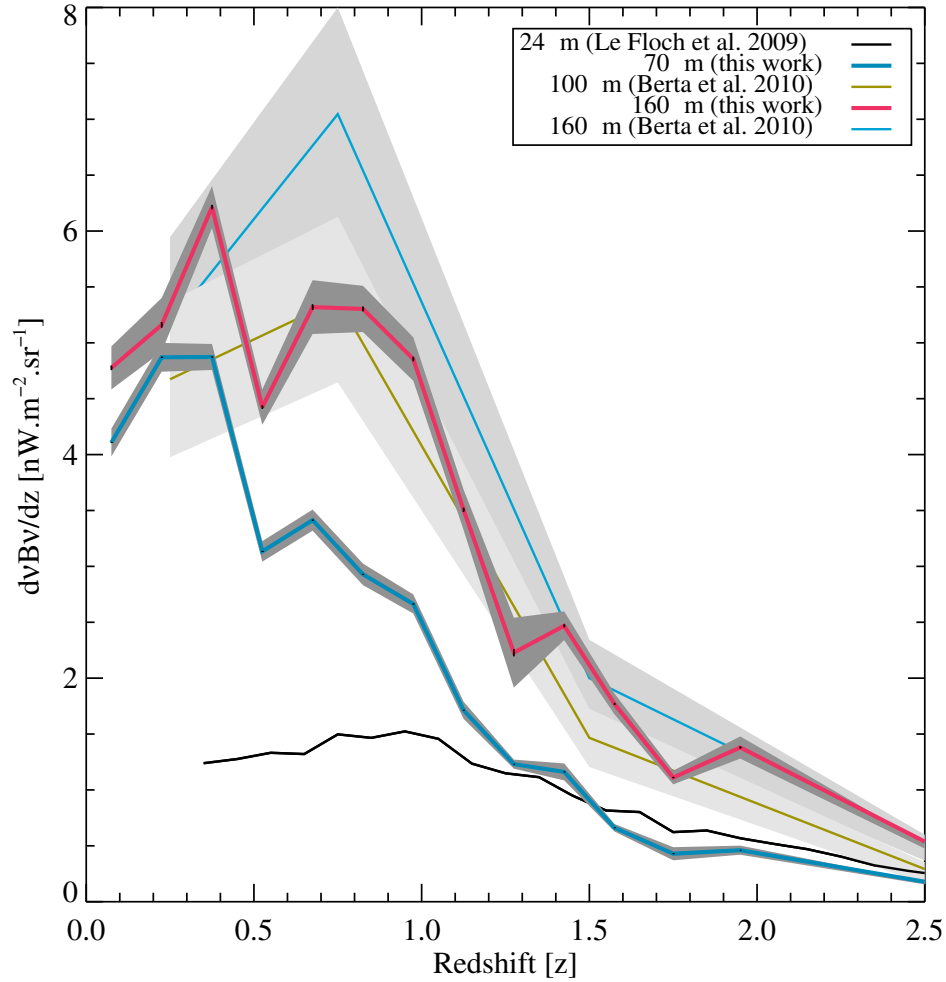


Fig. 9. The cosmic infrared background history since $z \sim 2$ at 24, 70, 100, and 160 μm as measured from galaxies selected at 24 μm with $S_{24} > 80 \mu\text{Jy}$. The 24 μm data come from [Le Floch et al. \(2009\)](#), and the 70 and 160 μm data from this work, all using the Spitzer/MIPS data of COSMOS field. The 100 and 160 μm data in four redshift bins are from [Berta et al. \(2010\)](#) in GOODS-N with Herschel/PACS (using the same 24 μm prior.).

is flatter (or broader) with redshift, and its greatest contribution is from sources at around $z \sim 1$. This mid-infrared distribution has a relative contribution at $z > 1.5$ larger than in the far-IR, i.e., the decay slope is shallower at 24 μm than at 70 μm and longer wavelengths.

A detailed comparison, however, is still difficult because of cosmic variance. The results from [Berta et al. \(2010\)](#) are based on GOODS-N, which has an area about 50 times smaller than considered here. We have furthermore shown that large-scale structure is visible at $z < 0.5$ in the COSMOS field.

That most of the CIB between 100 and 160 μm is identified as being produced by $z < 1$ sources agrees with expectations (e.g. [Lagache et al. 2005](#); [Bethérmin et al. 2010c](#)). The 24 μm background contains, however, a significant contribution from galaxies at $z > 1$ (30%, according to [Le Floch et al. 2009](#)). As expected and observed ([Marsden et al. 2009](#); [Pascale et al. 2009](#)), most of the submillimeter background consists of sources at higher redshifts ($z > 1.5$). Other analyses found conflicting results (see [Wang et al. 2006](#); [Serjeant et al. 2008](#)). This wavelength versus redshift dependence of the background can be

explained by analyzing the sum of the SED of galaxies at various redshifts, in particular the peak emission in the far-infrared of the reprocessed starlight by dust that is redshifted. Thus, the SED of the CIB is broader and flatter at far-infrared and submillimeter wavelengths than for any individual galaxy SED.

4.5. The models

These observations can be confronted to models. We considered three backward evolution models developed to fit infrared data: [Lagache et al. \(2004\)](#), [Le Borgne et al. \(2009\)](#), [Valiante et al. \(2009\)](#), and [Bethérmin et al. \(2010c\)](#), among an abundant literature (for the most recent: [Franceschini et al. 2008, 2009](#); [Pearson & Khan 2009](#); [Rowan-Robinson 2009](#)). The main feature of the [Lagache et al. \(2004\)](#) model is the use of two galaxy population spectral energy distributions (SEDs), normal/cold and starburst galaxies, parametrized by their total infrared luminosity. The local luminosity functions are fitted, and the evolution in redshift is applied to fit the additional constraints of the observed number counts, CIB SED, and CIB fluctuation level.

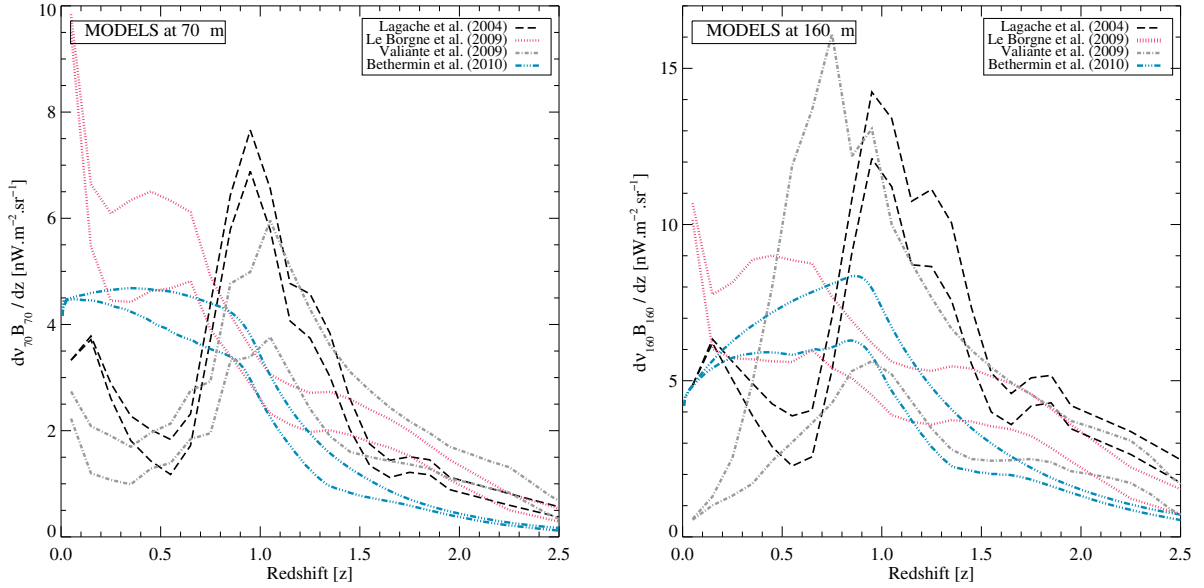


Fig. 10. Differential 70 (left) and 160 μm (right) background brightness dv_B/dz as a function of redshift, in units of $\text{nW m}^{-2} \text{sr}^{-1}$, as predicted by 4 models: dash black line: [Lagache et al. \(2004\)](#) model; Dot magenta line: [Le Borgne et al. \(2009\)](#) model; Dot-dash grey line: [Valiante et al. \(2009\)](#); Dot-dot-dash blue line: [Bethermin et al. \(2010c\)](#) model. For each model, the top line corresponds to all galaxies, and the bottom line to the prior selection (used in this work) of $S_{24} > 80 \mu\text{Jy}$.

The [Le Borgne et al. \(2009\)](#) model is based on an automated minimization of the difference between the model and selected datasets (local luminosity functions, number counts, CIB absolute level) with a given SED library ([Chary et al. 2001](#)). The [Valiante et al. \(2009\)](#) model introduces scatter into the SED by using Monte Carlo simulations for an extended library based on observations from the Spitzer archive, and contains starburst and AGN contributions as a function of IR luminosity. These three models used Spitzer data, and were developed prior to the availability of Herschel data. Finally, the [Bethermin et al. \(2010c\)](#) model is a fully-parametric approach, automatically fitting the latest Spitzer, BLAST & Herschel data with the Markov chain Monte Carlo (MCMC) ([Dunkley et al. 2005](#)) method, and using the [Lagache et al. \(2004\)](#) SED library of two galaxy populations.

Figures 6 and 7 overplot these three models for a prior selection at 24 μm (with $S_{24} > 80 \mu\text{Jy}$) to be consistent with the data we compare. Figure 10 shows the models, with this prior cut, but also without any cut, i.e. all the galaxies. The main differences can be summarized as follows:

- the [Lagache et al. \(2004\)](#) model predicts a contribution of infrared galaxies to the 70 and 160 μm backgrounds peaking at $z \sim 1$, which is not observed; the predicted dip at $z \sim 0.5$ is also not observed;
- the [Le Borgne et al. \(2009\)](#) model overpredicts the galaxy contributions at $z \leq 0.3$, i.e., disagrees with observations, despite the poor statistical quality of the observations; the reason for this disagreement is probably the lack of a cold galaxy component at $z \sim 0$. The general shape of the model at $z > 0.3$ agrees with the data, despite predicted peak and high-redshift ($z > 1$) tail being slightly higher than observed;
- the [Valiante et al. \(2009\)](#) model exhibits similar trends to that of [Lagache et al. \(2004\)](#): almost no contribution at low redshift (in disagreement with data at 70 and 160 μm), and a pronounced peak at $z \sim 1$, which is not observed. This

models reproduces well, however, the $z > 1$ tail at 160 μm (but not at 70 μm);

- the [Bethermin et al. \(2010c\)](#) model provides a closer fit to the data, most likely because its optimal use of Spitzer & Herschel data ([Bethermin et al. 2010a](#); [Oliver et al. 2010](#)) at far-infrared and submillimeter wavelengths already takes into account the statistical properties of galaxies in an empirical way;
- the selection of $S_{24} > 80 \mu\text{Jy}$ galaxies to estimate the background buildup with redshift produces an almost flat cut in redshift to the brightness (comparison of the two lines for each model in Fig. 10, except for [Valiante et al. \(2009\)](#) at 160 μm with larger variations). Thus, the peak and the structure in redshift observed with the $S_{24} > 80 \mu\text{Jy}$ cut is not significantly affected by this selection, and our conclusions based on this cut can be extended to the whole CIB buildup, at least for $z < 2.5$. However, the $S_{24} > 80 \mu\text{Jy}$ cut might cause a problem of strong incompleteness at Herschel SPIRE wavelengths, made-up by higher-redshift sources ([Lagache et al. 2005](#); [Marsden et al. 2009](#)). A need to use fainter 24 μm flux densities is thus required at submm wavelengths.

All these models predict similar star formation rates and evolutions of the luminosity function. Our work places stronger constraints on the models, which will have to fine-tune either the galaxies SED used or refine the luminosity function evolutions considered.

5. Conclusion

As shown by [Le Flocc'h et al. \(2009\)](#) and our results, comparing the CIB buildup (differential brightness vs. redshift) with models allows us to constrain the parameters and break degeneracies, since models usually predict the same number counts and CIB SED, but different redshift histories for the luminosity functions for instance. Using exquisite Spitzer data on one of the widest and deepest fields, we have been able to infer that the maximum

contributions to the 70 μm background (when selecting 24 μm galaxies with $S_{24} > 80 \mu\text{Jy}$) occur at both $z < 0.5$ and $0.3 < z < 0.9$ for the 160 μm background.

We have deduced that 74% of the 160 μm background was emitted at $z \leq 1$, and 81% at 70 μm . We have also estimated the AGN contribution to the far-infrared background to be less than about 10% for $z < 1.5$.

Results obtained for preliminary Herschel/PACS data on GOODS-N by Berta et al. (2010) agree with our findings, despite the uncertainties due to large-scale structure. This consistency with the results confirms that the stacking analysis method is a valid approach to estimate the components of the far-IR background using prior information about resolved mid-IR sources.

The Lagache et al. (2004) model predictions mainly disagree with data, since a peak in the contributions at $z \sim 1$ is not observed. The Le Borgne et al. (2009) model disagrees with the data at low redshift (most likely because of the SED used), but succeeds in reproducing most of the observed trend, despite there being an excess at $z > 1.5$. The Bethermin et al. (2010c) model is consistent with the data.

Our study, combined with those of Le Floch et al. (2009) and Berta et al. (2010), can allow to place tighter constraints on the models of galaxy evolution, since their predictions can strongly vary with redshift, despite close fits of the number counts, luminosity functions, and cosmic infrared background spectral energy distributions.

This study, and forthcoming analyses of Herschel data, will also help to refine the models used to compute the far-infrared and submillimeter emissivity with redshift, which is needed to compute the optical depth for (hundreds of) TeV photons. Since the opacity of the Universe to TeV photons depends on the infrared luminosity density along the line of sight, the buildup history of the CIB has a direct effect on the TeV photon propagation. We have shown that most (~80%) of the far-infrared background is produced at $z < 1$, in a regime where many blazars are observed (e.g. Aharonian et al. 2006; Albert & Magic Collaboration 2008). The model predictions for TeV obscuration models (e.g. Mazin & Raue 2007; Franceschini et al. 2008; Stecker & Scully 2009; Kneiske & Dole 2010; Younger & Hopkins 2010; Bethermin et al. 2010c) can be distinguished at $z \leq 0.3$, where the CIB has the greatest contribution to high energy photons emission, by comparing their CIB buildup history with our data.

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