

# Spatial field reconstruction with INLA: application to IFU galaxy data

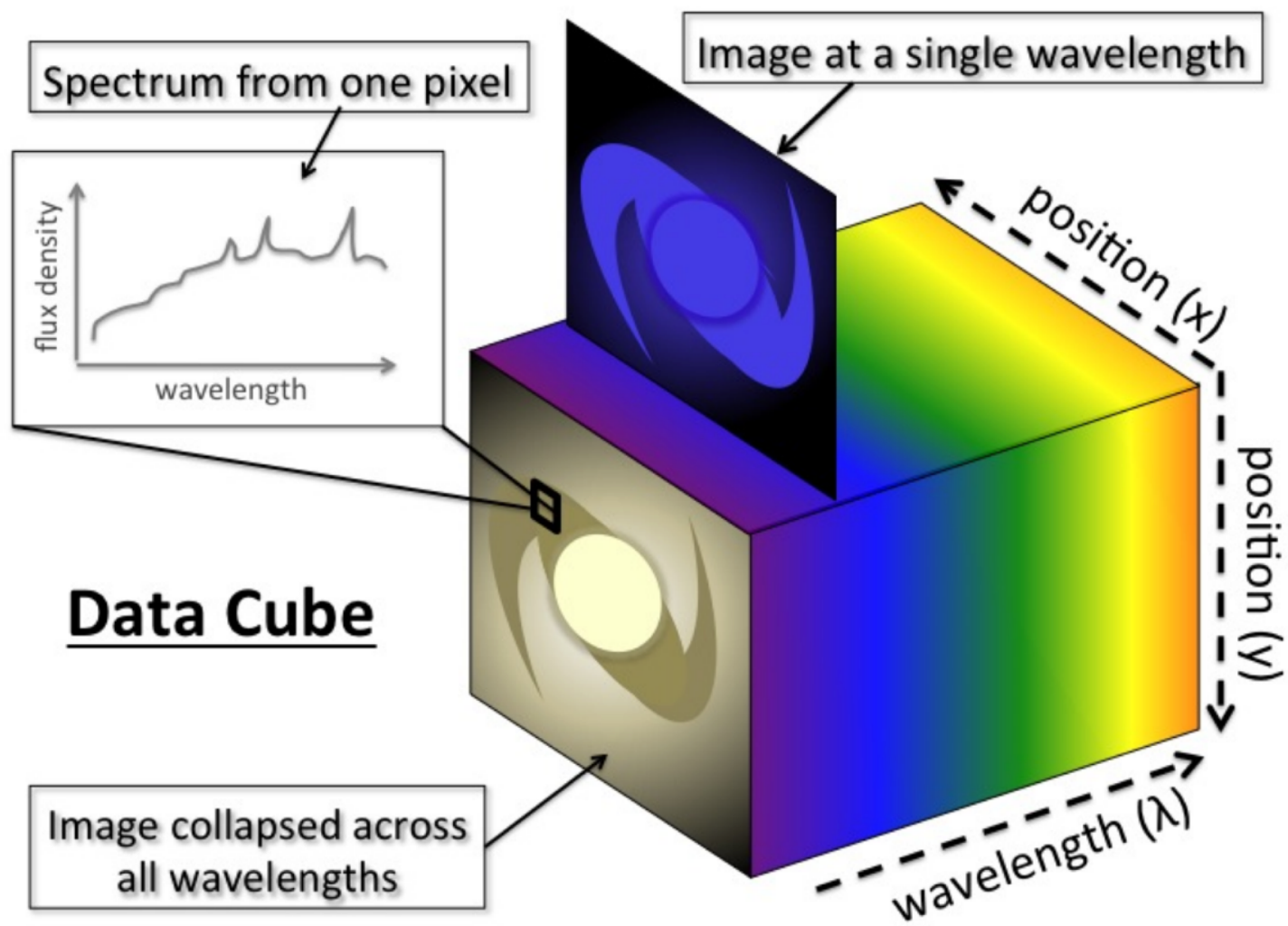
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L. Galbany <sup>ID</sup>, <sup>6</sup> E. E. O. Ishida <sup>7</sup> and for the COIN collaboration

Behzad Tahmasebzadeh

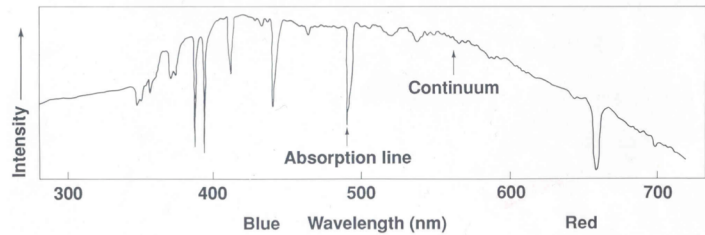
Astrostats club

11<sup>th</sup> Oct 2021

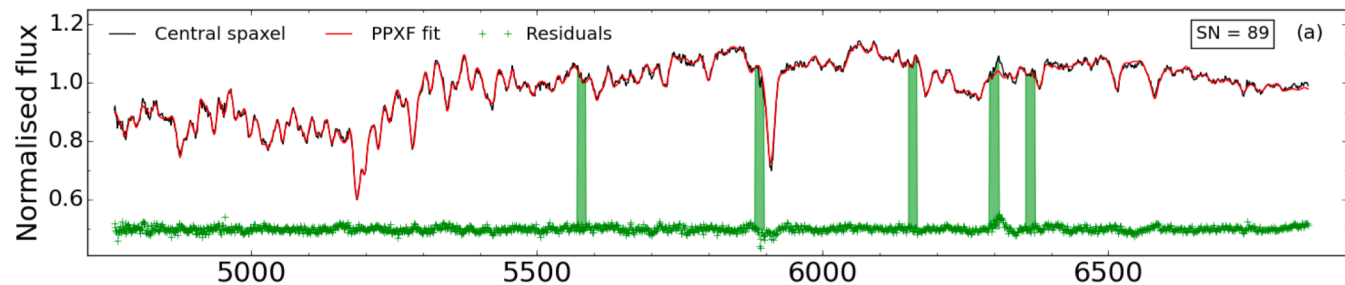
# IFU data



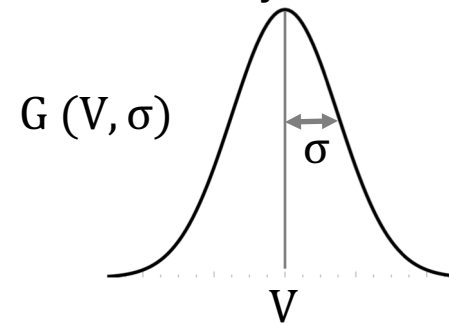
# Stellar Spectrum template



By spectral fitting we can get  
Age, metallicity and kinematics



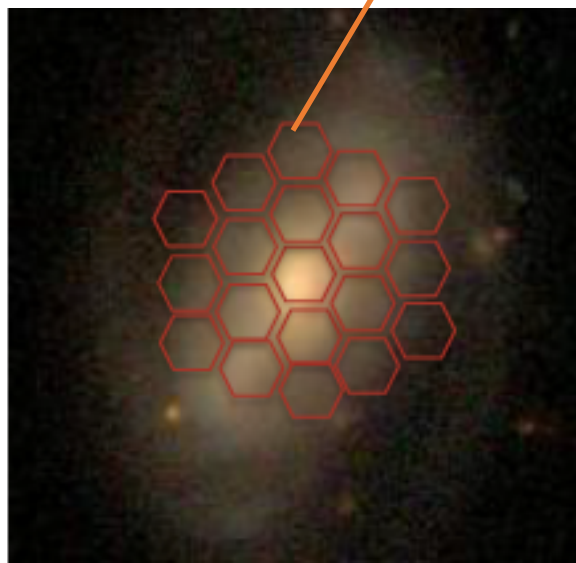
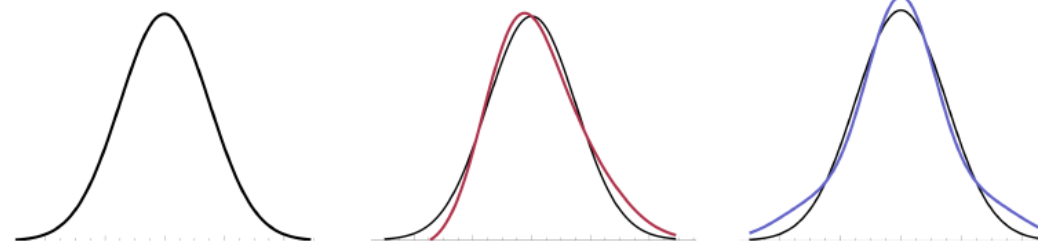
# LOS Velocity distribution



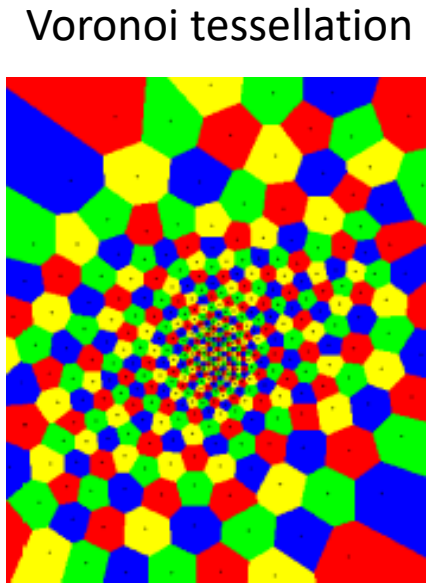
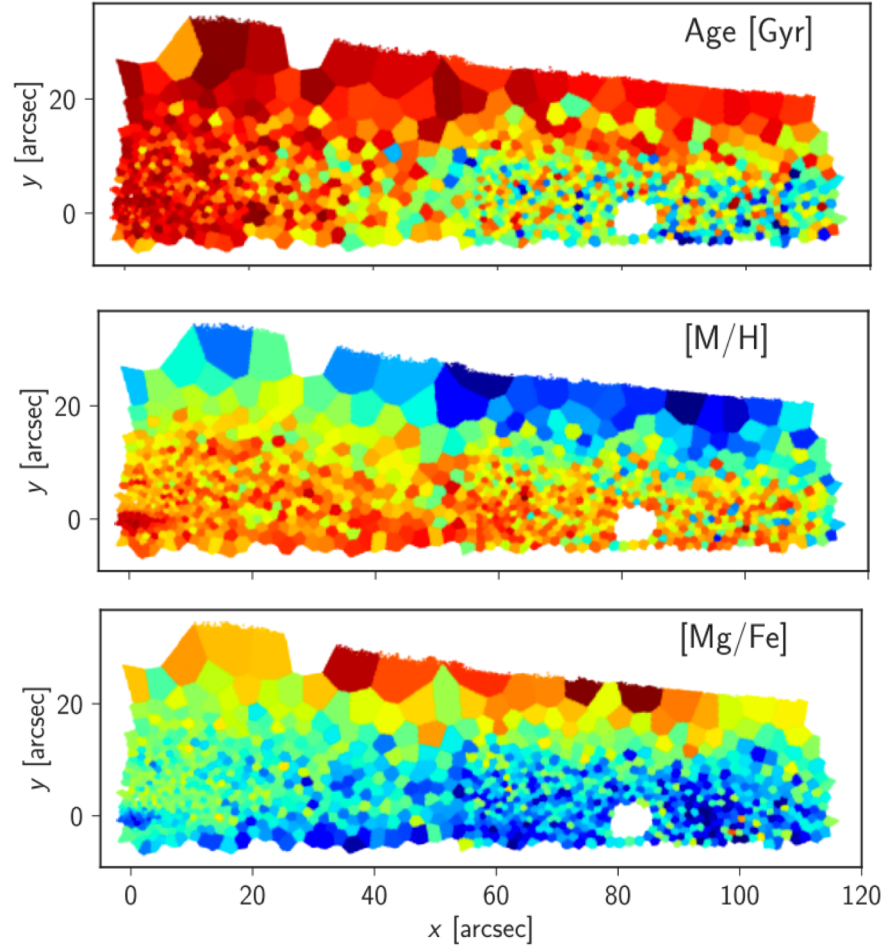
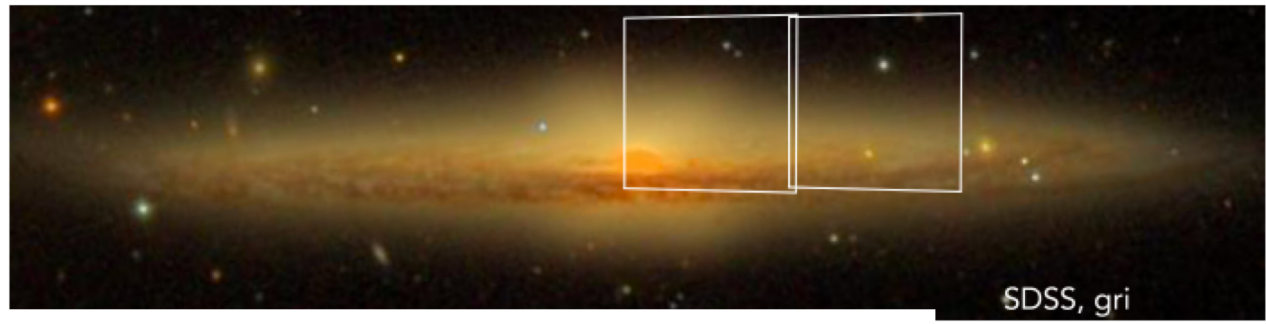
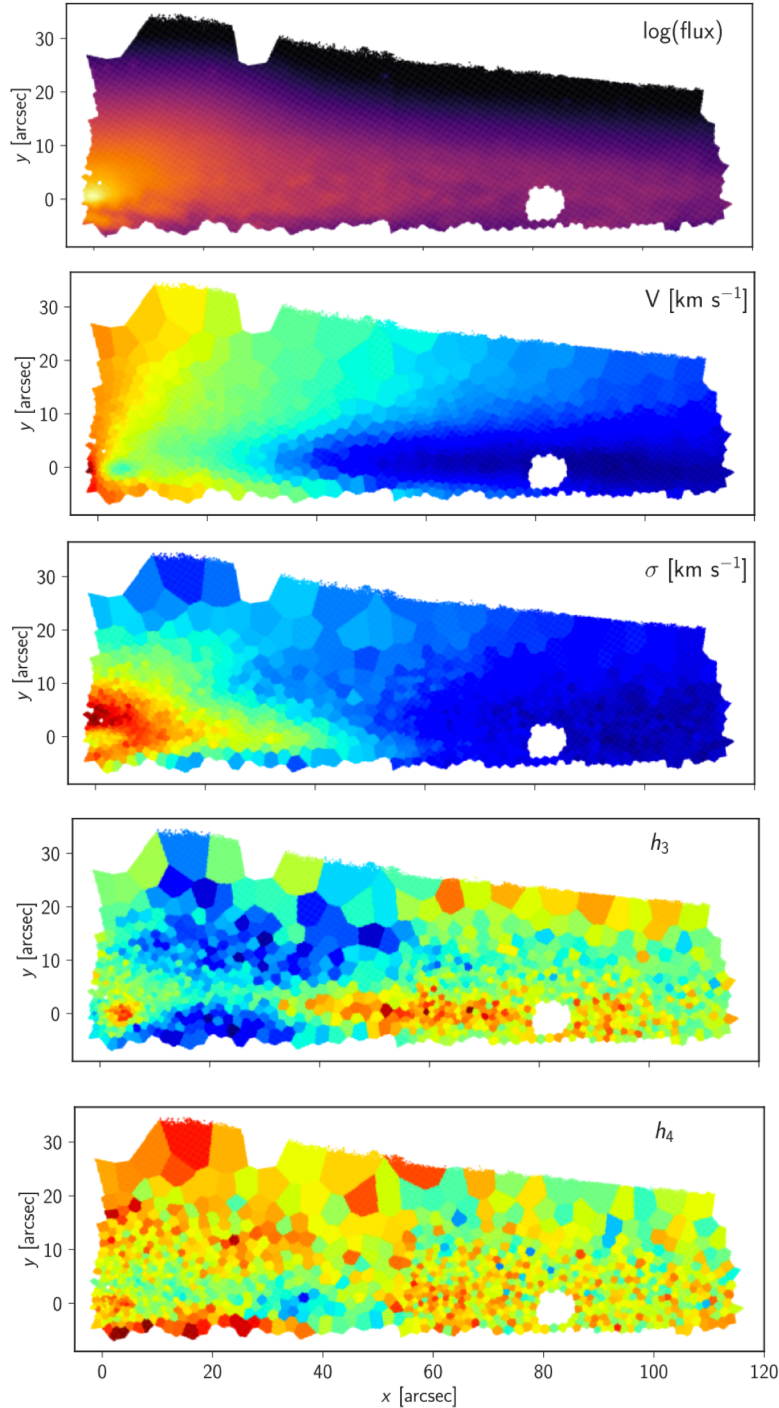
$h_3 = 0, h_4 = 0$

$h_3 = 0.1, h_4 = 0$

$h_3 = 0, h_4 = 0.1$



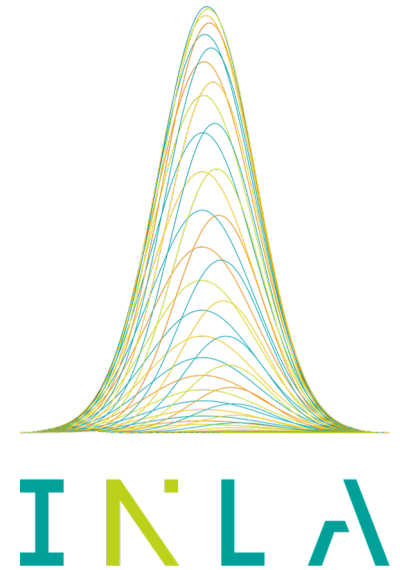
- ATLAS 3D: 260 early type galaxies
- CALIFA: 300 all Hubble types, field galaxies
- MANGA: ~10,000, all Hubble types, field galaxies
- SAMI: a few thousands, galaxies in clusters





# The integrated nested Laplace approximation (INLA)

- A method for approximate Bayesian inference.
- Focuses on models that can be expressed as latent Gaussian Markov random fields (GMRF)
- Faster than other methods such as Markov chain Monte Carlo.
- Ease of use via the R-INLA package.



Method: The **i**ntegrated **n**ested **L**aplace **a**pproximation (**INLA**)

- Bayesian inference

$$p(\theta|y) = \frac{\mathcal{L}(y|\theta)\pi(\theta)}{\int \mathcal{L}(y|\theta)\pi(\theta)d\theta}.$$

- Treat the entire matrix as a realization of an underlying random field of a given property.  
e. g. In other words, if treating an age map, the age at a given pixel is not treated as independent, but as spatially correlated to the estimated ages in nearby pixels

- Assumption: For a given property  $z$ , normally distributed around the  $i$ -th pixel with mean value  $\mu_i$  and variance  $\sigma_{px}^2$ .

$$z_i \sim \mathcal{N}(\eta_i, \sigma_{px}^2),$$

$$\eta_i = \mu_i.$$

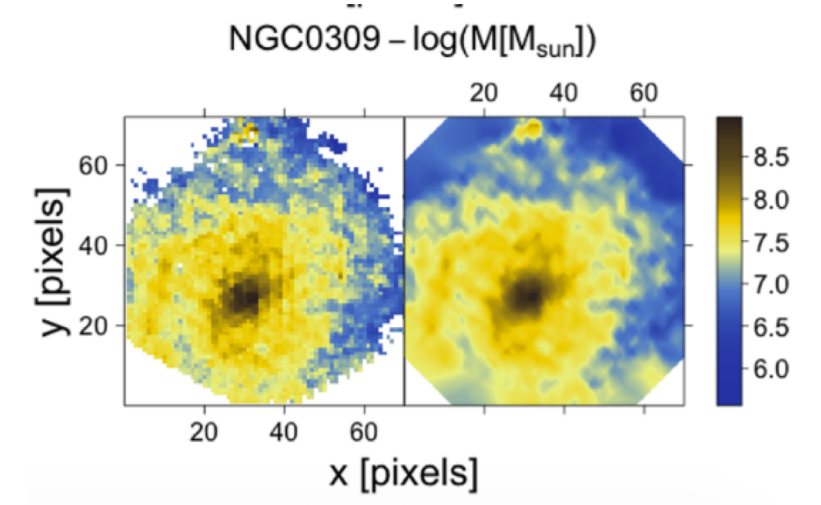
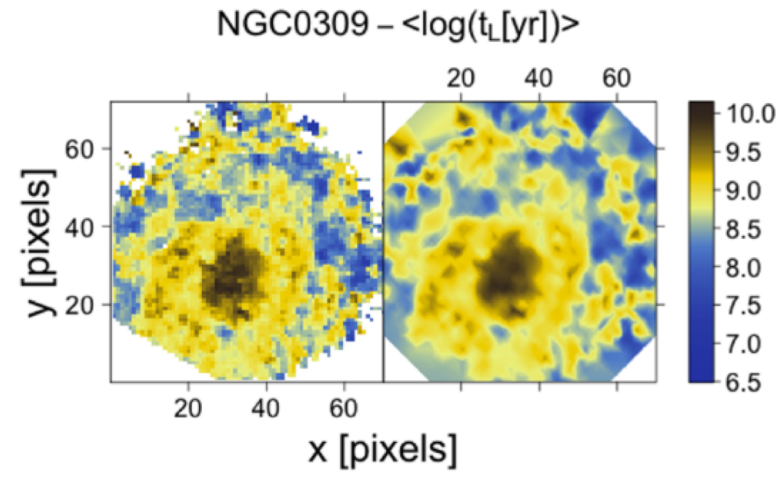
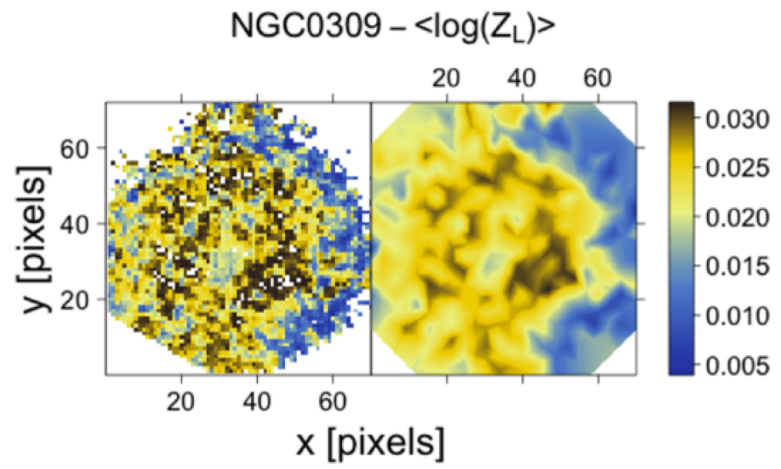
- To approximations of continuous random fields. This work use Gaussian Markov random fields.

With the GMRF definition in place, The model for the spatial distribution of measured galaxy properties can be written in Bayesian.

$$\begin{aligned} z_i &\sim \mathcal{N}(f(x_i), \sigma_i^2), \\ \text{latent image} &\longleftarrow f(\cdot) = g(\cdot) + h(\cdot), \\ g(\cdot) &\sim \mathcal{N}_{\text{GMRF}}[\sigma, \kappa], \\ h(\cdot) &= \alpha + \beta \times \text{edist}(\cdot), \\ \sigma, \kappa, \alpha, \beta &\sim \pi. \end{aligned}$$

# INLA Applications in Astronomy

- Dealing with noisy data

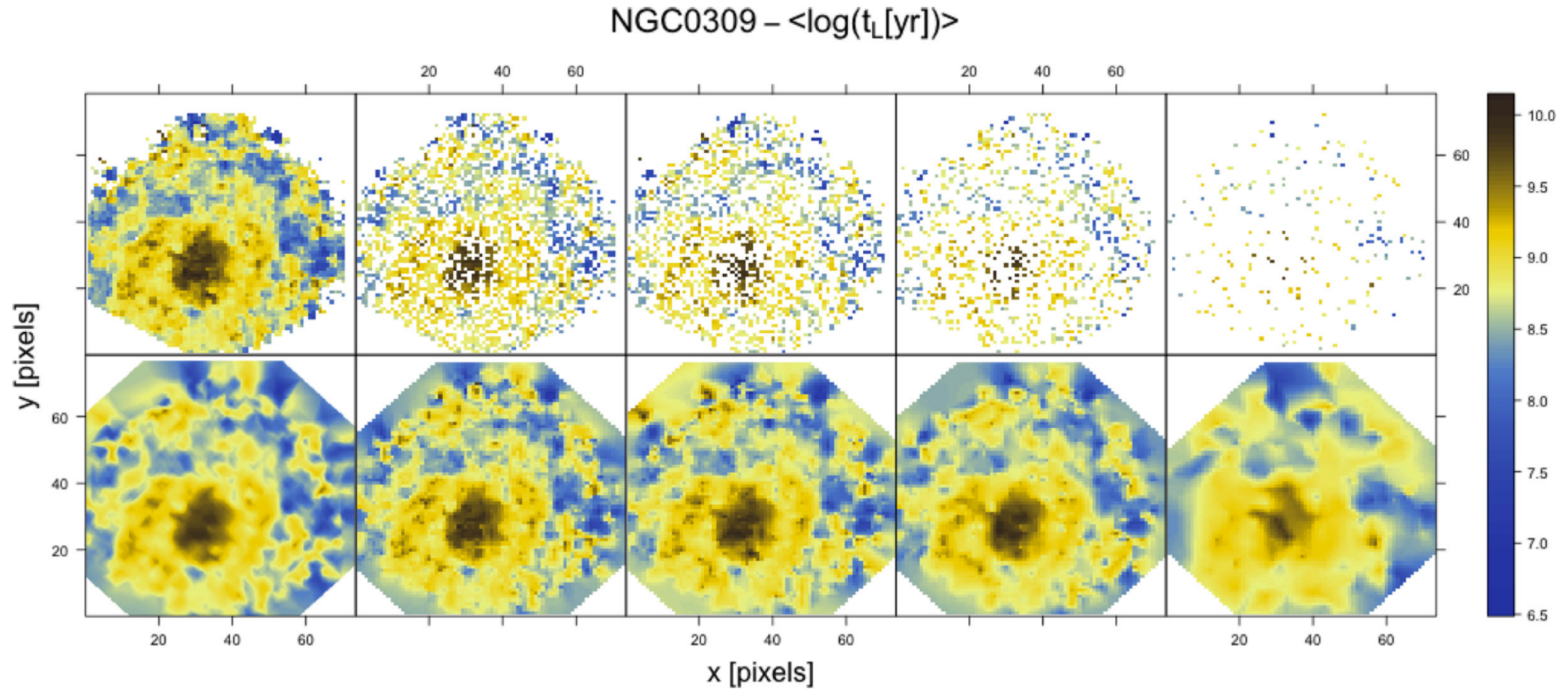


- INLA prediction is not a smoothing convolution of the original data
- Nor does it degrade unnecessarily the image resolution by prior binning of the maps to increase the signal.



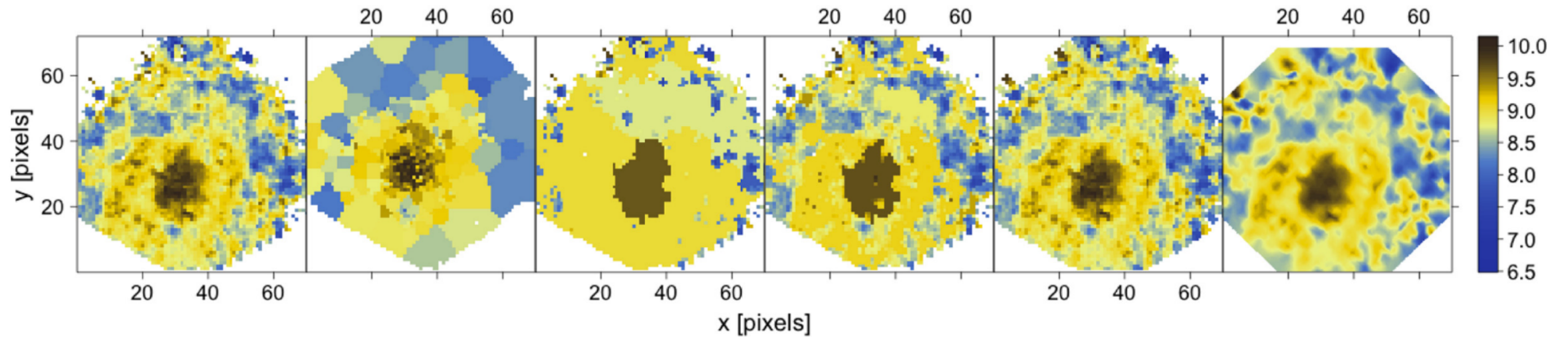
- INLA is able to reconstruct the missing data points

Predictions from INLA for input STARLIGHT age of NGC0309 when 100, 75, 50, 25, and 5 % of the data are used.



# Comparison to other techniques

NGC0309 -  $\langle \log(t_L[\text{yr}]) \rangle$



STARLIGHT map

Voronoi tessellation

BATMAN

INLA's prediction

Thank you