Constraining turbulence in galaxy clusters using X-IFU and Simulation Based Inference

Alexeï Molin

Workshop Lumière 14/01/2026

with Simon Dupourqué, Baptiste Sigal, Nicolas Clerc, Etienne Pointecouteau

Results in Molin et al. 2025 (A&A 702, A215)

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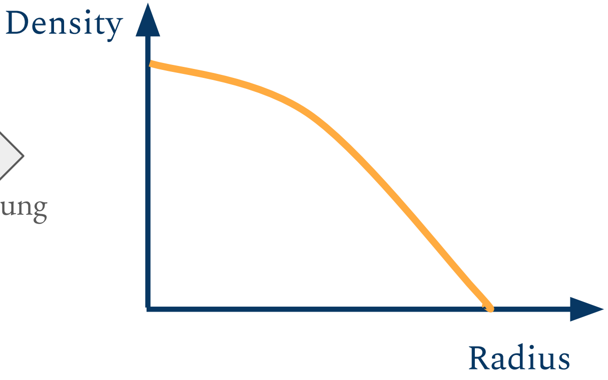
Reminder : Why study turbulence ?

Coma cluster as seen by Chandra
ESA/XMM-Newton/SDSS/J. Sanders et al. 2019

Bremsstrahlung



Hydrostatic equilibrium

M_{500}

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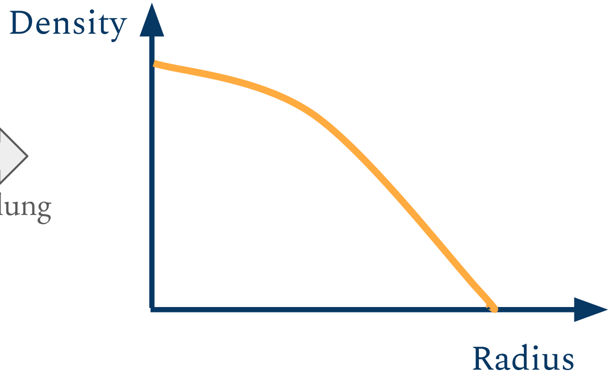
Bremsstrahlung



~~Hydrostatic equilibrium~~

Turbulence

M_{500}

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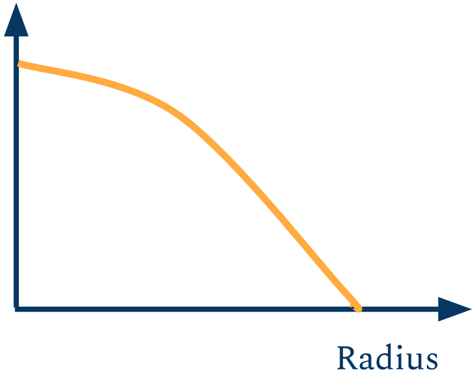


~~Hydrostatic equilibrium~~
Turbulence

M_{500}

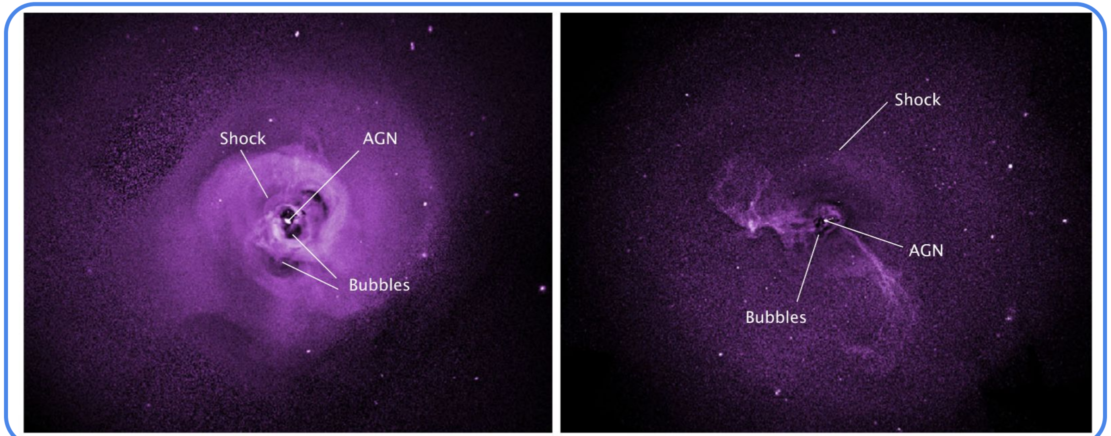
<u>In addition :</u>

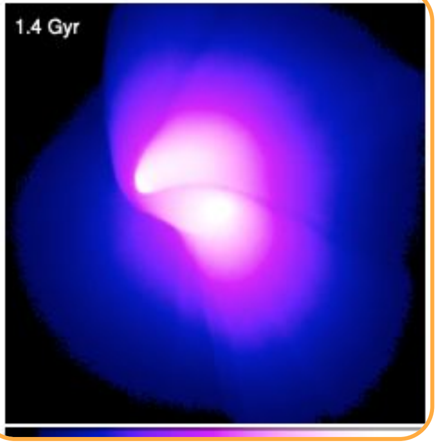
- Non-thermal heating of the ICM
- Generation of magnetic field in clusters
- Production of cosmic rays

What are the potential sources of turbulence?

- AGN feedback
- Cold fronts
- Matter accretion

Simionescu et al. (2019)





Cluster merger simulation
Markevitch et al. (2012)

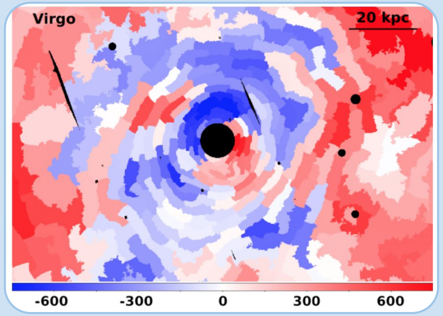
Uchuu : dark matter cosmological simulation

How do we measure turbulence in X-ray ? (ignoring XRISM)

Doppler Shift

(Dupke and Bregman, 2006; Ota et al., 2007; Sugawara et al., 2009; Tamura et al., 2014; Gatuzz et al., 2023)

- Limited by calibration of instruments for imagers (e.g. **100 km/s** with EPIC-pn on XMM-Newton)



Doppler Broadening

(Sanders et al., 2010, 2011, 2013; Pinto et al., 2015)

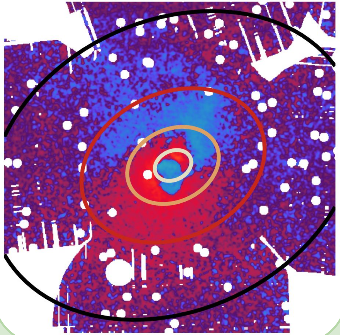
- Limited by spatial-spectral mixing for dispersive instruments (e.g. RGS on XMM-Newton)
- Best **upper limits at a few 100 km/s**

Surface Brightness fluctuations

(Schuecker et al. 2004, Churazov et al., 2012; Gaspari and Churazov, 2013; Gaspari et al., 2014; Sanders et al., 2011; Zhuravleva et al., 2012, 2014, 2018; Dupourqué et al. 2022, 2024)

- Relies on relation between surface brightness and turbulence

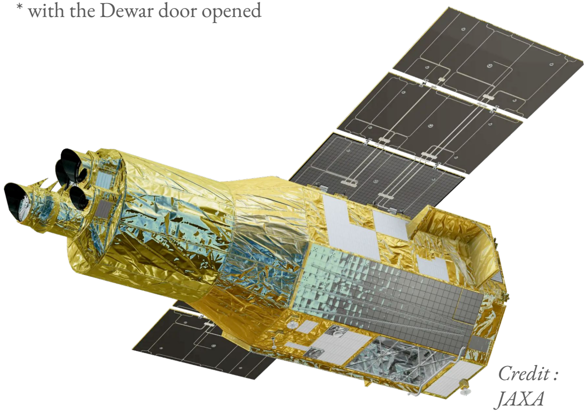
A2319



XRISM/Resolve

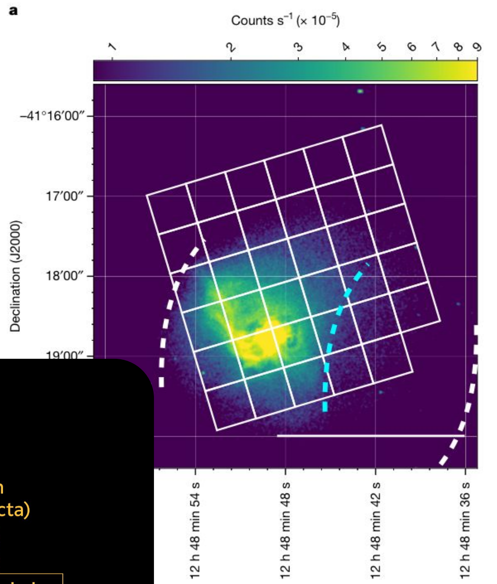
Energy resolution	5 eV
FoV	2.9 x 2.9 arcmin
PSF	1.7 arcmin (HPD)
Energy range*	0.3 - 12 keV

* with the Dewar door opened

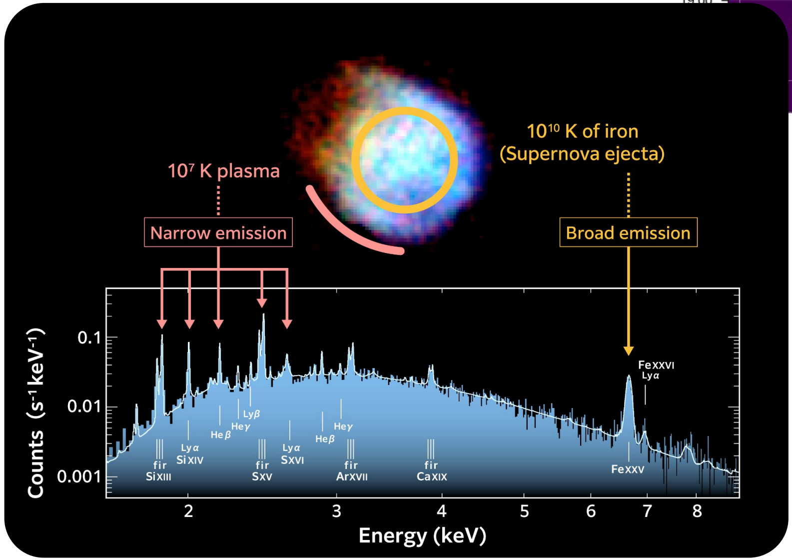


Credit : JAXA

Spatially resolved high resolution X-ray spectroscopy



XRISM Collaboration et al. 2024



Credit : JAXA

A summary of XRISM measurements so far

Adapted from XRISM Collaboration et al. 2025 [arXiv.2510.06322]

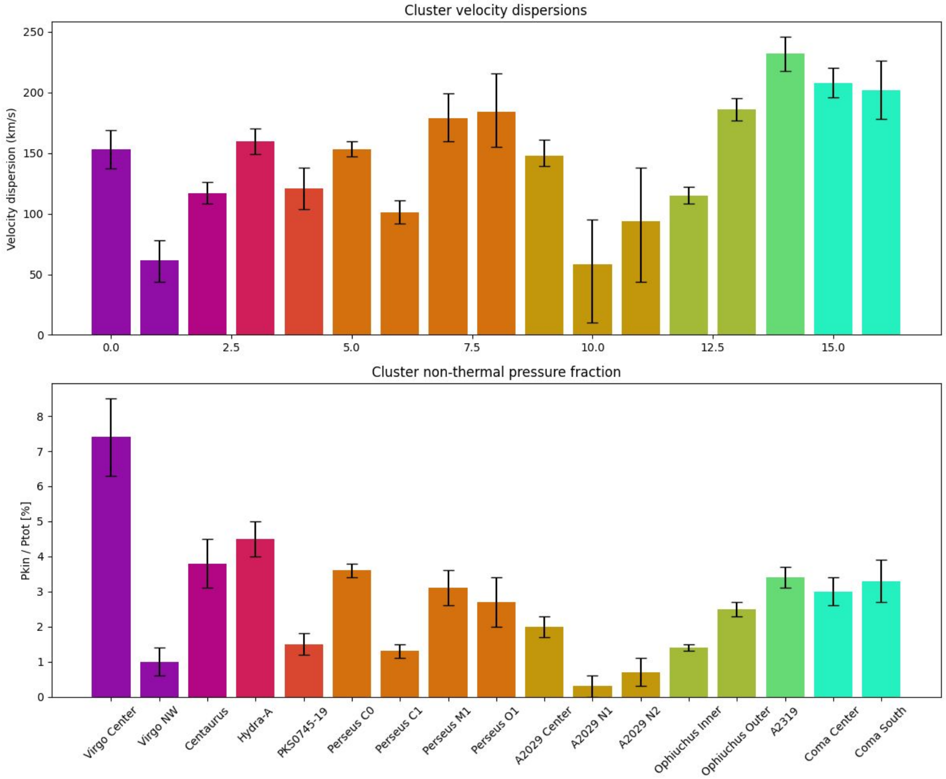
So far : mostly below the expected ~10% of Pkin/Ptot

Reminder :

Mach number : $M_{3D} = \frac{\sigma_v}{c_s}$

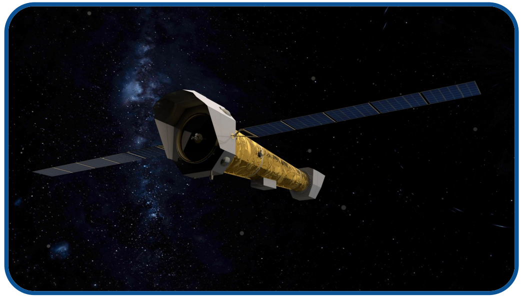
Fraction of non thermal pressure support :

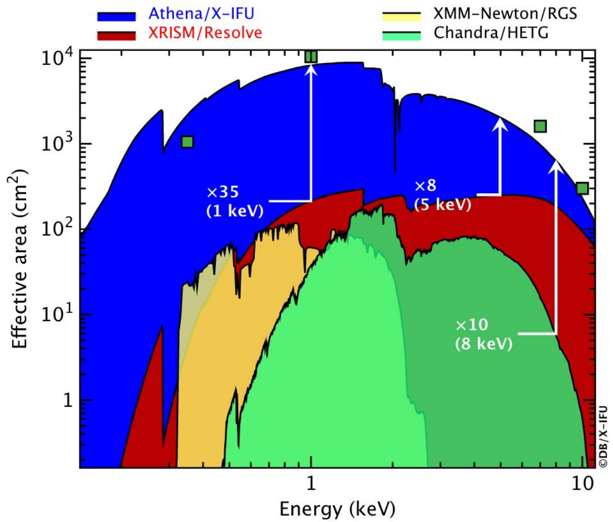
$$\frac{P_{kin}}{P_{tot}} = \frac{M_{3D}^2\gamma}{3+M_{3D}^2\gamma}$$



NewAthena/X-IFU

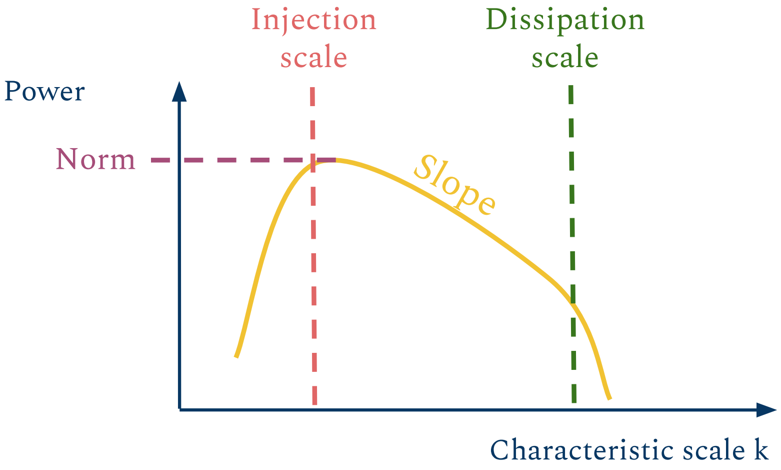
Field of view	4 arcminutes
Angular resolution	9 arcsecondes (HEW de la PSF à 1 keV)
Energy range	0.2-12 keV
Energy resolution	< 4eV (goal to 3 eV)
Pixel number	1504
Expected lifetime	5 ans
Orbit	Lagrange L1





Crédit : Barret et al. 2023

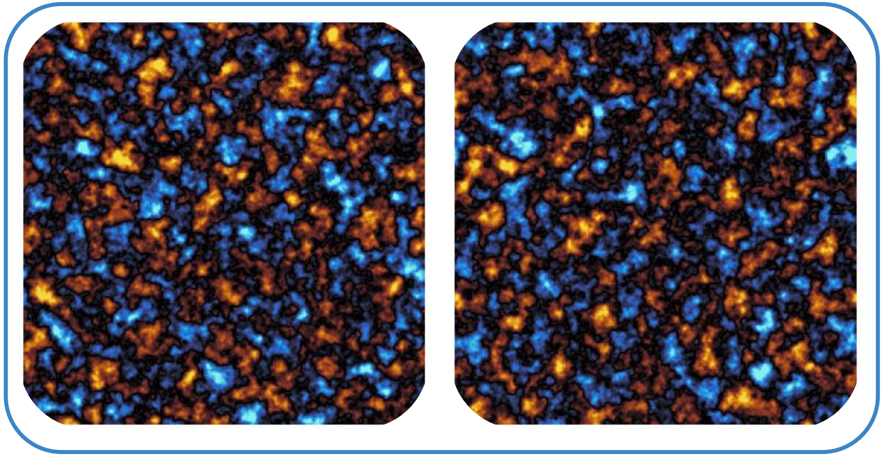
Predicting X-IFU's contribution



We assume turbulence is described by a Gaussian random field with power spectrum P(k)

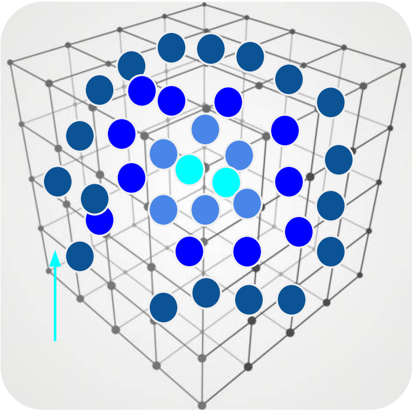
$$P_{3D}(k) = \sigma^2 \frac{k^{-\alpha} e^{-(k_{\text{inj}}/k)^2} e^{-(k/k_{\text{diss}})^2}}{\int 4\pi k^2 k^{-\alpha} e^{-(k_{\text{inj}}/k)^2} e^{-(k/k_{\text{diss}})^2} dk}$$

Stochastic process :



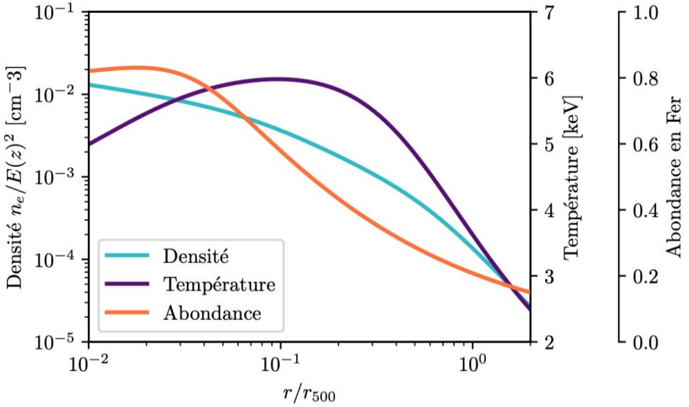
Predicting X-IFU's contribution

3D grid of cluster properties



Temperature, density, abundance, speed

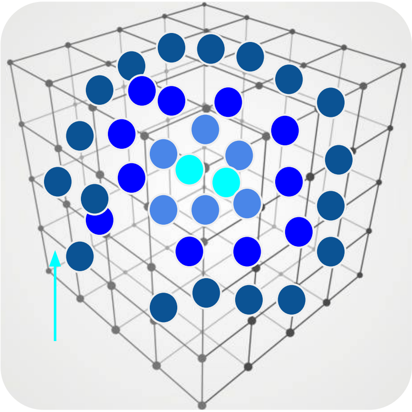
Average cluster from the CHEX-MATE sample (Ghirardini et al. 2019)



Redshift	z = 0.1
Mass	$M_{500} = 7 \cdot 10^{14} M_{\odot}$
Size	$R_{500} = 1309$ kpc

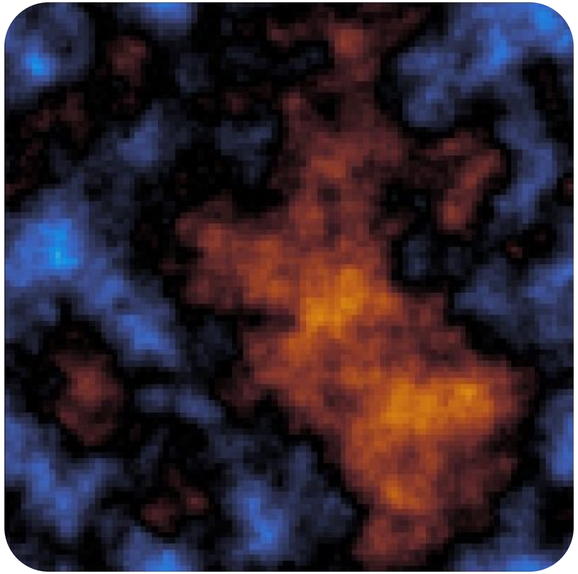
Predicting X-IFU's contribution

3D grid of cluster properties



Temperature, density, abundance, speed

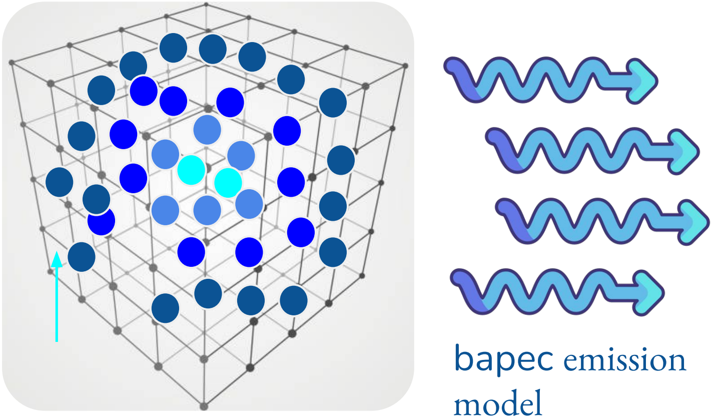
Random realization of a GRF with Kolmogorov power spectrum



Parameter	Symbol	Value
Inj. scale	L_{inj}	300 kpc
Diss. scale	L_{diss}	10 kpc
Norm	σ	250 km/s
Slope	α	11/3

Predicting X-IFU's contribution

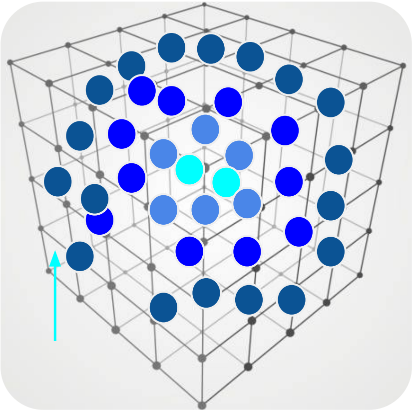
3D grid of cluster properties

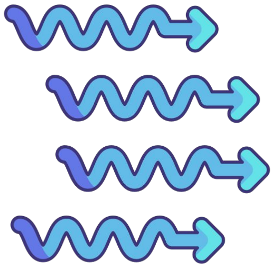


bapec emission model

Predicting X-IFU's contribution

3D grid of cluster properties





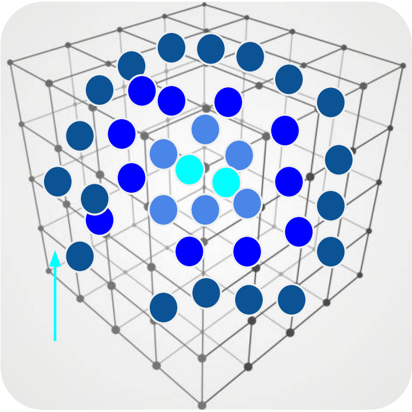
bapec emission model

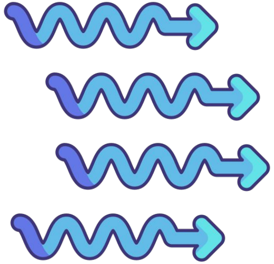
Instrument modeling with sixte

19 pointings with 125 ks each

Predicting X-IFU's contribution

3D grid of cluster properties





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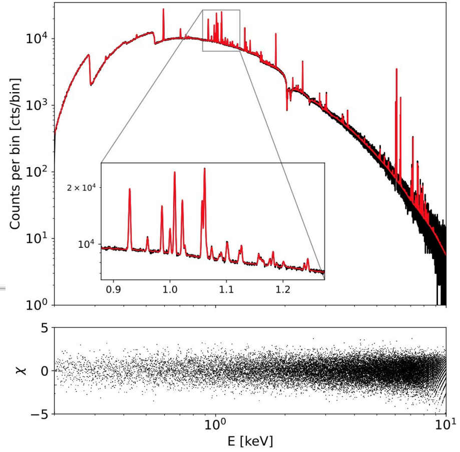
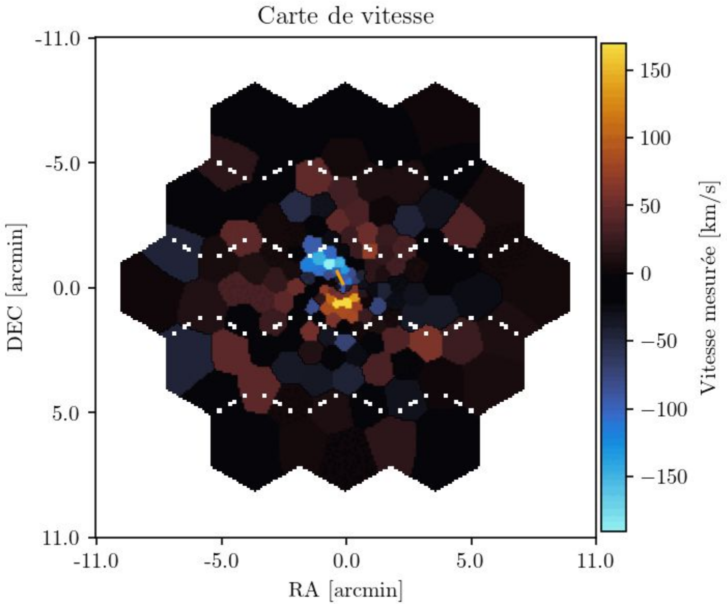
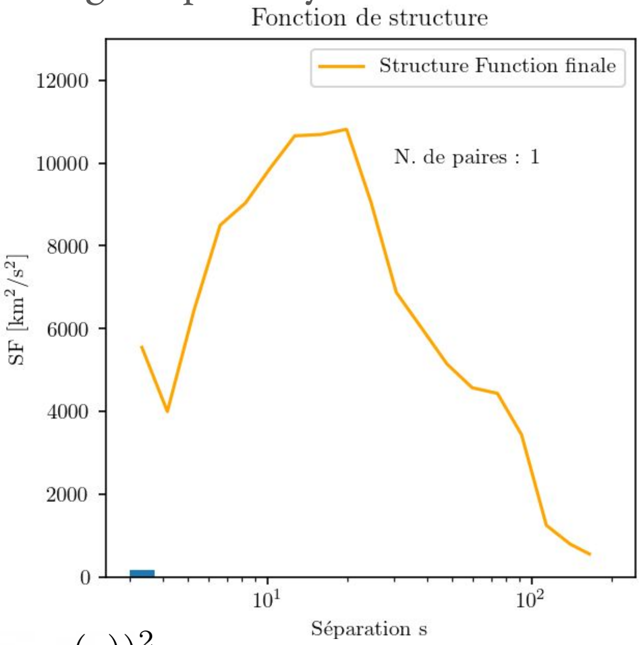


Spectral fitting with xspec
$\Rightarrow$ Temperature, norm, abundance, redshift

Predicting X-IFU's contribution

How do we go from an observed velocity map to a meaningful quantity ?





$$SF(s) = \sum_{r} \frac{(v(r+s) - v(r))^2}{N_{\text{paires}}(s)}$$

Predicting X-IFU's contribution

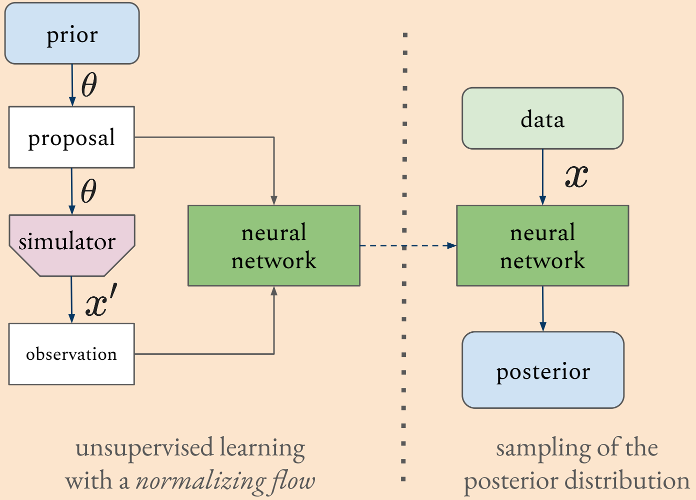
How do we infer the parameters of the power spectrum from the SF ?

Analytic inference

- Use the likelihood formulated in *Clerc et al 2019, Cucchetti et al. 2019*
- MCMC using the likelihood + priors
- Results shown in *Beaumont, Molin et al. 2024*
- Relies on approximations, computationally heavy, cannot include other probes of turbulence

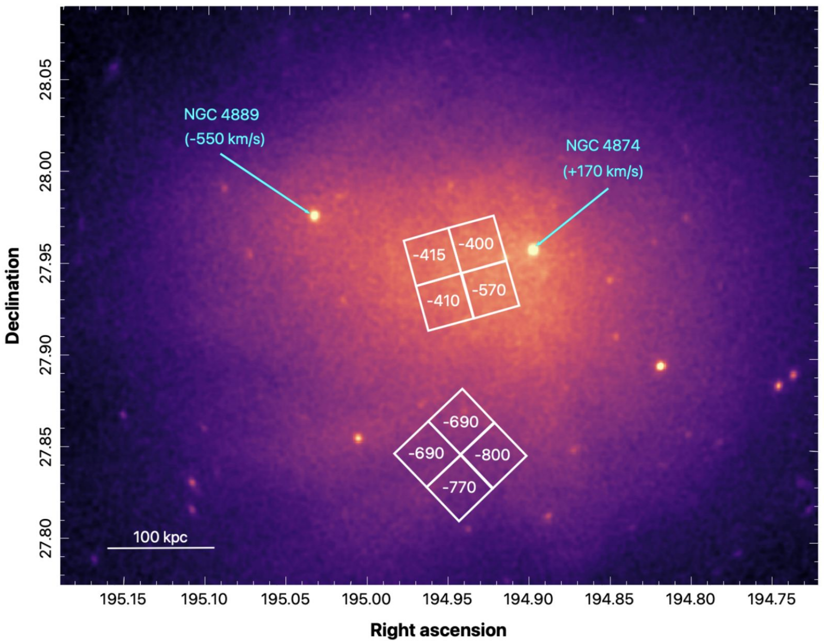
Simulation based inference

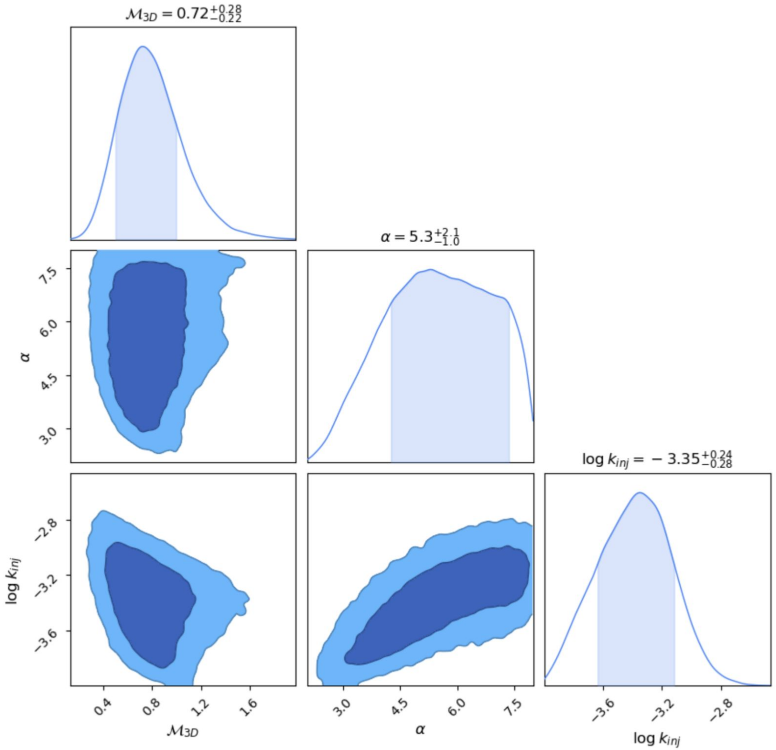
- Use a neural network to approximate the likelihood



sbi package
Boelts et al. 2025

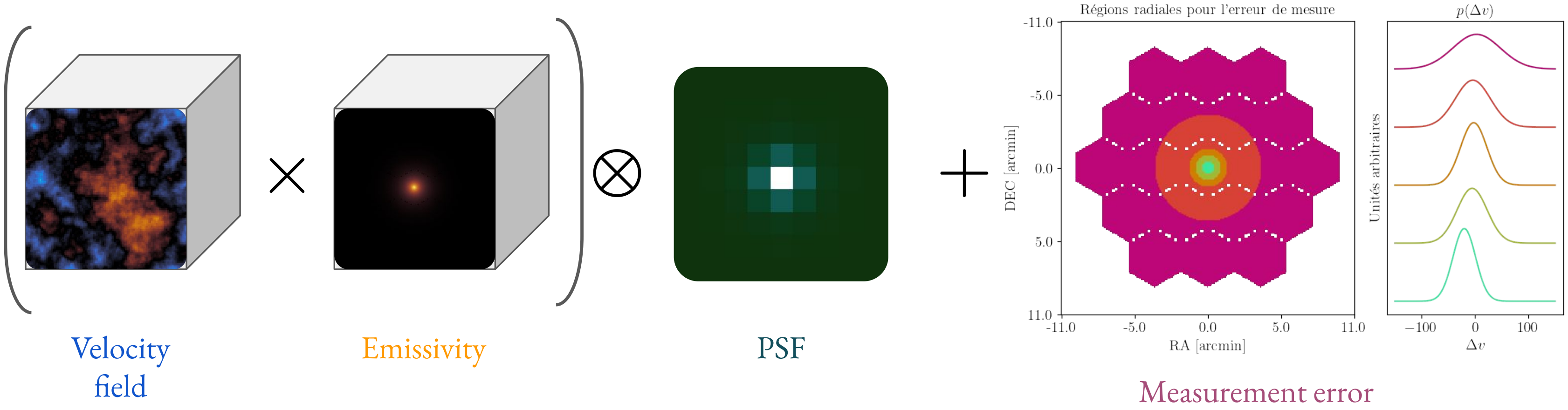
SBI & XRISM Measurements - Eckert et al. 2025





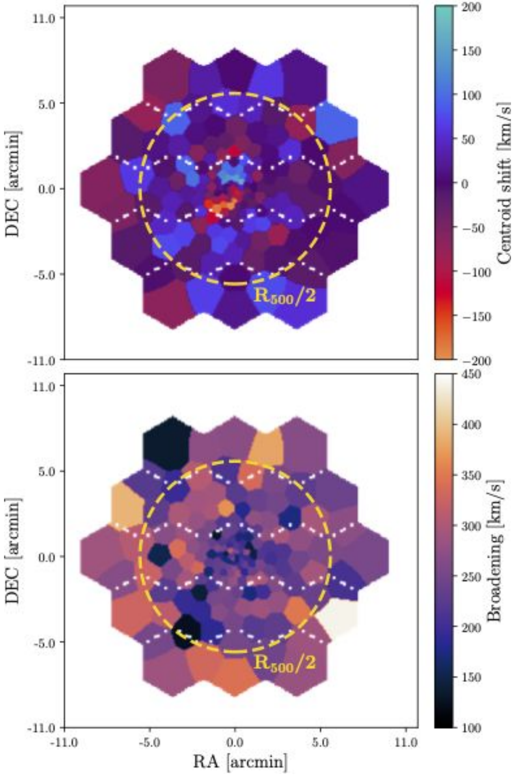
Predicting X-IFU's contribution

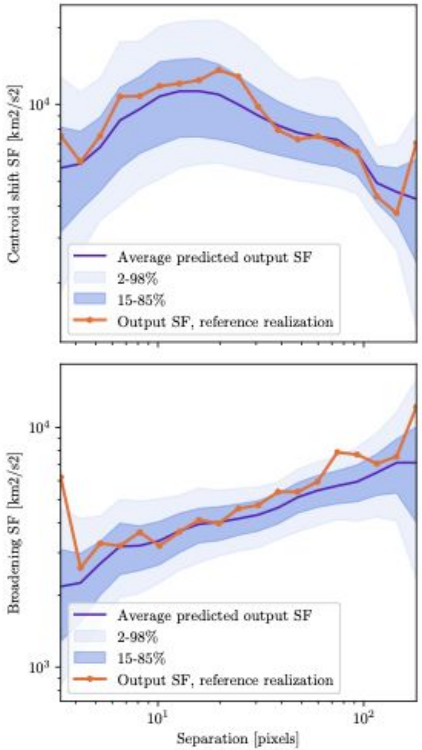
How do we produce the data to train the neural network ?



Operations that can be vectorized and computed on GPU
=> Possible to produce a large number of samples

Predicting X-IFU's contribution

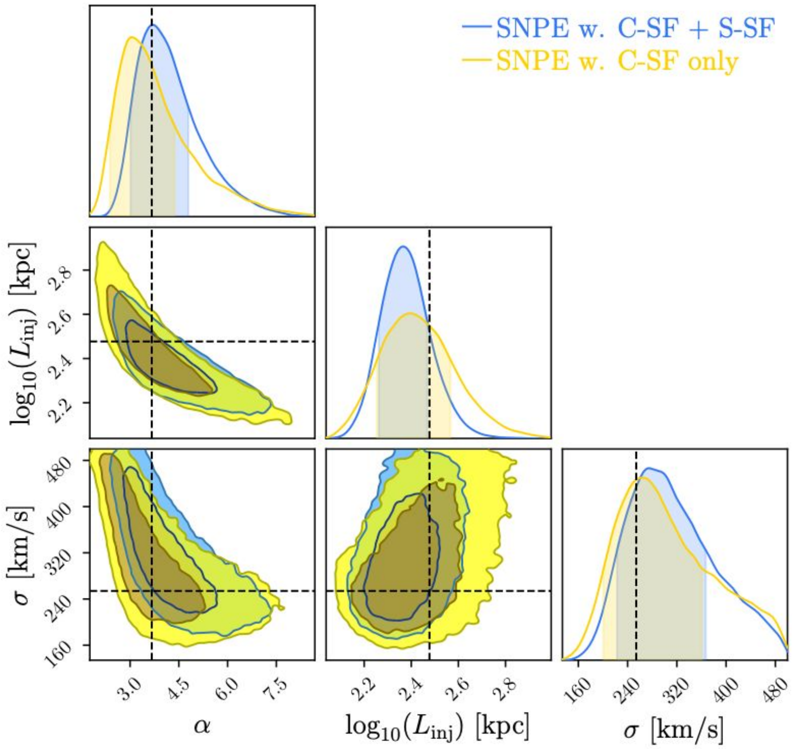




Observed quantity and method

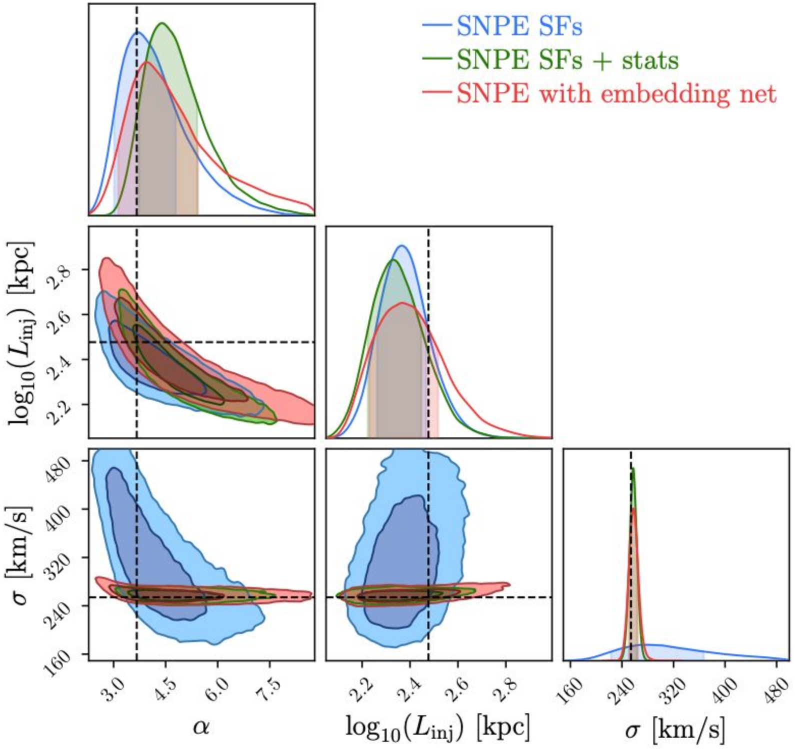
# of training samples	500 000
Training dataset #1	Centroid shift SF only
Training dataset #2	Centroid shift + broadening SF
Training dataset #3	Centroid shift + broadening SF + Mean of and STD of each map

Predicting X-IFU's contribution - Results



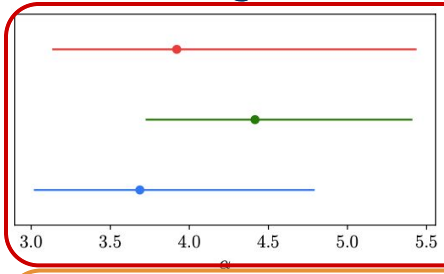
The SF of the broadening is too noisy to bring any information

Predicting X-IFU's contribution - Results

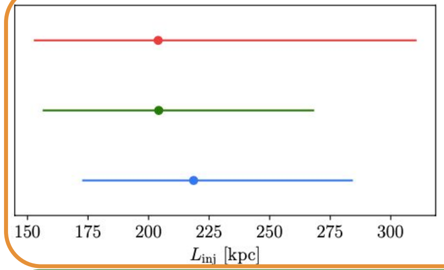


- Average value of the broadening is tightly correlated to σ
- Using a (simple) embedding network does not yield better constraints

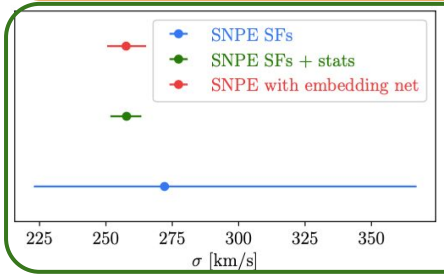
Predicting X-IFU's contribution - Results



Loose constraint on the slope :would not be able to distinguish between Kolmogorov and other scenario



+/- 50 kpc constraint on the injection scale : would be able to distinguish between AGN driven or accretion driven turbulence



+/-5 km/s constraint on σ = +/-1% constraint on the fraction of non-thermal pressure support

Predicting X-IFU's contribution - Way forward

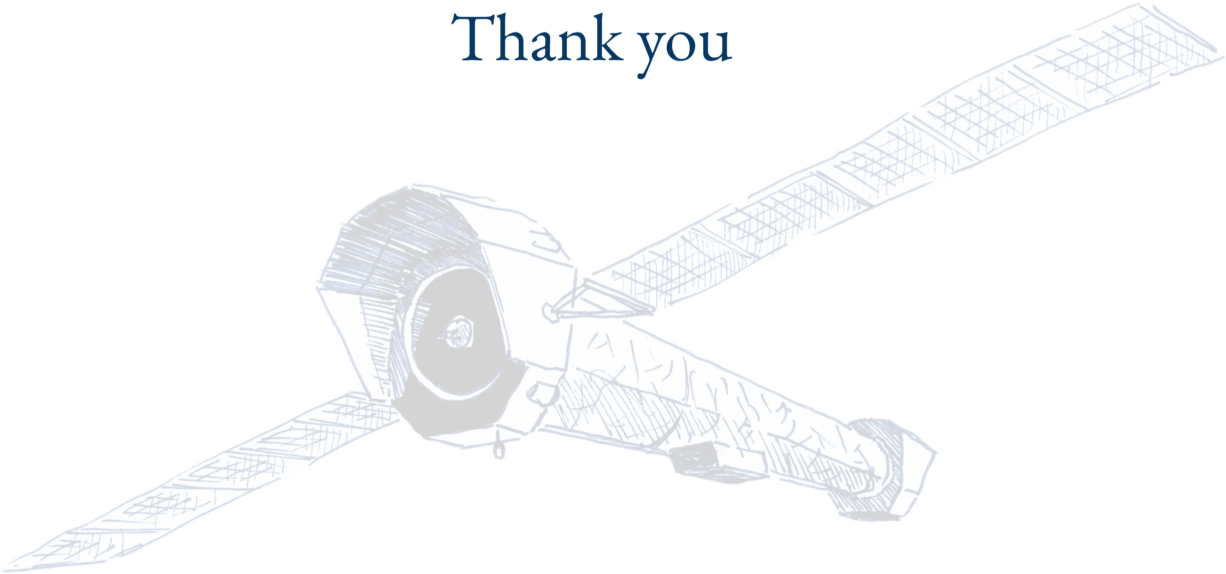
New Athena Science objective NAT-SCIOBJ-0004 :

> Map a sample of 10 nearby haloes (clusters and groups) out to a radius of 0.5 ×r500 with X-IFU and detect turbulent line broadening with a significance of 5σ (per spatial bin <100 kpc).

Our goal : **Implement a strategy for observing 10 clusters with realistic exposure times**

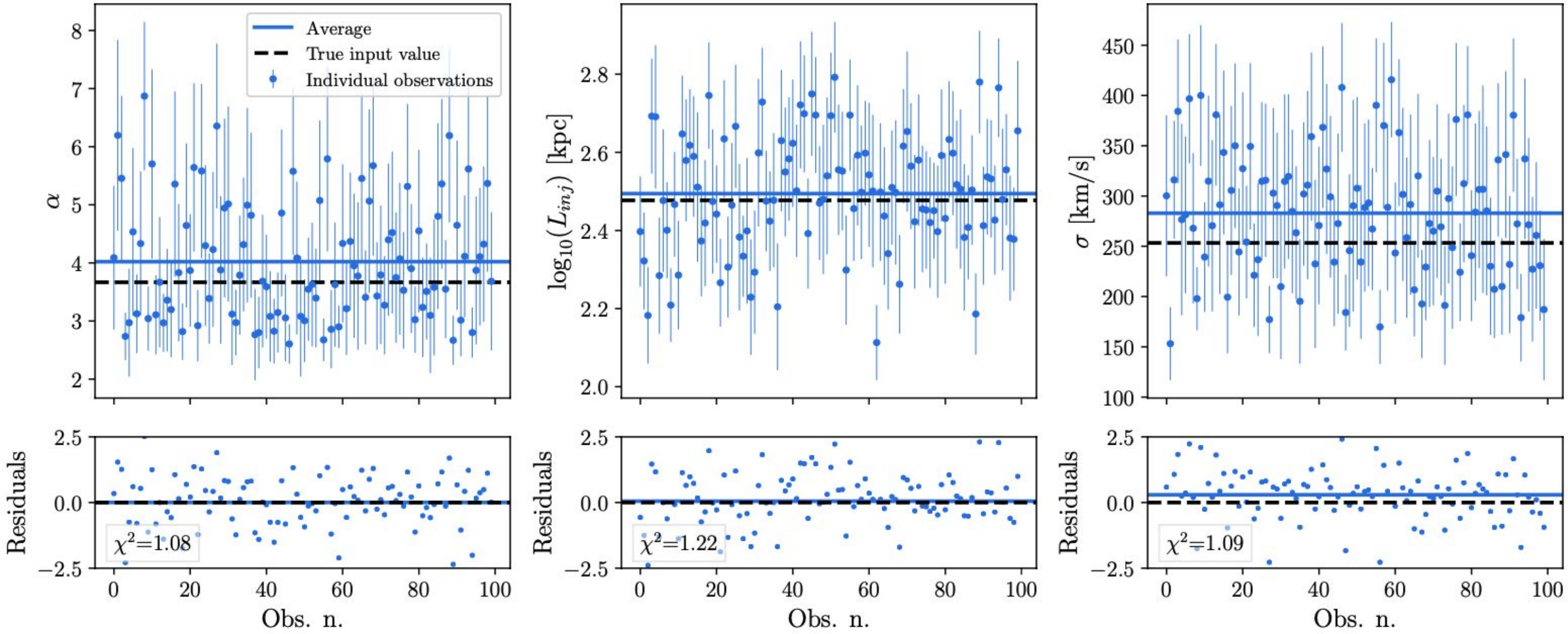
- Which clusters ? Nearby ? Far-away ?
- How many pointings ?
- How much exposure ?
- Spatial binning vs SNR ratio ?
- Implement new spectral fitting ?
- Implement new embedding method ?

Thank you

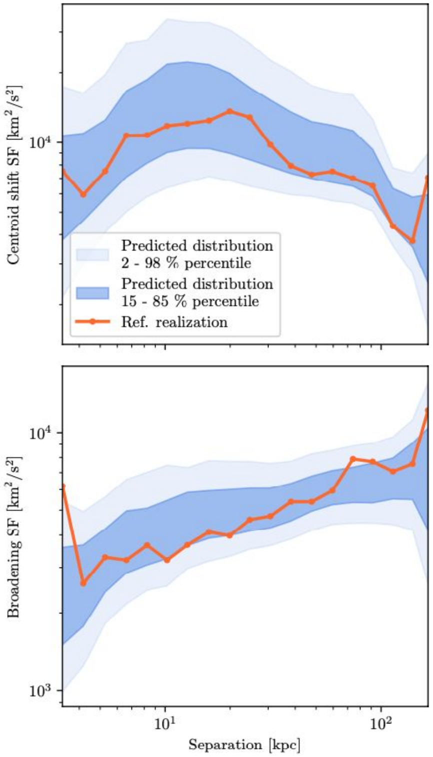


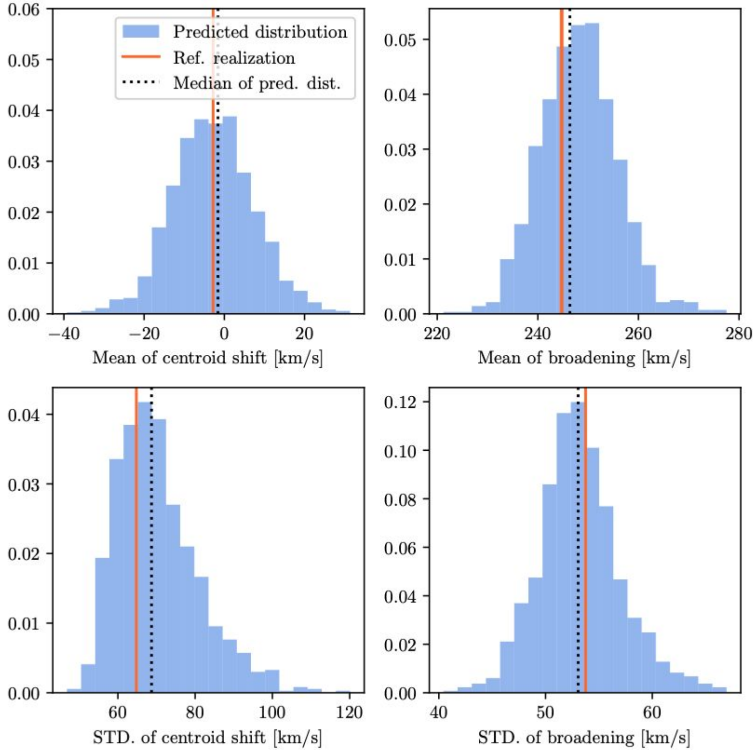
Collaborators : Simon Dupourqué, Baptiste Sigal, Nicolas Clerc, Etienne Pointecouteau

Validating the model

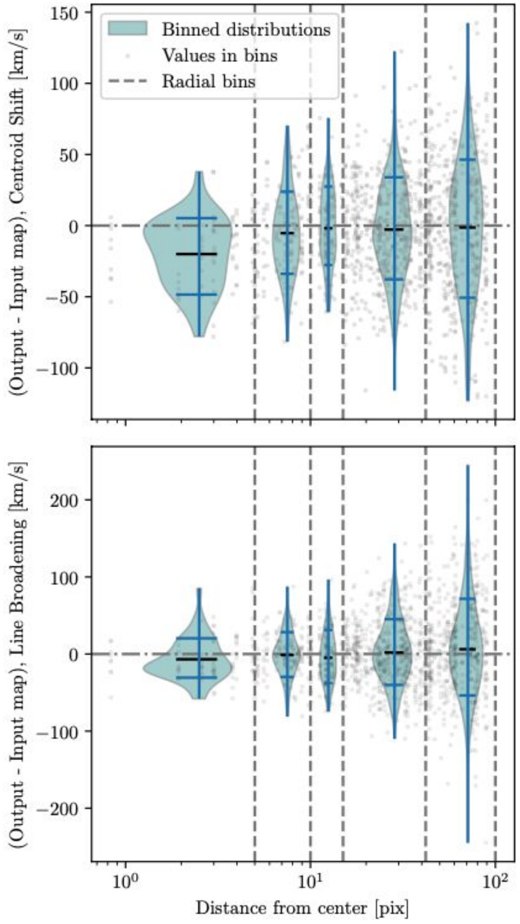


Posterior Predictive Check

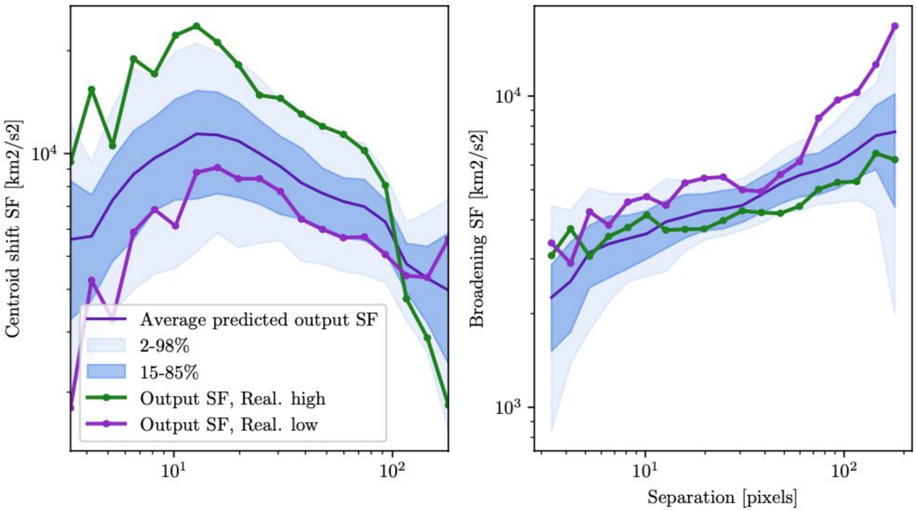


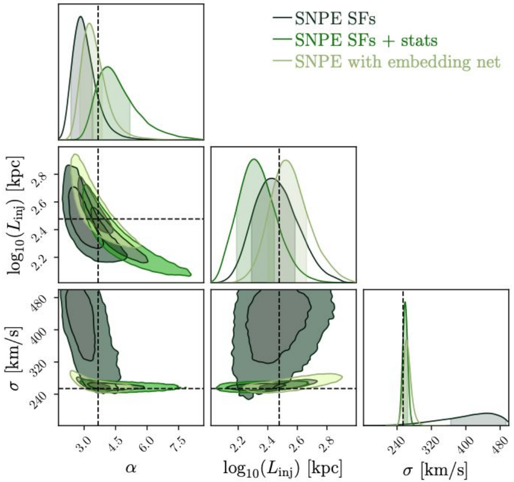


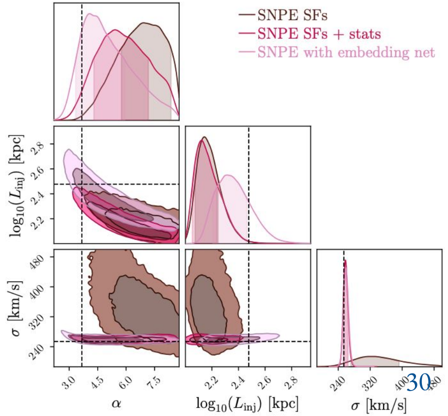
Modeling the measurement error



Different realizations







Current work