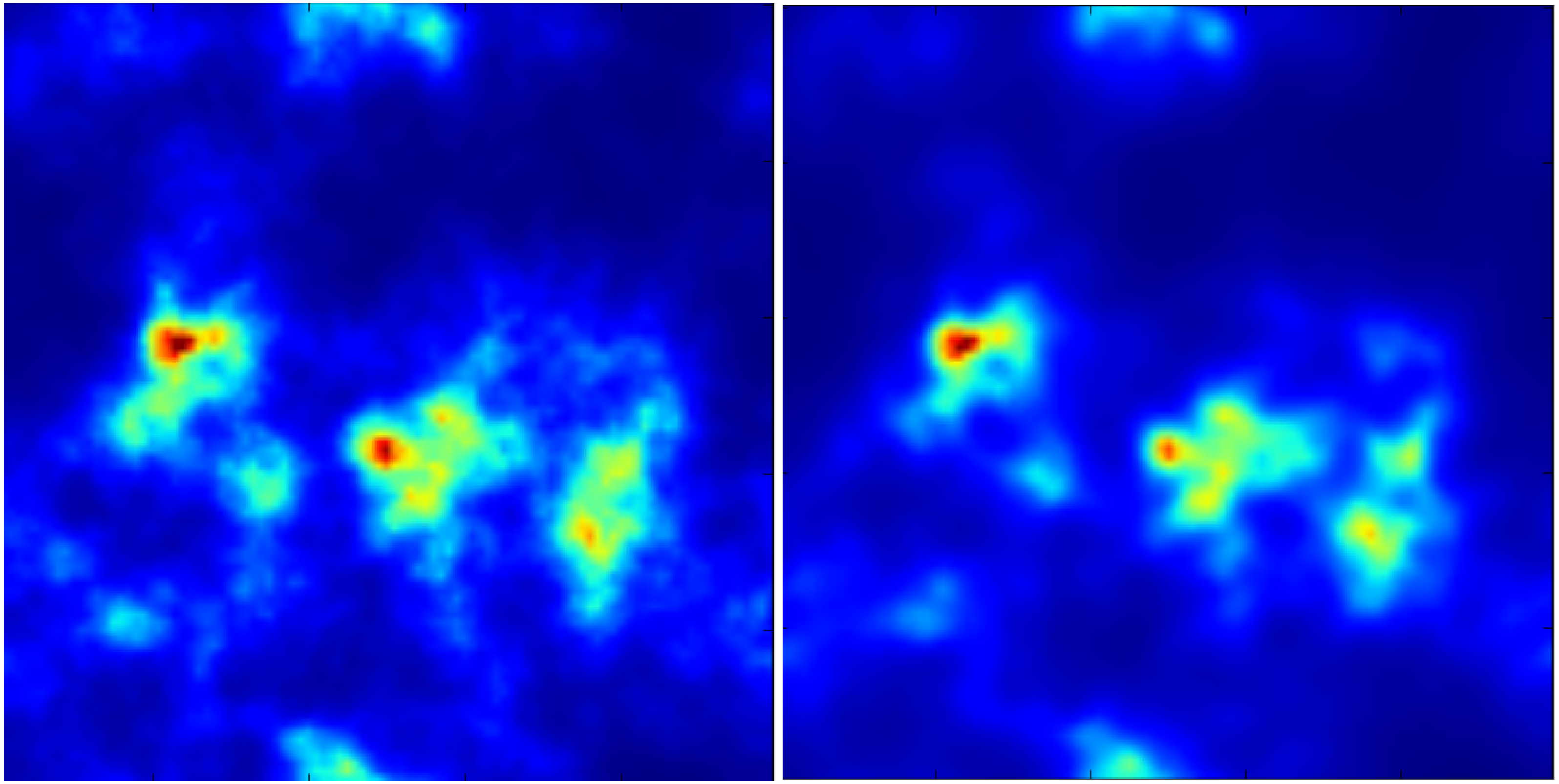
High fidelity imaging

A new method for radio imaging of diffuse fields



Henrik Junklewitz

Michael R. Bell, Torsten Enßlin

Max-Planck-Institut für Astrophysik

The aim: A new high fidelity imaging algorithm for diffuse emission

The approach: Information field theory, Bayesian data analysis,

- Targeted algorithm using information theory, here: Diffuse radio emission
- Incorporate available correlation information
- Consistent uncertainty propagation

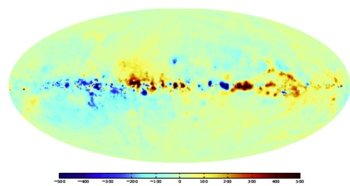
Obtaining information

physical signal s

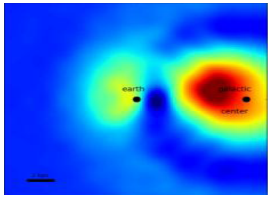
Obtaining information

physical signal s

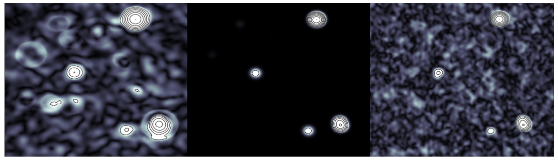
- Faraday rotation map φ



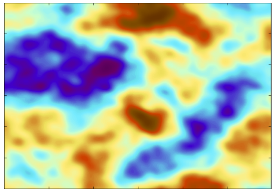
- Galactic thermal electron density



- Polarized intensity as a function of φ (Faraday spectrum)



- Total synchrotron intensity and spectral index maps



- 3D magnetic field, magnetic power spectra, ...

Obtaining information

physical signal s

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physical signal s

1) prior knowledge: *prior* P(s)

Obtaining information

physical signal s

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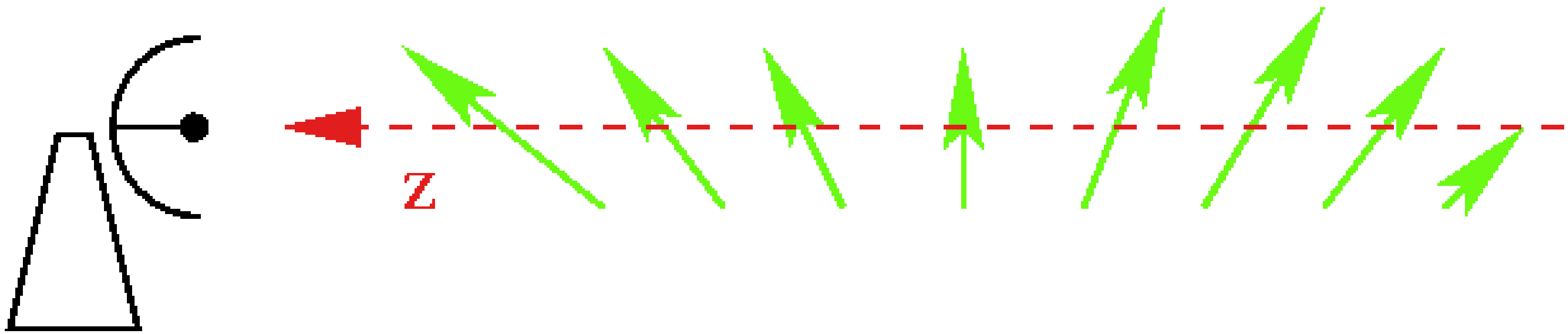
2) measurement: d = R(s) + n, linear response R, *likelihood* P(d|s)



Obtaining information

physical signal s

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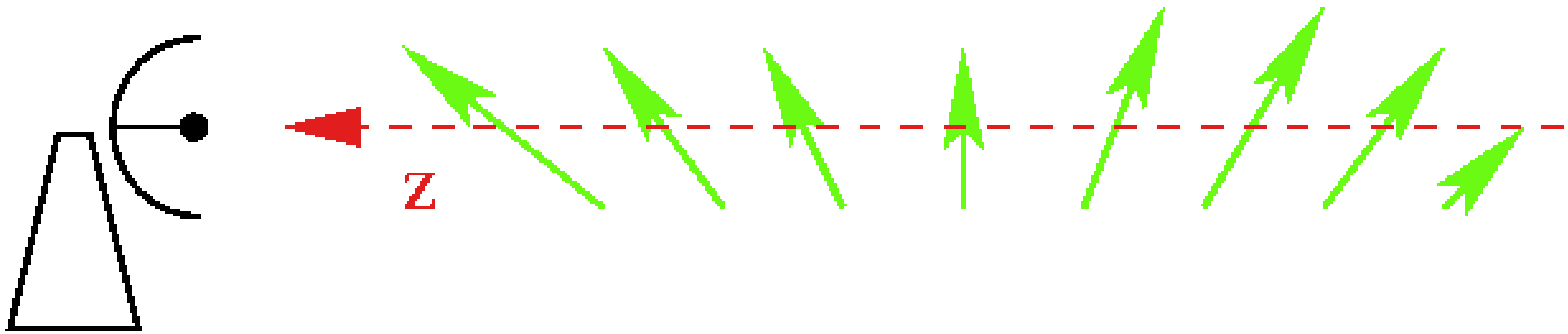

3) inference: *posterior* P(s|d)=P(d|s) P(s)/P(d), d → s

Processing information

Posterior mean $map = \langle s \rangle_{\mathcal{P}(s|d)} = D\,j$

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Signal and noise follow Gaussian statistics: $\mathcal{G}(s, S) \propto \exp[-\frac{1}{2} s^\dagger S^{-1} s]$

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Wiener Filter

$$j = R^\dagger N^{-1} d$$
$$D = (S^{-1} + R^\dagger N^{-1} R)^{-1}$$

Known signal (S) and
noise (N) covariance

Processing information

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Signal and noise follow Gaussian statistics: $\mathcal{G}(s, S) \propto \exp[-\frac{1}{2} s^\dagger S^{-1} s]$

Wiener Filter | e. g. Extended Critical Filter (Oppermann et al. 2011)

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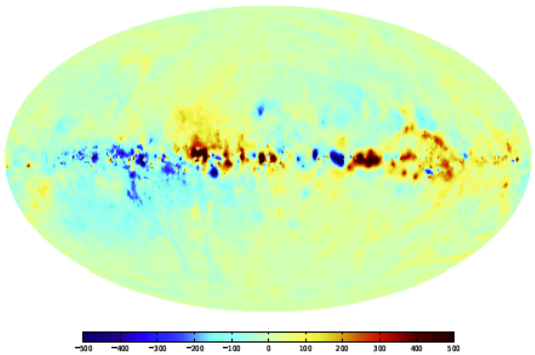
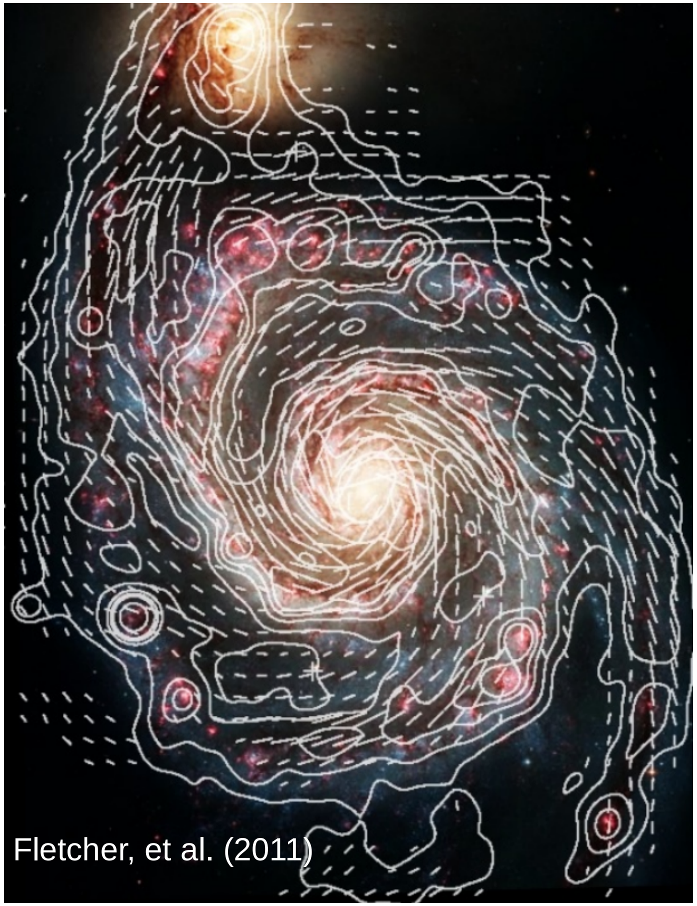
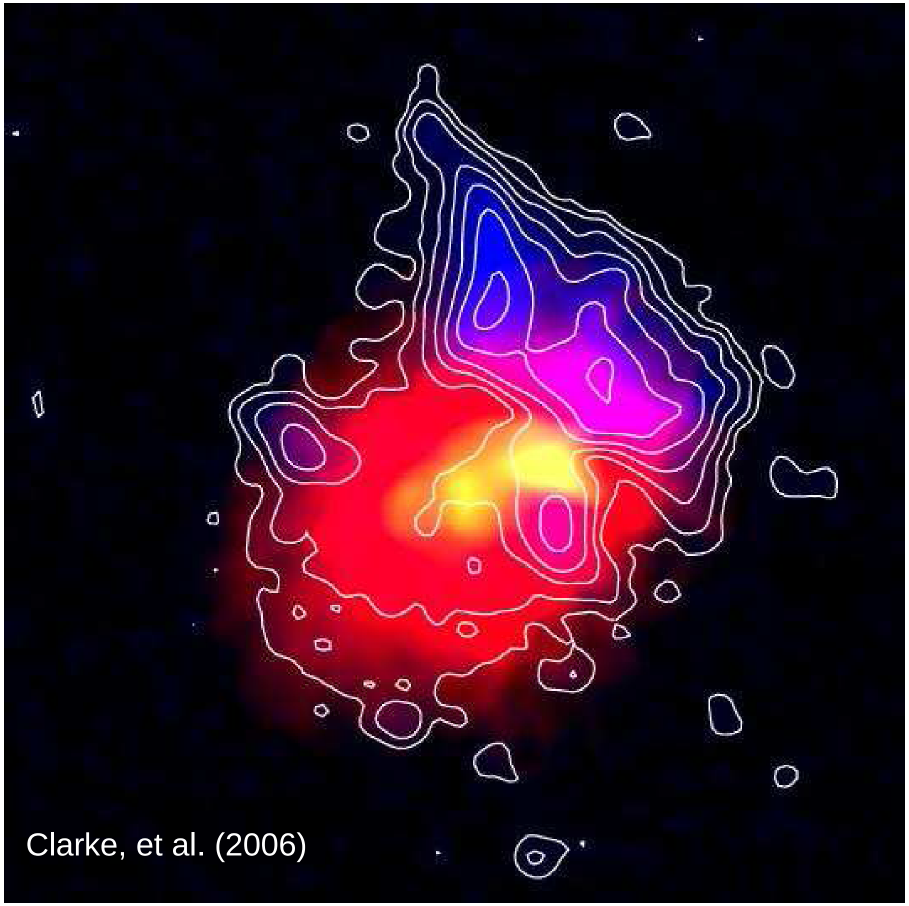



Fletcher, et al. (2011)


Clarke, et al. (2006)

Obtaining information

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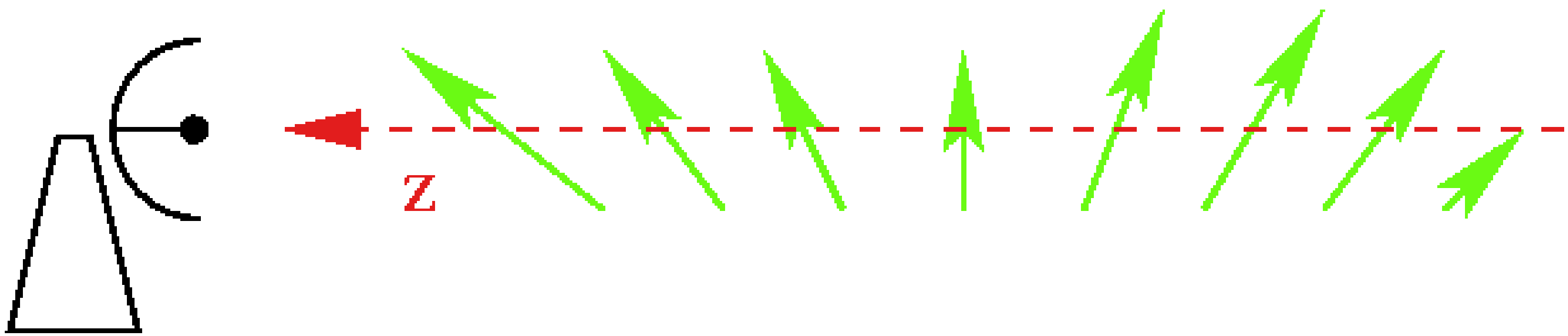
1) prior knowledge: *prior* P(s)

2) measurement: d = R(s) + n, linear response R, *likelihood* P(d|s)



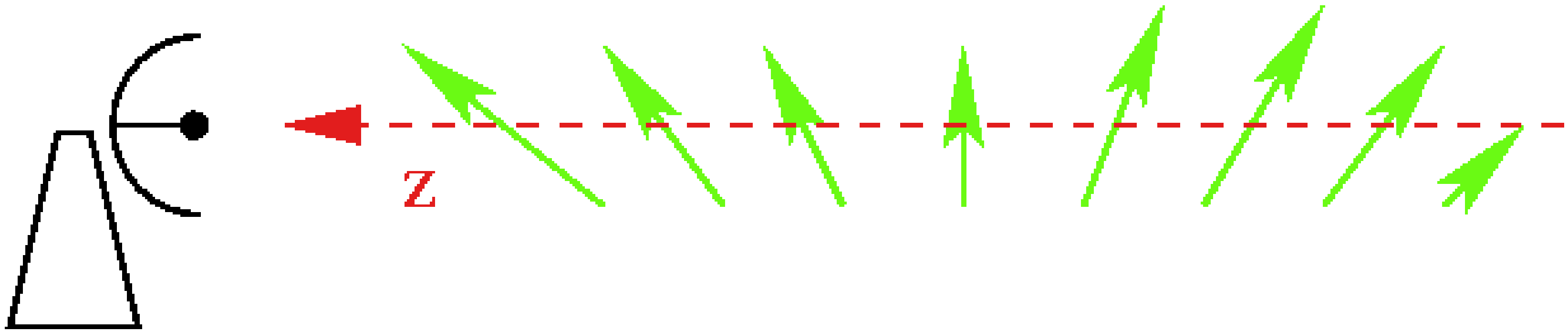
3) inference: *posterior* P(s|d)=P(d|s) P(s)/P(d),   d → s

Obtaining radio image information

physical signal s

1) prior knowledge: *prior* P(s)

2) measurement: d = R(s) + n, linear response R, *likelihood* P(d|s)



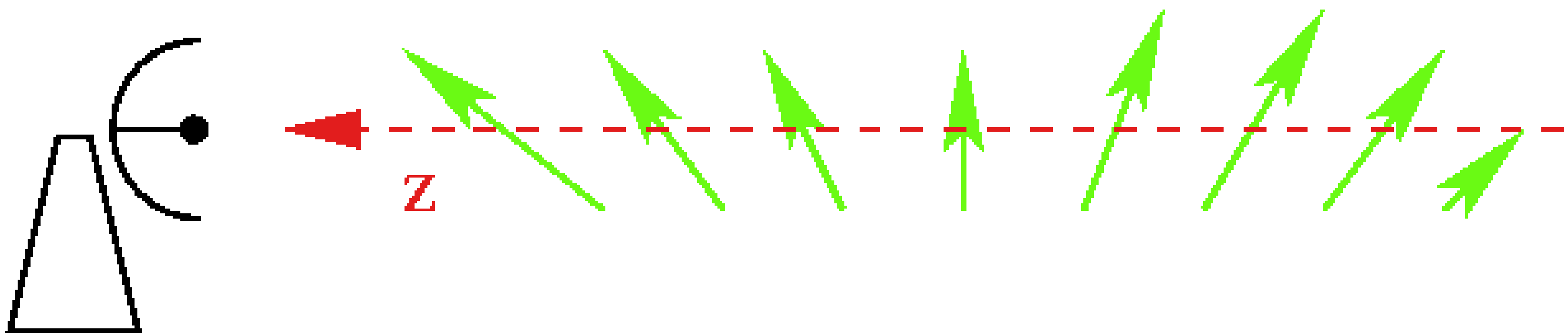
3) inference: *posterior* P(s|d)=P(d|s) P(s)/P(d), d → s

Obtaining radio image information

physical signal s

1) prior knowledge: *prior* P(s) ⟶ *Gaussian signal inappropriate*

2) measurement: d = R(s) + n, linear response R, *likelihood* P(d|s)



3) inference: *posterior* P(s|d)=P(d|s) P(s)/P(d), d → s

Obtaining radio image information

physical signal s

1) prior knowledge: *prior* P(s) ⟶ *log-normal signal!*

2) measurement: d = R(exp(s)) + n, non-linear response R,
likelihood P(d|s)

$$R = S(u,v)\ \mathcal{FT}[A(l,m)\ \exp(s(l,m))]$$

3) inference: *posterior* P(s|d)=P(d|s) P(s)/P(d), d → s

Log-Normal Reconstruction

Posterior mean $map = \langle s \rangle_{\mathcal{P}(s|d)} \neq D\,j$

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Log-Normal Reconstruction

Posterior mean $map = \langle s \rangle_{\mathcal{P}(s|d)} \neq D\, j$

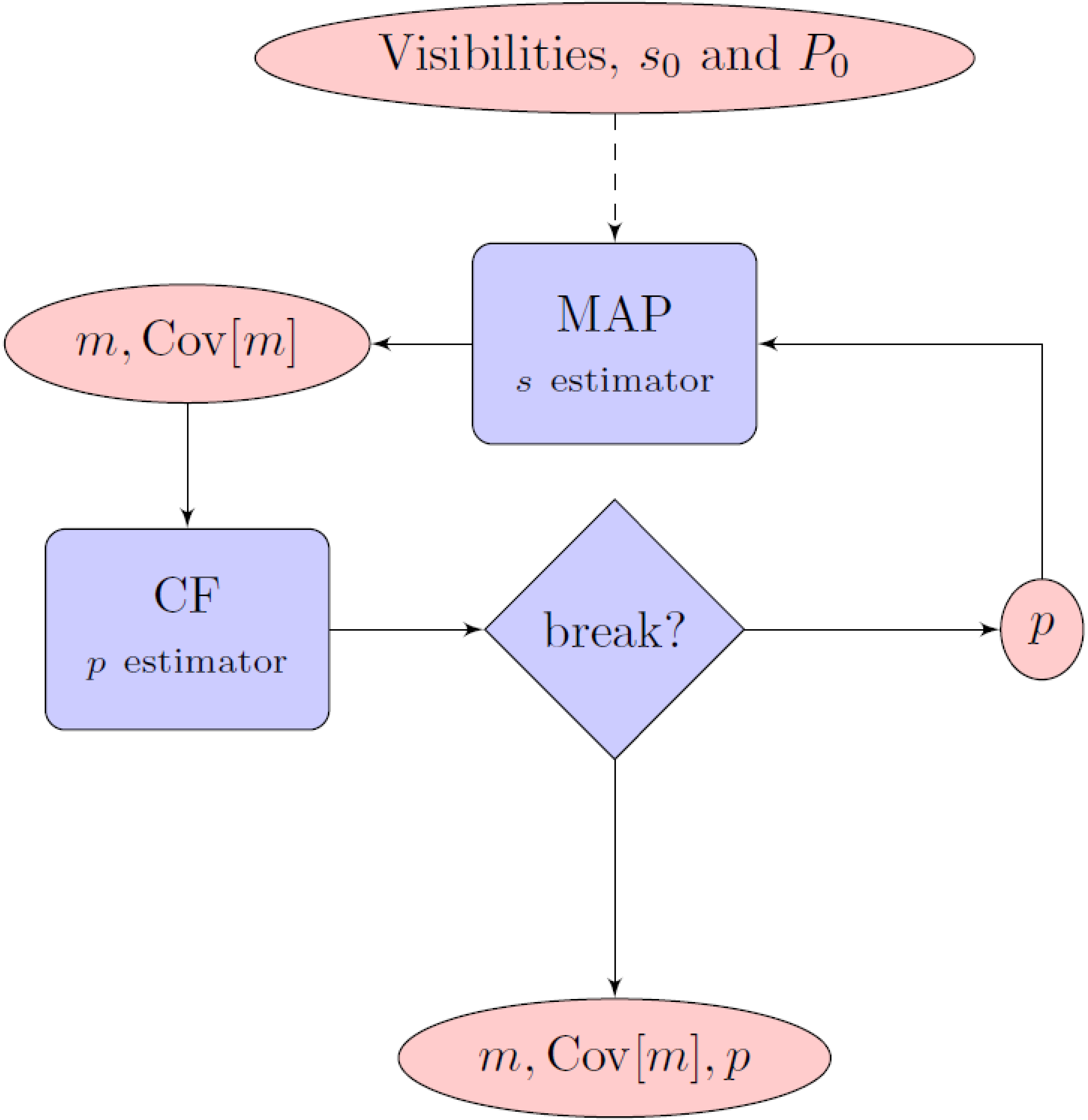
Maximum a Posteriori $= \mathrm{argmax}_s [\mathcal{P}(s|d)]$

Log-Normal Reconstruction

Posterior mean $map = \langle s \rangle_{\mathcal{P}(s|d)} \neq D\,j$

Maximum a Posteriori $= \mathrm{argmax}_s [\mathcal{P}(s|d)]$

+ a modified critical filter step for the
unknown signal covariance (power spectrum)

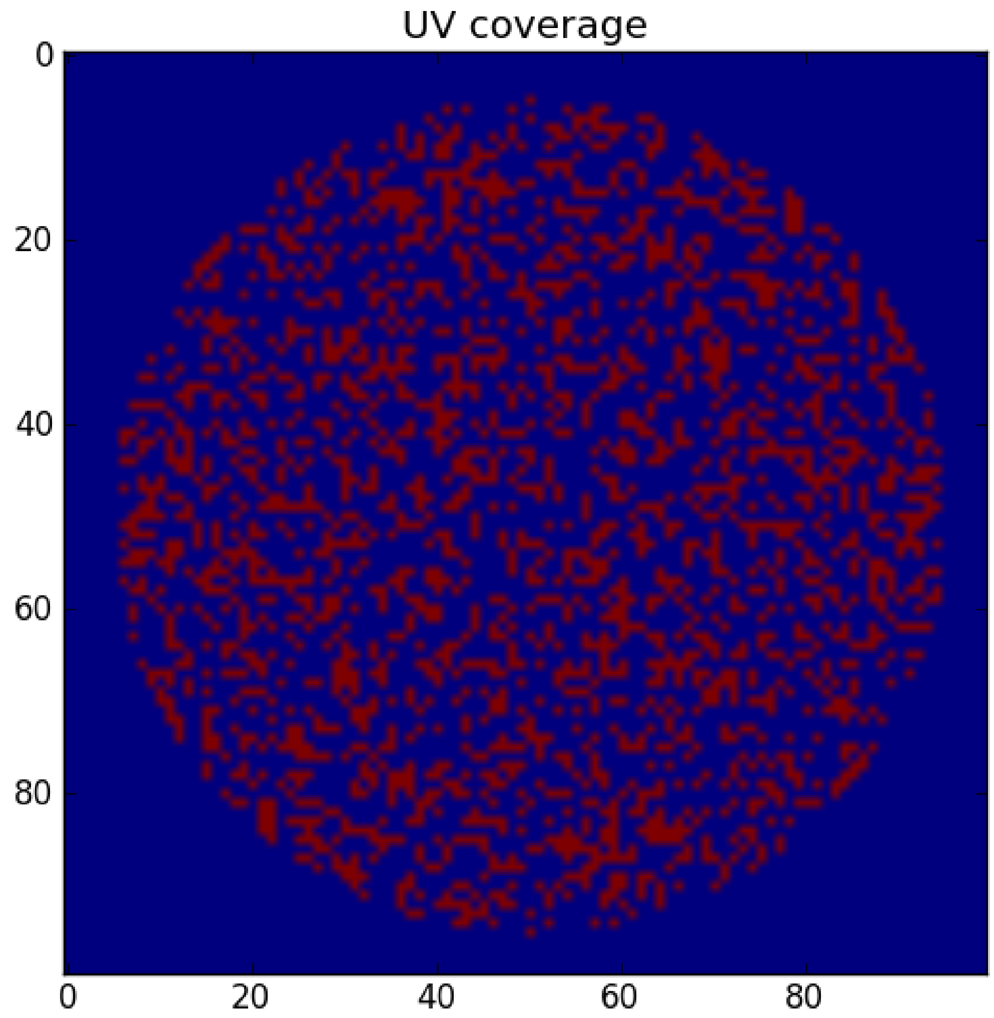


Visibilities, s_0 and P_0
MAP
s estimator
$m, \mathrm{Cov}[m]$
CF
p estimator
break?
p
$m, \mathrm{Cov}[m], p$

Simulations I

- Randomly placed uv-coordinates that fill a defined shell in uv-space

Simulations I



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- Additive white Gaussian noise in uv-space

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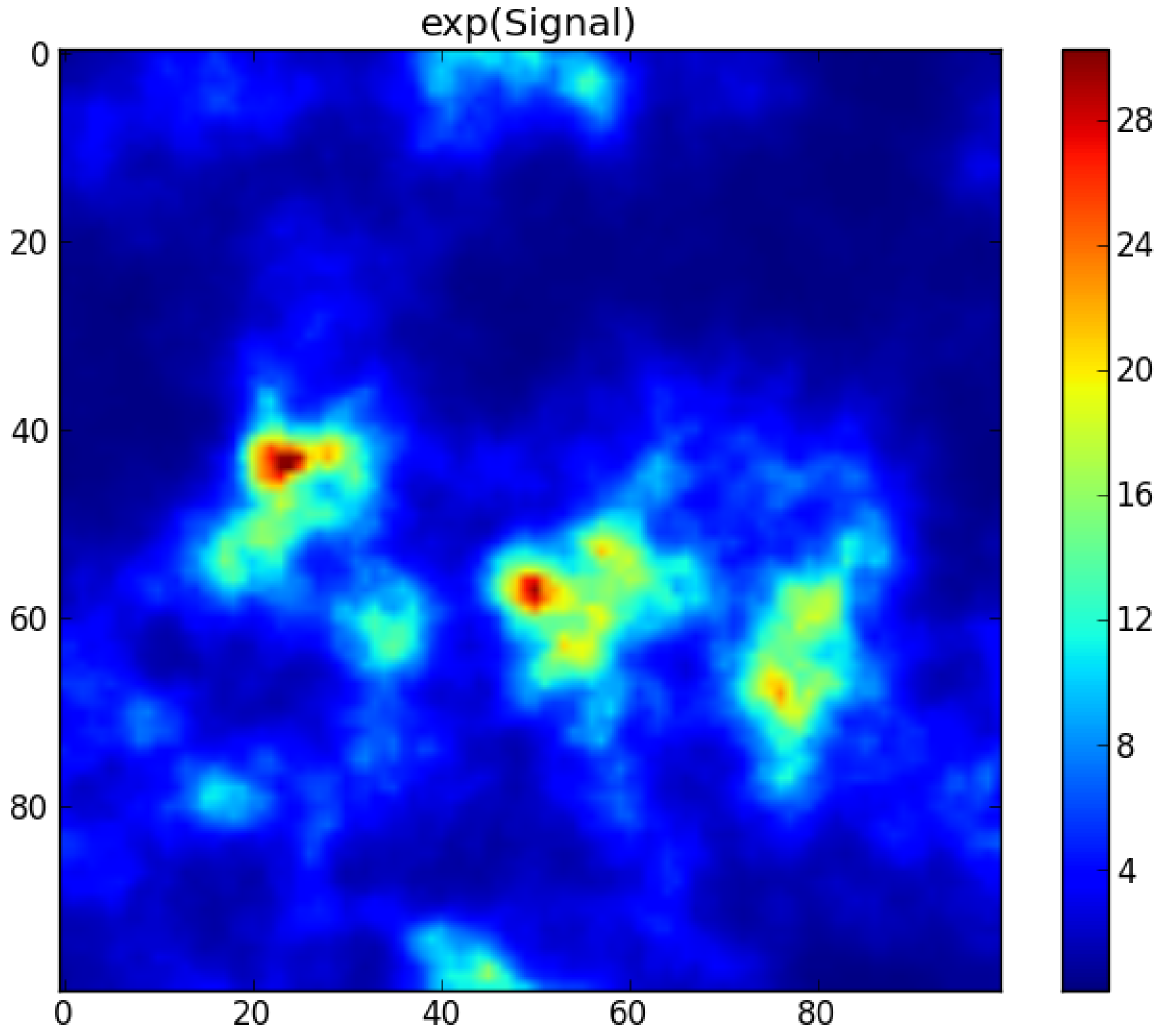
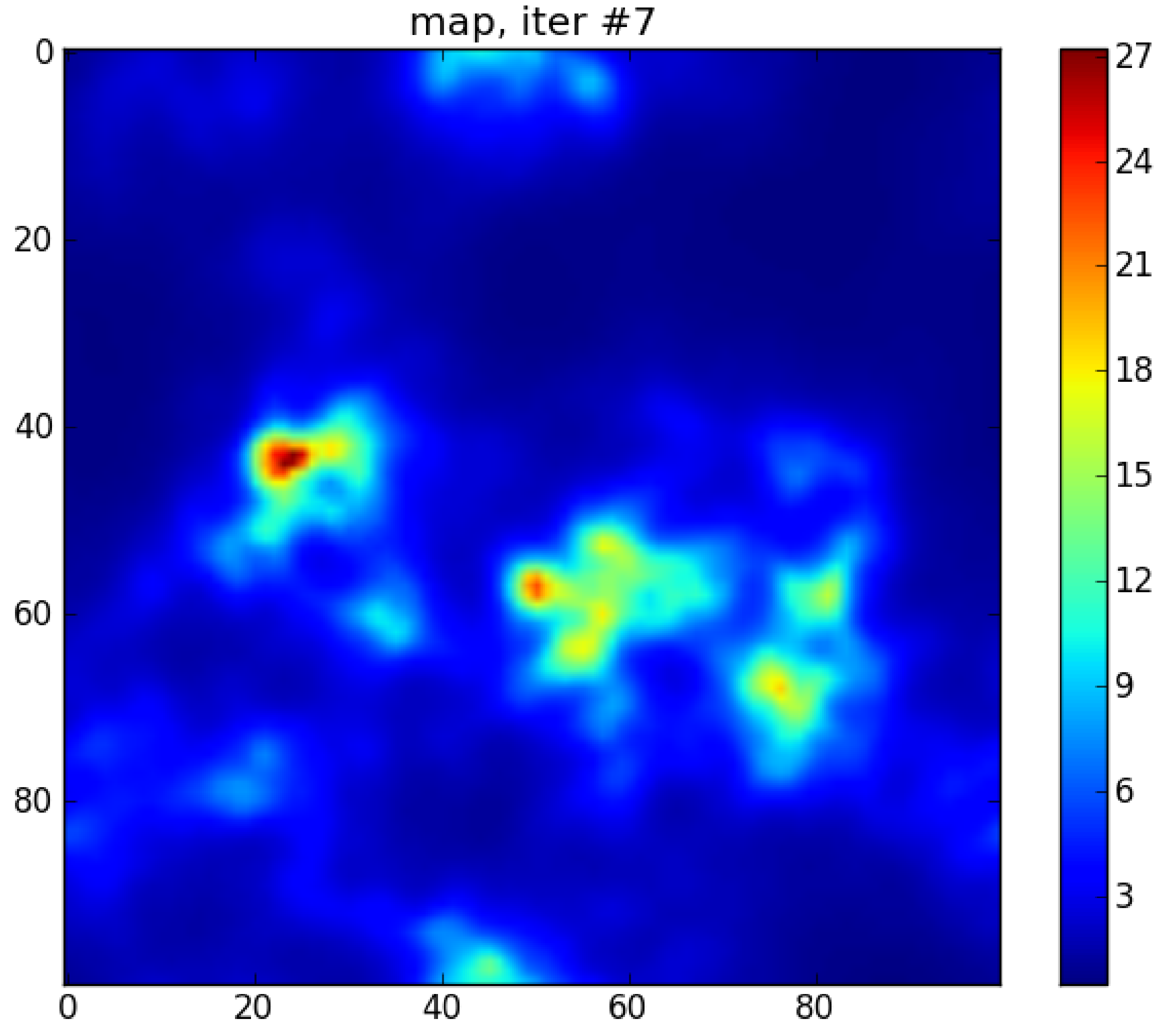
- Simulated log-normal signal

Simulations I: Low noise, 40 % uv - coverage



Simulations I: Low noise, 40 % uv - coverage



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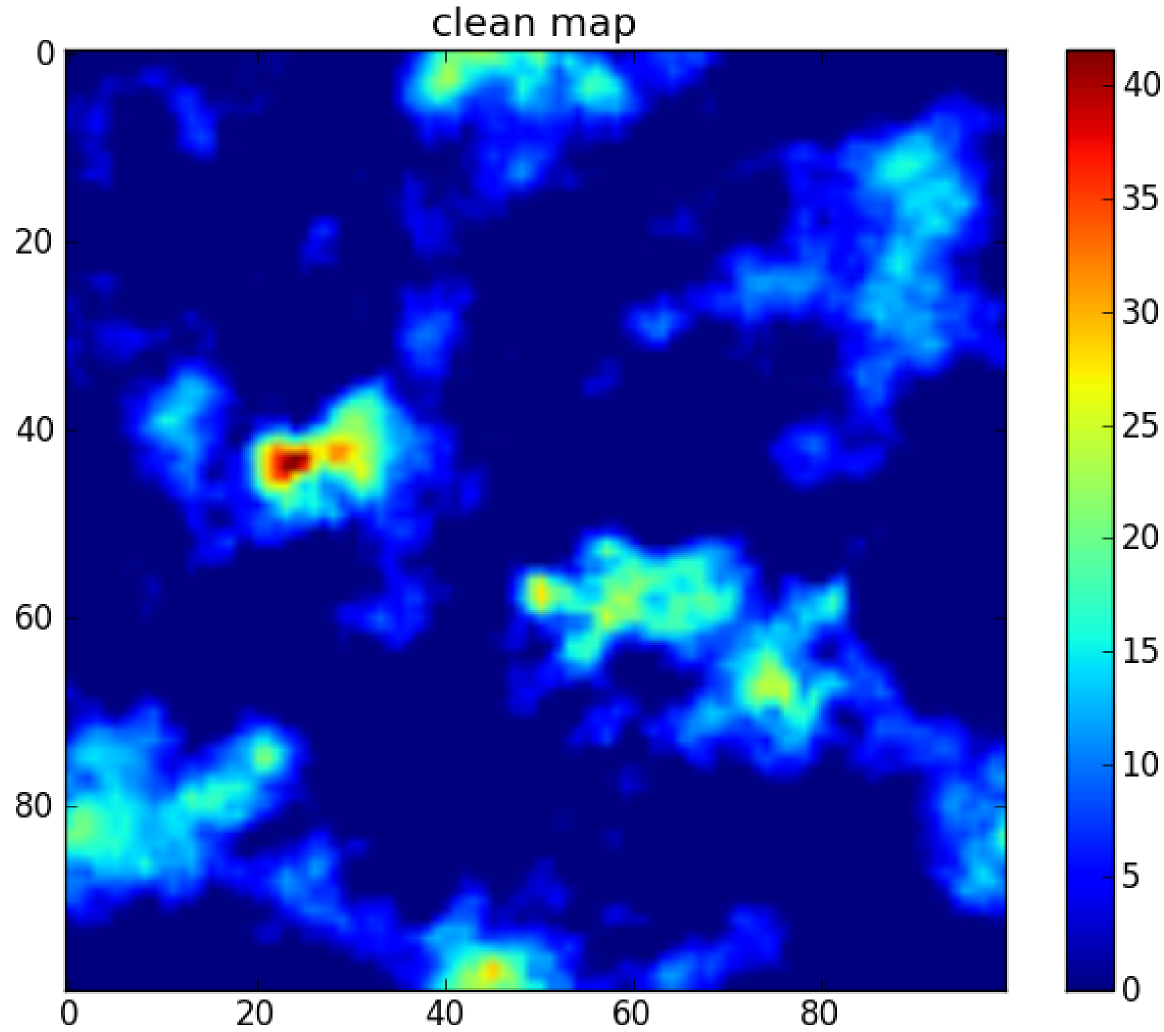

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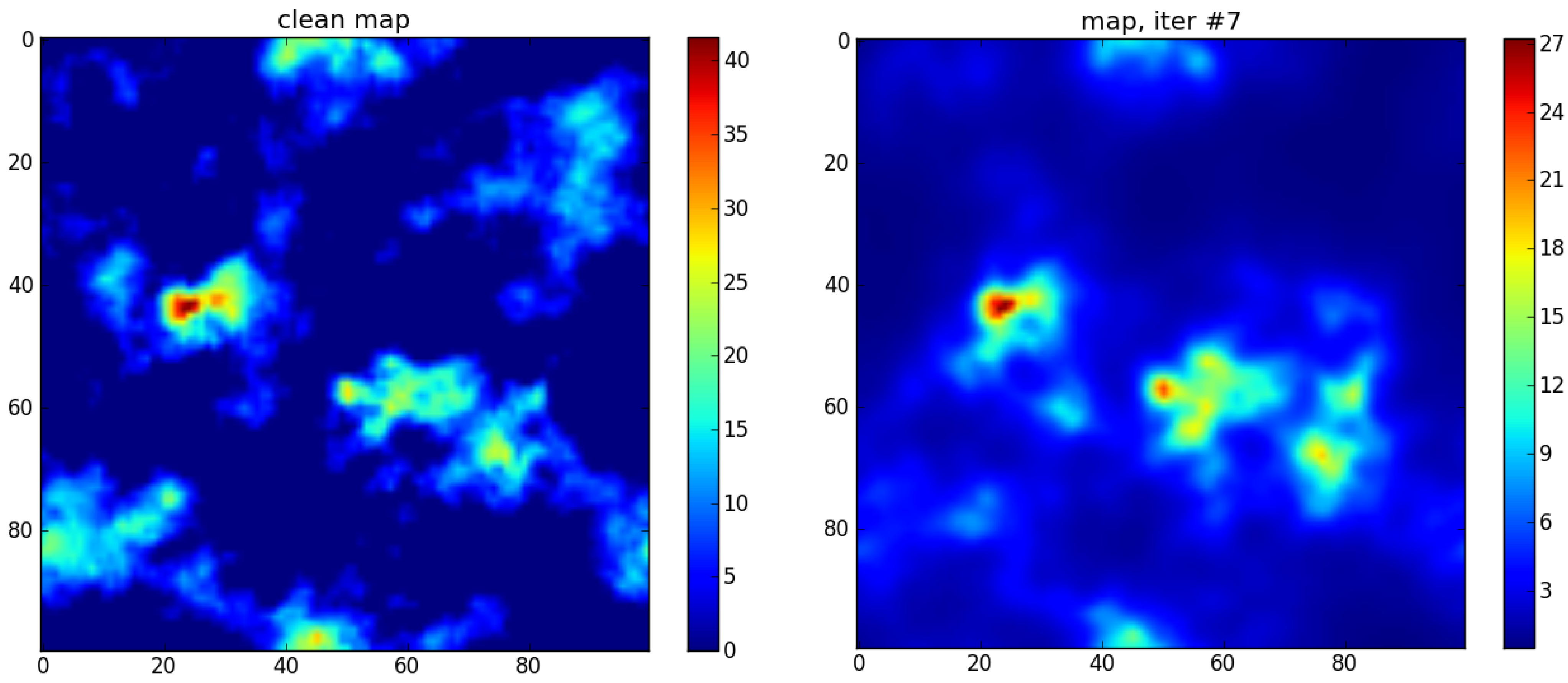
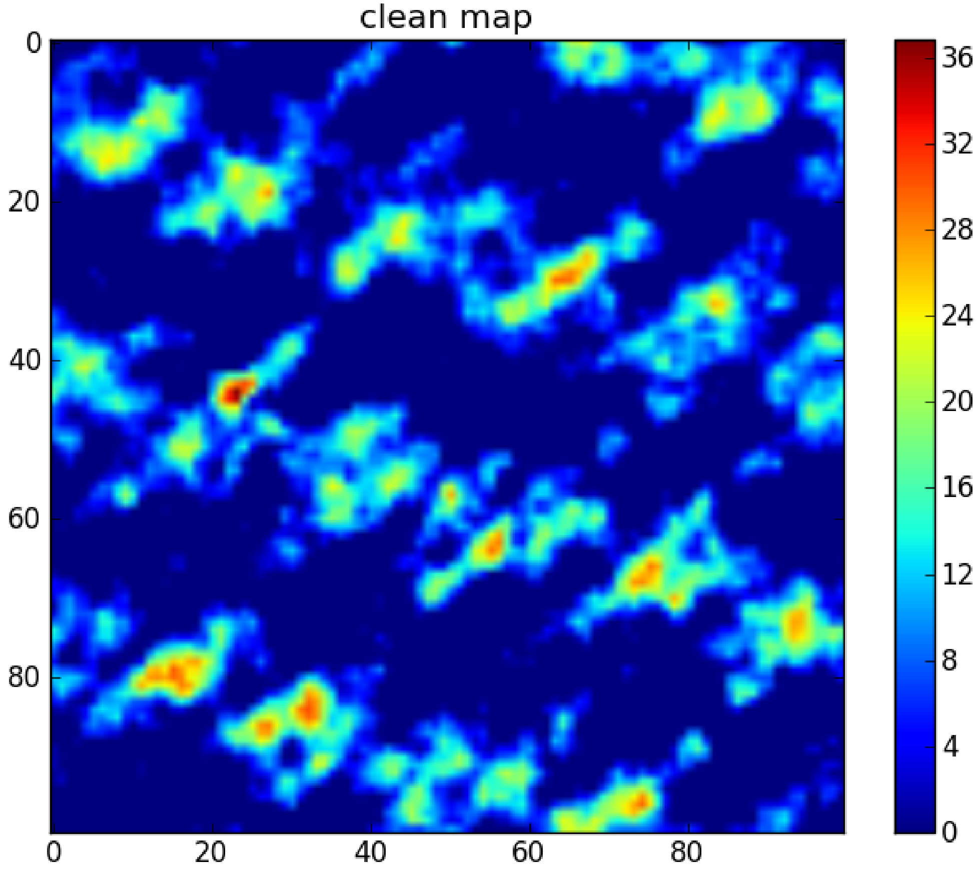
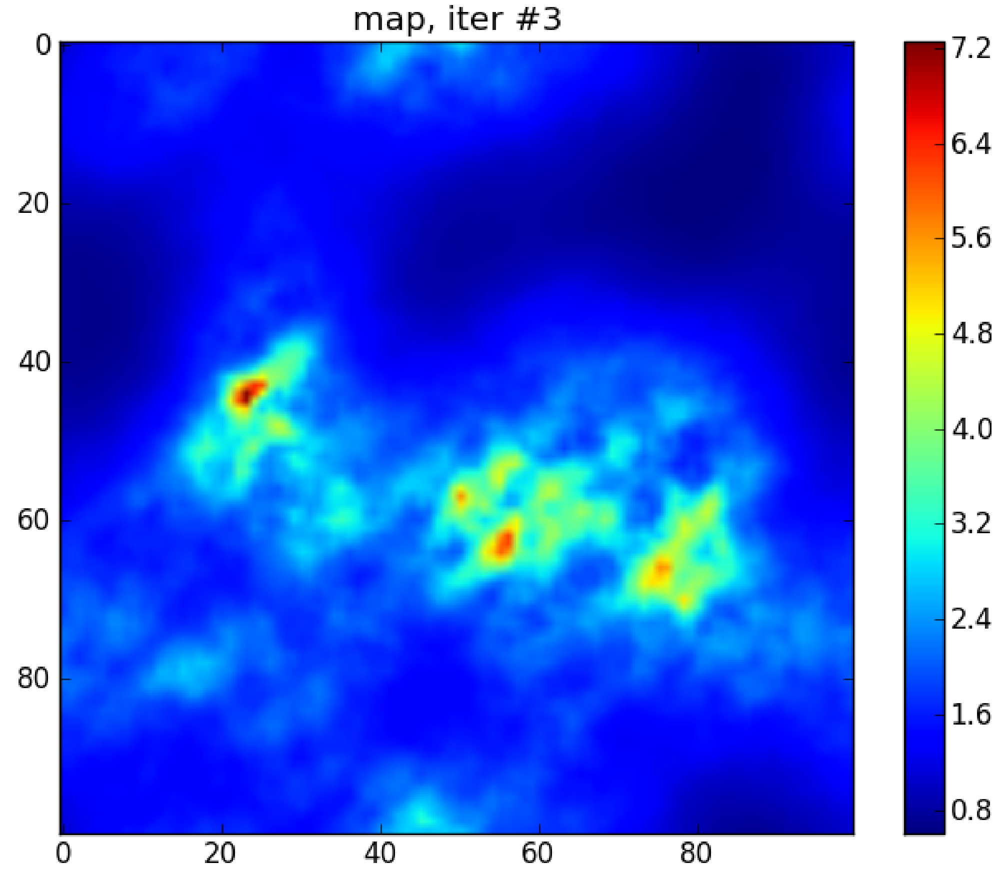


Simulations I: Low noise, 10 % uv - coverage





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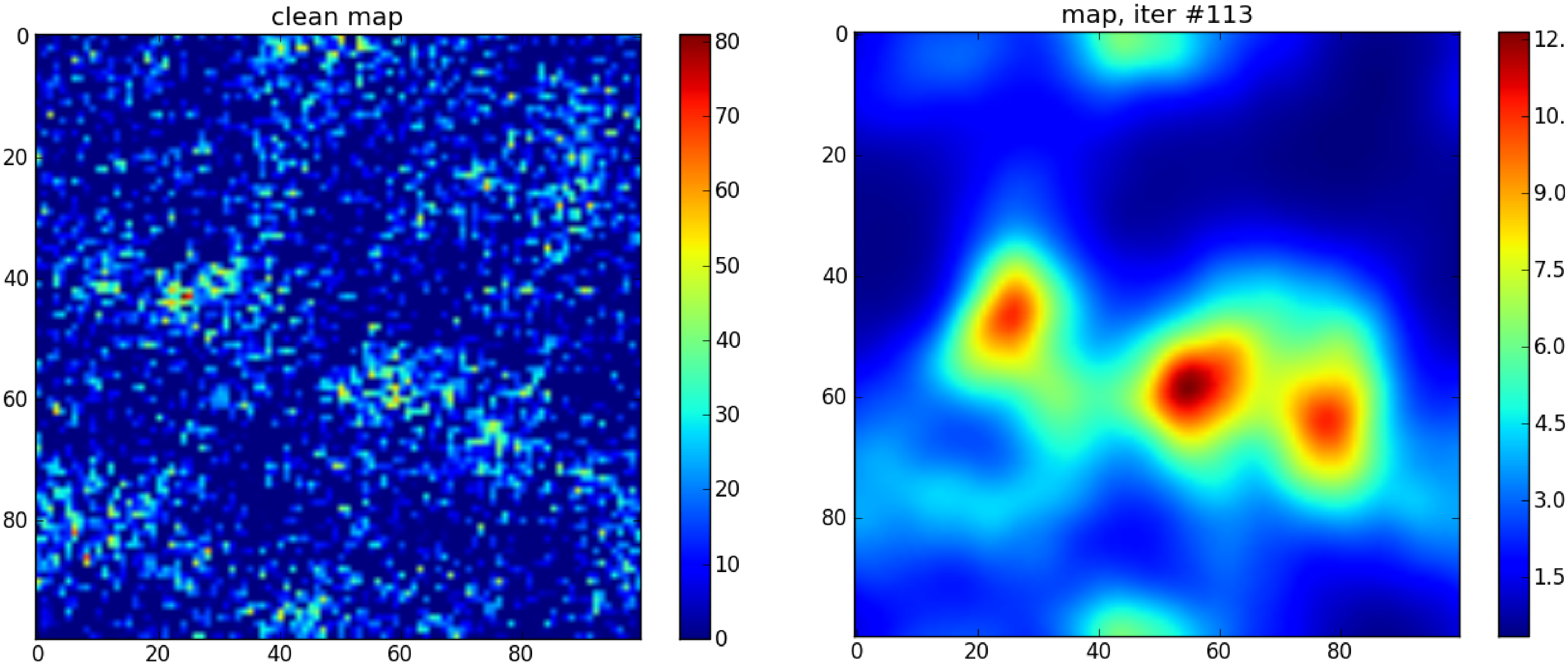

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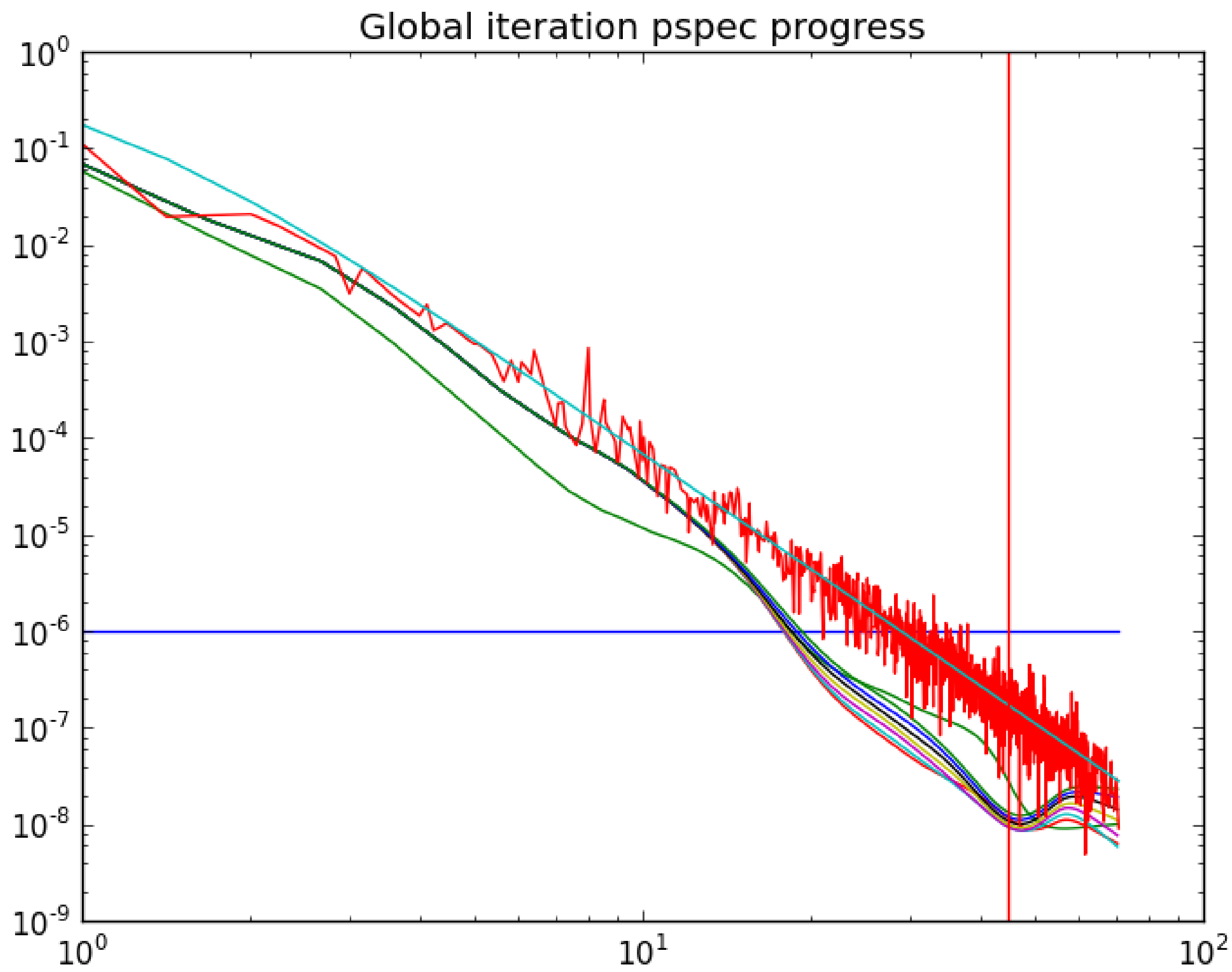
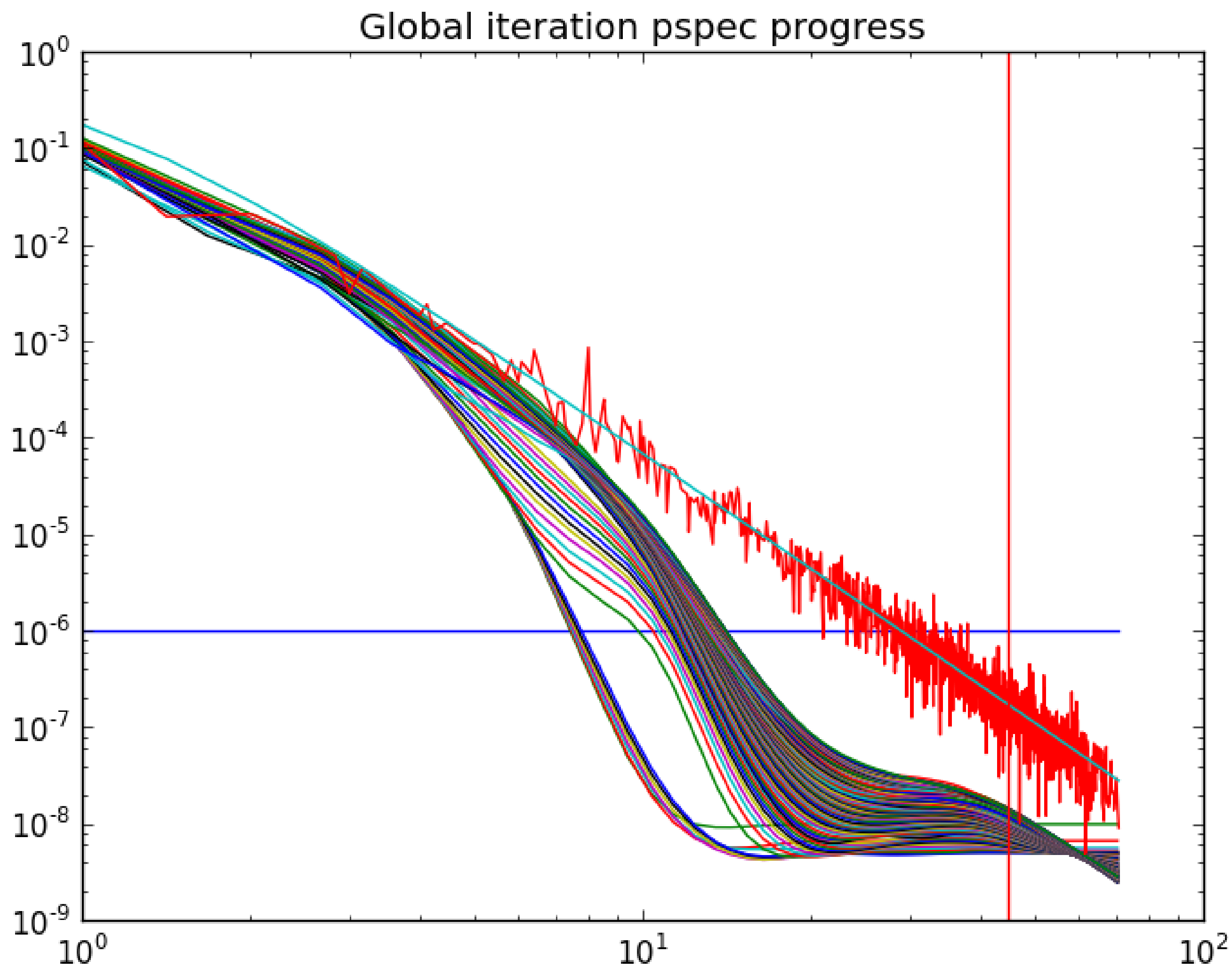


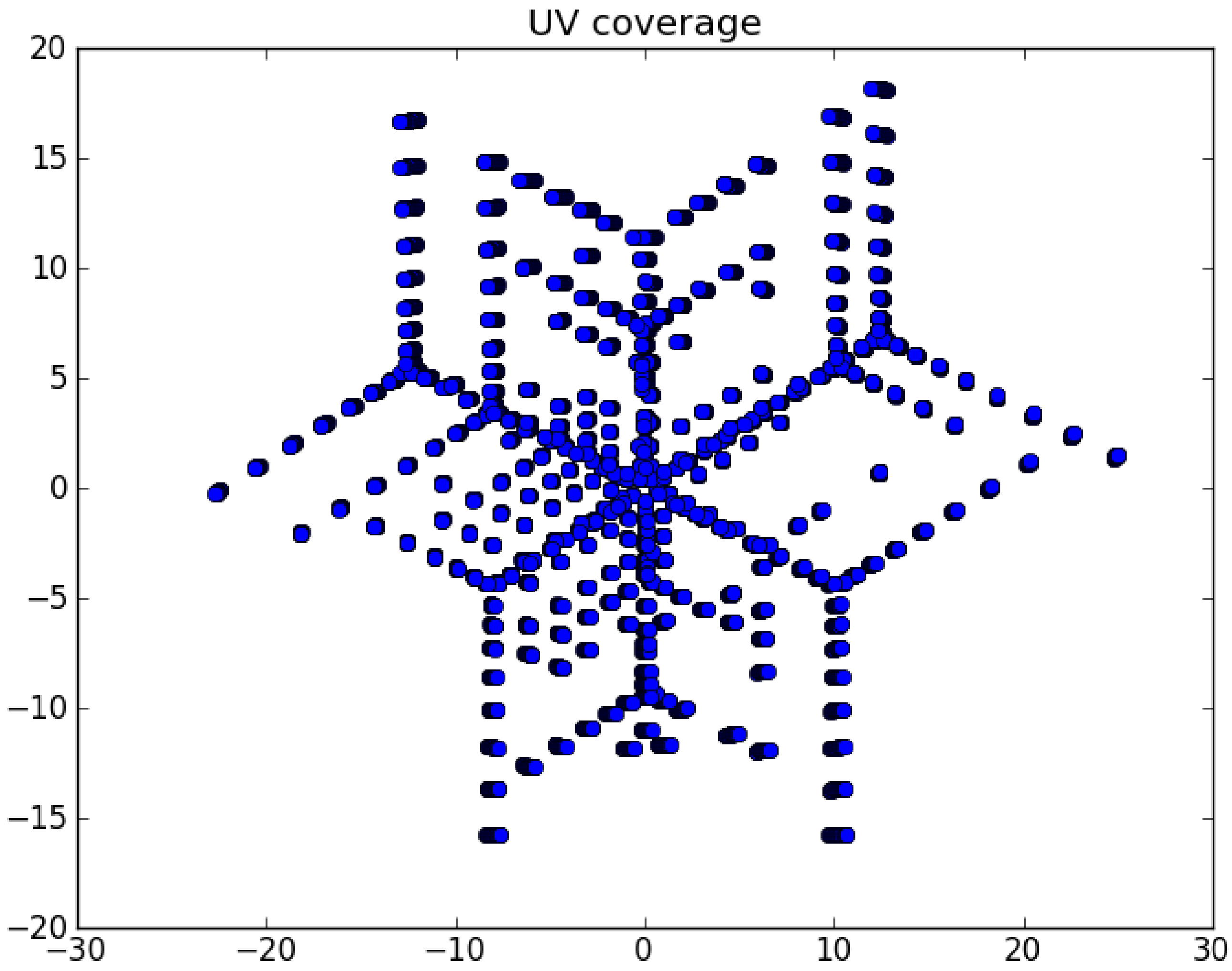
Simulations I: High noise, 40 % uv - coverage



Simulations II

- Realistic uv – coverage from a VLA-a snapshot observation

Simulations II



Simulations II

- Realistic uv – coverage from a VLA-a snapshot observation

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Simulations II

- Realistic uv – coverage from a VLA-a snapshot observation
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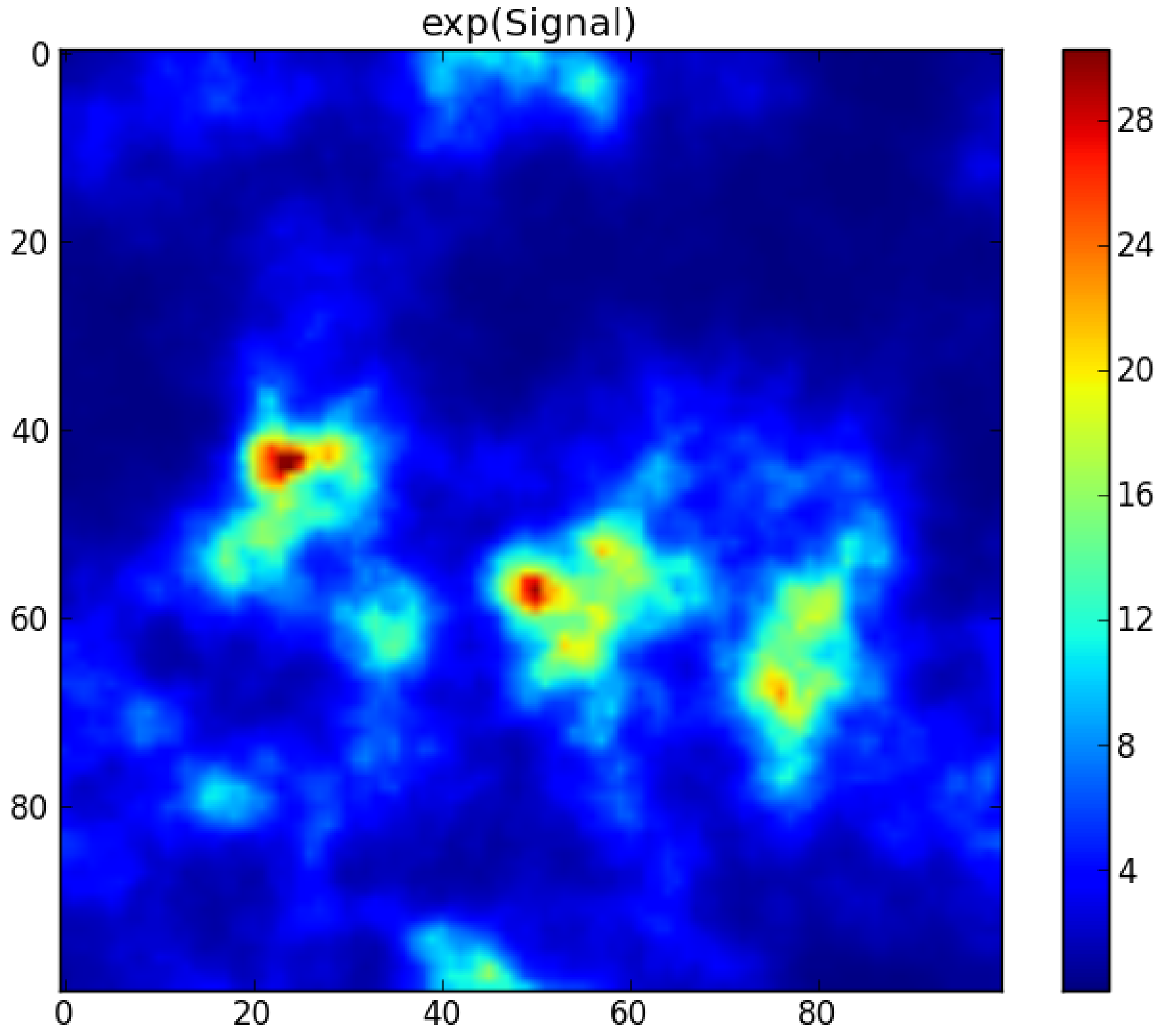
Simulations II



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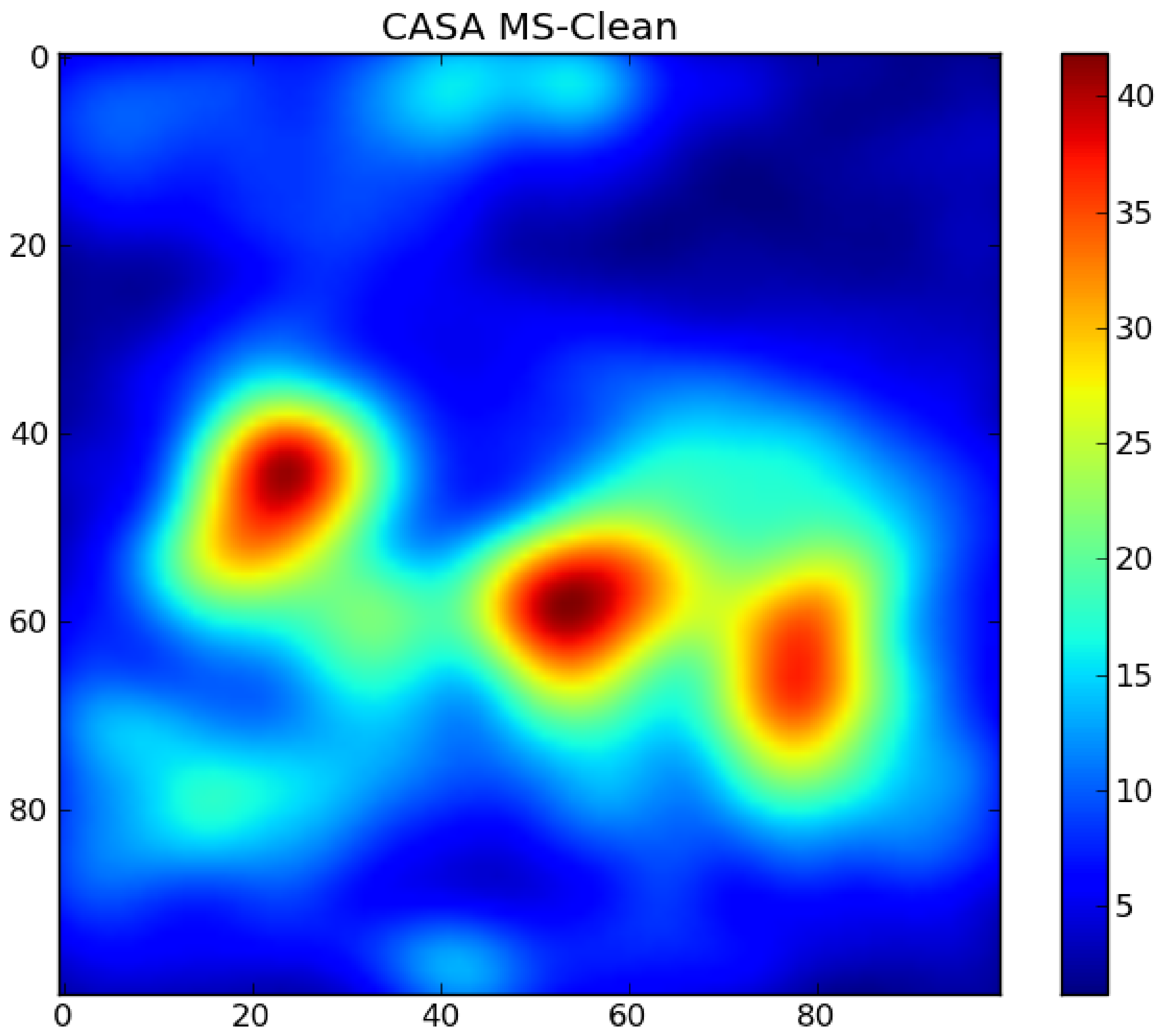

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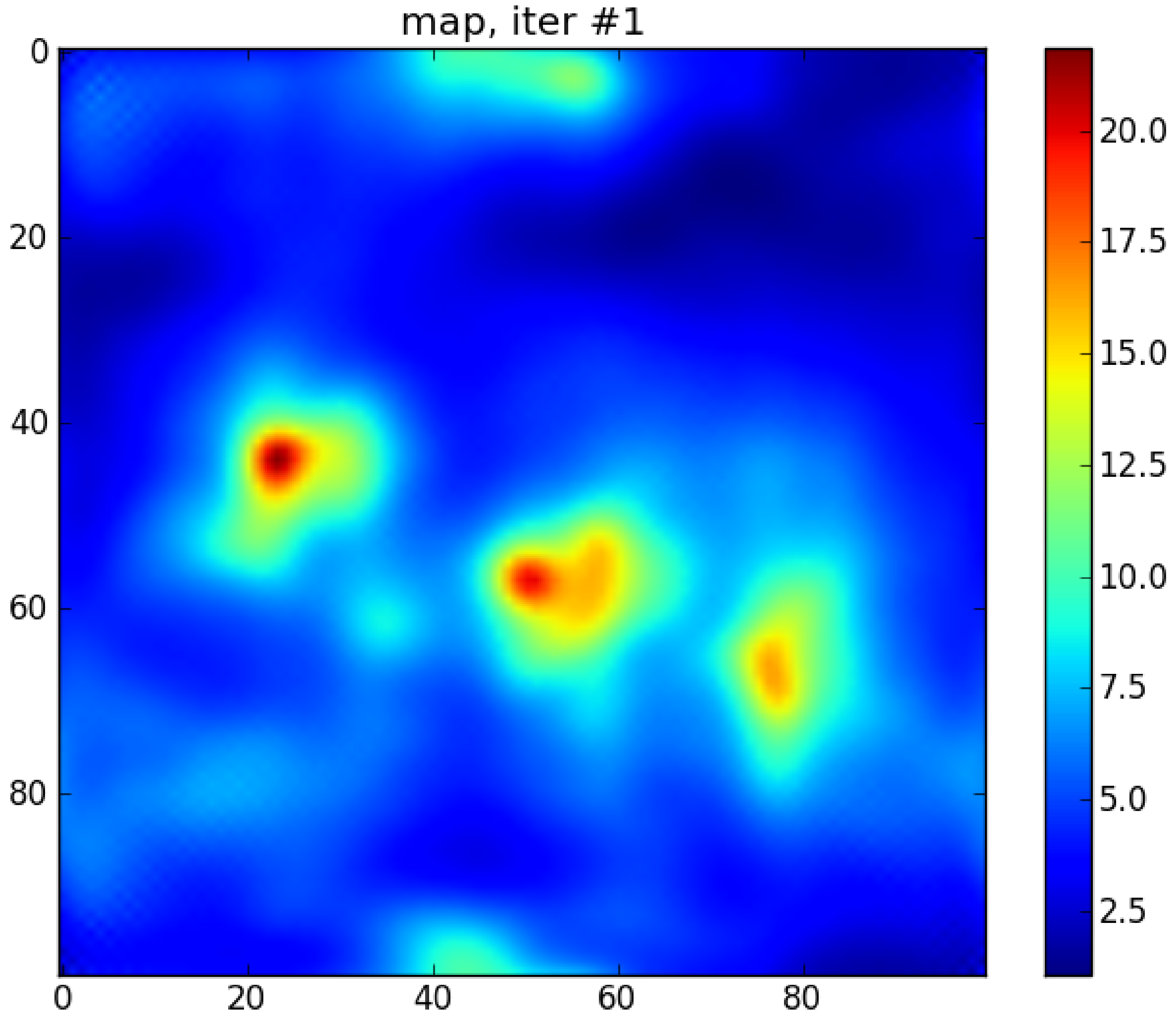

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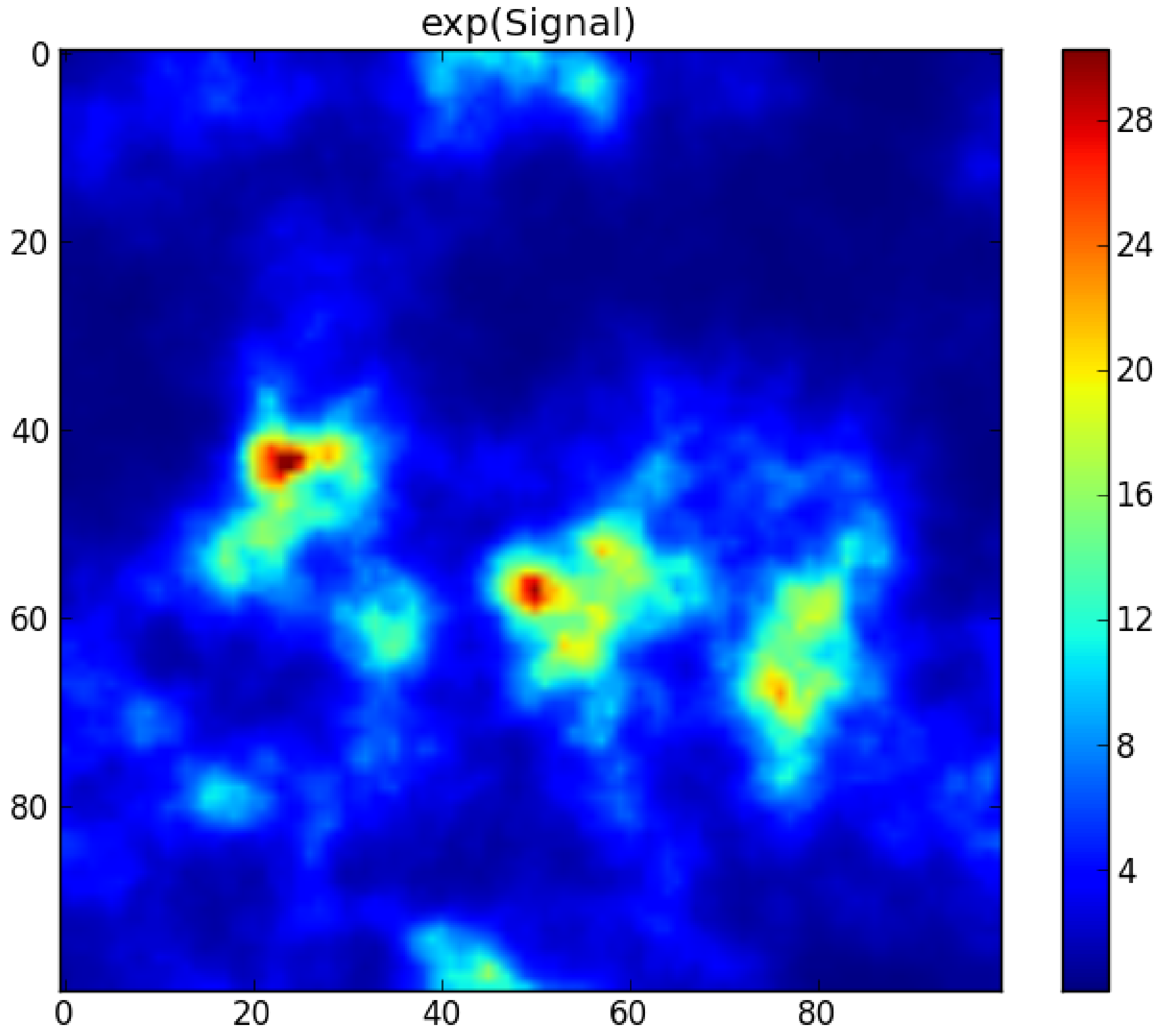


Conclusions

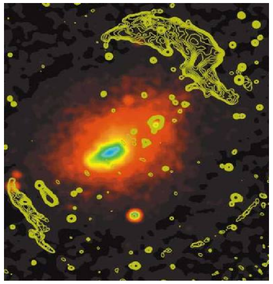
- We present a new method for radio imaging of diffuse fields.
- Outcomes:
  - optimal total intensity map
  - spatial power spectrum
  - consistent uncertainty estimate.
- Considerable improvement on MS-CLEAN in simulations.

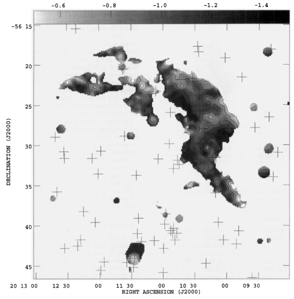
Thank You!

Towards a new multi-frequency imager

- *Simultaneously* image total intensity *&* spectral parameters

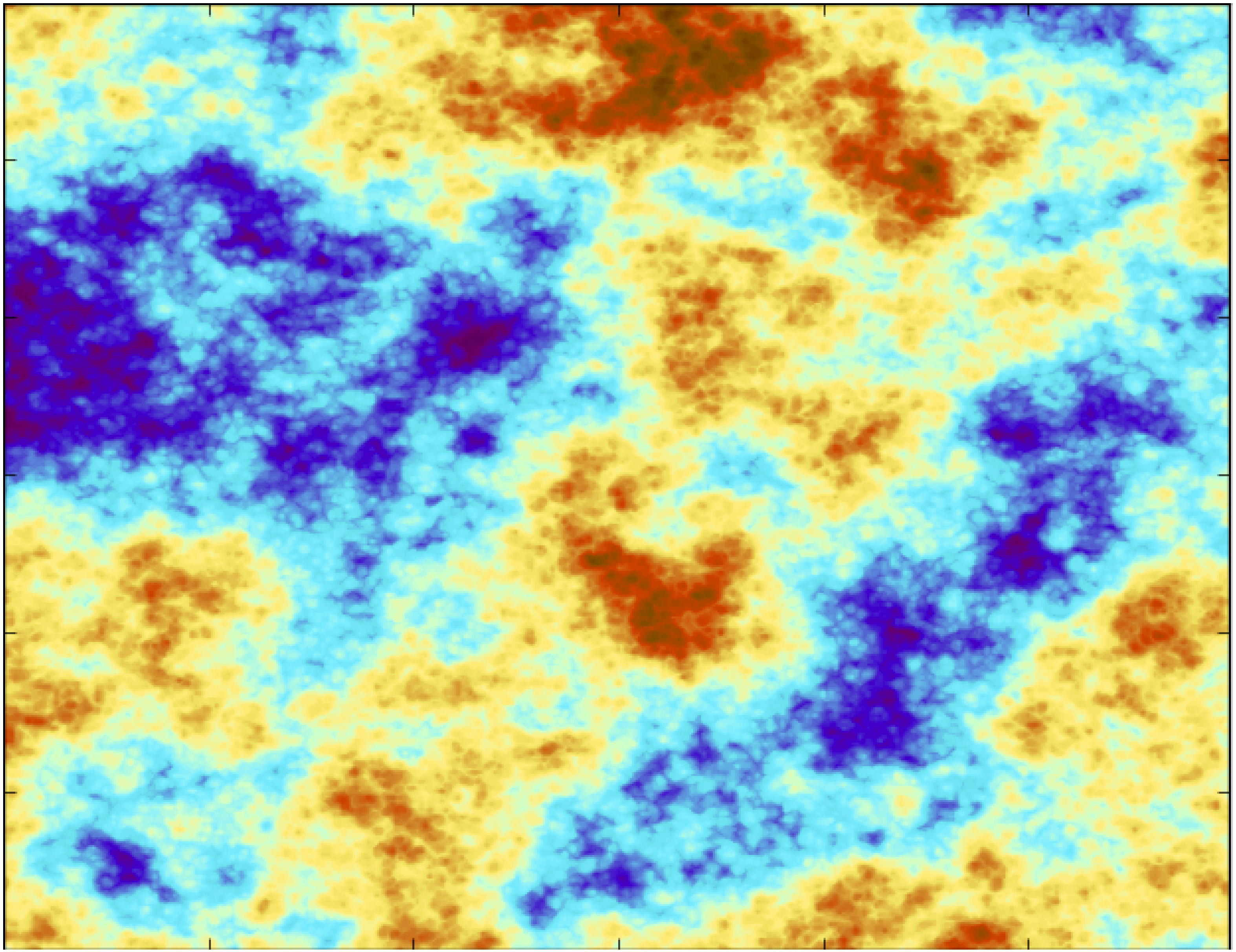
→ One more layer of iterations



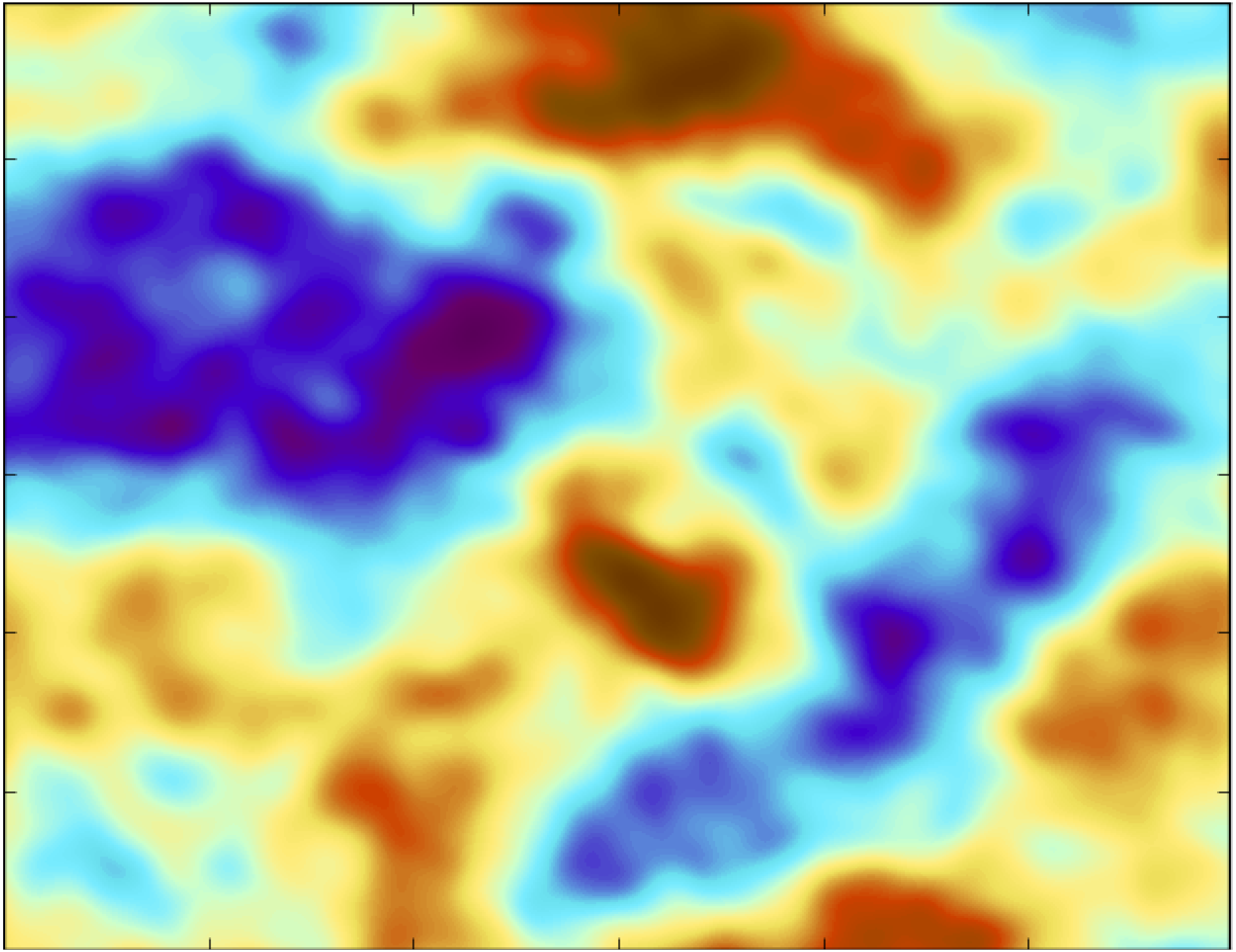


- Make use of spatial *&* spectral correlations in the data
- No spectral interpolation
- Preliminary Wiener Filter already working (see next slides)

Synthetic image



Wiener Filter



CASA CLEAN mode = 'mfs'