INLA and 1.5D IFU fitting

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centra

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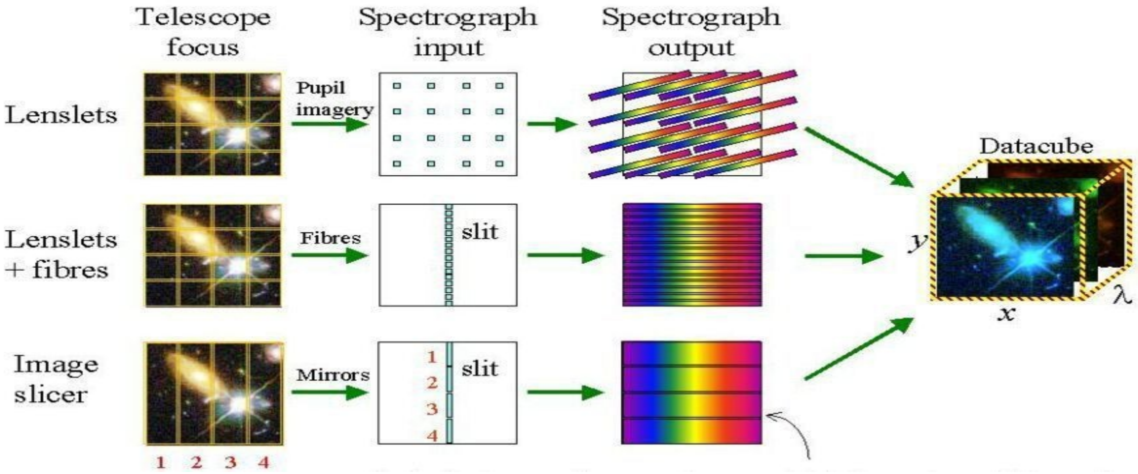
Integral Field Spectroscopy (IFS)

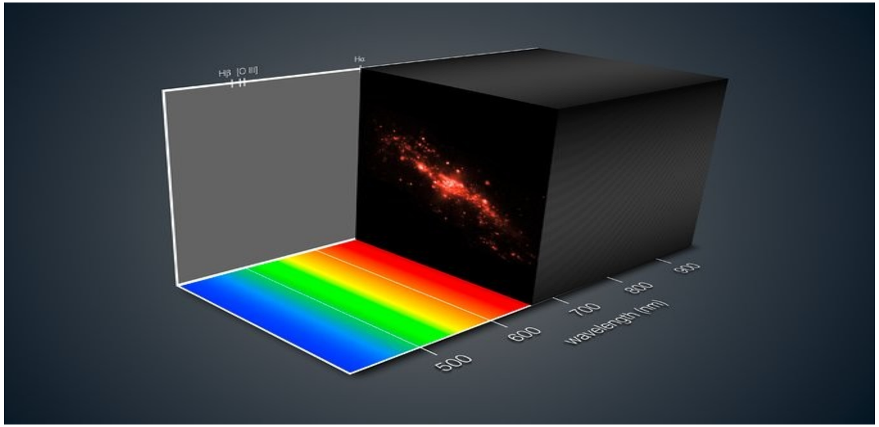
IFS provides spectral information of a 2D spatial field: each pixel (spaxel) contains spectral information

IFS techniques



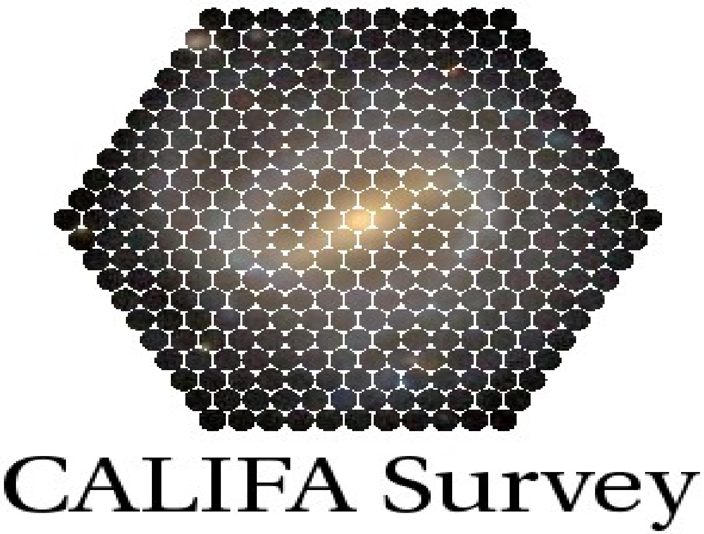
Credit:M. Westmoquette, Allington-Smith+98

3D data cube



Credit: ESO/MUSE consortium

CALIFA SURVEY



Specs: PMAS/PPAK instrument with 382 dibres and hexagonal Field of View of 74’’x64’’ at Calar Alto 3.5m telescope.

Obs: 667 galaxies at z<0.03 + 104 galaxies from PISCO (Sanchez+12,Galbany+18)

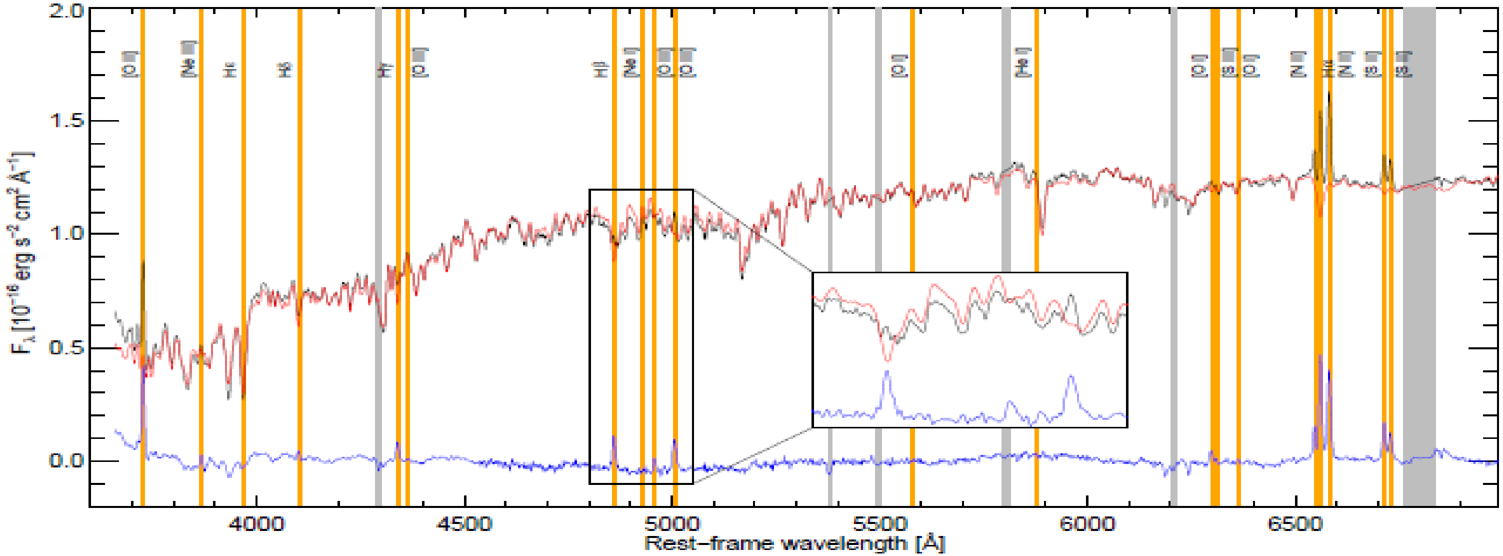
Stellar population fitting

Generally, to obtain physical parameters like age and metallicity of a stellar population (a galaxy, a cluster), the spectra+photometry are fitted to stellar population models with least squares minimization or Bayesian techniques.

Model examples: Bruzual & Charlot 2003, MNRAS, 344, 1000

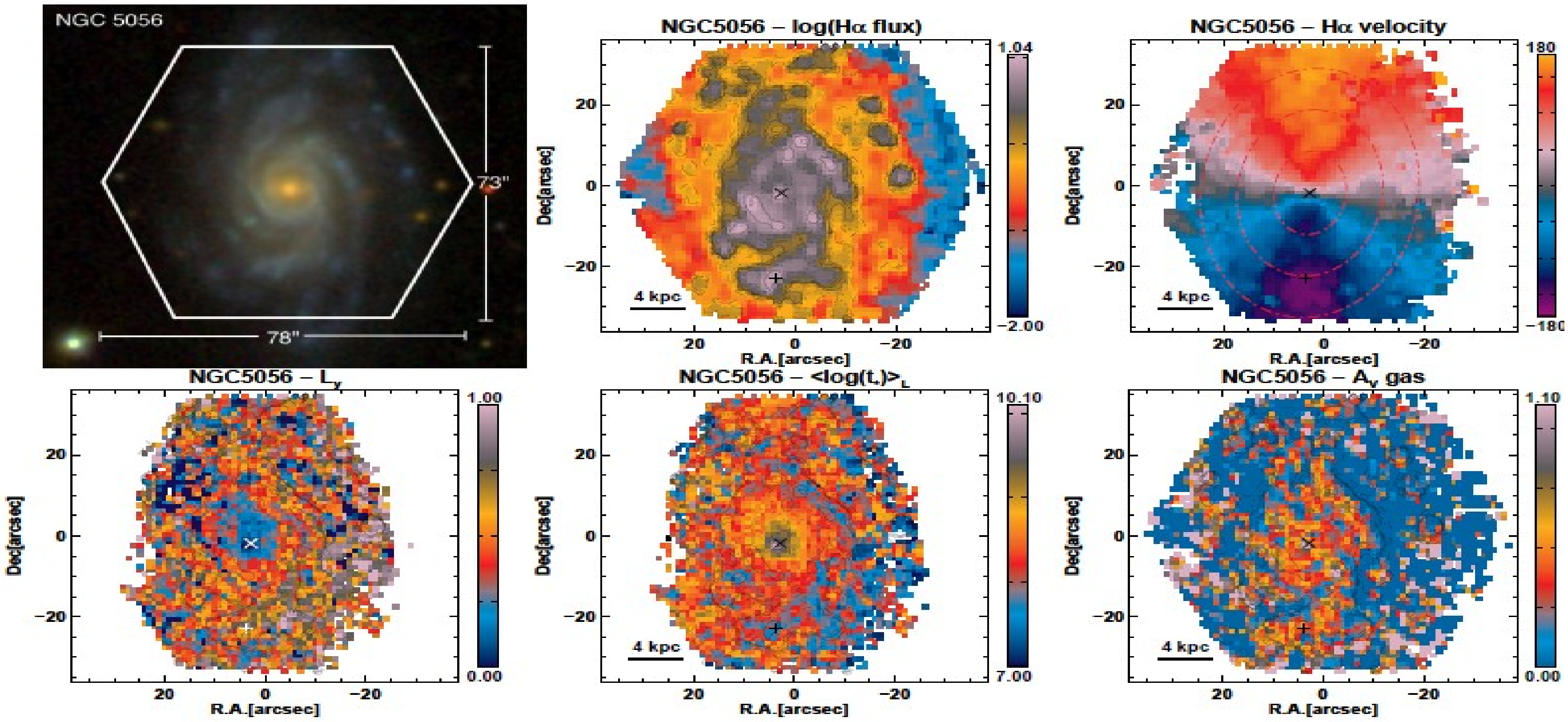
Fitter examples: STARLIGHT (Cid Fernandes et al. 2014, A&A, 561, A130),

Prospector-α (Leja et al. 2017, ApJ, 837, 170)



Example of spectrum of nucleus of NGC 2347 (black) compared to STARLIGHT fit (red) and difference (blue). *From Galbany et al. 2014, A&A, 572, 38*

Fitted stellar population and line maps

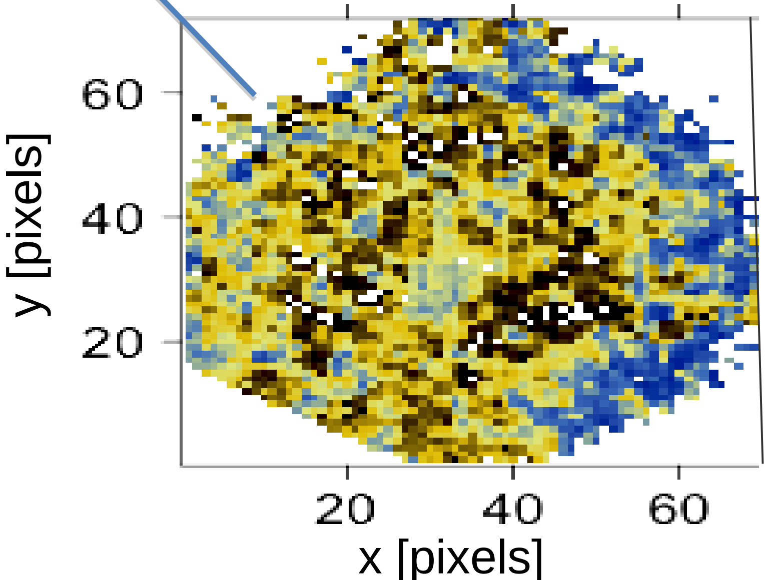


Top: NGC 5056 image, Hα flux, Hα velocity
Bottom: young stars (<100Myr), mean stellar age, extinction (Av) from STARLIGHT
From Galbany et al. 2014, A&A, 572, 38

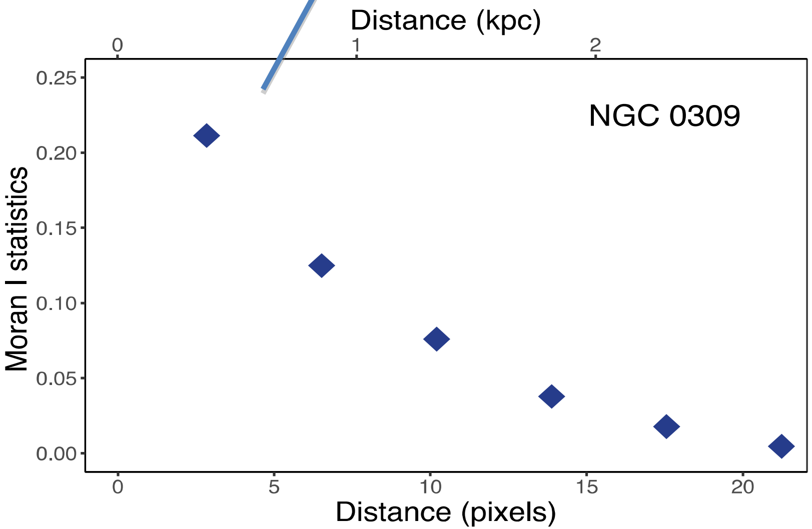
Spatial auto-correlations

NGC 0309 (SDSS)

Metallicity map of NGC 0309

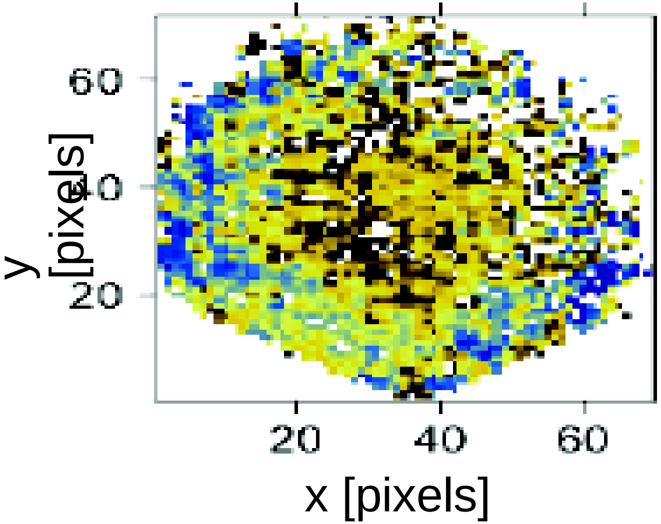


Moran Statistics: measures spatial correlation



Spatial auto-correlations

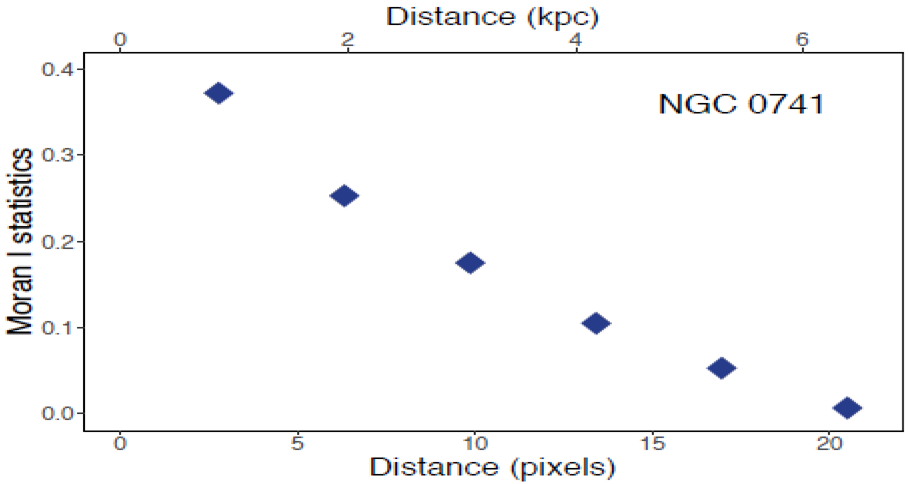
NGC 0741 (SDSS)



Correlations arise from:

➔**physical effects**: physical properties may extend regions that cover several spaxels

➔**instrumental effects**: crosstalks, multiple fibres within each spaxel (due to dithering in fibre-bundles IFUs)



1. INLA

Spatial inference with INLA

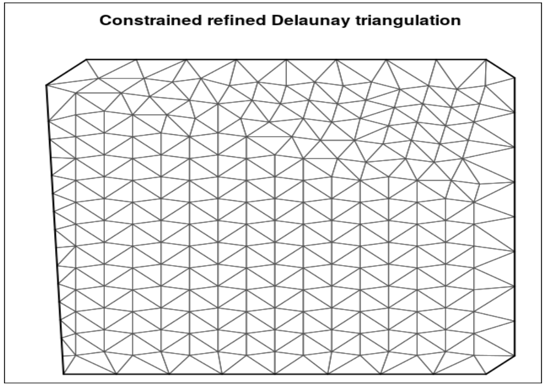
INLA is a powerful algorithm to reconstruct spatial fields based on:

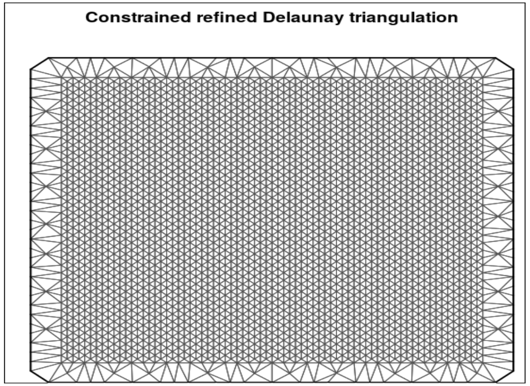
- Gaussian Markov Random Fields
- Integrated Nested Laplace Approximation for Bayesian inference

INLA has been extensively used outside of astronomy in geostatistics for epidemiology, ozone levels, air pollution, forestry, mining

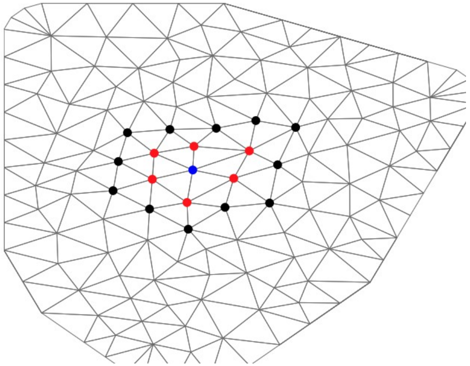
Gaussian Markov Random Fields

- **Mesh:** In a given mesh with node locations, we want to predict the values at unobserved locations.
- **Gaussian model:** at fixed nodes a field is modelled with a continuous multivariate normal distribution with Markov independence
- **Covariance:** sparse precision matrix approximating Matérn covariance function (Lindgren+11)





Meshes with increasing number of nodes



SOME VARIABLES:

- **Stationarity**: The hyperparameters of the GMRF can be kept constant in space (stationary) or are allowed to vary (non-stationary)
- **Parametricity**: Parametric functions of radius or ellipse vs Ornstein-Uhlenbeck process of the ellipse distance (non-parametric)

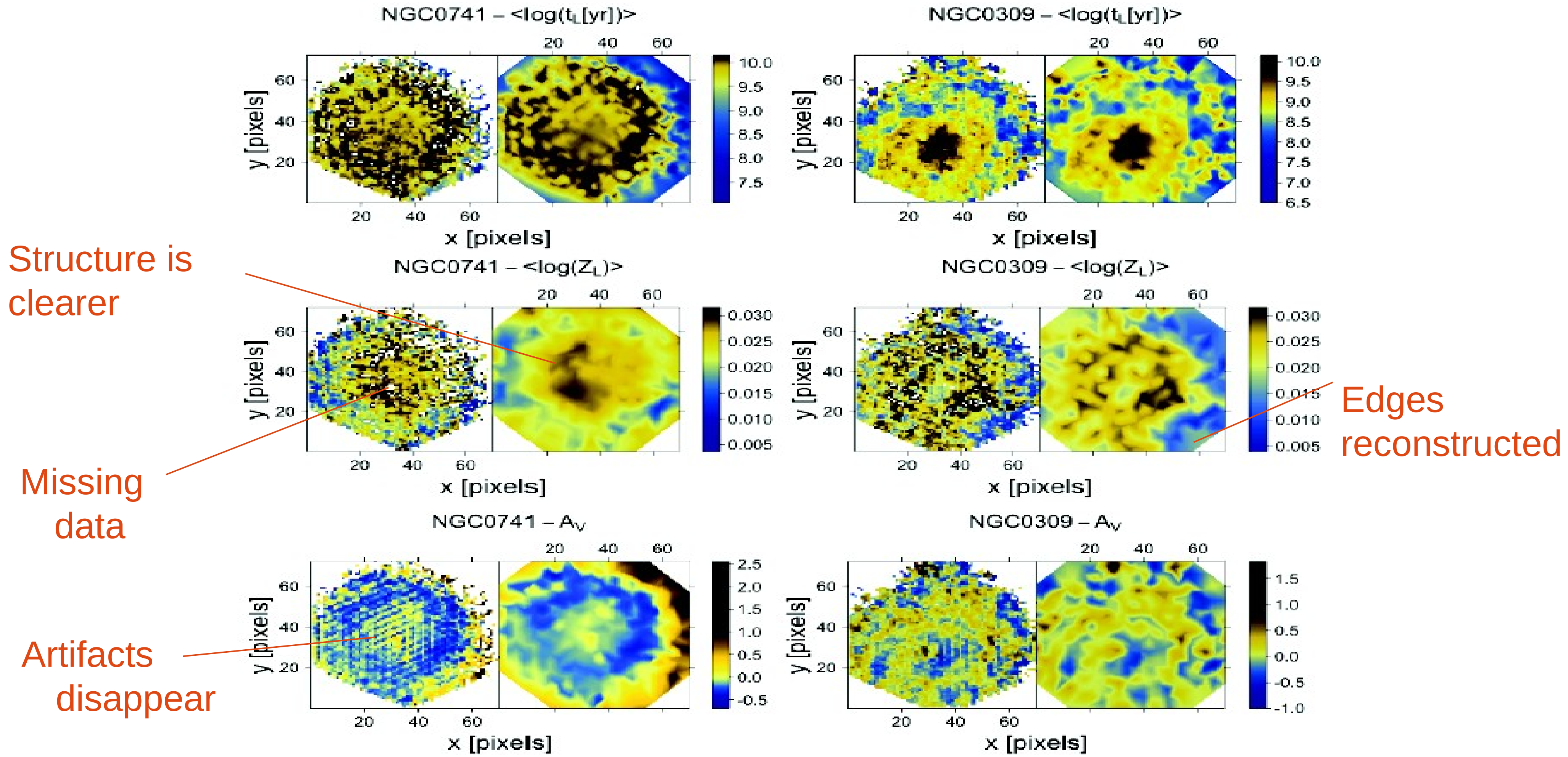
Bayesian inference: Integrated Laplace Approximation

In order to obtain the model that optimized the GMRF, we need a hierarchical Bayesian framework. An alternative to commonly used MCMC is **Integrated Laplace Approximation.**

Advantages:

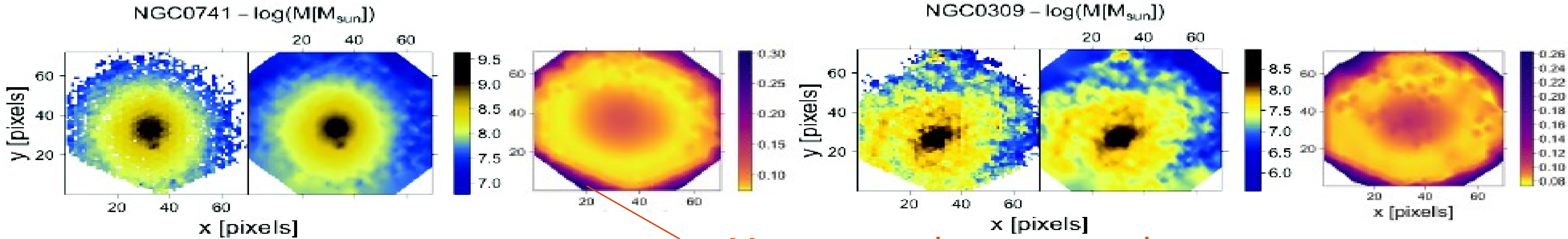
- Fast inference
- Use of Laplace approximation to represent the likelihood with a normal distribution (Rue+09)
- Grid-based integration instead of Monte Carlo exploration

Results on CALIFA maps

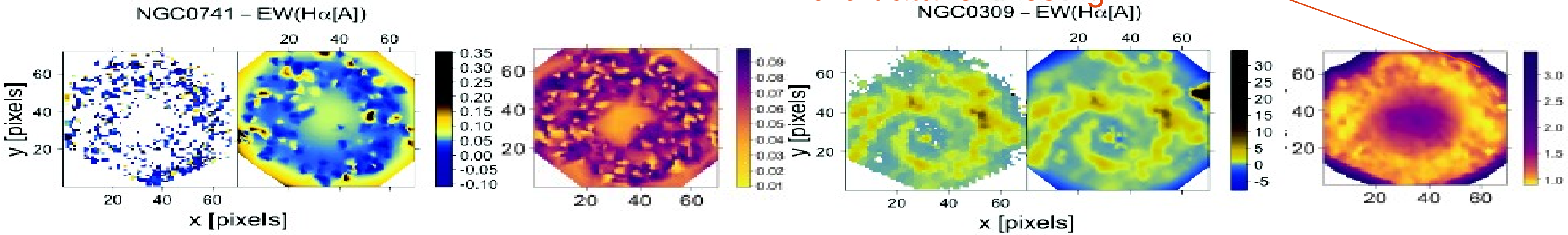


Results on CALIFA maps: **errors**

Given the Bayesian nature of INLA, we can obtain errors assuming here normally distributed 1sigma of posteriors

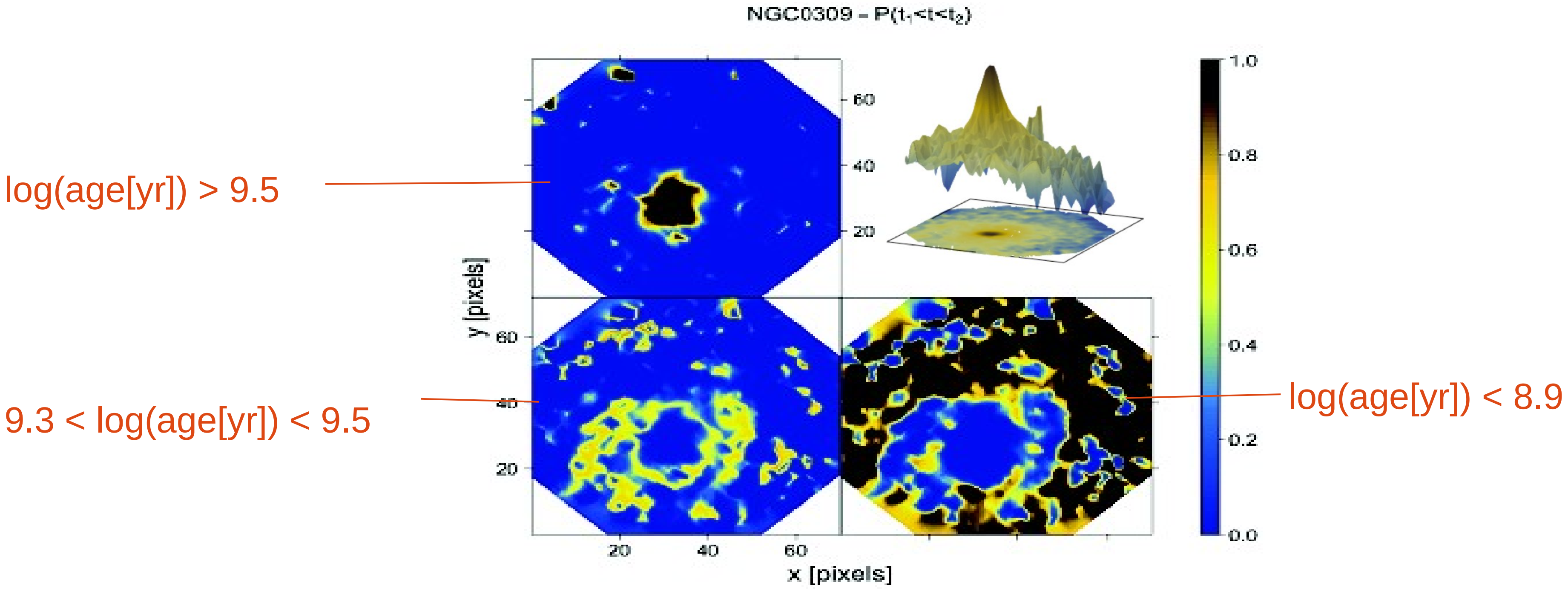


Most uncertain areas at edges where data is missing



Another advantage of Bayesian approach: confidence levels

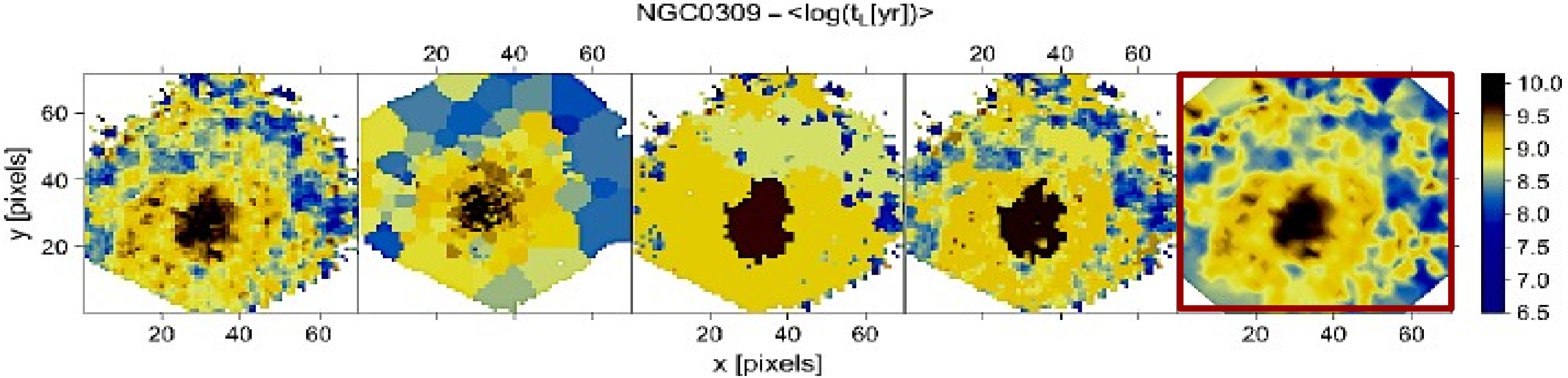
Proability maps that the age lies within a given range



→Oldest populations in bulge and youngest further away, now with quantitative arguments!

Comparison to other techniques

In the IFS field there is no real procedure to take into account spatial correlations, there are only methods to increase the desired S/N by co-adding the information of neighboring spaxels: Voronoi binning, BaTMaN (Casado+17)

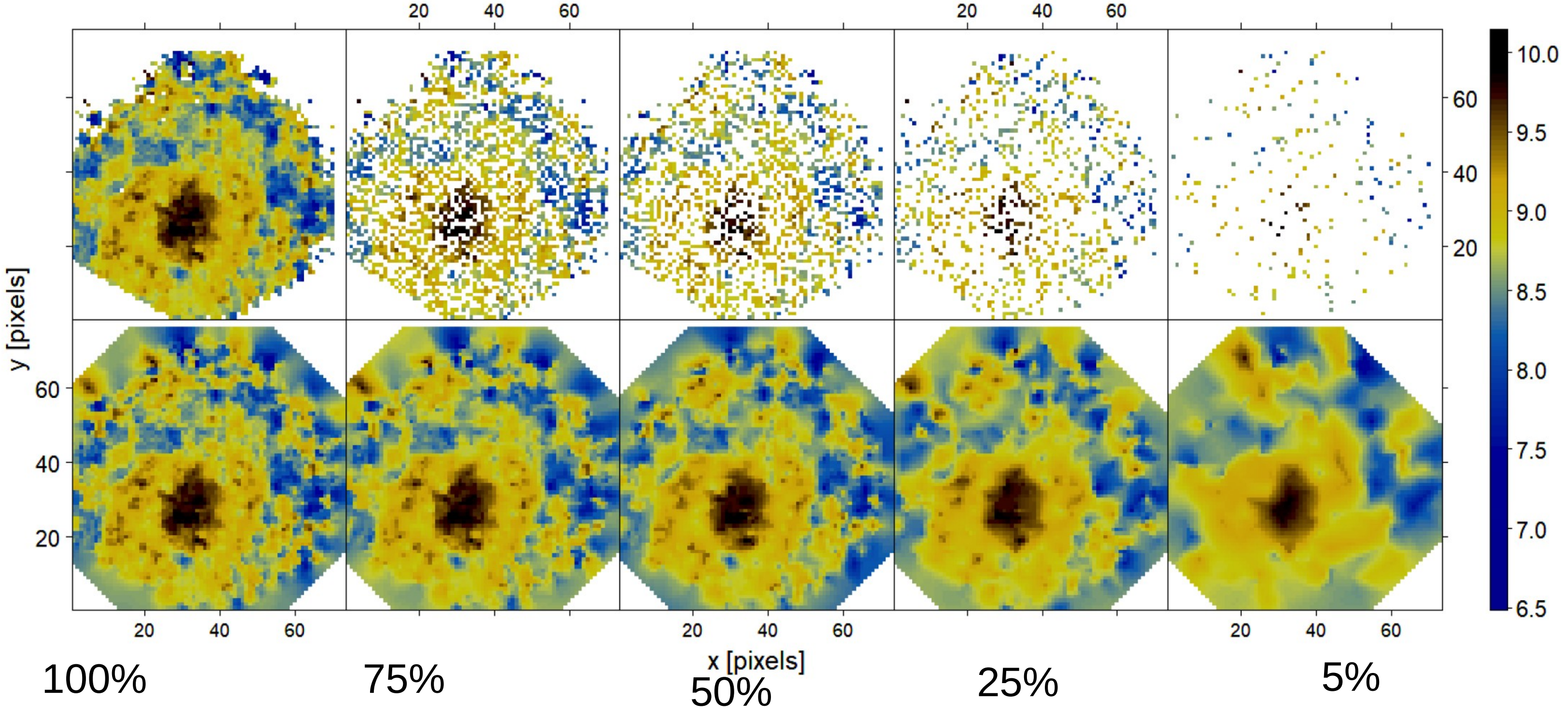


INPUT VORONOI BaTMAN_1 BaTMAN_2 INLA

→ INLA does not degrade spatial resolution but builds a spatial model that takes sptial correlation into account

Application to missing data

Being a predictive model that uses neighboring information, it has great potential for missing data, i.e. foreground stars, bad pixels, partial data, etc.



→INLA is capable of obtaining the large and even small structure!

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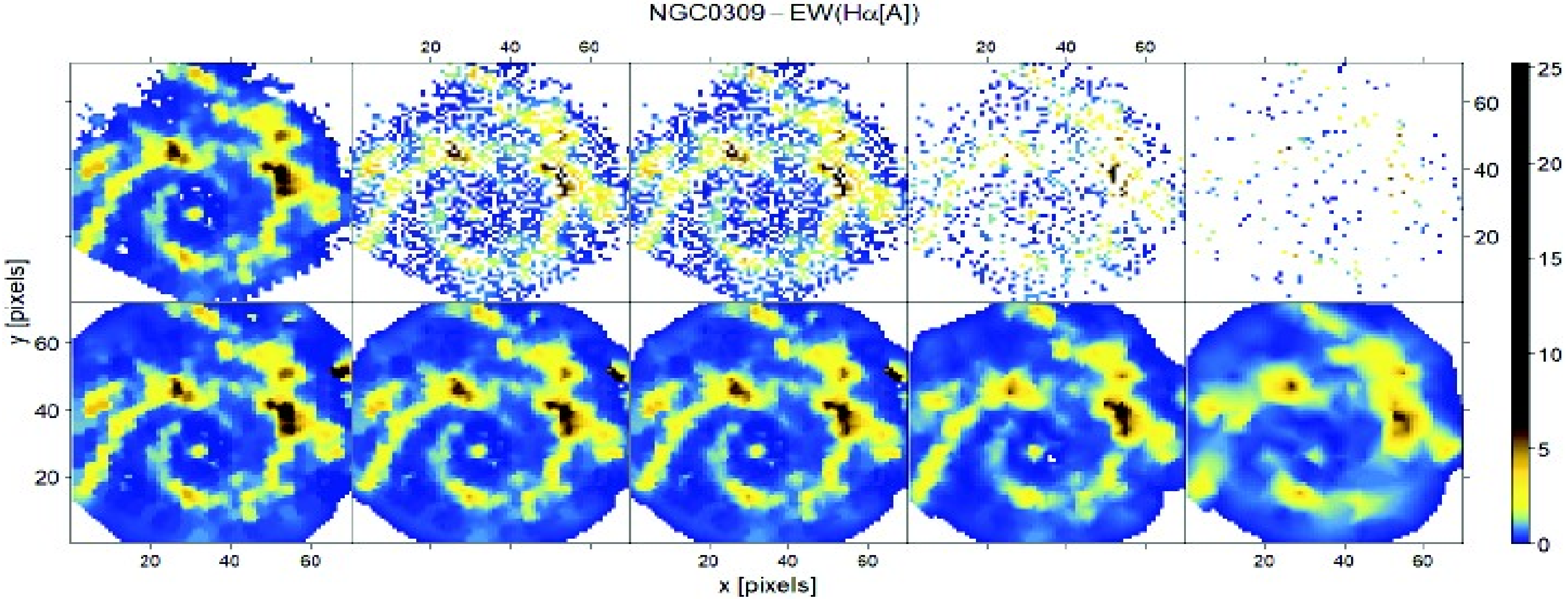
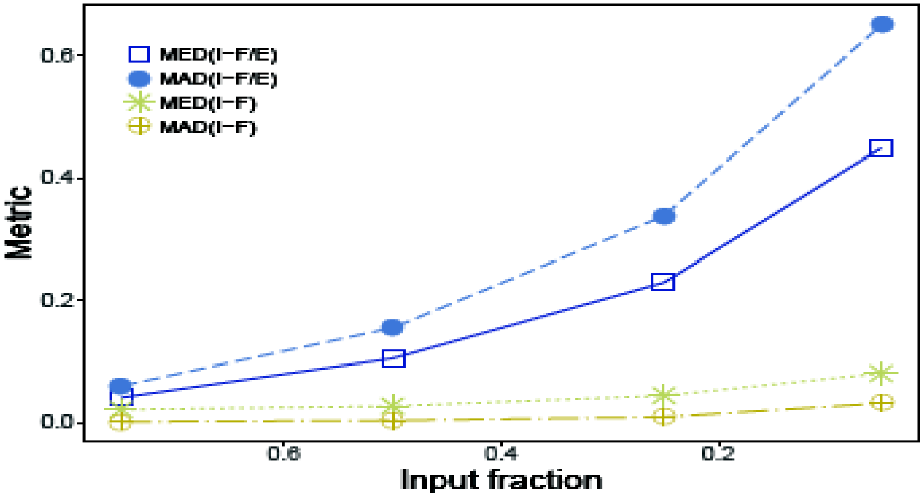


100% 75% 50% 25% 5%

→INLA is capable of obtaining the large and even small structure!

Application to missing data: errors



As the input fraction decreases the difference between input and reconstructed maps increases but the estimated uncertainties as well providing conservative predictions.

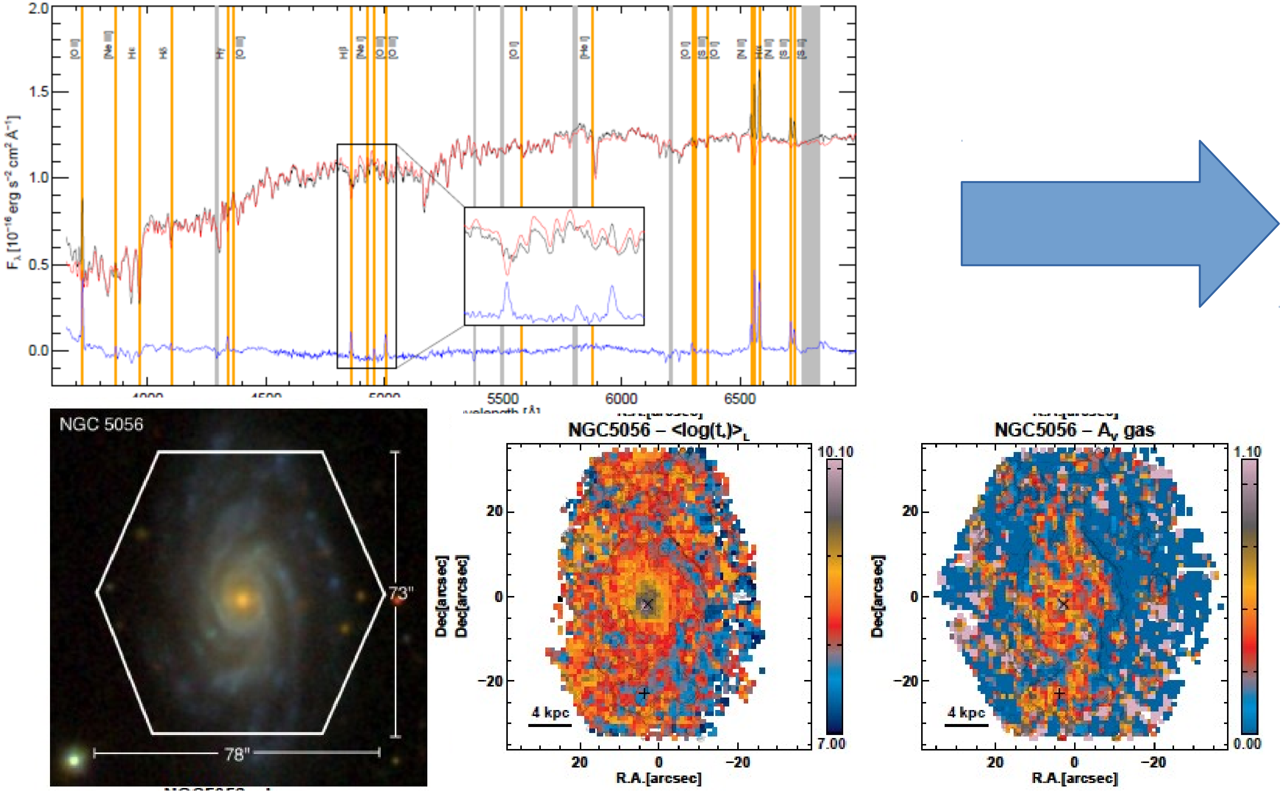
COIN
Cosmostatistics Initiative

https://github.com/COINtoolbox/Galaxies_INLA

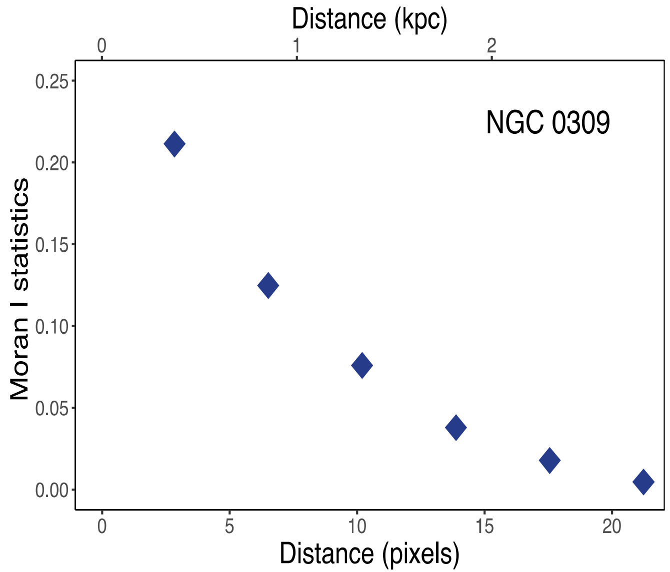
II. New methodology: 1.5D IFU fitting

1.5D IFU fitting

Traditional stellar population fitting to IFU data



Spatial correlations



1.5D IFU fitting

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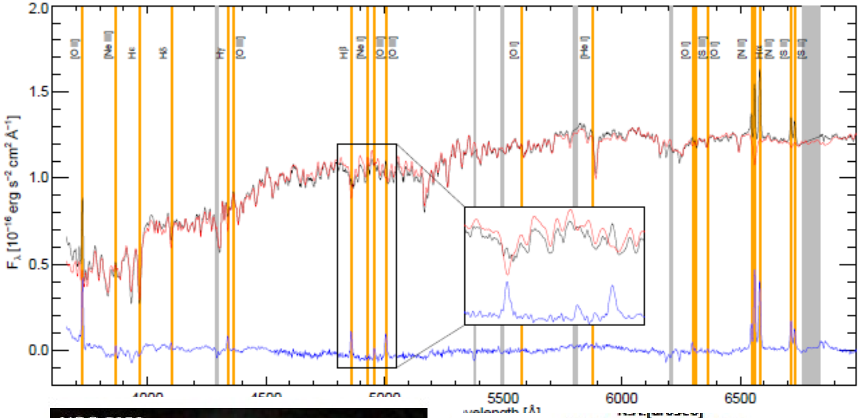
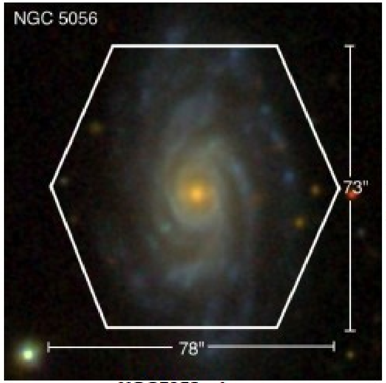
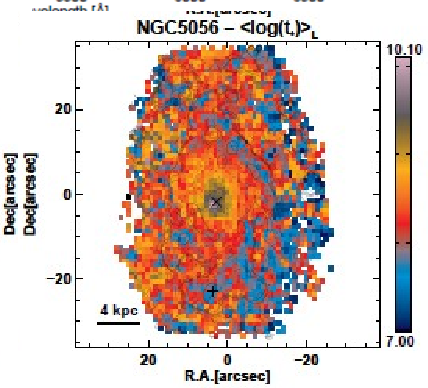
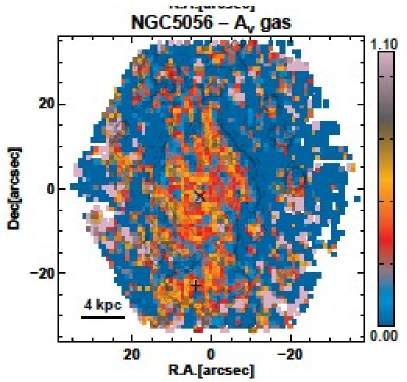








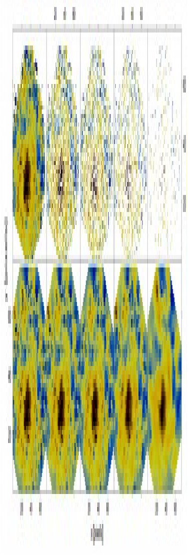
Computational cost:

Typical MCMC fit (prospector) may take 5-15mins per spaxel!!!

MUSE has > 100.000 spaxels!

1.5D IFU fitting

1.5 fitting: Do iterative process between SSP fits and INLA



SSP fits of small percentage of data

reconstruct full map with INLA

Use INLA output as prior guess into SSP fits

convergence

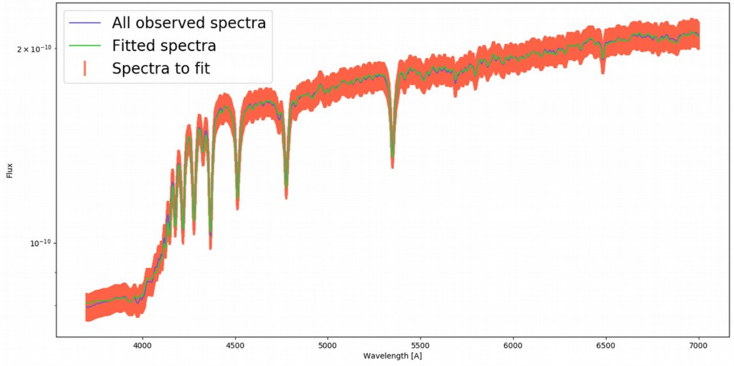
1.5D IFU fitting

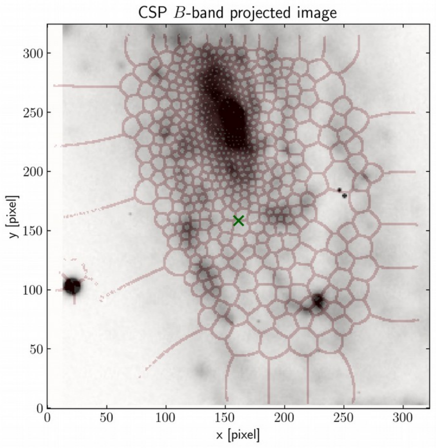
WORK IN PROGRESS:

I. Using prospector/INLA

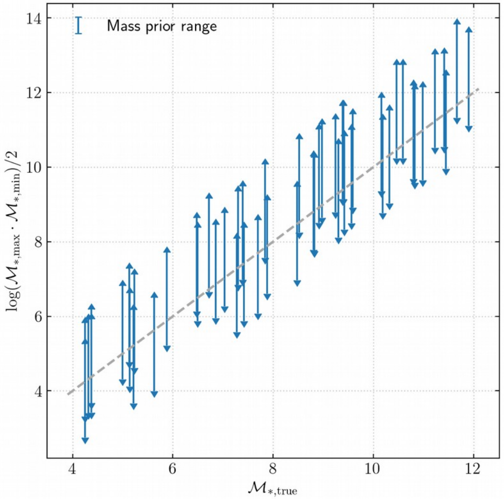
II. Start with few spaxels: Voronoi binning

III. Use of computer cluster





Voronoi binning to B-image
(Alessandro)



Mass prior
(Alessandro)