Tamasis

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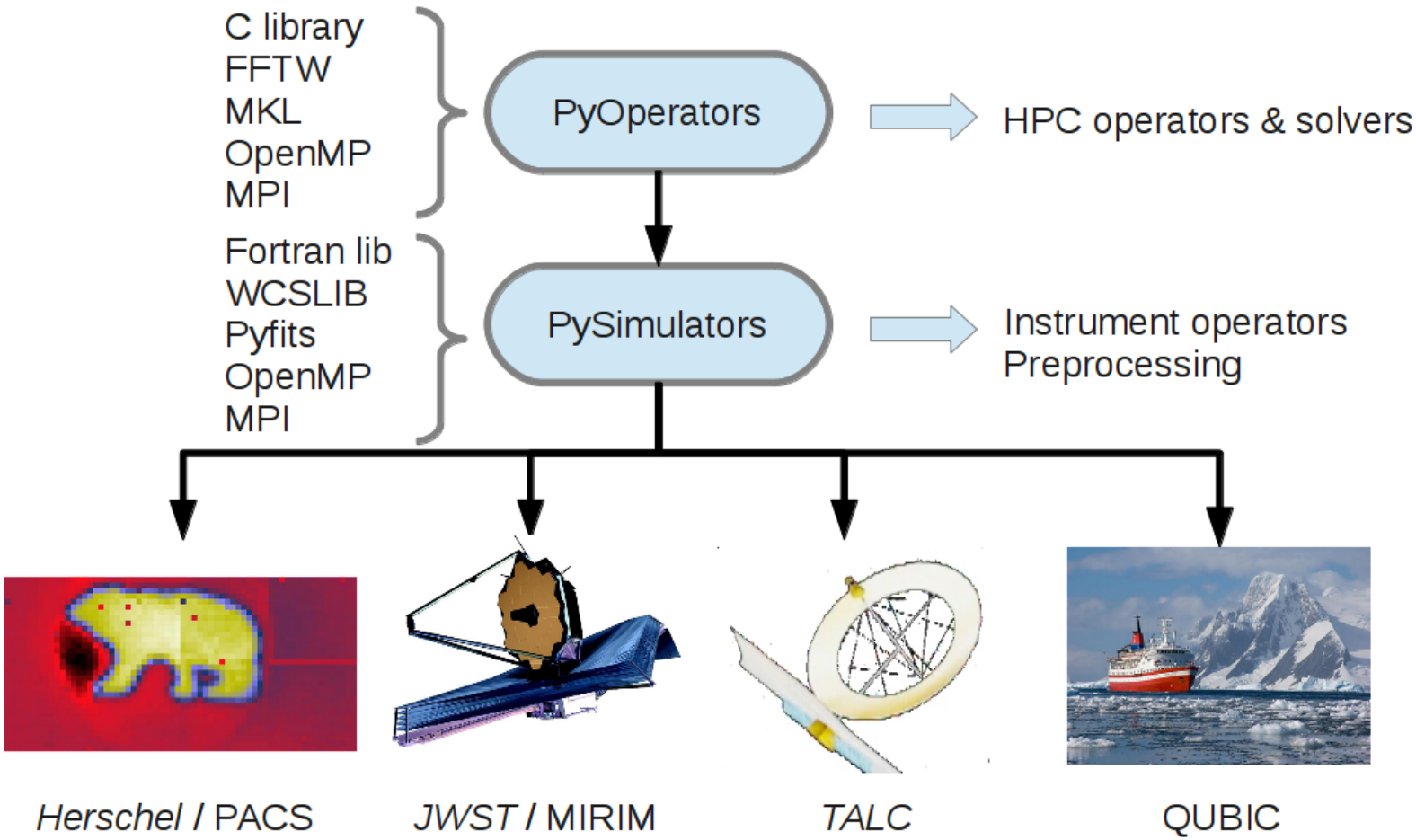
The Tamasis project

- Tools for Advanced Map-making, Analysis and SImulations of Submillimeter surveys.
- ASTRONET-funded project, P.I: Marc Sauvage
- Collaboration between 4 institutes:
  - Garching-ESO: cosmological light cones simulations
  - IAS: SPIRE advanced map-making (next talk)
  - Saclay: PACS advanced map-making
  - Leiden: stacking
- massively parallel + super-resolution
- Tools are publicly available to the community:
  - http://pchanial.github.com/pyoperators
  - http://pchanial.github.com/tamasis-pacs

The Tamasis project



A generic pipeline for PACS

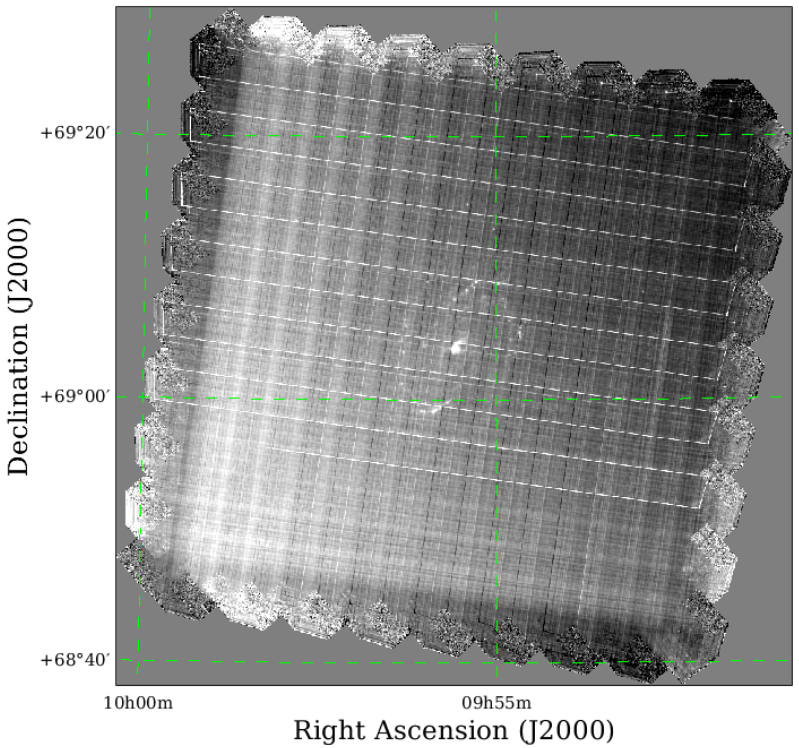
- Preprocessing
  1. Baseline removal
  2. Jump detection
  3. Second-level deglitching
- Map reconstruction by inversion
  1. Instrument model
  2. Objective function
  3. Minimisation

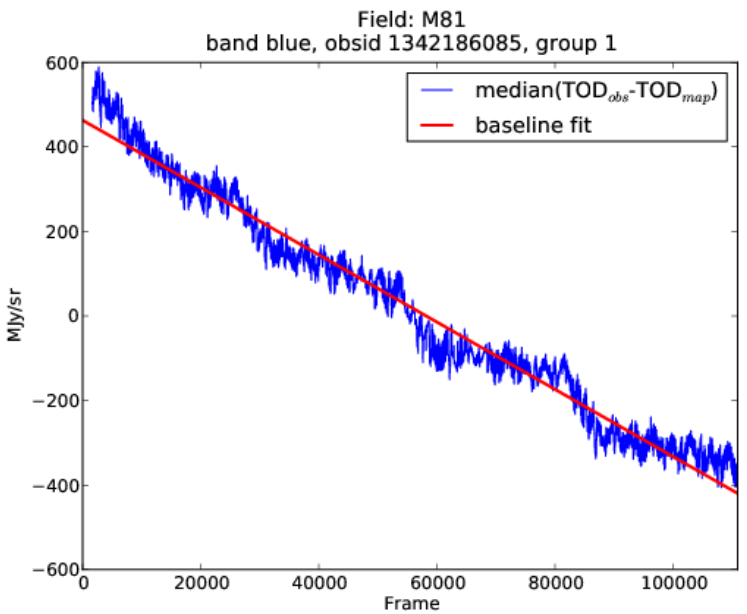
Baseline Removal, part 1

Inspired by the SPIRE destriper.

- Remove median over time for each bolometer and each observation $\Rightarrow y_0$,
- Repeat 3 times, starting with iteration $i = 0$:
  1. Backproject y_i into a map $x_i = \frac{P^{\mathrm{T}}(y_i)}{P^{\mathrm{T}}(1)}$
  2. Compute projection $\tilde{y}_i = P(x_i)$
  3. Compute drift $z_{i,\mathrm{group}} = \langle y_i - \tilde{y}_i \rangle_{\mathrm{group}}$
  4. Compute 1st-order polynomial fit $\tilde{z}_{i,\mathrm{group}}$ to $z_{i,\mathrm{group}}$
  5. $y_{i+1} = y_i - \tilde{z}_{i,\mathrm{group}}$
  6. $i = i + 1$

Baseline Removal, part 1

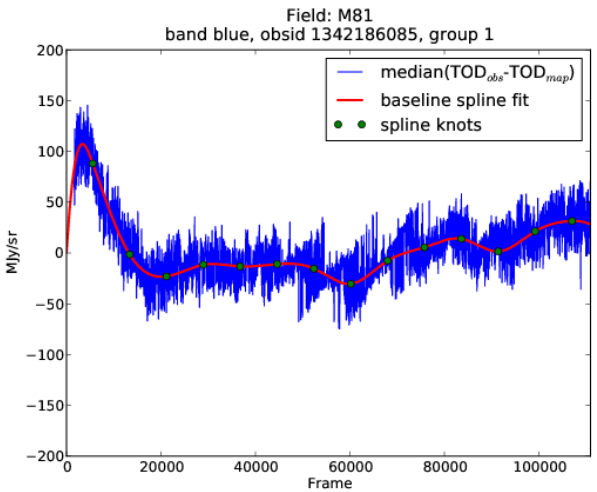




Baseline Removal, part 2

To remove non-linear drifts

1. Backproject y_i into a map $x_i = \frac{P^{\mathrm{T}}(y_i)}{P^{\mathrm{T}}(1)}$
2. Compute projection $\tilde{y}_i = P(x_i)$
3. Compute drift $z_{i,\mathrm{group}} = \langle y_i - \tilde{y}_i \rangle_{\mathrm{group}}$
4. Compute spline fit $\tilde{z}_{i,\mathrm{group}}$ to $z_{i,\mathrm{group}}$
5. $y_{i+1} = y_i - \tilde{z}_{i,\mathrm{group}}$
6. $i = i + 1$

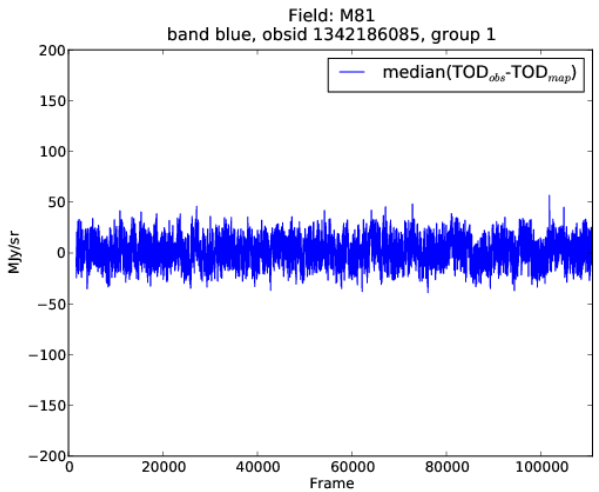


Baseline Removal, part 3

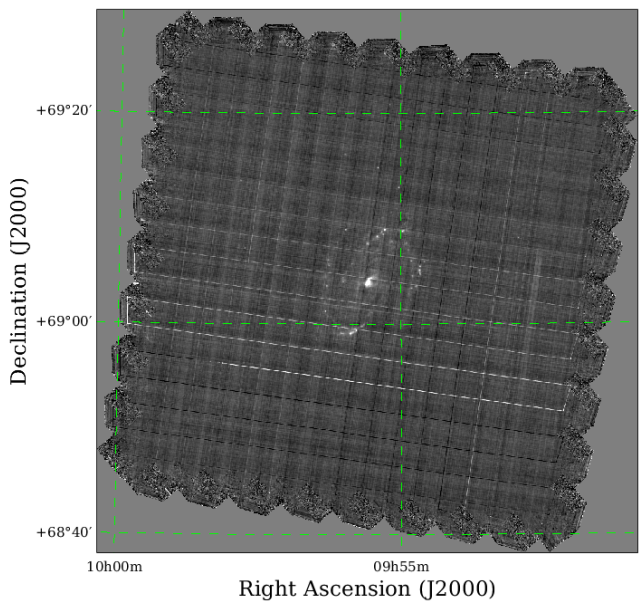
To remove non-correlated drifts

1. Backproject y_i into a map $x_i = \frac{P^{\mathrm{T}}(y_i)}{P^{\mathrm{T}}(1)}$
2. Compute projection $\tilde{y}_i = P(x_i)$
3. Compute drift $z_{i,\mathrm{detector}} = y_i - \tilde{y}_i$
4. Compute linear fit $\tilde{z}_{i,\mathrm{detector}}$ to $z_{i,\mathrm{detector}}$
5. $y_{i+1} = y_i - \tilde{z}_{i,\mathrm{detector}}$
6. $i = i + 1$

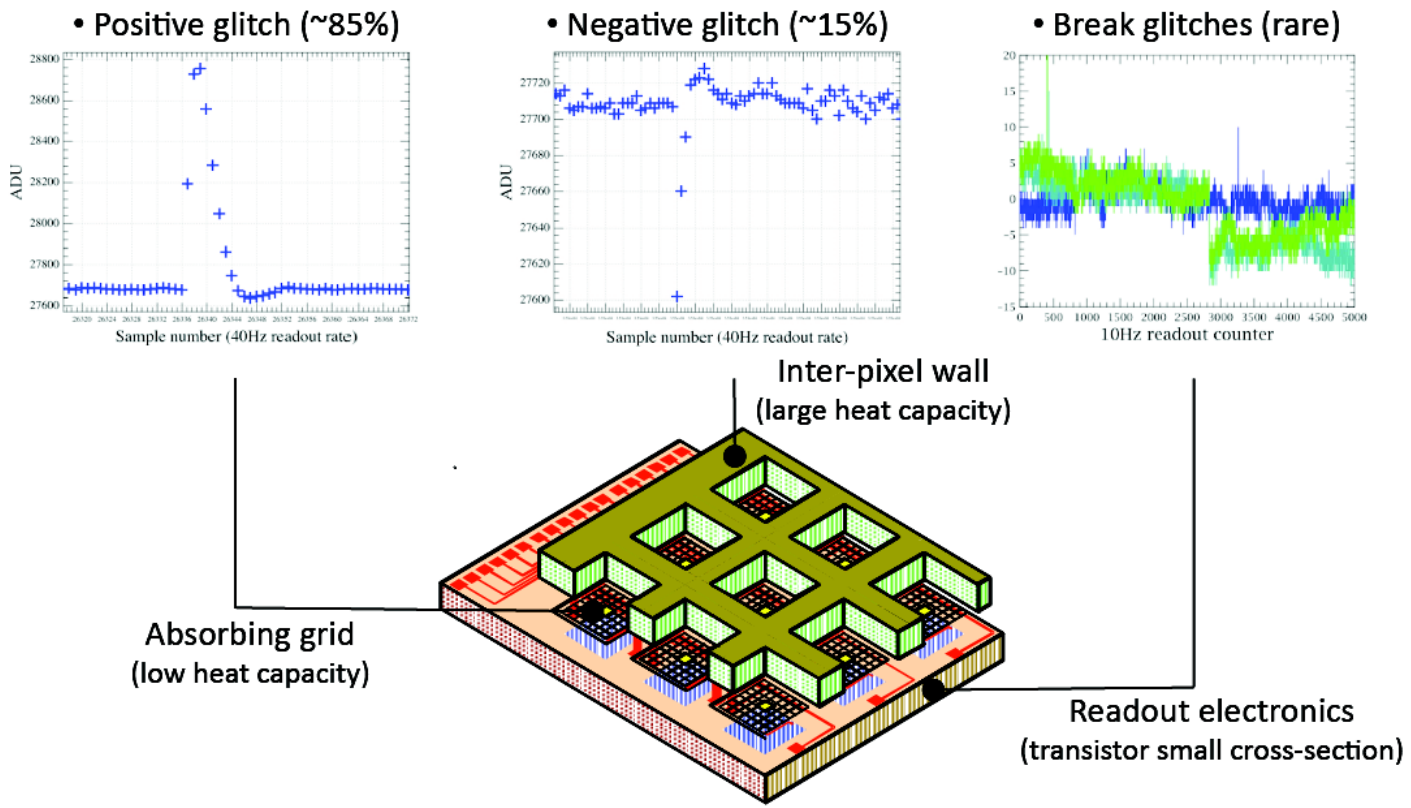
Final residuals.



Final map after baseline removal.

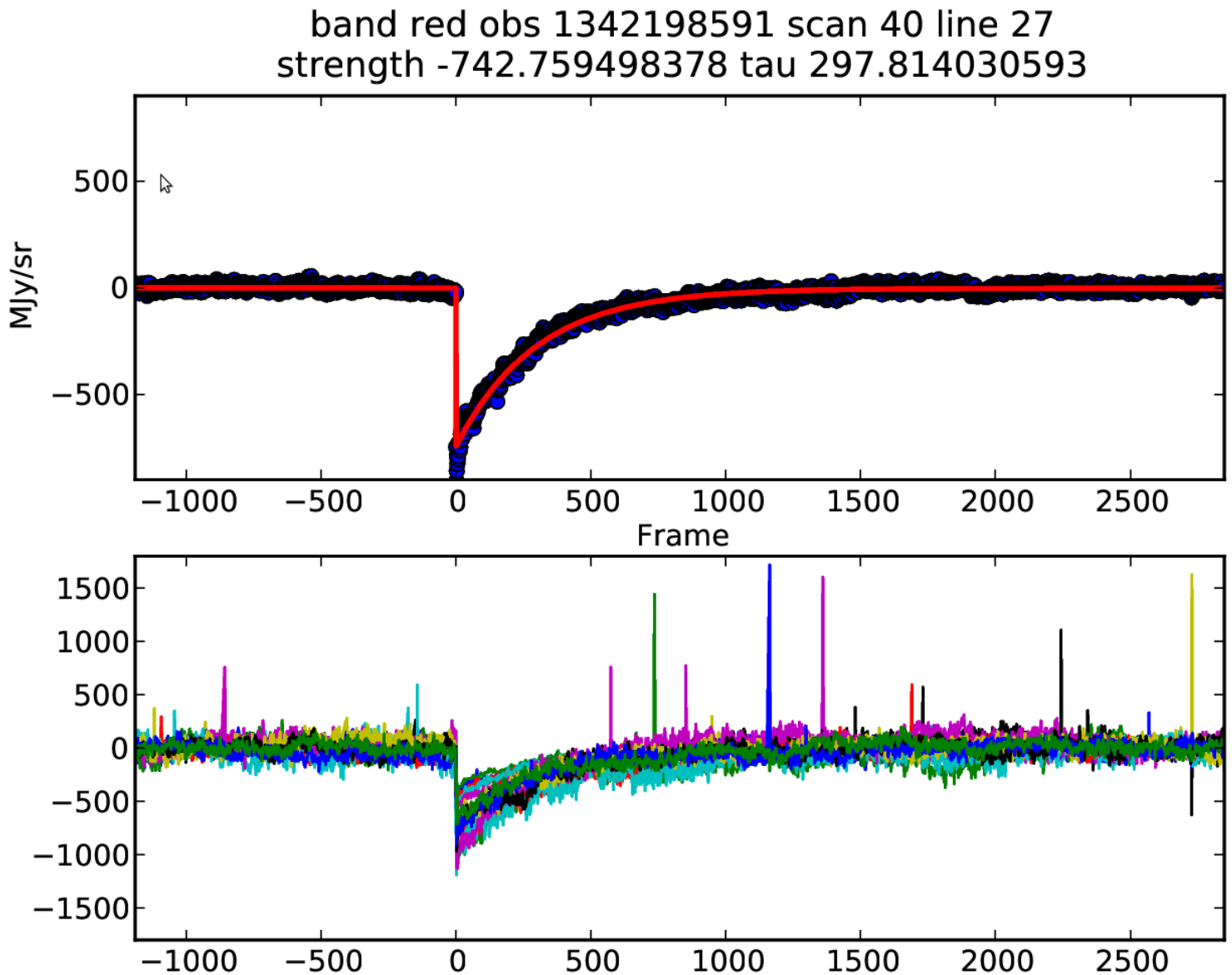


Glitch zoo



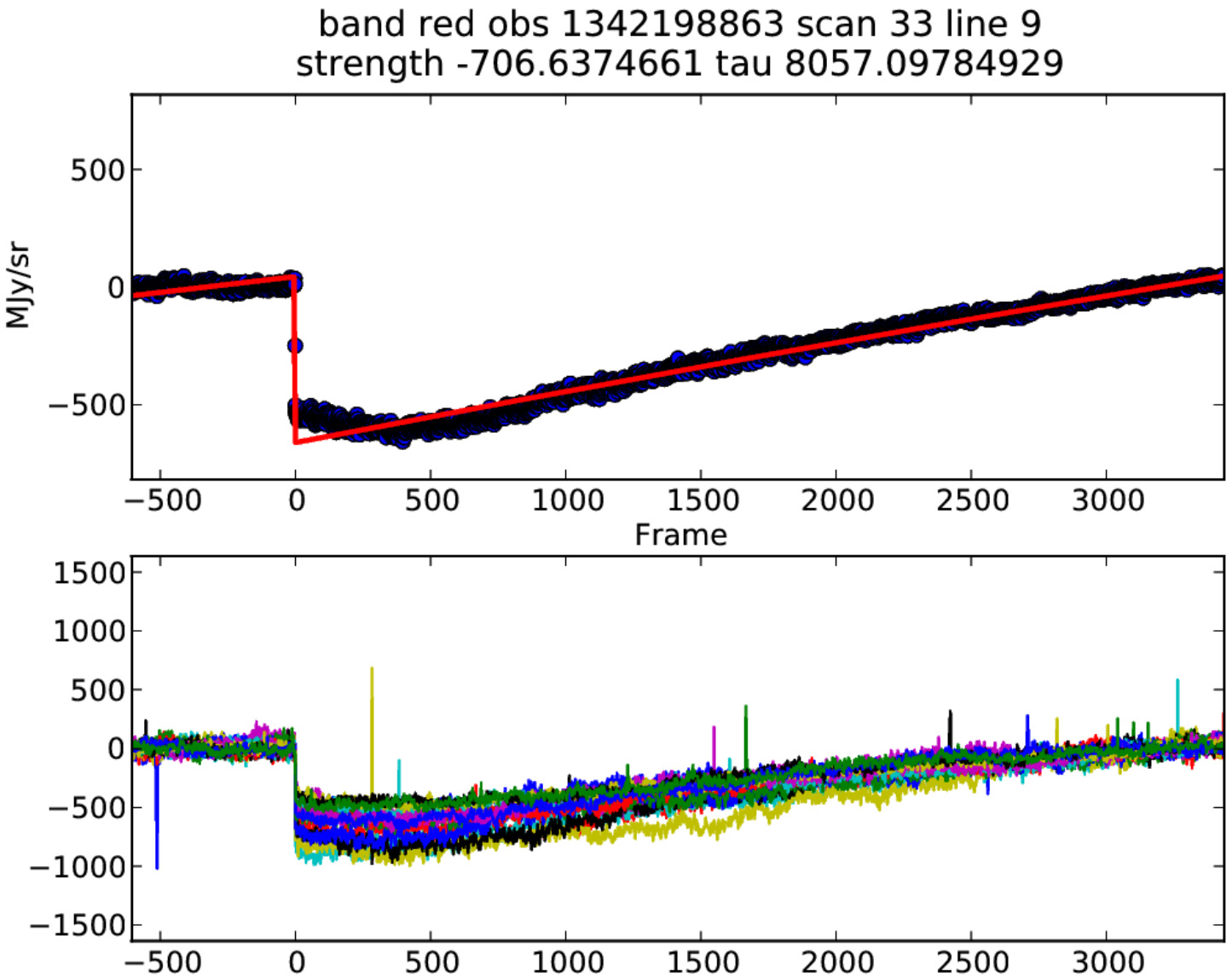
(N. Billot)

Glitch zoo



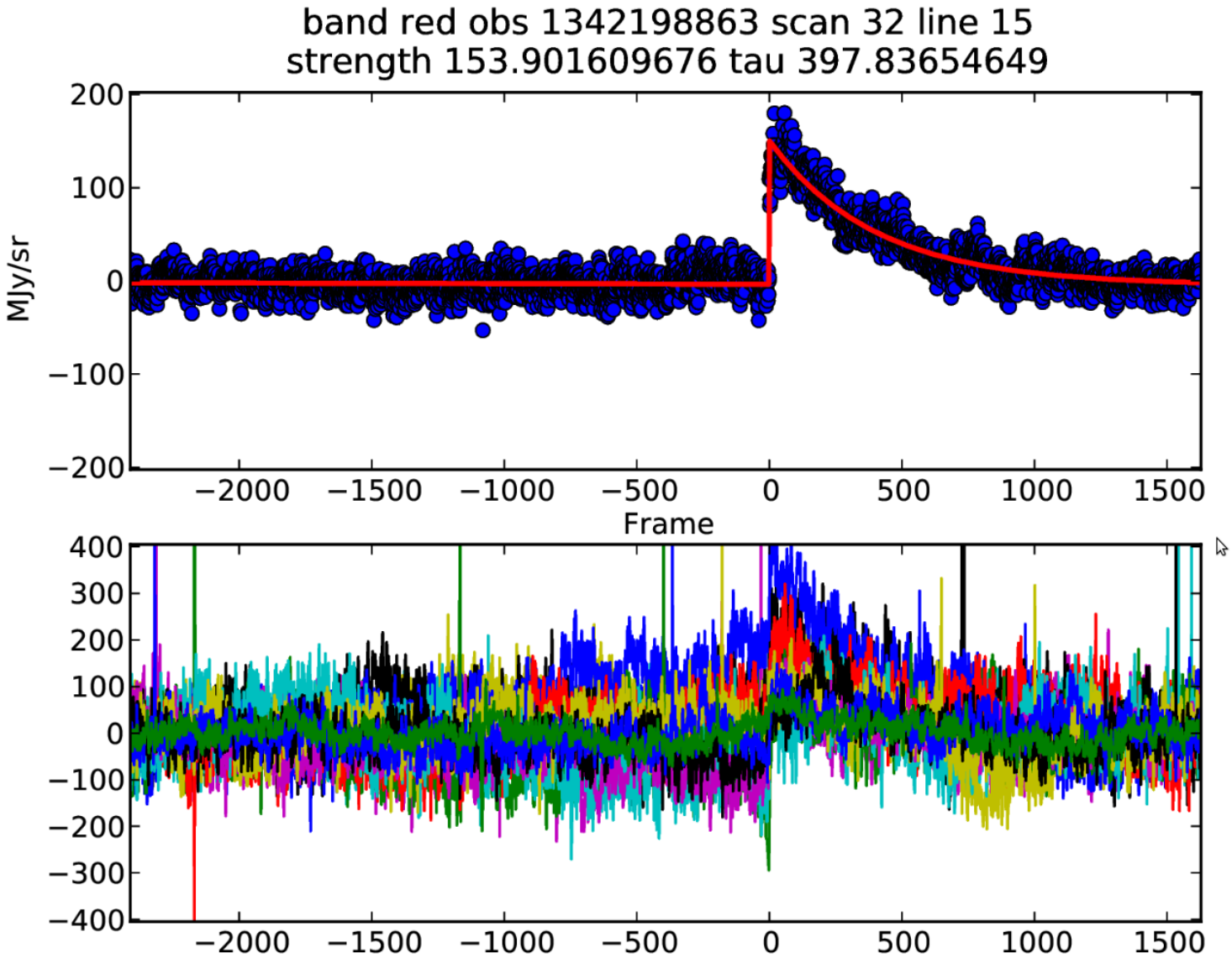
(P. Panuzzo)

Glitch zoo



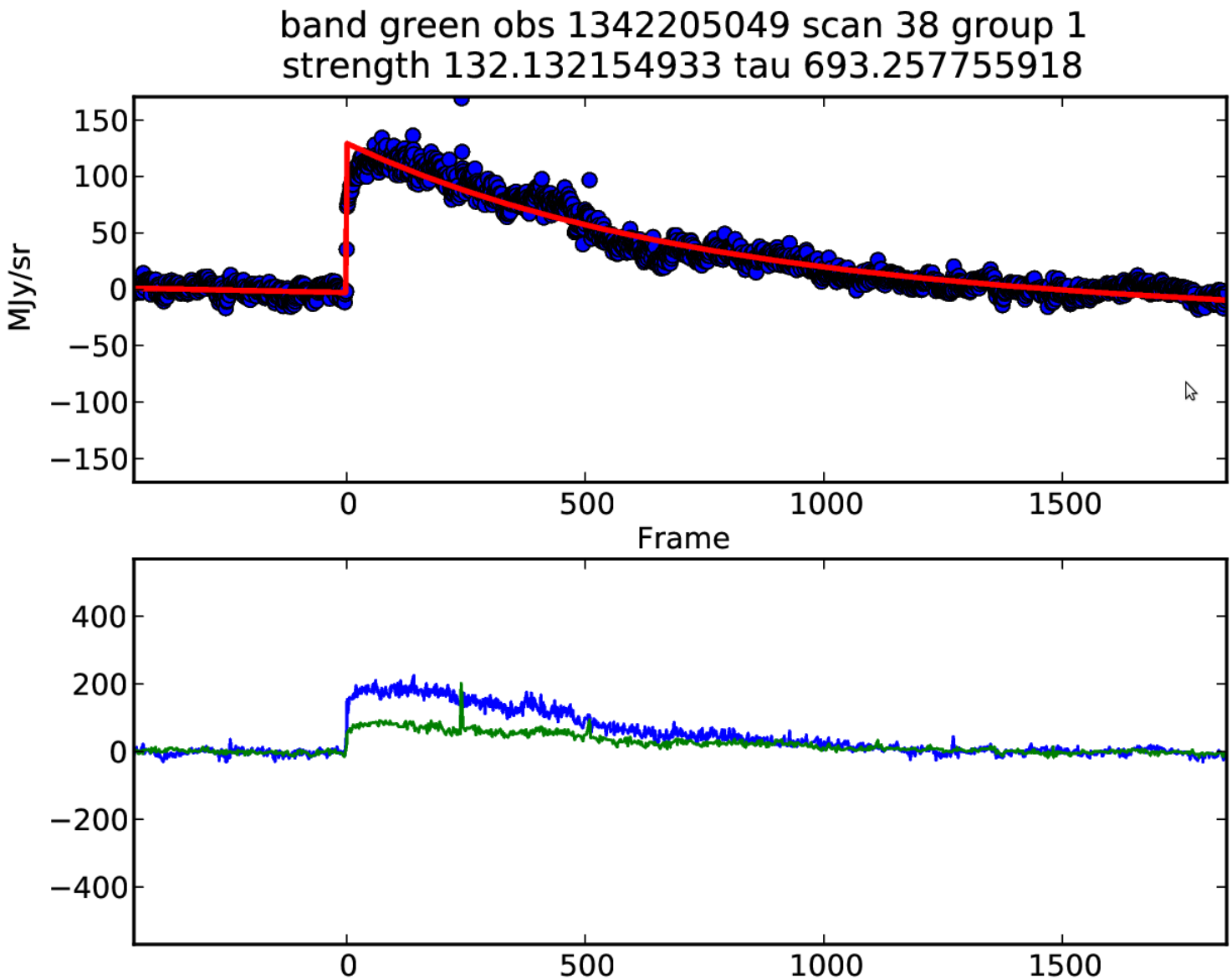
(P. Panuzzo)

Glitch zoo



(P. Panuzzo)

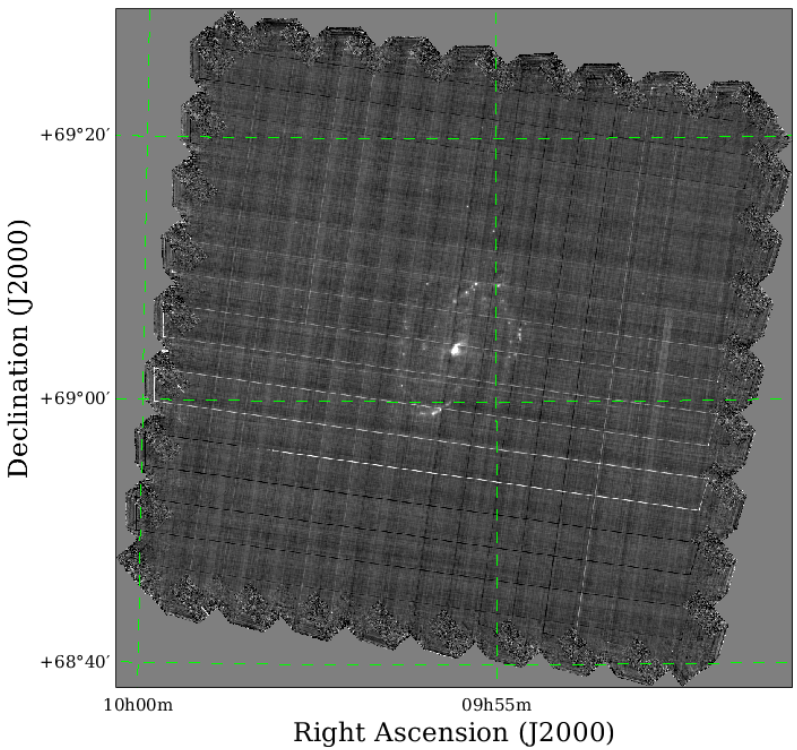
Glitch zoo

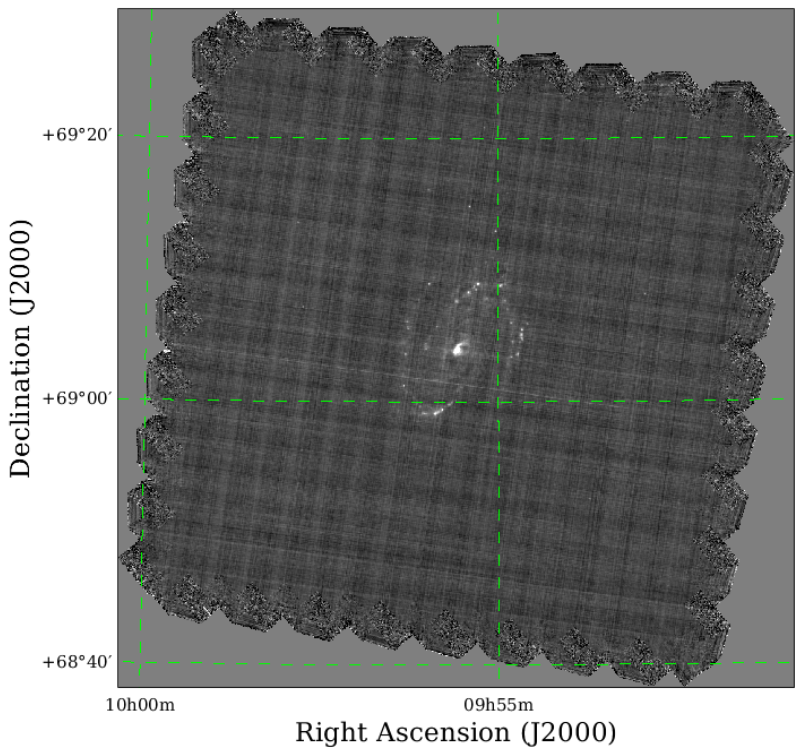


(P. Panuzzo)

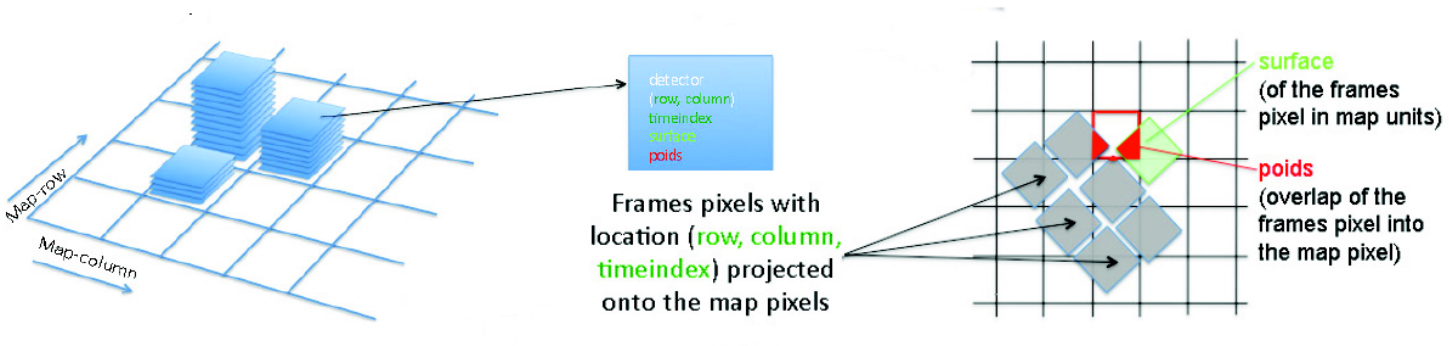
Long glitch removal: Jump detection

- Inspired by SPIRE preprocessing, but with Ω being a group, a line or a single bolometer:
  1. $x_\Omega = \frac{P^{\mathrm{T}}(y - y_\Omega)}{P^{\mathrm{T}}(1 - 1_\Omega)}$
  2. $\tilde{y}_\Omega = P(x_\Omega)$
  3. Detect jumps in $\langle y_\Omega - \tilde{y}_\Omega \rangle_\Omega$ using Haar transform





Short glitch removal: Spatial method (2nd level deglitching)



(N. Billot)

A generic pipeline for PACS

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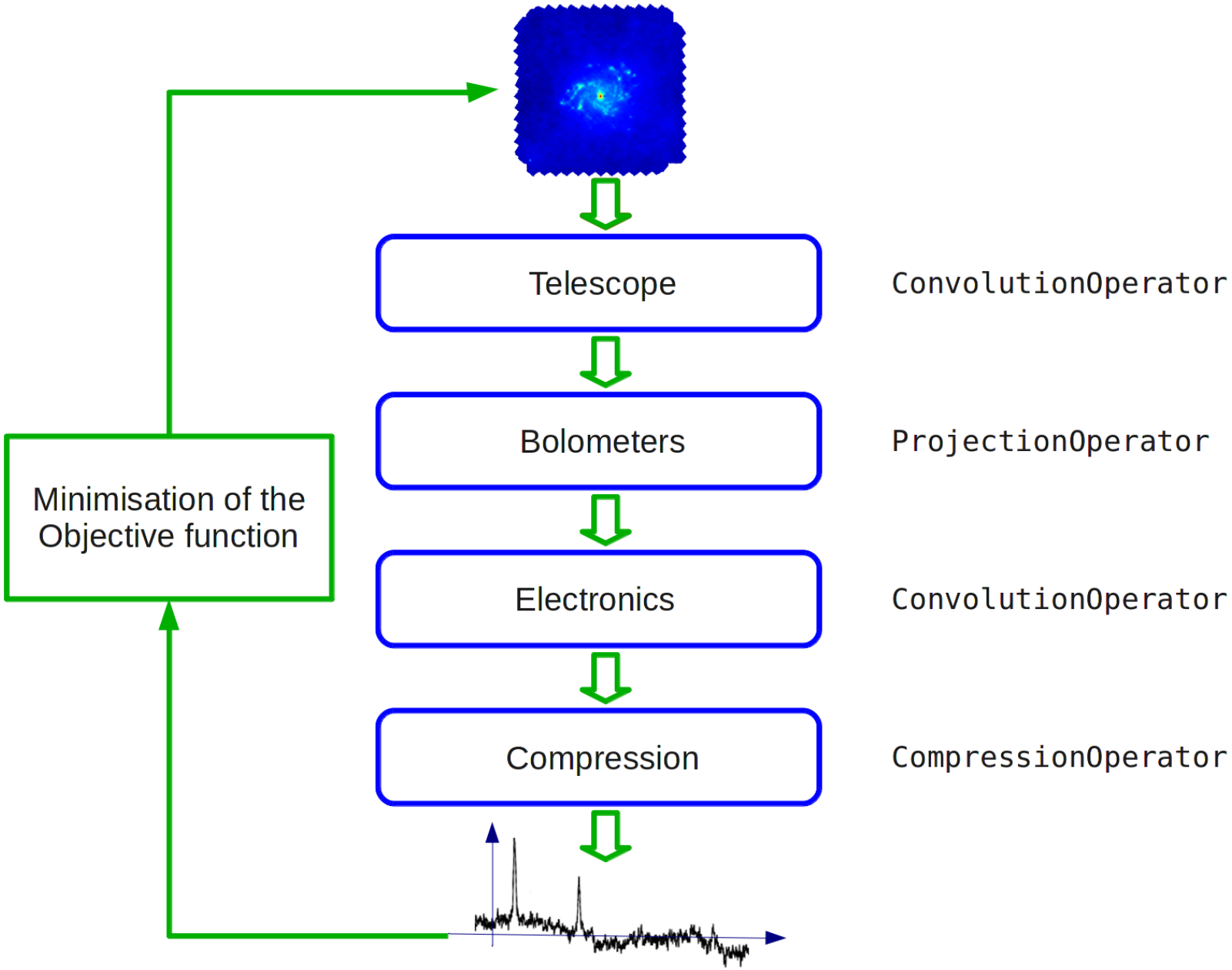
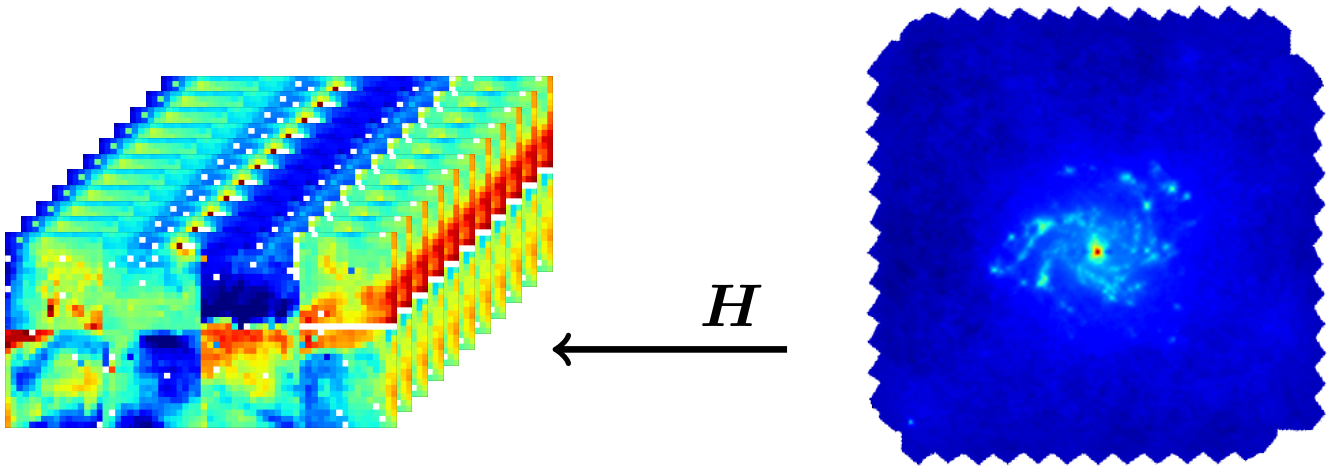

Telescope
ConvolutionOperator
Bolometers
ProjectionOperator
Minimisation of the Objective function
Electronics
ConvolutionOperator
Compression
CompressionOperator

Doing any science with any observation is attempting to solve an inverse problem

$$\boldsymbol{y} = \boldsymbol{H}\boldsymbol{x} + \boldsymbol{n}, \quad \boldsymbol{n} \sim \mathcal{N}(\boldsymbol{0}, \boldsymbol{N})$$



$\boldsymbol{y}$ $\boldsymbol{x}$

$$\hat{\boldsymbol{x}} = \arg\min_{\boldsymbol{x}} \left\{ ||\boldsymbol{y} - \boldsymbol{H}\boldsymbol{x}||^2_{\boldsymbol{N}^{-1}} + \Psi(\boldsymbol{x}) \right\}$$

This method requires $\approx$100$\times$ more compute power.

$\Rightarrow$ Acquisition model $\boldsymbol{H}$ must be very fast

Optimisations

Speed is one of Tamasis main drivers.

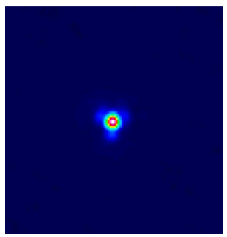
- $\Rightarrow$ gain $\times$180 (standard PACS pipeline, Java)
- $\Rightarrow$ gain $\times$2,4 (MADmap v1, pure C, scalar)

Optimisations

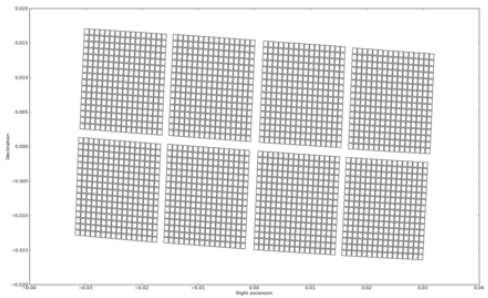
- As much preparation as possible before iterations
- Algebraic rule simplifications
- Pool-based Memory manager: no creation of array temporaries during iterations. Hand buffers to operators according to requirements (contiguity, alignment)
- In-place/out-of-place operators
- In-place reductions
- Block partition: crucial to take advantage of the cache

PACS artifacts

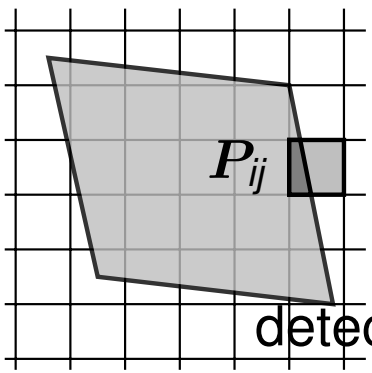
- **Telescope PSF**



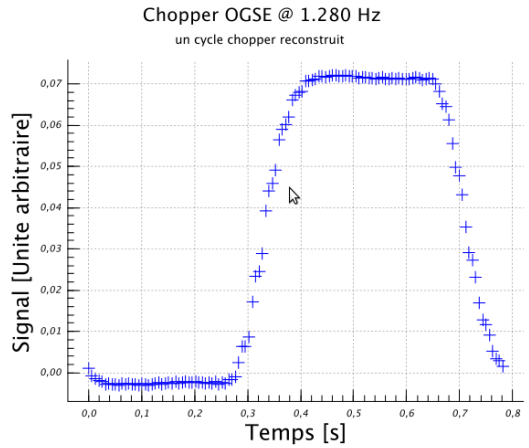
- **Distortion**



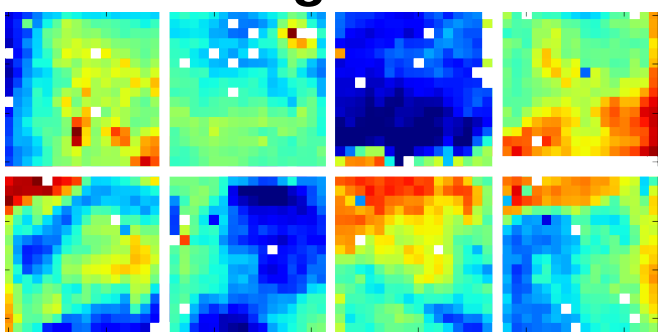
- **Projection**



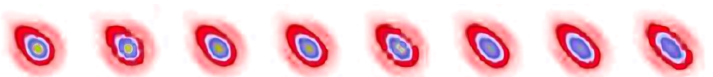
- **Bolometer response**



- **Bolometer gain**

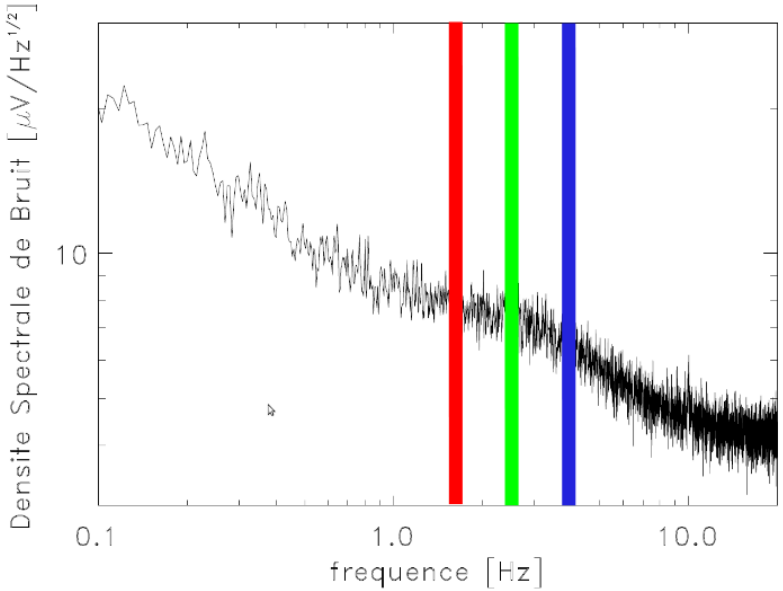


- **On-board Compression**



PACS artifacts

- **Offset drifts** $\Leftrightarrow$ 1/f noise



Even point sources are affected. The slower is the scan, the more we have to deal with underlying 1/f noise.

Step 1: build instrument model

```
obs = PacsObservation(['myobs1.fits', 'myobs2.fits'])

O = ConvolutionOperator(obs.get_psf(...))
P = ProjectionOperator(obs.get_pointing_matrix())
R = ConvolutionTruncatedExponentialOperator(...)
C = CompressionAverageOperator(8)
G = DiagonalOperator(..., broadcast='rightward')
M = MaskOperator(...)
H = M * G * C * R * P * O
```

Step 1: build instrument model

Tamasis can do plain HIPE's MADmap, too:

```
P = ProjectionOperator(obs.get_pointing_matrix(method='nearest',
                                               downsampling=True))
M = MaskOperator(...)
H = M * P
```

Step 1: build instrument model

Tamasis can do vanila HIPE's Photproject, too:

```
obs = PacsObservation(['myobs1.fits', 'myobs2.fits'])
y = obs.get_tod()
y = filter_median(y, 100)

P = ProjectionOperator(downsampling=True)
M = MaskOperator(y.mask)
H = M * P

m = H.T(y) / H.T(ones(y.shape))
```

Step 2: Objective Function

$$\boldsymbol{f}(\boldsymbol{x}) = \Phi(\boldsymbol{y} - \boldsymbol{H}\boldsymbol{x}) + \Psi(\boldsymbol{x})$$

- Likelihood (with inv. covariance matrix N^{-1} as an operator)
- prior: regularisation
  - smoothness: $\Psi(\boldsymbol{x}) = \lambda \, ||D_\alpha(\boldsymbol{x}) + D_\beta(\boldsymbol{x})||_2^2$
  - sparseness: $\Psi(\boldsymbol{x}) = \lambda \, |w(\boldsymbol{x})|_1$
  - positivity constraint
- norms: L_1, L_2, L_p, L_{Huber}

For a linear model, it can be equivalent to solving Ax=b

- least-square:

```
A = H.T * invNtt * H,    b = H.T * invNtt * y
```

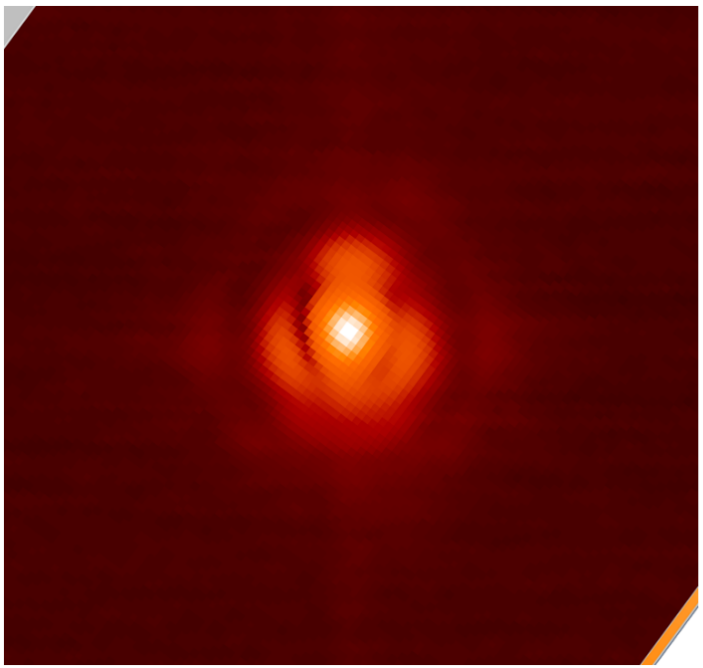
- least-square + prior:

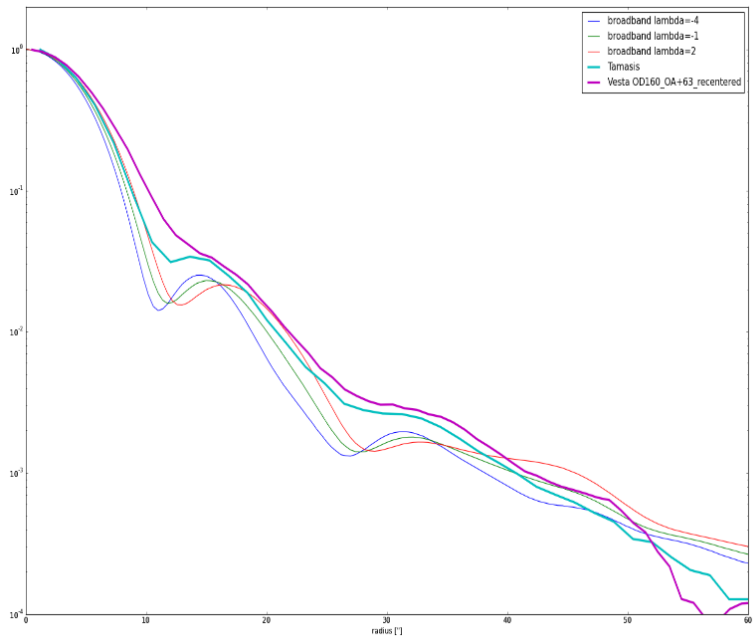
```
A = H.T * invNtt * H + h * D.T * D,    b = H.T * invNtt * y
```

Step 3: Minimisation

- PCG (MPI)
- non-linear PCG (MPI)
- scipy.sparse.linalg (CG, CGS, BICG, BICGSTAB, GMRES, LGMRES, ...)
- scipy.optimize (fmin_bfgs, ...)
- FISTA
- soon: PETSc

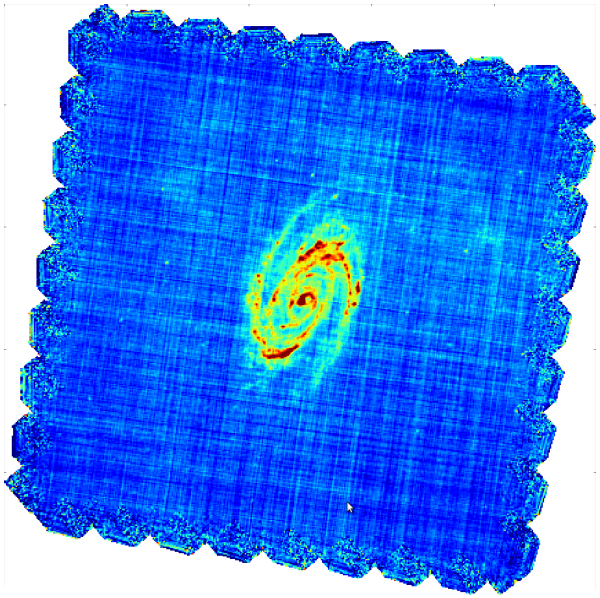
High frequency reconstruction



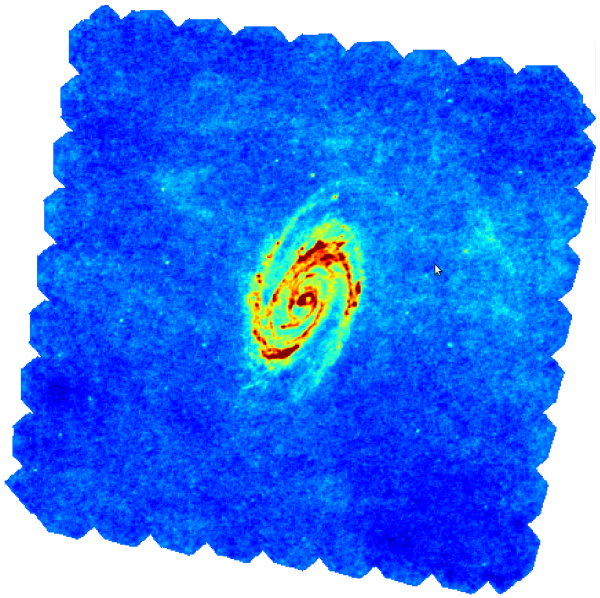


Red channel PACS PSF

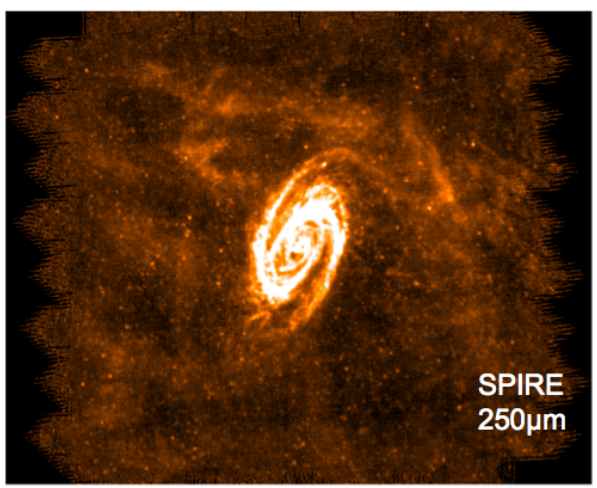
Low frequency reconstruction



“Pipeline” without hpf

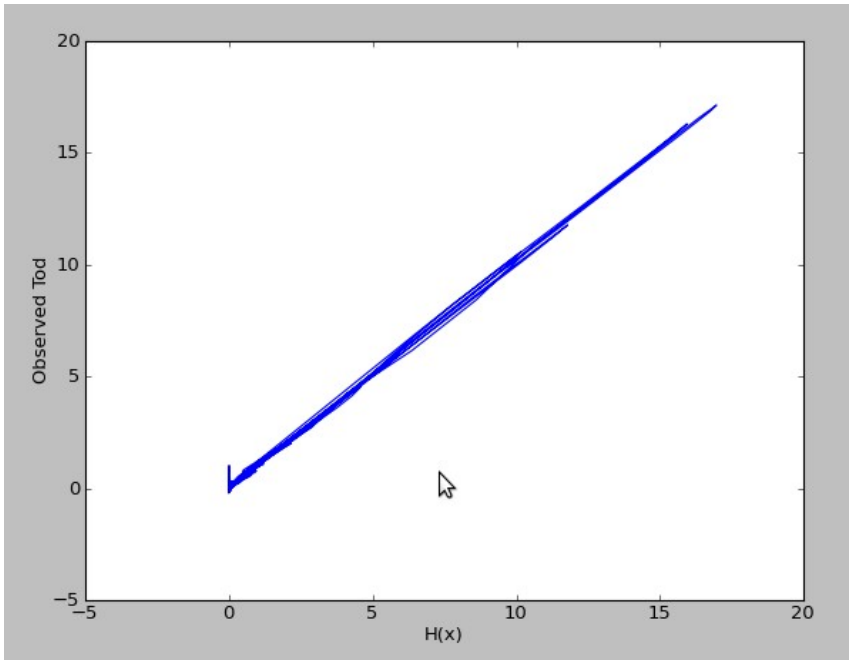


Tamasis RLS

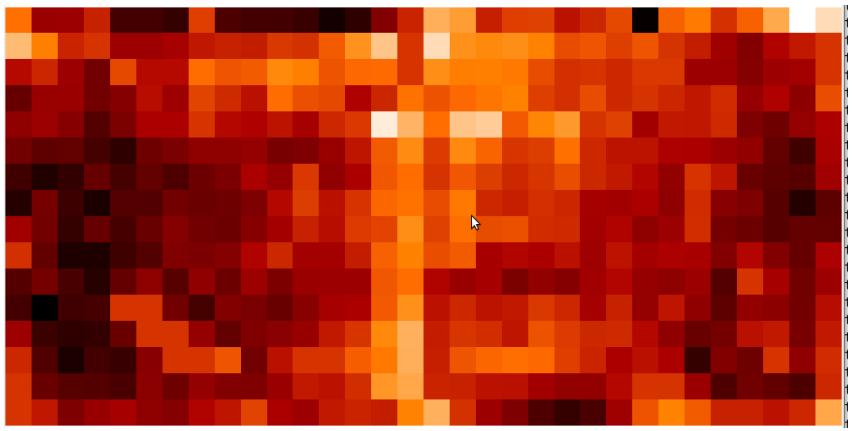


- Removed artifacts
- Real structures

Flat reconstruction

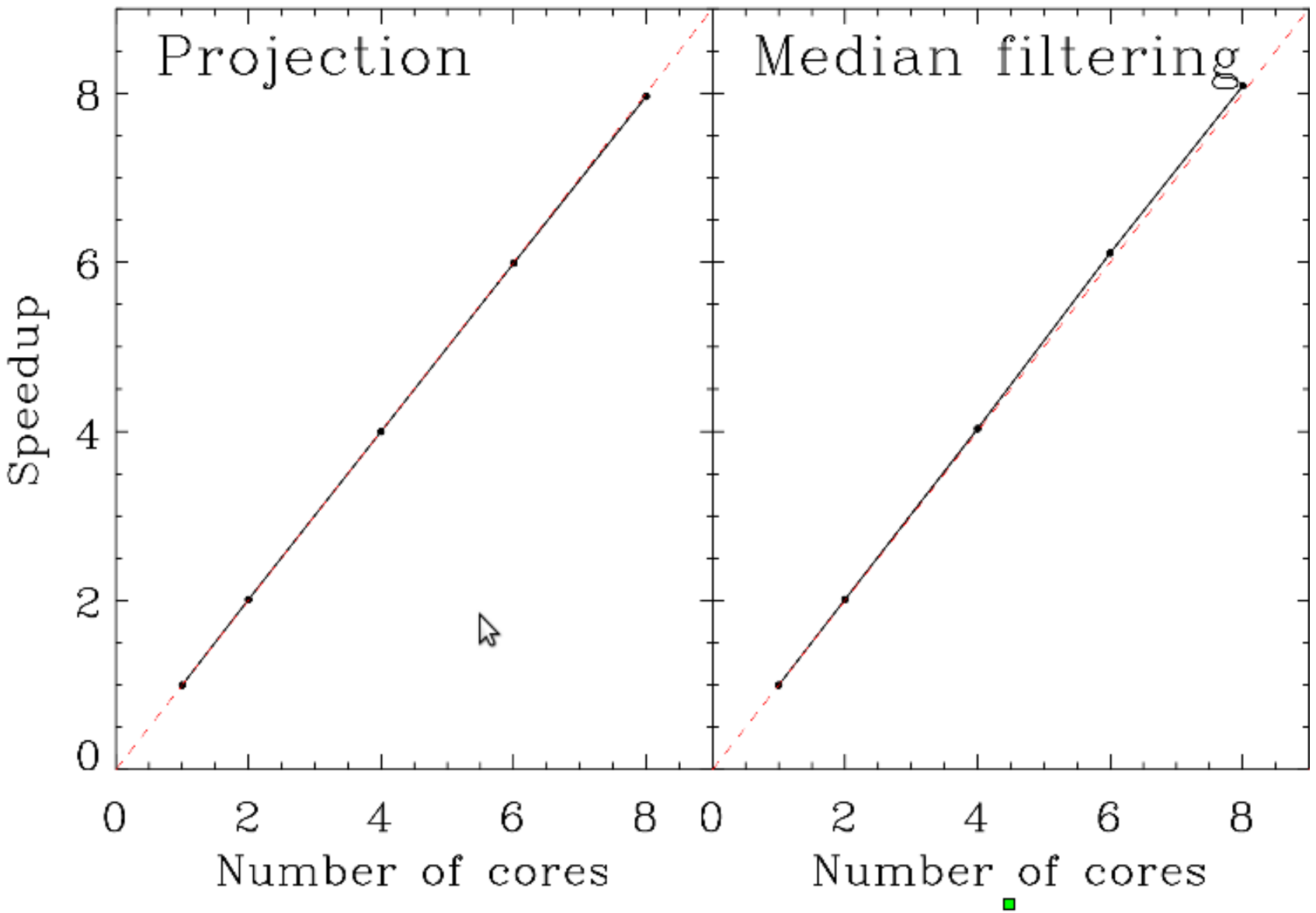


simulation vs observation

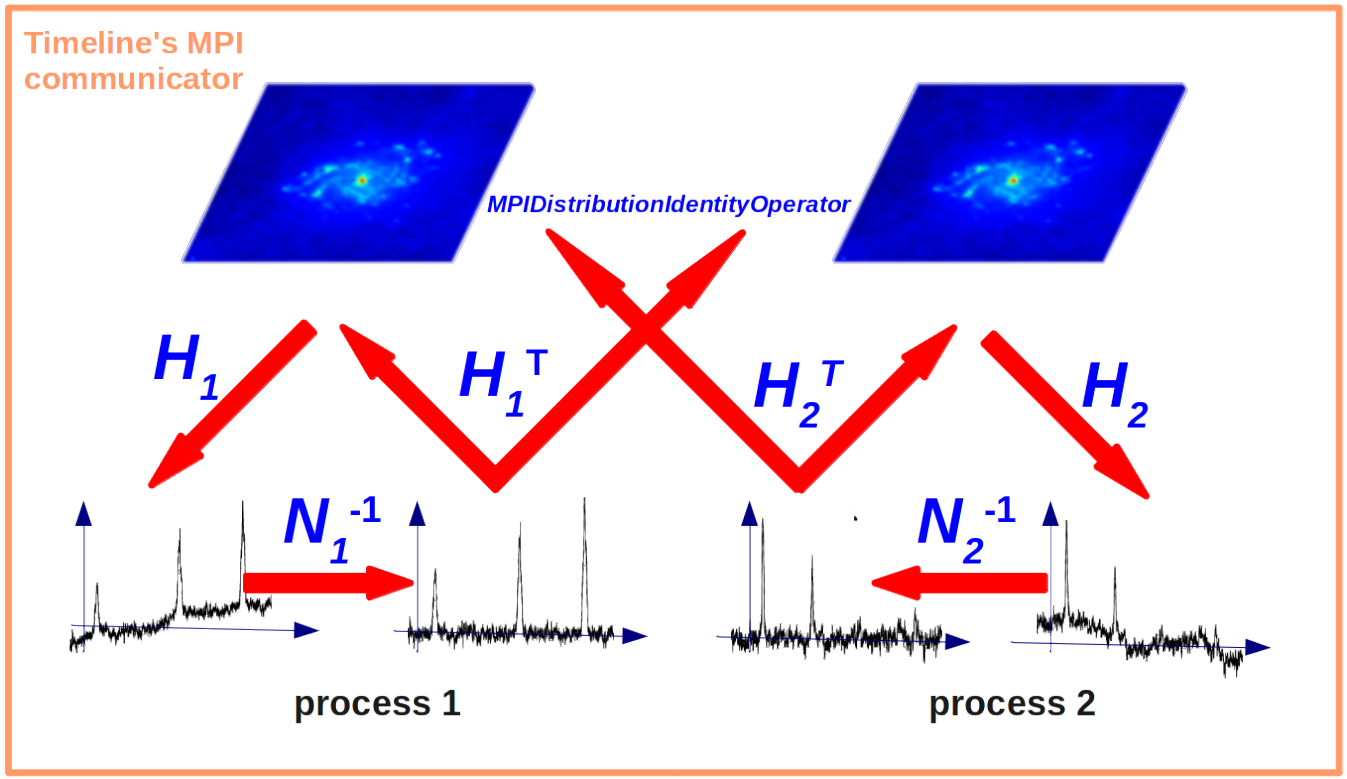


Resulting flatfield

Parallelisation OpenMP



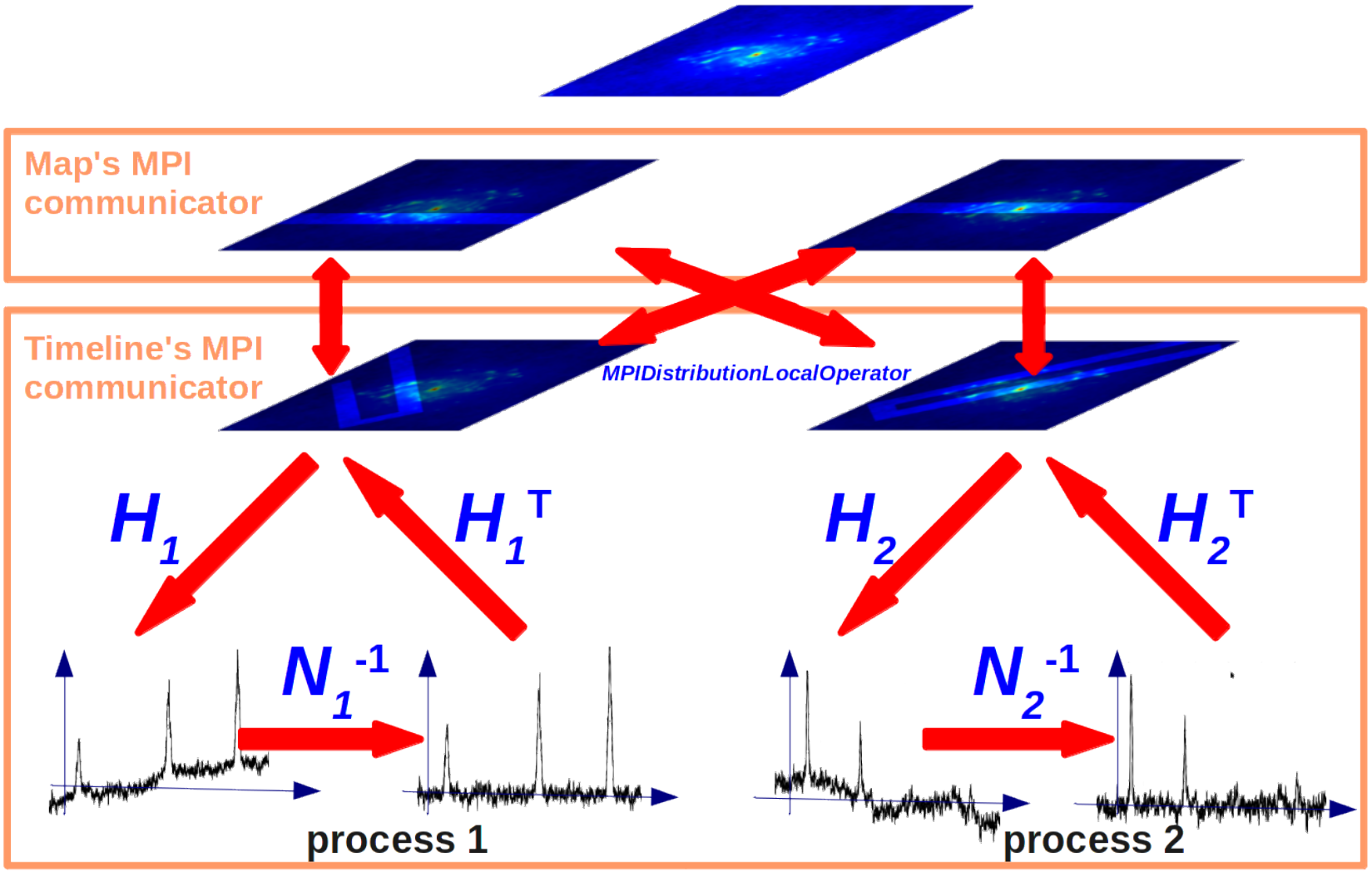
Parallelisation MPI: Distributed TOD



$$\boldsymbol{H}\boldsymbol{D} \Rightarrow \boldsymbol{D}^{\mathrm{T}}\boldsymbol{H}^{\mathrm{T}}\boldsymbol{N}^{-1}\boldsymbol{H}\boldsymbol{D}\boldsymbol{x} = \boldsymbol{D}^{\mathrm{T}}\boldsymbol{H}^{\mathrm{T}}\boldsymbol{N}^{-1}\boldsymbol{y}$$

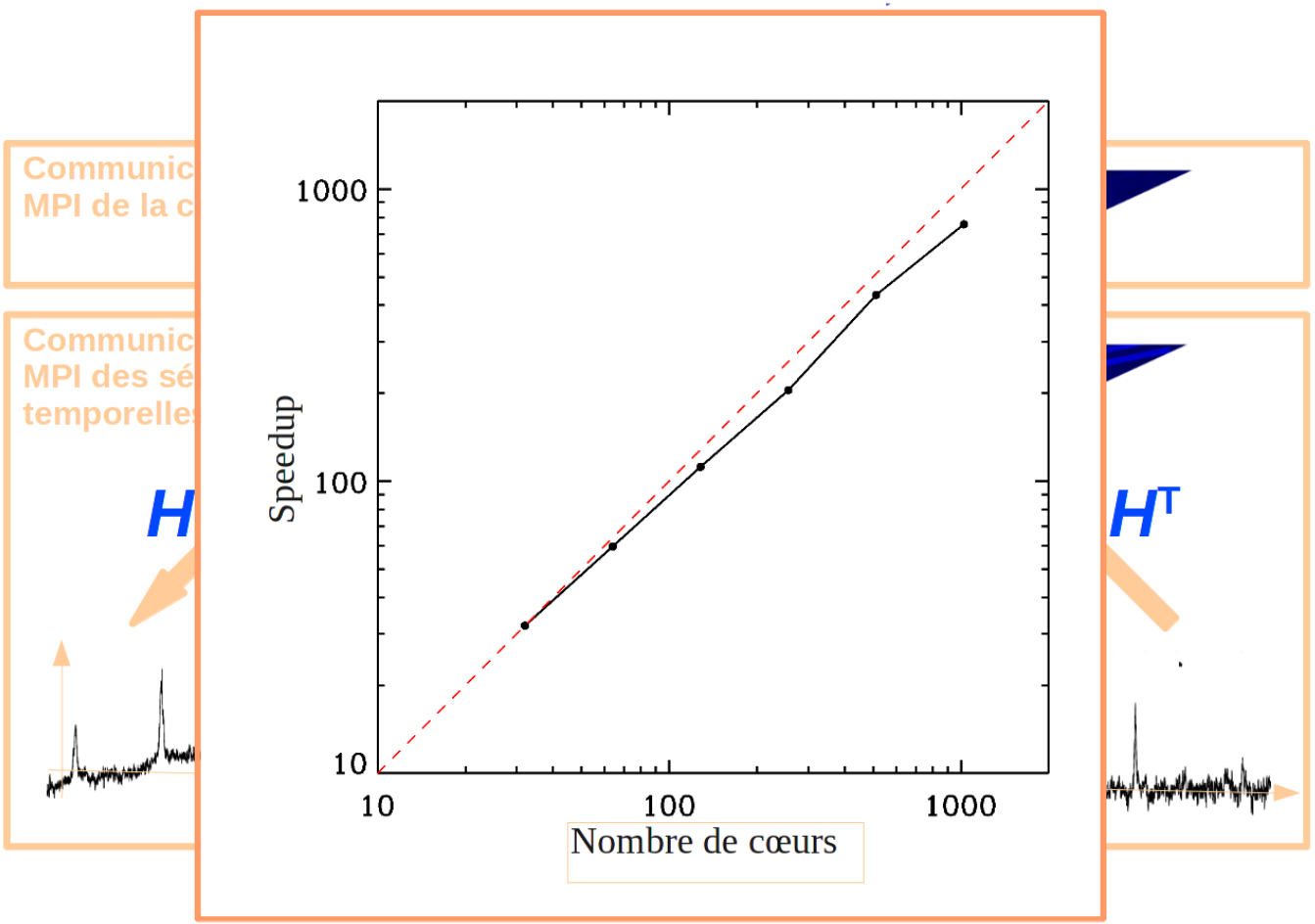
$$\boldsymbol{H} = \begin{pmatrix} H_1 & 0 & \cdots & 0 \\ 0 & H_2 & \cdots & 0 \\ \vdots & & \ddots & \vdots \\ 0 & 0 & \cdots & H_p \end{pmatrix} \quad \boldsymbol{D} = \begin{pmatrix} \boldsymbol{I} \\ \boldsymbol{I} \\ \vdots \\ \boldsymbol{I} \end{pmatrix}$$

Parallelisation MPI: Distributed TOD and map

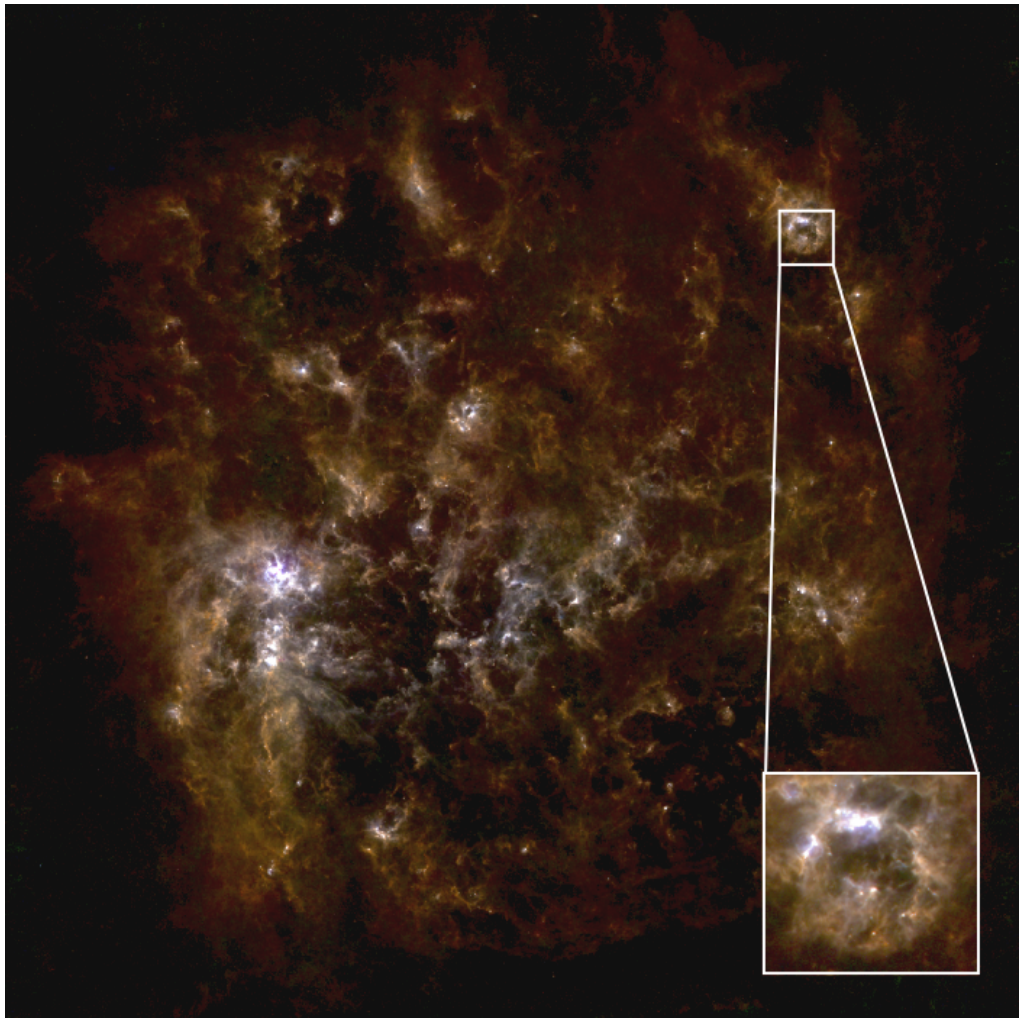


$$\boldsymbol{H}\boldsymbol{D} \Rightarrow \boldsymbol{D}^{\mathrm{T}}\boldsymbol{H}^{\mathrm{T}}\boldsymbol{N}^{-1}\boldsymbol{H}\boldsymbol{D}\boldsymbol{x} = \boldsymbol{D}^{\mathrm{T}}\boldsymbol{H}^{\mathrm{T}}\boldsymbol{N}^{-1}\boldsymbol{y}$$

Parallelisation MPI: Distributed TOD and map



Tamasis: large dataset (LMC)



- Map: $9.2^\circ \times 9.0^\circ \approx 3$ GB ($4\,10^8$ unknowns)
- TOD: 161h, 2048 detectors, $5.2\ 10^9$ samples at 5 Hz, $4.2\,10^{10}$ at 40 Hz.
- Pointing matrix: 3.3 TB (1 detector intersects 10 sky pixels)
- Hardware: 50min, CCRT/Curie, 2432 cores, 152 processors

Future work

- With decent pointing reconstruction:
  - Include telescope PSF *Rightarraow* deconvolution
  - Fix cross-artifacts in a natural way
- Integrate Panuzzo's preprocessing treatment
- Implement SUPREME's hyperparameter handling (next talk). For the workshop, a single value has been chosen for all observations.
- Ease installation

Outstanding issue: pointing reconstruction