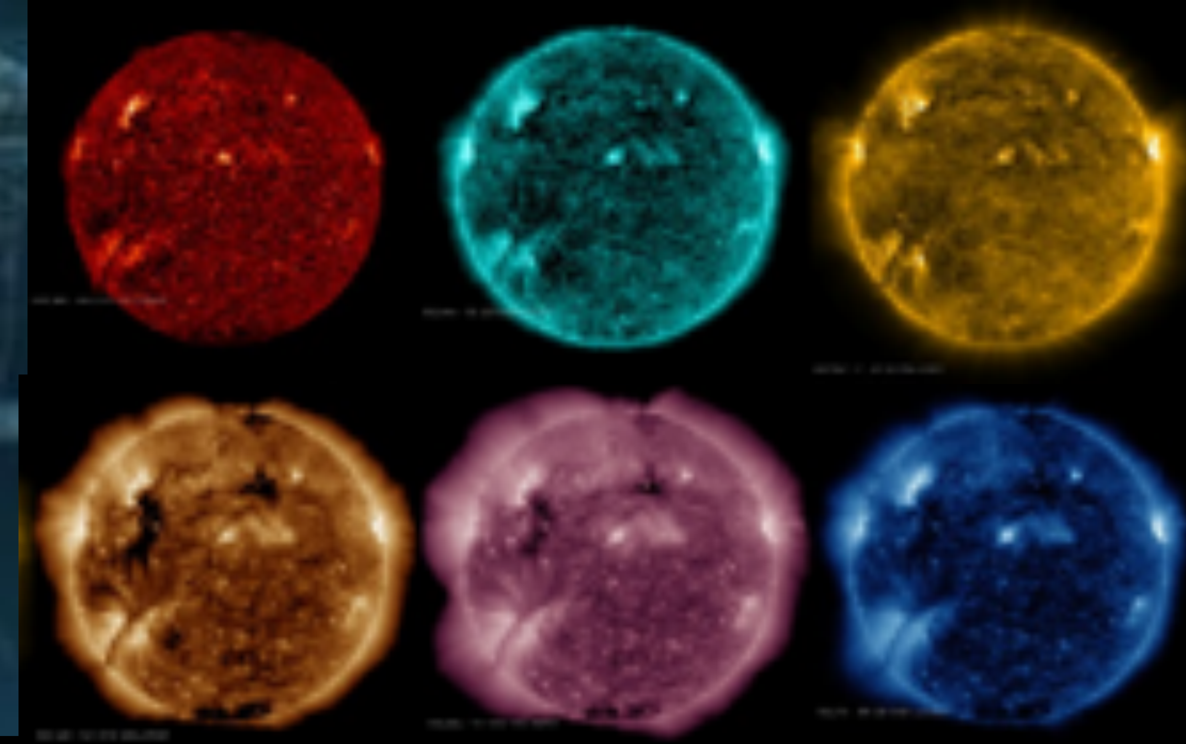


DEEP LEARNING AND IMAGE RECONSTRUCTION

a. asensio ramos
@aasensior
github.com/aasensio

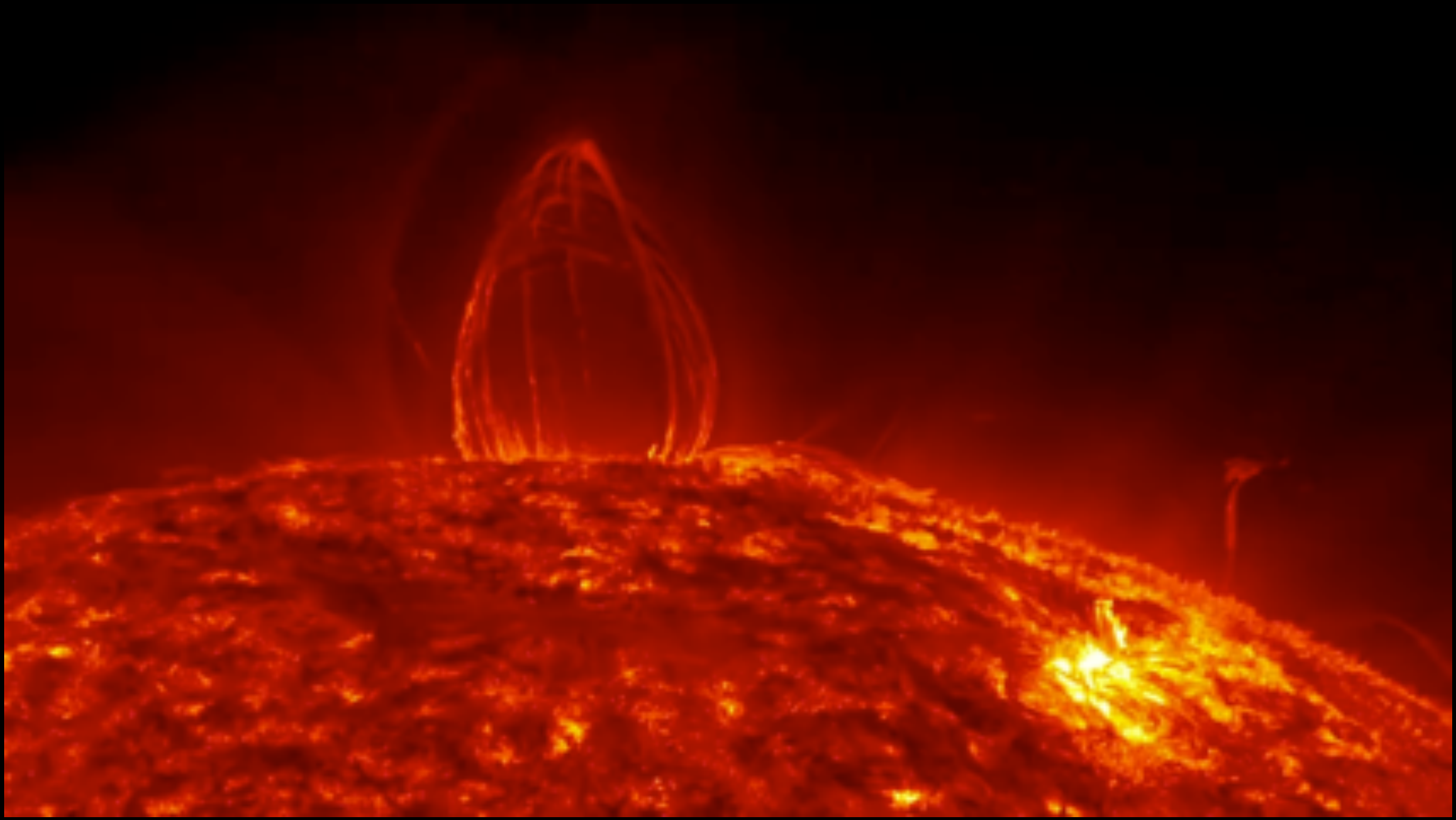
SUMMARY

- Motivation
- Image reconstruction: linear & non-linear
- Physics-based inference
- Conclusions

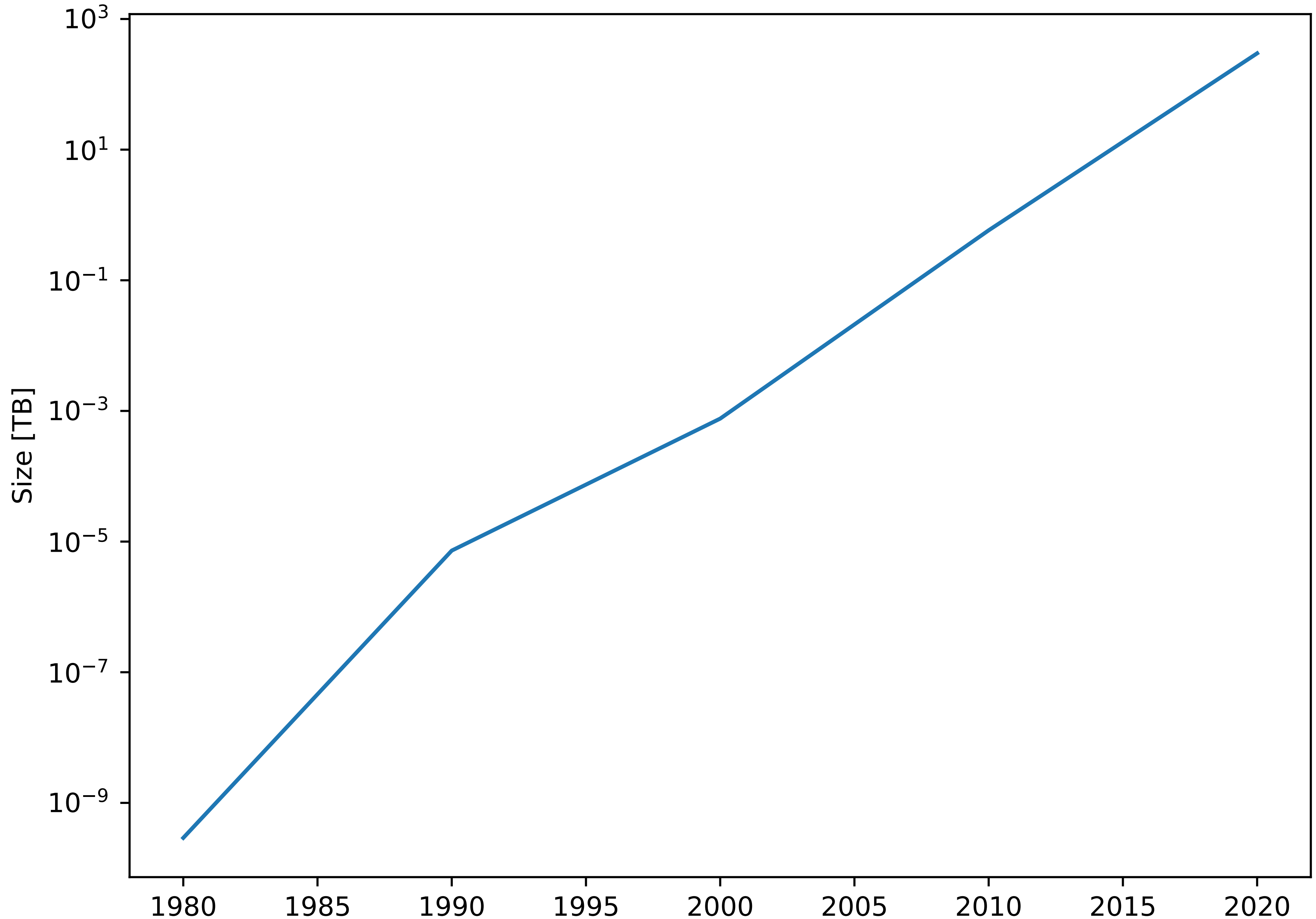
THANKS TO…

- C. Díaz Baso
- J. de la Cruz Rodríguez
- M. van Noort
- N. Olspert
- T. Felipe
- E. García Brook
- B. Tremblay

MY BACKGROUND



DATA IS INCREASING EXPONENTIALLY



Spatial	1x1	50x50	512x512	1000x1000	1000x1000
Wavelength	4x10	4x100	4x100	4x20	4x1024
Times	1	1	1	10x100	100x100

OUR MODELS ARE OFTEN COMPLEX

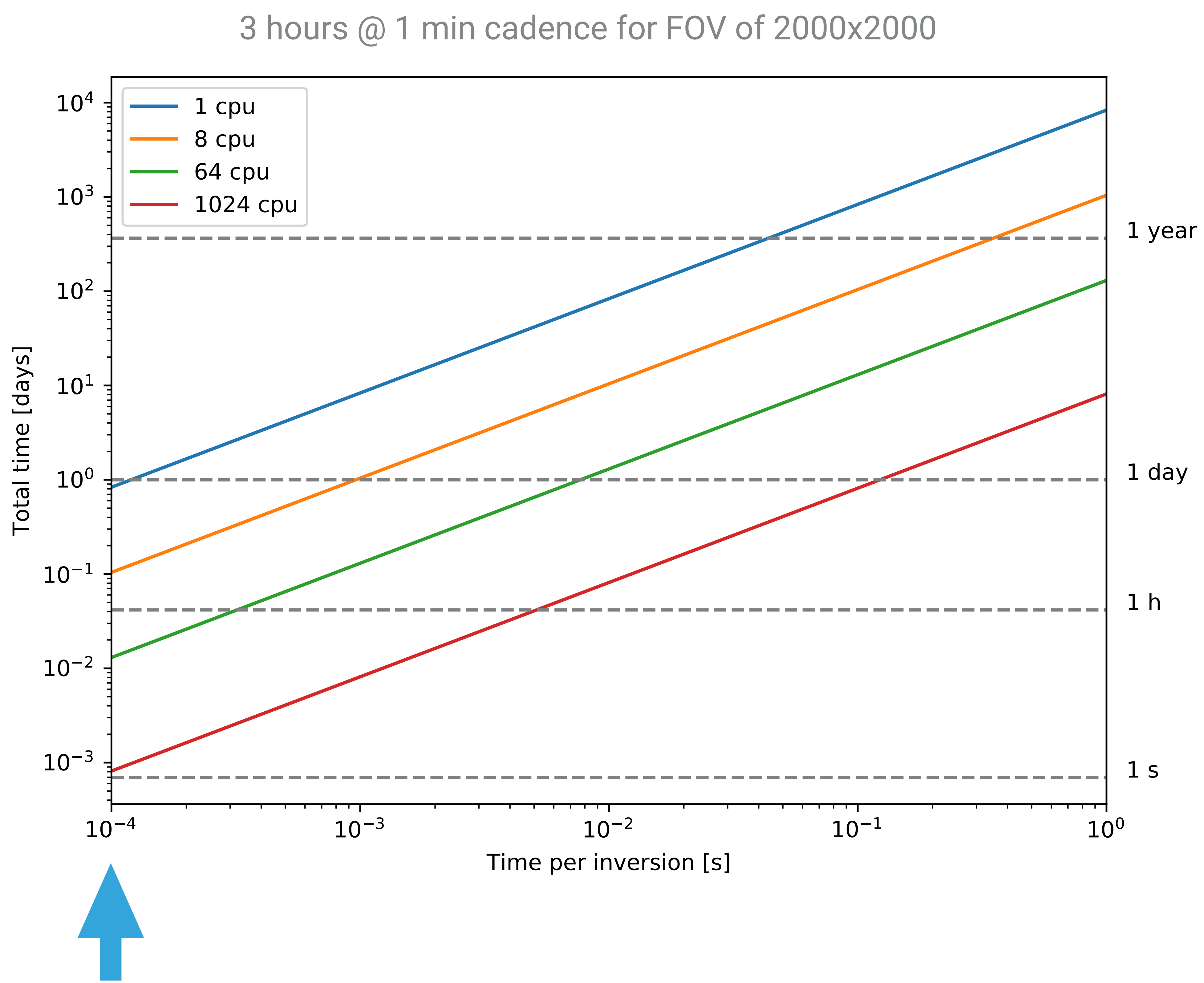
- 2000 x 2000 pixels
- 10 wavelength points
- One observation per minute
- Observe during 3 hours

720 million spectral lines per day

22.8 years to invert assuming 1 s per inversion

8.3 days to invert assuming 1 ms per inversion

SCALING WITH CPUS



Magic number : 100 μs per inversion

IMAGE RECONSTRUCTION

General problem

$$I = F(O) + n$$

$$\mathbf{I} = \mathbf{O} + \mathbf{n} \longrightarrow \text{Denoising}$$

$$\mathbf{I} = \mathbf{HO} + \mathbf{n} \longrightarrow \text{Deconvolution}$$

$$\mathbf{I} = \mathbf{DHO} + \mathbf{n} \longrightarrow \text{Deconvolution+superresolution}$$

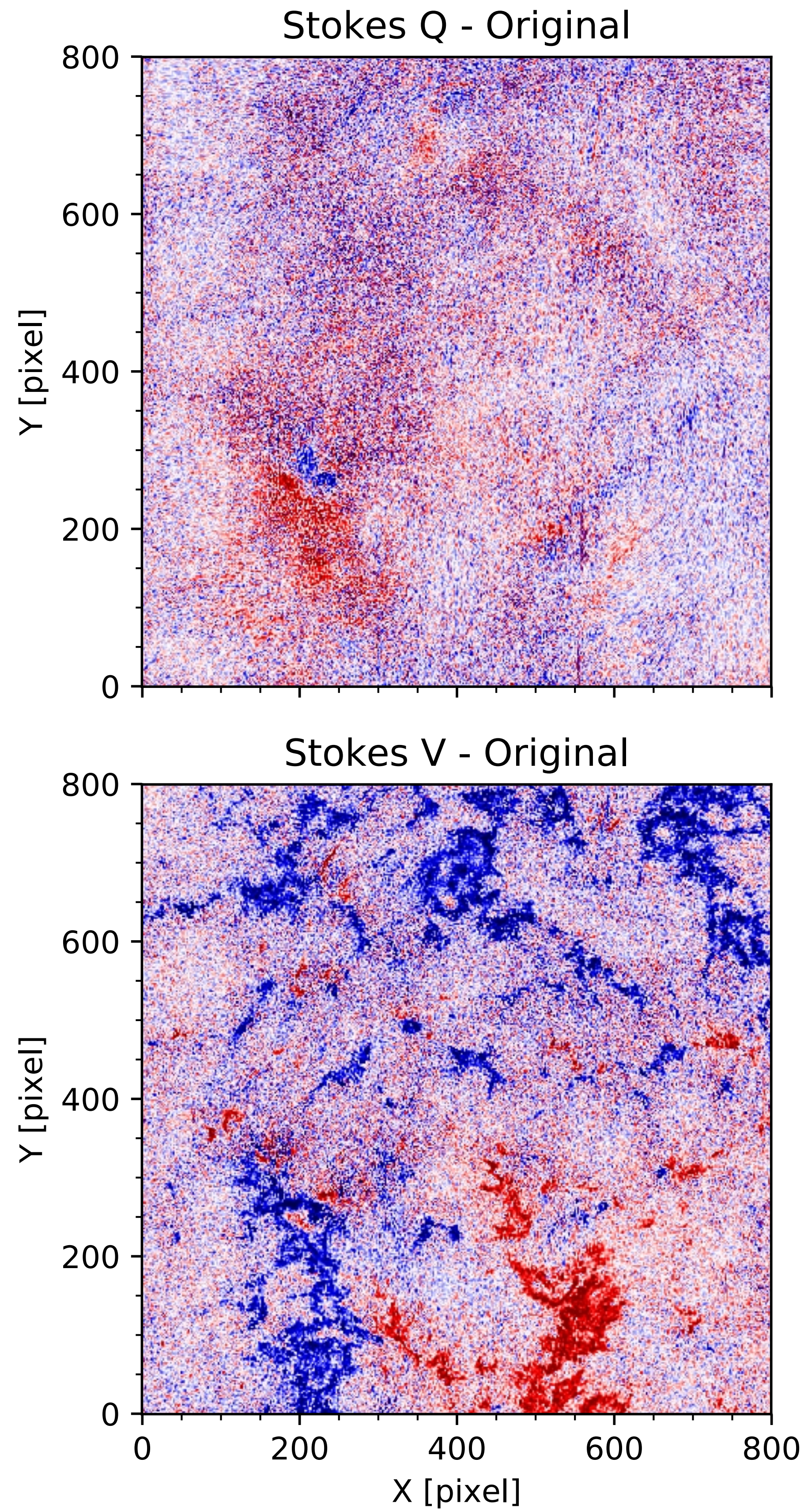
$$\mathbf{I} = RT(\mathbf{O}) + \mathbf{n} \longrightarrow \text{Reconstruction with nonlinear model}$$

image denoising

$$\mathbf{I} = \mathbf{O} + \mathbf{n}$$

NOISE FILTERING

$$\mathbf{I} = \mathbf{O} + \mathbf{n}$$



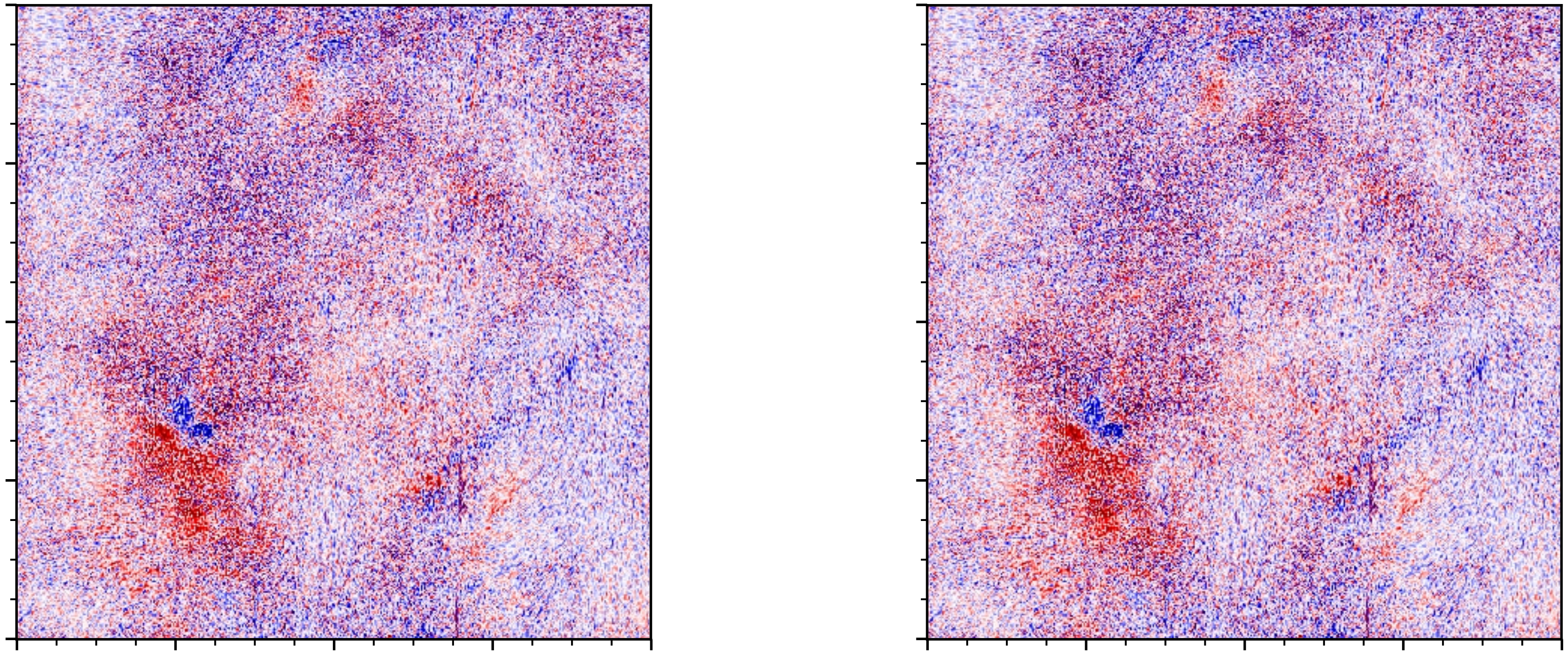
NOISE2NOISE: UNSUPERVISED TRAINING

$$\underset{\theta}{\operatorname{argmin}} \sum_i L\left(f_\theta\left(\hat{x}_i\right), \hat{y}_i\right)$$

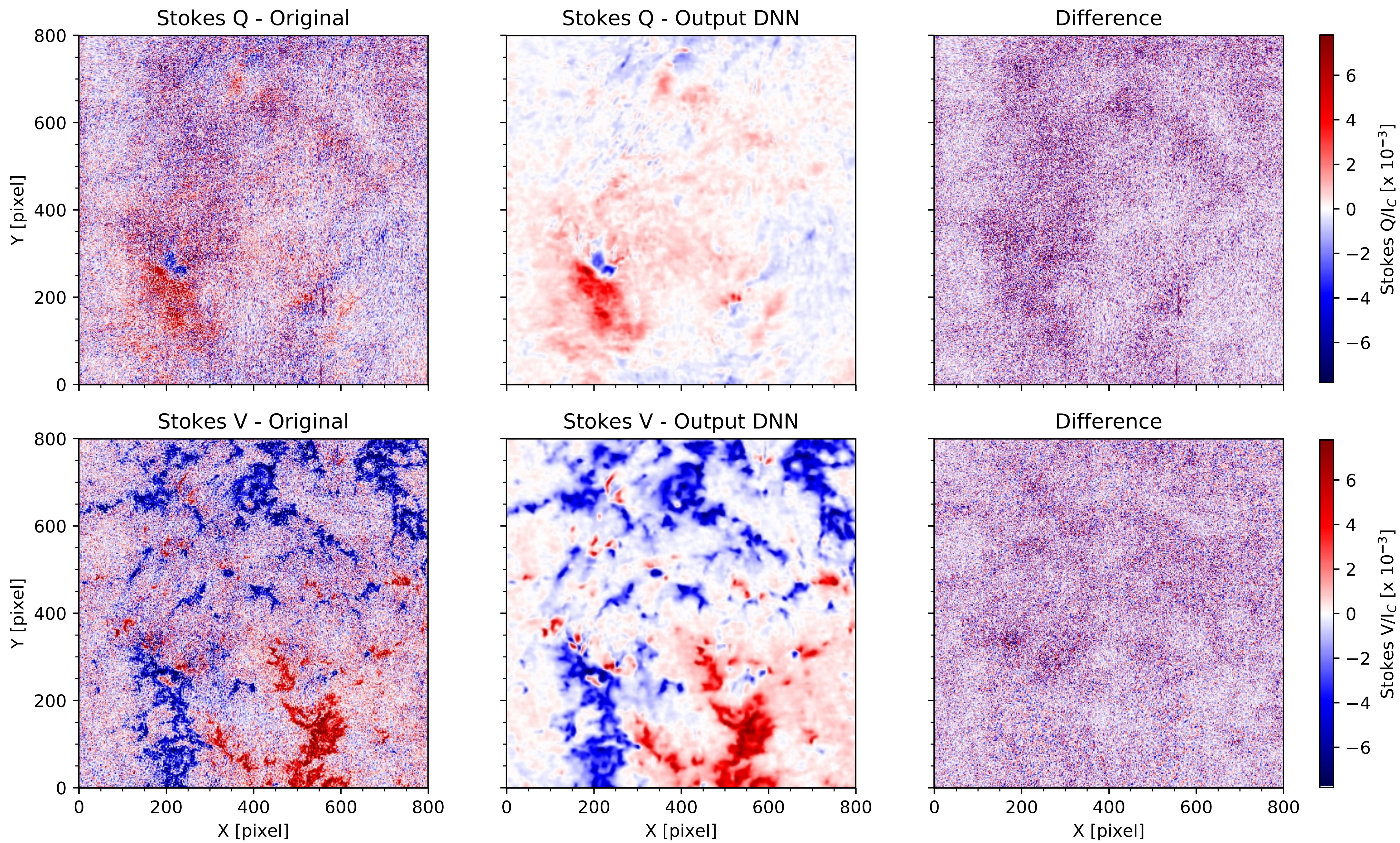
$\hat{y}_i$ ~ noisy distribution with same expectation

Lehtinen et al. (2018)

Two different realisations of noise

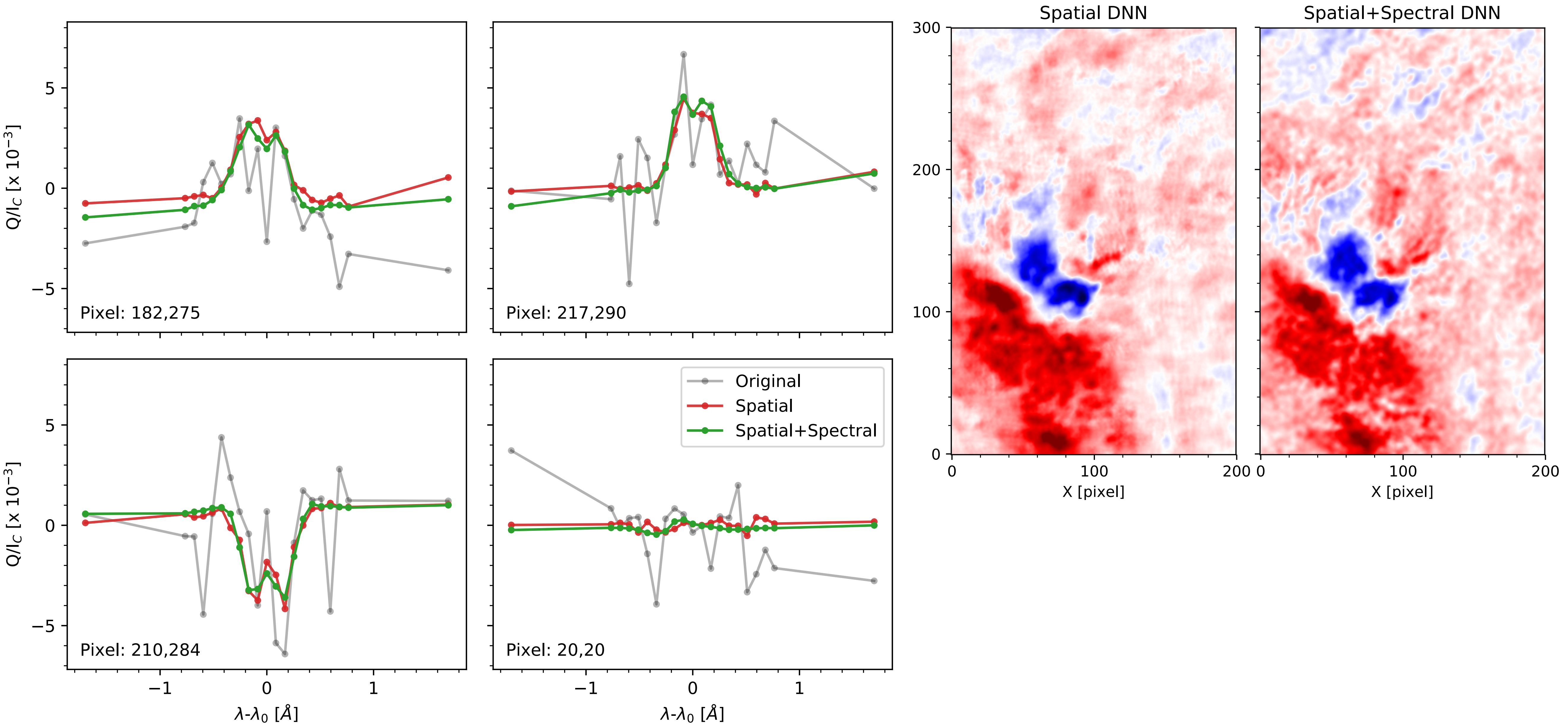


NOISE FILTERING : SST DATA



Díaz Baso et al. (2019)

NOISE FILTERING : PROFILES

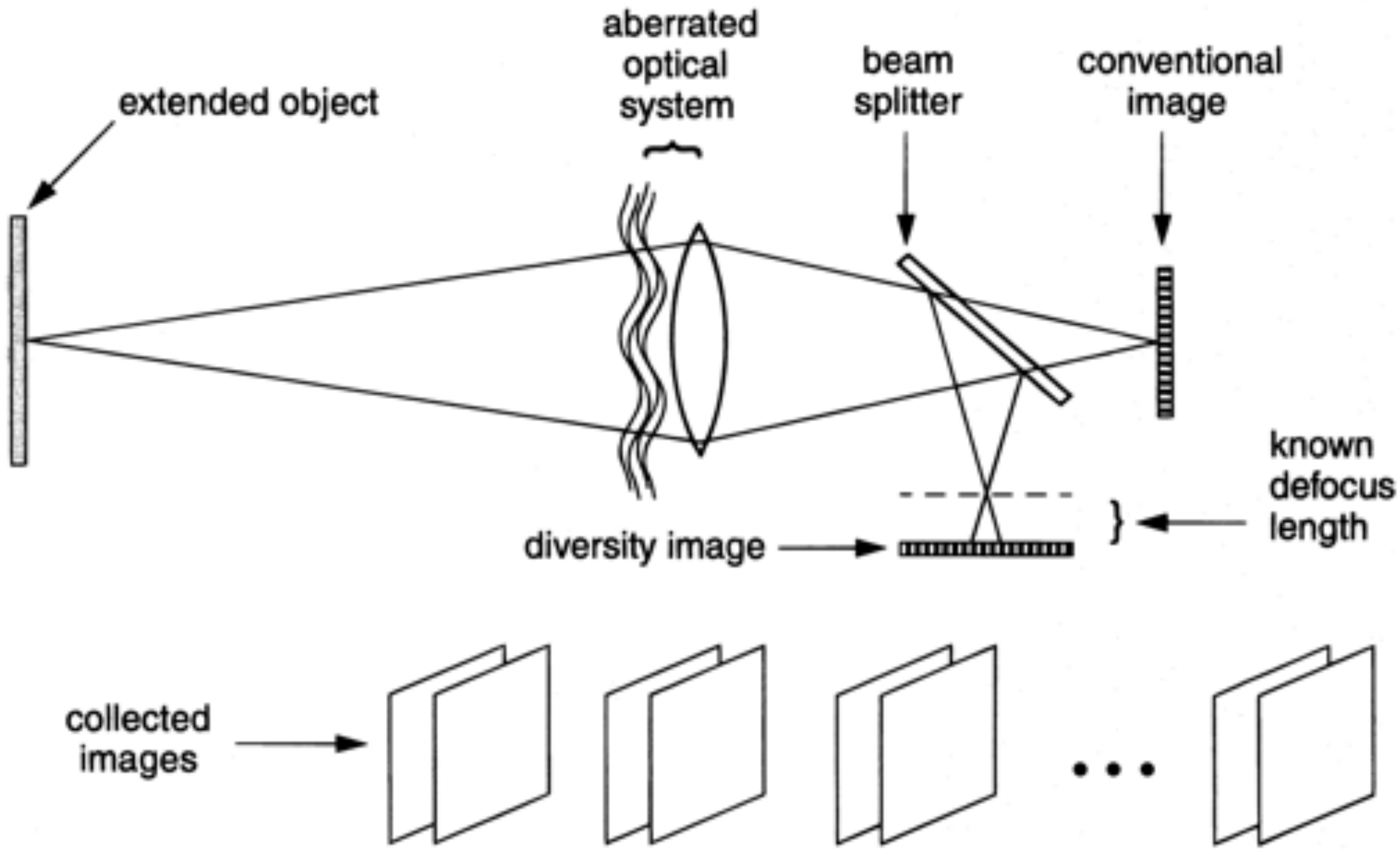


Díaz Baso et al. (2019)

image deconvolution

$$\mathbf{I} = \mathbf{H}\mathbf{O} + \mathbf{n}$$

MULTIFRAME BLIND DECONVOLUTION



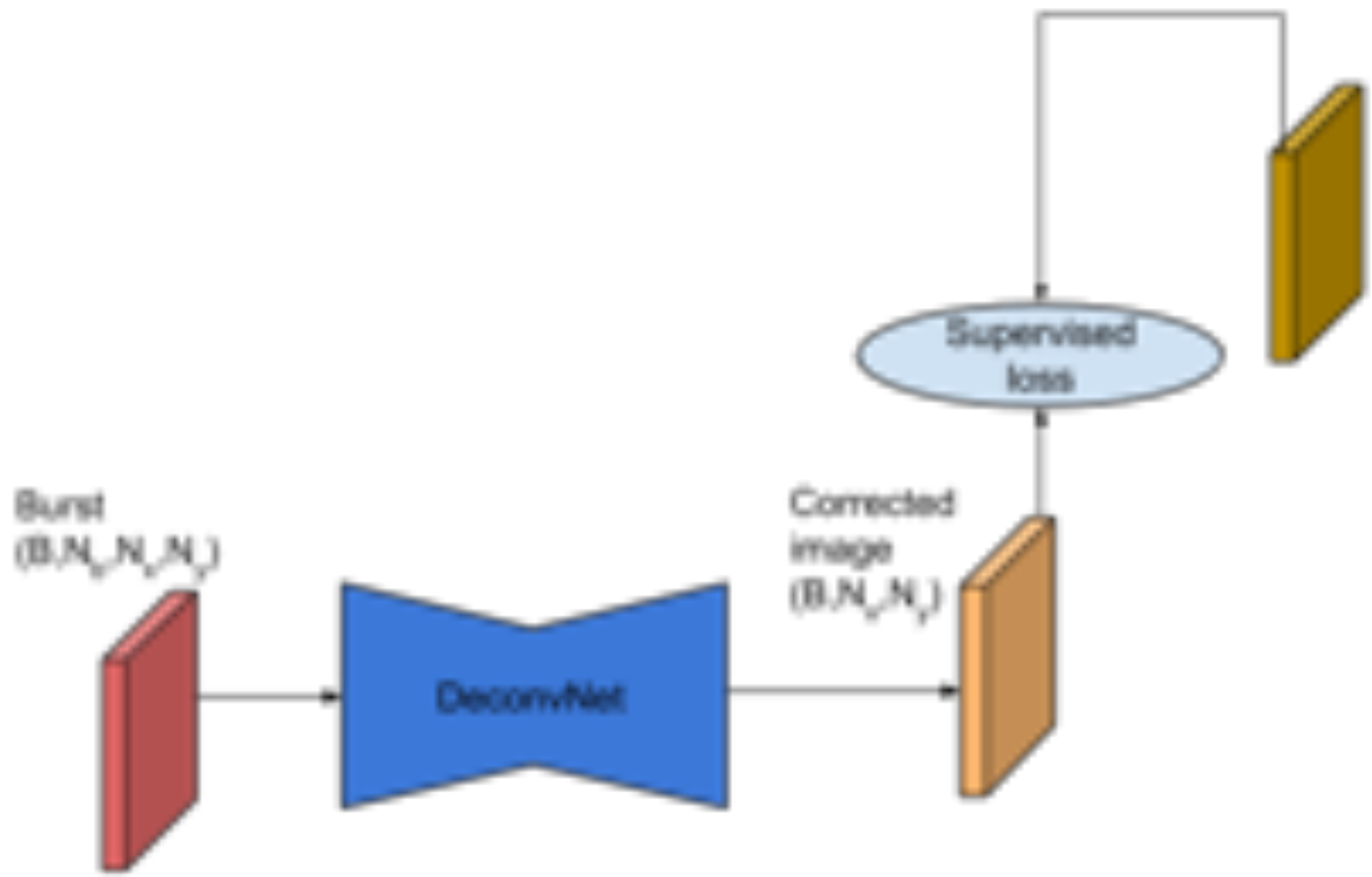
Paxman et al. (1996)

MFBD: SUPERVISED TRAINING

Burst of perturbed images

Corrected image

MFBD: SUPERVISED TRAINING

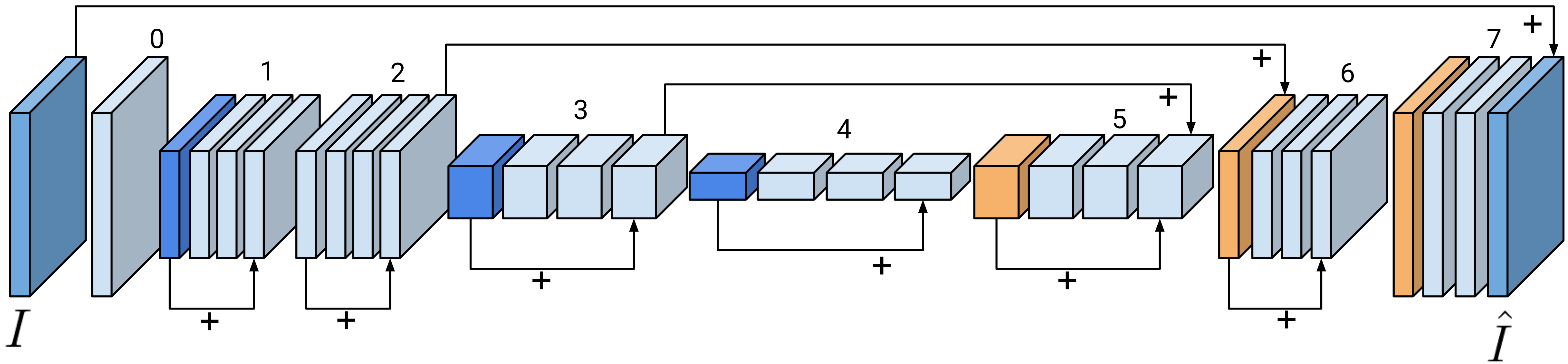


Asensio Ramos et al. (2019)

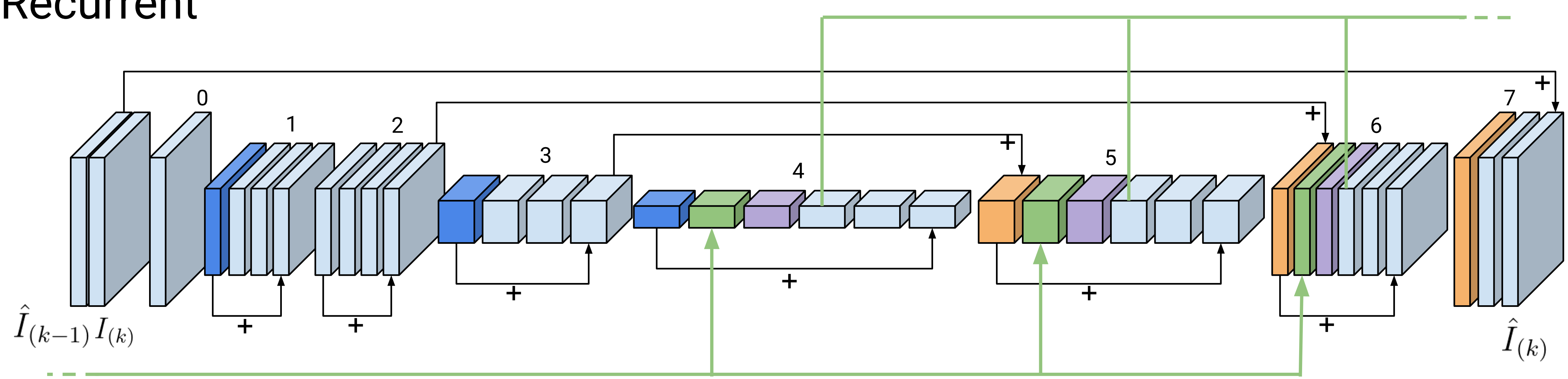
- 1k x 1k images at ~100 Hz
- https://github.com/aasensio/learned_mfbd

MULTIFRAME BLIND DECONVOLUTION

Encoder-decoder

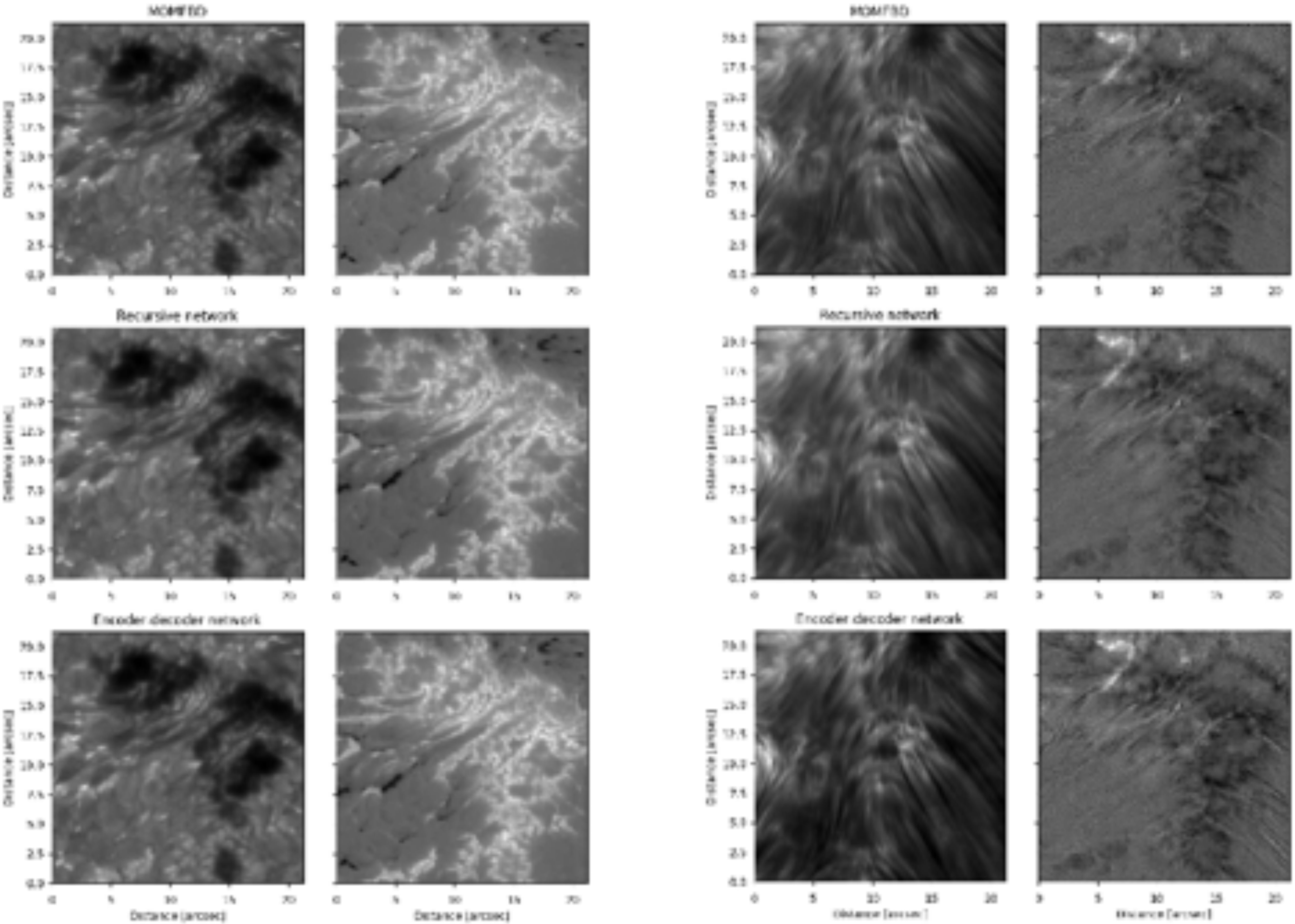


Recurrent

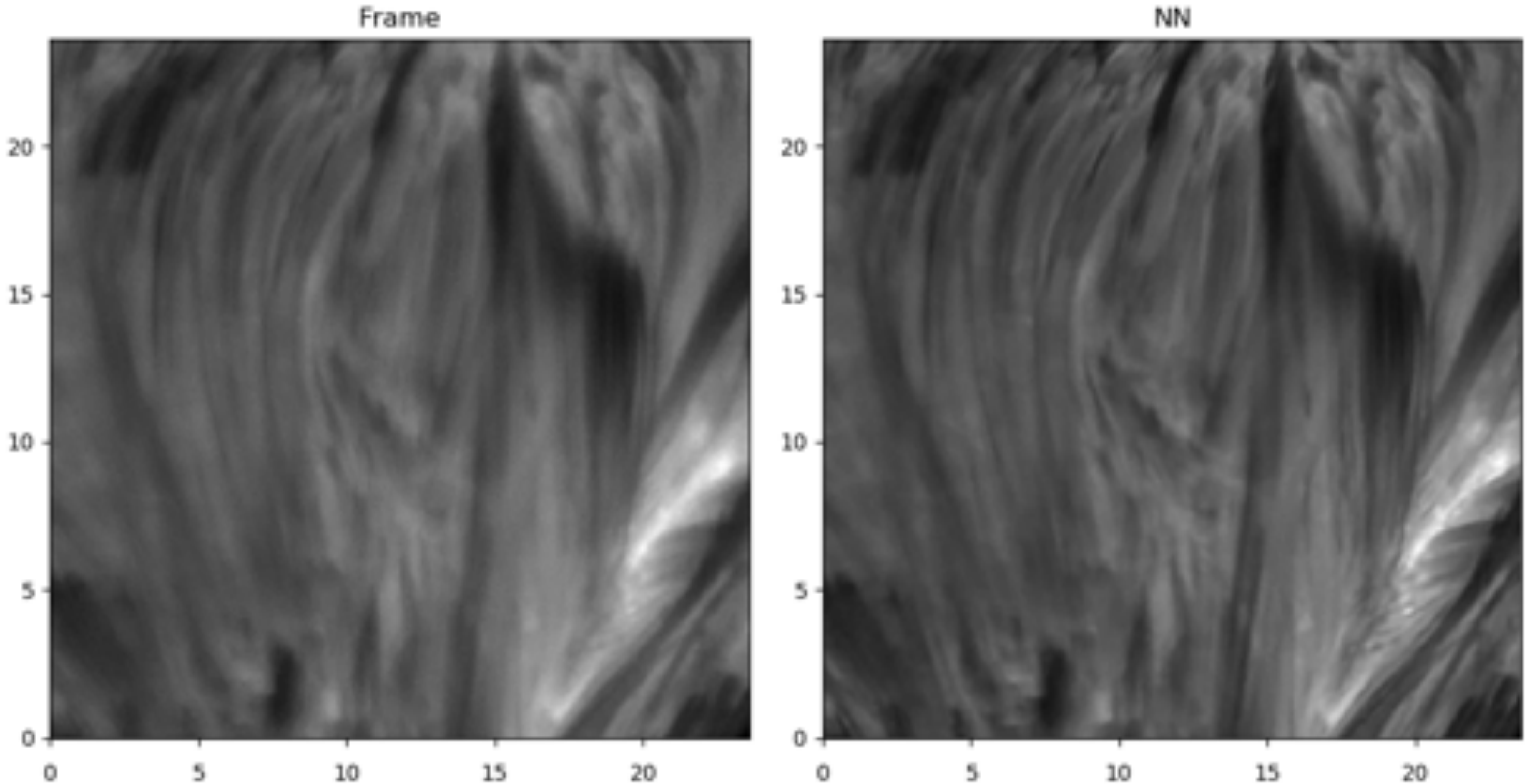


https://github.com/aasensio/learned_mfbd

POLARIMETRY



GENERALIZATION TO UNSEEN DATA



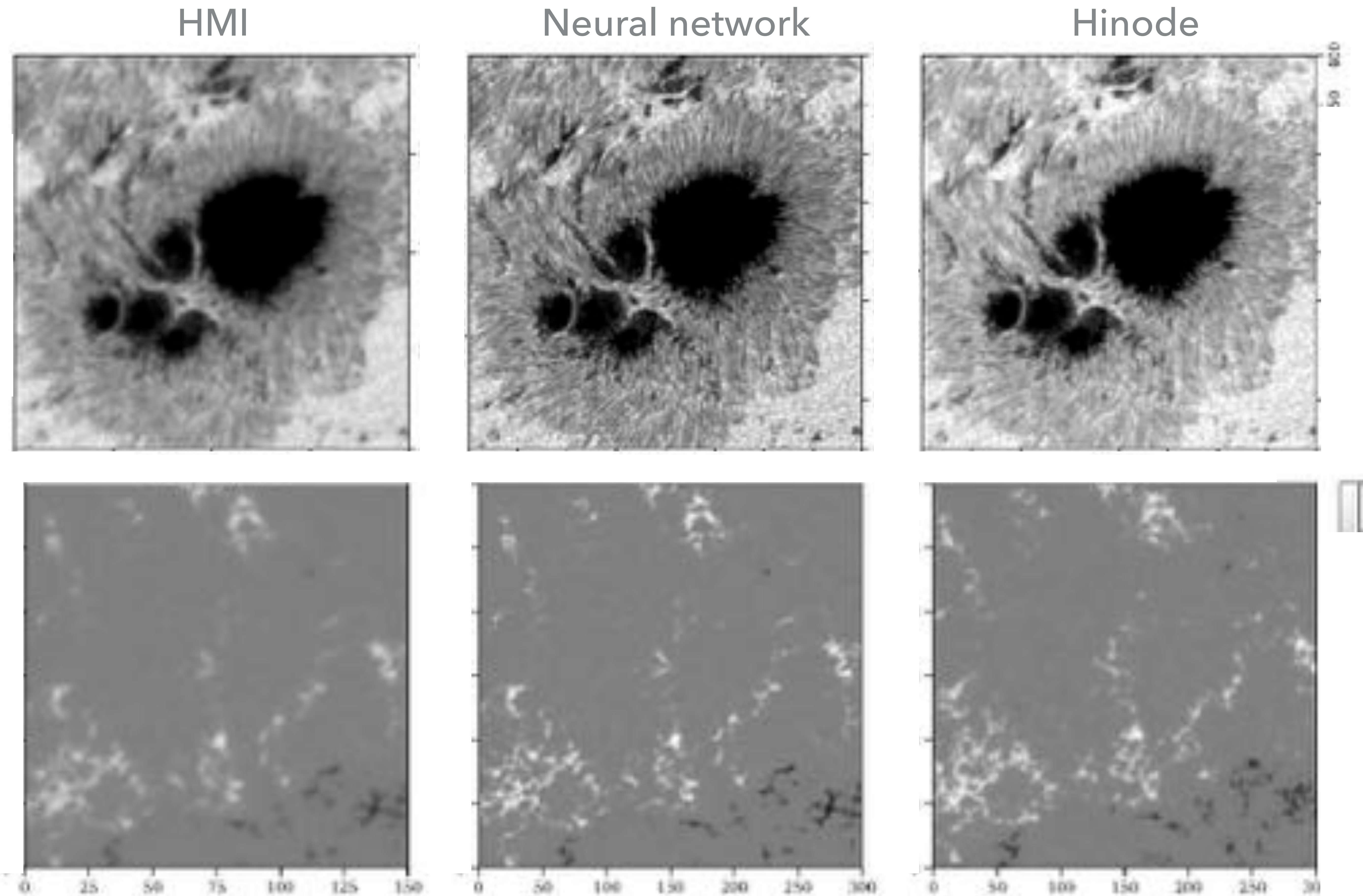
100 images/s

image deconvolution+superresolution

$$\mathbf{I} = \mathbf{DHO} + \mathbf{n}$$

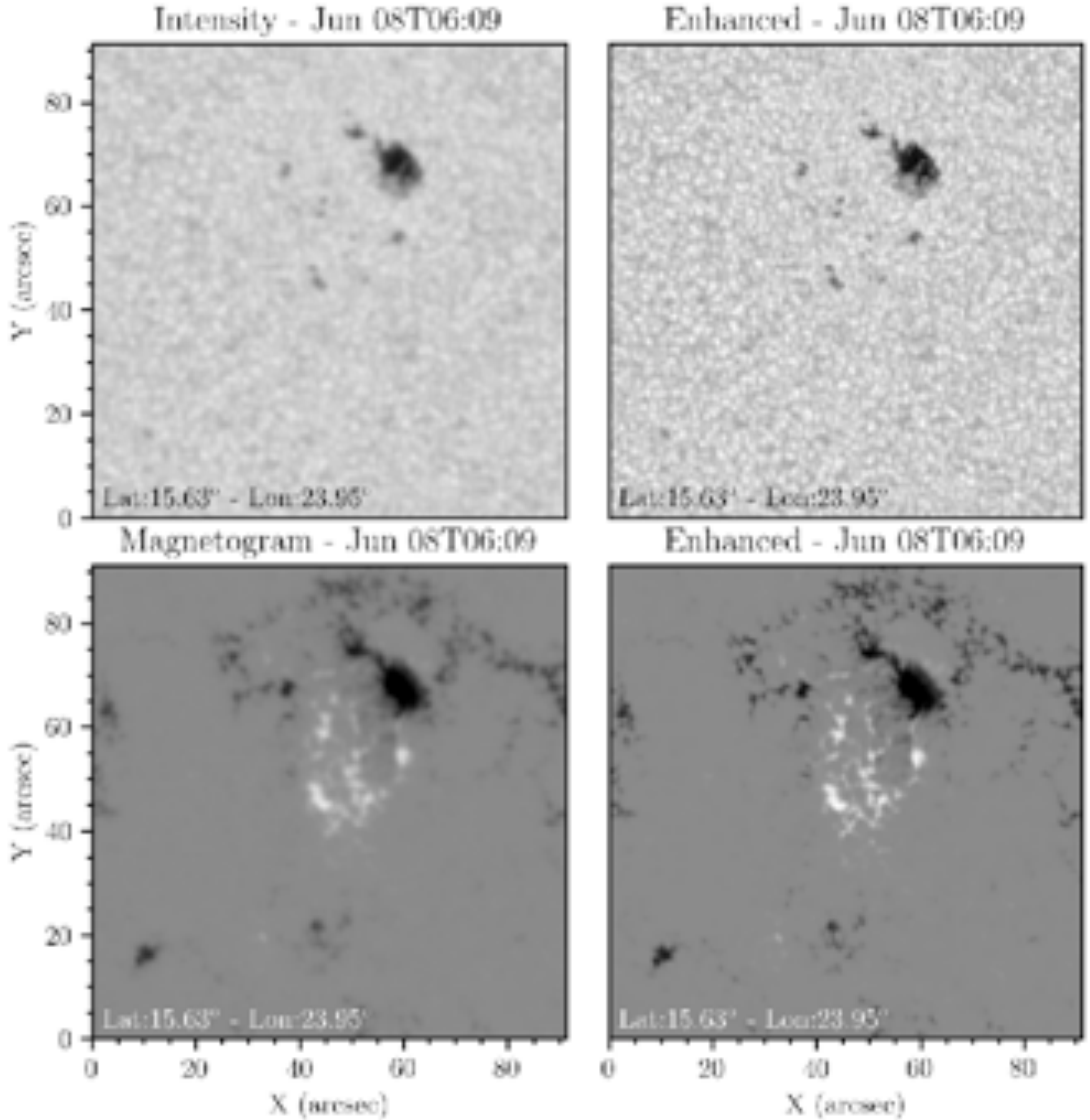
SINGLE IMAGE SUPERRESOLUTION

ENHANCE: SINGLE IMAGE SUPERRESOLUTION



Díaz Baso & Asensio Ramos (2018)

ENHANCE https://github.com/cdiazbas/enhance



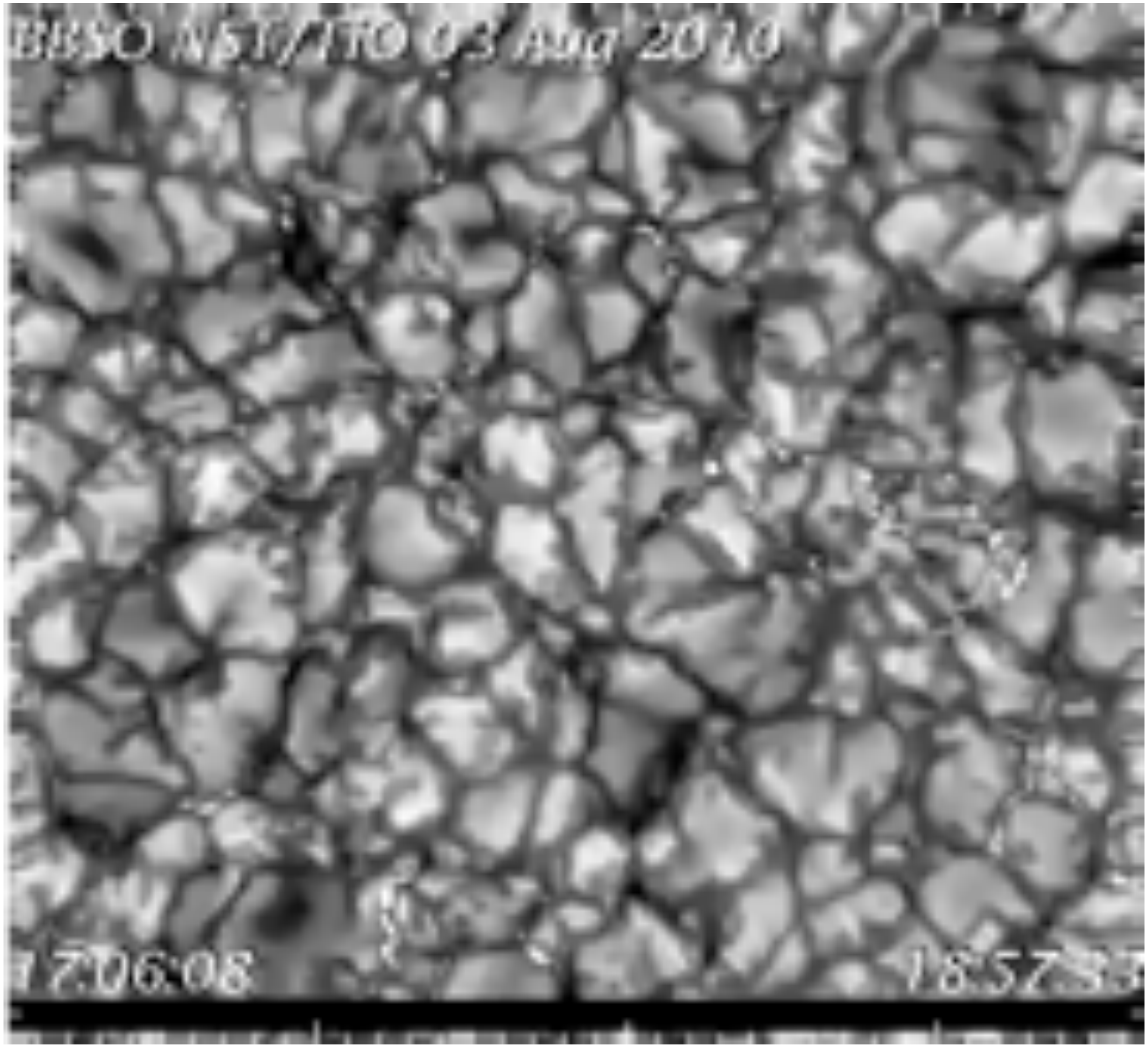
courtesy of S. Castellanos Durán

image nonlinear inversion

$$\mathbf{I} = f(\mathbf{O}) + \mathbf{n}$$

optical flow estimation

MEASURING VELOCITIES

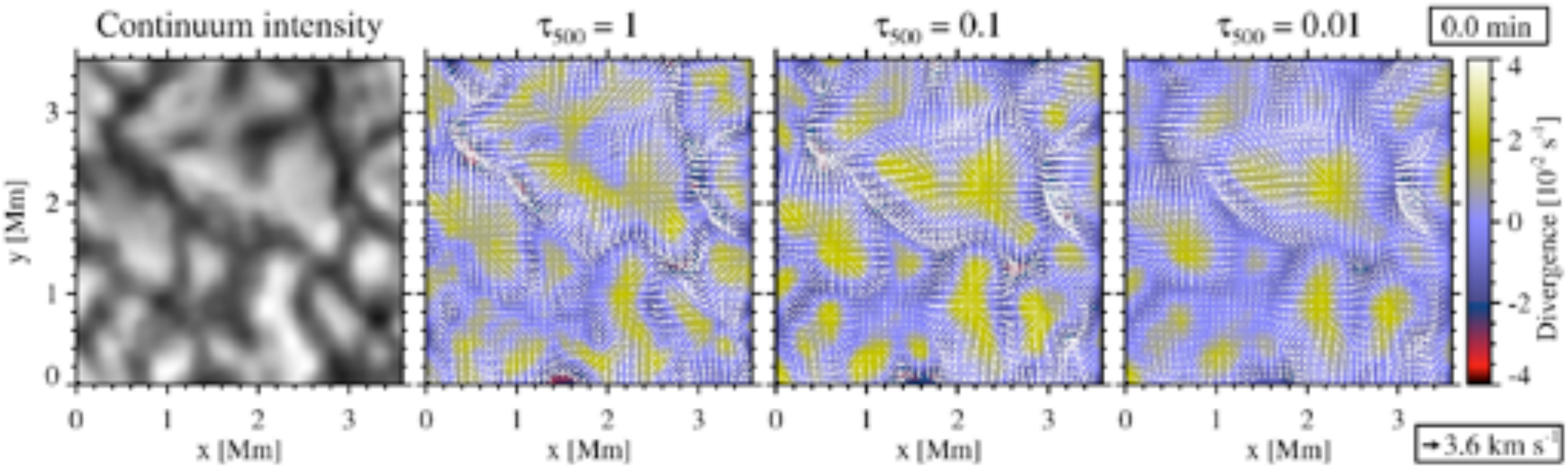


MEASURING VELOCITIES

Consecutive frames

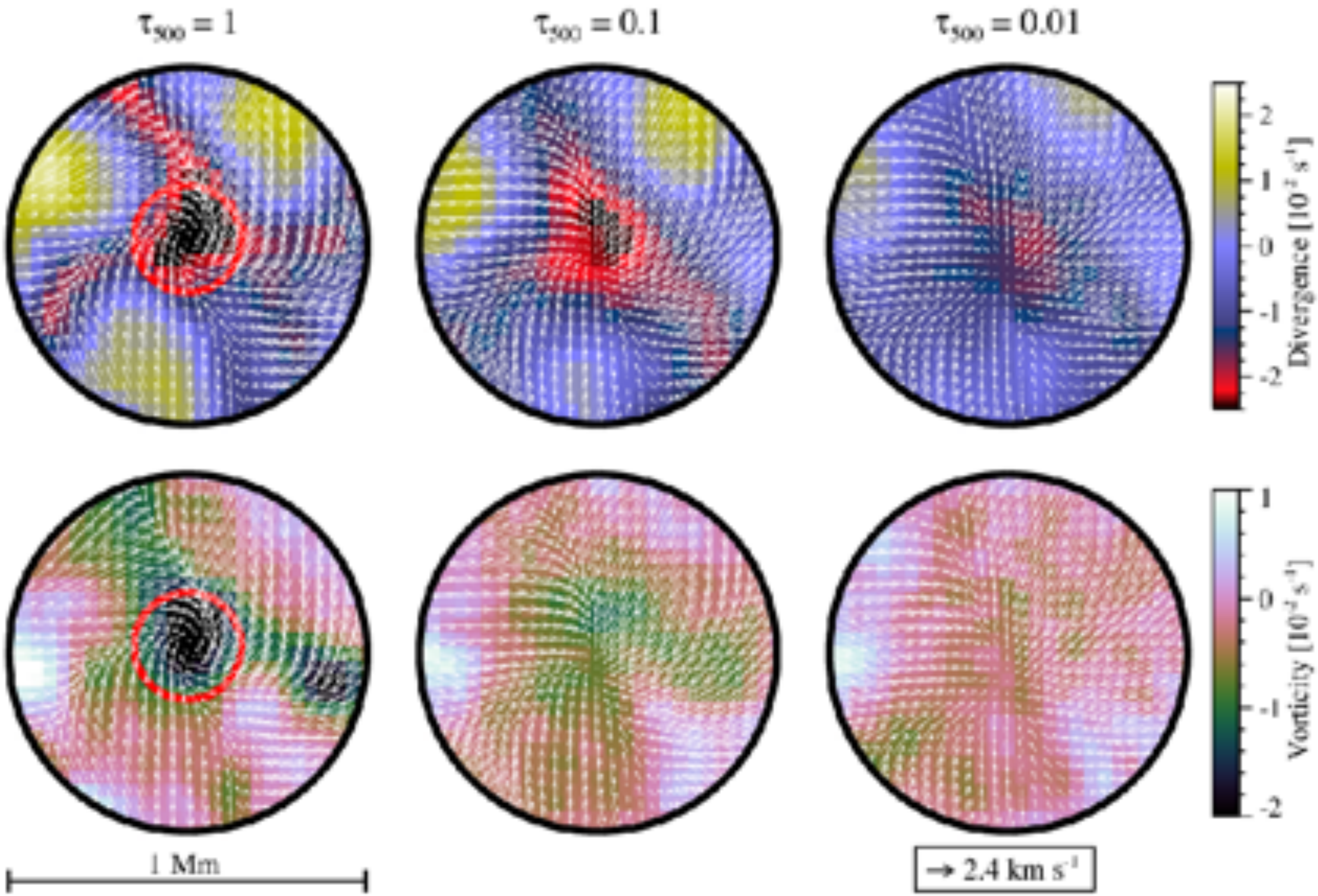
v_x, v_y

DEEPVEL https://github.com/aasensio/deepvel



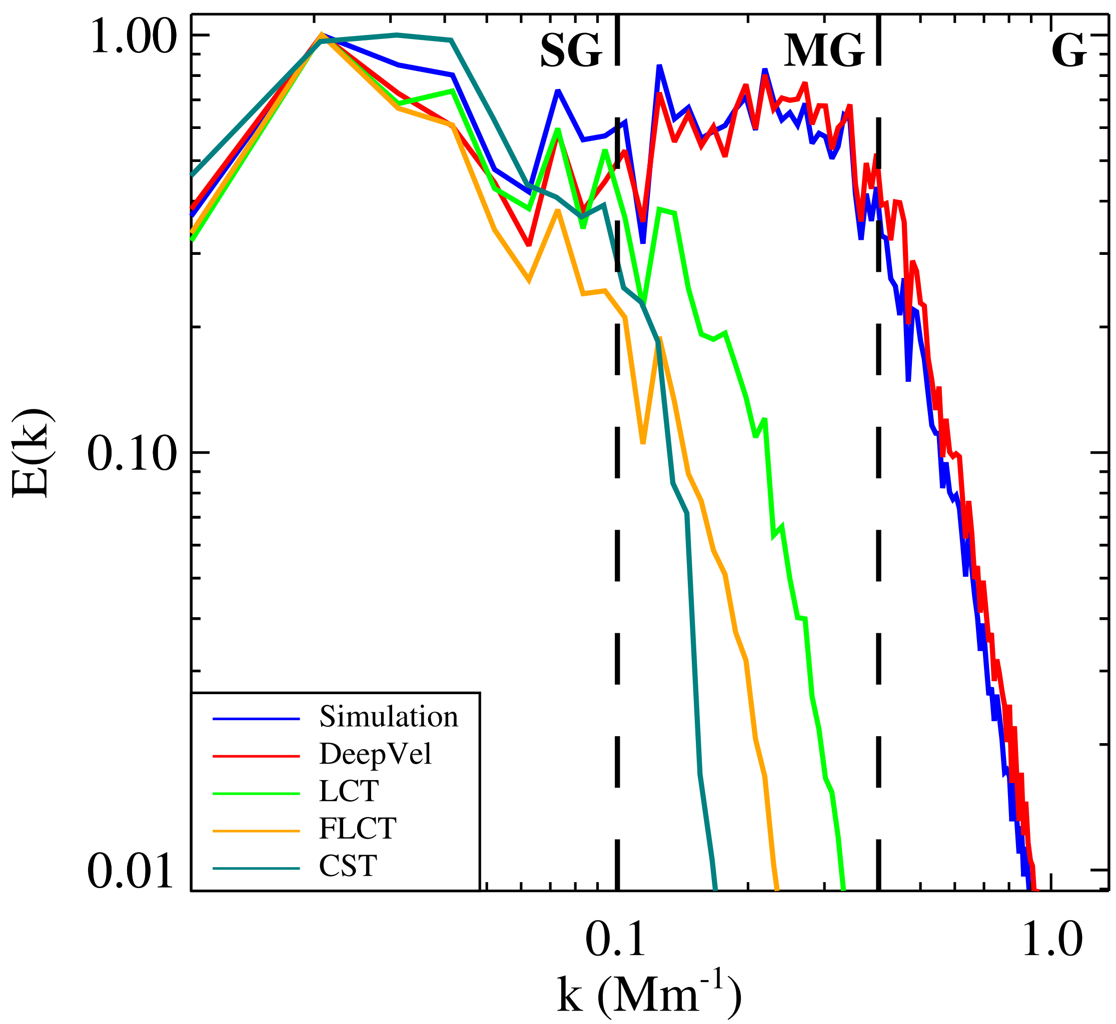
Asensio Ramos, Requerey & Vitas (2017)

SMALL SCALE VORTEX FLOWS

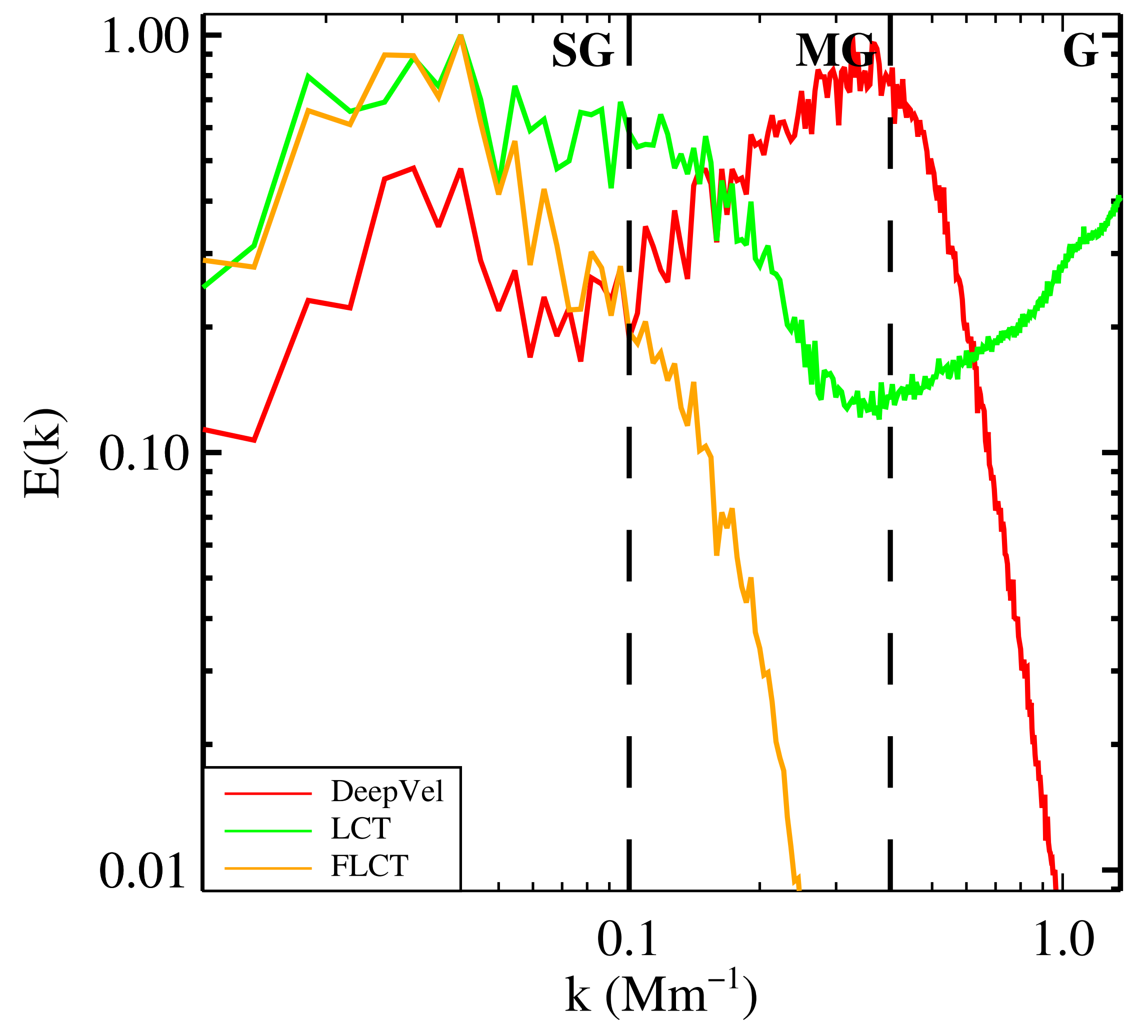


KINETIC ENERGY SPECTRUM

Simulations



SDO/HMI

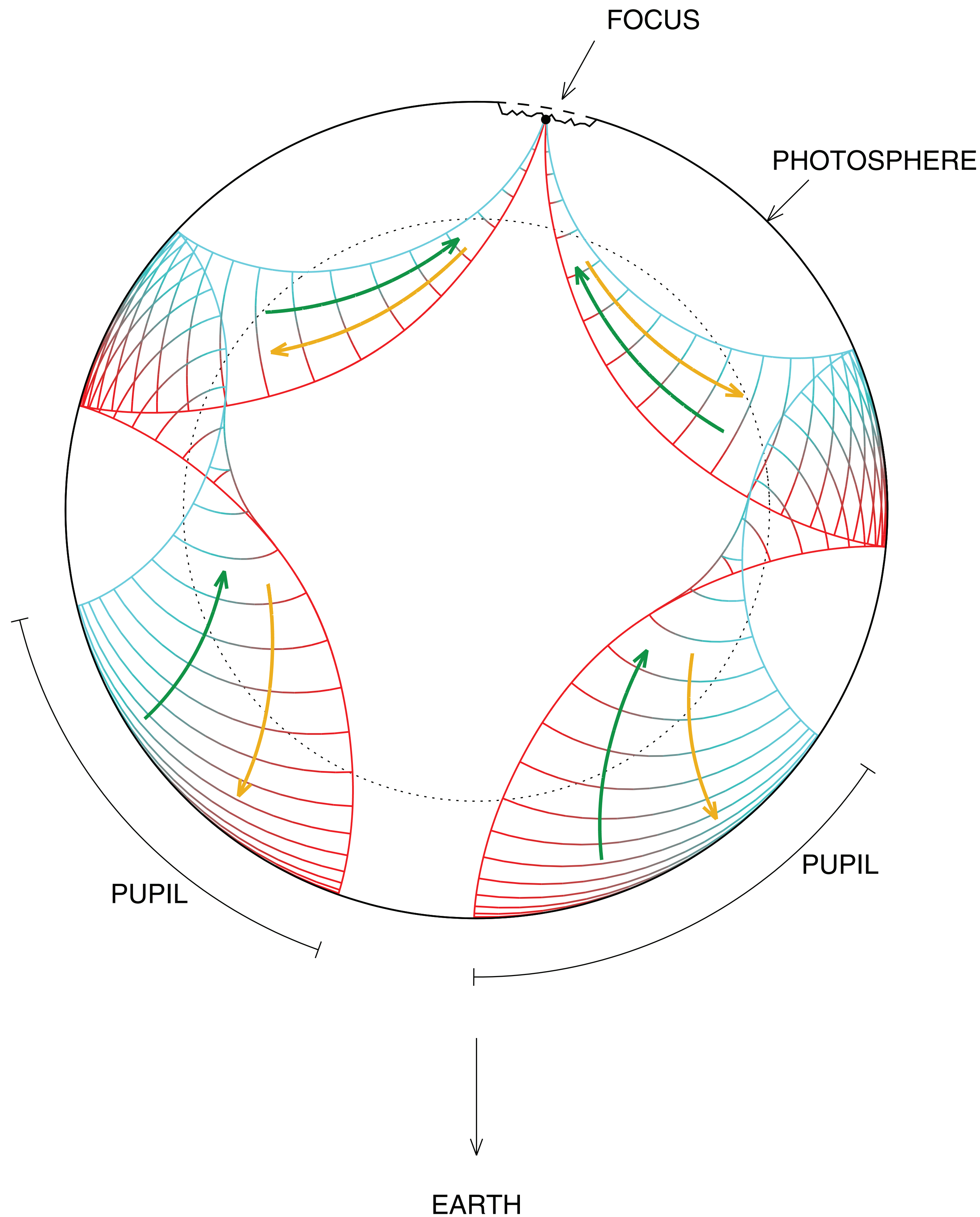


Tremblay et al. (2018)

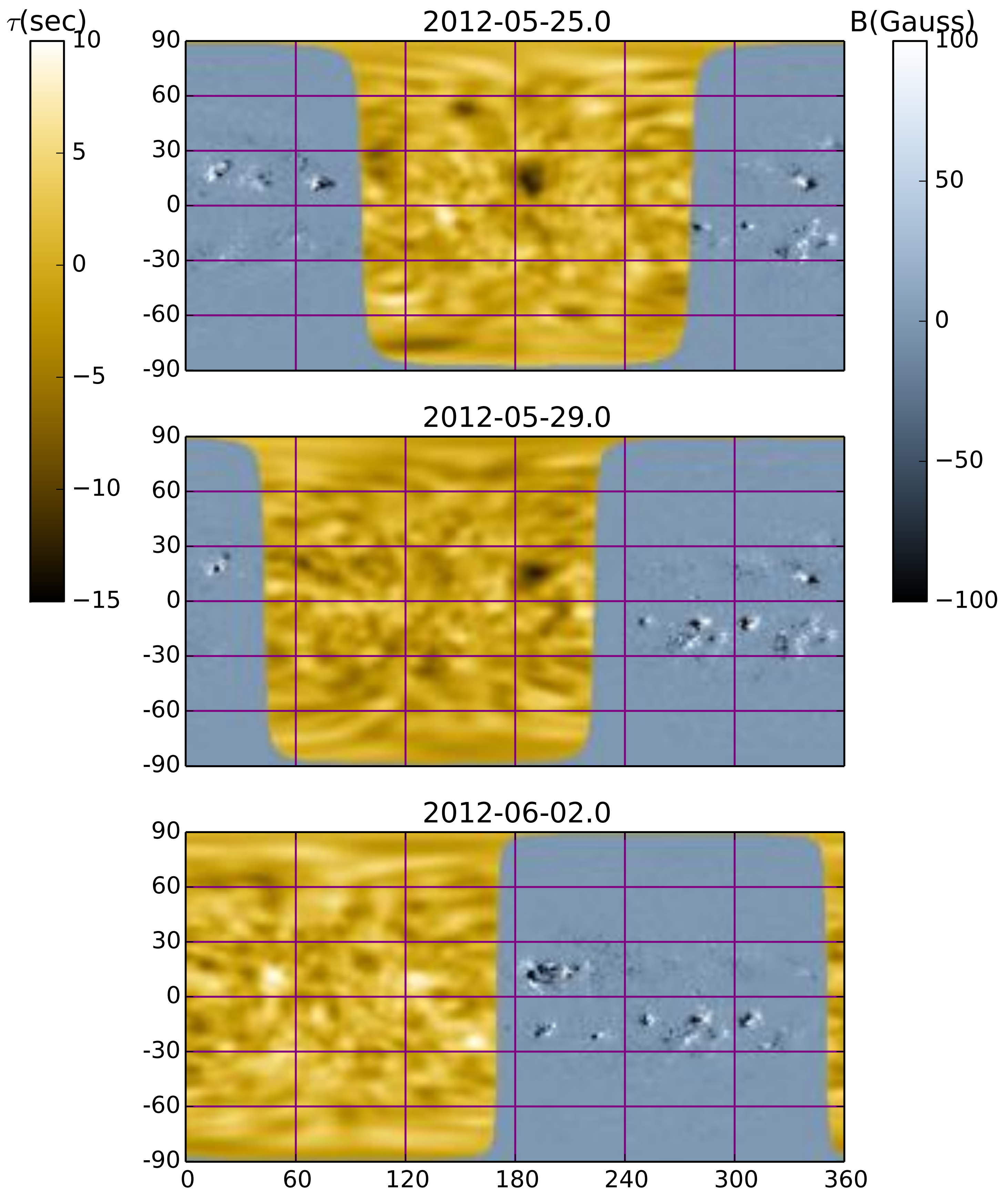
farside enhacement

image segmentation

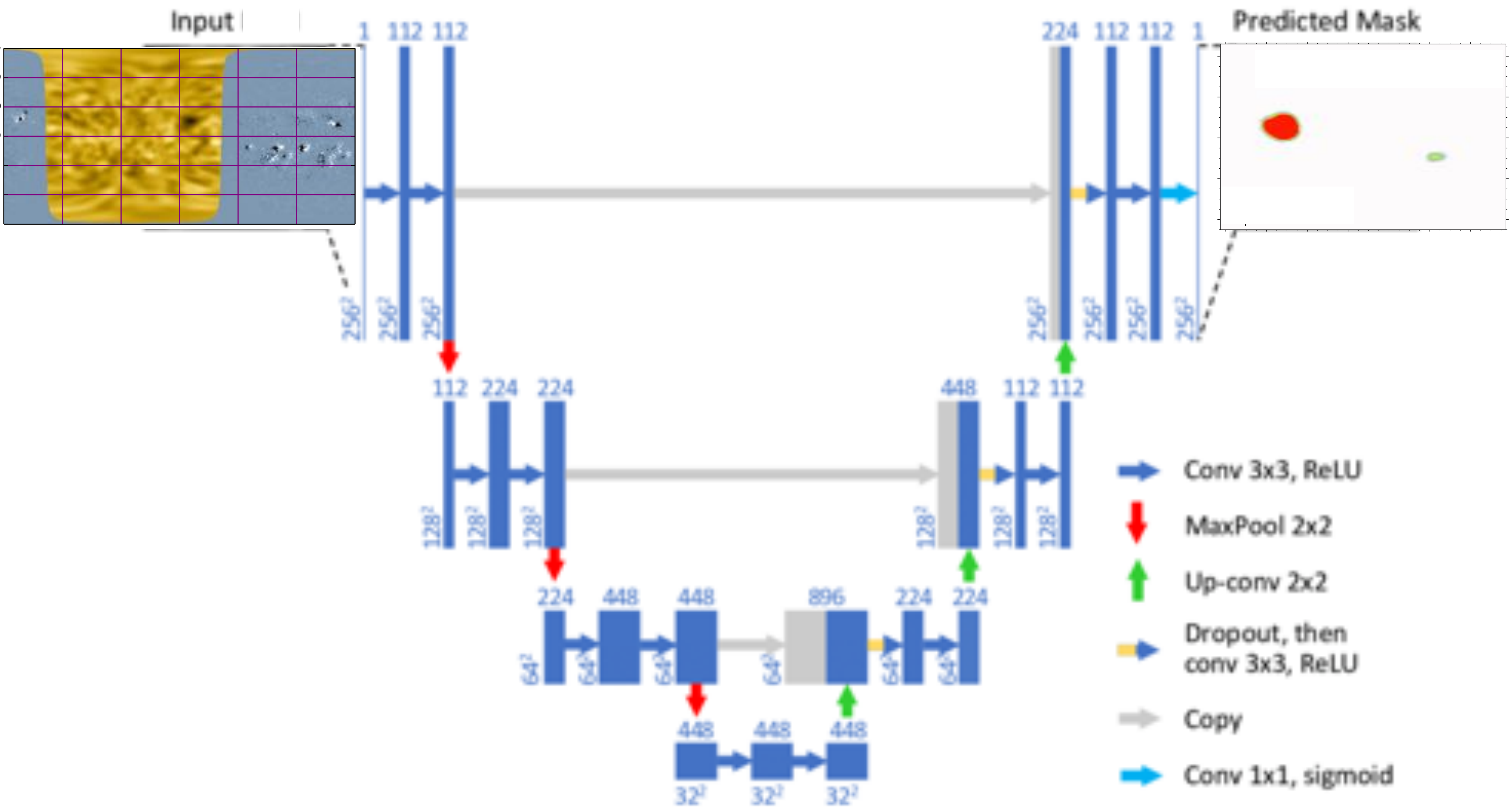
FARSIDE PROBLEM



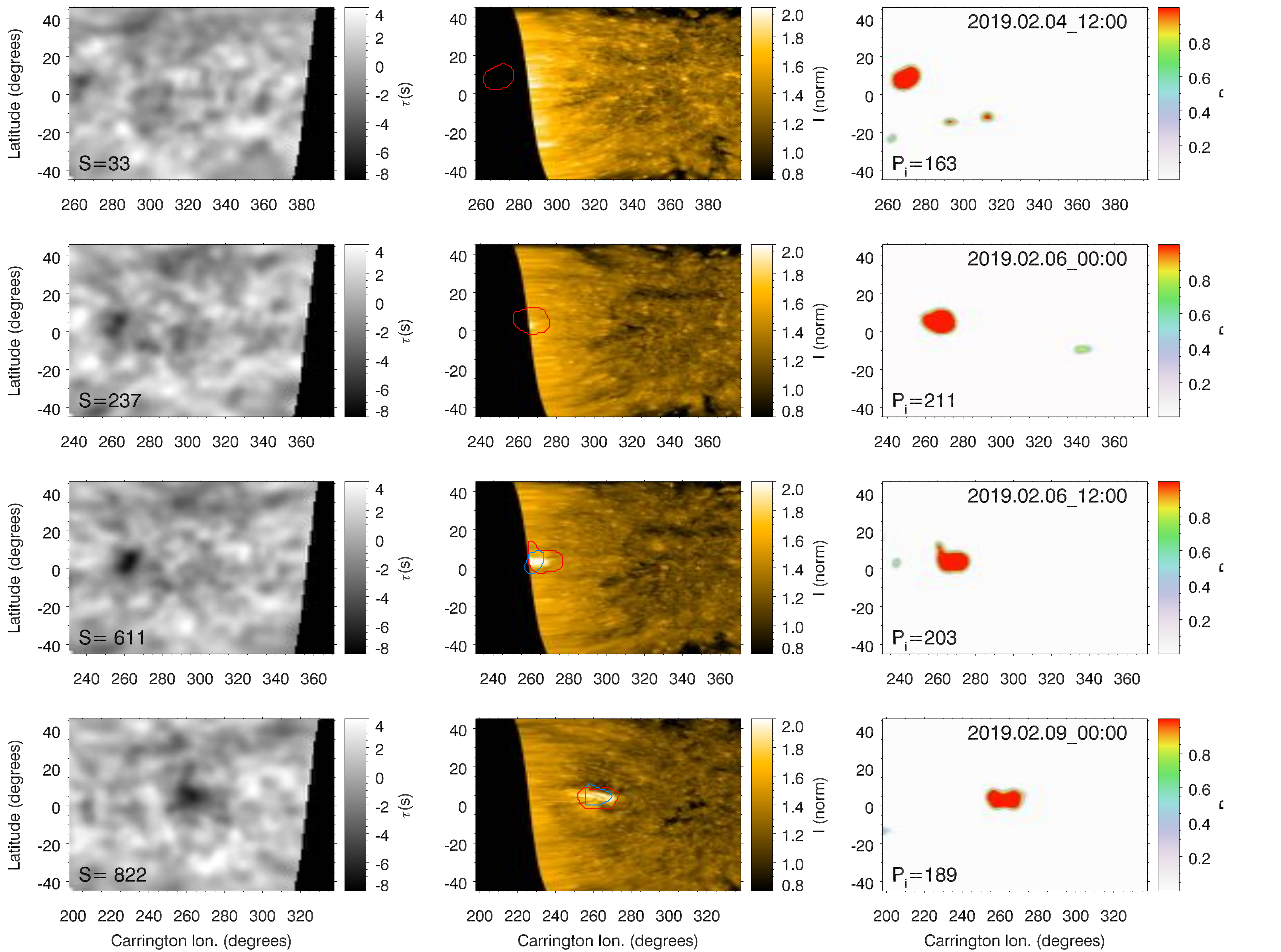
CURRENT FARSIDE PREDICTIONS



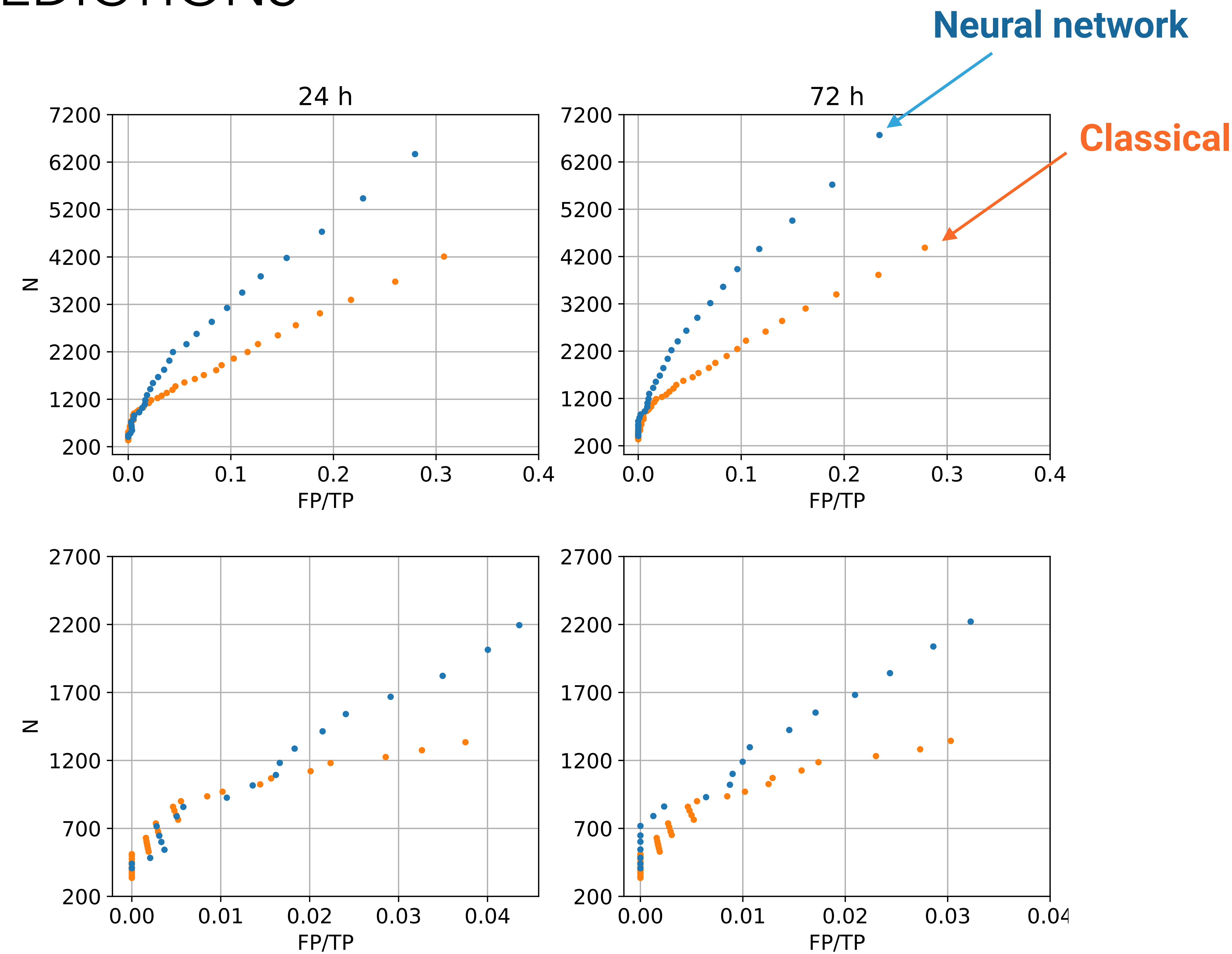
U-NET ARCHITECTURE



OUR PREDICTIONS



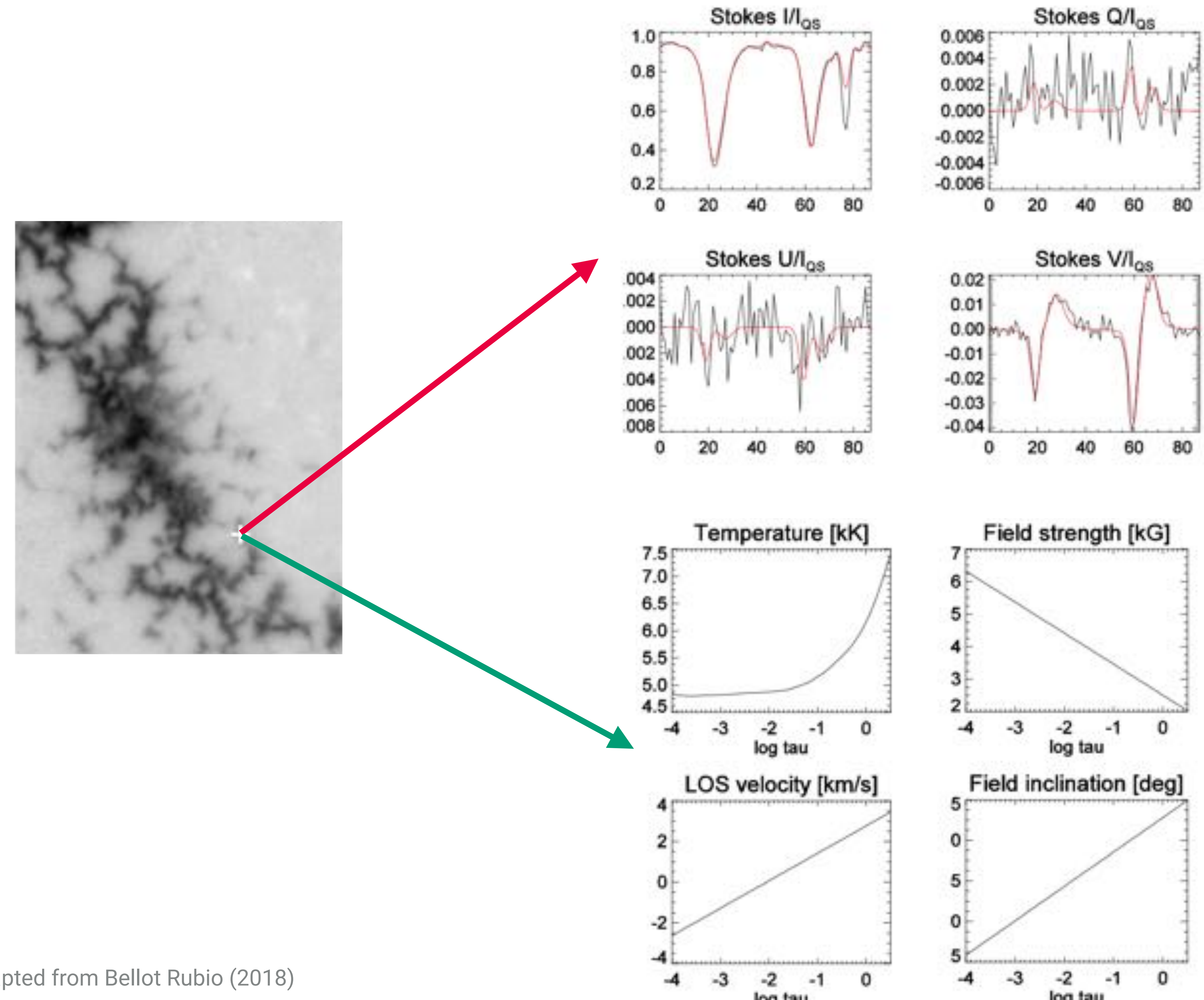
OUR PREDICTIONS



García Brook et al. (submitted)

spectropolarimetric inversions

SPECTROPOLARIMETRIC INVERSIONS



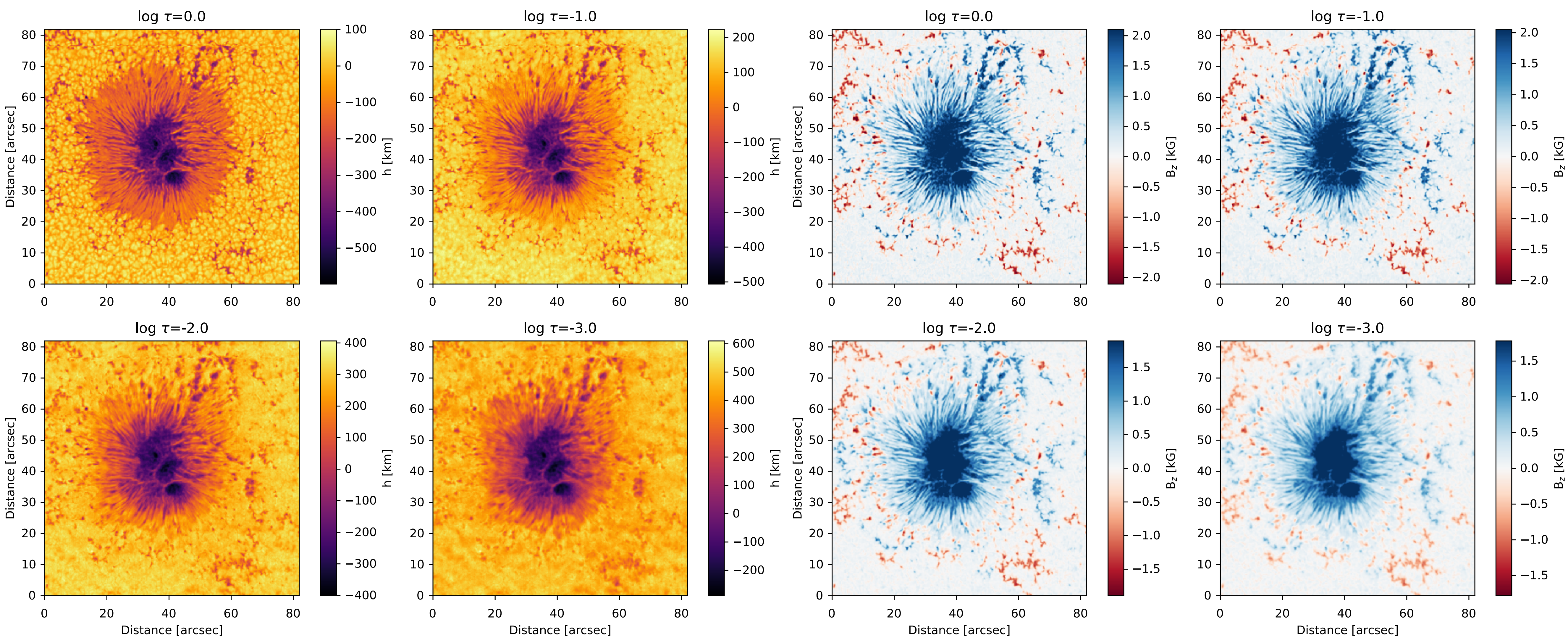
Adapted from Bellot Rubio (2018)

SPECTROPOLARIMETRIC INVERSIONS

AR10933 : INFERENCE

τ surfaces

Bz

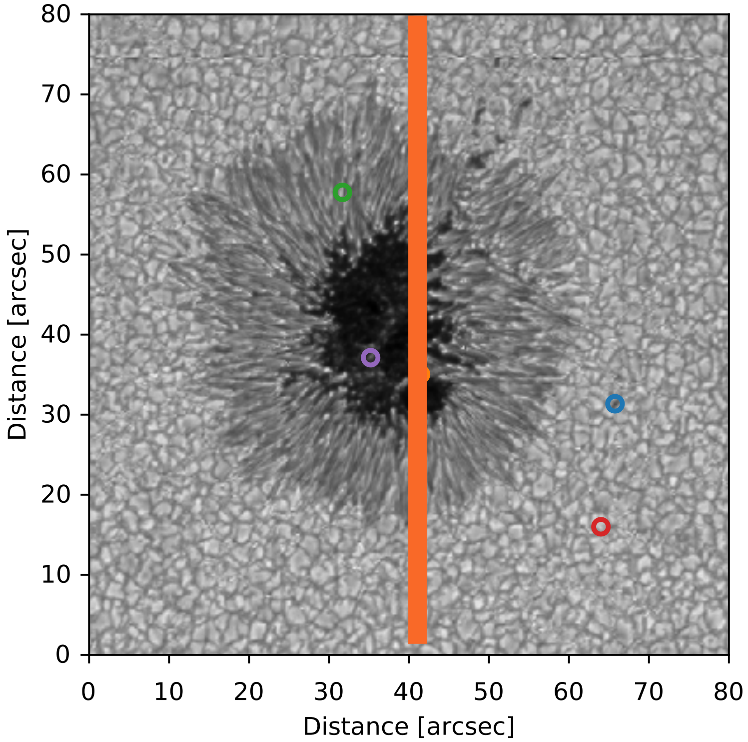


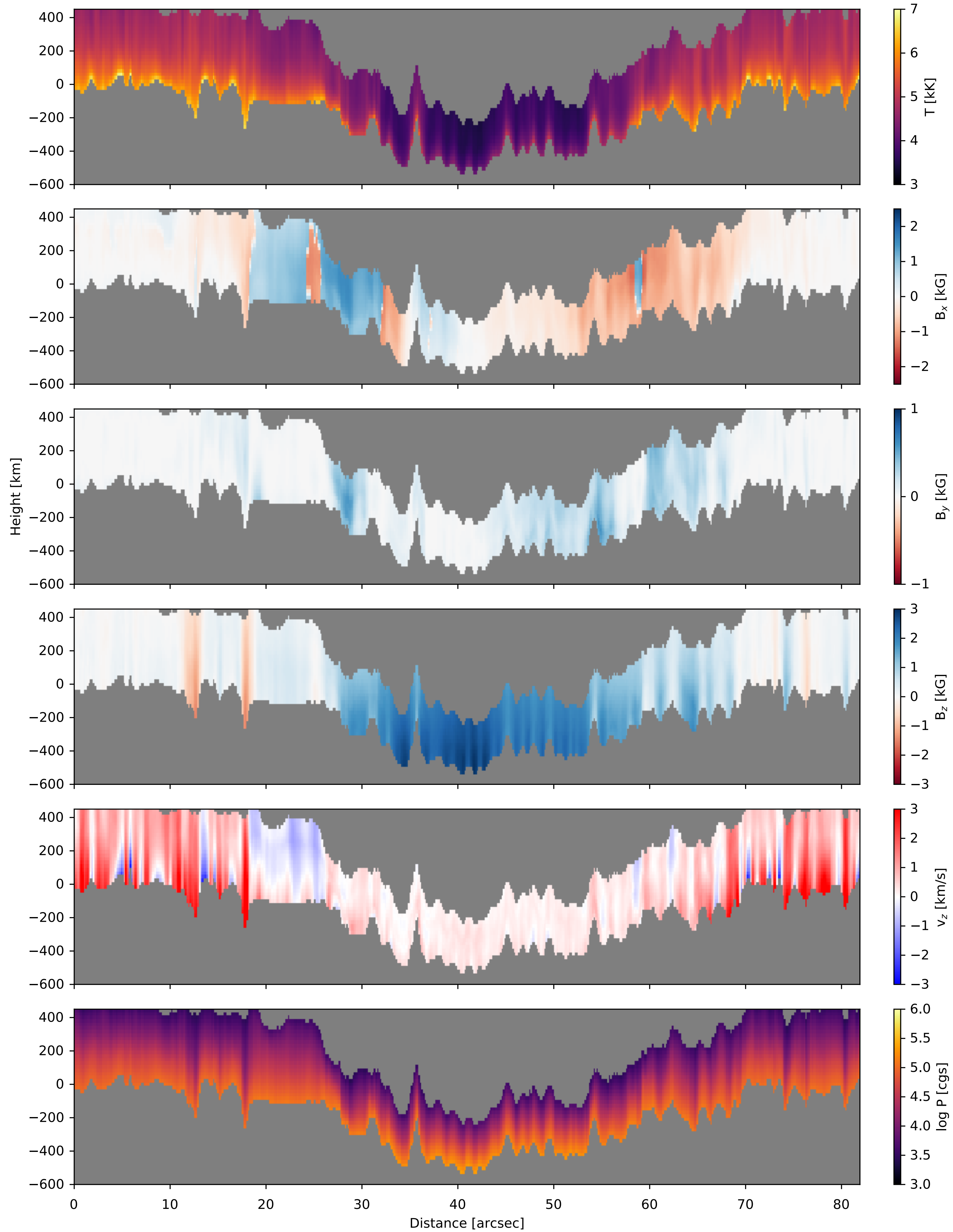
180 ms for 512x512

700 ns per pixel

30 minutes for all Hinode observations

LIGHT BRIDGE





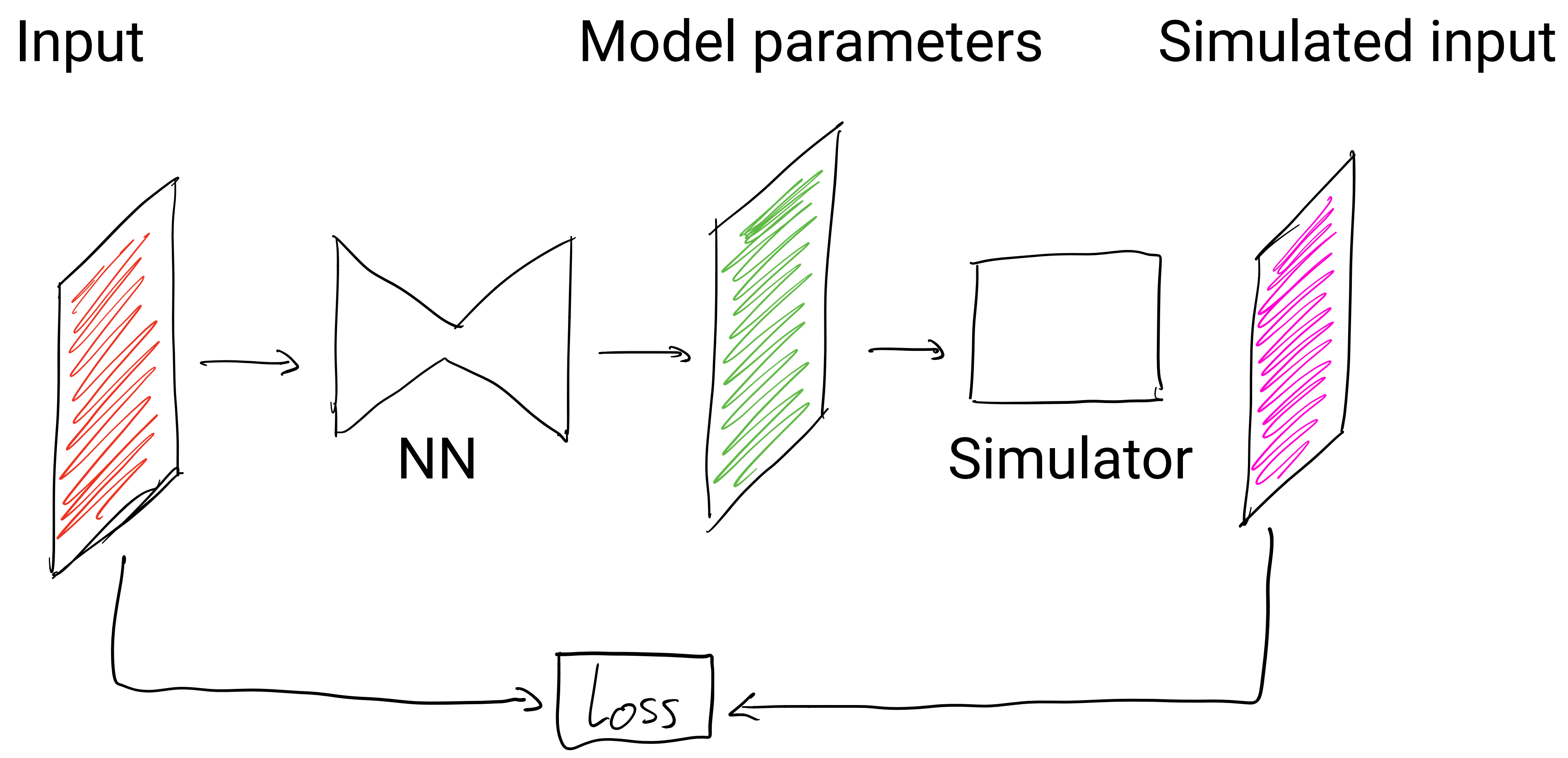
physics-based losses

&

surrogate models

PHYSICS-BASED LOSSES

- Use our knowledge of physics
- Make use of differentiable simulators
- Train unsupervisedly



SURROGATE MODELS

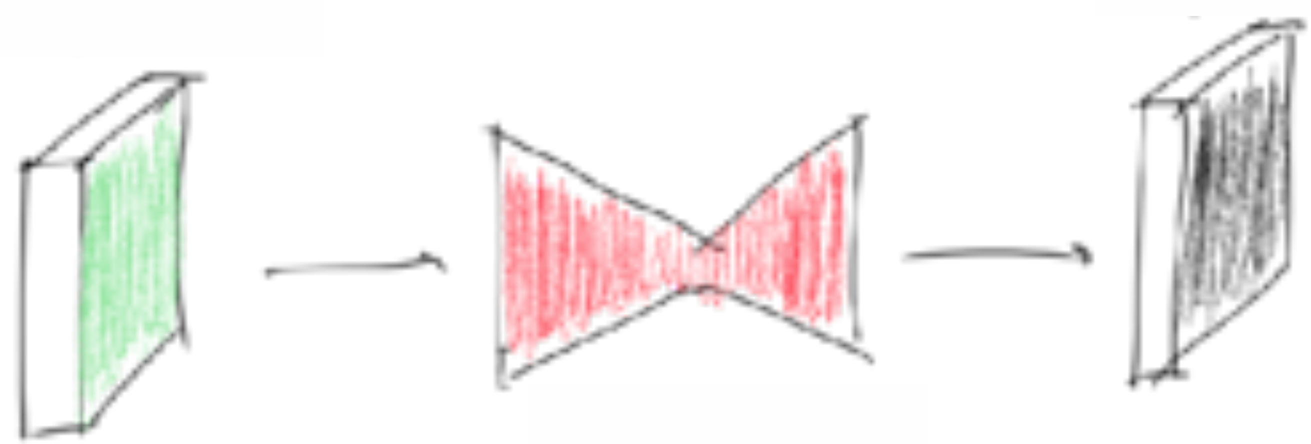
If model → output synthesis is complex and time consuming

Model parameters

Synthesis

and train this well-defined mapping on observations/simulations

SURROGATE MODELS



- Fast Bayesian inference (Hamiltonian Montecarlo)
- Fast classical inversions
- Fast classical inversions via emulators+loop unrolling

$$\theta_{i+1} = \theta_i + \left[\mathbf{J}^{\mathrm{T}}\mathbf{J} + \lambda\,\mathrm{diag}\left(\mathbf{J}^{\mathrm{T}}\mathbf{J}\right)\right]^{-1}\mathbf{J}^{\mathrm{T}}[\mathbf{y} - \mathbf{f}(\boldsymbol{\beta})]$$

$$\theta_{i+1} = \theta_i + g[\mathbf{J}, y, \mathbf{f}(\boldsymbol{\beta})]$$

UNSUPERVISED MULTIFRAME BLIND DECONVOLUTION

Can training be done unsupervisedly?

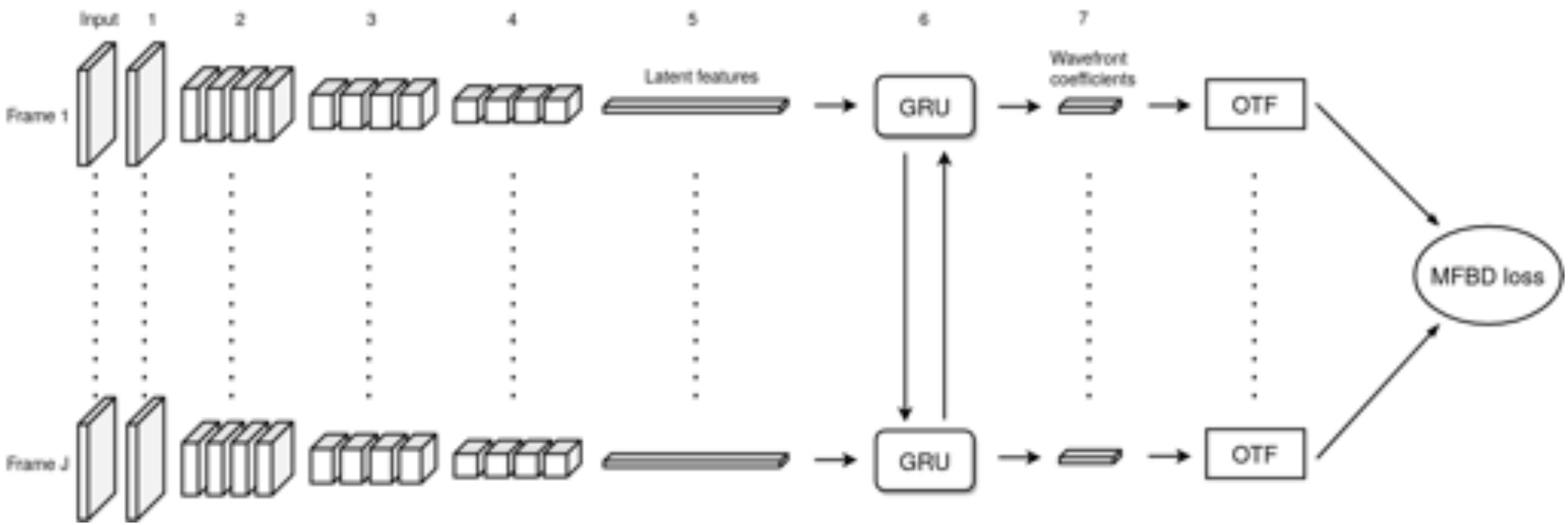
$$L_i\left(\boldsymbol{\alpha}_i\right) = \sum_u \left[\sum_j^J \left|D_{ij}\right|^2 - \frac{\left|\sum_j^J D_{ij}^* \hat{S}_{ij}\right|^2}{\sum_j^J \left|\hat{S}_{ij}\right|^2 + \gamma_i}\right]$$

$$P_{ij} = A_{ij} \exp\left\{\mathrm{i}\phi_{ij}\right\}$$

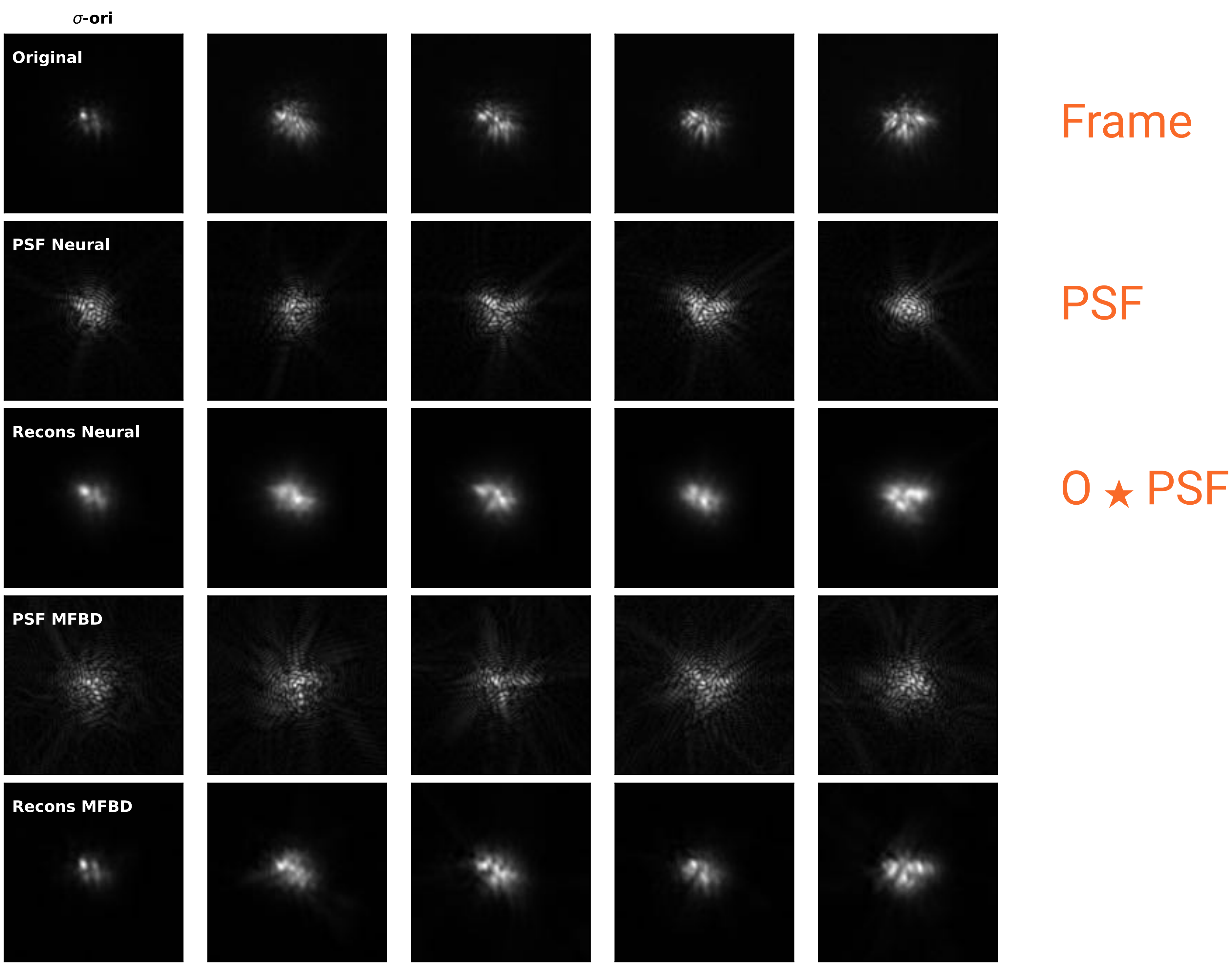
$$\phi_{ij} = \sum_k \alpha_k Z_k(r,\theta)$$

$$S_{ij} = P_{ij} \otimes P_{ij}$$

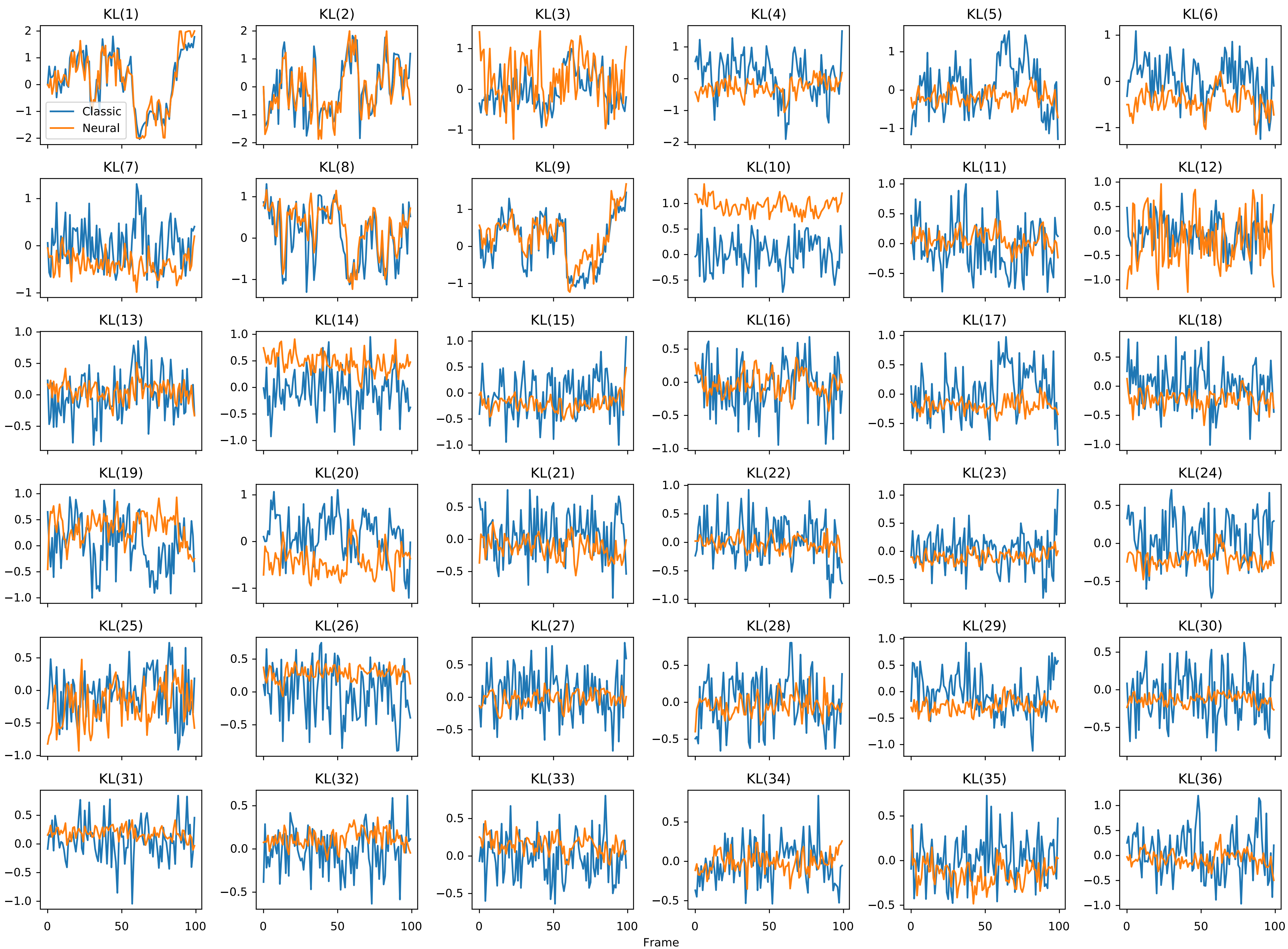
NEURAL MULTIFRAME BLIND DECONVOLUTION



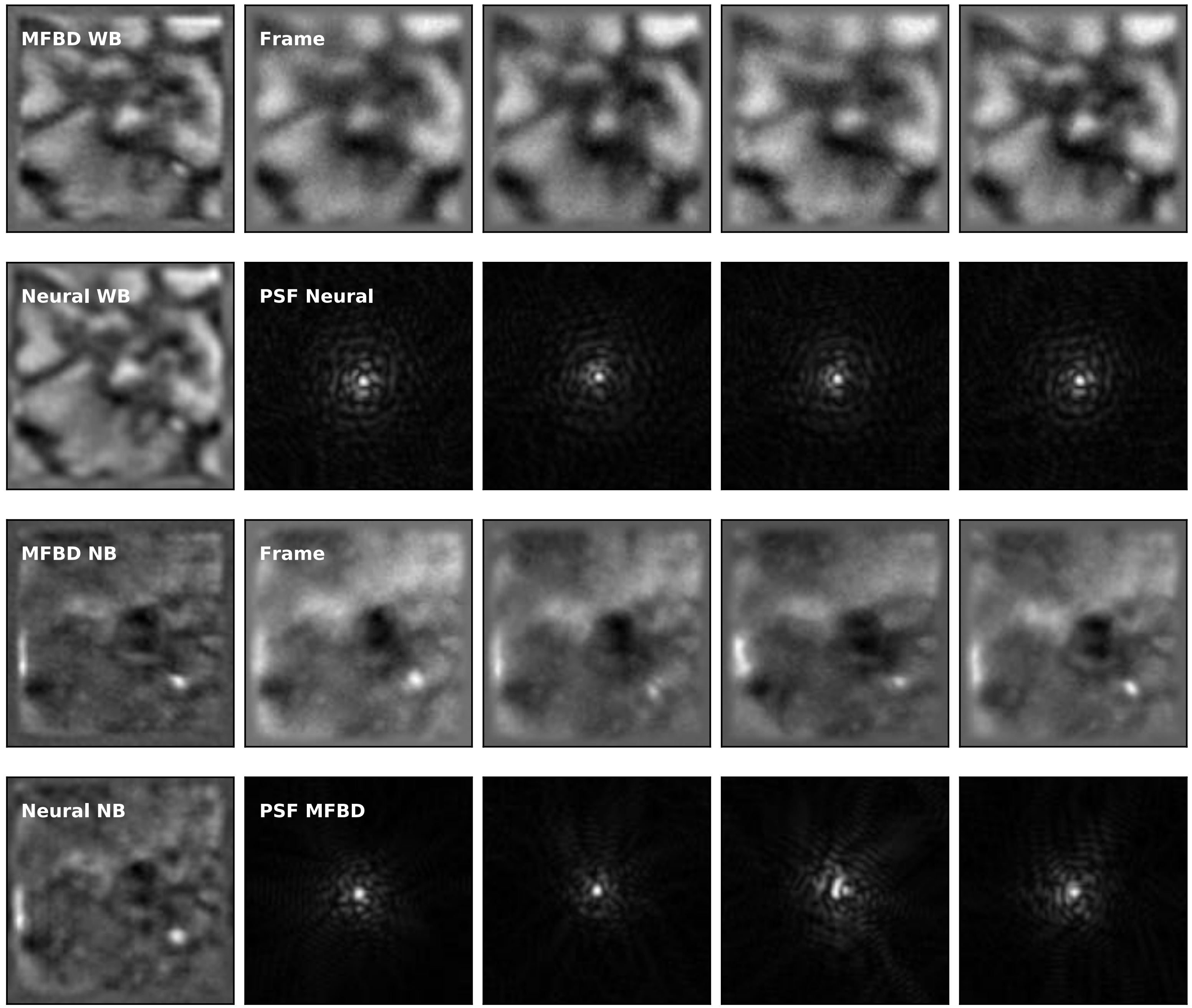
MULTIFRAME RECONSTRUCTION OF STARS



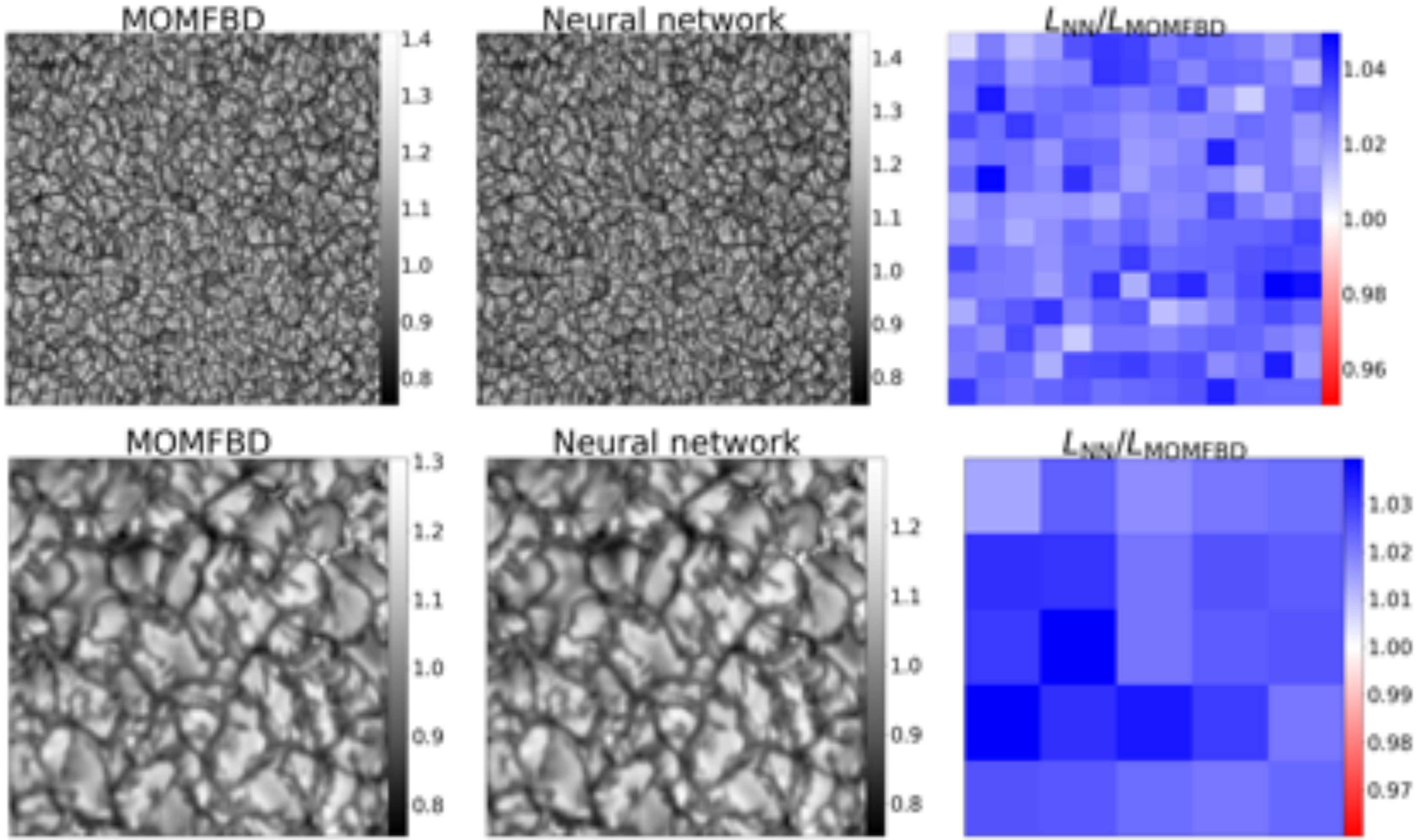
KARHUNEN-LOÈVE MODES



EXTENDED OBJECTS

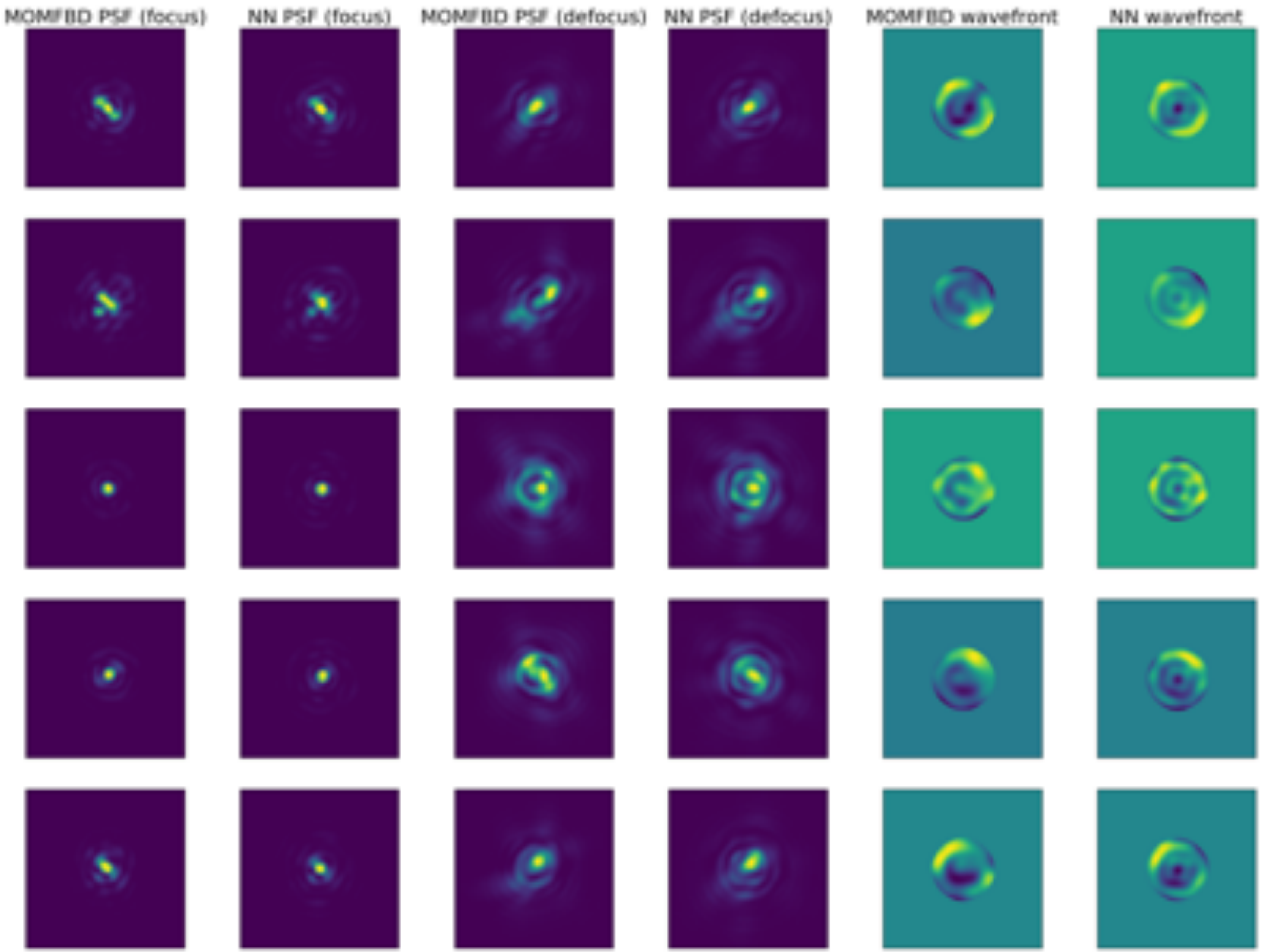


EXTENDED OBJECTS

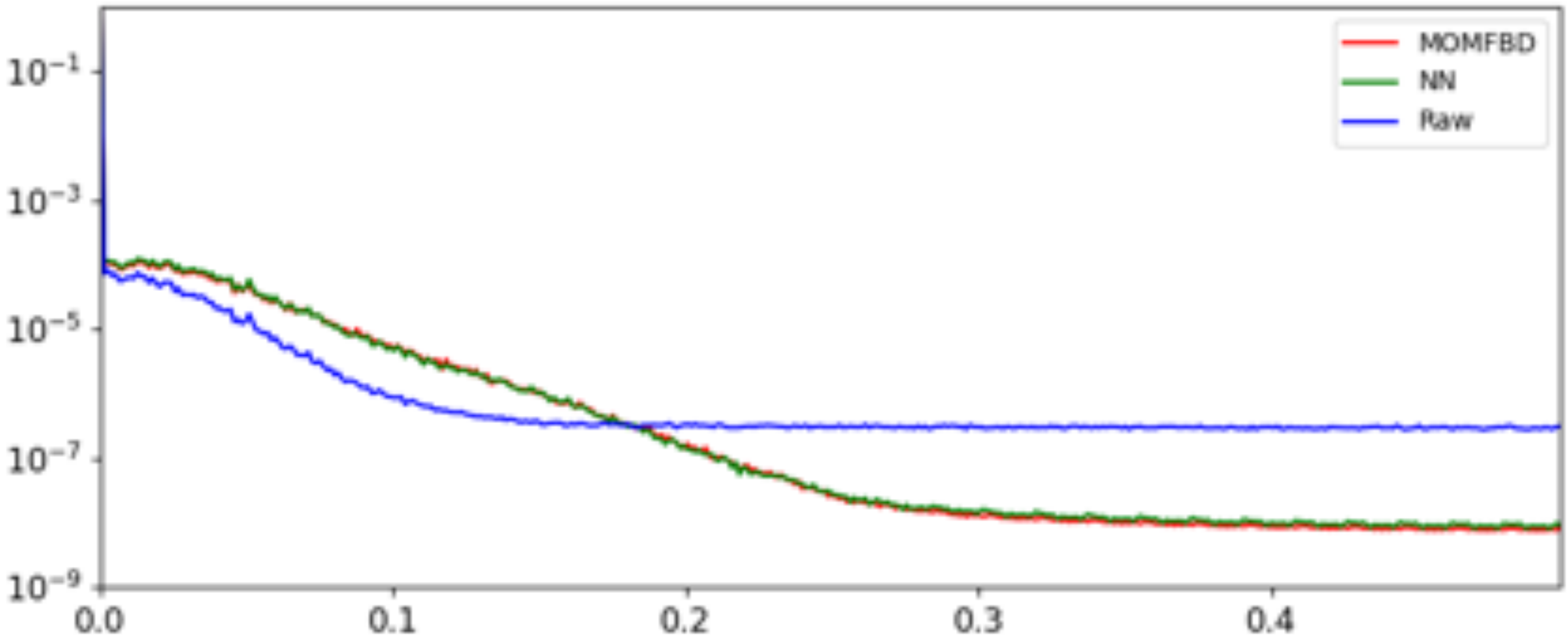


KL COEFFICIENTS

POINT SPREAD FUNCTIONS



POWER SPECTRUM



CONCLUSIONS

- ML can produce inferences for images/tensors at very fast rates
- Linear & nonlinear forward problems
- Tend towards physics-based losses
  - Inform algorithms
  - Train unsupervisedly with physics
  - Bayesian inference
  - Bypass some parts of the calculations with ML
- My examples were in Solar Physics but I hope they are motivating for applying them to your field