SKA1-Low低频大视场高动态范围成像

--Wideband Widefield Imaging for SKA1-Low

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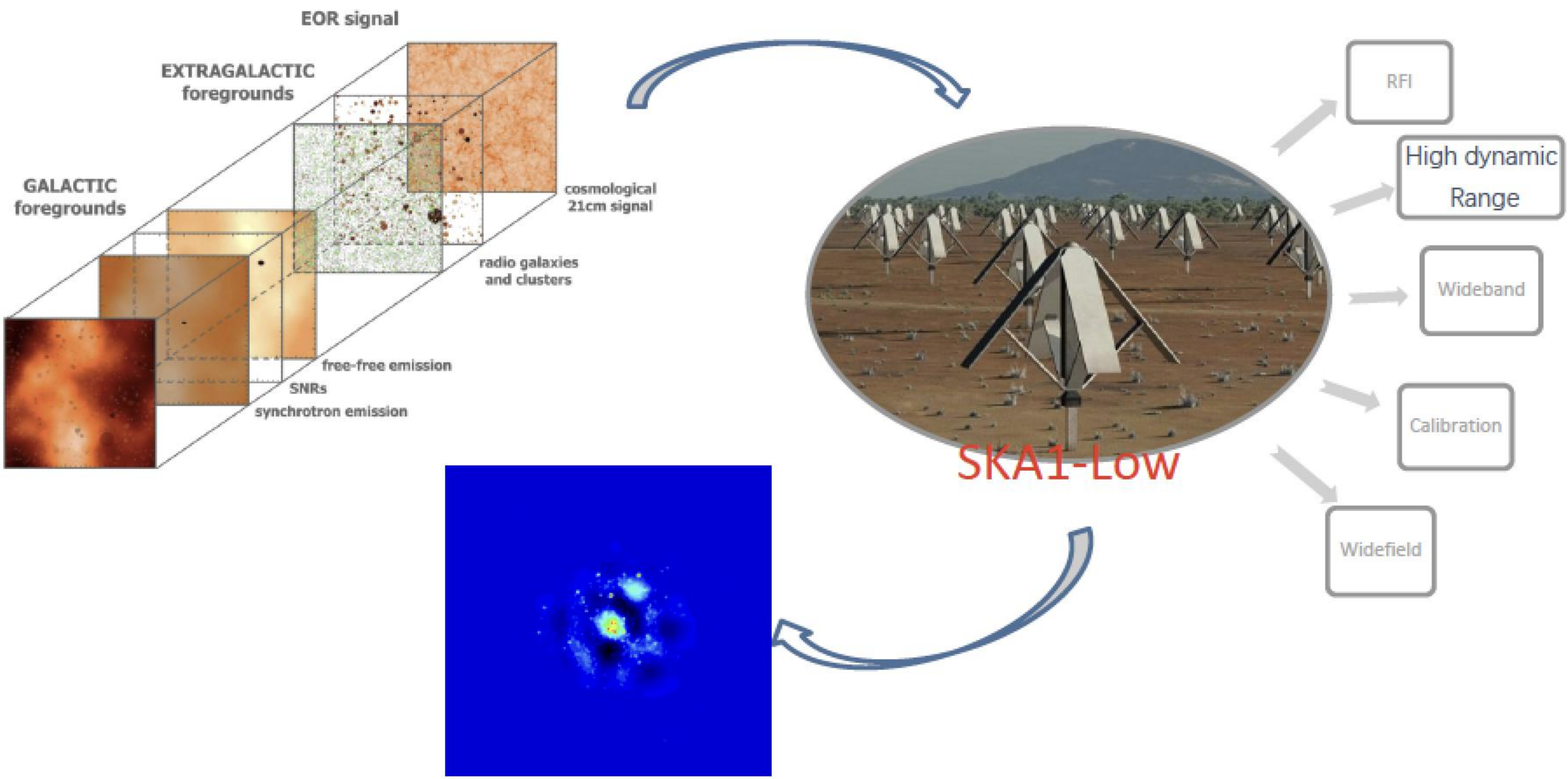
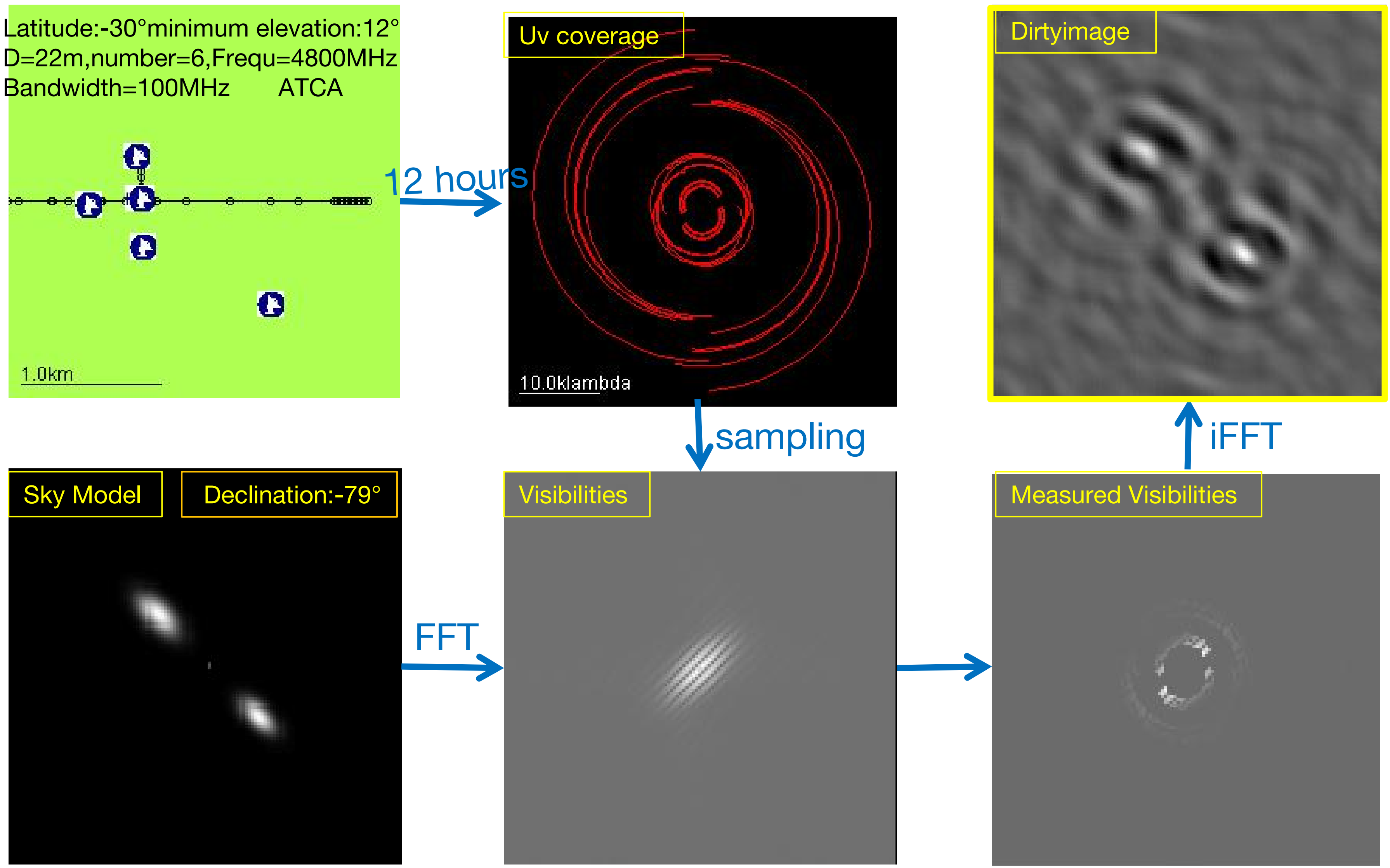
Challenge： Imaging & Recon

EoR ~ 1-10mK，

比前景信号低4-5个数量级



Radio Interferometry



Model-driven Methods

CLEAN Framework

Major Cycle

Data or Residual visibilities

Subtracted

Model Visibilities

Conv. + Gridding + iFFT

Imaging

Degridding + FFT

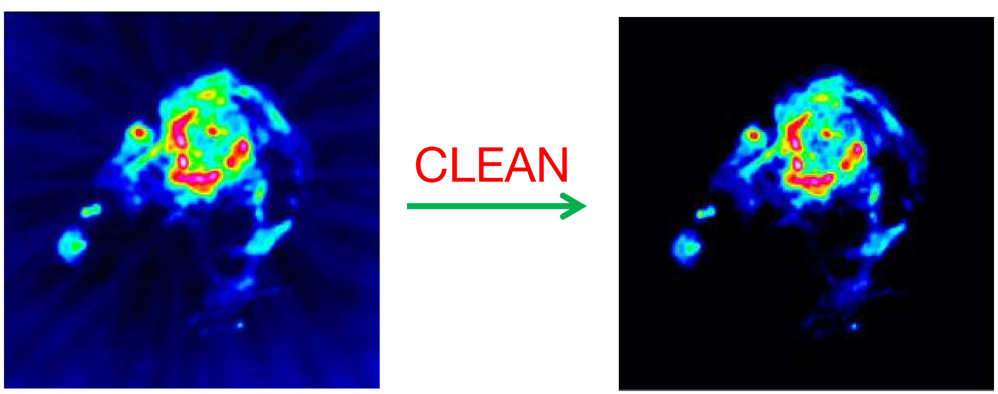
Prediction

Minor Cycle

Dirty or Residual Image

Iterative removal of dirty beam

Model Image



accumulation

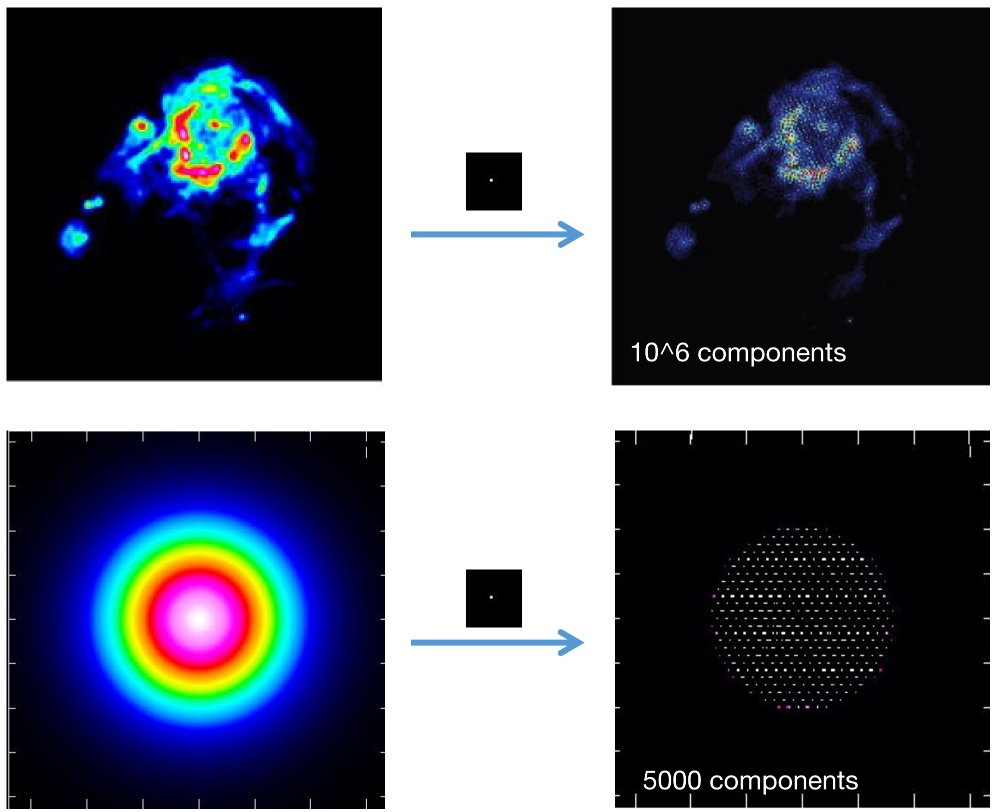
Convolve with CLEAN beam

CLEAN image

Problems of Scale-less Reconstruction

The original CLEAN algorithm is proposed by Högbom in 1974

True Image | Recon. Model



Cs-Clean

Peak of residual

↓

A loop gain

Peak of residual

↓

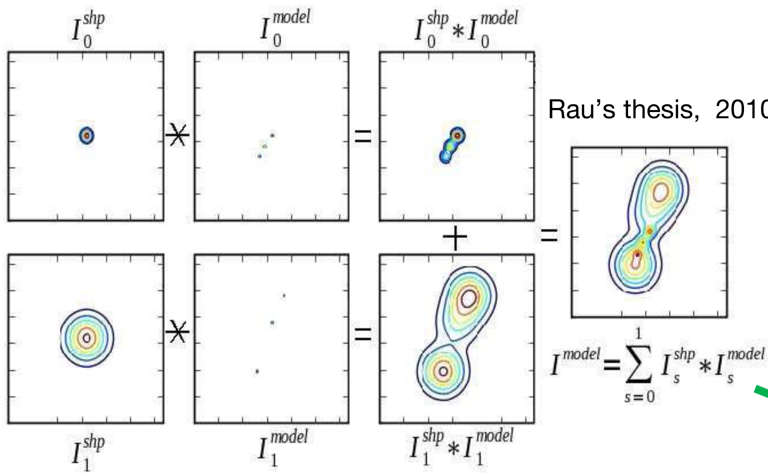
component

↓

Point sources: effective

Extended: *bad* model & physically inaccuracy

Problems of Ms-Reconstruction

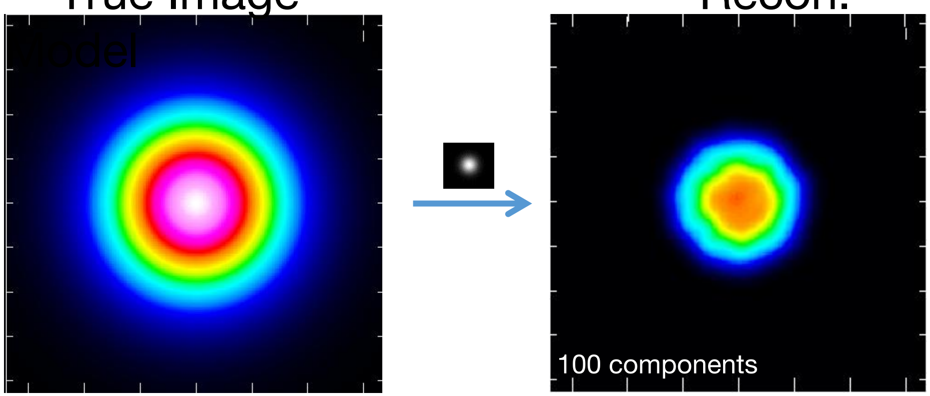


Ms-Clean

Matched Filtering

Truncated Paraboloids
+
Residual/Dirty Image

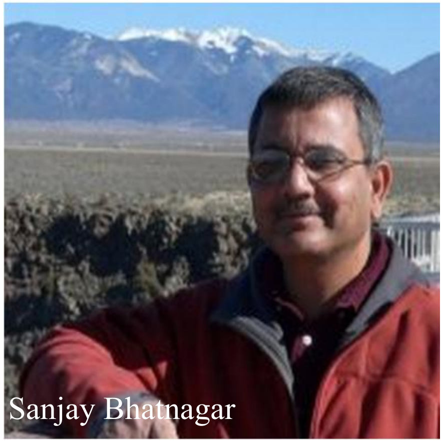
True Image | Recon.

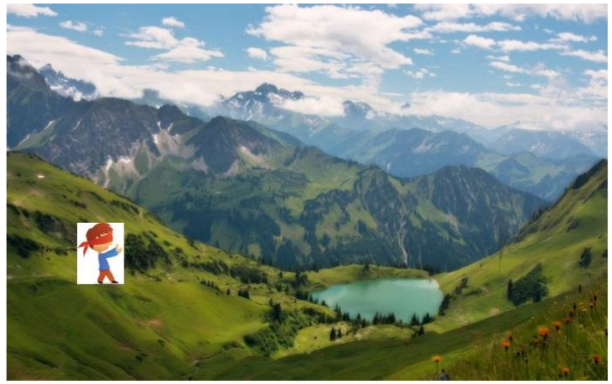


1. good for extended emissions
2. But with limited scales

Enumerated scales : limited performance
&
Complicated Images: computational expensive
&
More scales: prohibitive memory cost
&
Large Images: prohibitive memory cost

Problems of Asp-Reconstruction





Gradient-based minimization

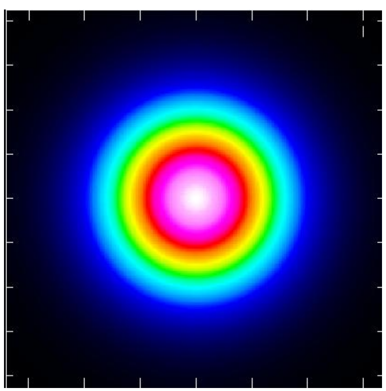
Asp-Clean

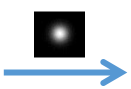
Constrianed Optimization

Initial Gaussian Components
+
Residual/Dirty Image

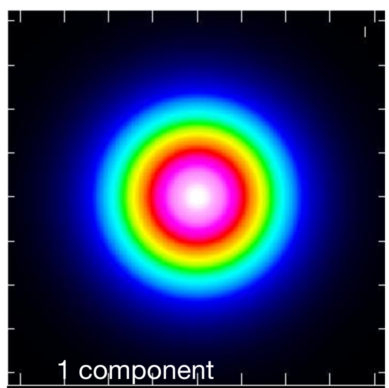
Iterative

True Image





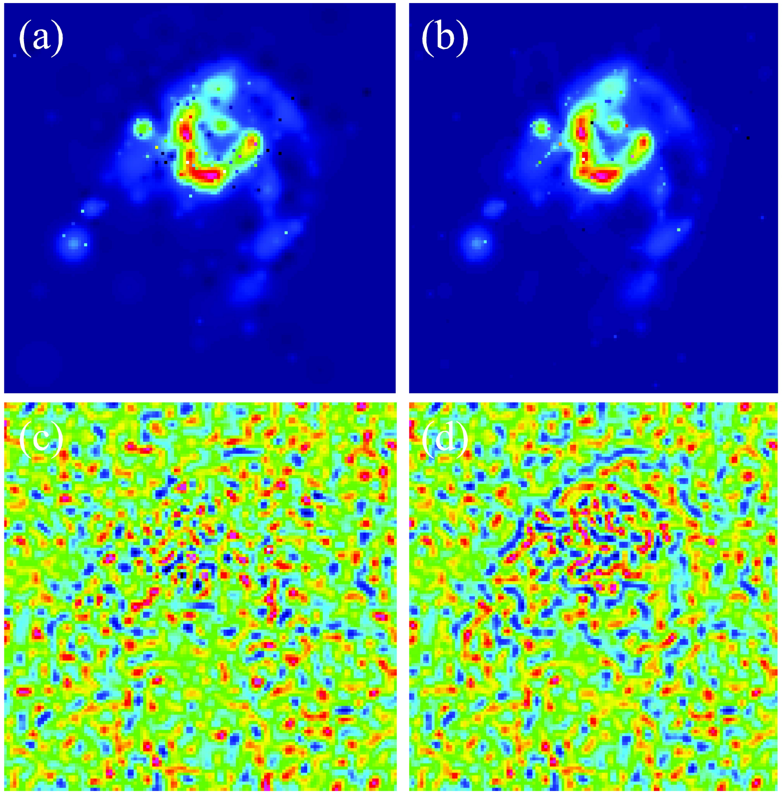
Recon. Model



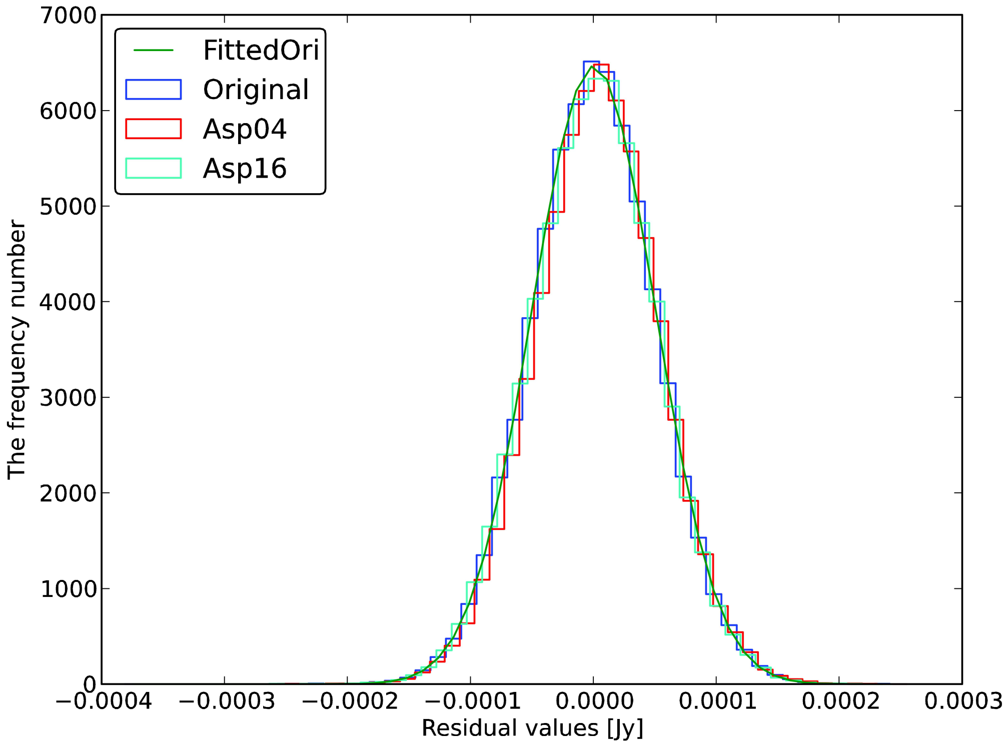
Small images: Computational expensive
&
large images: Comp. Prohibitive
&
Complicated images: Comp. Prohibitive

Best for extended emission

1: Asp *vs* Our (asp2016) -- CASA



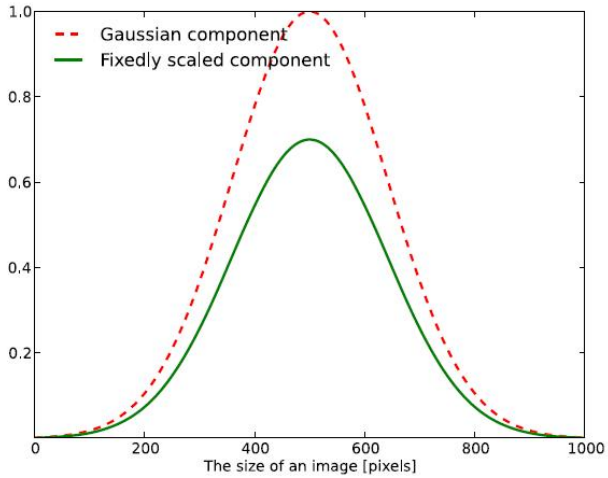
A little worse residuals, but
Residual noise profile is closer to the input Gaussian noise →
Sufficient extraction of the signal



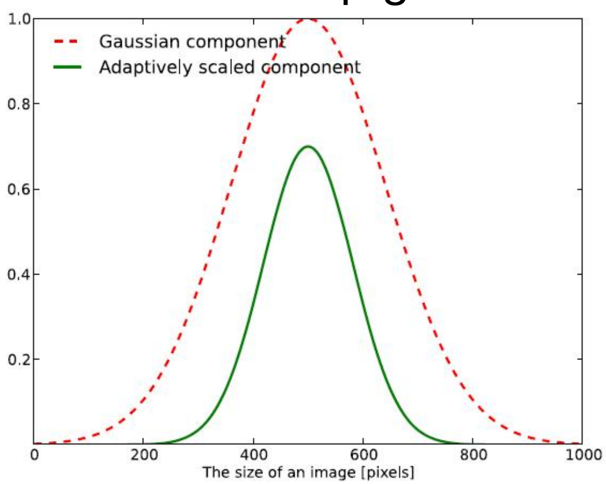
Asp vs Our: Comparable
Model: a little better
Residual: a little worse

Zhang, A&A

2: Adaptive Loop Gain Scheme



Fixed loop gain



Adaptive loop gain

The formula for adaptive Loop gain scheme:

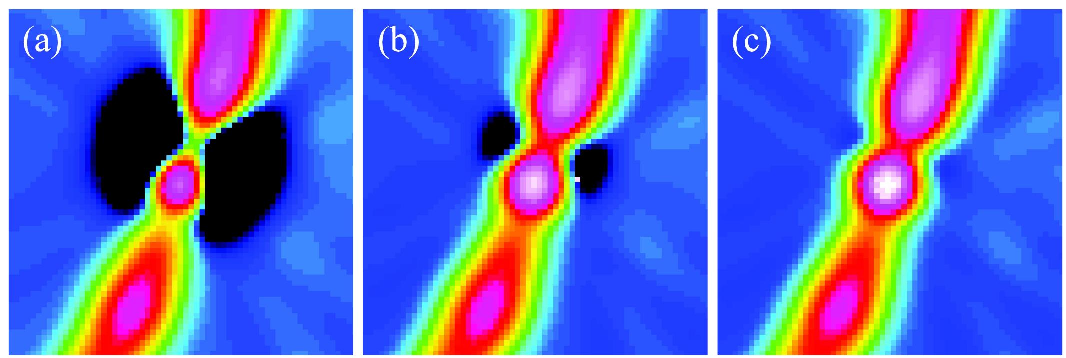
$$g(x) = \sqrt{a(1 - f(x)) + bf(x)}$$

where

$$f(x) = \frac{x - C_{min}}{C_{max} - C_{min}}$$

g_{min} and g_{max} are the minimum and maximum values of adaptive loop gain $g(x)$; C_{min} and C_{max} are the minimum and maximum values of component's amplitude

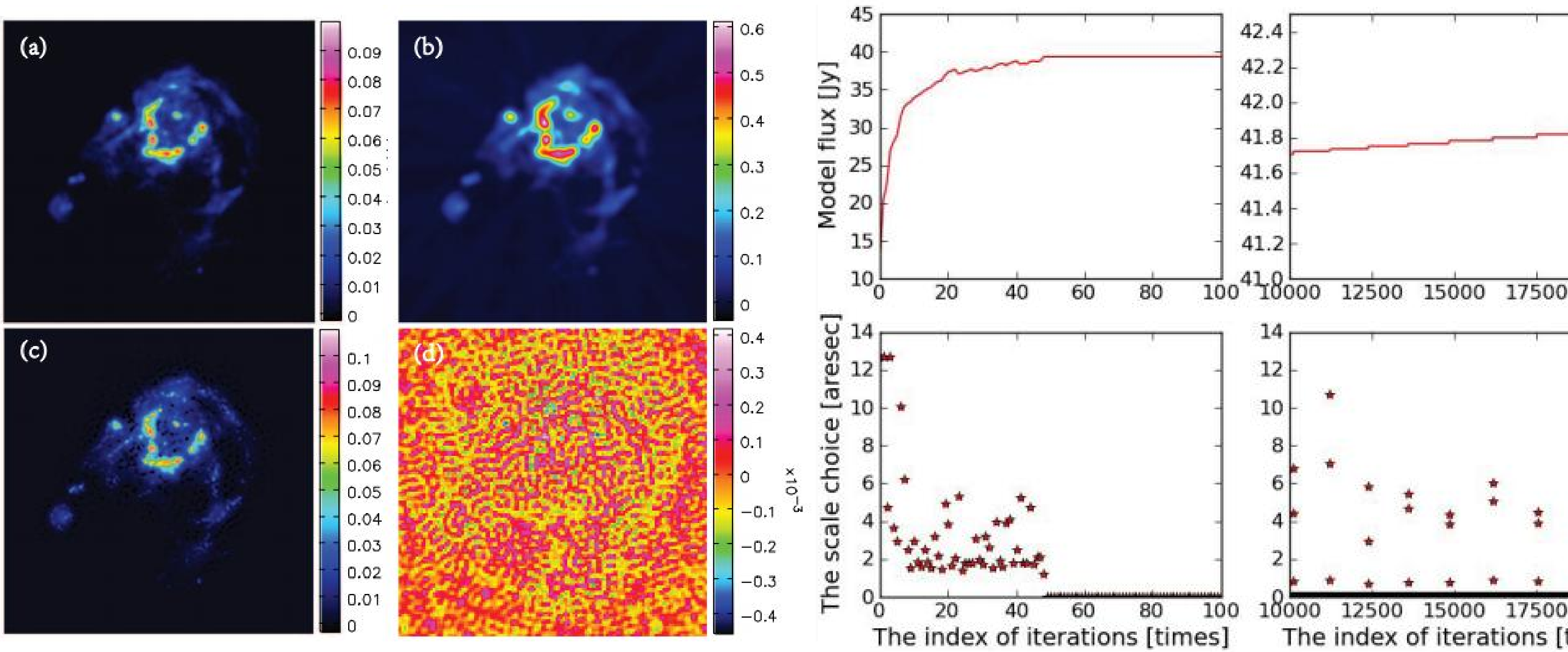
Zhang PASP



Without loop gain | Fixed loop gain | Adaptive loop gain

3: Fused CLEAN Deconvolution

Asp-Clean2016 + Hg-Clean ➔ Fused CLEAN



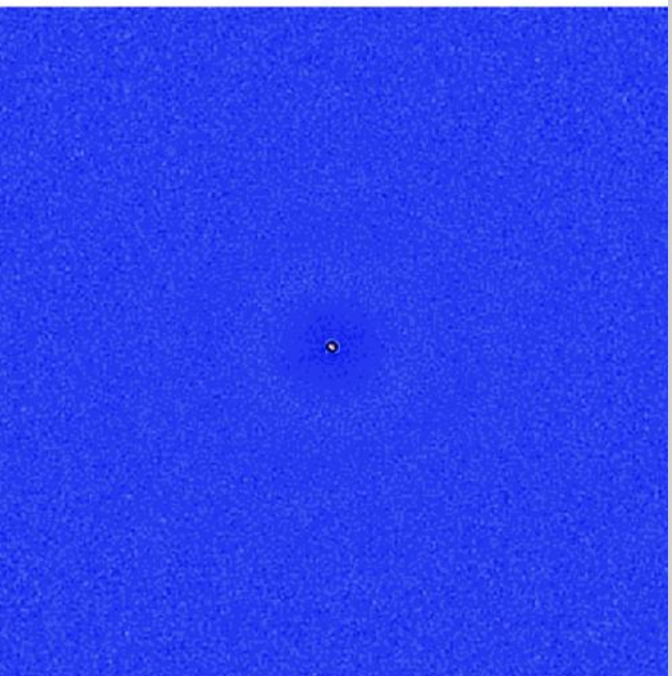
Zhang A&A

4: SKA Widefield Imaging

SKA simulation:

1. SKA1-LOW core

2. at 100 MHz



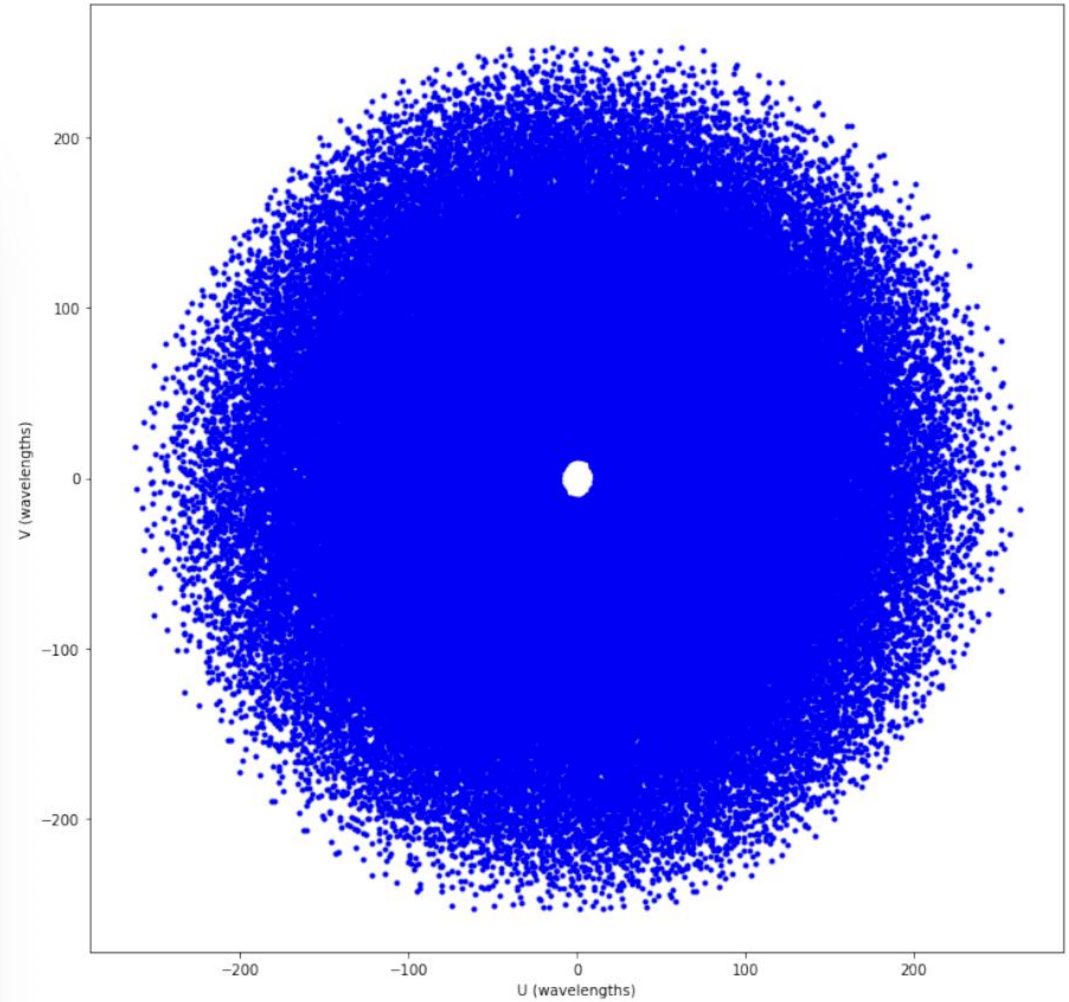
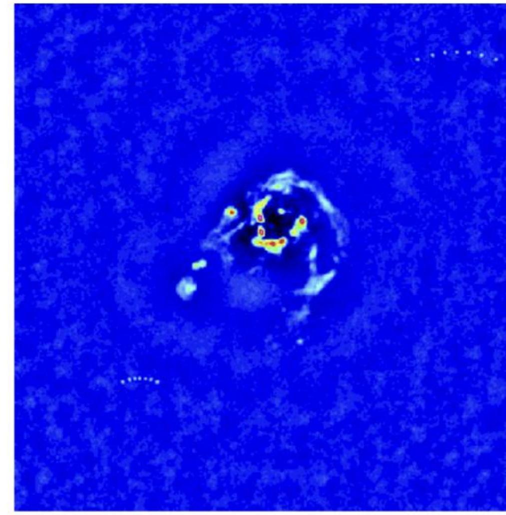


Fig. 1. Uv coverage for the SKA simulation, recorded as seven snapshots whose time distribution is in $[-3.0, -2.0, -1.0, 0.0, 1.0, 2.0, 3.0] * (\pi/12.0)$.

4: SKA模拟数据验证

$$V^{\mathrm{sky}}(u, v, w) = V^{\mathrm{sky}}(u, v, w = 0) * K(u, v, w),$$

1. Our imager
 = adaptive scale deconvolution
 + Widefield Correction



2. Tests： Simulated SKA data
 + JVLA observation data

4. Plan：
 Test for SKA EoR Imaging

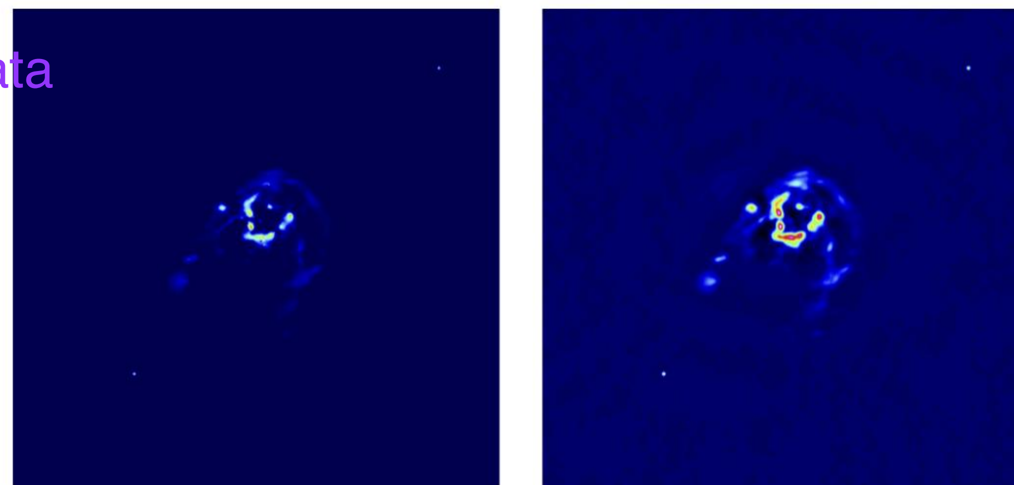


Fig. 3. Reconstruction results from our imager. *Left*: model image. *Right*: restored image.

4: JVLA实测数据验证(首次)

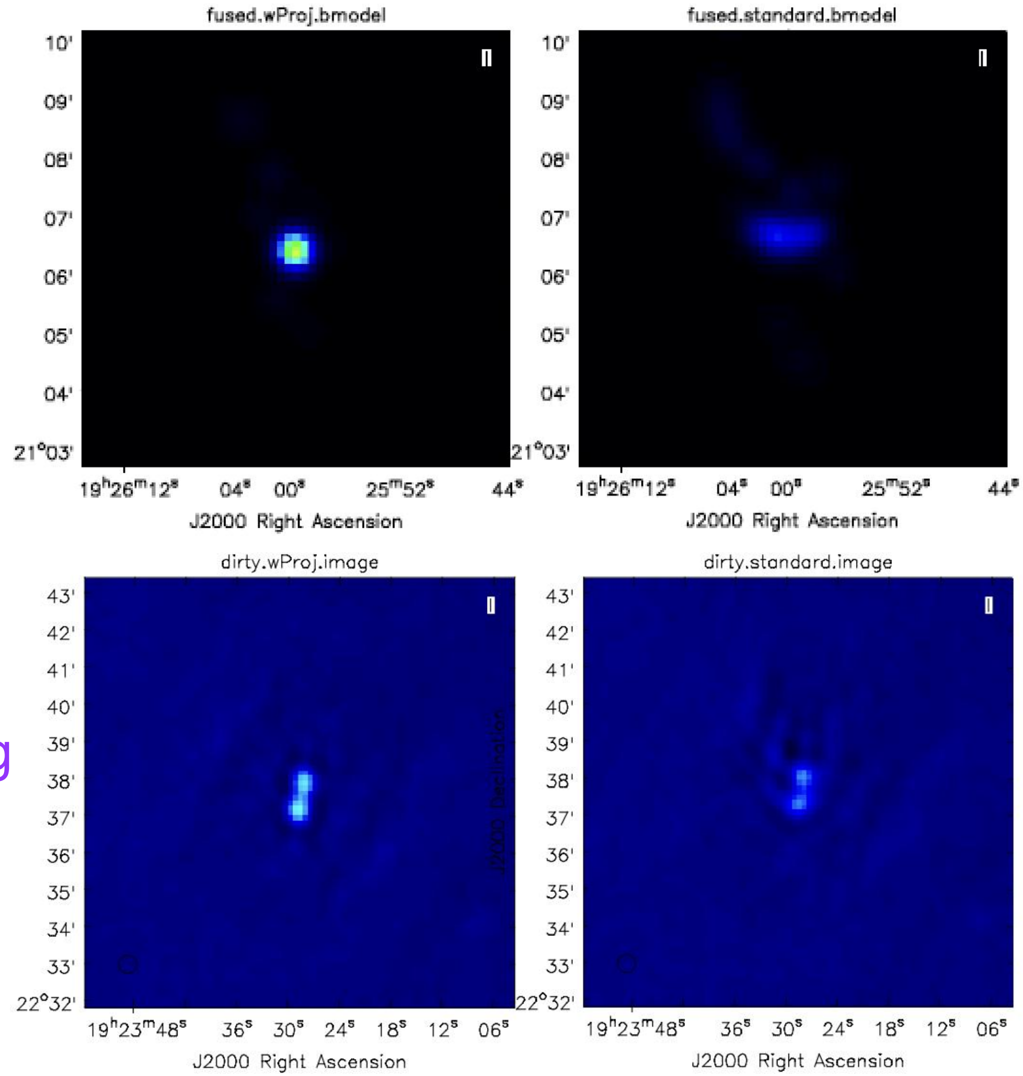
$$V^{\rm sky}(u,v,w) = V^{\rm sky}(u,v,w=0) * K(u,v,w),$$

1. Our imager
   = adaptive scale deconvolution
   + Widefield Correction

2. Tests: Simulated SKA data
   + JVLA observation data

3. Plan: test for SKA EoR Imaging

(Zhang, A&A)

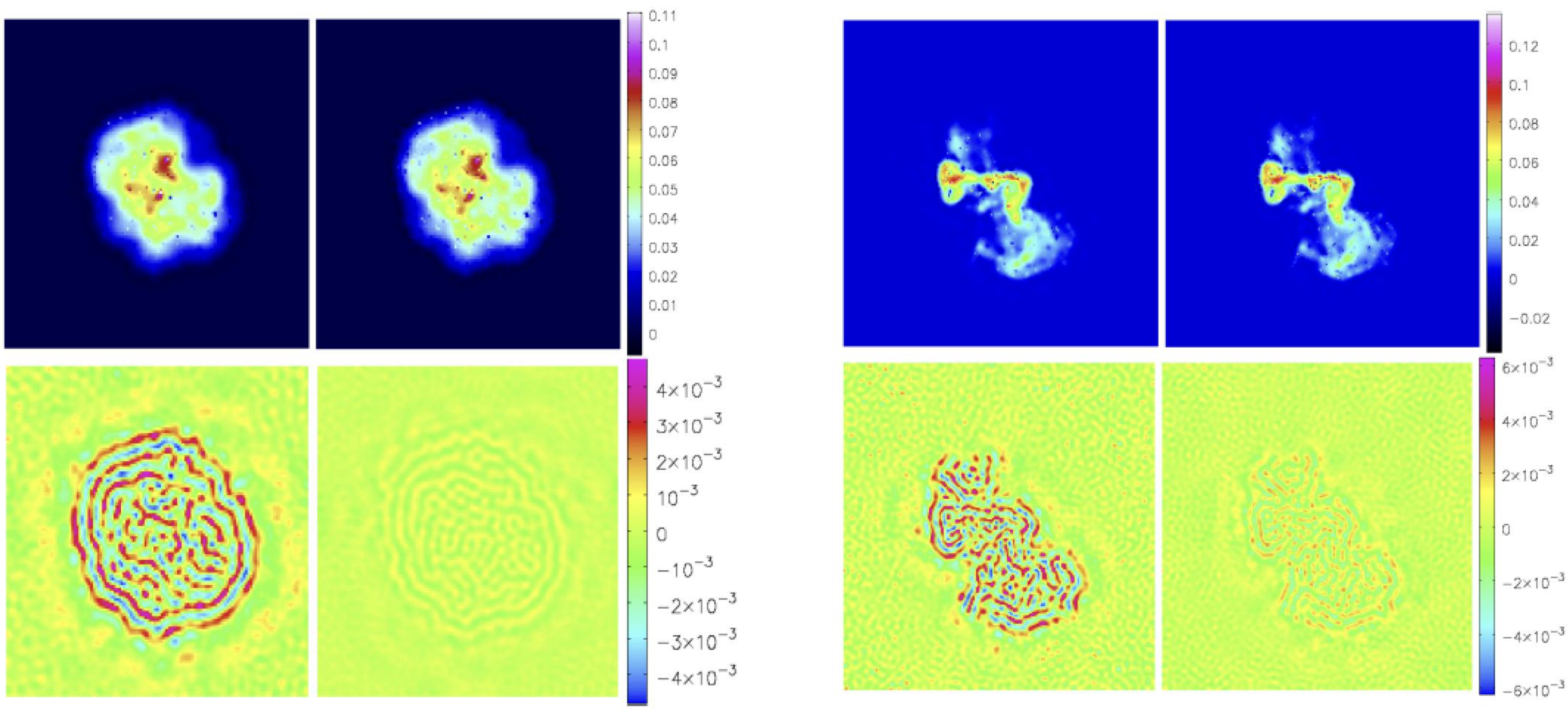


Our imager　　Standard imager

5: Deconv with Random Scales

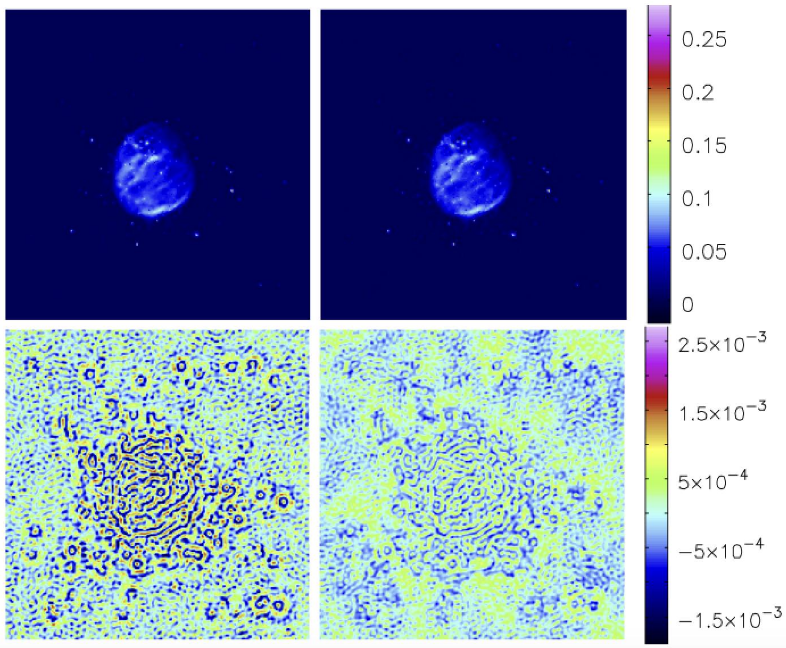
Specified scale lists	Algorithms	Off-source rms (10^{-4})	Full rms (10^{-4})	Dynamic range (10^{3})
[0, 4, 8, 16, 32]	MS-Clean	1.887	2.819	7.674
	RMS-Clean	0.871	1.084	19.957
[0, 3, 10, 30, 60]	MS-Clean	4.025	7.514	2.878
	RMS-Clean	3.022	5.133	4.212
[0, 6, 12, 18, 24]	MS-Clean	4.129	7.894	2.739
	RMS-Clean	1.012	1.354	15.974

(A&A)



6: Deconv with Hybrid Parameterization

Scale Lists	Algorithms	Runtime (s)	Off-source RMS (10^{-4})	Full RMS (10^{-4})	Dynamic Range (10^{3})
[0, 3, 6, 12, 24]	MsClean	88.659	8.075	9.967	2.675
	Our	79.346	3.256	3.243	6.635
[0, 3, 10, 20, 40]	MsClean	312.679	3.544	3.527	6.093
	Our	104.610	3.284	3.231	6.575
[0, 6, 12, 18, 32]	MsClean	216.191	4.199	4.561	5.145
	Our	76.164	3.240	3.336	6.668



Diffuse	Compact
Ms-Clean	Hg-Clean

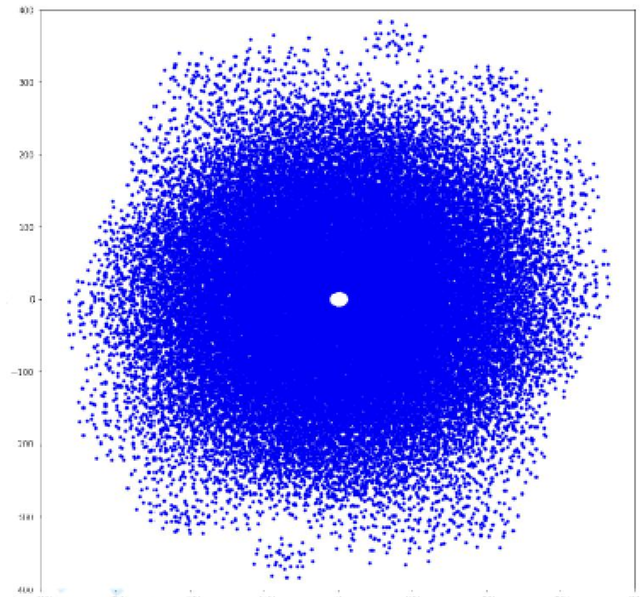
(RAA)

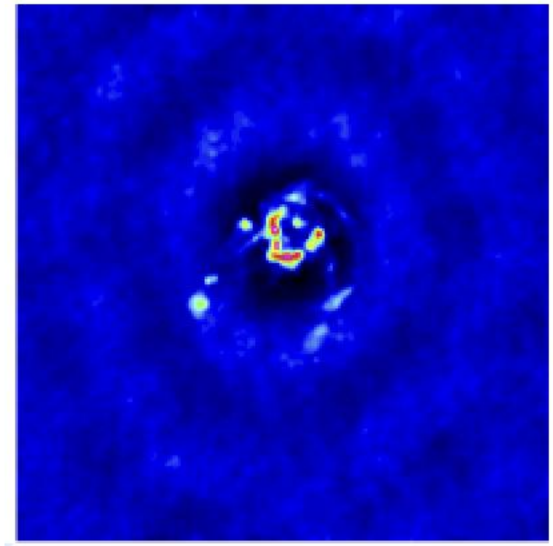
7: SKA Wideband Imaging

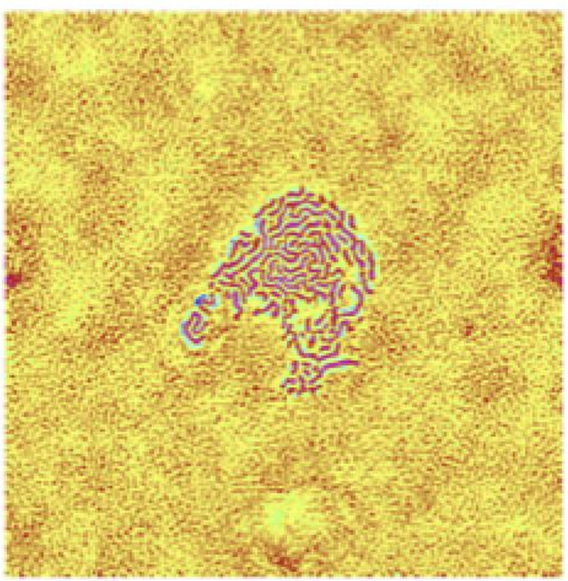
SKA simulation:

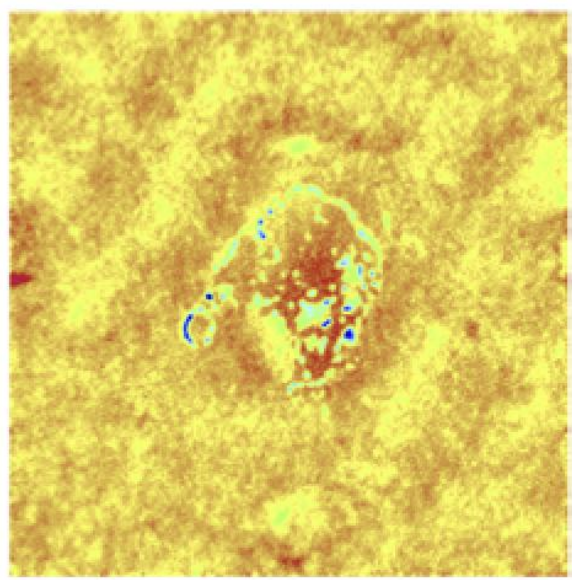
1. SKA1 'LOWBD2'

2. at 100 MHz







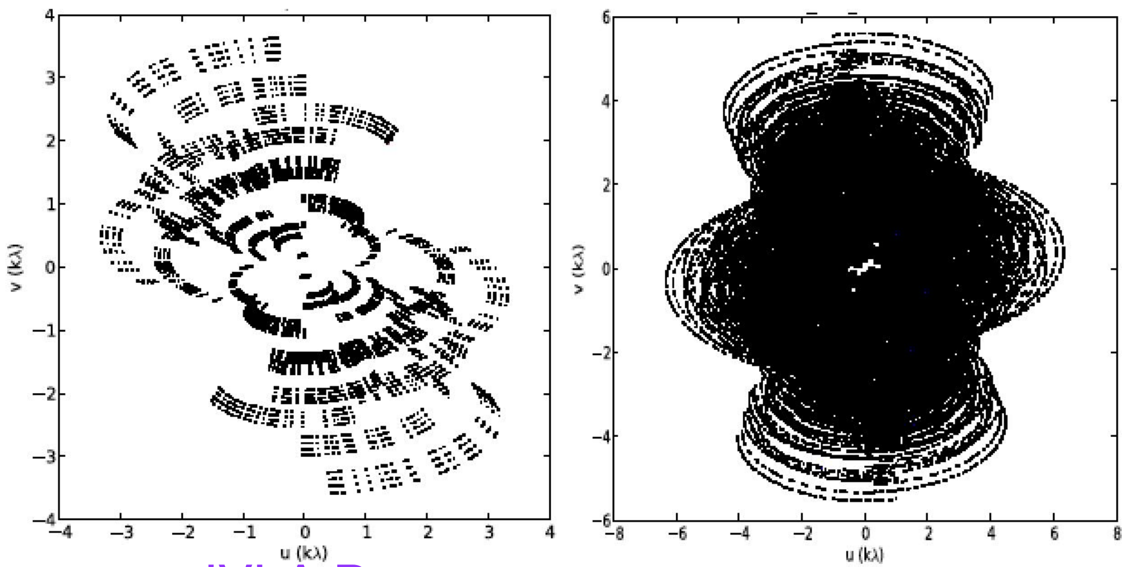


UV coverage	dirty image
Ms-Clean	Asp-Clean

(RAA, 2021)

SKA wideband widefield imaging

$$I^{obs} = F^{-1} \sum_{0}^{N-1} S_v V^{sky}$$



JVLA D, supernova remnants,
G55.7+3.4, 1-2GHz, 2MHzChannel,
time 1s

1. Our imager
= adaptive scale deconvolution
+ Wideband Correction

2. Tests: Simulated SKA data
+ JVLA observation data

4. Plan: test for SKA EoR Imaging

SKA wideband widefield imaging

$$V^{\text{sky}}(u,v,w) = V^{\text{sky}}(u,v,w=0) * K(u,v,w),$$

= adaptive scale deconvolution
+ Widefield Correction
+ Wideband Correction

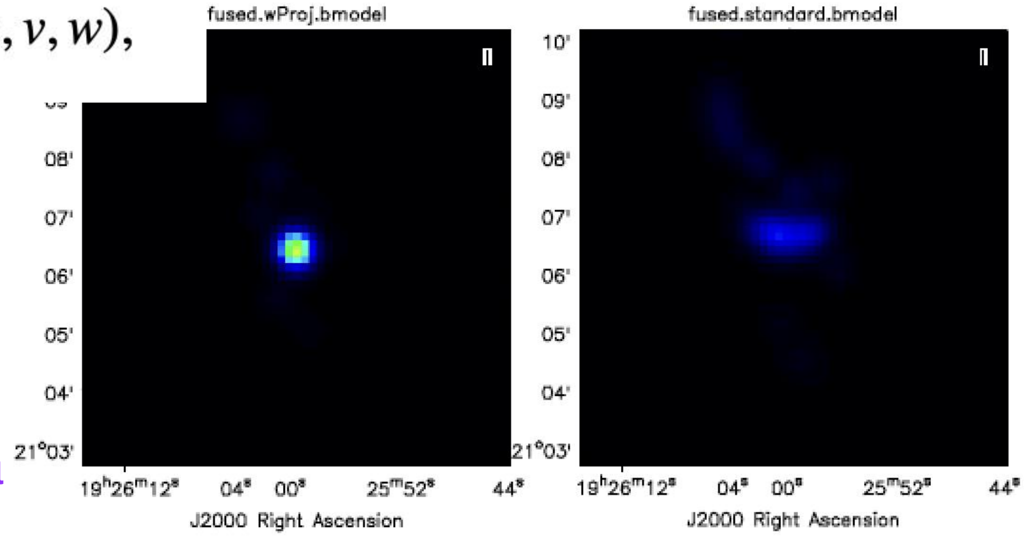
2. Tests: Simulated SKA data
+ JVLA observation data

3. We proposed 4 algorithms for accurate deconvolution
+ imagers for wideband widefield Imaging

4. Plan: test for SKA EoR Imaging

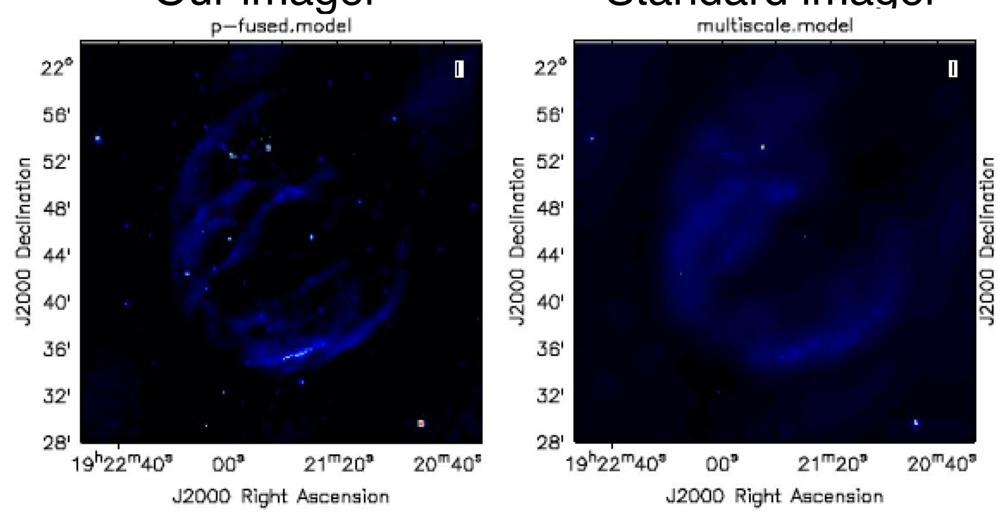
(A&A, 2020, A&A 2021, RAA, 2021a, RAA, 2021b)

eld imaging for JVLA observation data



Our imager

Standard imager



Wideband imaging for JVLA observation data

Data-driven Methods

1: Deep Learning for SKA imaging

1. *deepDeconv* for accurate reconstruction of compact emission + PSF Correction

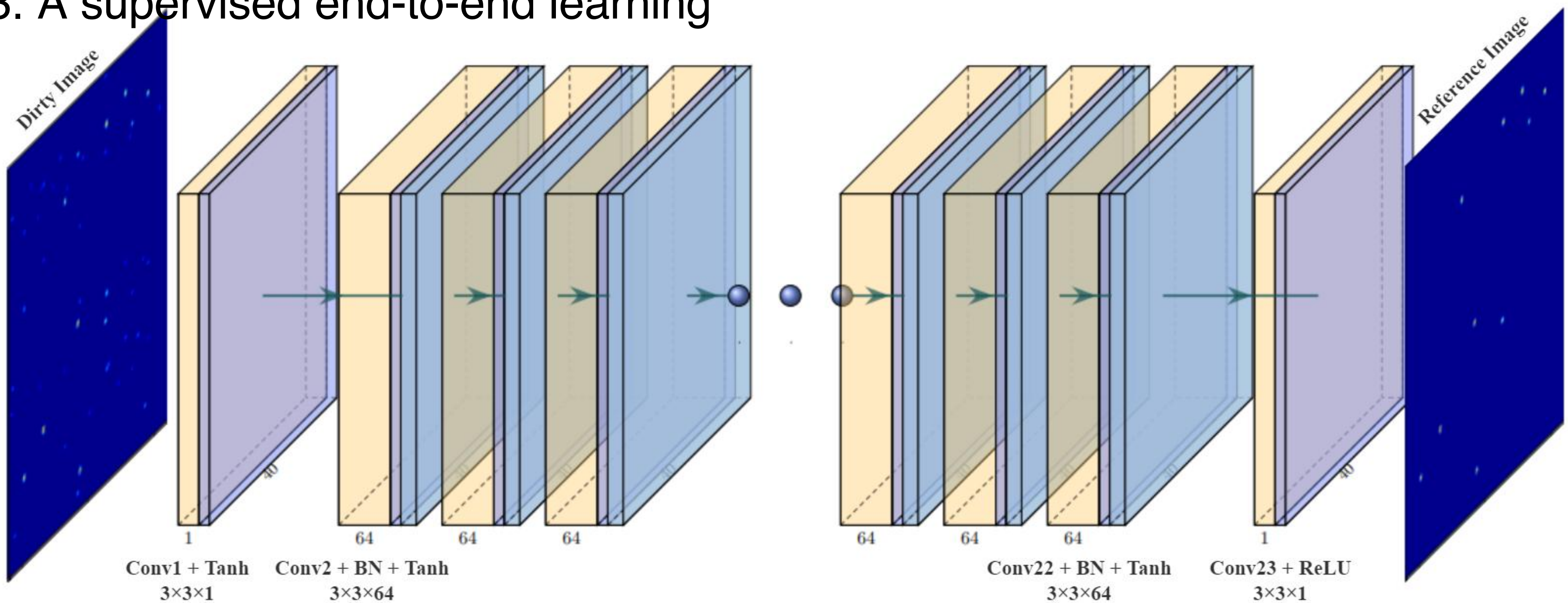
2. Tests： Simulated SKA data

3. A supervised end-to-end learning

4. Activation function scheme: tanh + ReLU

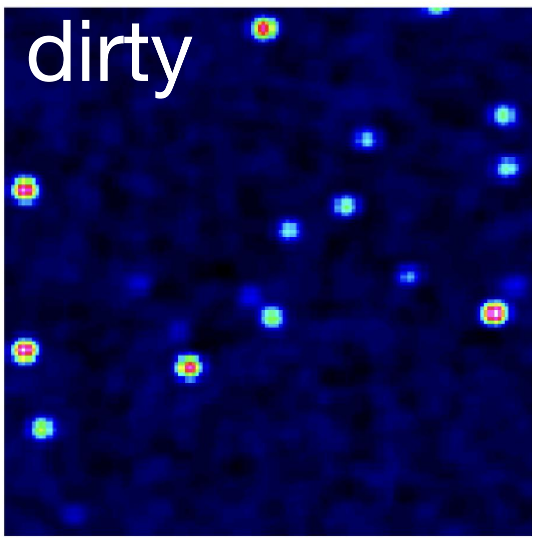
5. data-driven VS model-driven

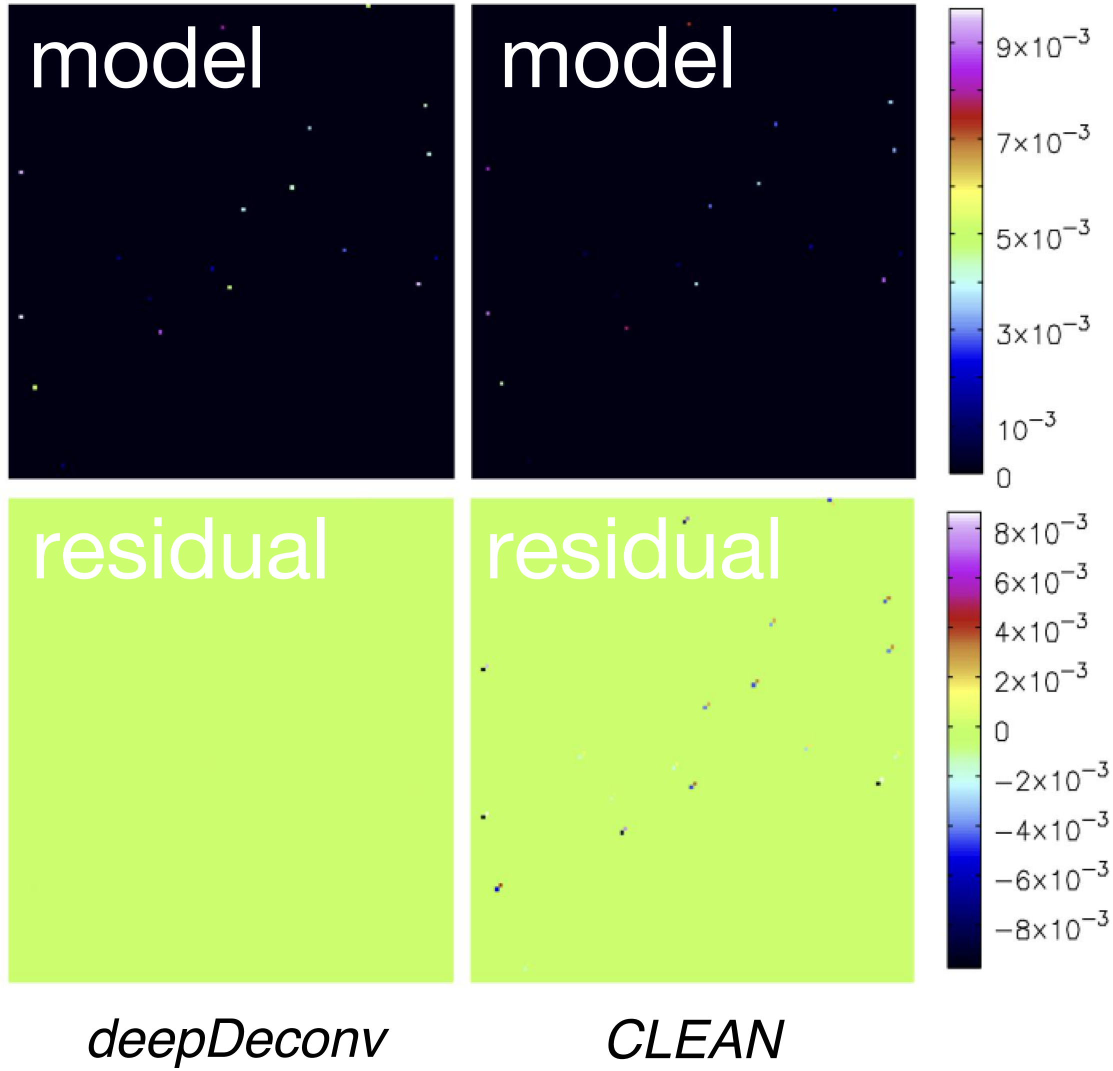
6. Plan: Test for SKA EoR Imaging



1: Deep Learning for SKA imaging

Reconstruction results for sparse-distributed compact emission.






Thanks for listening