

Extracting SZ signals in multi-component sky emission

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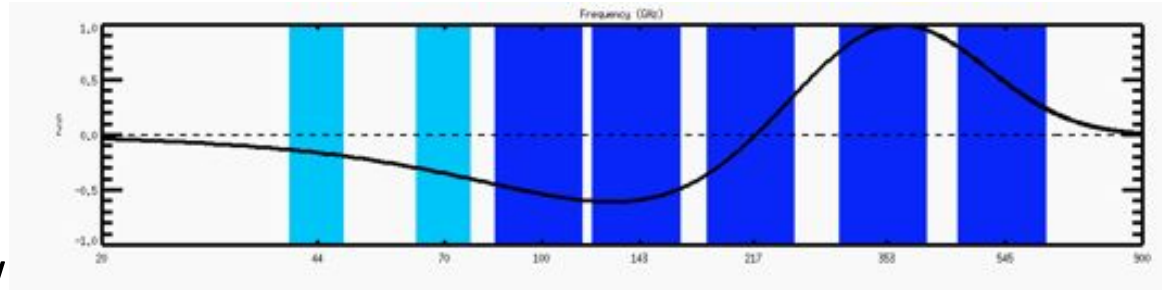
Outline

- ➔ • Introduction
- Multi-component sky emission models
- Component separation
 - Planck SZ challenges
 - ILC, MF and MMF
- ILC biases
- Improving cluster counts
- Conclusion

The multi-component sky

- Cosmic microwave background
 - Known emission law
 - Known spectrum (or nearly so)
 - Gaussian (or nearly so)
- Large scale structures
 - Dark matter haloes and filaments
 - Populated by galaxies (radio, infrared) and *clusters of galaxies*
 - Generates SZ effects
 - Generates lensing and ISW effect
 - Far infrared background from numerous distant unresolved sources
- Galactic Interstellar medium
 - Highly complex
 - Synchrotron from hot gas, Free-free from warm gas, thermal emission from cold dust, molecular lines, spinning dust...

SZ signals



- Thermal SZ
 - Known emission law
 - But relativistic corrections
 - Good guess about profile (parametric model)
 - Contamination of clusters by radio and infrared sources
- Kinetic SZ
 - Known emission law (but that of the CMB!)
 - Very faint
- Both effects originate primarily from galaxy clusters
 - But look for filaments
 - Patchy reionisation may generate detectable kSZ

SZ information

- Number counts $dN/dMdv$
 - Growth of structures
 - Spectrum $P(k)$
- Number counts $dN/dMdz(d\Omega)$
 - Geometry $D_A(z), H(z)$
- Cosmological tests
 - Velocity flows
 - Correlations (SZ, ISW, lensing...)
 - Power spectrum of thermal and kinetic SZ
- Angular vs. physical size
- Gas fraction M_g/M_{tot}
- Cluster physics

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Simulations

- Accurate and consistent simulations are needed
 - Of the SZ emission itself
 - Of all other components
- They are critical for developing, testing, understanding methods for the extraction of SZ information, and validating data pipelines.
- The Planck Sky Model (PSM)
 - Originally started for preparing Planck data analysis
 - Multi-component sky emission model
 - Consistency between the components
 - Based on interpretation of existing data
 - Prediction and simulation of sky emission (data/theory driven)
 - Contributions and suggestions welcome
- Web site
 - <http://www.apc.univ-paris7.fr/~delabrou/PSM/psm.html>

The PSM

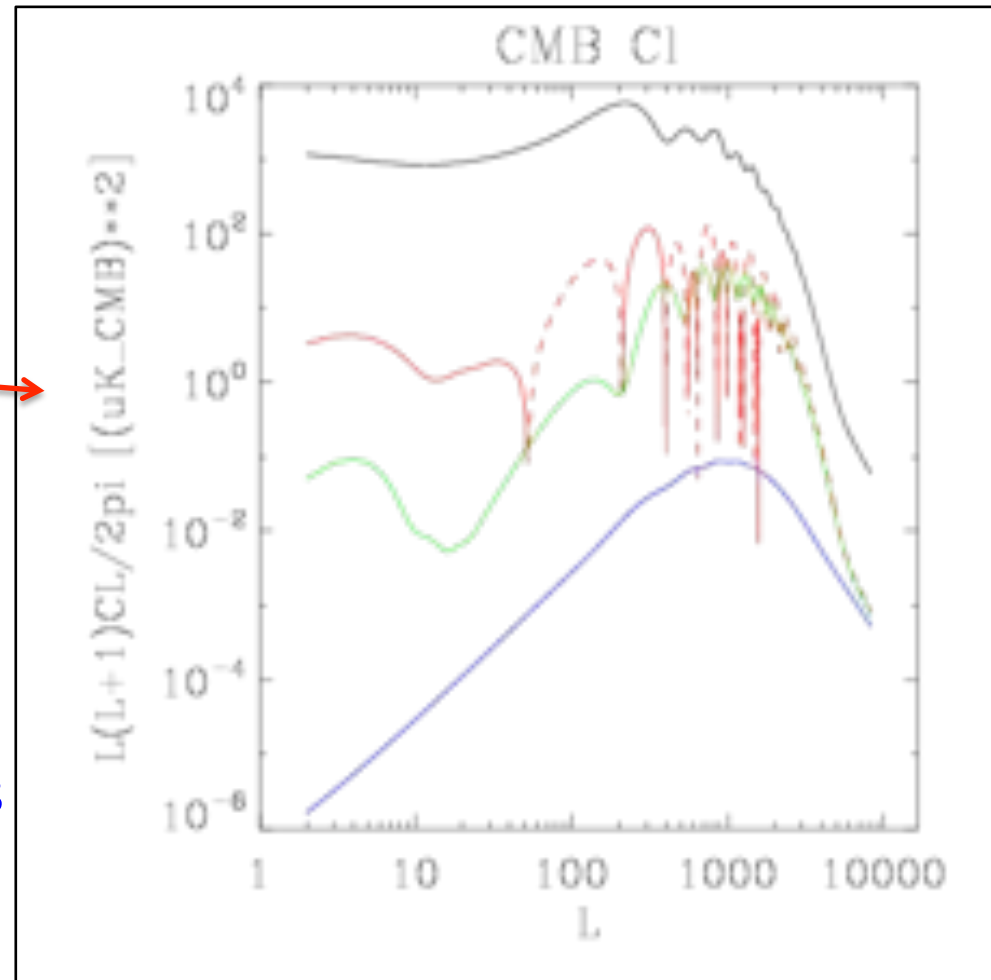
- Developed originally as part of Planck WG2 – collective work !
-
- About 10 main developers, many more contributors provided inputs
 - **Templates** (e.g. non gaussian CMB from F. Elsner & B. Wandelt)
 - **Point source catalogues** (e.g. IRAS sources from D. Clements)
 - **Small pieces of code** (e.g. free-free spectrum from C. Dickinson)
 - **Suggestions & bug reports**
-
- Currently 6 main elements to the code
 - General architecture (scientific and software)
 - CMB models
 - The galaxy (Marc-Antoine Miville Deschênes)
 - SZ effects (Jean-Baptiste Melin)
 - Point sources including FIRB (Joaquin Gonzalez-Nuevo)
 - Observation with mock instruments

CMB models in the PSM

- Gaussian models
 - Use C_l from current best fit model

or

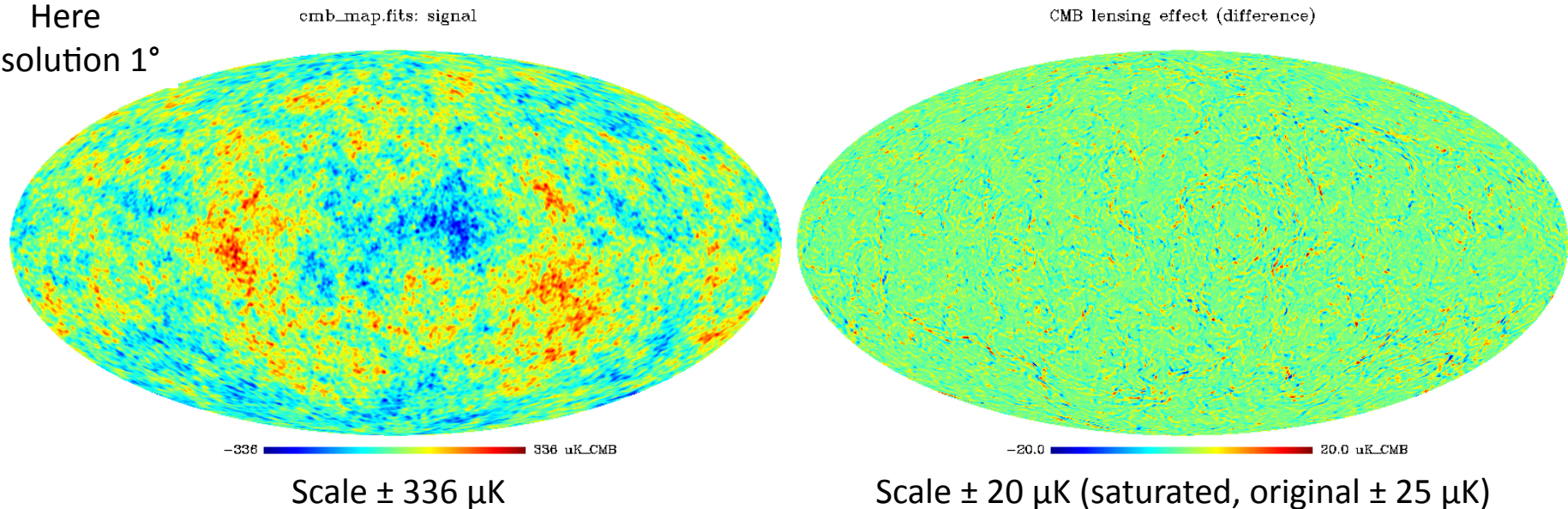
 - use C_l from CAMB (cosmological parameters set by the PSM user)



CMB models in the PSM

- Lensed CMB
 - Gaussian approximation (lensed spectra)
 - Or Lensing of CMB map

Here
resolution 1°

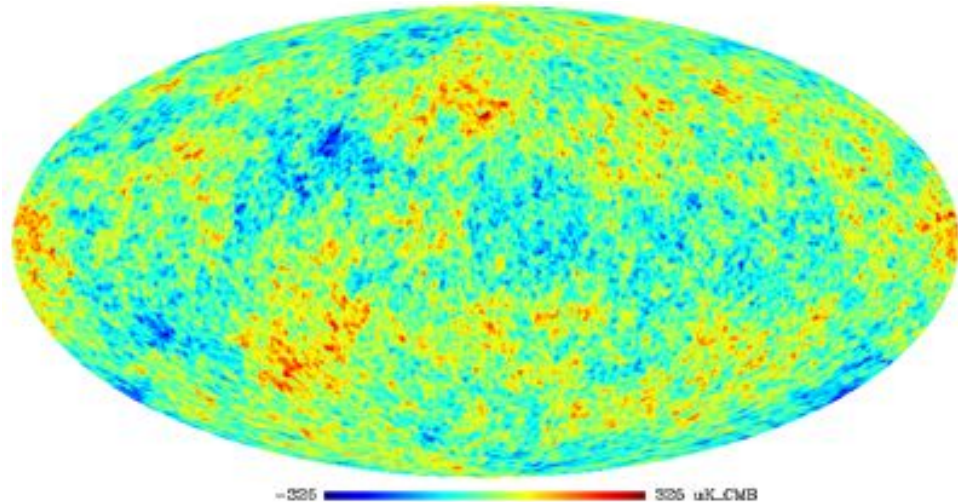


Basak et al. A&A 508, 53 (2009)

Non-Gaussian CMB model in the PSM

Linear part

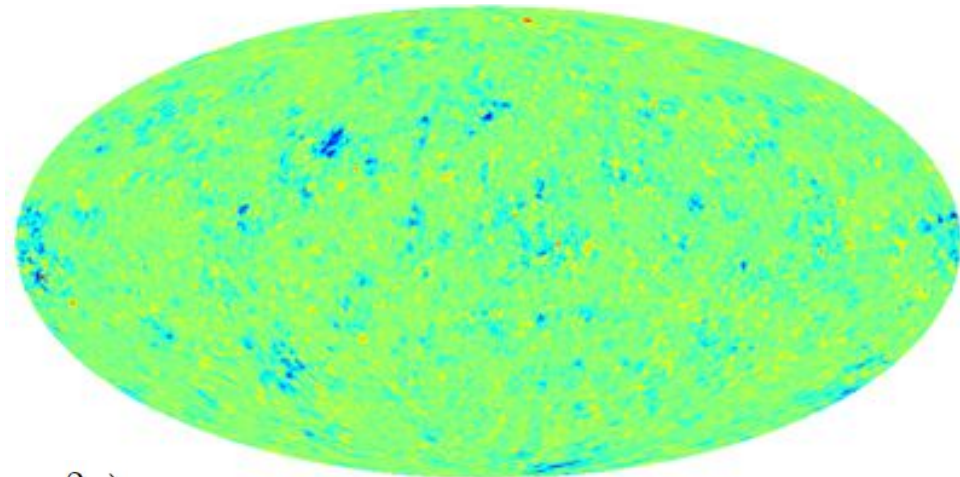
Elsner & Wandelt, ApJS 184, 234 (2009)



-325 325 μK_{CMB}

Scale $\pm 325 \mu\text{K}$

Non-linear correction (for $f_{\text{NL}}=1$)



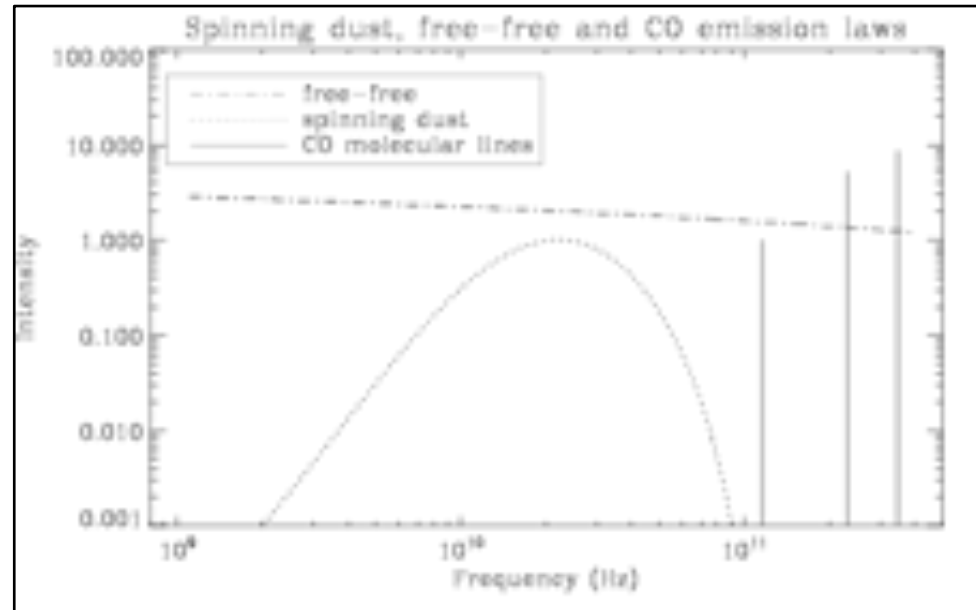
-0.071 0.071 μK_{CMB}

Scale $\pm 0.071 \mu\text{K}$

$$\Phi(\mathbf{x}) = \Phi_{\text{L}}(\mathbf{x}) + f_{\text{NL}} \left(\Phi_{\text{L}}(\mathbf{x})^2 - \langle \Phi_{\text{L}}(\mathbf{x})^2 \rangle \right)$$

Galactic emission in the PSM

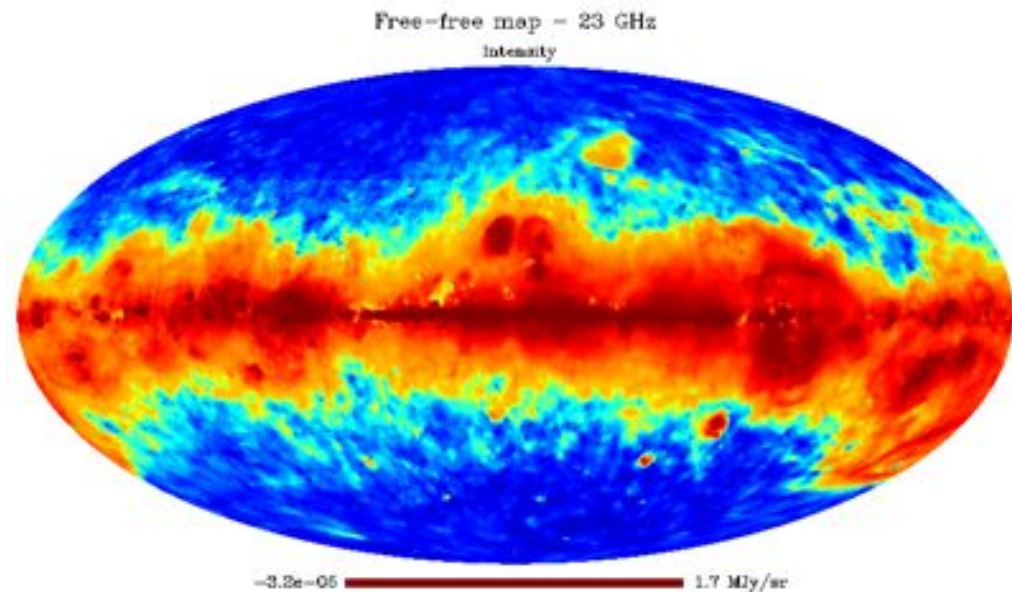
- 5 components
 - Synchrotron (polarised)
 - Free-free
 - Thermal dust (polarised)
 - Spinning dust
 - CO emission lines



- Emission templates from
 - WMAP
 - Haslam et al. 408 MHz data
 - Schlegel, Finkbeiner & Davis 100 micron map (IRAS+DIRBE)
 - Dame et al (CO survey)

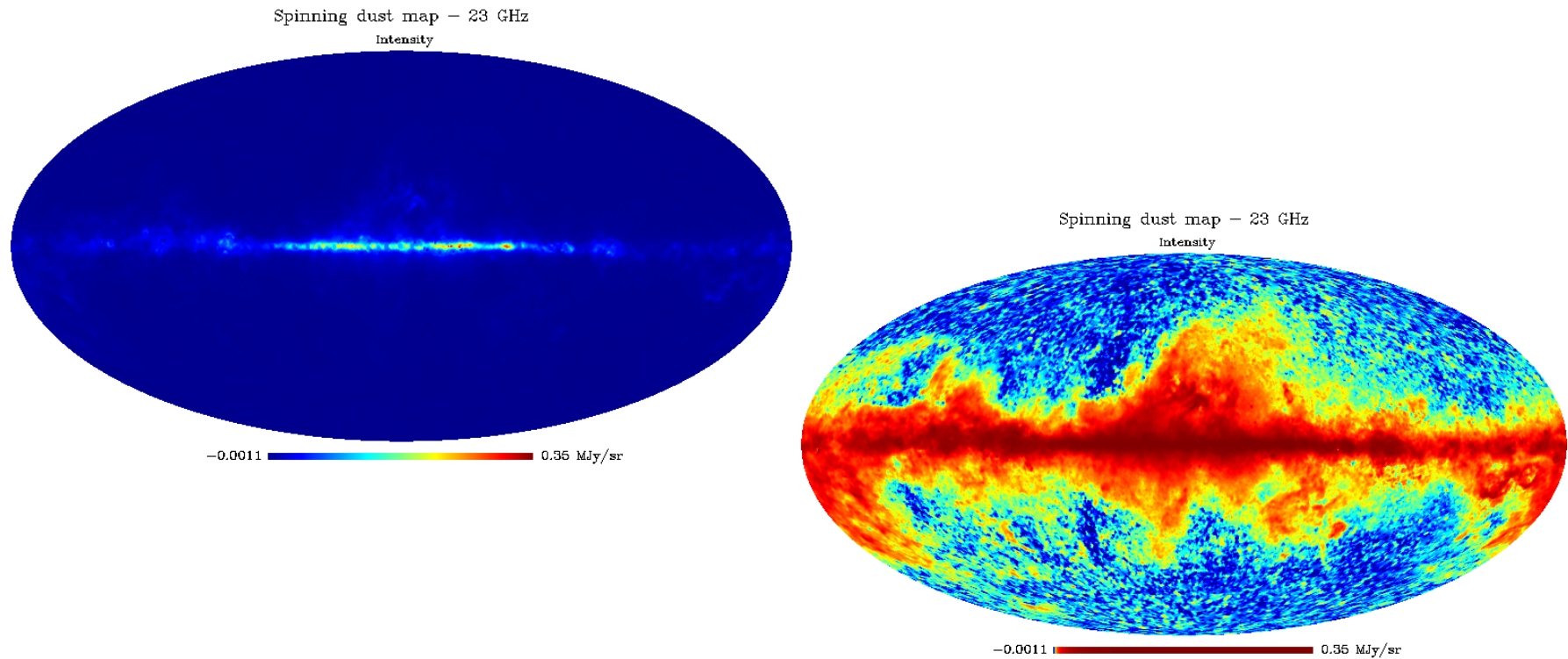
Free-free

- Composite template map
 - In dense regions ($E(B-V) > 2$) use WMAP MEM decomposition
 - Elsewhere use estimate from $H\alpha$, except where WMAP MEM estimate is lower
 - Resolution 1°



Spinning dust

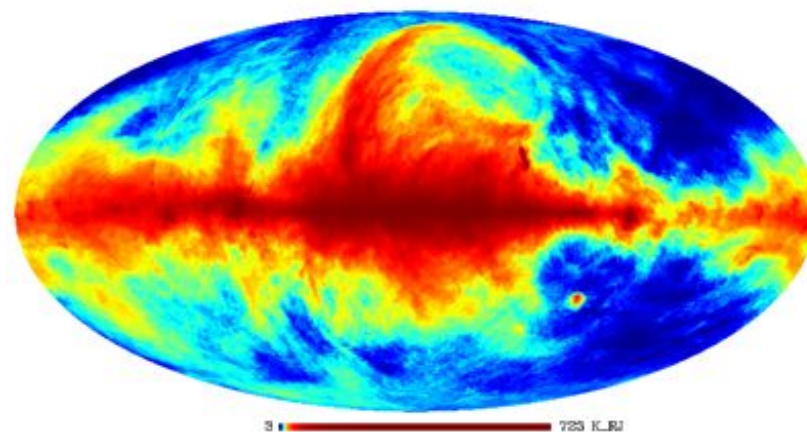
- Residual of WMAP 23GHz map after subtracting the synchrotron, free-free, and thermal dust



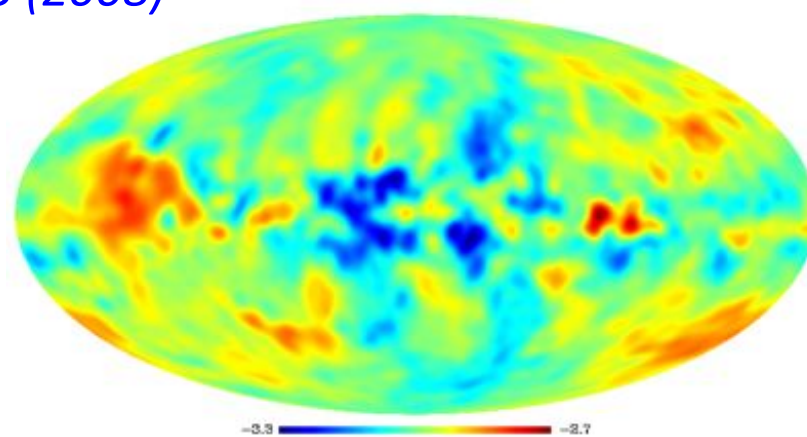
Synchrotron

- Template temperature map
 - *Haslam et al. A&AS, 47, 1 (1982)*
- Spectral index
 - From model of synchrotron polarisation fraction at 23GHz
 - *Miville-Deschênes et al. A&A, 490, 1093 (2008)*
- Resolution 1° (5° for spectral index)

Synchrotron template map at 408 MHz

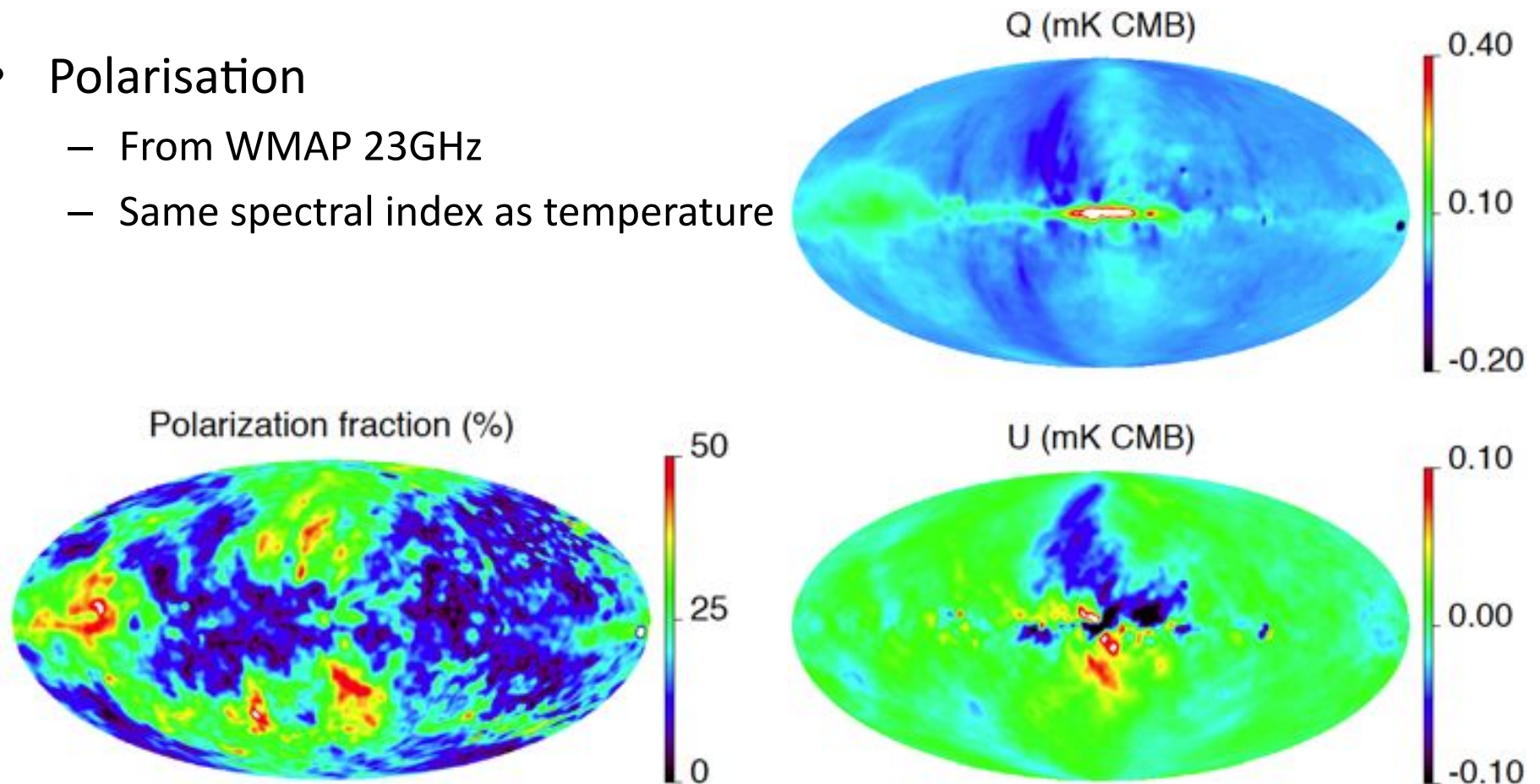


Synchrotron spectral index map



Synchrotron polarisation

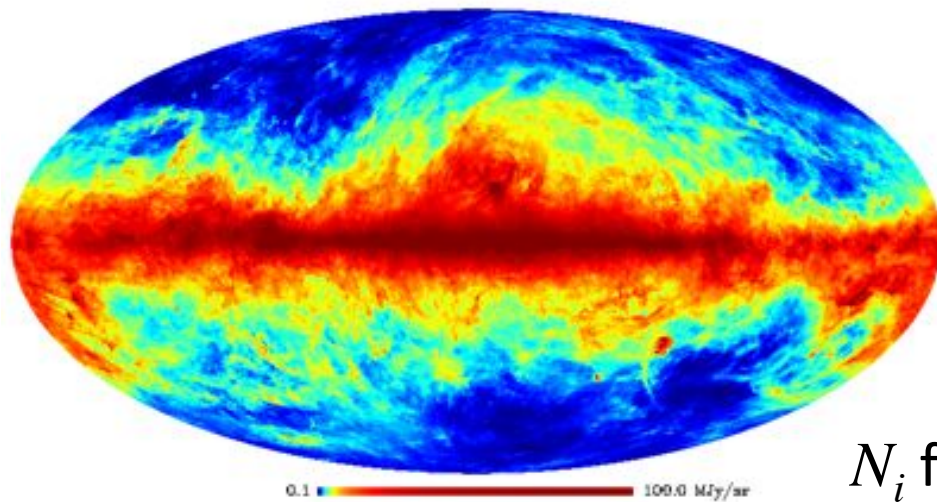
- Polarisation
 - From WMAP 23GHz
 - Same spectral index as temperature



Thermal dust

- Based on IRAS+DIRBE+FIRAS
 - Model 7 of *Finkbeiner, Schlegel, Davis, ApJ, 524, 867 (1999)*

Thermal dust emission 100-micron template



$$I_\nu = \sum_{i=1}^2 N_i \epsilon_i \nu^{\beta_i} B_\nu(T_i)$$

Column density

Opacity

N_i for two populations is obtained from color ratio

$$I_{100\mu\text{m}}/I_{240\mu\text{m}}$$

$$\beta_1 = -1.5$$

$$\beta_2 = -2.6$$

Thermal dust polarisation

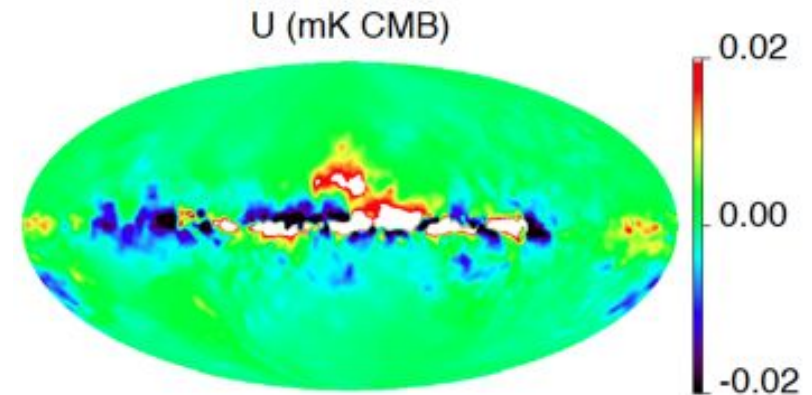
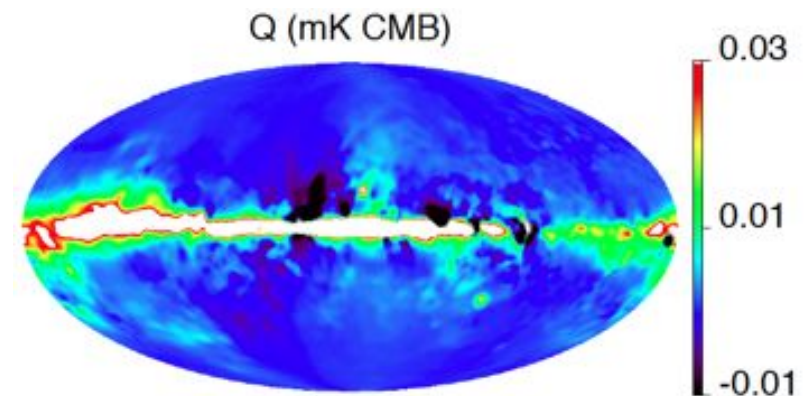
$$Q_\nu(p) = f_d g_d(p) I_\nu(p) \cos(2\gamma_d(p))$$

$$U_\nu(p) = f_d g_d(p) I_\nu(p) \sin(2\gamma_d(p))$$

intrinsic polarisation
fraction = 0.15

geometric
depolarisation
factor

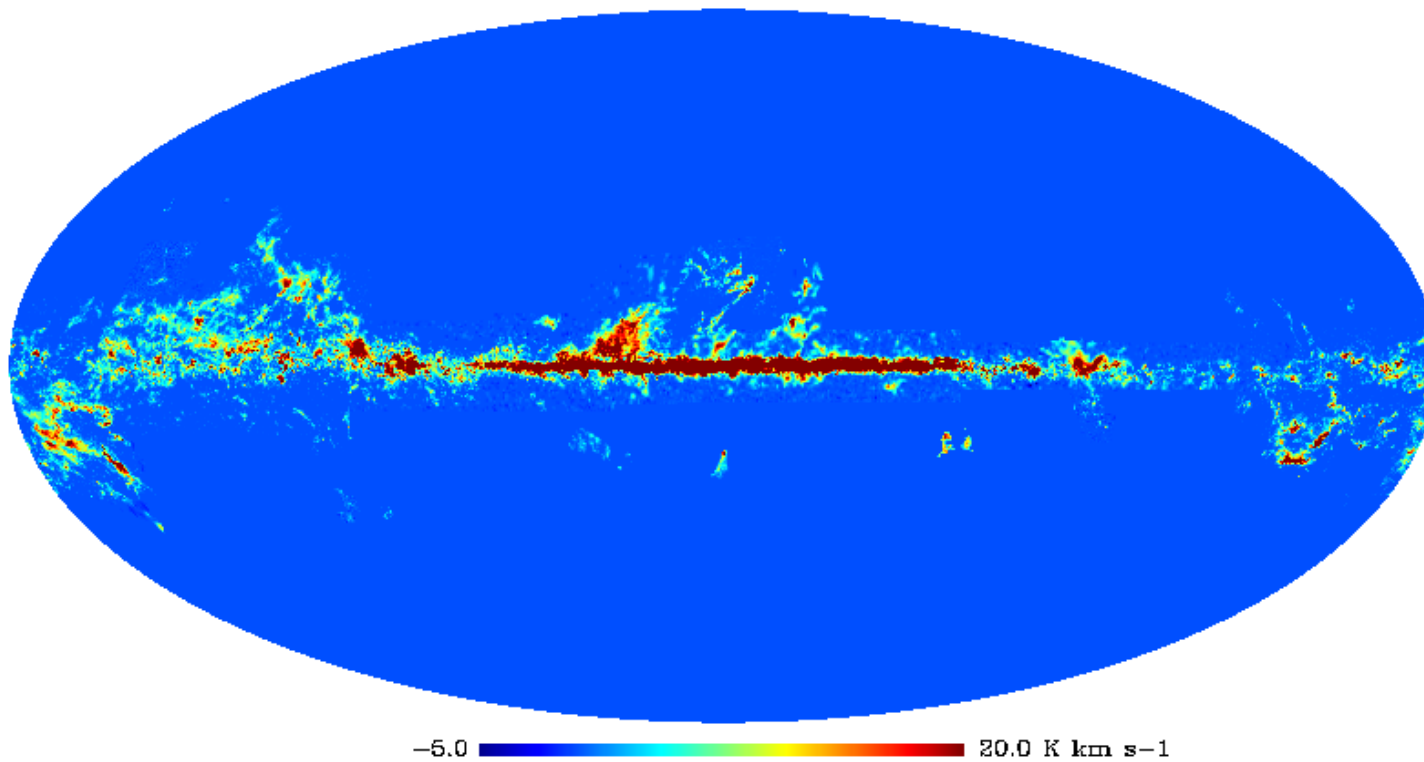
polarisation
angle



At 200 GHz

CO line emission

- Template of Dame et al. from the LAMBDA web site.



Small scales

- Galactic templates are at various resolutions
 - Synchrotron, free-free, spinning dust at $\approx 1^\circ$
 - Thermal dust at $\approx 6'$
- This is not appropriate for testing the extraction of SZ clusters (practically no galactic foregrounds on small scales)
- Random small scale fluctuations are added

Point sources

- Five main populations
 - Radio sources: from radio observations, extrapolated to higher frequencies
 - Two sub-populations: steep and flat
 - IRAS sources: catalogue from D. Clements, extrapolated to lower frequencies
 - FIRB: simulated map from Gonzalez-Nuevo et al.
 - WMAP sources: WYSIWYG
 - Ultra compact H-II regions: fit with greybody + free-free

SZ emission in the PSM

- Complete simulation of DM and gas in a Hubble volume
 - impractical
- N-body simulations of dark matter
 - Still computationally demanding
 - Need a prescription to add the baryons
- Using known clusters
 - Quite limited
 - Need a prescription to estimate the SZ effect from X or optical
- From number counts
 - Need a mass function
 - Need a prescription for γ (profile as a function of mass)

Original work

- Press-Schechter formalism, cluster counts $dN/dMdz$
 - Random generation of density contrast in a box
 - e.g. 600×600×6000 Mpc comoving, with 20Mpc cells, for 3°×3° field
 - Linear growth only
 - Clusters distributed at each redshift proportionally to $(1+b\delta\rho/\rho)$
-
- Kinetic and polarised SZ effect from velocity field (assumed irrotational)

$$\text{Newtonian potential } \nabla^2\Phi = 4\pi G a^2 \delta\rho$$

$$v = -\frac{2}{3} \frac{f(z)}{\Omega_m(z)H(z)} \frac{\nabla\Phi}{a} \quad \text{with} \quad f \equiv d \ln D_g(z) / d \ln a$$

Linear growth factor

Examples of SZ patches

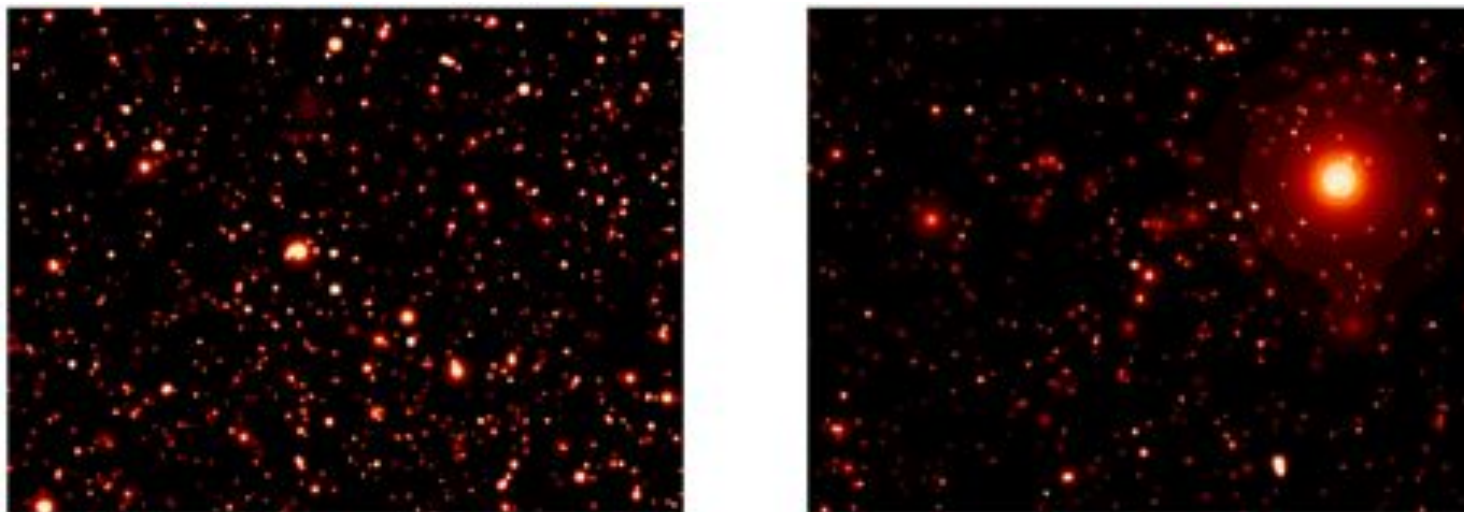
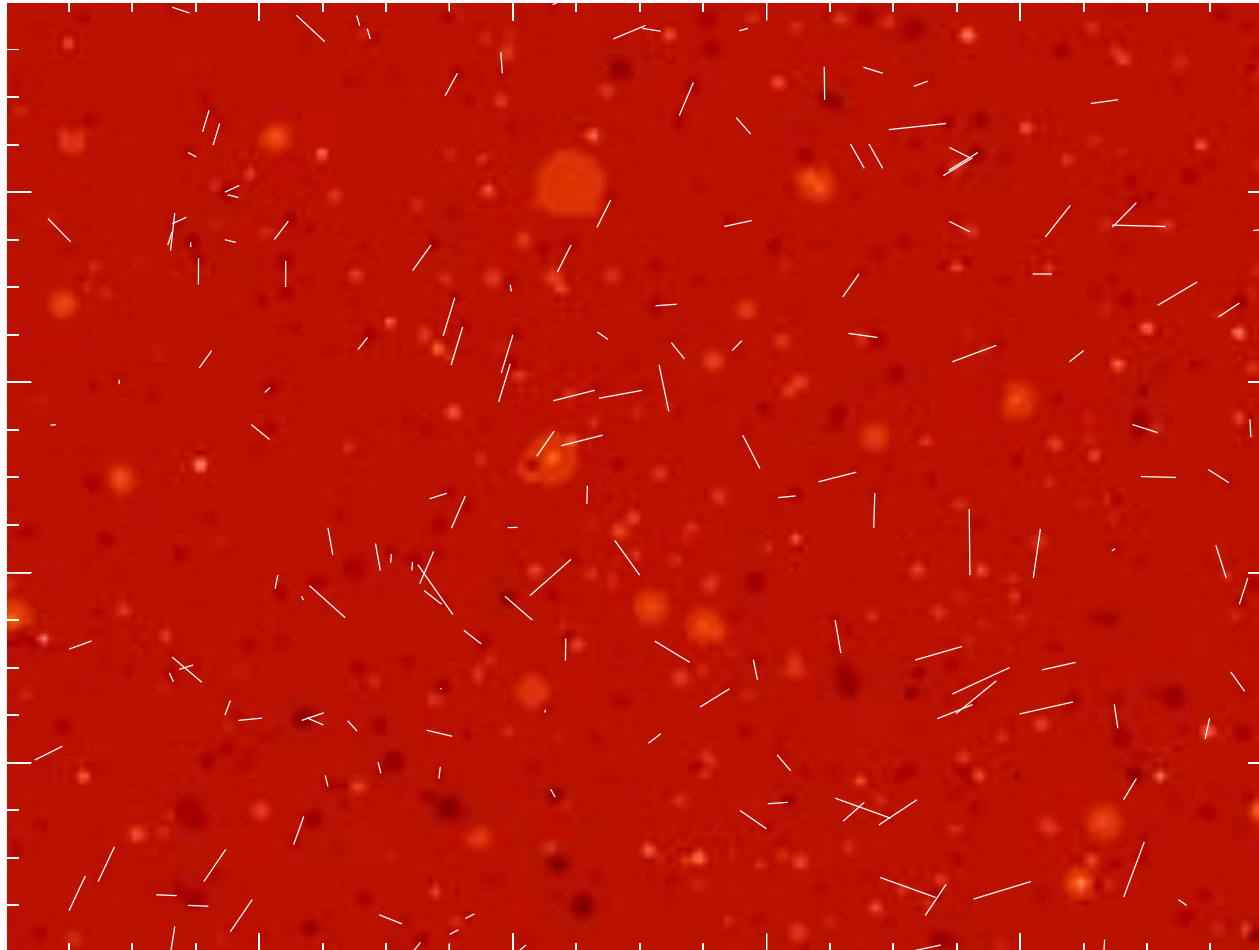


Figure 1. Thermal SZ map of 3 by 4 square degrees for a universe with $\Omega_m = 0.3$, $\Lambda = 0.7$, $h = 0.65$, $\Omega_b = 0.05$ (left panel), and with $\Omega_m = 1$, $\Lambda = 0$, $h = 0.5$, $\Omega_b = 0.07$ (right panel). Note that because of the different baryon fraction, the Λ universe clusters are brighter in SZ (respective color scales have been chosen such that they range from $y = 0$ to $y = 4 \times 10^{-5}$ on the left panel, and from $y = 0$ to $y = 1.5 \times 10^{-5}$ on the right one, with higher values saturated).

Delabrouille, Melin, Bartlett, AMIBA 2001 ASP conf. proc. 257 (2002)

Velocity flows



SZ in the PSM

- Catalogue from a mass function
 - Tinker et al. mass function (default, others implemented as well)
 - Y from Planck M - Y scaling relation, universal profile
 - Cluster velocities drawn at random according to $v(z)$
 - Cosmological parameters consistently used for cluster counts, scaling laws, velocities, CMB
-
- Constrained catalogue: replace randomly generated clusters by observed ones (with similar mass, redshift, direction)
 - MCXC, MaxBCG, or both

SZ in the PSM

- Prediction of SZ from known clusters
 - MCXC catalog of Piffaretti et al. (2010)
 - 1743 ROSAT clusters

$$E(z)^{-7/3} \left(\frac{L_{500}}{10^{44} \text{ erg s}^{-1}} \right) = C_{LM} \left(\frac{M_{500}}{3 \times 10^{14} M_{\odot}} \right)^{\alpha_{LM}}$$

$\log(C_{LM}) = 0.274$
 $\alpha_{LM} = 1.64$

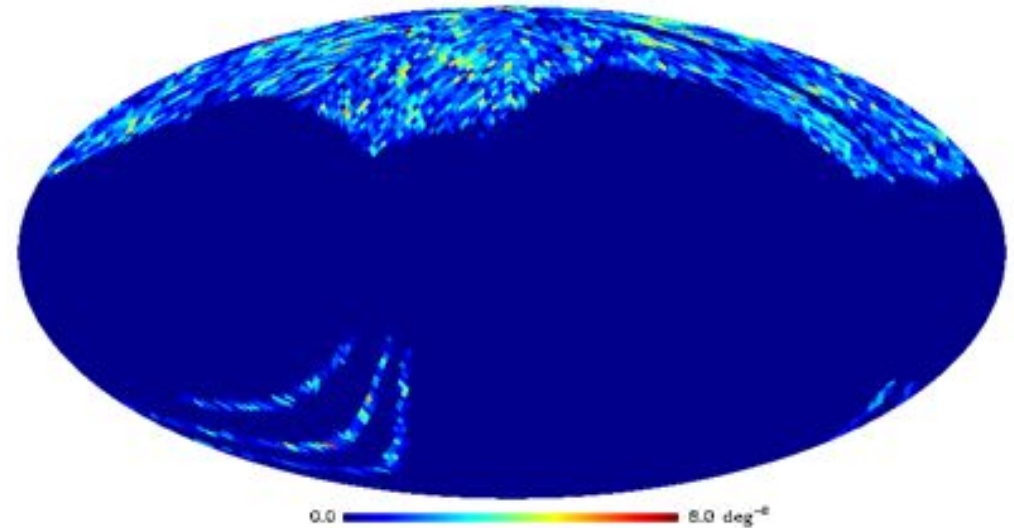
$$Y_{500} = 1.383 \times 10^{-3} I(1) \left(\frac{M_{500}}{3 \times 10^{14} M_{\odot}} \right)^{\frac{1}{\alpha_{MYX}}} \times E(z)^{2/3} \left(\frac{D_A(z)}{500 \text{ Mpc}} \right)^{-2} \text{ arcmin}^2$$

0.6145
 $1 / 0.561$

Pratt et al. 2009
Arnaud et al. 2010
Planck collaboration 2011

SZ in the PSM

- SZ from known clusters
 - MaxBCG catalog
 - Koester et al. (2007)
 - 13823 optical clusters



We compute the SZ flux Y_{500} using the $Y_{500} - N_{200}$ relation derived by the Planck Collaboration

$$Y_{500} = Y_{20} \left(\frac{N_{200}}{20} \right)^{\alpha_{20}} E^{2/3}(z) \left(\frac{D_A(z)}{500 \text{ Mpc}} \right)^{-2} \text{ arcmin}^2$$

where N_{200} is the cluster richness, $Y_{20} = 7.4 \cdot 10^{-5} \text{ arcmin}^2$ and $\alpha_{20} = 2.03$.

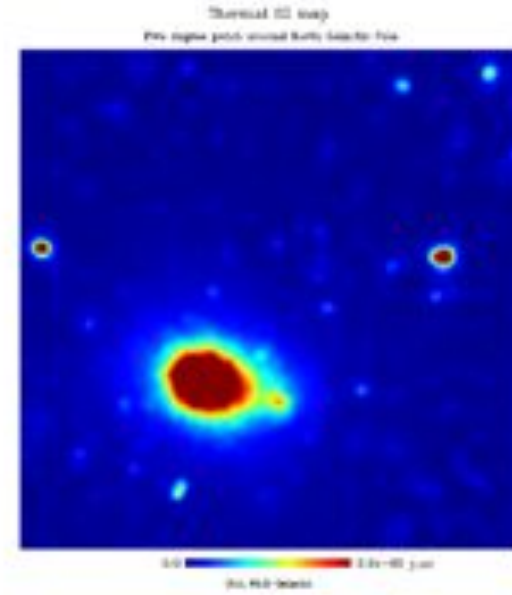
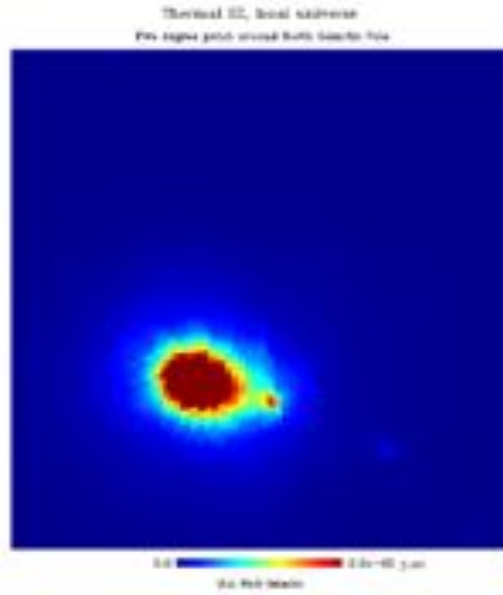
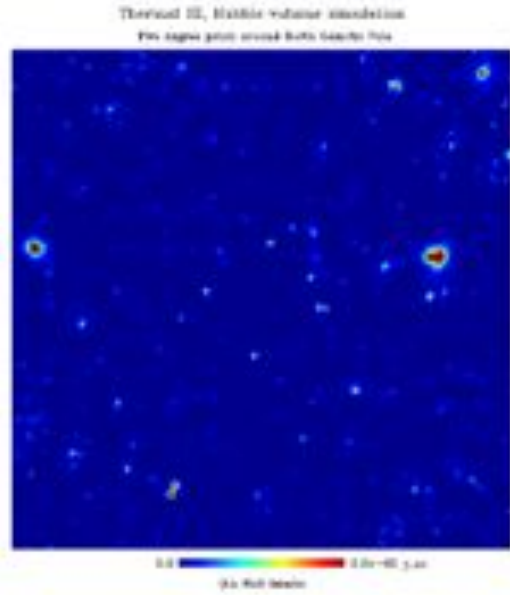
SZ in the PSM: N-body + hydro simulations

- Hydro+N-body model
 - Local ($z < 0.025$) from Dolag et al. (2005)
 - High z from Schäfer et al. (2006)
-
- Advantages and drawbacks
 - SZ from LSS more realistic
 - Fixed cosmology ($h=0.7$, $\Omega_\Lambda=0.7$, $\Omega_m=0.3$, $\Omega_b=0.04$, $\sigma_8=0.9$, $n_s=1$)
 - Clusters found in DM by post-processing – low mass objects may be missing or inaccurate
 - Replication of structures

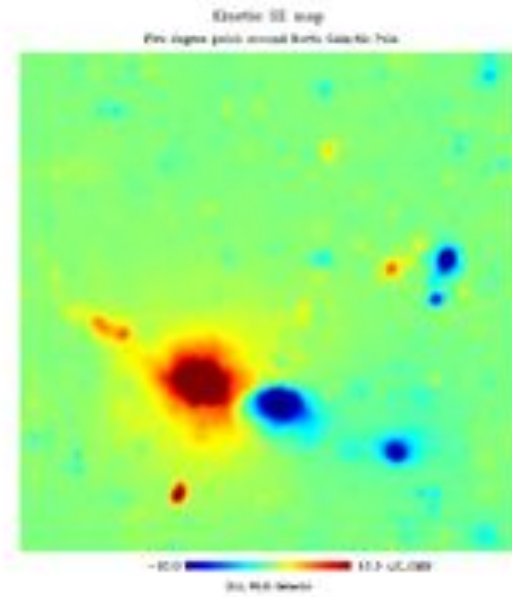
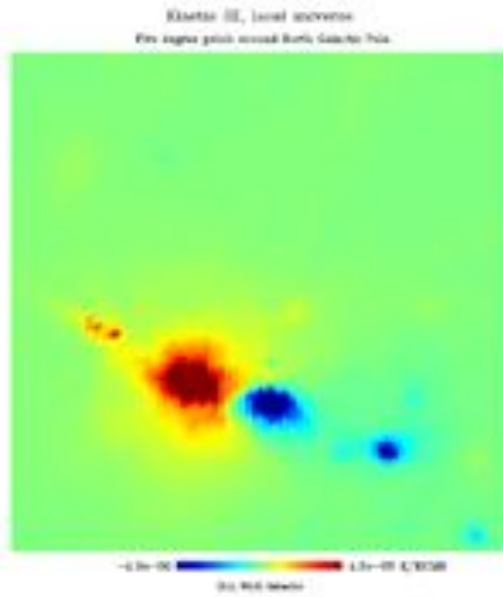
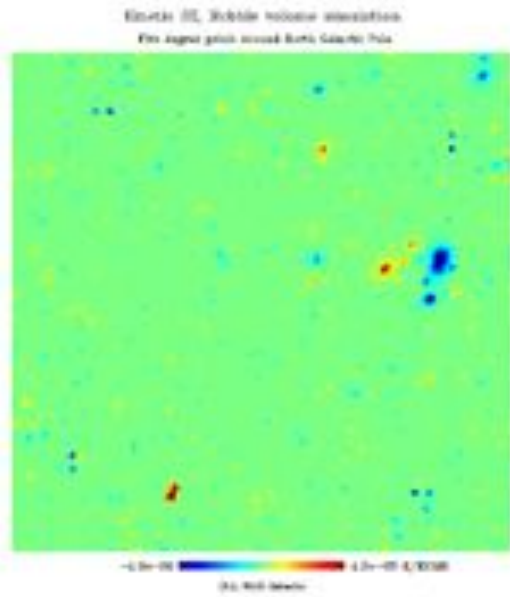
Input simulations

Total PSM maps

Thermal SZ



Kinetic SZ



SZ in the PSM: hybrid model

- Hydrodynamical simulations at low z ...
 - From Antonio da Silva
- ... completed by mass function simulations at high z !

PSM summary

- The PSM is not a physical simulation tool
- It is a phenomenological model which permits us to generate tuneable simulated sky emissions for
 - Developing and validating data analysis pipelines
 - Monte Carlo simulations of a complete pipeline for error propagation
 - Investigating modelling uncertainties and biases
- Public release planned for the near future
 - Not completely user-proof yet
 - Soon: release of simulated data sets
 - Software restricted at present to the Planck collaboration

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Component separation

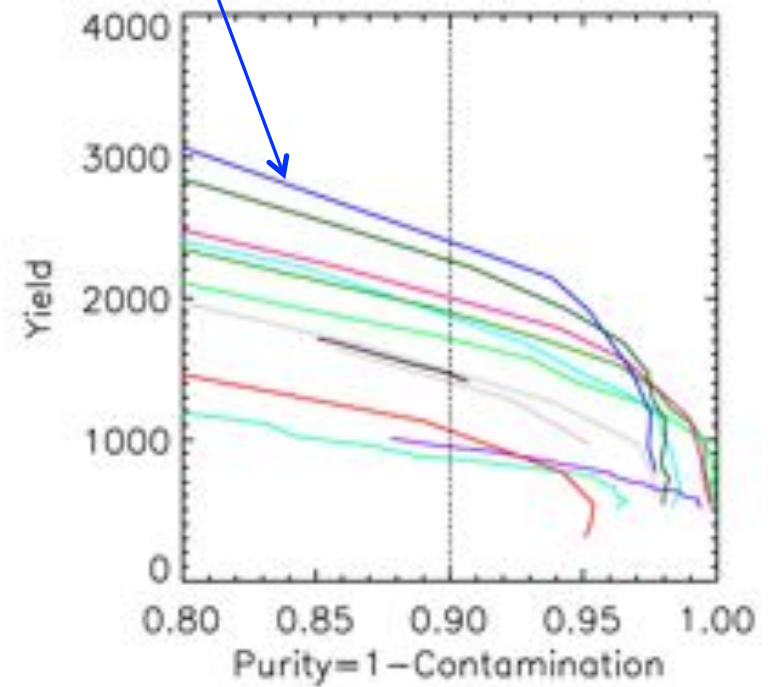
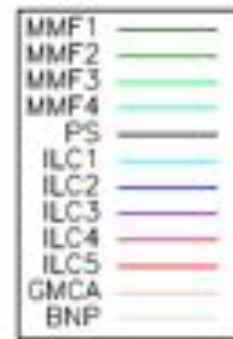
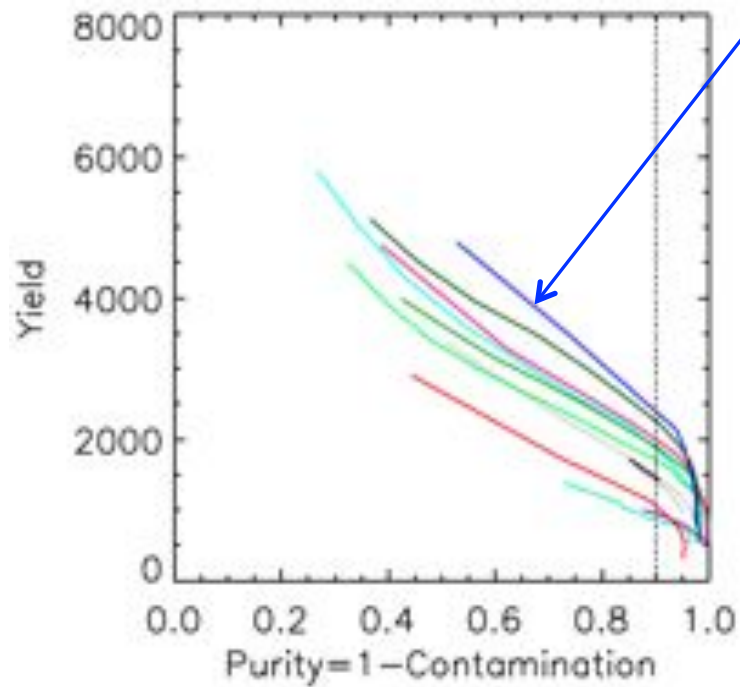
- Objective 1: extract SZ information alone
 - SZ map component separation (e.g. ILC)
 - Detect clusters objects of assumed shape (MF)
 - Cluster parameters parametric fit
 - (location, Y , kSZ , profile, temperature...)
 - Power spectrum spectral fit/matching (e.g. SMICA)
- Objective 2: joint analyses
 - Cross-correlate SZ with other signals

SZ data-challenges in Planck

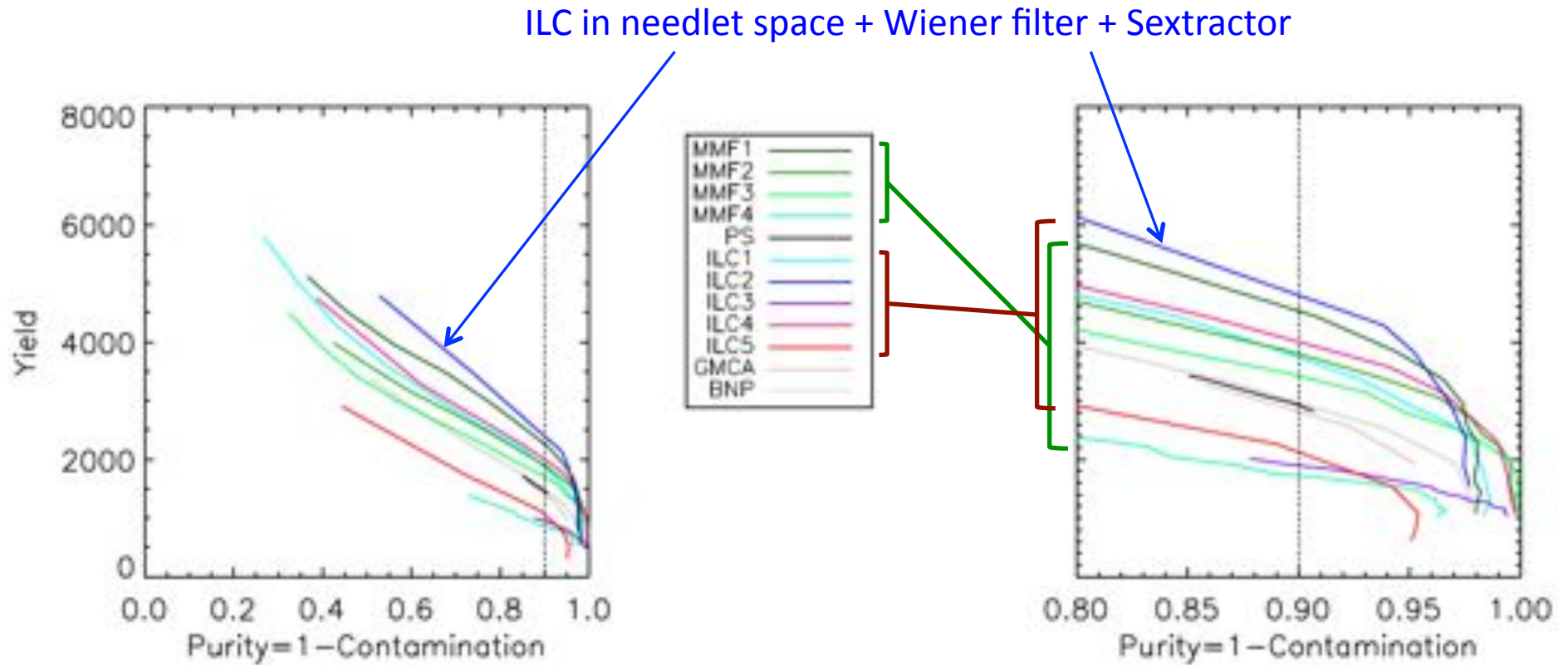
- Objective: test and compare algorithms for cluster detection on the same original data sets
- PSM simulations of Planck 14 month data
- 10 teams, 12 algorithms/pipelines
- Several challenges
 - First challenge blind, Sheth-Tormen mass function, beta-model for clusters, $\sigma_8=0.85$
 - Second challenge blind, Jenkins mass function, universal profile from Arnaud et al. 2009, $\sigma_8=0.798$
 - Third challenge: same as second, but inputs available to challengers

First challenge results

ILC in needlet space + Wiener filter + Sextractor

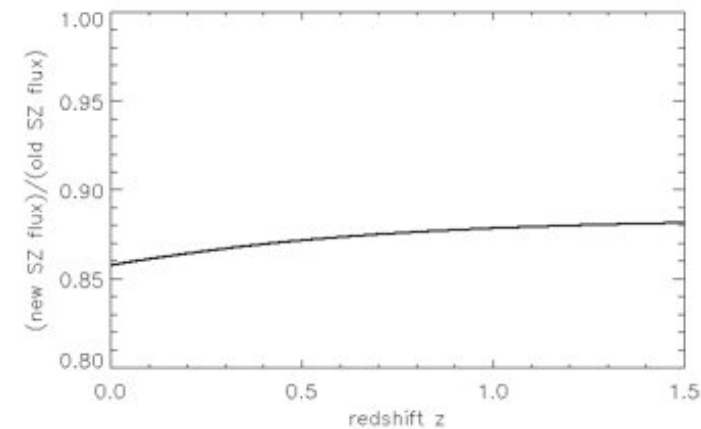
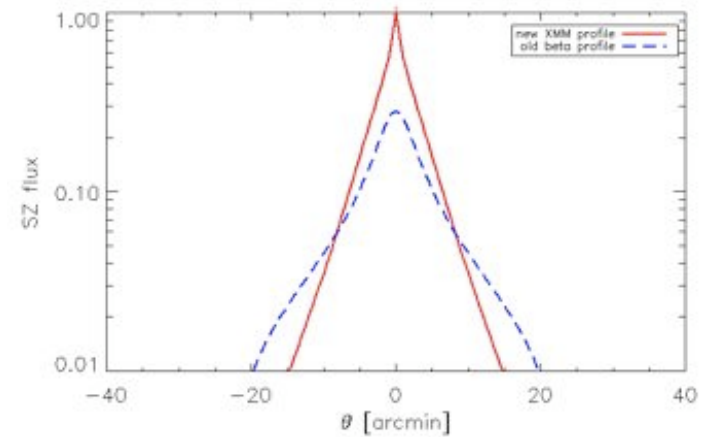


First challenge results




SZ updates

- New cluster profiles
- New normalisation



Number of detected clusters cut by half on recent simulations !

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Data models and linear filters

$$x(\nu_i, p) = \sum_j s_j(\nu_i, p) + n_i(p)$$

Cosmologist's model

$$x_i(p) = a_i s(p) + n_i(p)$$

$$\mathbf{x}(p) = \mathbf{a} s(p) + \mathbf{n}(p)$$

Astrophysicist's model

$$x_i(p) = \sum_j a_{ij} s_j(p) + n_i(p)$$

$$\mathbf{x}(p) = \mathbf{A} \mathbf{s}(p) + \mathbf{n}(p)$$



*Inverse of the noise
covariance matrix*

$$\hat{s}(p) = \frac{\mathbf{a}^t \mathbf{R}_n^{-1}}{\mathbf{a}^t \mathbf{R}_n^{-1} \mathbf{a}} \mathbf{x}(p)$$



$$\hat{\mathbf{s}}(p) = [\mathbf{A}^t \mathbf{R}_n^{-1} \mathbf{A}]^{-1} \mathbf{A}^t \mathbf{R}_n^{-1} \mathbf{x}(p)$$

Mixing matrix

The ILC

$$\mathbf{x}(p) = \mathbf{a}s(p) + \mathbf{n}(p) \qquad \hat{s}(p) = \frac{\mathbf{a}^t \mathbf{R}_n^{-1}}{\mathbf{a}^t \mathbf{R}_n^{-1} \mathbf{a}} \mathbf{x}(p)$$

- The “noise” covariance matrix is not known a priori
- But...

$$\begin{aligned} \mathbf{R}_x^{-1} &= [\mathbf{a}\mathbf{a}^t \sigma_{\text{cmb}}^2 + \mathbf{R}_n]^{-1} \\ &= \mathbf{R}_n^{-1} - \sigma_{\text{cmb}}^2 \frac{\mathbf{R}_n^{-1} \mathbf{a}\mathbf{a}^t \mathbf{R}_n^{-1}}{1 + \sigma_{\text{cmb}}^2 \mathbf{a}^t \mathbf{R}_n^{-1} \mathbf{a}} \end{aligned}$$

- And hence $\mathbf{a}^t \mathbf{R}_x^{-1} = \mathbf{a}^t \mathbf{R}_n^{-1} - \sigma_{\text{cmb}}^2 \frac{\mathbf{a}^t \mathbf{R}_n^{-1} \mathbf{a} \mathbf{a}^t \mathbf{R}_n^{-1}}{1 + \sigma_{\text{cmb}}^2 \mathbf{a}^t \mathbf{R}_n^{-1} \mathbf{a}}$
 $\mathbf{a}^t \mathbf{R}_x^{-1} \propto \mathbf{a}^t \mathbf{R}_n^{-1}$

The ILC

$$\hat{s}(p) = \frac{\mathbf{a}^t \mathbf{R}_n^{-1}}{\mathbf{a}^t \mathbf{R}_n^{-1} \mathbf{a}} \mathbf{x}(p) = \frac{\mathbf{a}^t \mathbf{R}_x^{-1}}{\mathbf{a}^t \mathbf{R}_x^{-1} \mathbf{a}} \mathbf{x}(p)$$

- Actual implementation $\hat{s}_{\text{ILC}}(p) = \frac{\mathbf{a}^t \hat{\mathbf{R}}_x^{-1}}{\mathbf{a}^t \hat{\mathbf{R}}_x^{-1} \mathbf{a}} \mathbf{x}(p)$

- Uses the empirical covariance matrix of the observations (and this is a very important distinction)

- Usually derived as the (internal) **linear combination** of the input maps which **minimizes the variance of the output**, with **unit response to the CMB (or SZ)**

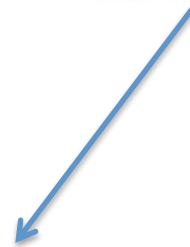
$$\hat{s}_{\text{ILC}}(p) = \sum_i w_i x_i(p) = \mathbf{w}^t \mathbf{x}(p)$$

$$\sum_i w_i a_i = \mathbf{w}^t \mathbf{a} = 1$$

$$\text{minimize } \sum_p |\hat{s}(p)|^2$$

ILC localisation

$$\hat{s}_{\text{ILC}}(p) = \frac{\mathbf{a}^t \hat{\mathbf{R}}_x^{-1}}{\mathbf{a}^t \hat{\mathbf{R}}_x^{-1} \mathbf{a}} \mathbf{x}(p)$$



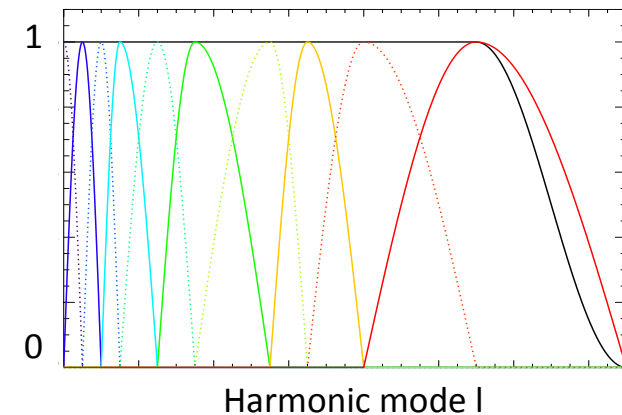
Can be implemented independently

- in different regions
- on different scales

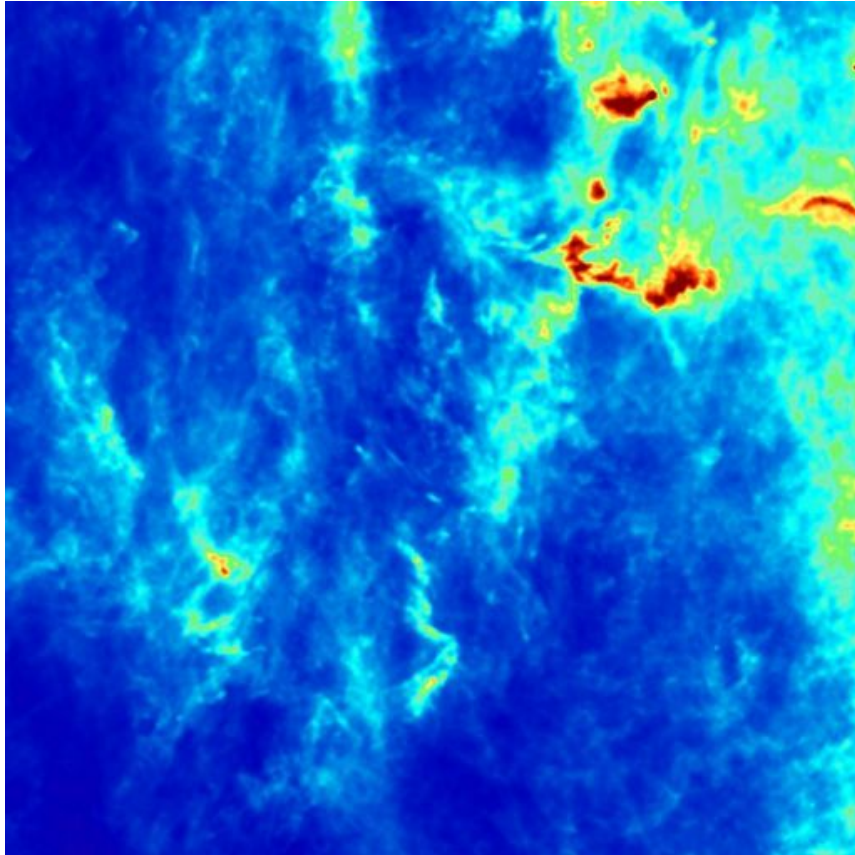
- or both: covariance matrix as a function of pixel and scale

Needlets

- Needlets are just wavelets on the sphere
 - Narcowitch, Petrushev & Ward, SIAM J. Math. Anal., 38, 574 (2006)
 - Marinucci et al., MNRAS, 383, 539 (2008)
- Very easy to implement
 - Choose a set of functions $h_j(l)$ such that
$$\sum [h_j(l)]^2 = 1$$
 - Make a set of filtered maps
$$\beta_j(k) = \text{SHT}^{-1}(a_{lm} h_j(l))$$
 - Work on the needlet coefficients $\beta_j(k)$
 - Re-synthesize a map from the sum of the $\beta_j(k)$ maps filtered using the same $h_j(l)$
- For experts
 - Needlets constructed in this way form a tight frame (= a redundant basis)
 - Parseval's theorem holds
 - Needlet analysis and synthesis using the same spectral windows



Why are they useful?



Non stationary foregrounds
require localised processing

Small patches ?

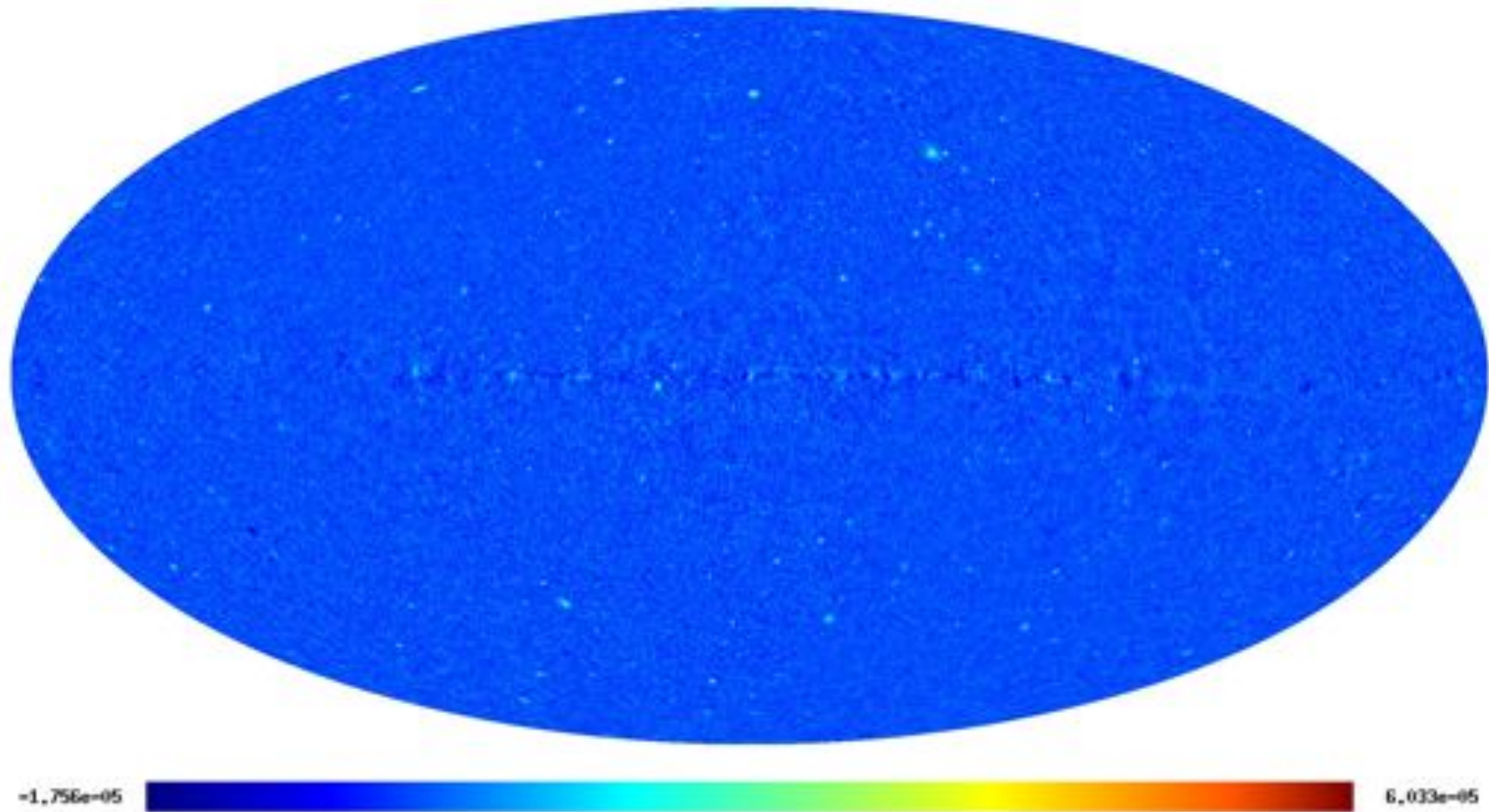
Difficult trade-off between
the adequacy to local
contamination and the
variance of estimated filters

Needlets !

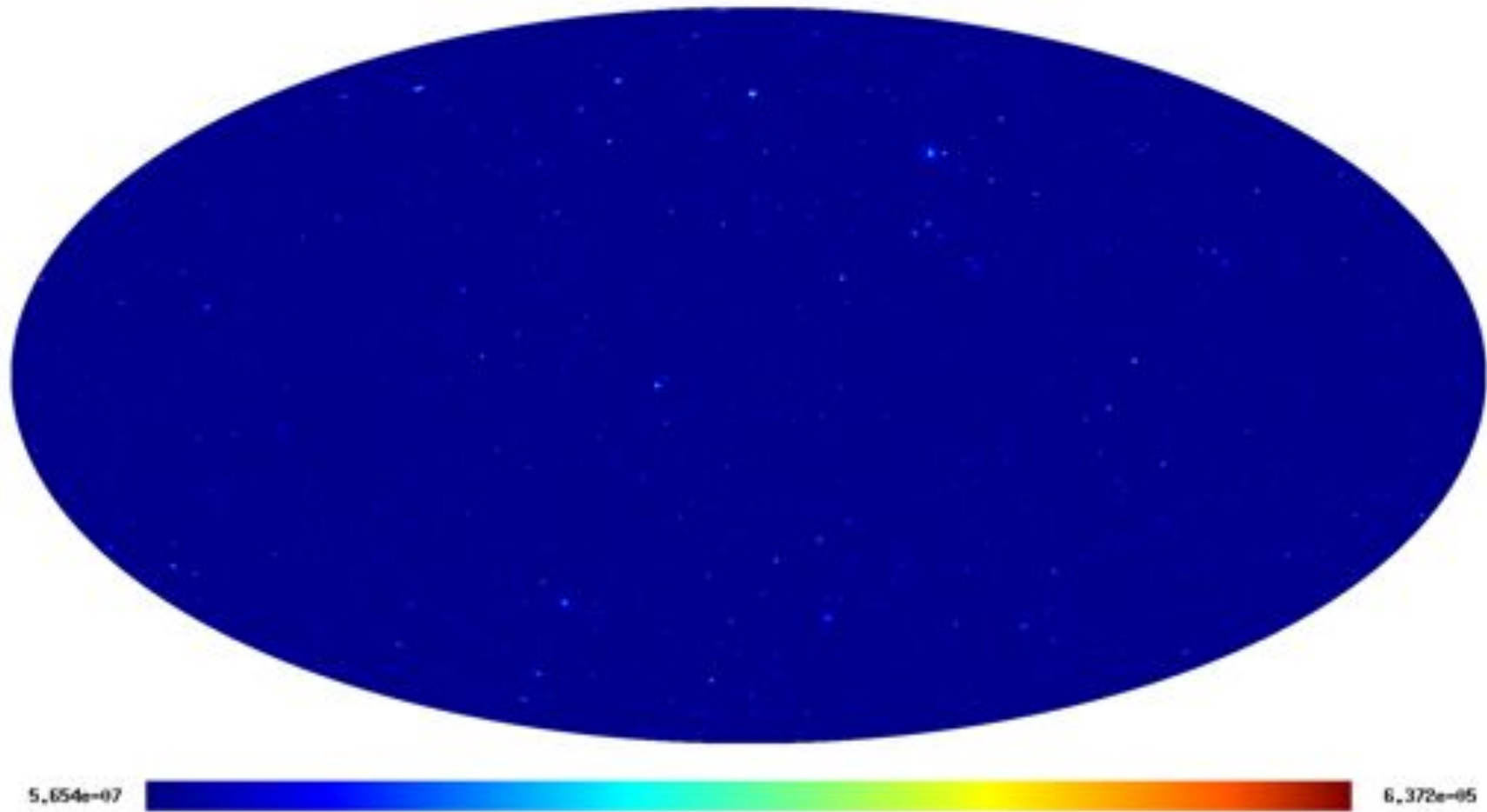
Big patches for large scales,
small patches for small scales!

Needlet ILC map

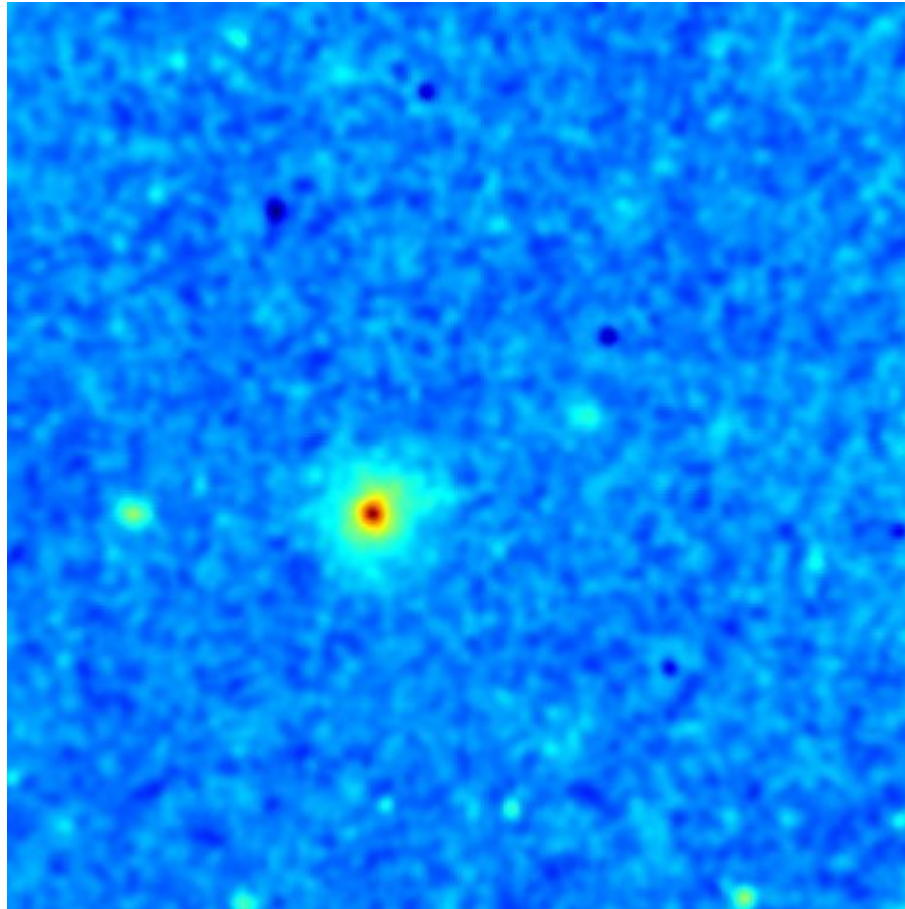
With Maude Le Jeune, Jean-Baptiste Melin, Marc Betoule



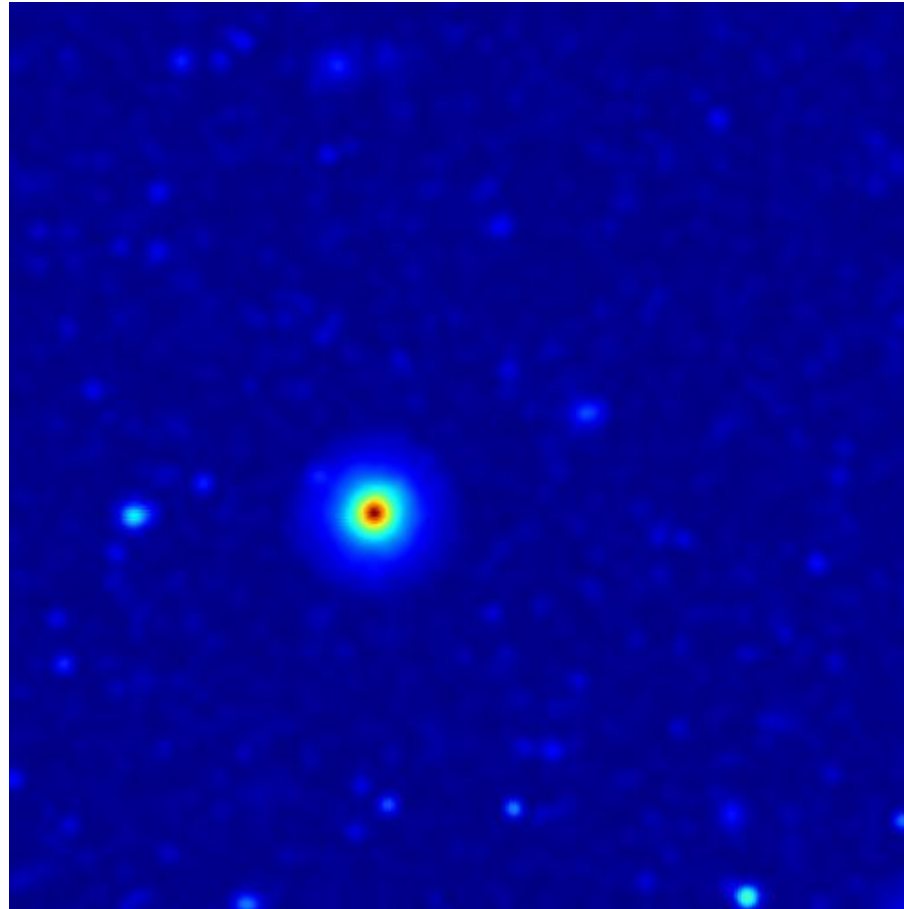
Input map



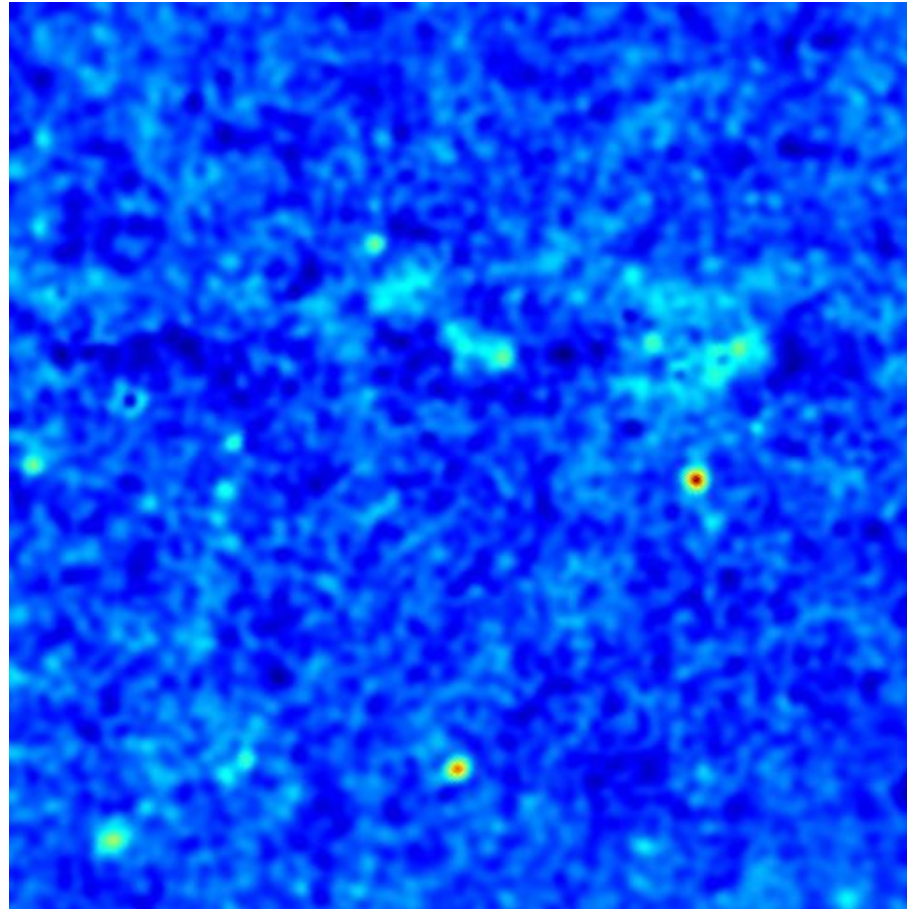
Needlet ILC map: Coma area



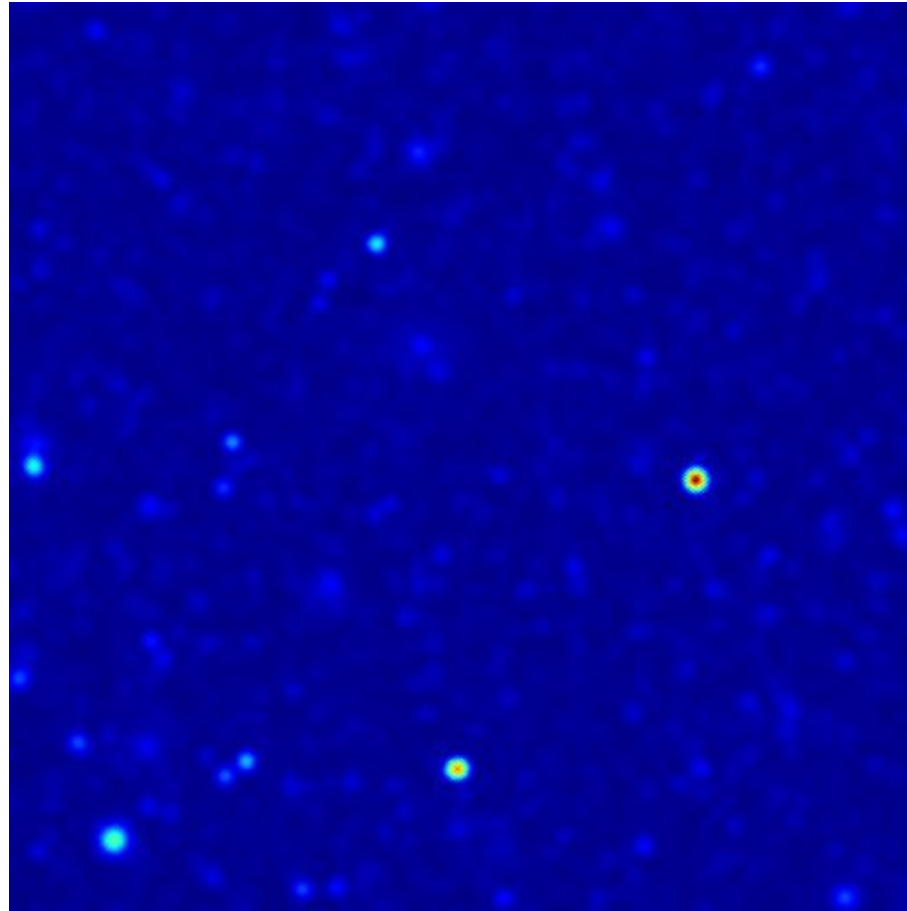
Input map: Coma area



Needlet ILC map: galactic plane (!)



Input map: galactic plane



ILC+MF vs. MMF what is best ??

If we look for a single SZ component in noisy observations (noise including foregrounds) modeled as

$$\mathbf{x}_{lm} = \mathbf{a} y_{lm} + \mathbf{n}_{lm}$$

The ideal map filtering solution (GLS, implemented in practice using an ILC in harmonic space) is

$$\hat{y}_{lm}^{\text{GLS}} = \frac{\mathbf{a}^t \mathbf{N}_l^{-1}}{\mathbf{a}^t \mathbf{N}_l^{-1} \mathbf{a}} \mathbf{x}_{lm}$$

The multifrequency matched filter (MMF) solution, assuming a known (symmetric) cluster profile p_l , such that $y_{lm} = y^0 p_l$, is

$$\hat{y}^0 \propto \mathbf{a}^t \mathbf{N}_l^{-1} \mathbf{x}_{lm} p_l$$

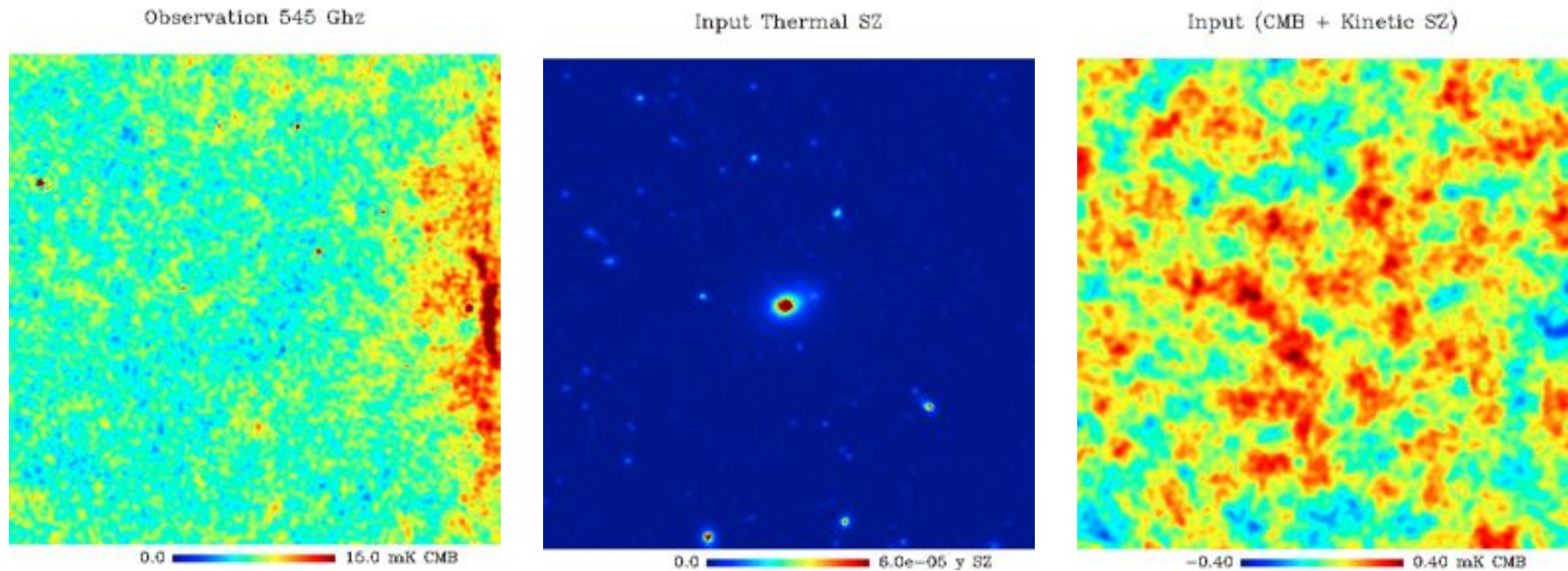
The covariance of the noise in the GLS map is $1/\mathbf{a}^t \mathbf{N}_l^{-1} \mathbf{a}$, and thus a simple matched filter applied on the GLS map gives

$$\hat{y}^0 \propto \mathbf{a}^t \mathbf{N}_l^{-1} \mathbf{a} \hat{y}_{lm}^{\text{GLS}} p_l = \mathbf{a}^t \mathbf{N}_l^{-1} \mathbf{x}_{lm} p_l$$

The MMF is hence equivalent to doing a single frequency matched filter on the GLS map.

kSZ + tSZ with constrained ILC

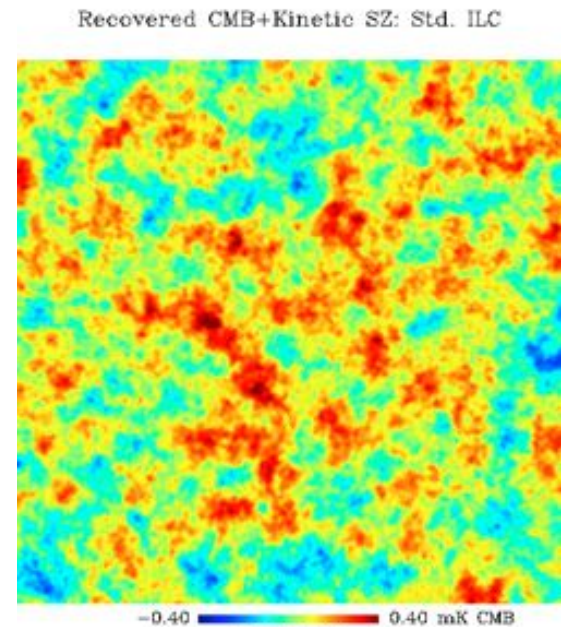
- The kSZ and the CMB have the same colour
 - Impossible to distinguish them on this basis
 - Morphological information (shape) hence MF
- How critical is the leakage of thermal SZ into CMB (+kSZ) maps after an ILC ?



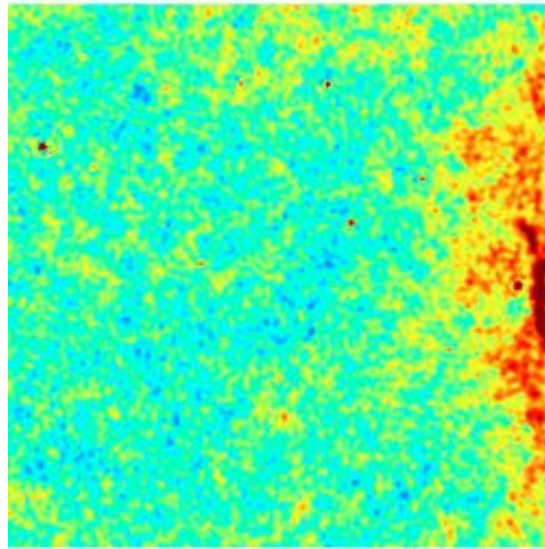
Around $l, b = (33^\circ, 89^\circ)$ – Coma cluster neighbourhood

$$\mathbf{x}(p) = \mathbf{a}s(p) + \mathbf{n}(p)$$

$$\hat{s}_{\text{ILC}}(p) = \frac{\mathbf{a}^t \hat{\mathbf{R}}_x^{-1}}{\mathbf{a}^t \hat{\mathbf{R}}_x^{-1} \mathbf{a}} \mathbf{x}(p)$$

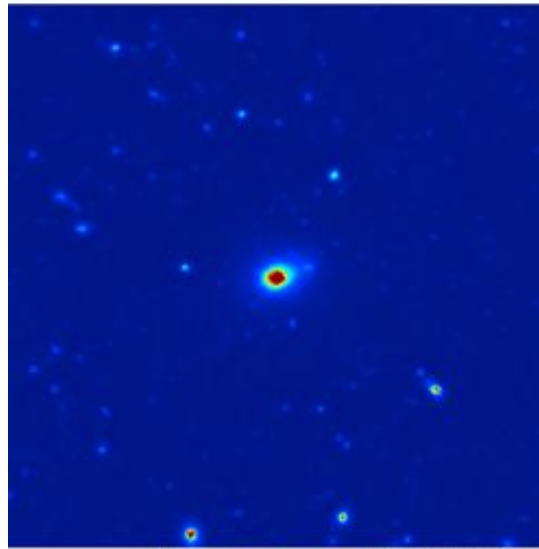


Observation 545 GHz



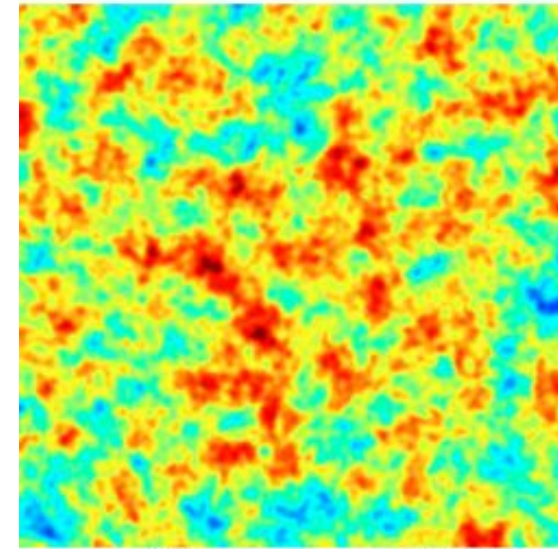
0.0 15.0 mK CMB

Input Thermal SZ



0.0 6.0e-05 y SZ

Input (CMB + Kinetic SZ)



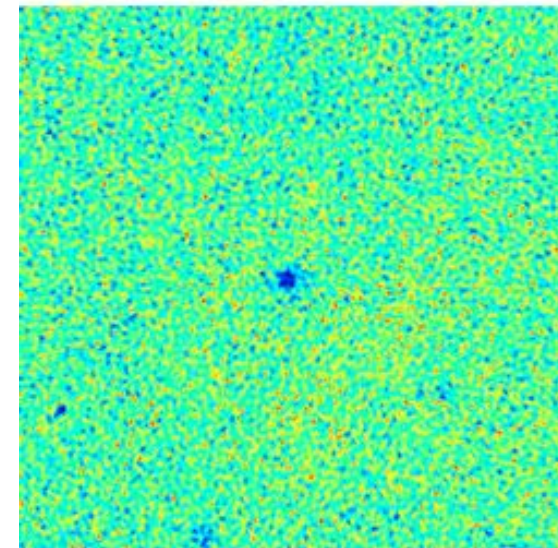
-0.40 0.40 mK CMB

Around $l, b = (33^\circ, 89^\circ)$ – Coma cluster neighbourhood

$$\mathbf{x}(p) = \mathbf{a}s(p) + \mathbf{n}(p)$$

$$\hat{s}_{\text{ILC}}(p) = \frac{\mathbf{a}^t \hat{\mathbf{R}}_x^{-1}}{\mathbf{a}^t \hat{\mathbf{R}}_x^{-1} \mathbf{a}} \mathbf{x}(p)$$

Reconstruction error: Std. ILC



-0.10 0.10 mK CMB

Constrained ILC

$$\mathbf{x}(p) = \mathbf{a}s(p) + \mathbf{b}z(p) + \mathbf{n}(p)$$

CMB

Thermal SZ

Everything else

$$\hat{s}_{\text{ILC}}(p) = \sum_i w_i x_i(p) = \mathbf{w}^t \mathbf{x}(p)$$

$$\text{minimize } \sum_p |\hat{s}(p)|^2$$

Two constraints

$$\sum_i w_i a_i = \mathbf{w}^t \mathbf{a} = 1$$

$$\sum_i w_i b_i = \mathbf{w}^t \mathbf{b} = 0$$

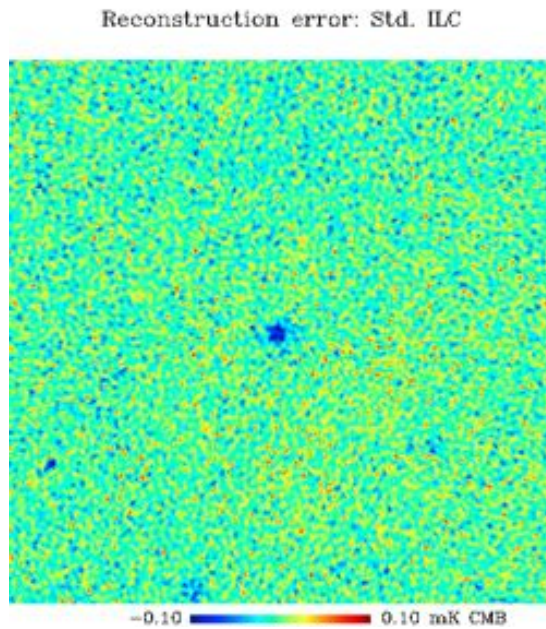
$$\hat{s}_{\text{constr.ILC}}(p) = \frac{(\mathbf{b}^t \hat{\mathbf{R}}_x^{-1} \mathbf{b}) \mathbf{a}^t \hat{\mathbf{R}}_x^{-1} - (\mathbf{a}^t \hat{\mathbf{R}}_x^{-1} \mathbf{b}) \mathbf{b}^t \hat{\mathbf{R}}_x^{-1}}{(\mathbf{a}^t \hat{\mathbf{R}}_x^{-1} \mathbf{a})(\mathbf{b}^t \hat{\mathbf{R}}_x^{-1} \mathbf{b}) - (\mathbf{a}^t \hat{\mathbf{R}}_x^{-1} \mathbf{b})^2} \mathbf{x}(p)$$

Constrained ILC

M. Remazeilles, J. Delabrouille, J.-F. Cardoso, MNRAS 408, 2481 (2011)

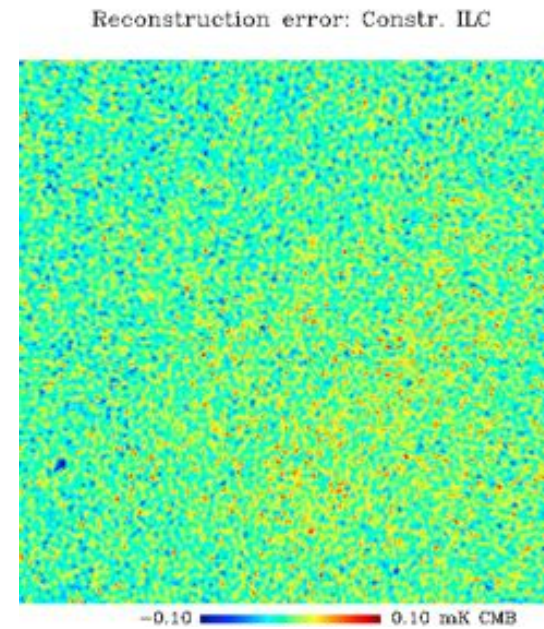
Standard ILC

Reconstruction error




Constrained ILC

Reconstruction error

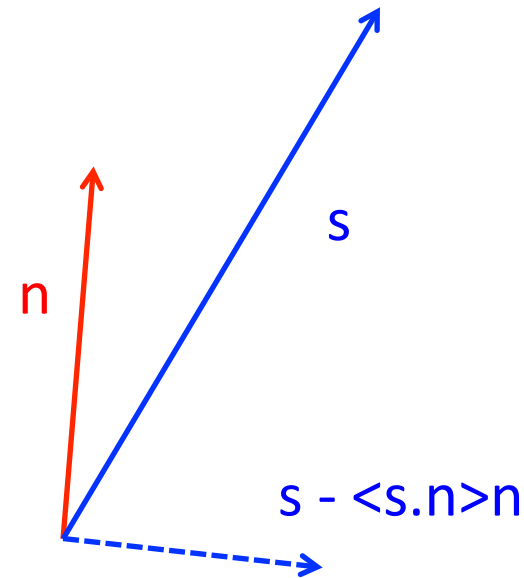


Outline

- Introduction
- Multi-component sky emission models
- Component separation
 - Planck SZ challenges
 - ILC, MF and MMF
-  • ILC biases
- Improving cluster counts
- Conclusion

ILC bias 1

- Example: suppose
 - $x_1 = s$ pure signal
 - $x_2 = n$ pure noise



- ILC solution:
 - minimize the norm of $w_1x_1 + w_2x_2$ with $w_1=1$
 - Solution: $w_1=1, w_2=-<s.n>$

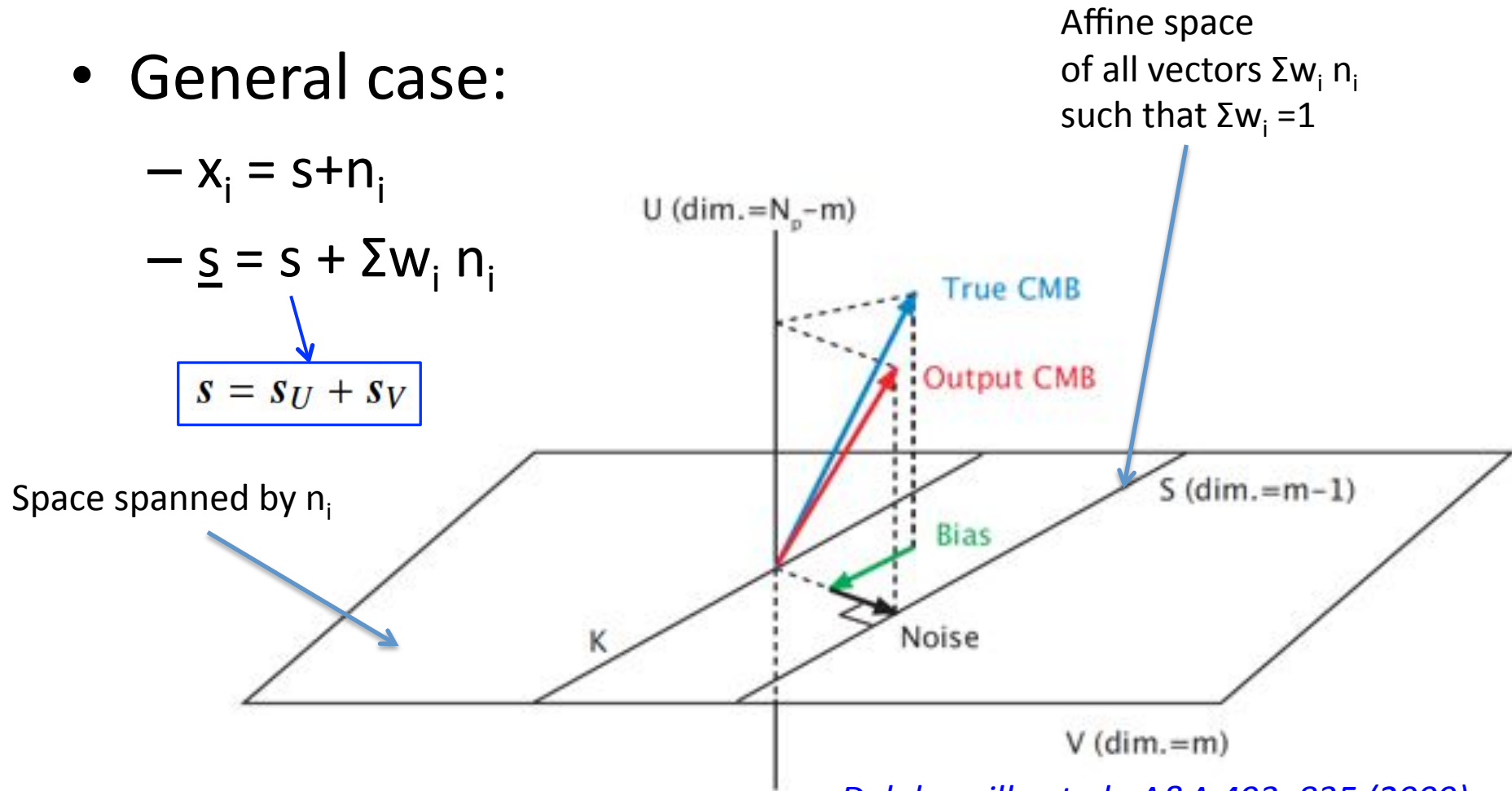
ILC bias 1

- General case:

- $x_i = s + n_i$

- $\underline{s} = s + \sum w_i n_i$

$s = s_U + s_V$




Delabrouille et al., A&A 493, 835 (2009)

ILC bias 2

- Suppose that the data is miscalibrated
 - $x_i = (a_i + \delta_i)s + n_i$
 - The constraint $\sum w_i a_i = 1$ does not guarantee anymore that the component of interest is conserved
 - $s = s (1 + \sum w_i \delta_i) + \sum w_i n_i$
 - Example: if no noise the recovered map vanishes!

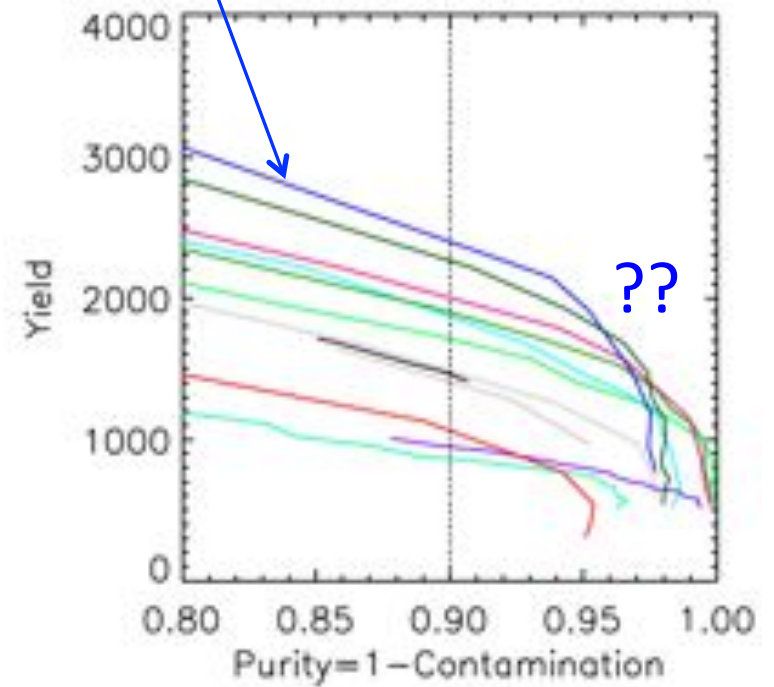
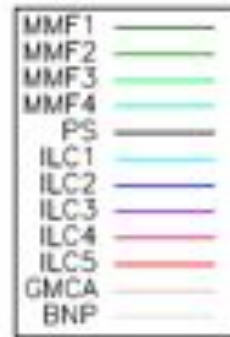
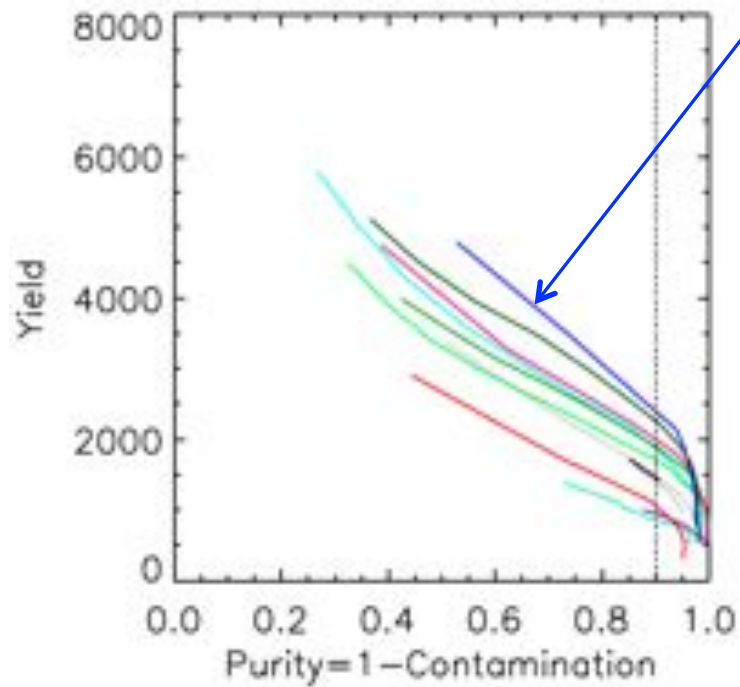
Dick, Remazeilles & Delabrouille, MNRAS 401, 1602 (2010)

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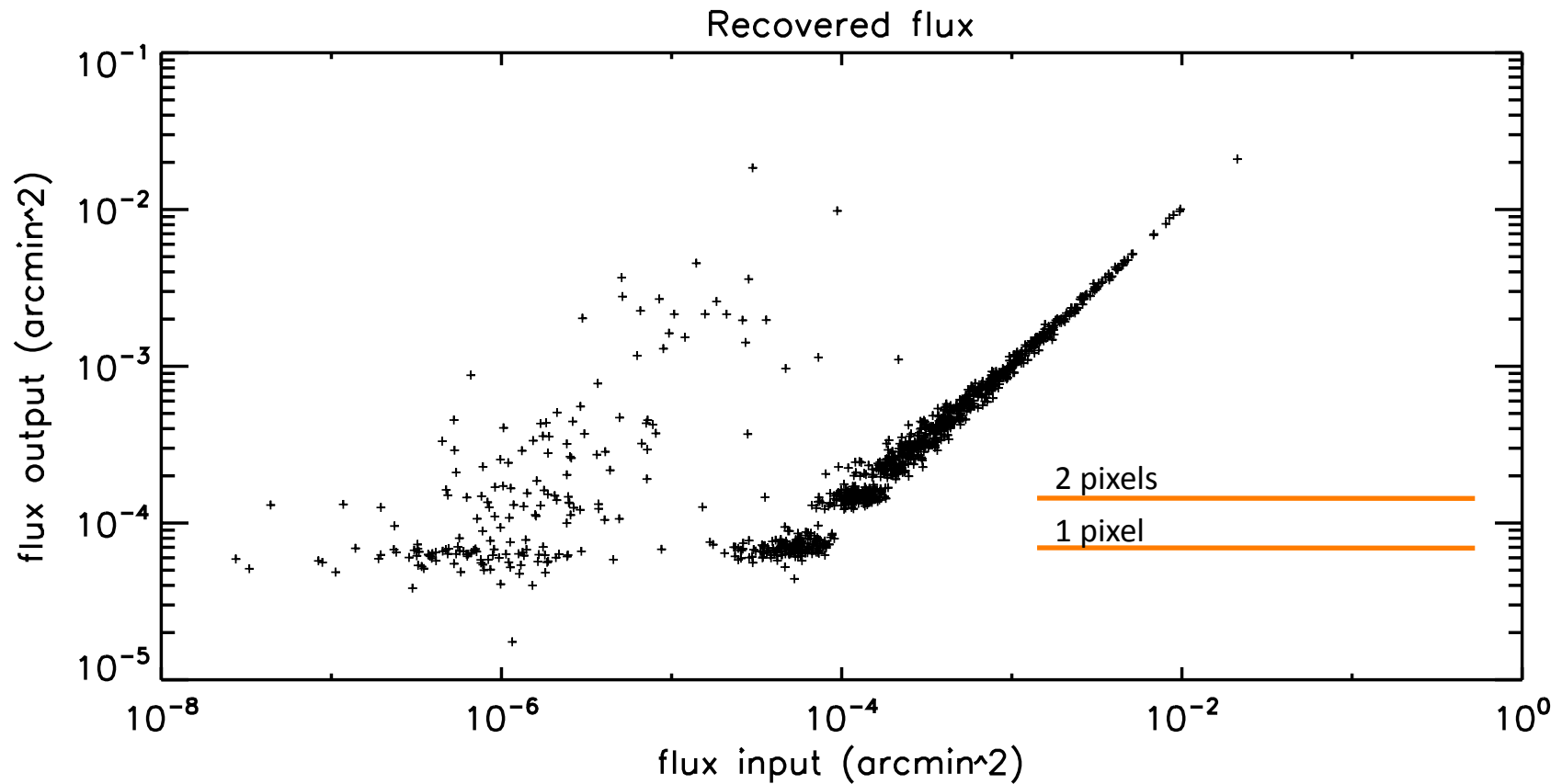
First challenge results

ILC in needlet space + Wiener filter + Sextractor

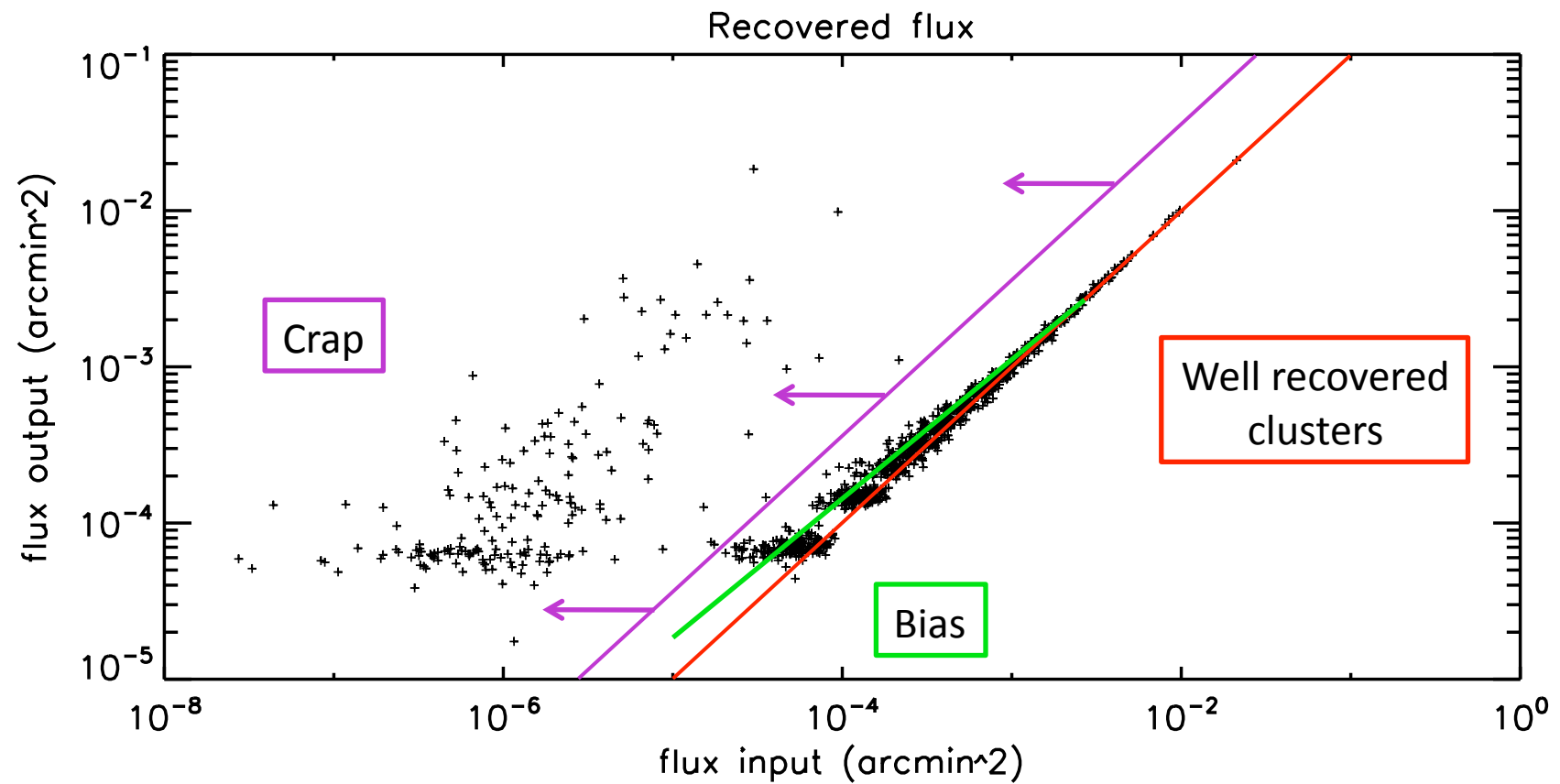


Fluxes (here sum of $> 4\sigma$ pixels)

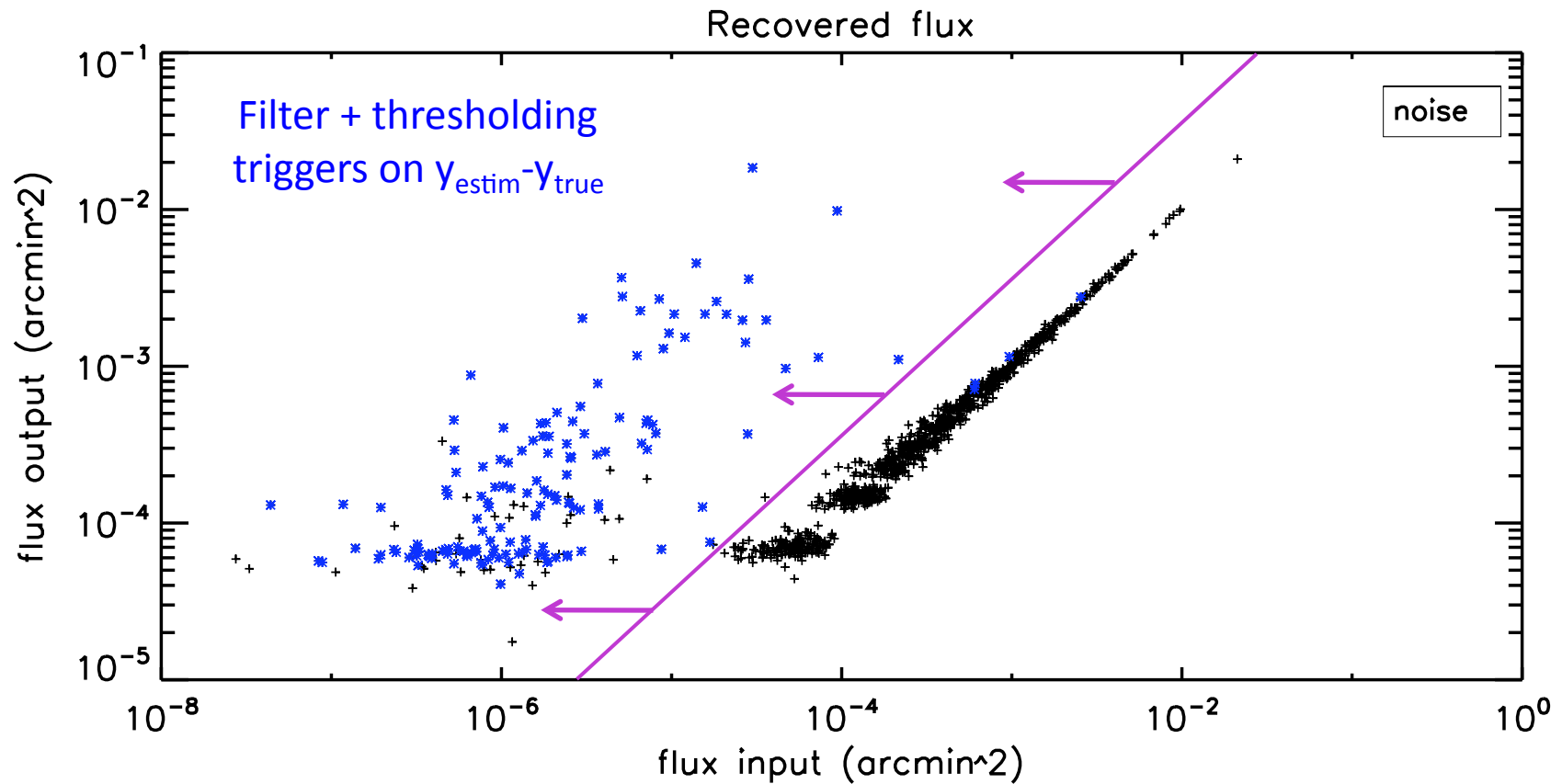
Detection of 4σ outliers in needlet ILC map of γ



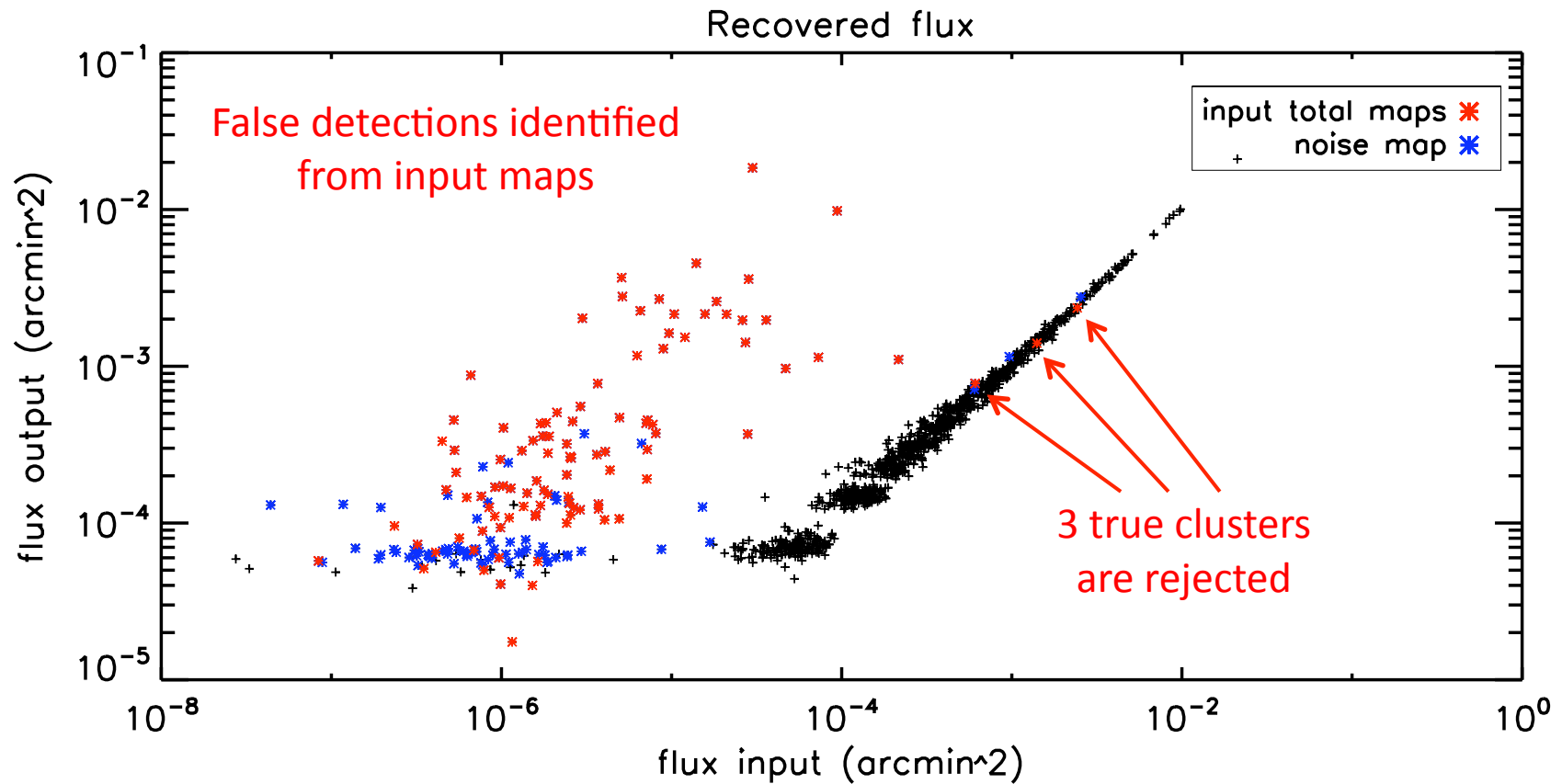
Fluxes



False detections on error map



False detections on frequency maps



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Conclusion

- The optimisation of data analysis methods for extraction of SZ information is not trivial
- Simulations are important
- Very sensitive data sets deserve optimised analyses
- Ongoing work in the Planck collaboration