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Study of clusters of galaxies by hydrodynamic simulations and observations with cosmological implications

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Dedicated to my parents

Abstract

This thesis delves into the critical role of galaxy clusters in constraining the cosmological model through meticulous examinations of cluster observables, primarily, the Sunyaev–Zeldovich (SZ) effect. Accurate cosmological tests based on cluster counts necessitate precise mass estimations, often derived from scaling relations connecting mass proxies to halo mass. This work leverages THE THREE HUNDRED (The300) simulations to refine cluster mass estimates and enhance related theoretical understanding in the context of high-angular-resolution observations from the NIKA2 Sunyaev–Zeldovich Large Program (LPSZ). The aim is to understand the systematic effects that cannot be inferred via observations but can affect the estimation of mass (M) and integrated Compton parameter (Y) for calibrating a scaling law between the two, with the use of simulations that support real observations.

In the first part, a detailed study is performed within the LPSZ, for one of its sample clusters: ACT-CL J0240.0+0116. The multi-wavelength composite reveals a disturbed cluster with non-aligned ICM gas and member galaxy distribution. The SZ inferred pressure profile aligns with the universal model for disturbed clusters, robust to point source contamination treatment. Cluster mass is estimated at $3.84^{+1.84}_{-1.15} \times 10^{14} M_{\odot}$ ($4.25^{+0.50}_{-0.45} \times 10^{14} M_{\odot}$) when modelling (masking) point sources in the pressure profile model, consistent with X-ray and Atacama Cosmology Telescope survey results. A SZ, X-ray combined temperature map reinforces the disturbed state of the cluster.

The second part of the thesis uses simulations to validate the LPSZ point source detection algorithm. Through purity and completeness analyses, we establish a framework to quantify the performance of the pipeline and assign reliability scores to detected point sources. The results indicate the best reliability score to be associated with a detection signal of SNR five and the preference for the use of the 260 GHz band for reliable point source detection. These findings are applied to real LPSZ point sources, assigning reliability ranks.

The final parts are devoted to theoretical studies by exploiting the The300 simulation products. Twin samples that are representative of the LPSZ are constructed and their NIKA2-like maps that mimic the observations are used to explore the recovery of pressure and mass profiles and calibration of the $Y - M$ scaling law. Discrepancies in the recovered 3D profiles are noted in the cluster core and outskirts. The bias quantifying this discrepancy is minimized at overdensity $\Delta = 2000$, where the hydrostatic mass bias is 0.15. The hydrostatic mass bias increases to 0.23 at $\Delta = 500$. The recovered pressure profiles suggest a potential redshift evolution in the universal pressure profile. These pressure and mass estimates, along with varied theoretical estimations of these quantities for multiple projections are used to investigate the $Y - M$ scaling laws at different overdensities while accounting for the projection effect. The projection-induced scatter and the intrinsic scatter of the scaling law are both found to decrease with decreasing Δ . The only exception is the scaling law for mass inferred from the NIKA2-like maps where the intrinsic scatter is minimum at $\Delta = 400$. The scatter is also lower for cylindrical mass estimates when compared to the spherical ones. The normalisation of the scaling laws complies with expectations and the slope is consistent with a self-similar value of $5/3$.

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Chapter 1

Introduction

Galaxy clusters represent the most massive gravitationally bound entities in the Universe, constituting the nodes of the cosmic web (Malavasi et al. 2023; Gott, Melott, and Dickinson 1986; Guzzo et al. 2014). They serve as valuable tools for both astrophysical and cosmological investigations (see, for instance, I. N. Chiu et al. 2023; Kuchner et al. 2020; Reiprich et al. 2021; Planck Collaboration et al. 2016e). The imprint of structure formation is carried by the galaxy cluster number density and spatial distribution of galaxy clusters. Hence, the abundance of galaxy clusters with mass and redshift is a well-known cosmological probe. The cluster mass function, which gives the number density of clusters above a given mass M at a given redshift (z), exhibits high sensitivity to cosmological parameters, namely, the normalized matter density parameter (Ω_m) and the power spectrum normalization (σ_8) (Press and Schechter 1974). Theoretical mass functions for various combinations of these parameters are illustrated in Fig. 1.1.

As is evident through Fig. 1.1, the cluster mass emerges as a pivotal parameter in studies aiming to constrain cosmological parameters through the distribution of galaxy clusters concerning mass and redshift, i.e., the galaxy cluster number density. The cluster mass, however, can only be inferred through cluster observables at multiple wavelengths under simple theoretical assumptions, as discussed below. Each method is susceptible to biases associated with the observations used, emphasizing the importance of accurately estimating the total mass of clusters while managing these inherent biases. A review of different methods to estimate cluster mass can be found in Allen, Evrard, and Mantz 2011, here we present a concise overview of the same, as follows:

1. Hydrostatic equilibrium (HSE) can be employed to estimate the hydrodynamical cluster mass. Assuming spherical symmetry, the density profile from the X-ray and the pressure profile from the Sunyaev–Zeldovich (SZ) effect (Sunyaev and Y. B. Zeldovich 1970) observations can be combined to infer the cluster mass, as shown by Lindley et al. 2012. However, this inference is prone to mass bias related to assumptions made for the HSE.
2. One of the more used ways to estimate the cluster mass is through measuring the gravitational lensing effect of clusters on the background source, see e.g. Zitrin et al. 2009; Sereno 2015; Muñoz-Echeverría et al. 2023a. It is claimed

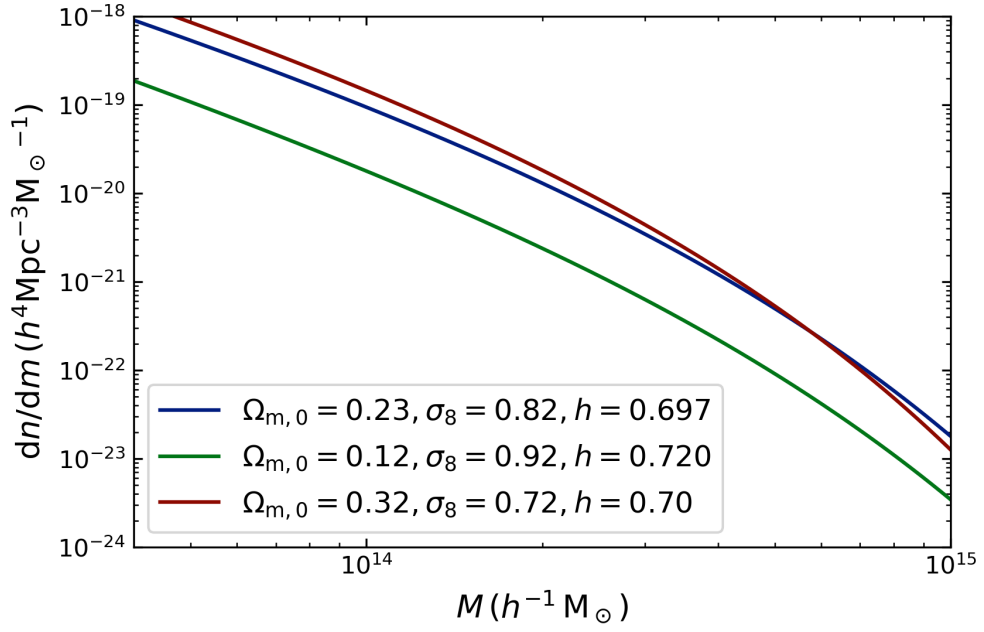


Figure 1.1 Theoretical galaxy cluster mass functions (Press and Schechter 1974) for different combinations of Ω_m and σ_8 , at $z = 0$. Notice the sensitivity of the mass function to these two cosmological parameters. The different coloured mass functions depict the degeneracy between the two parameters and also the fact that a large range of precise mass measurements is required to separate them.

to be one of the least biased ways to estimate the mass (M. R. Becker and Kravtsov 2011).

3. Another way of estimating the cluster mass is by performing kinematic studies of the member galaxies. By measuring their kinematics, i.e. velocity dispersion, the virial theorem can be invoked to infer the cluster mass. Alternatively, galaxy cluster dynamics can be used to calculate the cluster mass, see e.g. Łokas and Mamon 2003; Hatch et al. 2016. These calculations, however, are relatively expensive in terms of observational time as spectral information of a lot of member galaxies is required to get an accurate mass estimate with good precision. As an alternative, the scaling relation between the velocity dispersion and mass is used to estimate the cluster dynamical mass (see, *e.g.* Evrard et al. 2008).

Clearly, observations from each wavelength, as mentioned earlier, are susceptible to their own biases and systematic effects. In the majority of cases, however, the cluster mass is estimated using scaling laws between the cluster observable and its mass. Scaling laws (Sections 2.3.4), when correctly calibrated, relate the mass to observable such as X-ray luminosity, SZ brightness, optical richness or galaxies velocity dispersion, typically using a power law (Planck Collaboration et al. 2014; Schellenberger and Reiprich 2017; Bulbul et al. 2019; Nagarajan et al. 2019; I.-N. Chiu et al. 2022).

Albeit, establishing relations between observables and cluster mass from direct observations is challenging and not straightforward. An alternative approach to refine cluster mass estimates is by employing state-of-the-art N-body hydrodynamical simulations as efficient test beds to enhance theoretical understanding (Singh et al. 2020; Cui et al. 2018; Sembolini et al. 2013). Combining highly sensitive and high-angular-resolution observations with detailed hydrodynamical simulations of clusters can mitigate the challenges related to inherent biases and systematic effects related to cluster mass estimation. This approach allows for accurate estimation and minimizes the scatter in the inferred mass value. Our project aims to achieve this goal by using observations from the New IRAM KID arrays 2 (NIKA2) SZ Large Program (Perotto et al. 2023), hereafter referred to as LPSZ, along with simulated data from THE THREE HUNDRED Project (Cui et al. 2018), hereafter referred to as The300.

The thesis is structured as follows: in Chapter 2, we lay the foundation of the theoretical background for this work. We give a primer on the cosmological model and structure formation, delving into the cosmic microwave background (CMB) and its anisotropies. We also discuss galaxy clusters, elucidating their connection to the CMB and Cosmology and the various ways in which they are observed, including the SZ effect in the millimetre wavelengths.

Chapter 3 introduces the datasets used in this study. We describe both, the observations (LPSZ) and the simulations (The300) we use in this work. The instrumental and survey details of LPSZ and simulation specifics of The300 are presented. The complementary nature of these datasets is highlighted through the creation of twin samples that are later used throughout this work.

In Chapter 4 we focus on cluster ACT-CL J0240.0+0116 and its detailed study using the LPSZ data. We create multi-wavelength images and extensively analyse

the cluster medium to infer its integrated quantities while paying attention to the dynamical state of the galaxy clusters.

The next three chapters primarily focus on using the simulations, sampled and used in a way that represents the LPSZ, to analyse and understand various systematic effects and details that cannot be captured by observations. In Chapter 5, we validate using simulated NIKA2-like maps with artificially injected point sources, the LPSZ point source detection pipeline. A framework is established to assign reliability scores to sources detected by the pipeline.

Chapter 6 talks about the recovery of 3D cluster radial profiles from their 2D maps using the twin samples introduced in Chapter 3. The impact of cluster dynamical state on this recovery is scrutinized, emphasizing the radial point at which the recovery bias is minimized. Using these twin samples and their maps for multiple projections in Chapter 7, we investigate the scatter induced by projection on cluster mass and integrated Compton parameters at various overdensities. The estimates are then utilized to construct mass-observable scaling relationships at different overdensities, providing insights into the evolution of the scaling law with the said overdensity.

Finally, in Chapter 8, we provide an overview of the results obtained in this thesis, their limitations and ways they can be used and improved for observational applications.

Chapter 2

Theoretical background

In this chapter, we provide an overview of the literature relevant to this body of work. In Section 2.1 we give a primer on the basic concepts of Cosmology and structure formation. Section 2.2 entails a brief description of the CMB. Finally, in Section 2.3, we provide details about clusters of galaxies, and how they are observed and used for cosmological studies.

2.1 Basic concepts of Cosmology

2.1.1 The cosmological model

Modern cosmology builds upon the cosmological principle, asserting that the Universe exhibits spatial homogeneity and isotropy on scales larger than approximately $200 h^{-1} \text{ Mpc}$ (Sylos and Baryshev 2010, Planck Collaboration et al. 2016a, Appleby and Shafieloo 2014). This principle implies that there is no privileged point of observation, and the Universe appears the same in every direction. In the 1930s, within the framework of General Relativity, Robertson and Walker demonstrated that the metric for such a universe takes the form (Robertson 1935; Walker 1935)¹:

$$ds^2 = c^2 dt^2 - a^2(t) \left[d\chi^2 + f_K^2(\chi) \left(d\theta^2 + \sin^2 \theta d\psi^2 \right) \right], \quad (2.1)$$

Here, t is the cosmic time, χ is the comoving radial coordinate, and θ and ψ are angular coordinates on a unit sphere. The cosmic scale factor $a(t)$ describes isotropic expansion, normalized to unity today. The parameter K specifies spatial curvature and is related to the radial coordinate χ as:

$$f_K(\chi) = \begin{cases} \frac{1}{\sqrt{K}} \sin(\sqrt{K}\chi) & K > 0 \\ \chi & K = 0 \\ \frac{1}{\sqrt{-K}} \sinh(\sqrt{-K}\chi) & K < 0 \end{cases}, \quad (2.2)$$

where $K = 0$ corresponds to a flat universe.

The widely accepted cosmological model today is the standard Λ CDM model, dominated by the cosmological constant Λ (approximately 70% of mass-energy

¹**Note:** All equations, formulae, and concepts related to cosmology and structure formation mentioned in this thesis, unless specifically cited otherwise, are drawn from Dodelson 2003.

content today) and cold dark matter (CDM, approximately 25% today). Luminous baryonic matter constitutes the remaining 5%. Despite its current low energy density (supported by CMB observations; Komatsu et al. 2011; Planck Collaboration et al. 2020a), radiation was a dominant component at some point in the past of the expansion history of the Universe. Considering these components as fluids, the Robertson–Walker (also called Friedmann–Lemaître–Robertson–Walker) metric and Einstein’s field equations lead to the first Friedmann equation:

$$H^2 := \frac{\dot{a}^2}{a^2} = \frac{8\pi G}{3}\rho + \frac{\Lambda c^2}{3} - \frac{Kc^2}{a^2} \quad (2.3)$$

Here, $\dot{a}$ is the first-order time derivative of the scale factor $a(t)$, H is the Hubble parameter defining the expansion rate of the Universe, G is the gravitational constant, ρ is the total density (dark and baryonic matter, and radiation), and Λ is the cosmological constant. This equation leads to the second Friedmann equation:

$$\frac{\ddot{a}}{a} = -\frac{4\pi G}{3}\left(\rho + \frac{3p}{c^2}\right) + \frac{\Lambda c^2}{3} \quad (2.4)$$

Here, p accounts for the pressure of the components. These equations offer simple tools for examining the past and future of the Universe as a whole.

The critical density of the Universe ρ_{crit} , is defined as the density required to just halt the expansion of the Universe. Using Eq. (2.3) for the present-day Universe (t_0 and $a(t_0) = 1$) with vanishing curvature, considering a universe made up of only matter in order to avoid the expansion (i.e., $\Lambda = 0$ and $\rho = \rho_{\text{m}}$), we get:

$$\rho_{\text{crit},0} = \frac{3H_0^2}{8\pi G}. \quad (2.5)$$

This density is used to derive the dimensionless density parameters for all components:

$$\Omega_{\text{m},0} := \frac{\rho_{\text{m},0}}{\rho_{\text{crit},0}}; \quad \Omega_{\Lambda,0} := \frac{\Lambda c^2}{3H_0^2}, \quad (2.6)$$

yielding, once again using Eq. (2.3), $\Omega_{\text{m},0} + \Omega_{\Lambda,0} = \Omega_{\text{total}} = 1$. For the past, density parameter Ω_{r} for radiation is also considered.

The density ρ_i and pressure p_i of each component are related by the equation of state $p_i = w_i \rho_i$, where w_i is the equation of state parameter. The general density evolution rule for each component is obtained by combining the first law of thermodynamics with the equation of state:

$$\rho_i(t) = \rho_{i,0} a^{-3(1+w_i)}, \quad (2.7)$$

with w_i having different values for matter (0), radiation (1/3), and the cosmological constant (−1). Using this evolution rule and the dimensionless density parameters, the Friedmann Eq. (2.3) can be expressed as:

$$H^2 = H_0^2 \left(\Omega_{\text{m},0} a^{-3} + \Omega_{\text{r},0} a^{-4} + \Omega_{\text{K},0} a^{-2} + \Omega_{\Lambda,0} \right). \quad (2.8)$$

Alternatively, the scale factor a , a function of proper time t , can be converted to cosmic redshift z using:

$$1 + z = \frac{a(t_0)}{a(t)} = \frac{1}{a(t)}. \quad (2.9)$$

Eq. (2.8) can then be written as a function of the cosmic redshift:

$$E^2(z) := \frac{H^2(z)}{H_0^2} = \Omega_{m,0} (1+z)^3 + \Omega_{r,0} (1+z)^4 + \Omega_{K,0} (1+z)^2 + \Omega_{\Lambda,0}. \quad (2.10)$$

The function $E(z)$ describes the time evolution of the Universe's expansion rate and is utilized to obtain cosmological constraints on the involved parameters. It is essential to note that a cosmological constant is considered throughout this discussion, and a similar analysis can be conducted for dark energy with an equation of state w_{DE} , making $E(z)$ sensitive to the equation of state of dark energy.

2.1.2 Distances and volumes in an expanding Universe

The constraints on cosmological parameters using $E(z)$ (or $H(z)$) gain further clarity when considering cosmic distances. For a radial, null geodesic (followed by a photon) in a flat universe, Eq. (2.1) gives the comoving distance

$$d_{\text{com}} = c \int_t^{t_0} \frac{dt'}{a(t')}, \quad (2.11)$$

which on combining with the definition of H and Eq. (2.9) gives us

$$d_{\text{com}} = c \int_0^z \frac{dz'}{H(z')}. \quad (2.12)$$

This distance, however, is not directly observable. There are some distances which are, in principle, observable if the intrinsic properties of objects are well-known. For instance, objects with a well-known luminosity L_{Bol} (and measured flux f_{Bol}), referred to as 'standard candles' can be used to measure the luminosity distance

$$d_l = \sqrt{\frac{L_{\text{Bol}}}{4\pi f_{\text{Bol}}}}, \quad (2.13)$$

or objects with a well-known proper size D , referred to as 'standard rulers' can be used to measure the angular diameter distance

$$d_a = \frac{D}{\theta}. \quad (2.14)$$

There is a distance duality for these two observable distances given by

$$d_l = d_a(1+z)^2; \quad (2.15)$$

which is independent of the underlying cosmology. For a flat universe, it can also be shown that

$$d_l = d_{\text{com}}(1+z) = d_a(1+z)^2. \quad (2.16)$$

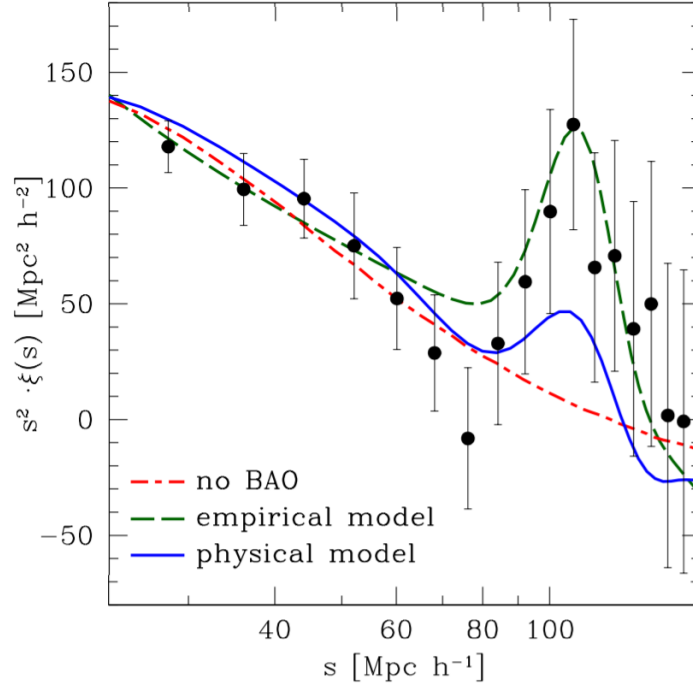


Figure 2.1 Baryonic acoustic oscillation signal seen at around $140 h^{-1} \text{Mpc}$ in the correlation function of approximately 25,000 WHL12 clusters from the Sloan Digital Sky Survey. Source: Veropalumbo et al. 2014.

This implies that measuring standard distances enables us to constrain the underlying cosmology.

A similar argument holds for the comoving volume (V_C) measured over solid angle $d\Omega$:

$$dV_C = \frac{c}{H_0} \frac{(1+z)^2 d_A^2}{E(z)} d\Omega dz, \quad (2.17)$$

which is then more sensitive to the cosmological parameters than one-dimensional distance measurements. These kinds of cosmological probes are commonly known as ‘geometric probes’. Galaxy clusters can be used as geometric probes for cosmological studies. For instance, their correlation function (shown in Fig. 2.1) can be used to constrain the baryonic acoustic oscillation (BAO) scale (which is a standard ruler) and hence confine the cosmological parameters.

2.1.3 Structure formation

Despite the large-scale homogeneity of the Universe, it is clear by the existence of stellar systems, galaxies, and clusters that on small scales ($\leq 100 h^{-1} \text{Mpc}$) the Universe is not homogeneous. Galaxy clusters represent density fluctuations in the universe with a present-day density $\rho \geq 100 \rho_{\text{crit}}$. It is known that inflation generated density fluctuations in the primordial Universe. These fluctuations were later amplified during the evolution of the Universe through the gravitational collapse of matter into denser regions, giving rise to the formation of the structure and the

large-scale distribution of matter in the contemporary Universe, forming the cosmic web.

Density fluctuations can be expressed as a first-order perturbation of the average density,

$$\rho(\vec{r}, t) = \bar{\rho}(t)[1 + \delta(\vec{r}, t)], \quad (2.18)$$

where $\bar{\rho}(t)$ is the average density of the Universe and $\delta(\vec{r}, t)$ is called the contrast parameter. In case of the linear regime, $\delta \ll 1$. Due to the assumption of the homogeneity principle, the average density of the Universe purely becomes a function of time.

On small scales, the growth of structure can be described in the framework of Newtonian gravity. Assuming that the matter in the Universe can be described as a pressureless, perfect fluid composing the Universe, the Euler, continuity (Euler 1757), and Poisson equations stand to be valid, with the former two signifying the conservation of angular momentum and mass:

$$\partial_t \vec{v} + (\vec{v} \cdot \nabla) \vec{v} = -\nabla \phi - \frac{\nabla p}{\rho}, \quad (2.19)$$

$$\partial_t \rho + \nabla \cdot (\rho \vec{v}) = 0, \quad (2.20)$$

$$\nabla^2 \Phi = 4\pi G \rho, \quad (2.21)$$

where $\vec{v}$ and p denote the fluid velocity and pressure, respectively, and Φ is the gravitational potential.

By injecting the expression of the perturbed density (Eq. 2.18) into these equations and combining them, we get the evolution of perturbations over time:

$$\ddot{\delta}(\vec{r}, t) + 2H(t)\dot{\delta}(\vec{r}, t) = \left[4\pi G \bar{\rho}(t) + \frac{c_s^2}{a^2} \nabla^2 \right] \delta(\vec{r}, t), \quad (2.22)$$

where c_s is the speed of sound in the fluid. In Fourier space, defining $\delta_k = \int d^3r \delta(\vec{r}, t) e^{-i\vec{k} \cdot \vec{r}}$, this equation takes the form

$$\ddot{\delta}_k + 2H\dot{\delta}_k = \frac{c_s^2}{a^2}(k_J^2 - k^2)\delta_k, \quad (2.23)$$

where the mode k_J is given by the Jeans scale, $\lambda_J = c_s \sqrt{\pi/\bar{\rho}G}$. The Eq. (2.23) has two asymptotic solutions in this case: i) perturbations larger than the Jeans scale, i.e., $k^2 \ll k_J^2$, gravity dominates the evolution of perturbations, allowing their growth with time; ii) perturbations on the small scale, when $k^2 \gg k_J^2$, where pressure dominates, preventing the growth of perturbations in the density field. At an epoch when the energy density is comparable for matter and radiation (at $z \lesssim 3000$), density fluctuations oscillate, increasing under the influence of gravitational force, and then decreasing because of the pressure forces. This oscillation prevents the development of structure by the growth of perturbations. At later stages when matter starts to dominate, giving $a(t) \propto t^{2/3}$ according to the Friedmann Eq. (2.3), pressure forces become negligible, allowing the growth of perturbations and hence leading to the formation of structures. At this stage, the solution for Eq. (2.23)

tells us that the contrast increases as $\delta(t) \propto a(t) \propto t^{2/3}$. Even later, when the cosmological constant starts to dominate, the scale factor grows as $a(t) \propto \exp(Ht)$, and the solution to Eq. (2.23) gives us $\delta(t) \propto \exp(-2Ht)$, showing an exponential decline in the growth of perturbations.

In the case of Gaussian fluctuations, the primordial density distribution can be summarized by the correlation function of the contrast parameter of two points in space separated by $\vec{r}$,

$$\xi(\vec{r}) = \langle \delta(\vec{x} + \vec{r}) \delta(\vec{x}) \rangle, \quad (2.24)$$

which is the mean value of the correlation, taken over every possible position $\vec{r}$ in the Universe. The Fourier transform of this correlation function gives us the primordial power spectrum $P_{\text{prim}}(k)$

$$P_{\text{prim}}(k) = \int \xi(\vec{x}) e^{-i\vec{k} \cdot \vec{x}} d^3x. \quad (2.25)$$

Observational constraints on the primordial power spectrum, obtained notably from the analysis of CMB anisotropies, favour a power-law form of the power spectrum, $P(k) \propto k^n$ with $n \approx 1$ (Planck Collaboration et al. 2020a). This case where $n = 1$ is called the Harrison-Zeldovich spectrum (Harrison 1970; Y. B. Zeldovich 1972). Scale invariance is a characteristic of this type of power spectrum. In the present-day Universe, structural features arise from the growth of primordial fluctuations. The power spectrum of the observable matter distribution at redshift z is thus closely related to the primordial power spectrum through

$$P(z, k) = P_{\text{prim}}(k) \times T^2(z, k), \quad (2.26)$$

where $T(z, k)$ is the transfer function characterizing the evolution of perturbations. An example of the observational measurement of the matter power spectrum inferred from present-day observations is shown in Fig. 2.2.

The standard deviation of the matter distribution in a sphere of radius x at redshift z is then given by:

$$\sigma^2(z, x) = \frac{1}{(2\pi)^3} \int |W(kx)|^2 P(z, k) d^3k, \quad (2.27)$$

where $W(kx)$ is the Fourier transfer of the window function used to smooth the matter distribution; for example, for the spherical top-hat window function considering a sphere of radius x , we get

$$W(k) = \frac{3 \sin(kx) - 3 kx \cos(kx)}{(kx)^3}. \quad (2.28)$$

Using Eq. (2.27), we can define the cosmological parameter σ_8 , which determines the average amplitude of fluctuations in a sphere of $8 h^{-1} \text{Mpc}$. Planck Collaboration et al. 2020a have constrained, using the CMB anisotropies, $\sigma_8 = 0.8102 \pm 0.006$.

2.1.3.1 Non-linear evolution and galaxy clusters

The formalism developed so far relies on the assumption of the linear growth of structure regime where the density contrast is of the order of one. In this regime,

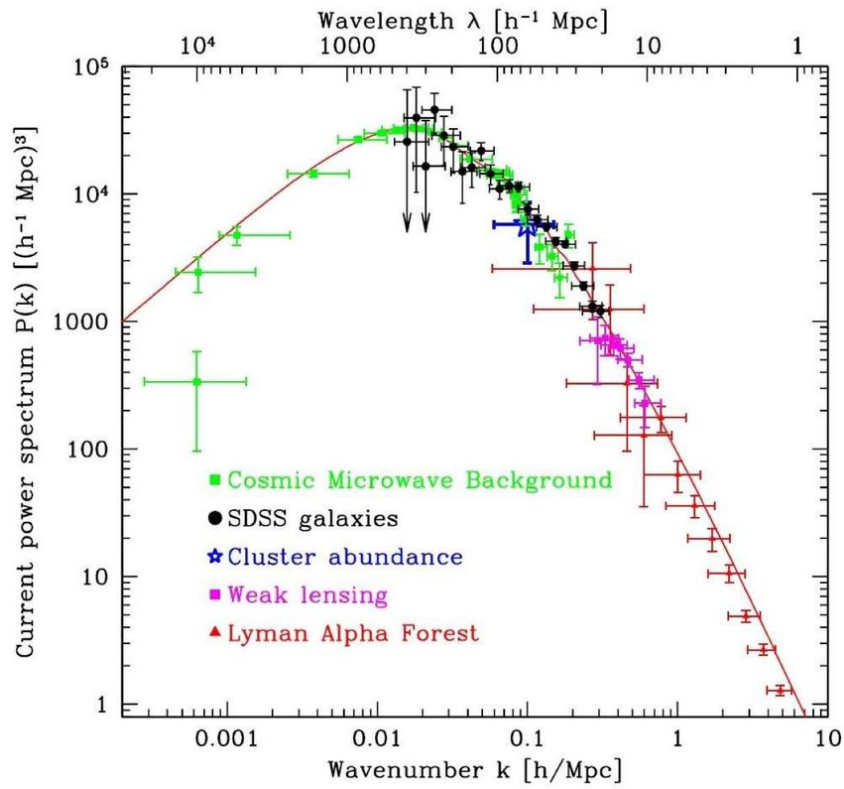


Figure 2.2 Observational measurement of the matter power spectrum using varied large-scale structure probes, indicated in the plot. The red solid line shows the predicted matter power spectrum for a flat Λ CDM cosmology. Image taken from Tegmark et al. 2004.

according to Eq. (2.18), the overdensities represent first-order perturbations in a globally homogeneous Universe, implying that $\delta \ll 1$: a condition not satisfied for the contemporary Universe. For instance, galaxy clusters today can reach central densities on the order of $\sim 10^{-22} \text{ kg m}^{-3}$, corresponding to a density contrast of about 10^4 . This evidently breaks down the assumption of linear growth of structure at the present day and invokes a need for a non-linear model.

One way to describe the non-linear structure formation is the spherical collapse model. This model suggests that as the density contrast of overdense regions increases, these regions still participate in the expansion of the Universe but at a slower rate. To form bound structures, these overdensities must detach from the Hubble flow and collapse under their gravitational self-interaction after reaching maximum expansion at some time, t_{max} . At this point, the linear theory becomes insufficient for an accurate description and numerical techniques are typically employed. Nonetheless, one simplistic analytical solution exists for this non-linear evolution of spherical overdensities in an otherwise homogeneous universe. Under idealized conditions, a spherical overdense region collapses to a single point at time $t_{\text{coll}} = 2t_{\text{max}}$. For galaxy clusters that we observe today, we can estimate that their turnaround occurred during the matter-dominated epoch. This epoch can well be approximated by an Einstein-de Sitter (EDS) universe where $\Omega_{\text{tot}} = \Omega_{\text{m}} = 1$. For an EdS universe, overdensities with a linearly extrapolated critical overdensity of $\delta_c = 1.69$ at the current epoch collapse within the age of the Universe. Due to imperfect homogeneity inside the collapsing sphere, particles scatter and eventually virialize. The average density of the collapsed structure surpasses the average density of an EdS universe by a factor $\Delta_{\text{vir}} = 178$. In a Λ CDM, this value is lower but, a common approximation for the mass of virialized structures is given by $M_{\text{vir}} \approx M_{200}$. The overdensity Δ is defined using the critical density of the universe (Eq. 2.5), as:

$$\Delta = \left[M_{\Delta} / \left(\frac{4}{3} \pi R_{\Delta}^3 \right) \right] / \rho_{\text{crit}}(z), \quad (2.29)$$

implying that within radius R_{Δ} , the average density exceeds the critical density of the Universe at the redshift of the structure by a factor of Δ . These collapsed, virialized structures are called dark matter halos.

One of the most theoretically motivated formalisms for the prediction of the abundance of such halos or galaxy clusters is the Press–Schechter mass function (Press and Schechter 1974), even though more recently, the mass functions are generated via simulations to better understand the contemporary large-scale structure or LSS (see e.g., Tinker et al. 2008). The Press–Schechter theory is based on the assumption that the initial density fluctuations are described by a Gaussian random field and that regions with $\delta > \delta_c$ collapse to form structure, where δ_c is the density contrast threshold (for clusters in our case). The probability P for a structure with mass M and volume V to have collapsed at redshift z is then given by the integral over the random field,

$$P = \frac{1}{\sqrt{2\pi}\sigma(M, z)} \int_{\delta_c}^{\infty} \exp\left(-\frac{\delta^2}{2\sigma^2(M, z)}\right) d\delta. \quad (2.30)$$

This probability can be looked at as a number density of the clusters. Using this probability, Press and Schechter showed that the halo mass function can then be

given by

$$\frac{dn}{dM} = \frac{1}{V} \left| \frac{dP}{dM} \right| = \sqrt{\frac{2}{\pi}} \frac{\rho_m}{M} \frac{\delta_c}{\sigma^2(M, z)} \left| \frac{d\sigma(M, z)}{dM} \right| \exp \left(-\frac{\delta_c^2}{2\sigma^2(M, z)} \right). \quad (2.31)$$

The above functional form reiterates the exponential sensitivity of the cluster mass function to the density contrast and hence $E(z)$, as shown in Fig. 1.1.

2.2 The Cosmic Microwave Background

Up to this point, our focus has primarily been on the matter component of the Universe and its historical trajectory. This gave us an insight into how galaxy clusters are formed and are potential tools for studying the cosmological model. In order to make such inferences using clusters, we need to observe them using different observables. A primary observable that we use in this work, is the SZ effect. This effect is, simply put, the inverse Compton scattering of the CMB photons by the cluster ICM. Before getting into details about the SZ effect, we need to understand the CMB itself and so, we shift our attention to the radiation component of the Universe.

In order to comprehend the genesis and evolution of the CMB, it is important to understand the thermal history of the Universe. The standard cosmological model outlines the evolution of the Universe from an immensely dense state immediately following the Big Bang. Initially, it is replete with hot ionized gas, constituting a primordial plasma wherein elementary particles are interconnected through interactions. During the era when radiation dominates the energy density budget, the scale factor evolves according to $a \propto t^{1/2}$. Then, the continued expansion of the Universe leads to the dilution and cooling of the primordial plasma, resulting in a reduction of its density and pressure. This, in turn, diminishes the interaction rate of specific particles within the plasma. Eventually, weakly interacting species such as neutrinos and dark matter undergo gradual decoupling. The decoupling event initiates primordial nucleosynthesis when the temperature reaches approximately 100 keV, giving rise to the formation of nuclei like helium and lithium.

As the Universe continues to expand, the radiation energy density diminishes at a rate described by $\rho_r \propto a^{-4}$, surpassing the rate of matter energy density, which follows $\rho_m \propto a^{-3}$. Consequently, the Universe undergoes a phase shift where the energy density of matter becomes dominant, initiating around a redshift of $z \sim 3400$ ($T \sim 10^4$ K). Throughout this phase, expansion persists with $a \propto t^{2/3}$. Subsequently, as the interaction rate continues to decline, the first hydrogen atoms emerge through the combination of electrons with nuclei formed during primordial nucleosynthesis—a phenomenon referred to as recombination. The Universe then transitions into a neutral state, allowing photons to propagate freely and decouple. This marks the emission of the CMB at a redshift of $z \sim 1100$. The CMB represents the initial light emitted in what was previously an opaque Universe and serves as a crucial tool in cosmology. It manifests as radiation with a black-body spectrum at a temperature of $T_{\text{CMB}} = 2.725$ K (Fixsen et al. 1996), demonstrating remarkable uniformity across the entire sky, with temperature fluctuations on the order of 10^{-5} K (Planck Collaboration et al. 2020a). The power spectrum of these fluctuations is intricately

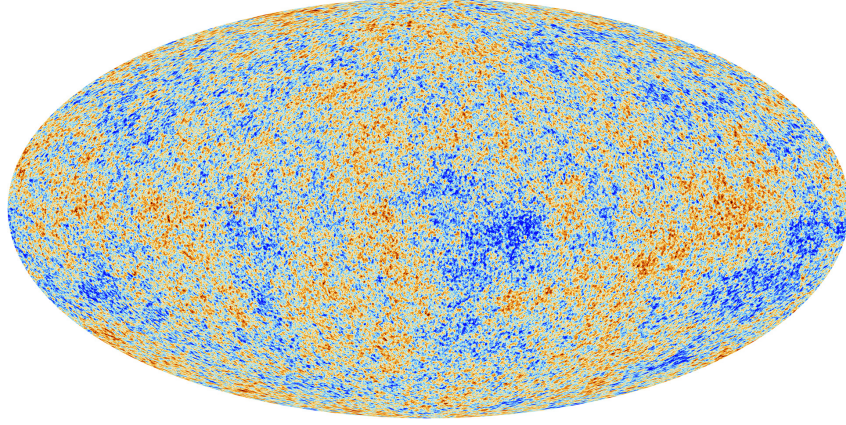


Figure 2.3 The anisotropies of the CMB as observed by Planck. The blue colour represents cold spots and the red colour, the hot spots. These anisotropies are of the level of 10^{-5} K level. Credits: ESA, Planck Collaboration et al. [2016d](#)

linked to the characteristics of the Universe at the time of photon decoupling and, consequently, to the underlying cosmological model. Subsequently, gravitational collapse leads matter to organize itself around the most densely concentrated regions, resulting in the formation of the large-scale structure of the Universe (see Section [2.1.3](#)). Finally, around a redshift of $z \sim 0.5$, the energy density of matter falls below that of dark energy, marking the onset of dominance of dark energy in the Universe, accompanied by the commencement of accelerated expansion.

The observed CMB photons experienced decoupling from baryonic matter approximately 380,000 years after the Big Bang during the recombination epoch. This phase marked the cooling of the Universe, facilitating the formation of the first atoms. Before recombination, photons and baryons formed a tightly coupled fluid that could oscillate in response to disturbances, such as gravitational potentials. Despite the CMB appearing as a nearly perfect black-body, these oscillations, known as baryon acoustic oscillations (BAOs), create a distinct pattern of small temperature anisotropies. Termed the CMB primordial fluctuations, these primary anisotropies exhibit a typical amplitude of $\Delta T/T_0 \approx 10^{-5}$. Serving as a snapshot of the matter distribution on the Large Scale Structure (LSS) during recombination, these primary anisotropies in the CMB have been observed by the Planck satellite, as depicted in Fig. [2.3](#). The following section outlines the origin of temperature anisotropies and how this information can be captured and utilized for cosmological inferences.

2.2.1 The CMB Power Spectrum

In a conceptual sense, we can visualize the CMB as emitted from the surface of a thin spherical shell known as the last scattering surface, situated at a redshift of approximately $z \approx 1080$. Describing the statistical characteristics of the CMB temperature fluctuation pattern involves expanding the observed temperature map using spherical harmonics $Y_{\ell m}(\theta, \phi)$ expressed as:

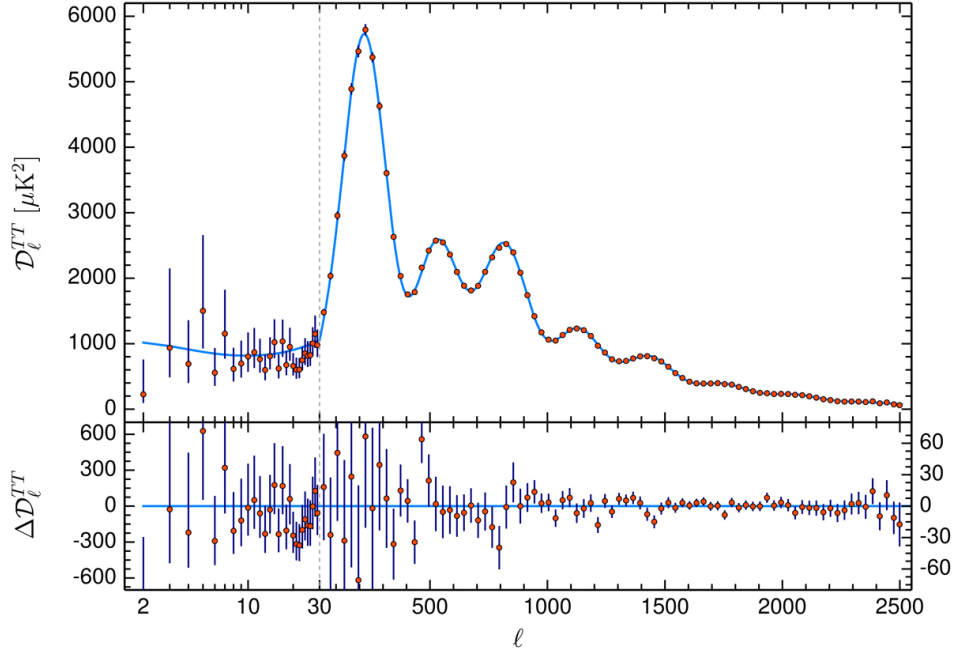


Figure 2.4 The angular power spectrum of the CMB temperature anisotropies constrained by Planck. Image taken from Planck Collaboration et al. [2020b](#).

$$\Delta T(\theta, \phi) = T(\theta, \phi) - T_0 = \sum_{\ell=1}^{\infty} \sum_{m=-\ell}^{\ell} a_{\ell m} Y_m^{\ell}(\theta, \phi), \quad (2.32)$$

where the coefficients $a_{\ell m}$ contain information about fluctuation sizes concerning angular scales ($\approx 180^\circ/\ell$). The statistical properties of these coefficients are quantified by the angular power spectrum, represented as

$$C_{\ell} = \langle |a_{\ell m}|^2 \rangle. \quad (2.33)$$

An example of visualisation of the CMB anisotropies using these harmonics can be seen in the measurements of the CMB angular power spectrum constrained by Planck, shown in Fig. [2.4](#).

The shape of the angular power spectrum is driven by diverse phenomena that convert primordial fluctuations in matter density into temperature fluctuations. These processes encompass the scattering of photons by baryons and gravitational effects. In the closely intertwined baryon-photon fluid, photons underwent interactions with free electrons through Thomson scattering, and free electrons interacted with nucleons through Coulomb scattering. Perturbations in the density field propagated through this fluid at the speed of sound, approximately $c/\sqrt{3}$.

Beyond the horizon scale, fluctuations influence the CMB through the Sachs-Wolfe effect, a composite of gravitational redshift, time dilation, and the Doppler effect arising from gas movement within extensive gravitational potentials. On scales smaller than the horizon, the relevance of BAOs becomes evident. These oscillations originate from the interaction between dark matter and baryons before decoupling. While dark matter, free-streaming post-decoupling, facilitates the growth of small

initial disturbances in its density field, baryonic matter opposes collapsing into dark matter potential wells due to photon pressure, resulting in fluid oscillations. These sound waves freeze at the recombination moment, manifesting as temperature fluctuations of around one degree in scale. This gives rise to a distinctive primary peak in the CMB angular power spectrum at $\ell_1 \approx 200$ (notice this in Fig. 2.4). Since this is a characteristic distance, the ability of the CMB to put a constraint on this value reflects its sensitivity to the geometry of the Universe. The consequent peaks and compressions of these oscillations can be observed at integer multiples of this scale, ℓ_1 . These acoustic peaks are a crucial cosmological probe of the CMB (Planck Collaboration et al. 2020b).

Apart from the primary anisotropies, after the epoch of recombination, several mechanisms also give rise to secondary temperature anisotropies in the CMB. These phenomena include, but are not limited to gravitational lensing, the integrated Sachs–Wolfe effect (Sachs and Wolfe 1967), the Rees–Sciama effect (Rees and Sciama 1968), and the SZ effect, which is discussed in Section 2.3.3. A detailed review of the CMB and its anisotropies can be found in Hu and Dodelson 2002.

2.3 Clusters of galaxies

As implied by their name, galaxy clusters constitute a gathering of 100–1000 galaxies bound together by gravitational forces. These clusters typically exhibit masses in the range of 10^{13} – $10^{15} M_\odot$ and diameters spanning up to a few megaparsecs. Their primary components include galaxies, the intracluster medium (ICM) comprising hot gas that permeates the space between galaxies, relativistic particles, and dark matter, the substantial mass responsible for gravitational cohesion within the system.

2.3.1 The composition of galaxy clusters

Galaxies, constituting approximately $\sim 5\%$ of the total cluster mass, play a minor role in the overall mass composition and are most prominently observed at the infrared and optical wavelengths. The majority of these cluster members tend to be evolved elliptical galaxies with old stellar populations and low star formation rates (Dressler 1984; Oemler 1992). A high fraction of clusters tend to have a giant elliptical galaxy at their centre, often referred to as the Brightest Cluster Galaxy (BCG). Often, BCGs have an active galactic nucleus that can strongly affect other baryonic components of clusters. The predominant share, accounting for nearly 80% of the cluster mass, is attributed to dark matter. This makes galaxy clusters ideal candidates for dark matter observations. One such well-known case of dark matter constraint from a galaxy cluster system is that of the bullet cluster (Markevitch et al. 2004). The remaining portion of the mass budget is filled by the hot ionized gas present in the ICM. The hot ionised gas of the ICM is typically smoothly distributed along the gravitational potential of the dark matter halos of clusters. The temperature of the ICM gas ranges up to a few keV (10^7 – 10^8 K), which makes galaxy clusters very bright in the X-ray regime and scatter the CMB photons, also making them visible at millimetre wavelengths via the SZ effect.

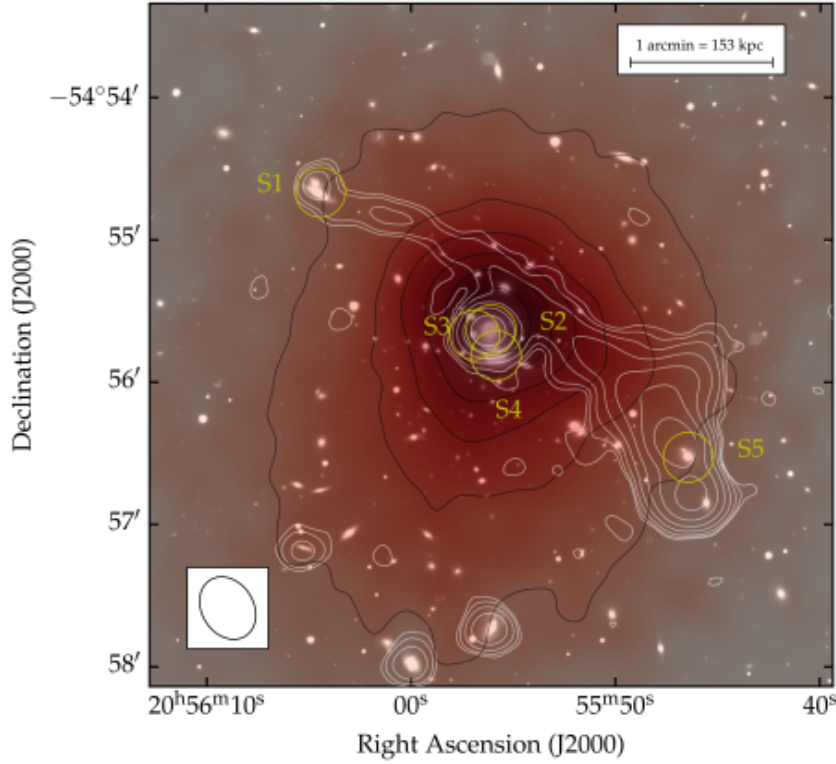


Figure 2.5 Multi-wavelength composite of galaxy cluster A3718. The coloured image in the background is an i, r, and g band composite image from the Dark Energy Survey (Abbott et al. 2021), depicting the member galaxies of the cluster. The overlaid red colour and black contours trace the X-ray surface brightness measured in the 0.3–7 keV range by XMM-Newton, tracing the hot ICM gas. Finally, the white contours show the total intensity surface brightness of the radio emission at 943 MHz, as traced by the Evolutionary Map of the Universe (EMU) survey, indicating the presence of a complex radio source interacting with the ICM. Image and details from Loi et al. 2023.

2.3.2 Observations of galaxy clusters

The multi-component nature of galaxy clusters makes them observable across the electromagnetic spectrum, ranging from radio waves to Gamma-ray radiation, offering diverse insights into their properties, including temperature, luminosity, pressure, and density. These observations yield astrophysical details about their dynamical state and cosmological information such as information about dark matter, the cosmic web structure, and so on. Figure 2.5 illustrates the multi-wavelength nature of galaxy clusters by showcasing the appearance of cluster A3718 in optical, X-ray, and radio bands. In this section, we briefly discuss the emissions from galaxy clusters that can be observed at varied wavelengths.

2.3.2.1 Radio waves

Although the ICM gas itself is exceptionally hot and does not emit directly in the radio spectrum, the motion of charged particles within a magnetic field causes them to gyrate along the magnetic field lines. This gyration accelerates the particles,

leading to the emission of radiation. When these particles attain relativistic velocities, they emit synchrotron radiation with a power-law form ($I_\nu \propto \nu^{-\alpha}$ with $\alpha > 1$). These emissions, categorized as radio halos or radio relics based on their morphology, play a significant role in studying the cluster ICM. Radio halos, typically found at the centres of many clusters, exhibit unpolarized emission with low surface brightness. In contrast, radio relics are elongated features observed on the outskirts of clusters, often displaying high polarization. Relics are increasingly linked to shock waves resulting from cluster interactions such as mergers (van Weeren et al. 2019).

2.3.2.2 Microwaves

The microwave spectrum can be effectively divided into two segments, where galaxy clusters manifest as cold spots in the CMB at millimeter wavelengths and hot spots at sub-millimeter wavelengths. This phenomenon arises from the emission resulting from the inverse Compton scattering of CMB photons by the hot ICM gas, commonly known as the SZ effect. The primary observable employed in this study is the SZ surface brightness, along with the derived Compton parameter values. Further insights into the SZ effect are given in Section 2.3.3.

2.3.2.3 UV, optical, and infrared

This wide range of the electromagnetic spectrum, as previously noted, essentially traces the member galaxies and, consequently, the stellar populations in and around the galaxy cluster. The categorization of galaxies based on their optical (photometric or spectroscopic) redshifts has historically been one of the initial methods to generate extensive catalogs of galaxy clusters and has persisted until recent times (see Abell, Corwin, and Olowin 1989; Rykoff et al. 2014). Additionally, as discussed in Section 1, the lensing effect induced by the potential wells of galaxy clusters on background objects and the dynamical studies of member galaxies have evolved into crucial tools, offering accurate measurements of the total mass of clusters (see Allen, Evrard, and Mantz 2011).

2.3.2.4 X-rays

The temperature of the ICM gas in galaxy clusters, affected by their deep gravitational potential wells, extends to a few keV, making them highly luminous in the X-ray spectrum. The dominant emission process is X-ray radiation through free-free interaction, often called the thermal bremsstrahlung emission. There are also bound-bound emissions that manifest as line features in the X-ray spectra and free-bound emissions that occur due to recombination, for a detailed review of these emissions, see Sarazin 1986. The bremsstrahlung emissivity ϵ_ν for a cluster with luminosity L at frequency ν in a specific volume V is given by:

$$\epsilon_\nu = \frac{dL}{dV d\nu} \propto Z^2 n_e n_i T^{-\frac{1}{2}} \exp\left(\frac{-h\nu}{k_B T}\right), \quad (2.34)$$

where Z is the metal abundance, n_e and n_i are electron and ion densities, T is the ICM temperature, and h and k_B are the Planck and Boltzmann constants, respectively. Examples of the X-ray spectrum of galaxy clusters can be seen in

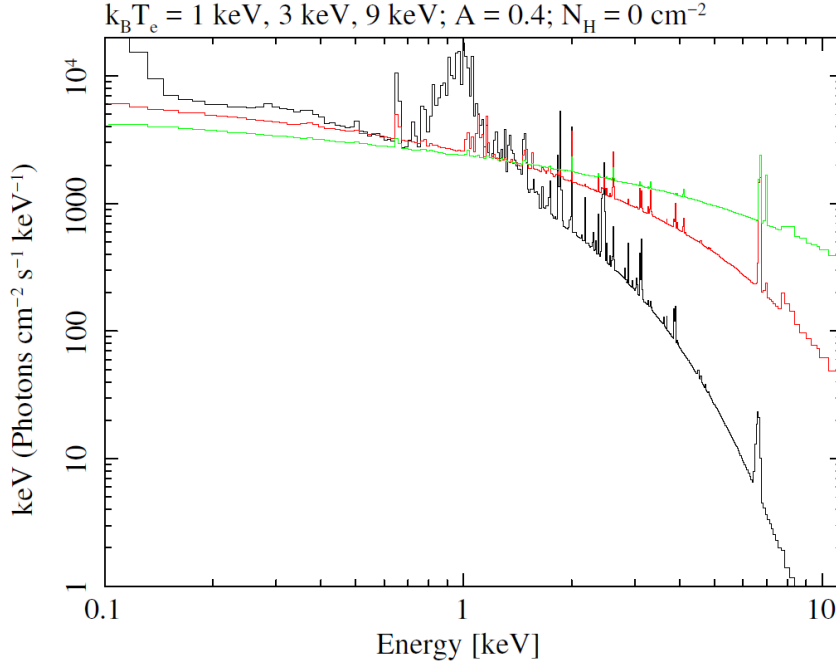


Figure 2.6 X-ray spectra including free-free, free-bound, and bound-bound emission. The green, red, and black spectra correspond to intracluster gas temperatures of 9 keV, 3 keV, and 1 keV, respectively. Notice the exponential cut-off of the spectra at the temperature of the intracluster gas. Source: Reiprich et al. 2013.

Fig. 2.6. We see in these spectra, the exponential cutoff in emission, which aids the determination of the isothermal temperature of the ICM. The X-ray emission is directly proportional to the square of the cluster medium density, allowing for the determination of the electron density profile. This profile is often approximated using the β -model (Cavaliere and Fusco-Femiano 1976).

$$n_e(r) \propto \rho_g(r) = \rho_{g,0} \left(1 + \frac{r^2}{r_c^2} \right)^{-\frac{3}{2}\beta}, \quad (2.35)$$

where $\rho_{g,0}$ is the central gas density, r_c is the core radius, and $\beta \approx 2/3$ (Voit 2005).

2.3.3 The Sunyaev–Zeldovich (SZ) effect

The SZ effect, initially theorized by Rashid Sunyaev and Yakov Zeldovich (Sunyaev and Y. B. Zeldovich 1970; Sunyaev and Y. B. Zeldovich 1972), is a secondary anisotropy of the CMB. This phenomenon results from the scattering of CMB photons by highly energetic free electrons in the cluster ICM, causing a distinctive distortion in the spectral energy distribution of the CMB in the direction of galaxy clusters. The collisions between electrons and photons lead to a specific redistribution of photon frequencies. Consequently, when observing the CMB in the direction of a galaxy cluster, there is a deficiency of low-energy photons compared to the average CMB signal, accompanied by a complimentary excess of higher-energy photons. In simpler terms, when looking through the line of sight (LoS) of a galaxy cluster, the

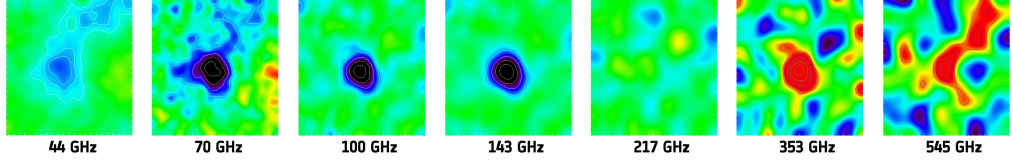


Figure 2.7 A view of cluster A2319 in the different channels of the Planck satellite. This shows the redistribution of the energy of the CMB photons by the hot ICM electrons, from lower energies (below 217 GHz) where the cluster appears as cold (blue) spots in the CMB, to higher energies (above 217 GHz) where the cluster appears as hot (red) spots. This depicts the SZ effect of galaxy clusters. Credits: ESA/Planck satellite.

CMB appears dimmer at lower frequencies and brighter at higher frequencies. This energy redistribution is illustrated for cluster A2319 in Fig. 2.7.

This effect manifests in different components, each associated with a distinct physical process responsible for the energy transfer from electrons to CMB photons. Each of these components provides insights into the physical properties of the ICM, allowing for the characterization of galaxy cluster physics. The two primary SZ effects frequently utilized are the thermal Sunyaev–Zeldovich (tSZ) and the kinetic Sunyaev–Zeldovich (kSZ) effect. Along with these two components, we introduce the relativistic impact on the SZ effect in the following discussion. Comprehensive reviews of various SZ effects and their applications in the cosmological context are available in Birkinshaw 1999; Carlstrom, Holder, and Reese 2002; Mroczkowski et al. 2019.

This thesis exclusively explores the thermal component of the SZ effect. Subsequent mention of the SZ effect, following this chapter, refers to the tSZ effect unless explicitly stated otherwise.

2.3.3.1 The Thermal SZ Effect

In most galaxy clusters, the primary contribution to the SZ effect is the tSZ effect. This effect arises from the inverse Compton scattering of CMB photons by the thermal electrons within the ICM, where the electron velocities conform to an isotropic Maxwell–Boltzmann distribution. The ICM gas temperatures typically range from $10^7 - 10^8$ K, representing thermal energies of $3k_B T/2$. These temperatures, varying from 1-10 keV, significantly exceed the energy of the CMB photons. Through inverse Compton scattering, the thermalised electrons in the ICM transfer a portion of their energy to CMB photons, inducing a shift in the CMB’s spectral energy distribution. The spectral characteristics of this distortion are determined by the Kompaneets equation (Kompaneets 1957). When dealing with the scattering by a population of non-relativistic electrons where $k_B T_e \ll m_e c^2$, the Kompaneets equation is expressed as:

$$\frac{\partial n}{\partial y} = \frac{1}{x^2} \frac{\partial}{\partial x} \left[x^4 \left(\frac{\partial n}{\partial x} + n^2 + n \right) \right]. \quad (2.36)$$

Here, n denotes the photon occupation index, defined for a specific intensity I_ν at a frequency ν , and x is the dimensionless frequency of the electrons, given by $x \equiv h\nu/k_B T_e$. The photon occupation index is given by:

$$n \equiv \frac{I_\nu c^2}{2h\nu^3}, \quad (2.37)$$

and the Compton parameter is expressed as:

$$y \equiv \int \frac{k_B T_e}{m_e c^2} d\tau_e, \quad (2.38)$$

where $\tau_e \equiv n_e \sigma_T l$ represents the optical depth, n_e is the electron density, σ_T is the Thomson scattering cross-section. The Compton parameter can also be written using the optical depth definition:

$$y = \int \frac{k_B T_e}{m_e c^2} n_e \sigma_T dl = \frac{\sigma_T}{m_e c^2} \int P_e dl. \quad (2.39)$$

For the tSZ effect, the incident photons have significantly lower energy compared to the electrons, i.e., $x \ll 1$. Consequently, $\partial n / \partial x \gg n, n^2$, leading to a simplification of Eq. (2.36). Combining this condition with the black-body spectrum expression for CMB photons, we obtain the expression for the change in specific intensity caused by the tSZ effect:

$$\frac{\Delta I_\nu^{\text{SZ}}}{I_0} = y \times \frac{x^4 e^x}{(e^x - 1)^2} [x \coth(x/2) - 4] [1 + \delta_r(x, T)], \quad (2.40)$$

where x now corresponds to $h\nu/k_B T_{\text{CMB}}$, $\delta_r(x, T)$ represents relativistic corrections to the tSZ effect, and $I_0 \equiv 2(k_B T_{\text{CMB}})^3/(hc)^2$ is the specific intensity of the CMB.

The spectral deformation resulting from the tSZ effect is depicted in Fig. 2.8. In the left panel, the spectrum of CMB photons is shown (navy solid curve), along with the spectrum of CMB photons interacting with the cluster ICM via the tSZ effect (red dotted curve). The latter, in principle, is shifted toward higher frequencies, indicating an energy gain of CMB photons through inverse Compton scattering. It's important to note that the effect in the spectrum may be subtle for a realistic value of $y = 0.0001$. For illustrative purposes, an exaggerated version is presented with $y = 0.1$ (green solid curve), where the redistribution of energy becomes more evident. In the right panel, the relative spectral distortion caused by the tSZ effect (Eq. 2.40) is shown for these cases. The distinctive feature of this relative distortion is that it is zero at around 217 GHz (referred to as the ‘null-point’), positive above this value, and negative below it. Consequently, observing the CMB in the direction of galaxy clusters reveals a decrease in CMB surface brightness at frequencies below 217 GHz and an increase at higher frequencies, as demonstrated in Fig. 2.7. This signature is highly characteristic of the tSZ effect, facilitating its distinction from other astrophysical sources.

The dependence of the amplitude of the distortion due to the tSZ effect on the Compton parameter y is evident via the different values in Fig. 2.8. Assuming the ICM hot gas to be well-described by a perfect gas, the expression for the Compton parameter y can be given by:

$$y(\theta) = \sigma_T \int \frac{P_e(l)}{m_e c^2} dl. \quad (2.41)$$

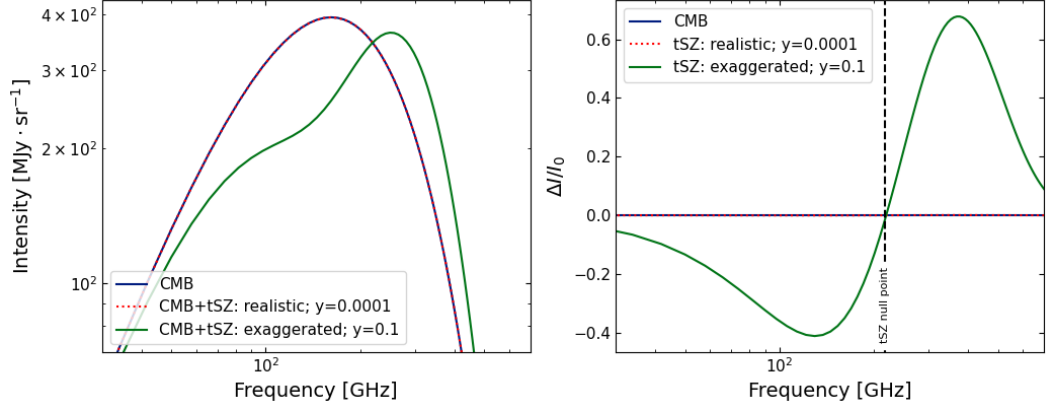


Figure 2.8 *Left:* The spectral energy distribution of CMB photons (navy solid curve) and CMB photons interacting with the cluster ICM through the tSZ effect for a realistic value of $y = 0.0001$ (red dotted curve). The impact of this effect is minimal, making it challenging to discern changes in the spectral distribution. The same spectrum is depicted with an exaggerated value of $y = 0.1$ (green solid curve), showcasing the redistribution of CMB photons from lower to higher energies. *Right:* The same curves are represented as the relative change in the intensity of CMB photons. The typical tSZ spectrum exhibits zero relative distortion at 217 GHz, referred to as the ‘null-point.’ Above and below this point, the relative change in intensity is positive and negative, respectively.

In this equation, θ denotes the observed sky coordinates, and P_e stands for the pressure exerted by electrons, expressed as $P_e = n_e k_B T_e$. Mapping the tSZ effect in the direction of galaxy clusters enables the determination of the electron pressure distribution within the ICM.

As depicted by the aforementioned equation, the magnitude of the spectral distortion resulting from the tSZ effect remains independent of the cluster redshift. This characteristic makes it a preferred method for detecting distant galaxy clusters. Unlike the X-ray surface brightness, which diminishes as $(1+z)^{-4}$ (Eq. 4.18) and results in distant clusters featuring less luminous galaxies, a high-redshift galaxy cluster remains relatively bright in millimeter wavelengths when compared to a nearby cluster of equivalent mass. Consequently, SZ effect surveys can identify more distant and, therefore, older clusters than their optical and X-ray counterparts. Moreover, tSZ observations enable the determination of the integrated Compton parameter Y_{SZ} (discussed in subsequent chapters), providing a metric for the thermal energy content in the intracluster medium. Thus, the tSZ effect offers crucial insights for the study of galaxy cluster properties and evolution.

2.3.3.2 The Kinetic SZ Effect

The origin of the kSZ effect lies in the scattering of CMB photons by a group of hot electrons experiencing bulk motion with respect to the CMB rest-frame (Sunyaev and I. B. Zeldovich 1980). During their motion in the ICM, these electrons transfer a portion of their energy to CMB photons through scattering, causing a spectral distortion in the CMB. Unlike the isotropic motion of electrons contributing to the

tSZ effect, the motion of electrons in the kSZ effect cannot be assumed to be uniform. The resulting spectral distortion in the CMB due to the kSZ effect is given by:

$$\frac{\Delta I_\nu^{\text{kSZ}}}{I_0} = y_{\text{kSZ}} \times \frac{x^4 e^x}{(e^x - 1)^2} [1 + \delta'_r(x, T, v_z)] \quad (2.42)$$

where δ'_r represents relativistic corrections to the kSZ effect, v_z is the speed of the gas along the cluster LoS, and $y_{\text{kSZ}}(\theta)$ is the Compton parameter for the kSZ effect, in the direction of sky coordinates θ , defined as:

$$y_{\text{kSZ}}(\theta) \equiv \frac{v_z(\theta)}{c} \int d\tau_e = \frac{\sigma_T v_z(\theta)}{c} \int n_e(l) dl(\theta), \quad (2.43)$$

where c is the speed of light.

The comparison between Eq. (2.40) and Eq. (2.42) underscores the distinction in the spectral characteristics of the tSZ and kSZ effects. This dissimilarity is depicted in Fig. 2.9, where the tSZ effect is represented by a red dotted curve, and the kSZ effect can manifest as either an increase (light blue curve) or a decrease (light green curve) in the surface brightness of the CMB, contingent on the direction of the bulk motion of ICM electrons. The maximum distortion caused by the kSZ effect is observed at the frequency of 217 GHz, which corresponds to the null point of the tSZ effect. Consequently, observing the sky at this frequency enables the measurement of the kSZ effect without interference from the tSZ effect. However, for large, spatially extended clusters that are both close and massive, the kSZ effect is frequently mistaken for the primary CMB anisotropies due to the similarity in their power spectra and the very indistinguishable change in CMB photon intensity (level of 10^{-4}).

Equation (2.43) illustrates that measuring the kSZ effect allows for the determination of the product of electron density and the bulk velocity of the gas. When combined with velocity field measurements in clusters obtained through optical observations, the kSZ effect offers an opportunity to assess the density of the intra-cluster medium. In this case, with the use of Eq. (4.23), the combination of tSZ and kSZ effects can potentially provide a measurement of cluster masses, assuming hydrostatic equilibrium, without relying on X-ray observations. Nevertheless, it's worth noting that the amplitude of the kSZ effect is significantly weaker than that of the tSZ effect. The ratio between the two is approximately $(k_B T_e / m_e c^2) / (v_z / c) \sim 10$ for velocities on the order of a few hundred km/s and temperatures on the order of a few tens of keV, as depicted in Fig. 2.9.

Detecting a substantial kSZ signal necessitates high sensitivity and measurements at multiple wavelengths to disentangle its contribution from the total signal, which includes that of the tSZ effect. Some detections of the kSZ effect have been reported, relying on techniques like stacking signals from multiple clusters (see Hand et al. 2012) or conducting deep measurements of clusters where large motion velocities are anticipated, such as the cluster MACS J0717.5+3745 (see Mroczkowski et al. 2012; Adam et al. 2017b). However, in the observations considered in this thesis, the kSZ effect is often negligible due to the low signal-to-noise ratio, where the kSZ signal level is lower than the noise of the LPSZ.

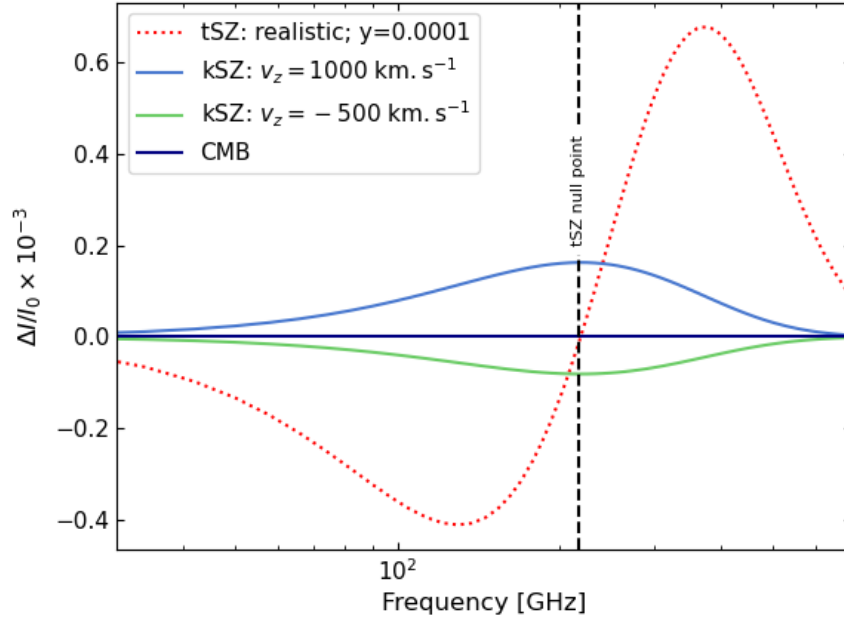


Figure 2.9 The relative change in the CMB photon intensity, shown due to the kSZ effect for electrons with bulk motion along the LoS (light blue curve) and against the LoS (light green curve). In comparison is the change in intensity due to the tSZ effect (red dotted curve), which is ≈ 10 times higher than the kSZ effect. The maximum distortion caused by the kSZ effect lies at the tSZ null point: 217 GHz.

2.3.3.3 Relativistic corrections to the SZ Effect

Relativistic corrections to the tSZ and kSZ effects, presented in Eq. (2.40) and Eq. (2.40), respectively, are collectively known as the relativistic Sunyaev–Zeldovich (rSZ) effect. This naming convention arises from the distinctive spectral signature of these relativistic corrections, enabling their differentiation from the first-order contributions of the tSZ and kSZ effects. Moreover, the rSZ effect carries information about ICM properties distinct from these primary effects. It’s essential to emphasize that the rSZ effect can only be identified in conjunction with the primary effects and is not an isolated phenomenon. Up to this point, we have omitted discussions about relativistic corrections to the SZ effects. This omission is easily justified for the kSZ effect, where the bulk motion of the ICM electrons exhibits velocities on the order of a few hundred km/s, resulting in $\beta = v_z/c \sim 10^{-4}$. Similarly, in the case of the tSZ effect, a temperature range of $k_B T \sim 1 - 10$ keV corresponds to $\beta = \sqrt{3k_B T_e / 2m_e c^2} \sim 0.1$.

Since relativistic corrections to the SZ effects are beyond the scope of this work, we refrain from detailed discussions. A comprehensive recap can be found in other sources, such as Mroczkowski et al. 2019. In summary, the rSZ effect primarily relies on the ICM temperature, resulting in the broadening of the tSZ and kSZ effect spectra and a shift in the frequency at which the tSZ null point occurs. Fig. 2.10 illustrates these effects, showing that with increasing temperatures, the amplitudes of the tSZ spectra reduce at frequencies below ~ 400 GHz and increase beyond that range. Additionally, the frequency corresponding to the null point of the tSZ effect rises from 217 GHz to a higher value with increasing ICM temperatures. Observationally, the rSZ effect induces a modification of tSZ and kSZ signals based on the ICM temperature. This modification can be discerned by observing SZ effects from clusters at multiple frequencies to separate the contributions of thermal, kinetic, and relativistic terms. Historically, the rSZ effect has primarily been detected through analyses involving the stacking of SZ signals from multiple clusters (see, e.g., Hurier 2016) or through its impact on the power spectrum of the SZ effect mapping across the entire sky (see, e.g., Remazeilles et al. 2019). Ongoing studies aim to obtain individual measurements, enabling a first measurement of the ICM temperature at millimeter wavelengths, for instance, with the CONCERTO spectrometer (CONCERTO Collaboration et al. 2020).

2.3.4 Self-similarity and scaling relations

In 1986, Kaiser laid out the framework for the formation and evolution of structures under the assumption of self-similarity (Kaiser 1986). At its core, the self-similarity principle asserts that all galaxy clusters are fundamentally identical; larger clusters are essentially scaled-up versions of smaller clusters, assuming pure gravitational effects in structure formation and evolution and a scale-free initial power spectrum of matter fluctuations. This inherent self-similarity leads to power-law predictions for relationships between observable properties of galaxy clusters and between cluster mass, albeit, self-similarity is not an essential condition to construct a scaling relation with a power-law form.

Consider the example where the temperature T of a cluster is proportional to its

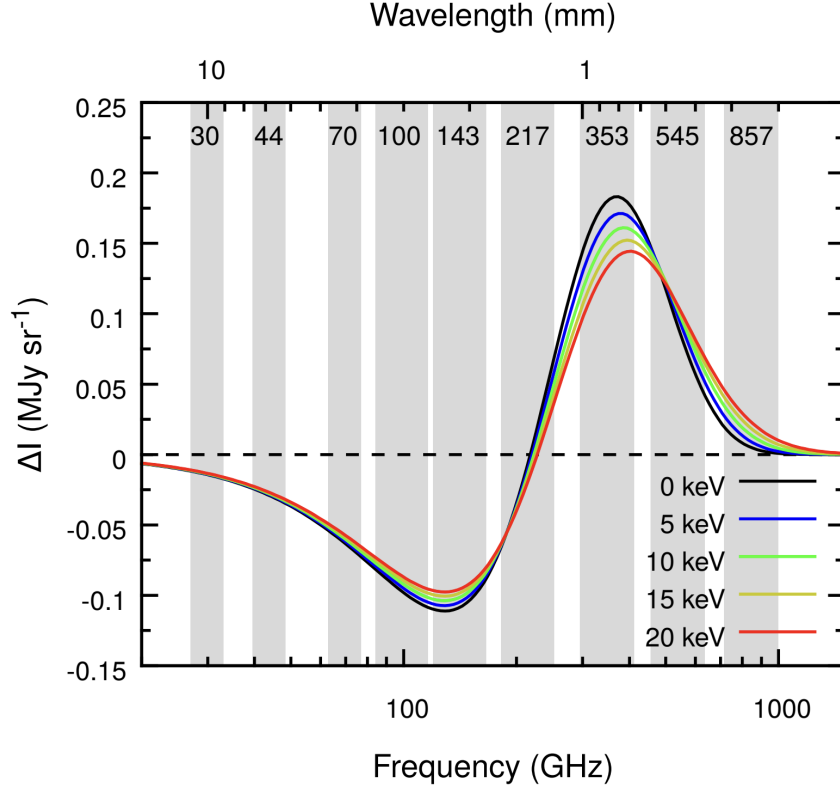


Figure 2.10 The spectral signature of the tSZ effect for $y = 0.0001$ with relativistic corrections depicted in different colours for various ICM temperatures. The amplitudes of the spectra decrease with increasing temperature, below frequency ~ 400 GHz and increase with increasing temperature, beyond this frequency range. The null point of the tSZ shifts to a frequency higher than 217 GHz with increasing temperature. The shaded grey regions correspond to the nine frequency bands of the Planck satellite. Image taken from Erler et al. [2017](#).

velocity dispersion σ^2 . The virial theorem yields:

$$T \propto \sigma^2 \propto \frac{M}{r}, \quad (2.44)$$

where M and r represent the mass and radius of the cluster. Assuming a spherical collapse, the relation

$$M \propto r^3 \quad (2.45)$$

emerges. Combining these equations results in the self-similar scaling relation

$$M \propto T^{\frac{3}{2}}, \quad (2.46)$$

which links the mass and temperature of the cluster.

In practice, perfect self-similarity is not feasible, as astrophysical processes such as cooling flows in the cluster core and mergers disrupt this ideal scenario (see Mittal et al. 2011, Pratt et al. 2009). However, this does not preclude the establishment of scaling relations, reiterating that self-similarity is not a prerequisite for these relations. For our purposes, we model mass-observable, particularly mass-integrated Compton parameter (Y - M) scaling relations. In a general form, a power-law scaling relation between an observable O and cluster mass M can be expressed as:

$$\ln O = \alpha + \alpha' \ln E(z) + \alpha'' \ln(1+z) + \beta \ln M \pm \sigma. \quad (2.47)$$

The first three terms on the right side of this equation are normalization terms, where α' and α'' describe the redshift evolution of the mass-observable scaling relation, β is the slope, and σ is the intrinsic scatter. Typically, the term associated with α'' is disregarded, and the redshift trend is expressed explicitly as a function of the Hubble function $H(z) = H_0 E(z)$, as defined in Eq. (2.10). This approach is applicable when the evolution is assumed to be self-similar. In cases where there is a deviation from self-similarity, introducing the term related to α'' allows α' to be fixed to a self-similar value, quantifying the departure from self-similarity without being implicitly tied to the expansion history. Given the uncertainty about the nature of the actual galaxy cluster population, it is justifiable not to fix any of the redshift evolution terms if deemed reasonable for a given analysis; for instance, leaving both terms free might be useful if the evolution of the normalization with redshift is non-monotonic. For this work, we are particularly interested in the scaling relation $Y - M$ between the integrated Compton parameter Y and cluster mass M . We later describe in detail and discuss the theoretical origin of this scaling relation in Section 7.2.1 and the intricacies of modelling it, in Section 7.2.3.

2.3.5 Galaxy cluster universal pressure profile

As we have seen in Section 2.3.3, the amplitude of the thermal SZ effect is proportional to the projected electron pressure profiles of the ICM. This is of particular importance to us since we use the tSZ effect as the primary observable throughout this work. We also saw in Section 2.3.4 that self-similarity allows clusters to essentially be considered scaled versions of each other. Towards this direction, Nagai, Kravtsov,

and Vikhlinin 2007 proposed a model for the average scaled profile of a cluster population, given by:

$$P(x) = \frac{P(r)}{P_{500}} = \frac{P_0}{(c_{500}x)^\gamma [1 + (c_{500}x)^\alpha]^{\frac{\beta-\gamma}{\alpha}}}. \quad (2.48)$$

Here $x \equiv r/r_s$, where $r_s = r_{500}/c_{500}$ is the scale radius, and P_{500} is pressure at radius R_{500} . The model encompasses five independent parameters: the pressure amplitude P_0 , the concentration parameter c_{500} , and the slopes (γ, α, β) , defining the shape of the profile at $r \ll r_s, r \sim r_s, r \gg r_s$.

M. Arnaud et al. 2010 applied this parametric model to fit the average pressure profile of a representative set of 33 local clusters ($z < 0.2$) with $10^{14}M_\odot < M_{500} < 10^{15}M_\odot$ from the **REXCESS** sample (Böhringer et al. 2007). They reconstructed pressure profiles from 3D gas density and temperature profiles that were derived from *XMM-Newton* data. Using the self-similar model, they scaled the pressure profiles by their characteristic pressure P_{500} and radius R_{500} and extended the measurements out to $\sim R_{500}$. Due to limitations in the X-ray data to measuring $P(r)$ at higher radii, the authors utilized the average profile of simulated clusters to constrain the pressure profile at those ranges, finding good agreement between data and simulations for radius higher than $\sim 0.2 R_{500}$. These scaled profiles were averaged and fit with the model in Eq. (2.48). The resulting fit of the scaled and averaged profile is denoted as the universal pressure profile (UPP). The authors provide the best-fit parameters as $(P_0, c_{500}, \gamma, \alpha, \beta) = (8.403 h_{70}^{-3/2}, 1.177, 0.3081, 1.0510, 5.4905)$. This UPP is shown in Fig. 2.11 using the green line, where the scaled profiles of individual clusters are shown using black curves. It can be seen that the scaled profiles of the individual cluster show good agreement with the UPP above approximately $0.2 R_{500}$, depicting self-similarity in this range.

This specific profile has been used as a reference for many works to simulate the expected SZ effect signal from galaxy clusters or to verify if there are any deviations to this profile at different redshifts and radial ranges. For instance, Planck Collaboration et al. 2013 examined the pressure profile of clusters using SZ effect data from the Planck 14-month nominal survey. They observed a deviation in the average profile at large radii when compared to the UPP. Although Planck covers a higher radial range up to almost R_{500} , it is limited by its spatial resolution preventing it from examining the cluster core. This was compensated for by using complementary X-ray data. While keeping γ fixed to the value of the reference UPP, the authors found $(P_0, c_{500}, \gamma, \alpha, \beta) = (6.41, 1.81, 0.31, 1.33, 4.13)$. Some studies have tried to constrain the outer slope β while keeping other parameters fixed, using data from SZ surveys of the South Pole telescope, APEX, etc., see, for example, Ramos-Ceja et al. 2015; Sayers et al. 2016.

In this work, we have utilised the UPP to generate physical profiles $P(r)$ and compare them to real profiles of the ACT-CL J0240.0+0116 inferred from the NIKA2 data observations of the cluster. We use this comparison to comment on the dynamical state of the cluster (see Section 4.2.2 for details). We also use it in Chapter 6 to compare the statistical value of the scaled pressure profile we recover for our sample.

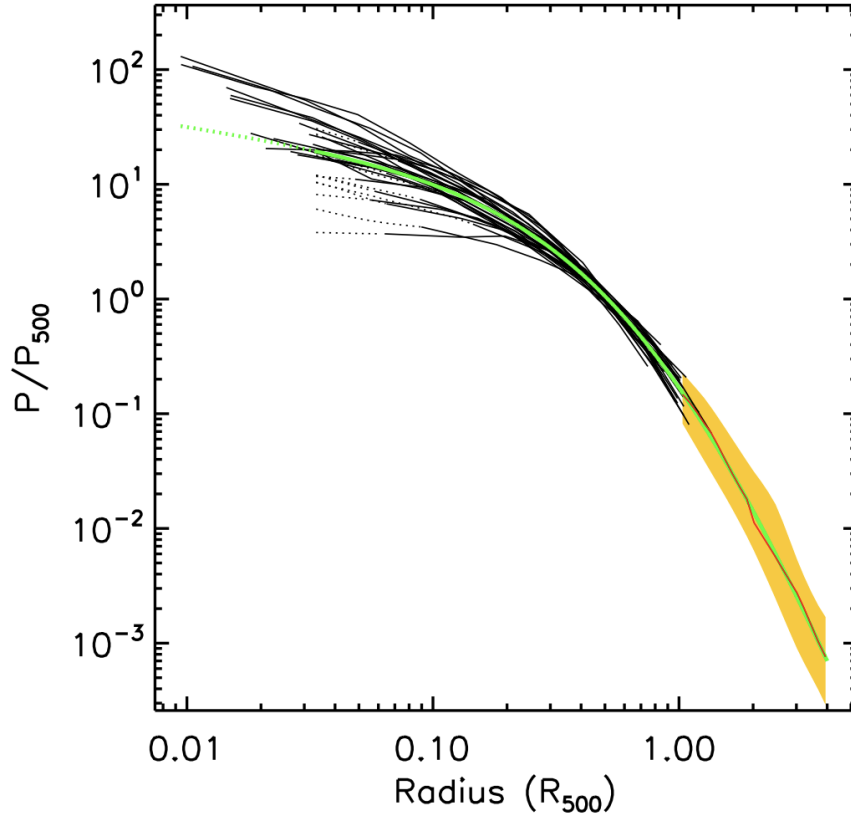


Figure 2.11 The best-fitting Generalized Navarro-Frenk-White (gNFW) model for the universal pressure profile (UPP, shown with a green line), derived by averaging the scaled pressure profiles of clusters in the REXCESS (black lines). The average profile obtained from simulated clusters beyond R_{500} is shown as the red line with the yellow area indicating the dispersion of the pressure profile of the simulated clusters. The different dynamical states of the clusters can be noticed for $r < 0.2 R_{500}$ where the observed profiles show significant scatter. Image taken from M. Arnaud et al. 2010.

2.3.6 Cosmology with galaxy clusters

Through different elements in this chapter, we have discussed the cosmological model and how, through various examinations of cluster observables, we can use galaxy clusters to constrain the cosmological model. Clusters serve as geometrical probes to measure volumes and distances and as probes to measure the growth of structure. Both these studies can be used to constrain the cosmological model. Examples of these are given previously in the chapter. The review by Allen, Evrard, and Mantz 2011 delves deeper into cosmological tests using galaxy clusters. In this section, we briefly recapitulate how galaxy clusters aid cosmological studies:

1. Cluster mass function: the number distribution of clusters with mass and redshift, known as cluster counts, serves as a sensitive indicator of the high-mass segment of the halo mass function. The presence of high-mass clusters incongruent with the calculated halo mass function for a specific cosmology has the potential to challenge and potentially refute that cosmological model. Effective utilization of galaxy cluster number counts requires accurate mass estimations, often achieved through scaling relations that connect low-scatter mass proxies like the integrated SZ signal (Y_{SZ}) to the overall halo mass. These scaling relations are typically calibrated using small clusters with direct mass constraints. Diverse methods exist for obtaining mass estimates, as we discussed in Chapter 1. To conduct accurate cosmological tests based on cluster counts, it is imperative to address potential biases in mass calibration. Furthermore, understanding the selection function of the cluster survey is crucial for estimating sample completeness.
2. Distance measurements: an alternative approach for conducting cosmological tests entails leveraging the measurement of distances using galaxy clusters (see Section 2.1.2). Cluster matter power spectrum can be used to measure the BAO scale (Fig. 2.1). On the other hand, a combination of cluster SZ and X-ray observables can be used to constrain angular diameter distance (see *e.g.* Ameglio et al. 2006), and consequently the underlying cosmological model, as explained in Section 2.1.2.
3. Gas mass fraction: this fraction holds particular significance in cosmology, given by $f_{\text{gas}} = M_{\text{gas}}/M_{\text{tot}}$, it can constrain the matter density of the Universe (Ω_m) if the baryon density (Ω_b) is independently known from some probe like CMB measurements. The composites of large galaxy clusters reflect very well, the matter content of the Universe. Hence the measure of the gas mass fraction of these clusters can be used to constrain the matter density of the Universe. The first evidence for $\Omega_m < 1$ was obtained by one such study in S. D. M. White et al. 1993. A more recent estimate can be found in Mantz et al. 2014.

Chapter 3

Datasets

As outlined in Chapter 1, investigations of sensitive, high-resolution observations can gain value by the addition of complementary information on specific systematic effects that are studied using simulations. To address this requirement, we initially conduct a thorough analysis utilizing the NIKA2 LPSZ data. Subsequently, to explore the potential impact of systematic errors and to study the characteristics of the ICM profile recovered using the NIKA2 data, we employ The300 simulations, which incorporate a diverse set of physics modules to replicate galaxy clusters. To facilitate our study, we create ‘twin samples’ (TSs) by selecting synthetic galaxy clusters from the simulations that closely match the properties of the observational targets within the LPSZ. This chapter details the observations (LPSZ) and simulations (The300) utilized, elucidating the methodology employed to integrate them for a comprehensive analysis, borrowing from and utilising the samples and methodology described in Paliwal et al. 2022.

3.1 Observations: The NIKA2 Sunyaev–Zeldovich Large Program (LPSZ)

In the previous chapter, we delved into the prospect of employing galaxy clusters as a tool for cosmological investigation. We underscored the importance of methodically monitoring cluster samples to enhance the precision of cosmological studies based on clusters. This thesis is positioned within the broader framework of the NIKA2 LPSZ. The following section provides a detailed description of the NIKA2 camera and the LPSZ. Key aspects of the 30-meter IRAM telescope and the NIKA2 camera are outlined in Section 3.1.1, explaining their relevance in the context of the scientific objectives of the LPSZ, which are discussed in Section 3.1.2.

3.1.1 The 30-meter Institute of Millimetric Radioastronomy telescope and NIKA2

We have mentioned by now that the SZ effect is a primary observable used in this work. The observations of SZ effects in galaxy clusters can be conducted within the sub-millimeter spectrum. The primary obstacles to detecting astronomical emissions at sub-millimeter wavelengths using ground-based observatories include atmospheric



Figure 3.1 The IRAM 30-meter telescope at the Pico Veleta, site of the NIKA2 camera. Credit: IRAM, K. Zacher.

emissions, noise, and attenuation. In this spectral range, atmospheric emission fluctuations represent a significant source of noise (Pardo, Cernicharo, and Serabyn 2001). The sub-millimeter atmosphere is characterized by multiple absorption bands of water vapor. Observations are feasible only within specific “windows” between these bands. An optimal sub-millimeter observing location would be characterized by low humidity, cool temperatures, and consistent weather patterns. Situated at an elevation of approximately 2900 meters above sea level, adjacent to the Pico Veleta summit, the 30-meter telescope belonging to the Institute of Millimetric Radioastronomy (IRAM), as shown in Fig. 3.1, is positioned within the Sierra Nevada mountain range near Granada, in southern Spain (Baars et al. 1987). The elevation of the telescope contributes to noise mitigation, primarily arising from the time and spatially varying water vapour, by effectively reducing the atmospheric thickness that millimeter-wavelength photons traverse before reaching the telescope.

The value of water vapour in the atmosphere varies from season to season since the atmospheric temperature variation changes the saturation vapour pressure and hence the water content that the atmosphere can hold. The typical values at the site of the 30-m telescope are ~ 7 mm in the summer and ~ 3 mm in the winter (Kérúzoré 2021). This variation in the water content is important to measure continuously since it must be used to correct for the in-band transmission. This water content monitoring is done in real time by the telescope using an instrument called the taumeter. It measures the atmospheric opacity, τ_ν for a given frequency ν , at the zenith, which is related to the atmospheric transmission T_ν , as follows:

$$T_\nu = \exp\left(-\frac{\tau_\nu}{\sin(h)}\right), \quad (3.1)$$

where h is the sky elevation. At the frequency of 225GHz, the band of the taumeter, the typical average value of the opacity for the 30-m telescope is 0.2 and 0.5 in the winter and summer, respectively.

Another concern associated with the telescope pertains to its response to temperature variations, particularly regarding the construction materials used. The telescope

features a 30-meter diameter parabolic primary mirror composed of polyurethane panels and aluminium (Baars et al. 1987). Thermal gradients, particularly during sunrise and sunset, can induce deformation in the primary mirror. To address this issue, the mirror undergoes coating to reflect infrared radiation and active thermalization measures are implemented (Baars et al. 1988). The secondary mirror is positioned at 10.5 meters (focal length of the secondary) from the primary mirror. The 2-meter diameter secondary mirror operates in a Cassegrain configuration. This secondary mirror redirects reflected light rays from the primary, back to the vertex at the centre of the primary mirror, where the beams enter the cabin. The angular response of the telescope, called the instrument lobe, describes the distribution of the signal expected at this vertex. For a monochromatic signal from a point source, the angular response is determined by the Airy disk pattern *i.e.*, the expected diffraction point spread function for an aperture of the size of the primary mirror. The aperture width, D , determines the full-width at half-maximum (FWHM) of the main peak, which is given by

$$\theta = \arcsin \left(1.029 \times \frac{\lambda}{D} \right) \quad (3.2)$$

for a light of wavelength λ . In practice, incident radiation is polychromatic and is filtered within specific spectral bands and the resultant lobe shows a larger FWHM. Hence, the effective angular resolutions of various receiving instruments in the telescope cabin are poorer than their values for monochromatic light.

Finally, we address the observable sky region accessible with the IRAM 30-m telescope. The telescope’s observational capabilities are confined to the northern celestial sphere. Objects with a declination below -20° in equatorial coordinates never reach elevations exceeding 30° . At such elevations, the atmospheric layer traversed by incident rays becomes thick and the telescope begins to deform under its weight, leading to a compromise in the telescope’s pointing accuracy and influencing the shape of its lobe. Declination values below -20° are thus deemed inaccessible for the telescope. Consequently, the observation of clusters identified in surveys conducted in the southern hemisphere, such as the South Pole Telescope (SPT) (Bleem et al. 2015; Bleem et al. 2020), is precluded. As depicted in Fig. 3.2, a noteworthy implication is the inability to utilize the 30-meter telescope for tracking clusters from approximately half of the catalogs generated by the Atacama Cosmology Telescope (ACT) (Hilton et al. 2021). Consequently, the galaxy clusters monitored by the NIKA2 LPSZ program predominantly stem from the Planck catalog (Planck Collaboration et al. 2016c), which covers the entire sky, along with some clusters from the northern section of the ACT catalog.

Deployed on the 30-m telescope, the NIKA2 camera plays a pivotal role as the primary instrument within the scope of this research. Designed by the international NIKA2 collaboration based in Grenoble, we provide a concise overview of the instrument and its operational principles. Further comprehensive details can be referenced in Perotto, L. et al. 2020; Adam et al. 2018. Unlike the majority of millimeter-wave instruments, which typically employ bolometric detectors, NIKA2 utilizes kinetic inductance detectors (KIDs). These detectors are superconducting and consist of a material with a critical temperature T_c below which electrons form Cooper pairs and quasi-particles. The density of Cooper pairs (n_s) is determined by

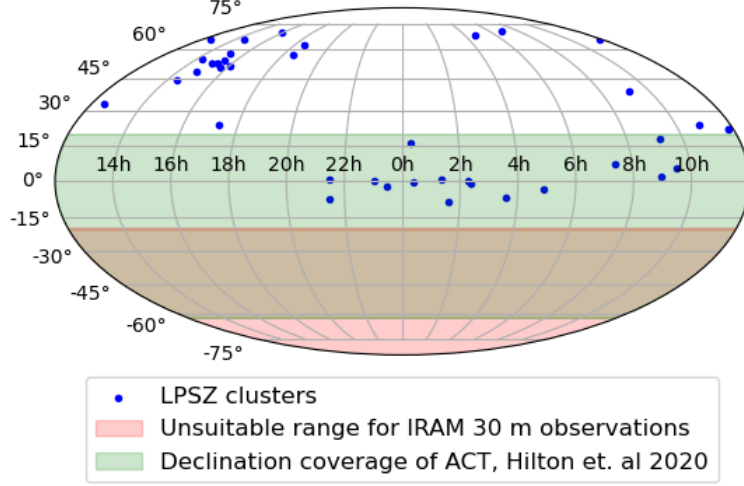


Figure 3.2 Declination coverage, in equatorial coordinates, of ACT (Hilton et al. 2021) shown in green along with the declination inaccessible to 30-m IRAM telescope, in red. The blue dots represent the coordinates of the clusters in NIKA2 LPSZ (see Section 3.1.2).

(Gorter and Casimir 1934):

$$\frac{n_s}{n} = 1 - \left(\frac{T}{T_c} \right)^4. \quad (3.3)$$

Cooper pairs exhibit characteristics of Bose-Einstein condensates, and incident photons with energy greater than the so-called gap energy, $2\Delta \simeq 3.53k_B T_c$, can disrupt these pairs. According to Eq. 3.3, for temperatures $T \ll T_c$, $n_s \simeq n$, indicating that the majority of charges are carried by Cooper pairs. In the presence of an electric current in a superconductor, conduction can be facilitated by either of the charge carriers. However, in the case of alternating current, the inertia of Cooper pairs slows their movement, opposing conduction. This phenomenon results in the creation of a kinetic inductance L_k in the material, and its impedance is expressed as

$$Z = R_{qp} + i\omega L_k \quad (3.4)$$

where R_{qp} represents the resistance associated with quasiparticles, and ω denotes the frequency of the alternating current. Naturally, a change in the density of Cooper pairs, induced by the disruption of some pairs by incident photons, leads to a variation in kinetic inductance δL_k . This variation is inversely proportional to the change in Cooper pair density and, consequently, proportional to the change in the power of the incident light.

The operation of KIDs is grounded in measuring the resonance frequency variation resulting from a change in received power. NIKA2 detectors are of the LEKID (Lumped Element KID Roesch et al. 2012) type inductance detectors. Each KID

constitutes a resonant circuit of the RLC type, encompassing capacitive (C), inductive (kinetic L_k and the additional geometric component L_g), and resistive (R) elements. The resonance frequency (f) is determined using:

$$f = \frac{1}{2\pi\sqrt{(L_g + L_k)C}}. \quad (3.5)$$

A shift in power induces a modification in the Cooper pair density, causing a change in kinetic inductance and, consequently, a shift in the resonance frequency. The relationship between the frequency shift (δf) and the change in kinetic inductance (δL_k) is expressed as:

$$\delta f = -2\pi^2 C f^3 \delta L_k. \quad (3.6)$$

As previously mentioned, the change in kinetic inductance exhibits a proportionality to the change in incident power, leading to the relationship

$$\delta f \propto \delta L_k \propto \delta P. \quad (3.7)$$

Consequently, NIKA2 utilizes the measurement of frequency shift to ascertain variations in incident power. To quantify δf , the detectors are linked to transmission lines, through which an alternating signal is transmitted. These transmission lines are inductively coupled to the KIDs meanders, causing the transmitted signal to be influenced by the presence of each detector. The alterations in phase and amplitude of the transmission line signal, induced by the presence of a KID, are correlated with its resonant frequency. Measurement of the phase and amplitude of the output signal from the readout line enables the reconstruction of variations in the resonance frequency of the detectors.

The resonance frequency of a KID is interconnected with the capacitance (C) of its capacitor. Consequently, manipulation of the geometric properties of the capacitor allows for the adjustment of the resonance frequency for each detector. This inherent property of KIDs makes them well-suited for multiplexing, facilitating the integration of numerous detectors with distinct resonance frequencies onto a single readout line. This configuration significantly reduces the number of electronic cables required compared to bolometers. Fig. 3.3 illustrates one of the detector arrays incorporated in NIKA2. While the individual detectors appear indistinguishable, the image showcases the eight transmission lines utilized for reading the 1140 detectors.

The KIDs in the NIKA2 system consist of a thin aluminium layer with an approximate thickness of 18 nm. Aluminum’s critical temperature (T_c) is 1.19 K, corresponding to a gap energy of approximately 0.36 meV. This configuration is well-suited for detecting photons at frequencies around 90 GHz, which is an optimal frequency range for observing the CMB and the SZ effect (refer to Section 2.2 and Section 2.3.3). NIKA2 is equipped with three KID matrices: A1 and A3 each incorporate 1140 detectors operating at 260 GHz, while A2 is dedicated to observing photons at 150 GHz. These two frequency bands are carefully chosen to align with the available atmospheric transmission windows (see Fig. 1 Perotto, L. et al. 2020) and the spectral characteristics of the SZ effect. This includes a band on either side of the null point of the spectral distortion (see Fig. 2.8). With a large diameter of 30 m, NIKA2 also offers a high resolution with the resolution of about 11'' and 17'' at 260 GHz and 150 GHz, respectively. This capacity of NIKA2 is utilised for the LPSZ, as will be described in the following section.

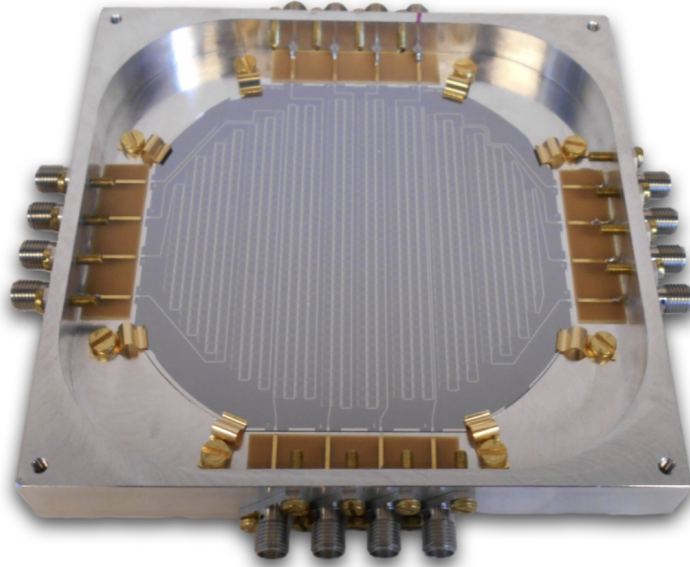


Figure 3.3 KID matrix in the NIKA2 260 GHz band, comprising 1140 KIDs and 8 transmission lines. Image taken from Adam et al. [2018](#).

3.1.2 The NIKA2 Sunyaev–Zeldovich Large Program

In Section [2.3.6](#), we explored the cosmological significance of specialized analyses focusing on galaxy clusters. Now, we delve into one specific observational initiative known as the NIKA2 LPSZ (Perotto et al. [2023](#)). As discussed in Section [2.3.5](#), the average pressure profile of the ICM serves as a crucial element for cosmological investigations based on the SZ effect. Within the self-similar hypothesis, the radial distribution of the thermodynamic properties of the intracluster medium is expected to be accurately characterized by a universal profile, adjusted to their characteristic mass and size. Departures from this assumption arise due to the diverse range of baryon-related physical phenomena that can alter the energy content of clusters. However, the pressure profile, directly linked to the gravitational potential of the cluster through Poisson’s equation, is presumed to be the least influenced by these phenomena and is particularly well-represented by a scaled mean profile. This makes samples selected through SZ effects have the advantage of being close to mass-selected samples.

As we will explore later in Section [7.2.1](#), the integrated Compton parameter is closely tied to the thermal energy content of the cluster and, consequently, its mass. Therefore, constructing a sample with a criterion of a Y value surpassing a specified threshold enables the selection of clusters based on a criterion associated with their mass, eliminating bias toward a particular cluster type. Such a sample is referred to as representative, as the distribution of the physical properties among the clusters it comprises, follows the same distribution as clusters in the Universe within the

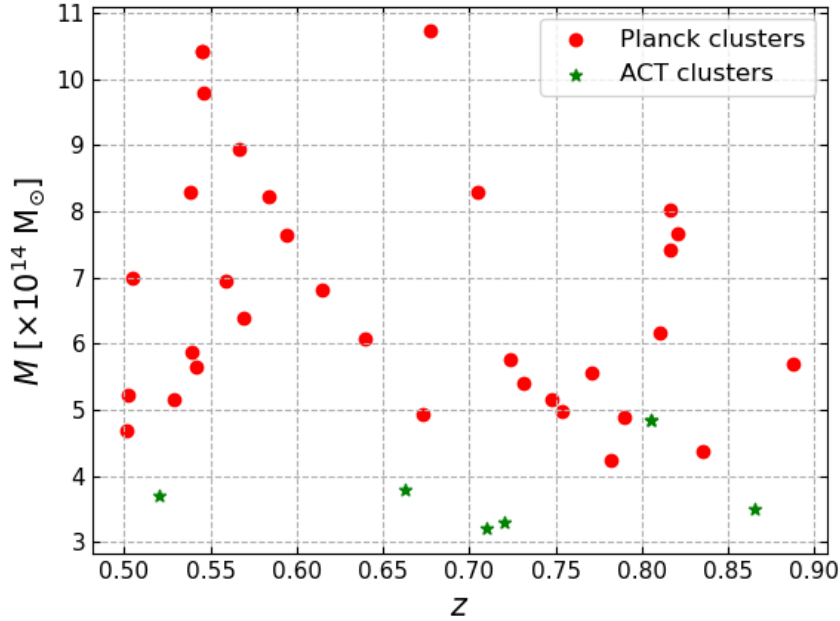


Figure 3.4 The mass-redshift distribution of the LPSZ clusters. Clusters chosen from the ACT catalog (Hilton et al. 2021) are shown using green stars while those from Planck (Planck Collaboration et al. 2016c) are shown with red circles.

considered mass range.

The LPSZ is a program that entails a dedicated allocation of 300 hours of observation time (now completed) with the NIKA2 instrument, of the SZ effect of clusters. The designated observation time for the LPSZ has been distributed across a sample of 38 galaxy clusters. The strength of this program lies in its carefully selected sample, which spans a diverse range of masses $3 \leq M_{500}/10^{14} \text{ M}_{\odot} \leq 11$ and relatively high redshifts of $0.5 < z < 0.9$. As previously mentioned these are high-resolution follow-up observations of clusters selected from previous SZ catalogs, as shown (and cited) in Fig. 3.4. Clusters were chosen from these catalogs, that were visible from the 30-meter telescope (see Fig. 3.2) while ensuring uniform coverage in the mass range. To achieve this, ten “boxes” were defined, with two intervals in the redshift range and five in the mass range. In each of these boxes, clusters were randomly chosen, with clusters from the ACT catalog filling the two low-mass boxes and clusters from the Planck catalog filling the others. This mass-redshift plane division procedure was implemented to prevent clusters from being randomly selected from the Planck and ACT catalogs, ensuring that the selected distribution in mass and redshift does follow the underlying mass function. Consequently, the LPSZ offers consistent coverage within the specified mass and redshift range.

The high-resolution SZ follow-up of a sizable cluster sample spanning redshifts above 0.5 and a broad mass range facilitates the comparison of properties of distant galaxy clusters, as measured using high-angular-resolution SZ observations, with those obtained from samples of nearby clusters assessed through either X-ray or

low-resolution SZ measurements.

The split of the allocation of the 300 observation hours relied on a highly specific definition, calculated as the observation time required to achieve a 3σ signal-to-noise ratio for the SZ profile at the characteristic radius R_{500} (where R_{500} , as defined in Eq. 2.29, comes from the parent catalogs). This computation is grounded in the assumptions that the pressure profile of each cluster follows the universal pressure profile proposed by M. Arnaud et al. 2010, and that the mass M_{500} of the clusters in the sample equals that provided by the Planck and ACT catalogs from which the clusters are selected. Consequently, any deviation from these assumptions leads to variations in the expected signal quality. Therefore, a cluster with a poorly estimated mass from the parent catalog scaling relations or a pressure profile deviating from the universal profile may exhibit data quality significantly different from the anticipated outcome. This aspect necessitates careful consideration, as for the calibration of tools essential for cosmology, the sample must be representative, and observations of clusters must possess comparable quality to avoid overemphasizing specific cluster types.

After introducing the LPSZ, let us now briefly explore how it utilizes the capabilities of NIKA2, specifically its high-resolution SZ effect measurements, to address cosmological questions related to galaxy clusters.

- In-depth examination of sample clusters: the observations of clusters within the LPSZ using NIKA2 allow for detailed imaging, facilitating the study of individual cluster properties, as demonstrated in previous works such as Ruppen, F. et al. 2018; K  r  zor  , F. et al. 2020; Mu  noz-Echeverr  a et al. 2023b. This involves creating NIKA2 SZ maps of the clusters, analyzing the cluster pressure profile and investigating signs of disturbance from it, and estimating the integrated Compton parameter. A specific case study within this context is presented in Chapter 4.
- Establishment of a universal pressure profile: the UPP outlined in M. Arnaud et al. 2010 has served as a calibration reference for various scaling laws, such as those employed by ACT (Hasselfield et al. 2013). However, it relies on X-ray observations and is calibrated for a cluster sample with redshifts below 0.2. The LPSZ provides an opportunity to investigate two aspects. Firstly, to assess whether the SZ-derived profile deviates from the established universal profile, and secondly, to explore any potential evolution with redshift (see Hanser et al. 2023). This exploration, also aims to identify and understand any sources of deviation from the M. Arnaud et al. 2010, if any. In this context, we use simulations (The300) to examine systematic effects in the recovery of 3D pressure profiles from 2D maps, as detailed in Chapter 6.
- Establishment of an observable mass scaling law: Similar to the situation with pressure profiles, scaling laws utilizing the integrated Compton parameter have primarily been calibrated for nearby clusters, relying on mass estimates derived solely from X-ray measurements. The objective of LPSZ is to extend these scaling laws to higher redshifts by incorporating mass estimates derived from a combination of SZ and X-ray measurements. Furthermore, the joint use of SZ and X-ray data enables the classification of clusters based on their dynamical

state, allowing an investigation into how their scaling laws may differ, or conversely, remain consistent. We undertake the calibration of equivalent scaling laws using simulations, as discussed in Chapter 7.

3.2 Simulations: THE THREE HUNDRED project

To fully leverage the high-quality observational data obtained from NIKA2, this project complements it with data from THE THREE HUNDRED Project (The300) (Cui et al. 2018). The base of the simulation comprises 324 spherical regions, each centred on the most massive clusters identified at redshift $z = 0$ using the ROCKSTAR halo finder¹ (Behroozi, Wechsler, and Wu 2013) within the dark-matter-only MDPL2, MultiDark simulation (Klypin et al. 2016). These simulations adopt the cosmological parameters from the Planck cosmological results (Planck Collaboration et al. 2016b). The MDPL2 is a periodically defined cube with size $1 h^{-1}\text{Gpc}$ comoving length (where $h = 0.677$, from the adopted cosmology). It contains 3840^3 dark matter particles, each of mass $1.5 \times 10^9 h^{-1}M_{\odot}$.

These 324 clusters are re-simulated in The300, in spherical regions of $15 h^{-1}\text{Mpc}$ radius, centred at the identified clusters. The initial selection of the clusters positioned at the centre of each re-simulation region was based on them having the largest halo virial mass at $z = 0$, with $M_{\text{vir}} \gtrsim 8 \times 10^{14} h^{-1}M_{\odot}$. The cluster dark matter halo centre served as the simulation region centre. The GINNUNGAGAP code², was used to generate the initial conditions that possess multiple levels of mass refinement while maintaining the same mass resolution as the original dark matter-only simulation that serves as the foundation for the sample. For the high-resolution regions, gas particles are added next to each dark matter particle with a mass according to the cosmic baryon fraction. Since the size of the re-simulated region significantly exceeds the virial radius of the central cluster, it encompasses additional groups and filamentary structures that may or may not necessarily be associated with the cluster. To optimize computational efficiency, dark matter particles outside the re-simulated region underwent gradual degradation across multiple layers. This approach ensured identical tidal fields at significantly reduced computational costs, compared to the original simulation.

After generating the initial conditions, they underwent simulation using the contemporary smooth-particle-hydrodynamic (SPH) code GADGET-X (Beck et al. 2016), which includes feedback from active galactic nuclei and black holes, the GADGET-MUSIC code (Sembolini et al. 2013), which only includes feedback from supernovae, and the GIZMO-SIMBA code (Cui et al. 2022), which also includes feedback from active galactic nuclei and black holes but with a varied hydrodynamic code than GADGET-X. Snapshots were saved for selected redshifts ranging from $z = 17$ to $z = 0$. A total of 128 distinct snapshots were recorded for each simulation. Both codes employ SPH to monitor the evolution of the gas component, although they utilize different SPH techniques and models for sub-resolution physics, the details of which can be found in Cui et al. 2018.

Following data collection, a standardized analytical pipeline was employed,

¹<https://bitbucket.org/gfstanford/rockstar>

²<https://github.com/ginnungagapgroup/ginnungagap>

including the **AHF** halo finder (Knollmann and Knebe 2009). This halo finder integrates both gas and stars in its halo identification process. For each identified halo, the radius R_{200} was computed, defined as in Section 2.1.3.1 (Eq. 2.29). Sub-halos, which are categorized as halos situated within the R_{200} region of a more massive host halo, were also marked. Their properties like mass and velocity dispersion were estimated by marking their boundaries using their characteristic radius called the ‘truncation radius’, R_t , and only using gravitationally bound particles within this radius. On the other hand, properties for host halos are estimated using their R_{200} . To build the cosmic web structure in the simulation, halo merger trees were made to establish connections between objects at different redshifts, using the **MERGERTREE** utility of the halo finder. Additionally, the luminosity for the galaxies within halos and sub-halos was estimated in varied spectral bands, by considering stellar components within the halos (see Cui et al. 2018 for the details). Moreover, to include the details about member galaxies into the DM-only MDPL2 simulation, three distinct Semi-Analytic Models (SAMs) were used: **SAG** (Cora et al. 2018), **SAGE** (Croton et al. 2016), and **GALACTICUS** (Benson 2012).

The300 simulations hence encompass 324 re-simulated areas, extending over a broader volume (up to $15h^{-1}$ Mpc in radius) than the virial radius of the central halo. This expanded coverage includes diverse objects beyond the central halo. It includes the cluster environment including its sub-halos and surrounding filaments and cluster groups. This diversity enables the exploration of the dynamics within the galaxy cluster and its surroundings. A plethora of studies have been performed using The300 simulations like studying the impact of the intra-cluster environment on the properties of member galaxies (Wang et al. 2018), estimating the cluster dynamical state (Cialone et al. 2018; Hagggar et al. 2020), estimating the hydrostatic mass bias of clusters and its evolution (Gianfagna et al. 2021), and so on. We utilise the richness of information provided by The300 by constructing the so-called twin samples (TSs, Paliwal et al. 2022) for the LPSZ, whose details are discussed in the following sections.

3.2.1 THE THREE HUNDRED-NIKA2 twin samples

To construct TSs for the LPSZ, a meticulous selection process was implemented, utilizing the simulated clusters from The300. This involved a cross-matching procedure considering various parameters of clusters in both datasets. Initially, redshift snapshots in the simulation (particularly, the **GADGET-X** run) were identified to match with the median redshift of each LPSZ redshift bin. The redshift distribution of clusters in both catalogs, depicted in Fig. 3.5, illustrates the varied range of clusters available in the simulation for selecting twins of the LPSZ at different redshifts.

After identifying snapshots in the simulation at optimal redshifts for LPSZ, certain characteristics between the simulations and the real clusters were cross-referenced to find the closest match of the LPSZ cluster in the simulation, resulting in the formation of three TSs:

1. Total mass twin sample (TS_{TM}): follows the matching of the previous mass estimates of the LPSZ clusters (primarily from Planck, Planck Collaboration et al. 2016c and ACT, Hilton et al. 2021) with the total mass of simulated

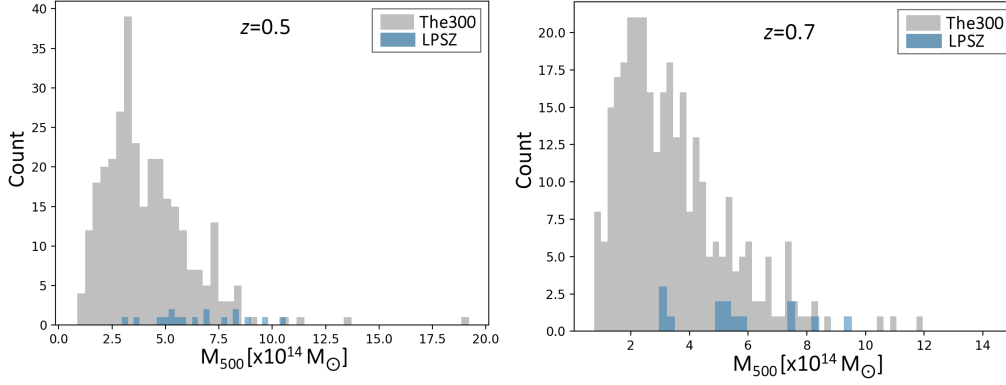


Figure 3.5 Redshift distribution of clusters in two of the four LPSZ redshift bins, compared to the redshift distribution of clusters in the closest identified redshift snapshot of The300. Plots taken from Paliwal et al. 2022.

clusters (at $\Delta = 500$). The average mass ratio for this sample with respect to the LPSZ was $\langle M_{\text{LPSZ}}/M_{\text{TS}_{\text{TM}}} \rangle = 1.01 \pm 0.02$. This indicates an almost perfect match, based on total mass, found for the LPSZ in the simulation.

2. Hydrostatic equilibrium mass twin sample (TS_{HSE}): is obtained by finding clusters in the simulation whose hydrodynamic mass (at $\Delta = 500$) is closest to those in the LPSZ. For this sample, the hydrostatic mass bias is estimated to be $\langle M_{\text{LPSZ}}/M_{\text{TS}_{\text{HSE}}} \rangle = 0.93 \pm 0.02$, which is consistent with mass bias estimated in Gianfagna et al. 2021.
3. Integrated Compton parameter twin sample (TS_{Y}): is the cluster sample where the integrated Compton parameter Y at R_{500} is used as the matching criteria. In this case, we have $\langle M_{\text{LPSZ}}/M_{\text{TS}_{\text{Y}}} \rangle = 0.9 \pm 0.1$, implying no mass bias.

Each of these twin samples comprises a unique assemblage of clusters that mirrors the LPSZ according to specific criteria. The distinctiveness of these twin samples becomes evident in the redshift-mass distribution when compared with the LPSZ target clusters, as depicted in Fig. 3.6. The list of all three twin samples, containing the identification in terms of the snapshot, redshift, and region ID of the cluster in the simulation can be found in Appendix A. We would like to make a note here that when the analyses in this work were performed, the LPSZ comprised its original 45 cluster targets (see Perotto et al. 2022) and the TSs used in this work correspond to twins of these said clusters. The latest LPSZ, due to some non-detections and bad quality data, is a sample of 38 clusters, as we described in Section 3.1.2

As elaborated previously, The300 offers an extensive array of data products for each cluster. Including all analyses in this work, we use the following products of the TS cluster, from the simulation:

- Cluster 3D radial mass profile estimated by summing the mass of all particles within a given aperture.
- Cluster 3D radial pressure profile.

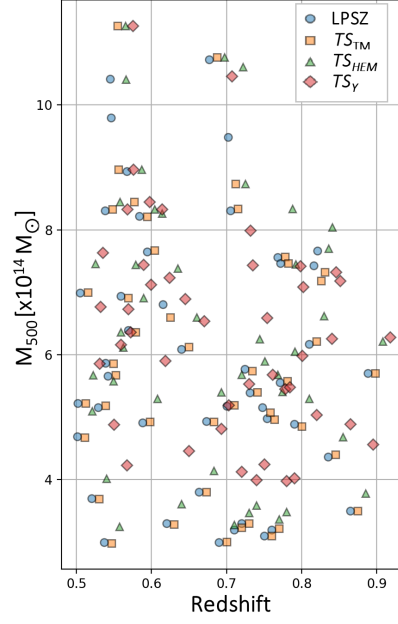


Figure 3.6 Redshift–mass distribution of the LPSZ clusters (blue dots, Perotto et al. 2022), compared to the twin samples generated using The300. The twin samples TS_{TM} , TS_{HEM} , and TS_Y are represented in orange square, green rectangles, and red diamonds respectively, and depict unique representation of the LPSZ based on their selection criteria. Plot taken from Paliwal et al. 2022.

- Cluster 3D radial gas density profile.
- Compton parameter (y) maps of clusters, along 29 random (relative to the inertial axes of the cluster) projections.
- Projected mass maps of the clusters along the same 29 projections as y .

We present the use of these data products in Chapters 5, 6, and 7.

3.2.1.1 Simulation of NIKA2-like maps from The300 Compton parameter maps

As we employ the TSs for investigating systematic effects in the context of the LPSZ, it is essential to generate maps that represent the LPSZ observables, specifically the SZ surface brightness. This section outlines the methodology utilized to generate the NIKA2 SZ maps from the Compton parameter maps associated with the TS clusters, as illustrated schematically in Fig. 3.7.

We illustrate this process using Cluster 29 from Snapshot 101 as an example. Positioned at $z = 0.82$, this cluster has a mass and radius of $4.58 \times 10^{14} h^{-1} M_{\odot}$ and 998.23 kpc. Following the procedure outlined in Fig. 3.7, we initiate by converting the y map of the cluster (cropped to the NIKA2 field of view size of 6.5 arcmin, depicted in the left panel of Fig. 3.8) into the SZ surface brightness. This conversion involves multiplying it by the telescope calibration factor, which is determined by integrating the spectrum of the SZ effect into the NIKA2 band-passes at 150 GHz

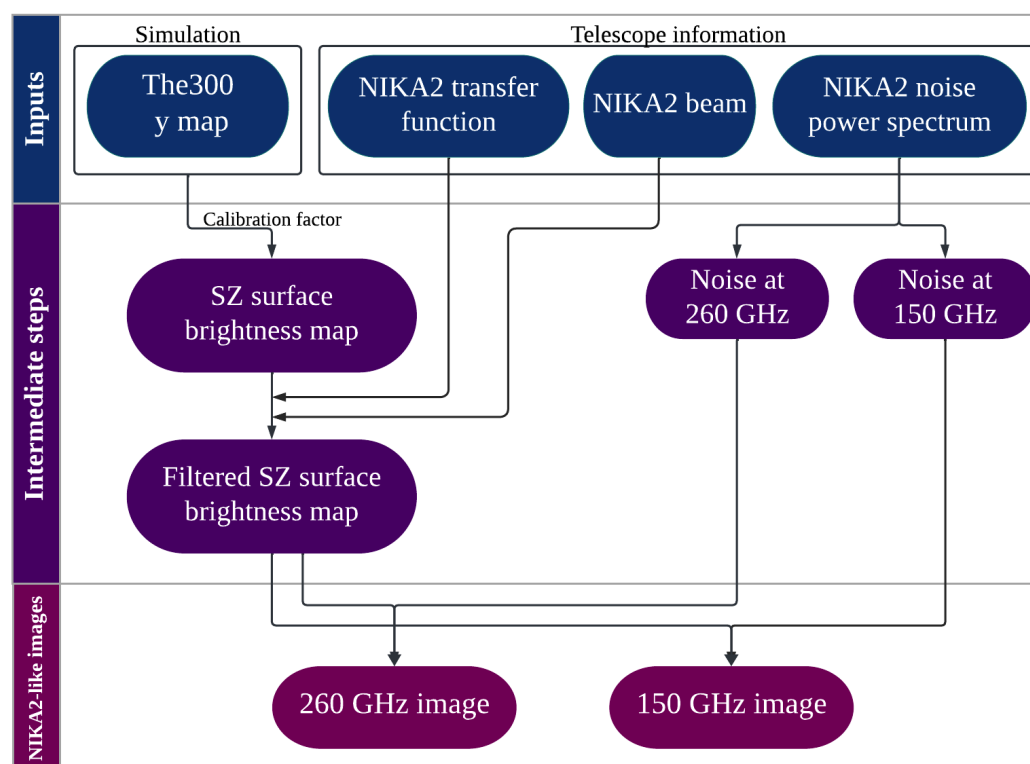


Figure 3.7 Schematic representation of the process used to create NIKA2-like SZ surface brightness maps using y maps from The300.

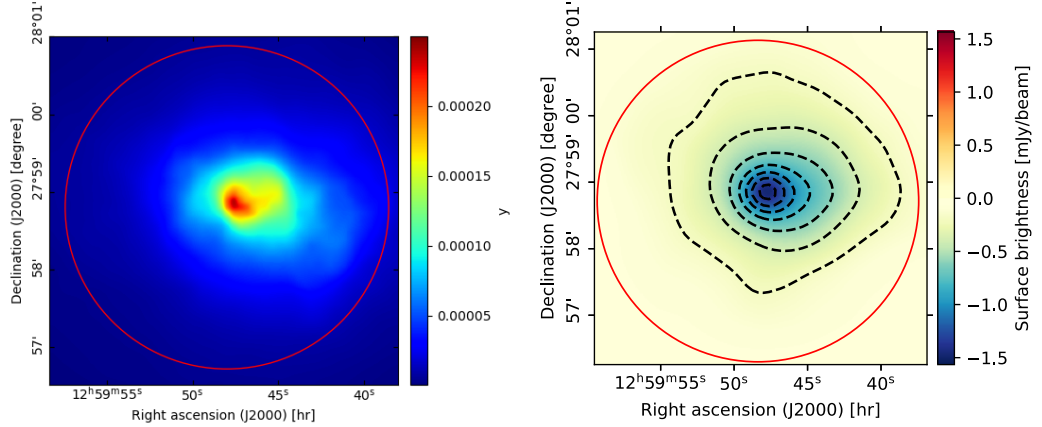


Figure 3.8 The y map from The300 (left) and the corresponding SZ surface brightness image at 150 GHz (right) for cluster 29 of snapshot 101 of The300. The surface brightness image has been filtered with the NIKA2 beam and transfer function. The red circles in both plots correspond to the AHF inferred R_{500} . The dashed contours on the right show the significance levels above 3σ .

and 260 GHz. The spatial distribution of the resulting SZ signal in the generated maps undergo convolution with a Gaussian kernel corresponding to the reference FWHM of both NIKA2 channels ($18''$ and $12.5''$, respectively), which are different from the FWHM mentioned earlier, see Perotto, L. et al. 2020 for the details of the difference in the two definitions.

To account for the spatial filtering introduced by the data processing of real LPSZ clusters (details in Section 4.1), we convolve the calibrated and smoothed maps with the LPSZ data processing transfer function. In this case, we use the transfer function from the first NIKA2 LPSZ observations (Ruppin, F. et al. 2018), as shown for 150 GHz in the right panel of Fig. 3.9. At this stage, we obtain the filtered SZ surface brightness images of the TS cluster in both bands, requiring only the addition of noise maps to create realistic NIKA2-like images. The filtered SZ surface brightness image at 150 GHz is presented in the right panel of Fig. 3.8.

To simulate noise resembling the correlated noise in LPSZ, we utilize the normalised residual noise power spectrum from Ruppin, F. et al. 2018, depicted in the left panel of Fig. 3.9. The process begins by generating a white noise map, where values are randomly drawn from a Gaussian distribution centred at zero, with a standard deviation of one, for each pixel in the map. Subsequently, this white noise undergoes convolution with the square root of the previously mentioned power spectrum of the noise, resulting in a noise map normalized to the input power spectrum. To re-scale this normalized map, it is multiplied by the noise variance map, also obtained from Ruppin, F. et al. 2018. However, the variance map is adjusted to match the theoretical signal-to-noise ratio (SNR) definition of the LPSZ: $\langle \text{SNR}(\theta_{500}) \rangle = 3$ for the SZ pressure profile (as described in Section 3.1.2). To ensure that the noise in the two channels is not spatially correlated, two distinct white noise maps are initially used, with the noise variance in the two bands scaled to reflect the actual scenario: the noise in the 260 GHz channel is 3.33 times that of the 150 GHz channel. Adding these noise maps with the filtered surface brightness

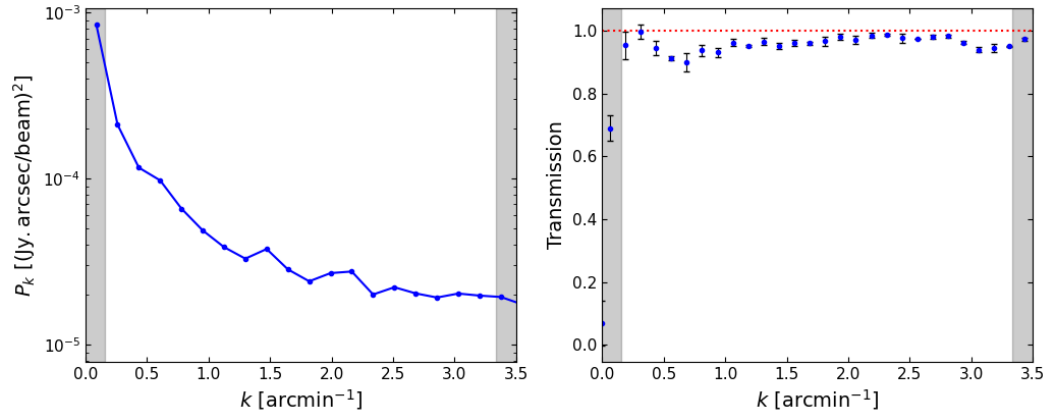


Figure 3.9 The noise power spectrum (left) and the data processing transfer function (right) at 150 GHz taken from Ruppin, F. et al. 2018. We use these functions to generate noise for and filter the y maps from simulation, in order to create NIKA2-like maps. The shaded grey regions on the left and right depict the telescope FWHM and beam size, respectively.

images yields NIKA2-like images for both bands, as depicted in Fig. 3.10.

The generated NIKA2-like maps are subsequently employed in this study for several purposes within the framework of LPSZ. We adapt them to validate the LPSZ point source detection pipeline in Chapter 5, to assess the retrieval of pressure and mass profiles from SZ maps of the TSs in Chapter 6, and ultimately, to establish scaling laws in Chapter 7 based on the findings from Chapter 6.

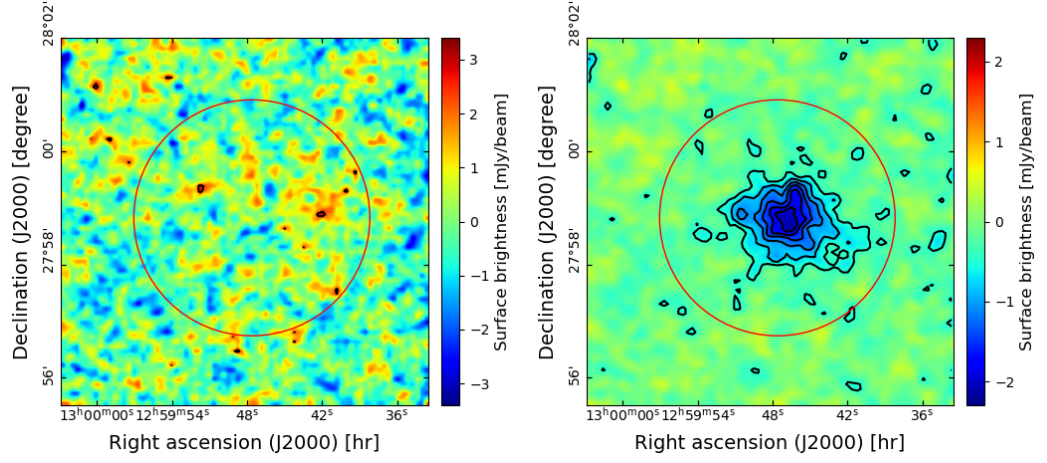


Figure 3.10 The NIKA2-like SZ surface brightness maps at 260 GHz (left) and 150 GHz (right), generated from the y map of cluster 29, snapshot 101 of the simulation, with realistic noise levels. The red circles in both plots correspond to the AHF value of R_{500} and the black contours depict the SNR levels above 3σ . The maps have been smoothed for visualisation.

Chapter 4

The analysis of LPSZ observed cluster ACT-CL J0240.0+0116

In Chapter 3, we describe the LPSZ sample that maps the ICM of 38 galaxy clusters via their SZ effect. This chapter focuses on the analysis of one of these galaxy clusters, namely ACT-CL J0240.0+0116, hereafter referred to as ACTJ0240. The cluster was first identified as such, under the name WHL J024001.7+011606 (Wen, Han, and Liu 2012) using data from the Sloan Digital Sky Survey (SDSS)-III (Aihara et al. 2011). The galaxy cluster was essentially identified by photometrically recognising member galaxies at a given redshift and associating a high galaxy density with the presence of a galaxy cluster. We report the position and redshift of the cluster identified using SDSS-III data in Table 4.1. Soon after, the galaxy cluster was observed and identified using SZ observations by the ACT (Hasselfield et al. 2013). In this work, the cluster mass was estimated to be $(3 \pm 0.8) \times 10^{14} h_{70}^{-1} \text{M}_{\odot}$ (see Table 4.1 for more details). Since then, ACT has taken follow-up observations of the cluster in polarised mode (Hilton et al. 2018) and included it in its SZ cluster large catalog release (Hilton et al. 2021) but there have been no dedicated SZ studies that trace the ICM in details with high-resolution data, for this cluster. On a similar note, as a part of a catalog release, this mass estimate was used in Wen and Han 2015 to calibrate the optical mass proxy (cluster richness) for the cluster.

ACTJ0240 was also observed by *XMM-Newton* as a part of the X-ray follow-up of 15 low-mass LPSZ clusters (details about the observation are in Section 4.1.2). Once again, this X-ray data has not been previously used to infer the ICM profiles but, it has been used for complementary analyses. There has been a detailed study to estimate the dynamical state of galaxy clusters using their X-ray images in Yuan, Han, and Wen 2022 where they analyse the *XMM-Newton* image for ACTJ0240. The estimates of the varied dynamical state indicators, as defined and reported in Yuan, Han, and Wen 2022, are summarised in Table 4.1. In this work, the authors define clusters with $\delta \geq 0$ as disturbed, while those with $\delta < 0$ are classified to be relaxed. Hence, ACTJ0240 is classified as a disturbed cluster, with $\delta = 0.99 \pm 0.01$, based on its X-ray image. On the other hand, based on multi-wavelength indications of dynamical disturbances shown by ACTJ0240, the cluster was included in a pilot study performed for The MeerKAT Exploration of Relics, Giant Halos, and Extragalactic Radio Sources (MERGHERS) survey (Knowles et al. 2021). This pilot

Wavelength	Parameter	Parameter description	Value	Reference
Optical	-	Alternate ID	WHL J024001.7+011606	1
Optical	(RA, Dec) [Deg]	Brightest central galaxy position	(40.0072, 1.2685)	1
Optical	Photometric redshift	z	0.5870	1
Millimetre	(RA, Dec) [Deg]	Peak of the SZ detection	(40.0102, 1.2693)	2
Optical	Photometric redshift	z	0.62 ± 0.03	2
Millimetre	M_{500} [$10^{14} h_{70}^{-1} M_{\odot}$]	Hydrostatic mass estimated for a UPP	3.3 ± 0.8	2
X-ray	c	Dynamical state indicator: concentration index	-0.91 ± 0.03	3
X-ray	ω	Dynamical state indicator: centroid shift	-1.31 ± 0.01	3
X-ray	P_m	Dynamical state indicator: power ratio	-6.17 ± 0.30	3
X-ray	κ	Morphology parameter: profile parameter	2.21	3
X-ray	$\log \alpha$	Morphology parameter: asymmetry factor	-1.22 ± 0.01	3
X-ray	δ	Dynamical state indicator: morphology index	0.99 ± 0.01	3

Table 4.1 A summary of various parameter estimates for ACTJ0240, found in literature, for studies performed before the analysis presented in this work. Coordinates are reported in the J2000 standard equinox. References are as follow: 1-Wen, Han, and Liu 2012; 2-Hasselfield et al. 2013; 3-Yuan, Han, and Wen 2022.

study, however, found no diffuse radio emission detection in the region associated with cluster ACTJ0240.

With the lack of detailed ICM studies and the establishment of the cluster being disturbed, the aforementioned studies pose ACTJ0240 as an interesting target for the LPSZ. The sensitivity and high resolution of NIKA2 enable us to map the cluster ICM in detail and infer its dynamic state and how the state can impact the inference of the cluster properties. In this context, for this work, we analyse the high-resolution SZ data (from the LPSZ) of this cluster in combination with its X-ray and optical data. The details of these analyses can be found in the following sections.

4.1 Multi-wavelength images

As already established in the preceding discussion, multi-wavelength studies of ACTJ0240 point to the cluster being an under-explored, disturbed cluster system. In this section, we describe the data processing performed to obtain multi-wavelength images of the cluster that are consequently used to infer ICM properties.

We lay a special focus on the novel high-resolution SZ observations of the cluster recorded using the NIKA2 camera. All the NIKA2 LPSZ results provided in this chapter are preliminary results from unpublished LPSZ data and are a part of the publication draft based on this chapter, which is currently under preparation (Paliwal A. et al. 2024, in prep).

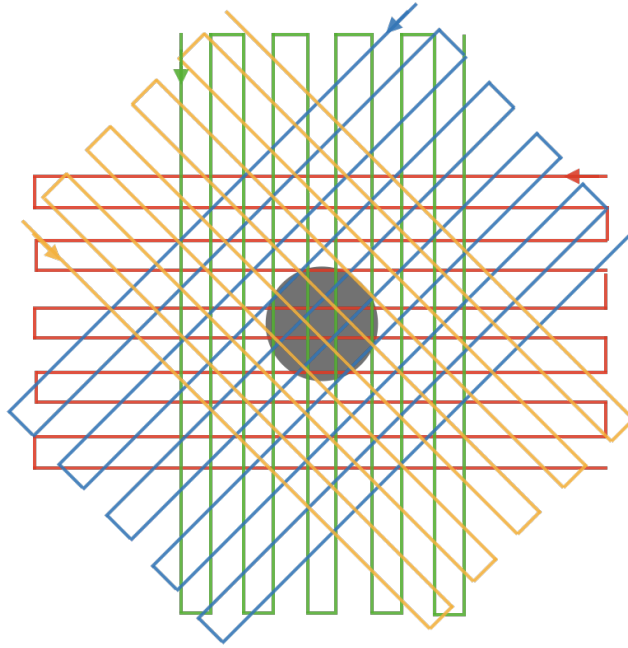


Figure 4.1 Illustration of the scanning strategy of the LPSZ. The observations consist of a series of four raster scans that are centred at the observation target, which is depicted here with a black circle. These four scans, performed in a series of sub-scans, are at angles 0, 45, 90, and 135 degrees with respect to the right ascension axis and are illustrated in red, blue, green, and yellow colours, respectively.

4.1.1 SZ image

ACTJ0240 was observed as a part of the LPSZ (project 199-16 of the NIKA2 guaranteed time) for a total integration time of ~ 7.9 hrs. The observation was split over multiple sessions in the January and November 2020 observational shifts. We show in Fig. 4.1, an illustration of the scanning strategy used to observe the cluster. The data, acquired simultaneously at 150 and 260 GHz, comprises several raster scans of $8' \times 4'$ in a series of four raster scans that are at angles 0, 45, 90, and 135 degrees with respect to the right ascension axis, and are illustrated in red, blue, green, and yellow, respectively, in Fig. 4.1. Each of these four raster scans, as shown in the illustration, is made up of subscans that, in reality, are separated by steps of $10''$. The observation was centred at the X-ray peak estimated using *XMM-Newton* data of the cluster, (R.A., Dec.) $_{J2000} = (02^{\text{h}}40^{\text{m}}03.384^{\text{s}}, +01^{\text{d}}15^{\text{m}}58.32^{\text{s}})$. During the observations, sky dip readings were performed to measure the atmospheric opacity, required to account for the atmospheric noise (refer to Section 3.1.1). With a mean elevation of 50.99° , the average opacity for the observation was $\tau_{225} = 0.19 \pm 0.06$. To calibrate and reduce the data from the time-ordered scans to convert them into SZ images, the baseline method developed for the performance assessment of NIKA2, described in Perotto, L. et al. 2020, was followed. This method has since been used and adapted for other LPSZ studies (see *e.g.* Kéruszoré, F. et al. 2020; Muñoz-Echeverría et al. 2023b).

The raw data from the instrument consists of Time-Ordered Information (TOI)s, which depict the time evolution of the light intensity received by each NIKA2 pixel

during a sky scan. To understand how the raw TOI is processed, we need to understand the various components of the signal and how they are consequently used to isolate the signal of interest, the SZ signal in our case, from the rest. The performance of this data processing is eventually quantified by evaluating the residual noise in the data and the filtering undergone by the signal of interest, as later described in this section.

Besides the astrophysical signal of interest, the TOI has other components and as such, for a given KID, k and frequency, ν the TOI can be expressed as a functions of time (t) as (Kéruszoré 2021):

$$\text{TOI}_k(t, \nu) = S_k(t, \nu) + \alpha_k(t)A(t, \nu) + \epsilon_k(t)E_k(t) + G_k(t) + C_k(t) + N_k(t). \quad (4.1)$$

The data processing aims to isolate the astrophysical signal of interest, $S_k(t, \nu)$, from other unwanted signals. Below, we discuss the various terms in Eq. (4.1):

1. **Astrophysical Signal of Interest ($S_k(t, \nu)$):** In the case of the LPSZ, the astrophysical signal contains the primary signal of interest *i.e.*, the SZ signal from a galaxy cluster as well as other astrophysical signals from the region of interest. These include but, are not limited to, foreground and background astrophysical objects, member galaxies, the diffuse CMB, as well as the cosmic infrared background (CIB). These signals combine to generate the surface brightness sky map for NIKA2, denoted by, say $M(x, y, \nu)$. The celestial coordinates are denoted by (x, y) . During a scan, a KID at frequency ν , records the surface brightness variation as (Kéruszoré 2021): $S_k(t, \nu) = P_k(t, x, y) \times M(x, y, \nu)$, where, $P_k(t, x, y)$ is the pointing matrix describing the detector's position on the sky at time t such that:

$$P_k(t, x, y) = \begin{cases} 1 & \text{if KID } k \text{ is on-source at position } (x, y) \text{ at time } t, \\ 0 & \text{otherwise.} \end{cases}$$

As described in Perotto, L. et al. 2020, the construction of the pointing matrix is essentially a two-step process: at first, the telescope provides an absolute pointing of a reference point of the focal point, coinciding with a reference KID. Then, the offset positions of each KID with respect to the reference KID are estimated using the focal plane reconstruction (described in Section 5 of Perotto, L. et al. 2020). This helps locate the KIDs that are on or off-source, providing important information in dealing with the pixel-to-pixel correlated noise in the SZ maps. The details of the removal of the correlated noise are discussed later in this section.

2. **Atmospheric Noise ($A(t, \nu)$):** As already mentioned in Section 3.1, atmospheric noise is a major contaminant for ground-based, millimetric sky observations. As a function of atmospheric opacity τ_ν and temperature T_{atm} , it can produce both, emission and absorption features in the signal (Pardo, Cernicharo, and Serabyn 2001). This atmospheric emission can hence be modelled as a grey-body emission and depends on the opacity measured at the zenith (τ_ν), the elevation of the observations target (h), and observation

frequency (ν) as follows:

$$I_{\text{atm}}(\nu) \propto \nu^2 T_{\text{atm}} \left[1 - \exp\left(-\frac{\tau_\nu}{\sin(h)}\right) \right]. \quad (4.2)$$

For NIKA2, atmospheric emission seen by detectors at a given time is the same for all detectors. To understand this, we look at the Fraunhofer distance of the telescope, which provides us the limit between the near and far field for the observation. The Fraunhofer distance, given by $2D^2/\lambda$, at the observation frequencies of NIKA2 and an aperture of $D = 30$ m is ~ 1000 km. This distance is well beyond the atmosphere, enabling us to approximate the atmospheric signal to be in the near field and treat it as homogeneous across the sky at a given time. Consequently, the atmospheric emission manifests in the same way for all detectors in the TOI obtained during a scan. The coefficient $\alpha_k(t)$ then quantifies the common response of all detectors to atmospheric noise.

3. **Electronic Noise ($E_k(t, \nu)$):** The KID readout system in NIKA2 is a multiplex where many detectors are read simultaneously by a single line. This readout system induces a non-negligible noise component and is correlated for the detectors read by the same electronic box. This correlation property enables the isolation and removal of the electronic noise component from the TOIs. Contrary to atmospheric noise which is correlated for all detectors, the correlation in electronic noise exists only for detectors in the same readout line. This allows the separation of electronic noise from the signal of interest and the atmospheric noise.
4. **Glitches ($G_k(t)$), Cryostat Noise ($C_k(t)$), and Intrinsic Detector Noise ($N_k(t)$):** Clubbed into low-level processing, these sources of signal contamination are primarily associated to the instrument electronics and their response to stray astrophysical signals. Sometimes, events of stray cosmic radiation contaminate the sky observation of NIKA2 by impacting the detectors. These events are referred to as Glitches, $G_k(t)$. These are rather straightforward to detect and isolate as Dirac peaks in the raw data, corresponding to high flux values. Detectors are also subject to additional noise, $C_k(t)$, from cryostat system vibrations. Again, these are relatively easy to detect as they manifest as sinusoidal oscillations in the TOIs. Both, glitches and cryostat noise, are identified by searching for peaks in TOI or their Fourier transforms and subsequently subtracted from the data.

The final source of instrumental noise comes in the form of intrinsic noise of the detectors $N_k(t)$. Dominantly, it is produced by spontaneous Cooper pair breaking and photon noise. Consequently, it is inherently random and unique to each detector, eventually limiting the instrument's sensitivity. This is because the lack of correlation in this noise among detectors limits its assessment and subtraction from the TOIs. The inability to deal with this noise introduces spatially uncorrelated white noise to the sky maps constructed from NIKA2 observations. Hence, if all other noise components are perfectly subtracted from the TOIs, it would result in NIKA2 sky maps with entirely decorrelated noise, justifying the assumptions of white noise in the maps. However, we will

find in the following discussion that this ideal case is not achieved and we find some residual correlated noise in the processed sky maps.

It is evident from the aforementioned discussion that the TOIs are a combination of varied signals and noise components. While some non-correlated (among detectors) noise components such as the cosmic radiation and contribution from the cryostat can conveniently be isolated and removed based on their unique features, others are hard to manage. These include the more significant noise components. Namely, the atmospheric emission and electronic noise lead to surface brightness variations of several Jy during observation. Given that the peak value of the SZ surface brightness maps of clusters in the LPSZ is of the order of mJy, making it several orders of magnitude lower than the noise, it is crucial to remove these contributions from the data to generate reasonable sky maps or images. The procedure of removal of these noise components that have correlation among different KIDs is called **decorrelation**. This process, when performed perfectly, leaves behind only the intrinsic white noise of each detector.

The level of correlated noise present in the data can be estimated through the correlation between different KID detectors, enabling the assimilation of this correlated noise to a common mode (CM) in the TOIs of the various KIDs. There are levels of this CM depending on which noise component (atmospheric or electronic) is being dealt with and it can be estimated in different ways that are described in the following sections. The performance of these methods in terms of cleaning the noise also differs and can be evaluated using the residual power spectrum.

4.1.1.1 Common Mode

As discussed earlier, the atmospheric noise in the TOIs, representing the major source of noise, is the same for all KIDs in a NIKA2 detector array. This correlation can be exploited to remove atmospheric contamination from the data. Considering how NIKA2 scans the sky during observation, each KID passes over the source at different times, resulting in the astrophysical signal of interest appearing shifted in time in the TOIs of different KIDs. On the contrary, the atmosphere can be integrated as a source of common noise for each KID. This signal behaviour can be noted clearly in the left panel of Fig. 4.2. As an unbiased estimator, the median of the TOIs of all the KIDs can be used to estimate the CM.

Essentially, to calculate the CM, at first the TOIs of each of the considered detectors are cross calibrated on the atmospheric emission, estimated as the median of the TOIs, by calculating for each KID k a gain g_k such that:

$$\text{TOI}_k(t, \nu) = g_k \times \text{Med}[\text{TOI}_{k'}(t, \nu)]_{k'}.$$

The CM for the detectors can then be calculated as the weighted average of the TOIs of all KIDs, weighted by their gains:

$$CM(t, \nu) = \frac{1}{N} \sum_{k=1}^N \frac{1}{g_k} \text{TOI}_k(t, \nu). \quad (4.3)$$

The CM, as an estimator of the correlated noise can be subtracted from each KID's TOI. However, as seen in Eq. (4.1), each detector has a different response to

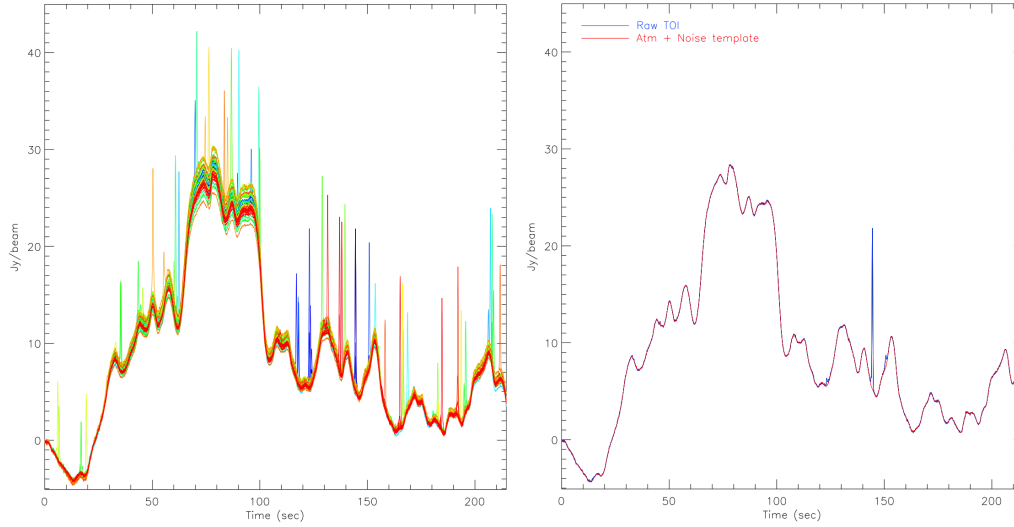


Figure 4.2 *Left:* Example of variations of NIKA2 TOIs for 40 different KIDs during an observation of Uranus. Notice the shift in time for the astrophysical signal for each KID and the correlation in the noise components (atmospheric and electronic noises). *Right:* one of the TOIs (in blue) from the left panel and the common mode that is subtracted from it (in red). Image credit: Perotto, L. et al. 2020

different components of correlated noise. To account for these different responses, a noise model can be calculated as an affine function of the common mode to estimate the coefficients α_k . By subtracting this individual detector-specific noise estimator from its time data, we obtain data cleaned of a common mode, albeit assuming that the noise is entirely driven by atmospheric contamination.

This procedure is illustrated in Fig. 4.2. The left panel shows the raw data with the astrophysical signal appearing as time-shifted peaks, and the atmospheric noise as the large-scale behaviour of all detectors. In the right panel, we see (in red) the CM estimated from the TOIs of the entire KID array. Removing this CM from the TOIs mitigates the large-scale behaviour of the noise, leaving us with only the astrophysical signal and minor, apparently uncorrelated noise between detectors.

4.1.1.2 Common mode one block

We have already discussed that atmospheric noise is largely commonly seen as the same for all the KIDs and hence can be handled using the CM subtraction discussed in the previous section. However, as shown in Eq. (4.1), there exists another component of correlated noise in the data. The noise due to the electronic readout, by construction, does not show a correlation between all detectors in the matrix but only between those read by the same electronic box. Thus, after subtracting an atmospheric common mode, there remains in the data a component of correlated electronic noise. Once the CM is subtracted from the TOIs, the level of correlation between different KIDs drops significantly, from about 90% to around 20% (Kérusoré 2021). This residual correlated noise is attributed to the KIDs read by the same electronic box and the KIDs coupled to the same readout line. This highlights the

fact that CM is not a perfect decorrelation method in the context of the LPSZ.

Although the electronic noise is generally lower than atmospheric noise, for SZ effect observations, where the surface brightness is at most of the order of mJy, electronic noise becomes non-negligible. It is, therefore, important, like for the atmosphere, to remove it from the TOI. To do this, the previously detailed CM estimation is used with some modifications. Instead of calculating a CM for all detectors in a matrix, the same operation can be performed for groups of KIDs by grouping them according to the electronic box by which they are read. The CM estimated in this fashion, consequently contains both, the atmospheric and the electronic noise. To best eliminate these correlations related to electronic noise, a common mode calculation between correlated detectors is performed. For this, the correlation matrix between the TOIs of all detectors is calculated. The detectors are then grouped by blocks of the most correlated detectors, regardless of any other considerations. A common mode is calculated for each of these groups of correlated KIDs and subtracted from the TOIs. According to Eq. (4.1), the components of the TOI remaining after subtracting this kind of common mode, the glitches, and cryostat noise, are simply the signal of interest and the intrinsic noise of the detectors. There might be other correlations present in the data, but these are difficult to quantify and are hence referred to as residual correlations and the corresponding noise element is the one that prevents the residual noise in the LPSZ maps from purely being white noise.

This CM removal method is currently the preferred method within the NIKA2 collaboration (called the ‘common mode one block’ method), especially for the LPSZ (called the ‘most correlated pixels’ method). This method exploits, to the maximum, the correlations between detectors to remove correlated noise from the TOIs. Furthermore, after extensive testing on simulations and real data, it has demonstrated superior performance in minimizing residual noise (Perotto, L. et al. 2020; Kérusoré 2021). However, as mentioned earlier, even after the ‘common mode one block’ decorrelation, residual noise exists. A part of this noise is the intrinsic white noise of each detector, which cannot be subtracted from the time data by virtue of its random nature. The remaining part comes from the imperfection of the decorrelation method leaving behind some atmospheric and electronic noise. This residual noise is projected into the surface brightness SZ maps of the clusters. The correlation of this noise introduces the extra risk that some parts may be misinterpreted as components of the signal of interest. This makes it critical to understand the role of this residual noise in the measurement of cluster properties from the associated SZ maps.

As one of the primary goals of decorrelation is to eliminate correlated noise, its efficacy can be assessed by quantifying the residual correlated noise. The information about residual correlated noise can be evoked from the angular power spectrum of the cleaned data. The spectrum, however, cannot directly be estimated from the SZ maps since they also contain the cluster signal. To evaluate the power spectrum, half-difference maps are generated for in-between the scans. For this purpose, maps from n different scans are co-added with every other map being multiplied by -1 during the co-addition. This kind of multiplicative addition ensures that the cluster signal cancels out in the resulting map, leaving behind only the noise component. The properties of these noise maps are the same as those of the noise present in

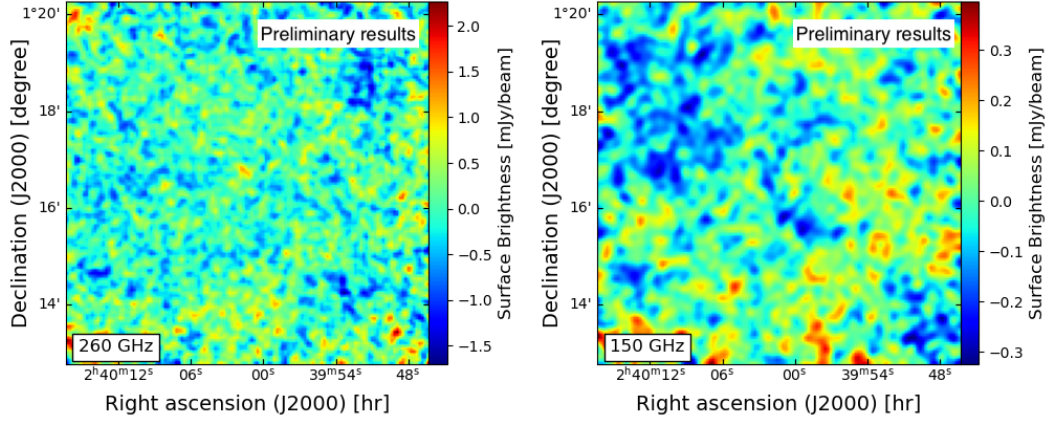


Figure 4.3 The 260 GHz (left) and 150 GHz (right) jackknife maps for the NIKA2 images of ACTJ0240. For visualisation, the left (right) map has been smoothed with a Gaussian kernel of $6''$ ($10''$).

the signal map obtained by coaddition. In the LPSZ, these are referred to as the jackknife maps. These maps for cluster ACTJ0240 can be seen in Fig. 4.3.

The normalised power spectrum of the residual noise is calculated on the Fourier transform, F , of these maps (I), normalized by the standard deviation map ($\sqrt{V}$) of the noise:

$$P_{\text{noise}}(k) = \left| F \left(\frac{I(x, y)}{\sqrt{V(x, y)}} \right) \right|^2. \quad (4.4)$$

The normalization accounts for the different integration times as one moves outwards from the pointing centre of the observation.

The shape of the power spectrum provides insight into the correlation of the residual noise. For a white noise-dominated background, which entails no residual correlations, the power spectrum must be flat. In contrast, the power spectrum of noise strongly correlated at large scales manifests as a power-law function, $P(k) \propto k^{-\alpha}$. We applied the common mode one block decorrelation method to cluster ACTJ0240 and its power spectrum (without normalisation by the variance map, for 150 GHz) can be seen in the left panel of Fig. 4.4. The residual correlated noise is clearly visible by the shape of this spectrum, peaking sharply at smaller wave numbers.

The presence of this correlated noise in the SZ maps must be accounted for during the ICM analysis of the cluster. This can be done by incorporating a covariance matrix of the noise into the modelling. The procedure is explained in detail in Section 4.2.

4.1.1.3 Transfer function and masking processes during decorrelation

When estimating and removing the CM from the TOIs of KIDs, there is an underlying assumption that no signal of interest is present in the CM. However, it is essential to note that the CM is indeed affected by the presence of astrophysical signal in these data despite using the median of TOIs in estimating the CMs. It must be considered

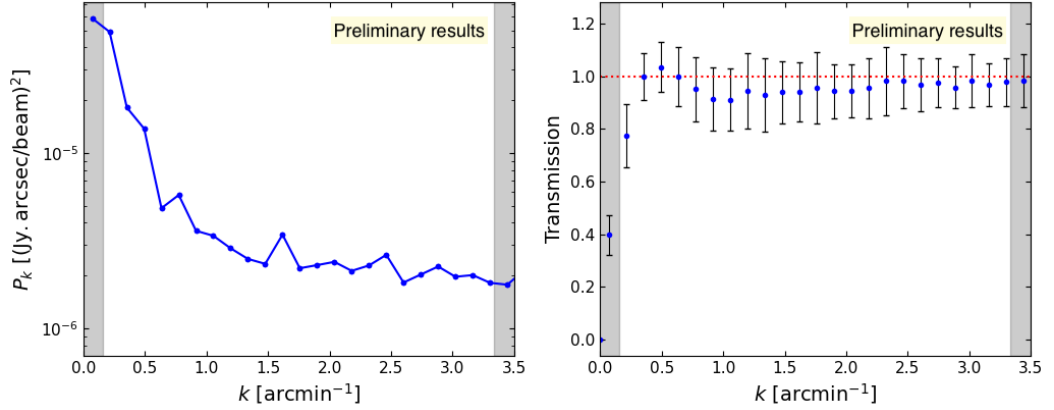


Figure 4.4 *Left:* The power spectrum of the residual noise at 150 GHz, estimated for ACTJ0240 using the jackknife map. The correlation in the residual noise is evident by the power law shape of the spectrum. *Right:* The 150 GHz transfer function for ACTJ0240, quantifying the large-scale filtering of the TOIs. Small-scale data ($k > 0.5 \text{ arcmin}^{-1}$) are almost perfectly recovered with filtering close to unity. The shaded region on the left (right) in both plots depicts the NIKA2 field of view (instrumental FWHM).

that when a significant fraction of detectors used in CM estimation passes over the source simultaneously, the CM no longer comprises purely of correlated noise but also the signal of interest. When such a CM is subtracted from the TOIs, data of interest is also lost from the SZ maps, making the CM a biased noise estimator. This issue becomes more pronounced for extended sources where the probability of two detectors seeing the source simultaneously is higher. Understandably, for LPSZ, which exclusively studies extended sources (galaxy clusters), this loss of signal of interest is an important concern. Not only in the 150 GHz band where the cluster signal is dominant but also in the 260 GHz band which (in the case of LPSZ) is used to detect PSs that act as contaminants to the SZ signal of galaxy clusters. Eventually, if the CM of TOIs is constructed without distinguishing between signal and noise, the KIDs simultaneously seeing a similar signal will be correlated not only due to noise but also due to the signal. Such KIDs will have a greater correlation than two others that see the source at different times and will be grouped for CM estimation. This makes it crucial to enable the isolation of signal from noise during the CM estimation.

For the LPSZ, masking is deployed to exclude regions containing the signal of interest from the CM estimation. This mask, $M(x, y)$ is defined such that its value is zero for a point (x, y) where a signal of interest is expected and one, otherwise. This mask is then multiplied with the previously discussed pointing matrix of the KIDs, to give a time-domain mask $M_K(t)$ whose value is zero when the signal of interest is expected to be seen by the KID K at a given time t and one, otherwise. The CM estimation we discussed in the previous section can now be recalculated by only including the regions of TOIs where the mask is non-zero. This kind of masking avoids biasing the CM with the signal of interest by eliminating the regions of concern from the CM estimation.

Calculating the mask requires prior knowledge of the region being observed.

Having this knowledge a priori is difficult since decorrelation itself helps distinguish between the signal of interest and the noise, making it challenging to guess, beforehand, the shape of the signal of interest. For one of the LPSZ studies, the mask was defined iteratively (see Muñoz-Echeverría et al. 2023b). At first, the mask was defined as a disk, centered on the cluster’s coordinates, with a radius large enough to include all the significant signal from the cluster. Then decorrelation was performed by estimating the CM by blocks of correlated detectors using this mask, providing an initial estimate of the astrophysical signal’s distribution in each detector’s time-domain data. This procedure was applied to all the scans of the cluster observations. After projecting this map onto the sky and co-adding all the scans (discussed in the next section), the resultant map was used to determine a new realization of the mask. For this purpose, a signal-to-noise (S/N) map was calculated and used to define the new mask such that $M(x, y)$ is zero where $S/N > 3$ and one, everywhere else. The decorrelation procedure was repeated using the new mask which provides a more reliable estimation of the region with the signal of interest, iteratively. The mask was updated with each iteration and the procedure was repeated till two successive iterations no longer produced significantly different masks (difference < 0.1 mJy/beam). Though this procedure worked for this particular cluster, its effectiveness remained inconclusive for the survey at large, making a single iteration with a predefined mask, the standard choice.

For ACTJ0240, we defined an initial mask of radius $0.55\theta_{500}$ where θ_{500} is the angular radius at overdensity 500 (see Eq. 2.29). We assume θ_{500} to be $2.022'$ from the ACT survey (Hasselfield et al. 2013). Additionally, we included masks for the point sources (PSs) in the cluster region. For this, we ran the LPSZ PS detection pipeline (see Chapter 5) to detect PSs in the NIKA2 SZ maps of the cluster with $S/N > 4$. We created a hybrid mask which masked the cluster region with a large disk of radius $0.55\theta_{500}$, centred at the cluster centre coordinates and each PS with a small disk (size corresponding to the extent of the 4σ detection contour of the PS) centred on the PS itself.

Previously, we demonstrated how the residual noise power spectrum measures the performance of the decorrelation method in terms of mitigating the background correlated noise. However, as we just discussed in the above paragraphs, preserving the signal of interest is as important an aim for the decorrelation procedure, as removing the correlated noise. By construction of the iterative decorrelation pipeline, any cluster signal with $S/N < 3$ remains unprotected by the mask used in the LPSZ, making this signal vulnerable to removal by the CM method. This in turn leads to the filtering of the signal of interest at large scales. The iterative process, which starts with a mask of a sufficiently large radius, may also result in a mask that does not provide sky coverage that is enough to obtain a decent number of KIDs for the CM estimation. As a result, the noise estimation may suffer. These issues remain more significant for extended sources and hence the LPSZ. This pushes the need to enhance the understanding of this signal filtering: to relate the detected signal with the actual SZ signal from a galaxy cluster.

The filtering effect is accounted for by the analysis transfer function, which is estimated by measuring the filtering effect on a known signal that undergoes the same filtering and decorrelation process as the target LPSZ clusters. For a given LPSZ cluster, once the analysis is complete, an SZ map is simulated for the

cluster by integrating a universal pressure profile (UPP, M. Arnaud et al. 2010) corresponding to the cluster mass, redshift, and radius, along the line of sight. This map is projected onto the same pixel grid as the actual LPSZ cluster. Further, to avoid any zero values in the map (and hence divergence in the estimated transfer function, as will become evident later), a realisation of white noise with negligible amplitude compared to the simulated signal, is added resulting in the input simulated map $S_{\text{sim,in}}$. This simulated map is then converted to TOIs using the real pointing matrices of the KIDs. These TOIs dominated by the simulated signal are finally added to the real data, generating TOIs that contain various contaminants that are characteristic of the LPSZ observations, the astrophysical signal of interest, and the simulated signal. These TOIs then undergo the same decorrelation process that we have discussed so far, in a way that ensures that the processing of the data containing the simulated signal is identical to that undergone by raw/actual data. The de-correlated map containing only real data is then subtracted from the one also containing the simulated signal, to obtain the simulated signal map, $S_{\text{sim,out}}$. Finally, the transfer function (TF) of the analysis $TF(k)$, is calculated as the ratio between the power spectra of the simulated signal maps after ($S_{\text{sim,out}}$) and before ($S_{\text{sim,in}}$) decorrelation. The uncertainties of this transfer function are computed using the dispersion of the transfer functions computed via multiple realisations of the simulation described above.

By ensuring identical decorrelation processes for simulated and real signals, we make sure that the transfer function estimated in this fashion is a decent estimator of the large-scale filtering of the raw signal of interest in the LPSZ maps. Notice, in retrospect, that adding white noise to $S_{\text{sim,in}}$ ensures that the denominator in the transfer function definition is always non-zero and the value never diverges.

The resulting transfer function for cluster ACTJ0240 is shown in the right panel of Fig. 4.4. Its shape is a characteristic marker of the common mode one-block decorrelation method used in the LPSZ. The filtering of large angular scales (small wave numbers, $k < 0.5 \text{ arcmin}^{-1}$) is evident by the fall of the TF in this region. This marks a strong suppression of the signal of interest beyond physical scales corresponding to the telescope field of view ($6.5'$). On the other hand, the signal at small angular scales is well preserved with filtering close to unity. This TF, along with the residual noise power spectrum discussed earlier is used in estimating thermodynamic properties from the cluster SZ map. The details are described in Section 4.2.

4.1.1.4 Map projection of TOIs

Once the decorrelation is performed, clearing the TOIs of correlated noise, the last step in creating surface brightness SZ maps from NIKA2 observations includes projecting all the data onto a sky grid and combining all the scans. For the LPSZ, a method briefly described in the following lines, called the nearest grid point scheme is used for map projection (Perotto, L. et al. 2020). The pointing information is deployed to project the cleaned and calibrated TOI of all the valid KIDs onto a flux density map. The pointing matrix, as earlier discussed, contains information about the position of each detector relative to a reference detector at any given moment. Additionally, the telescope pointing provides the sky position of the reference detector.

Hence, for every flux measurement made by a KID, the sky position at which this measurement occurred, is known. Using this information, each flux measurement can be associated with the pixel on the map closest to the sky position at which it was made. The map pixel size is a variable parameter in the analysis. The optimal size depends on both, the sky scanning speed during observations and the sampling frequency at which KIDs are read. These two quantities determine the angular distance separating two consecutive samples. The pixel size, $2.99''$, is chosen to ensure that two consecutive samples are never separated by more than one pixel. This in turn enables every map pixel to be associated with at least one sample.

To generate a surface brightness map, the weighted average associated with each pixel is calculated. The weight associated with each detector (pixel) is calculated as the inverse of the variance of the detector's TOI outside the mask $M_k(t)$ defined to conserve signal of interest during the decorrelation process. In short, this is the inverse, off-source, variance of the TOIs. This weighing method ensures that KIDs with heavy noise post the decorrelation are given lesser weight.

As a result of this projection method, two other maps are generated, namely, the hit count map and the noise variance map. The hit count map represents a mapping of the number of samples used for the projection. It gives, for each pixel in the map, the number of samples associated with it by the nearest grid point projection. This map is obtained by summing the pointing matrices of all KIDs for all samples. On the other hand, we have seen that producing a surface brightness map requires weighing each pixel value by the inverse of the variance of its TOIs outside the source. The variance associated with each detector is projected, with pixelization identical to the signal map, to generate the noise variance map. The square root of this map then gives a standard deviation or noise map that quantifies the uncertainty of the astrophysical signal at each pixel in the surface brightness map.

The surface brightness maps are produced for all the scans performed in the four directions covered during the observations of the LPSZ. These maps for different scans are combined to create the final surface brightness map by calculating their weighted average. In this case, the weights are defined for each map based on the hit count map and the variance of the surface brightness map outside the source mask. Once again, this weighting aims to give less importance to scans where the noise remains significant after decorrelation. The hit count and noise maps for the co-added surface brightness maps for all scans are shown for cluster ACTJ0240 in the left and right panel of Fig. 4.5, respectively. Note that the count map shows a higher number of hits in the centre of the map than at the periphery. This coverage inhomogeneity is explained by the fact that more detectors pass through the central regions of the map for geometric reasons, while fewer KIDs visit its periphery. For the same reasons, the noise standard deviation is higher in the external regions of the map, resulting in higher-quality observations in the centre. It is also evident that combining scans at four different angles increases the coverage in the map (considering four scans instead of one) and makes it more isotropic along with making the noise fall off slowly with better circular symmetry.

The final surface brightness images obtained from the NIKA2 observations of cluster ACTJ0240 are shown in the top panel of Fig. 4.6. The 260 GHz map of the cluster can be seen in the top left panel. Typically, we would expect to see the

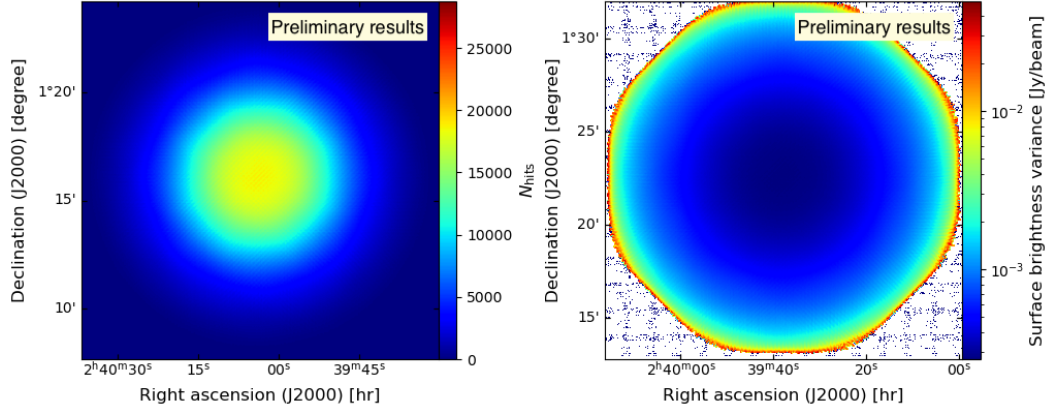


Figure 4.5 The 150 GHz hit count (left) and noise map (right) associated with the co-added surface brightness maps for all scans of cluster ACTJ0240.

positive signature of the thermal SZ effect at this frequency but, for the LPSZ, the noise level in this range is above the expected signal intensity (~ 0.2 mJy/beam). Regardless, we notice in this map, the strong PS near the centre of the cluster, at the position where we find an apparent signal compensation in the top right panel, which shows the NIKA2 map at 150 GHz. At this frequency, the cluster can be identified as a decrement or negative signal, with a peak detection of $S/N = 9$ at the centre of the map. This depicts the characteristic of the thermal SZ effect expected at this frequency. Right near the centre of this map, we also see an indication of strong contamination by a PS, almost creating a hole in the cluster map. This happens because the positive fluxes of PSs compensate for the SZ effect decrement, creating holes in the apparent shape of the ICM. This is particularly significant for this cluster as the source sits right near the centre and can significantly alter or impact the estimation of ICM properties from this SZ map. Careful consideration has to be given to this PS when measuring the thermodynamic properties of the ICM using the SZ map. This has been discussed in Section 4.2.

In addition to the SZ surface brightness, we also point to the position of the different centres of the cluster in Fig. 4.6. The SZ centre (green cross) refers to the peak of the SZ signal centre reported by Hasselfield et al. 2013. The X-ray centre (white cross) is the X-ray peak inferred from the *XMM-Newton* observations of the cluster (Section 4.1.2). The most luminous galaxies of the cluster (often referred to as the brightest central galaxy or BCG) are marked with the yellow (BCG1) and the orange (BCG2) stars. For ACTJ0240, the difference in magnitude of the two galaxies is negligible (magnitude difference ~ 0.038 in the SDSS-III r band), rendering it difficult to define a clear BCG candidate that coincides with the centre of the cluster's potential well. Ideally, for a dynamically relaxed cluster, the SZ and X-ray centres, align well with its BCG (Ota et al. 2023; Yuan, Han, and Wen 2022). For ACTJ0240, the two centres are displaced from each other and the optical centre, indicating non-homogenous distribution of the galaxies with respect to the ICM gas. Further, there are two extremely optically bright galaxies serving as BCG candidates, that are displaced from each other, indicating an inhomogeneous distribution of galaxies. We also notice two tail-like structures in the cluster SZ image pointing

in the northwest–southeast direction. With the SZ image alone, the ICM shows signs of disturbance and asymmetry. This is further explored with multi-wavelength images of the cluster in the following sections.

4.1.2 X-ray and optical images

To complement the SZ data and give a more rounded view of the state of ACTJ0240, we also use its X-ray (*XMM-Newton*) and optical (SDSS) data. In this section, we describe the process of creating images of the cluster using these datasets.

4.1.2.1 X-ray data processing

ACTJ0240 was observed by *XMM-Newton* (Obs ID 0800971001) for a total observation time of 69 ks. The raw data were processed¹ by following the procedure outlined in Bartalucci et al. 2017, using the *XMM-Newton* Science Analysis System (SAS) version 16 (Gabriel et al. 2004)². The contamination in X-ray data is a combination of instrumental noise and sky background. To reduce the contamination induced by the high-energy particles, only standard events with the SAS keyword `PATTERN < 13` and `< 4` were retained for the European Photon Imaging Camera (EPIC) pn and Metal Oxide Semiconductor (MOS 1 and 2) detectors, respectively. Further, parts of the data involving an anomalous count rate, also known as flares, were removed following the procedure described in Pratt et al. 2007. Simply put, sigma clipping was used on the light curves of the time-ordered data, by removing intervals of time where the count rate exceeded the 3σ limit of the mean value. After this cleaning, we had data worth 36/29 ks for the MOS/pn detectors, to generate X-ray images and radial profiles. The high-energy particles also interact with the detectors and with the telescope itself, generating events that contaminate the signal of interest. To evaluate and remove this component, we used the filter wheel closed datasets (see Kuntz and Snowden 2008 for details of the procedure). A vignetting correction was also applied to data, following the process outlined in Bartalucci et al. 2017. Finally, to clean the data of PSs, exposure-corrected images in the [0.3 – 2.0] keV and [2.0 – 5.0] keV bands were used. The images were run through the Multiresolution wavelet software (Starck, Murtagh, and Bijaoui 1998) to detect the PSs and inspection was done by eye to add any missing sources/structures or remove the fake detections. The generated catalogue was masked for all further steps of data processing. The sky background in X-ray data includes a local component, formed by the Local Hot Bubble and the halo Galactic emission, and an extragalactic component comprising the cosmic X-ray background and unresolved PS (see, *e.g.*, Snowden et al. 1995; Kuntz and Snowden 2000; Giacconi et al. 2001). This sky component was modelled and consequently removed from the data, as a constant background in the surface brightness estimation process.

The instrumental and sky background cleaned data was used to project all the events to a common sky projection to obtain a combined (MOS1, MOS2, and pn) X-ray image of the cluster. We also used the X-ray data to obtain an electron density

¹Credits to G.W. Pratt and I. Bartalucci for X-ray data processing, including all X-ray images and profiles

²<https://www.cosmos.esa.int/web/xmm-newton/sas>

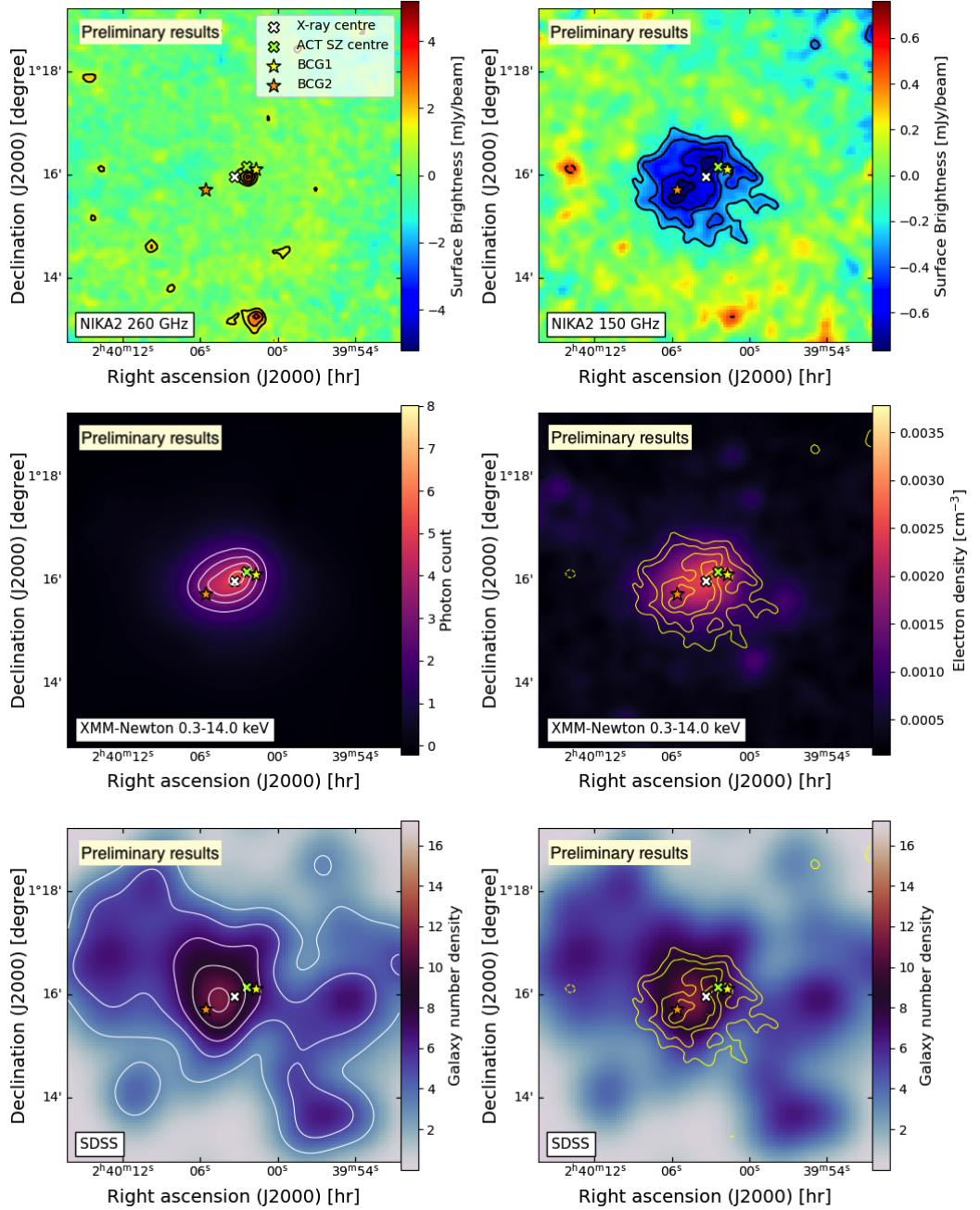


Figure 4.6 A multi-wavelength view of ACTJ0240. The images are square grids of size $6.5' \times 6.5'$, centred at the X-ray peak of the cluster. In all the images, we show the ACT peak emission representing the SZ centre (green cross), the *XMM-Newton* image peak depicting the X-ray centre (white cross), and the two cluster BCGs (yellow and orange stars). **Top panels:** the 260 GHz (left) and 150 GHz (right) NIKA2 surface brightness images. The black contours in both images show the S/N levels starting from $\pm 3\sigma$, spaced by 2σ . For visualisation, the left (right) map has been smoothed with a Gaussian kernel of $6''$ ($10''$). **Central panels:** The image on the left shows the wavelet-smoothed *XMM-Newton* photon count image of the cluster with the white contours depicting signal above 2σ and each successive contour is spaced by 1σ . The right-side image shows the electron density map (smoothed using a $7.5''$ Gaussian kernel) inferred from the X-ray observations with overlaid SZ contours corresponding to the top right panel. **Bottom panels:** Both the images show the galaxy number density of the cluster estimated from SDSS data. The image on the left is overlain with white equally spaced (by 2σ) contours depicting galaxy number density above 3σ . The yellow contours in the right-hand side image are the same as the top right panel.

map (see Eq. 2.34 for the relation between electron density and X-ray emission). The wavelet-smoothed photon count and electron density map of ACTJ0240 are shown in the central-left and right panel of Fig. 4.6. The wavelet photon count map shows us the general alignment of the gas distribution depicted individually by the SZ and X-ray data. To envision more structural details mapped by the X-ray observations, we look at the electron density map on the right side of the central panel. Of particular interest, are the two gas clumps we notice right next to the extended tail-like structures detected in the southeast region of the SZ map (shown here using yellow contours). Since the X-ray emission is more sensitive to colder, clumped gas (see Section 4.3), we tried to measure the spectroscopic temperatures in these two regions using apertures of diameter $1'$. While the temperature of the northern clump was unconstrained, the southern clump was estimated to have a temperature of $2.3^{+2.05}_{-0.87}$ keV. The pressure corresponding to these temperatures was below the NIKA2 noise level in these regions in the map, which is why we do not see the corresponding SZ signal associated with these clumps. The SZ tails and clumps detected in the X-ray observations potentially point to in-falling structures onto the cluster. A further indication that the cluster is a disturbed, interacting system.

4.1.2.2 Optical data processing

We utilized information of member galaxies obtained from the SDSS data release 16 (Blanton et al. 2017) to create an optical galaxy number density map for ACTJ0240³.

Using the X-ray coordinates of the cluster (previously mentioned in this chapter) and its redshift, we retrieved optical wavelength data from the SDSS archives. Unfortunately, the available spectral data for galaxies in this region was insufficient for a reliable estimation of their velocity dispersion and, consequently, the dynamical mass of the cluster. As an alternative, we employed the photometric data of galaxies within the cluster region, specifically utilizing information from the g, r, and i bands. To identify member galaxies, red-sequencing (refer to *e.g.* Bower, Kodama, and Terlevich 1998 for an early reference) was applied to the data. The essence of the red sequence lies in the fact that the red-dead galaxies within the cluster exhibit a distinctive location in the colour–magnitude (C–M) diagram due to their similar properties. Galaxies of varying stellar masses, *i.e.*, different magnitudes, display very similar colours with a slight tilt (Gladders et al. 1998), thus form a line in the C–M diagram known as the red sequence of cluster galaxies, indicating a collectively evolved population of galaxies.

For ACTJ0240, we used the magnitude in the r band and colour using the r and i bands to find the red sequence of the member galaxies. The identified member galaxies were used to create a galaxy number density map of the cluster. To estimate the number density map, we smoothed the galaxy map in the region of interest with a Gaussian kernel whose normalisation was equal to the total number of galaxies present in the region. This provided the number density of galaxies at each point in the grid. The resulting number density map can be seen in the bottom panel of Fig. 4.6. On the left side, we show the number density map and on the right, we show the map together with the SZ map contours (in yellow). From the left figure, we

³Acknowledgments to A. Ferragamo for optical data processing

can see that one of the BCGs (BCG 2, shown using an orange star) is closer to the peak of the galaxy distribution while the other (BCG1, shown using a yellow star) is far from the peak of the galaxy distribution. This is unusual since, for a relaxed or virialised system, the brightest galaxies sit at the centre of the halo. From the figure on the right panel we see that the distribution of gas is not aligned with the distribution of the galaxies as the significance contours for the SZ detection are at an angle with respect to the direction of the galaxy number density contours (white contours in the left-side image). This is another indication of a disturbed cluster system. We also notice an enhanced galaxy number density in the southeast region near the tail structures detected in the SZ maps, coinciding with the gas clumps detected in the X-ray (right-side figure of the central panel). This further supports the hypothesis of infalling matter onto the cluster.

4.2 Estimation of the ICM pressure profile

The preceding sections have described the process of creating and visualising the images of galaxy cluster ACTJ0240 in multiple wavelengths. While this gives us a qualitative insight into the structure and state of the cluster, we still need to characterise the ICM and its properties to gain more knowledge of it in the context of LPSZ. One of the main aims of LPSZ is to estimate and calibrate the masses of its galaxy clusters to enable the estimation of a $Y - M$ scaling law at high redshift (Perotto et al. 2023). In this and the following sections, we describe the methodology used to estimate the ICM profiles and present the associated results.

To estimate the pressure profile from the NIKA2 SZ maps, we make use of the PANC02 software (Kéruzoré et al. 2023), currently the official SZ pipeline for the NIKA2 collaboration. The estimation of pressure profiles from the projected SZ maps is done in PANC02 using a forward modelling approach. Therein, the physical state of the cluster is modelled based on some parameters (discussed below) related to the cluster and the instrument. A 3D pressure profile model obtained in this manner is then projected to a map while taking into account instrumental and observational details, generating a kind of model (discussed later), which is then compared to the actual data from NIKA2 to estimate cluster properties using the Markov chain Monte Carlo (MCMC) technique.

As described in Section 2.3.3, the SZ effect is a spectral distortion of the CMB caused by inverse Compton scattering of photons by electrons in the hot ICM. The energy transferred by electrons comes from their energetic thermal state. The amplitude of the distortion, called the Compton parameter, is proportional to the electron pressure P_e of the ICM integrated along the corresponding LoS, as given by Eq. (2.41).

In practice, observers only get a projected view of the cluster and cannot directly measure the pressure along the LoS. Consequently, spherical symmetry has to be assumed to enable the pressure distribution dependence solely only on the distance from the centre of the cluster. Under this circumstance, a SZ effect can be used to constrain this pressure profile. For this case, we can use Abel transformation and Eq. (2.41) can be projected to a 2D radial profile (function of 2D radius R) as follows:

$$y(R) = \frac{2\sigma_T}{m_e c^2} \int_R^\infty \frac{r}{\sqrt{r^2 - R^2}} P_e(r) dr. \quad (4.5)$$

To fit a pressure profile using this projected equation, we initially describe our pressure profile using the so-called ‘non-parametric’ (NP) model, where the pressure profile is described by a radially falling power-law function distributed in concentric spherical shells (Romero et al. 2018), given by:

$$P_e(r_i < r < r_{i+1}) = P_i \left(\frac{r}{r_i} \right)^{-\alpha_i}, \quad (4.6)$$

where P_i and α_i are the values of the pressure and the numerical slope for the radial bin r_i . This functional form offers a less model-dependent approach to estimating the pressure profile and thus the ability to detect irregularities in the pressure profile. This is useful for detecting anomalies such as jumps or shocks, in the pressure profile.

To obtain a projected map corresponding to the above pressure profile, the profile is first integrated along the LoS to obtain a Compton parameter map (y map) in the cluster region. For the NP model, this integration is essentially the sum of the analytical integrals of the pressure profile in each of the spherical shells. The analytical integrals have been calculated as in Romero et al. 2018. This y map must then be converted to an SZ map comparable to the actual cluster map. First of all, the y values are converted to SZ surface brightness values using a telescope calibration factor (see Section 3.2 for definition). The calibration factor, however, depends on the effective bandwidths and beam of NIKA2. Additionally, it depends on the shape of the SZ effect spectrum and consequently the ICM temperature. To allow the variation in calibration factor based on these parameters, PANC02 treats it as a nuisance parameter in the likelihood, with a Gaussian prior and initial guess of -11.9 (Perotto, L. et al. 2020; Ruppen, F. et al. 2018). The obtained SZ map then goes through two forms of filtering: i) convolution with the instrumental beam characterised by a Gaussian filter of FWHM of the 150 GHz channel; ii) the filtering resulting from the NIKA2 data noise subtraction procedure in time, this is quantified by the analysis transfer function described in Section 4.1. The resulting map can finally be used as a model to compare to the surface brightness map of the SZ effect observed by NIKA2 together with the consideration of a zero level (additive bias), which is fitted as a nuisance parameter.

We have to keep in mind that the LPSZ decorrelation process filters information on large scales, preventing any constraints on the SZ signals and derived quantities in the cluster outskirts. Nonetheless, the information on large scales can be captured via the integrated SZ signal of the cluster. This quantity is reliably measured in surveys with a larger field of view than the LPSZ, specifically the Planck (Planck Collaboration et al. 2014) and ACT (Hasselfield et al. 2013) surveys. It is obtained by integrating the y parameter over a solid angle:

$$Y = 4\pi\sigma_T \int_0^R \frac{r^2 P(r)}{m_e c^2} dr. \quad (4.7)$$

For our modelling, using Eq. (4.7), this value can be estimated from the pressure profile model discussed above. Since the statistics in this region are not sufficient

in the LPSZ, we use values of the Y parameter known from the ACT survey to impose an effective constraint on the pressure profile in these regions unconstrained by NIKA2 observations. We describe later in this section, how we include this in our likelihood function to enhance the pressure profile constraint in the outskirts of the cluster.

It must be kept in mind that the pressure profiles estimated using the NP model are not suitable for deriving the hydrostatic mass profiles (see Section 4.4) as doing so leads to non-physical results. This happens because the irregular and non-continuous shape of the NP pressure profile does not impose any condition on the sign of the pressure profile slope. This consequently leads to negative mass contributions (following Eq. 4.23) in the corresponding radial bin of the mass profile, preventing the integrated mass profile from monotonically increasing. To prevent this from happening we fit a generalized Navarro-Frenk-White (gNFW) profile model to the NP pressure profile data points obtained above. The gNFW model is given by Nagai, Kravtsov, and Vikhlinin 2007:

$$P_e(r) = \frac{P_0}{\left(\frac{r}{r_p}\right)^c \left[1 + \left(\frac{r}{r_p}\right)^a\right]^{\frac{b-c}{a}}}, \quad (4.8)$$

where P_0 is the normalization constant. Parameters b and c represent the external and internal slopes of the pressure profile, with r_p marking the characteristic radius at which the profile slope changes and parameter a quantifies the steepness of this transition.

Finally, it must be noted here that the PS mentioned in Section 4.1 (Fig. 4.6) must be handled with caution when estimating the pressure profile. Since the PS emission is positive and compensates for the cluster signal, it holds the potential of introducing a negative bias in the reconstructed ICM pressure profile from NIKA2 observations and consequently in the mass estimate. To emphasize this point, we adopt three approaches to handling this PS:

1. Be blind to the PS: completely ignore its presence to see the impact on ICM analysis.
2. Masking the PS: in this case, we assign zero weight to the pixels at the position of the PS in both, the NIKA2 SZ map and model map during the likelihood analysis.
3. Modelling the PS: PANC02 offers the possibility of treating PS contamination as a nuisance parameter in the ICM pressure profile fitting. For this purpose, sources modelled as 2D Gaussians with their width corresponding to the FWHM of the NIKA2 beam can be added to the previously presented surface brightness map model before it is compared to the data. The source flux, which corresponds to the amplitude of 2D Gaussian in the model, is then considered as an additional parameter of the model. Previously, the prior on the flux of the sources has been estimated as a probability distribution function obtained using the flux of this same PS in other catalogs such as PACS (Poglitsch et al. 2010) and SPIRE (Griffin et al. 2010), see *e.g.* Kéruzoré, F. et al. 2020; Muñoz-Echeverría et al. 2023b. Unfortunately, our PS was not found in any

external catalog. In this situation, we take recollection of the fact that the main contaminants for SZ observations are submillimetre galaxies and for such objects, the typical relation of fluxes in the two NIKA2 bands is given by $S_{150}/S_{260} = 0.2$ (Ricci 2018). For this reason, we estimated the PS flux in the 260 GHz band and using the aforementioned flux relation we impose an upper limit on the PS flux, for the 150 GHz band as 0.3 times that of the 260 GHz band.

4.2.1 Markov Chain Monte Carlo Fitting

We use a Markov Chain Monte Carlo (MCMC) algorithm to fit our models to the data. First, we fit the generated surface brightness model map to the NIKA2 SZ map, to infer its best-fit NP pressure profile model and then we fit a gNFW model to the binned data points of the NP profile. Ultimately, we aim to find a posterior distribution which gives us the probability function of the parameters of interest, given the measurements made by NIKA2 for the LPSZ. This posterior distribution, $P(\vartheta | D)$, for a set of model parameters (ϑ), and given observations or data, D , is defined using the Bayes' theorem:

$$P(\vartheta | D) = \frac{L(D | \vartheta)P(\vartheta)}{P(D)}. \quad (4.9)$$

In our case, the data D refers to the NIKA2 surface brightness map for the SZ observations of the cluster along with the Y_{500} measured by ACT (Hasselfield et al. 2013). The term $P(\vartheta)$ is our prior knowledge of the parameter values before the observations. In our case, the prior distribution is modelled as the product of individually defined distributions for each parameter, considering no correlation between the individual distributions. The individual prior for each parameter is given by a Gaussian centred on the M. Arnaud et al. 2010 value with a very large σ which is approximately five times the central values. Probability $P(D)$, sometimes also referred to as evidence, is the normalisation constant for Eq. (4.9) and is given by the marginalised probability for the data, $P(D) = \int P(D | \vartheta)P(\vartheta)d\vartheta$.

The distribution $L(D | \vartheta)$ is the likelihood function that compares the model to the data. It gives the probability that a dataset D originates from a model ϑ .

In our case, when fitting our model map to the NIKA2 SZ map, the likelihood is defined by a multivariate Gaussian function, with each pixel of the NIKA2 map as a dimension:

$$\begin{aligned} \log L(D | \vartheta) = & -\frac{1}{2} \sum_{i=1}^{n_{\text{pixels}}} \left[(\mathcal{M}(\vartheta) - \mathcal{D})^T C_{\text{pix-pix}}^{-1} (\mathcal{M}(\vartheta) - \mathcal{D}) \right]_i \\ & -\frac{1}{2} \left(\frac{Y_{500}(\vartheta) - Y_{500}^{ACT}}{\Delta Y_{500}^{ACT}} \right)^2. \end{aligned} \quad (4.10)$$

Here, $\mathcal{D}$ represents the NIKA2 map at 150 GHz and $\mathcal{M}(\vartheta)$ is the model map calculated from the parameters ϑ . Similarly, Y_{500}^{ACT} and $Y_{500}(\vartheta)$ are the ACT-measured integrated SZ signal and the integrated SZ signal corresponding to the considered model, at $R = R_{500}$, respectively. The value ΔY_{500}^{ACT} gives the uncertainty

associated with the ACT-measured integrated SZ signal. The term $C_{\text{pix-pix}}^{-1}$ represents the pixel-to-pixel covariance matrix of the noise in the NIKA2 map. This matrix can be calculated from the power spectrum we estimated in Section 4.1, using Eq. (4.4). First, we produce $\sim 10^5$ realisations of white noise with map and pixel size the same as that of the NIKA2. In each realisation, every pixel is randomly drawn from a Gaussian distribution with a mean of 0 and a variance of 1. We then convolve each of these maps with the square root of the power spectrum of the noise that we estimated for ACTJ0240, thus generating realizations of noise normalized as per the input power spectrum. These normalised noise realisations are further multiplied by the variance map of the noise that we presented in Section 4.1, right panel of Fig. 4.5. In this way, we produce realizations of residual noise with the same amplitude and correlations as in the jackknife map of the cluster. Finally, to estimate the covariance matrix, we flatten each $n \times n$ map to a vector of dimension $(n^2 \times 1)$. The covariance of these $n \times n$ vectors of shape $(n^2 \times 1)$ gives us the noise covariance matrix, $C_{\text{pix-pix}}^{-1}$, of size $(n^2 \times n^2)$, where each element (p, q) represents the covariance of the noise in pixels p and q of the map.

To further fit the gNFW model to the binned data point of the NP profile, the likelihood function is defined by:

$$\log L(\vartheta) = -\frac{1}{2} \left[(P_{\text{gNFW}}(\vartheta) - P_{\text{NP}})^T C^{-1} (P_{\text{gNFW}}(\vartheta) - P_{\text{NP}}) \right]. \quad (4.11)$$

Here, P_{gNFW} and P_{NP} are the gNFW model at a given point in the chain and the NP pressure profile bin value, respectively. The associated covariance matrix for P_{NP} is given by C . The parameter vector ϑ is constructed by the gNFW model parameters described in Eq. (4.8). To ensure that there are no negative mass contributions in the mass profiles, we impose an extra condition that ensures a negative slope term $\frac{r^2}{n_e(r)} \left[\frac{dP_e(r)}{dr} \right] < 0$ in Eq. (4.23), later discussed in Section 4.4.

The MCMC is a statistical method based on iterative sampling from a probability distribution to produce realisations of a random vector. It is constructed in a way that ensures the full set of random vectors follows a target distribution. A proposal density distribution for the parameter space (in our case, a multivariate Gaussian) is defined. A chain (called a ‘walker’) is used to walk randomly from one point in the sample space to another, thus defining a chain of parameters resulting from a stochastic process. Each new point in the chain depends only on the present state of the chain, a property which defines the Markov Chain. These chains are used to obtain random draws from a posterior distribution of the parameter of interest. The random walk can be described by a series of successive steps:

1. The random walk starts at a point in the parameter space with coordinates defined by a vector θ and the probability density, $f(\theta)$ is estimated
2. The walker moves to a new step, θ' , in the parameter space using the proposed distribution. The new probability density, $f(\theta')$, is estimated
3. If $f(\theta') \geq f(\theta)$, then θ' is automatically accepted as the new position of the sampler; otherwise, the point is randomly accepted or rejected with an acceptance probability that decreases rapidly as θ' is less probable than θ

4. Steps 2 and 3 are repeated until the chains have converged to the target distribution

Common examples of the above MCMC algorithms are the Metropolis (Metropolis et al. 1953) and the Metropolis–Hastings algorithm (Hastings 1970). These algorithms are limited by a proposal probability density function that remains unchanged during sampling. In this work, we use the Python implementation of the `emcee` library (Foreman-Mackey et al. 2019), which provides adaptive sampling (Goodman and Weare 2010). In particular, we use the `DEmove` sampler (Nelson, Ford, and Payne 2014). It is the fastest sampler in terms of producing the most independent samples per unit time.

4.2.1.1 MCMC Convergence tests

The MCMC analysis is an iterative method and can be performed using multiple walkers in parallel. Naive inferences from the Markov chains, however, can give misleading results if the number of steps is insufficient to achieve convergence toward the target posterior function, or the chains are not cleaned properly. We can use several ways to judge whether the generated results have converged to the target density with a sensible value *i.e.*, enough sampling has been done. We use three criteria to judge the convergence of our chains:

1. **Chain adaption:** To begin with, it must be noted that choosing a random starting point can have an impact on the convergence because this point might completely lie outside the region of interest. To ensure that this does not affect our results, we discard the first few iterations of the sampling until the chains reach the convergent distribution, independent of the starting point. This period of initial iterations is often regarded as the ‘burn-in’. Once this section of the chains is discarded, we can perform further checks to verify the convergence of our sampling.
2. **Autocorrelation:** The position of each point in the Markov chain, by construction, depends on the previous position, resulting in the autocorrelation of chains. But for Markov chains, these points must be independent. The average length separating two points that can be considered independent can be calculated from the series of accepted positions forming the Markov Chain. This parameter, called the autocorrelation length is estimated by:

$$\tau = 1 + 2 \sum_{i=1}^n \rho(\theta_0, \theta_i)$$

where n is the length of the considered chain, and $\rho(\theta_0, \theta_i)$ is the correlation coefficient between θ_0 and θ_i . To consider the sampling to have converged, we use the criterion that the chains must have traversed more than fifty times their autocorrelation length.

3. **Chain mixing:** For a converged MCMC posterior distribution, all the different walkers will produce chains that are stationary and statistically similar. This similarity is referred to as chain mixing. A criterion for evaluating the chains

mixing is the Gelman and Rubin test (Gelman and Rubin 1992). Two estimators are used to calculate the variances in the chains and the ratio of their square root values decides whether the chains have converged. Say we run m Markov chains with n being the number of steps in each chain, then, the average variance of all chains can be calculated as

$$s^2 = \frac{1}{m} \sum_{i=1}^m s_i^2. \quad (4.12)$$

Here, s_i^2 is the variance within the i^{th} chain. For independent samples, variance in each chain, s_i^2 , is simply given by the standard formula σ^2/n . Realistically, for the samples of MCMC, this variance is much greater than σ^2/n (Vats and Knudson 2018). Gelman and Rubin 1992 correct for this bias by introducing the scaled bias B as

$$\frac{B}{n} = \frac{1}{m-1} \sum_{i=1}^m (\bar{\mu}_i - \hat{\mu})^2, \quad (4.13)$$

where $\bar{\mu}_i$ is the mean of a parameter θ , for the i^{th} chain and $\hat{\mu}$ is the combined mean estimate from all the m chains. Using this scaled bias, the estimator for the average variance in each chain is then defined as

$$\hat{\sigma}^2 := \frac{n}{n-1} s^2 + \frac{B}{n}. \quad (4.14)$$

The Gelman–Rubin R potential scale reduction factor (PSRF), commonly called the ‘ R value’ is defined as

$$\hat{R} := \sqrt{\frac{\hat{\sigma}^2}{s^2}} \quad (4.15)$$

and decides the convergence of the sample. Gelman and Rubin 1992 argue that for converged chains, $\hat{R}$ approaches the value of 1 and the sampling is considered to be sufficient when $R \leq \delta$ for some $\delta > 1$. Vats and Knudson 2018, however, find that a smaller value for δ is more satisfactory. We adopt $\hat{R} < 1.02$ as our convergence criterion.

For fitting the NP model to the SZ maps, we used 30 chains, after discarding 1000 steps as burn-in while for fitting the gNFW model to the NP data points, we used 50 walkers with a burn-in period of 1500 steps. In both cases, we checked at regular intervals of 500 steps during sampling whether the mixing and autocorrelation criterion mentioned above were satisfied or not. Once the convergence was achieved, the sampling terminated itself. The obtained chains were used to infer the properties of the ICM after discarding the poorly mixed chains and using only points in the chain that are not correlated to each other (quantified by the autocorrelation length).

The converged and cleaned Markov Chains produced by the sampler constitute the posterior probability distribution in the parameter space of the model. This is represented as a vector θ , with a dimension corresponding to the number of points in the chains, and each component $i \in [1...n]$, is a vector in the parameter space. Using this we can estimate the vector for the pressure profile in Eq. (4.6) and Eq. (4.8),

where each component i is the profile associated with the pressure profile parameters of the point θ_i from the Markov Chains. The distribution of the components of $P(r)$ creates the posterior distribution in the space of pressure profiles. The uncertainty on this pressure profile is estimated by the 16th and 84th quantiles of this distribution. To estimate the binned values of pressure using the NP model, we sampled the pressure profile in five logarithmically-spaced bins between the NIKA2 beam and FoV, centred at the X-ray peak. The same centre and the binned values obtained for the NP model were used to estimate the gNFW fit to the NP pressure profile.

4.2.2 Results

As mentioned in Section 4.2, the SZ signal of the cluster is contaminated by a bright PS in its centre and we deal with it in three different ways. Further, since the NP model used to estimate the pressure profile from the SZ maps is not suitable for mass inference (see also, Section 4.4), we fit a gNFW model to the binned data of the NP model. Henceforth, we refer to the pressure profiles obtained via modelling the SZ map with the NP model as $P_{\text{NP}}(r)$ and the gNFW fit on these NP profile data points as $P_{\text{gNFW,NP}}(r)$. For the case where we ignore the presence of the PS in the centre, we do not achieve a convergence of the gNFW fit of the NP data even with 5×10^5 iterations, since the PS creates an effective hole in the map (and corresponding dip in the related pressure profiles) which is not accounted for using a simple gNFW model.

The median value of the inferred pressure profiles, along with their uncertainties is shown in Fig. 4.7. The best fit NP pressure profiles, $P_{\text{NP}}(r)$, are represented by the circular markers. The cyan, magenta, and green circular points represent the best-fit NP models for the cases where we are blind to the PS, where we mask the PS, and where we model the PS as a nuisance parameter, respectively. The profiles are consistent with each other, within their error bar. However, in the case where we are blind to the PS (cyan circles), we see that the value of the pressure in the radial bin corresponding to the PS position in the map (~ 200 kpc), is lower than the other two cases. This is an intuitive result because when we are blind to the PS, we do not account for the negative SZ signal that is compensated for by the positive PS flux. The gNFW fits to the NP profile binned data points, $P_{\text{gNFW,NP}}(r)$, are shown using the same colour scheme, with solid curves. Once again, when it comes to the treatment of the PS contamination, we find complete consistency between masking and modelling the PS, especially at R_{500} , where we infer the integrated quantities. Comparing P_{NP} data points with their gNFW fit, $P_{\text{gNFW,NP}}$, we see that the two agree with each other only in the cluster core and inner regions ($r \lesssim 800$ kpc). Specifically around R_{500} , the NP model shows significant deviation from their respective gNFW fits. In a sense, this feature displays the flexibility of the NP model over the typically used gNFW model, to probe the cluster signal more freely. In that context, the NP model can constrain the cluster outskirts signal in a way that gNFW cannot.

We also show, using empty blue diamonds, the X-ray pressure profile estimated using a combination of the *XMM-Newton* electron density and temperature profiles presented in Section 4.3. We find agreement, within their respective errors, between the $P_{\text{gNFW,NP}}(r)$ (shown using solid curves) and the *XMM-Newton* pressure profile.

Sample	P_0	c_{500}	α	γ
Complete	$8.403 h_{70}^{-3/2}$	1.177	1.0510	0.3081
Cool-core	3.249	1.128	1.2223	0.7736
Morphologically disturbed	3.202	1.083	1.4063	0.3798

Table 4.2 Best-fit gNFW parameters from M. Arnaud et al. 2010, for the average dimensionless pressure profile (Eq. 2.48) of the three cluster sub/samples used in the work. The parameter β was estimated to be 5.49 for the complete sample and was fixed for the remaining two.

This reaffirms the fact that sensitive SZ data can be used to infer the ICM properties just as well as X-ray data, which has a redshift-dependent emission (see Eq. 4.18) and requires much more time to be able to observe the cluster with the same sensitivity. The SZ estimated pressure profiles $P_{\text{NP}}(r)$, shown using circular data points, agree with the X-ray profile in the radial range $r \lesssim 800$ kpc. Eventually, for this radial range, all estimates of the ICM are consistent with each other, no matter whether derived from SZ or X-ray and how the PS is treated. The only inconsistency we find is the value of $P_{\text{NP}}(r)$ at $r \sim 200$ kpc for the case where we are blind to the PS (cyan points) but, this is expected since we completely ignore the SZ signal compensated for by the PS, thereby underestimating the ICM pressure in that radial bin.

In M. Arnaud et al. 2010, the authors have used the cluster sample REXCESS (Böhringer et al. 2007), not only to derive an average dimensionless pressure profile for the entire sample (called UPP) but also for clusters with cool cores, whose central electron density $> 4 \times 10^{-2} \text{ cm}^{-3}$, and clusters that are morphologically classified as disturbed using the criteria that their centre shift parameter $> 0.01 \times R_{500}$ (see M. Arnaud et al. 2010 for more details). The best-fit values, taken from M. Arnaud et al. 2010, for the parameters (described in Section 2.3.5) of the dimensionless pressure profile for all three cases are reported in Table 4.2. These dimensionless profiles, $P(x)$ given by Eq. (2.48), can be used to describe the physical pressure profile of a cluster as a function of redshift and mass (M_{500}) as follows (M. Arnaud et al. 2010):

$$P(r) = 1.65 \times 10^{-3} h(z)^{8/3} \left[\frac{M_{500}}{3 \times 10^{14} h_{70}^{-1} M_{\odot}} \right]^{2/3 + \alpha_P + \alpha'_P} \times P(x) h_{70}^2 \text{ keV cm}^{-3}, \quad (4.16)$$

where $h(z)$ is the Hubble function at redshift z , $\alpha_P = 0.12$ gives the slope of the relation between the X-ray observable and cluster mass, and α'_P gives the radial variation of this slope. The parameter h_{70} is the present-day Hubble constant normalised by 0.7.

For ACTJ0240, we estimate the physical pressure profiles corresponding to the dimensionless profiles for all three scenarios, the UPP, the average profile for the cool-core sample, and the average profile for the morphologically disturbed clusters. For this estimation, we use Eq. (4.16) with values reported in Table 4.2 and mass and redshift values, $M_{500} = (3.3 \pm 0.8) \times 10^{14} h_{70}^{-1} M_{\odot}$ and $z = 0.62$ from Hasselfield et al. 2013. The resulting physical pressure profiles, equivalent to ACTJ0240 hypothetically belonging to a population representing the UPP, the cool-core sub-sample, and the morphologically disturbed sub-sample are shown in

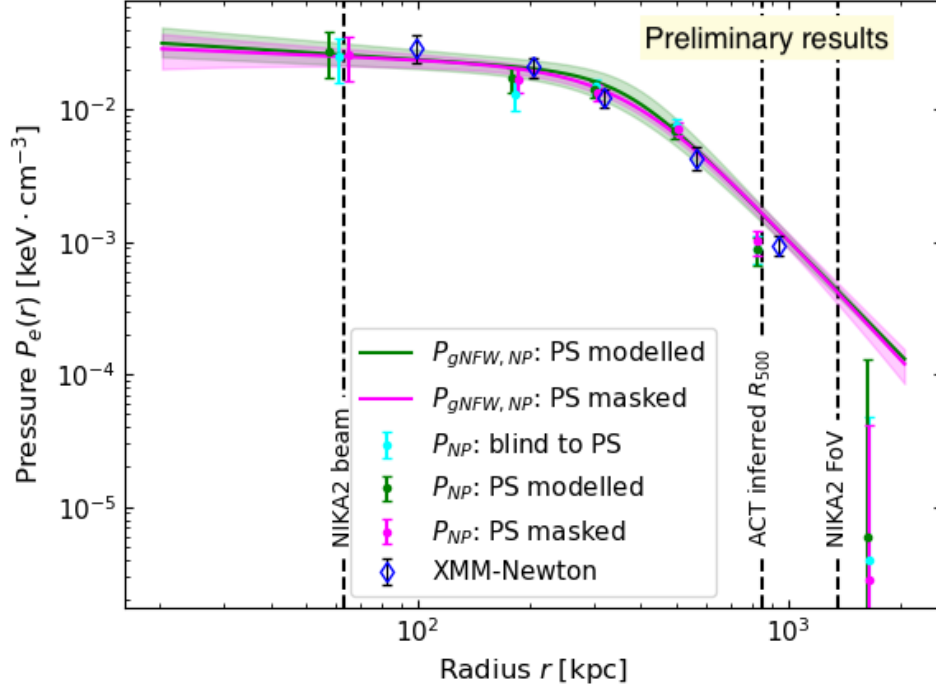


Figure 4.7 Pressure profiles of the ICM of ACTJ0240. The dotted markers correspond to the results obtained by modelling the NIKA2 150 GHz SZ maps of the cluster using a NP pressure profile model. The error bars correspond to 1σ uncertainty in the data points. Note that these data points have been slightly horizontally displaced from each other for visualisation, in reality, their radial positions are the same. The cyan, magenta, and green markers correspond to the cases where ignore the contaminating PS, mask it, and model it with pressure profile, respectively. The solid lines in magenta and green represent the best fit of the gNFW model to the binned data points of the two latter cases. The shaded regions show the 16th and 84th percentiles associated with the solid lines. The blue empty diamond markers correspond to the pressure profile obtained from the combination of the *XMM-Newton* electron density and temperature profiles. The vertical dashed lines indicate the NIKA2 beam, the R_{500} inferred by ACT survey (Hasselfield et al. 2013), and the NIKA2 FoV, moving from left to right.

Fig. 4.8 with solid, dotted-dashed, and dotted mustard lines, respectively. It is evident that the SZ pressure profiles $P_{\text{gNFW, NP}}$ (solid green and magenta curve) and the X-ray pressure profile (blue empty diamonds) are not well described by the UPP, nor the cool-core pressure profile. The SZ profiles are not perfectly consistent within their error bars, with the disturbed pressure profile for the entire radial range. However, they overlap with the disturbed profile in some regions, and are closest to this model, of the three used. On the other hand, the X-ray pressure points are completely consistent, within their own 1σ limits, with a disturbed pressure profile for the cluster. This comparison reiterates, this time using the 3D ICM pressure profile, instead of a cluster 2D map, that ACTJ0240 is a (morphologically) disturbed cluster system.

4.3 Estimation of the ICM temperature and electron density

Temperature and density profiles are key observables for characterising the ionised gas of the ICM. For instance, for X-ray observations, accurate electron density and temperature measurements are required to infer the cluster mass under the hydrostatic equilibrium assumption (Sarazin 1988). As we have discussed in Section 1, these masses eventually hold key importance for cluster-based cosmological studies. Additionally, the temperature and electron density information (2D or 3D) of the cluster provides insight into the dynamical state of the cluster. While temperature profiles/maps can give information about the shock-heated gas and cold fronts in merger events, peaks in electron density point at gas clumping or high density regions in the ICM (see Markevitch and Vikhlinin 2007 for a comprehensive review). Temperature and electron densities are primarily inferred from the X-ray observations of a cluster. In Section 2.3.3 we saw that the density can be easily inferred from X-ray imaging using Eq. (2.34) and Eq. (2.35). We also see the exponential cut-off of the X-ray spectrum at the isothermal temperature of the ICM in Eq. (2.34). This property, under the assumption of the ICM being isothermal, can be used to infer the cluster temperature using X-ray spectroscopy.

The X-ray inferred electron density and temperature profiles for ACTJ0240 were extracted from its *XMM-Newton* data, following the methodology described in Pratt et al. 2010 and Bartalucci et al. 2017. For the temperature profile, initially, the projected 2D temperature profile was estimated. Spectrum was extracted from concentric annuli centred on the X-ray peak, with the bin width for each annulus defined such that the signal-to-noise ratio of at least 30σ was attained above the background level in the [0.3-2] keV band for XMM-Newton. The binning also ensured a minimum of 25 counts per energy bin after subtracting the instrumental background. The spectrum was fitted using a combination of models to include both, the cluster signal and the sky/background emissions. The normalized sky background levels and temperatures were determined through sophisticated modelling (detailed in Bartalucci et al. 2017) of the spectrum derived from a region devoid of cluster emission in the X-ray image. Before the spectrum extraction, this region was corrected for vignetting and instrumental background. The cluster emission was then characterized using an absorbed MEKAL model with fixed absorption

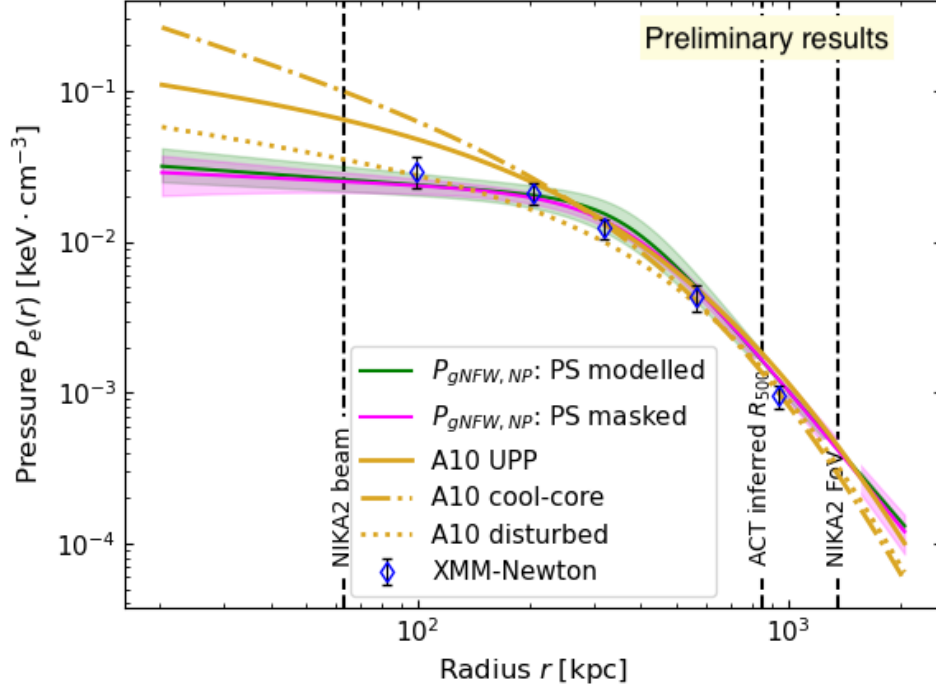


Figure 4.8 Comparison of NIKA2 SZ and *XMM-Newton* inferred pressure profiles estimated in this work with the results of M. Arnaud et al. 2010 (referred to as A10 in the plot). The solid lines in magenta and green represent the best fit of the gNFW model to the binned data points of the SZ inferred NP pressure profiles. The shaded regions show the 16th and 84th percentiles associated with the solid lines. The blue empty diamond markers correspond to the pressure profile obtained from the combination of the *XMM-Newton* electron density and temperature profiles. The solid, dotted-dashed, and dotted mustard lines represent a physical pressure profile representing ACTJ0240, corresponding to the average dimensional profiles inferred for the complete sample, the cool-core sub-sample, and the sub-sample of morphologically disturbed clusters, respectively, in A10. The vertical dashed lines indicate the NIKA2 beam, the R_{500} inferred by ACT survey (Hasselfield et al. 2013), and the NIKA2 FoV, moving from left to right.

values. The fitting process was performed using XSPEC⁴ (K. A. Arnaud 1996; K. Arnaud, Gordon, and Dorman 2020). The 3D temperature profile was estimated via the application of a parametric model to the afore-derived 2D profile, akin to the description provided in Vikhlinin 2006. During the convolution of the models, a response matrix was included accounting for both, projection and point spread function (PSF) redistribution. Finally, the density profile was determined via deprojection, employing the regularization technique outlined in Croston et al. 2006. A PSF-corrected, deprojected emission profile was extracted from the X-ray surface brightness profile. This emission profile was then converted to a density profile using a redshift (z) and temperature (T) dependent factor $\Lambda(T, z)$ where the temperature was obtained from the temperature profile.

Although the X-ray temperature is an effective way to measure cluster temperature, it is prone to limitations. Since the X-ray emission is proportional to the square of the ICM electron density, the derived spectroscopic temperatures are driven by the colder, denser regions along the line of sight and are thus sensitive to gas clumping. Further, and more relevant for our case with ACTJ0240 sitting at $z \sim 0.62$, the inference of spectroscopic temperature for clusters at high redshift requires high statistics and hence high integration time for reliable temperature profile estimation with high radial sampling. This happens because the X-ray emission intensity falls rapidly with redshift ($\propto (1+z)^{-4}$). The tSZ effect, on the other hand, is related to the mass-weighted temperature along the line of sight and the electron density. The tSZ effect can thus be used to obtain an alternative estimate of the gas temperature provided that a measurement of the density is available from an alternate source. To this end, a combination of the tSZ and X-ray observations can, in principle, be used to decouple temperature and density. In studies like Basu et al. 2010 and Ruppin et al. 2017, such a method has been used to extract gas temperature profiles. The same application has been explored and applied to 2D maps in Adam et al. 2017a. They use resolved ($< 20''$) tSZ observations from NIKA (Adam et al. 2017b), combined with X-ray imaging, to infer the spatial distribution of the gas temperature of the merging cluster MACS J0717.5+3745 at $z = 0.55$.

Since the X-ray temperature map for ACTJ0240 is not reliable (based on the available integration time), we follow the method adopted in Adam et al. 2017a to create a combined temperature map using the NIKA2 SZ intensity map and the *XMM-Newton* electron density maps. The SZ signal, as seen by combining Eq. (2.40) and Eq. (2.39), is proportional to the electron pressure ($P_e \propto T_e n_e$) integrated along the LoS. This pressure is related to the electron density n_e and the mean gas-mass-weighted temperature along the LoS by

$$T_{\text{GMW}} \equiv \frac{\int T_e n_e dl}{\int n_e dl}. \quad (4.17)$$

On the other hand, the X-ray surface brightness of a cluster at redshift z with ICM temperature T_e , depends on the electron density as

$$S_X = \frac{1}{4\pi(1+z)^4} \int n_e^2 \Lambda(T_e, Z) dl. \quad (4.18)$$

⁴<https://heasarc.gsfc.nasa.gov/xanadu/xspec/>

The function $\Lambda(T_e, Z)$ is the emissivity function and it accounts for the absorption in the X-ray spectrum along the LoS and the instrumental response to the spectrum.

To produce a combined temperature map from the two aforementioned observables, we infer the density map from the X-ray and the pressure map from the SZ observations, respectively. Following Eq. (4.18), we used the *XMM-Newton* surface brightness map of ACTJ0240 to produce a map of the square of the electron density integrated along the line of sight. This was combined with the SZ observations ($\propto \int n_e dl$) of the cluster using the effective electron length of the cluster

$$l_{\text{eff}} = \frac{(\int n_e dl)^2}{\int n_e^2 dl}. \quad (4.19)$$

Plugging the expression 4.19 in Eq. (4.18) gives us the average density along the LoS:

$$\bar{n}_e = \frac{1}{l_{\text{eff}}} \int n_e dl = \frac{1}{\sqrt{l_{\text{eff}}}} \sqrt{\frac{4\pi(1+z)^4 S_X}{\Lambda(T_e, Z)}}. \quad (4.20)$$

The pressure along the LoS for the SZ observations can similarly be expressed using the effective length:

$$\bar{P}_e = \frac{1}{l_{\text{eff}}} \int P_e dl = \frac{m_e c^2}{\sigma_T} \frac{y_{\text{tSZ}}}{l_{\text{eff}}}. \quad (4.21)$$

This pressure was obtained in a straightforward manner using the NIKA2 map of ACTJ0240. In Adam et al. 2017a, a relativistic correction is also applied to infer the pressure from y . However, in our case, the temperature estimated by X-ray spectroscopy is not high enough to suggest a relativistic regime and we apply no relativistic corrections.

Finally, to produce a combined SZ and X-ray imaging temperature map, we use

$$k_B T_{\text{SZX}} = \frac{\bar{P}_e}{\bar{n}_e} = \frac{1}{\sqrt{l_{\text{eff}}}} \frac{m_e c^2}{\sigma_T} y_{\text{tSZ}} \sqrt{\frac{\Lambda(T_e, Z)}{4\pi(1+z)^4 S_X}}. \quad (4.22)$$

The map T_{SZX} represents the estimate of the gas-mass-weighted temperature in Eq. (4.17). However, the effective electron depth, l_{eff} , is a key parameter in the estimation process. There are different ways of modelling this parameter but essentially it has been found that assuming a constant value throughout the region of interest in the map is a good approximation (details in Adam et al. 2017a). Hence, following the analysis in Sayers et al. 2013 and Adam et al. 2017a, we assume a typical, constant value of 1000 kpc for l_{eff} to obtain our combined SZ and X-ray temperature map, a value consistent with our cluster density profile.

4.3.1 Results

We described in Section 4.3, the process involved in deriving temperature and density information of the cluster. The X-ray-derived temperature (and electron density) profile is shown in the left (right) panel of Fig. 4.9. Immediately, the problem with having to sample the X-ray temperature profile using broad radial bins to ensure enough statistics, for a high redshift cluster, is evident via the temperature profile.

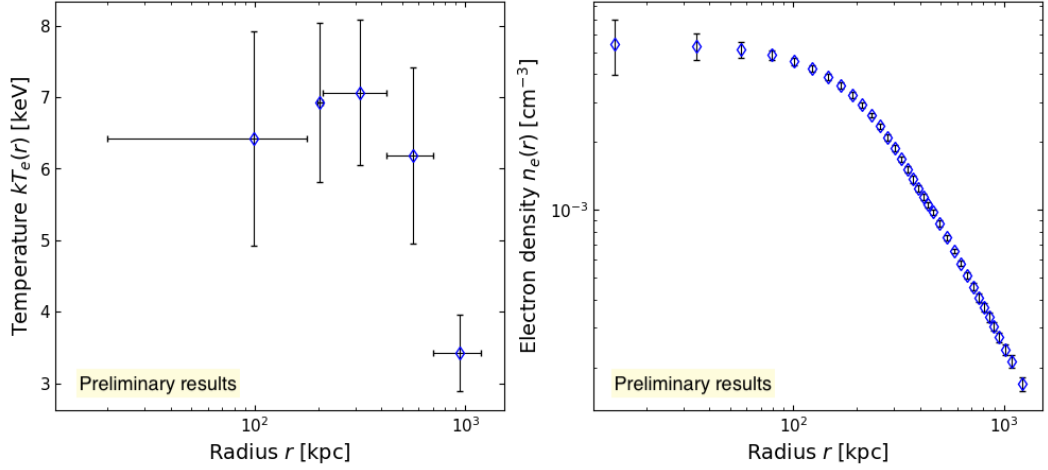


Figure 4.9 The X-ray temperature (left) and electron density (right) profiles reconstructed from *XMM-Newton* observations of ACTJ0240. The vertical errors represent the 1σ errors in the profiles. The horizontal error bars in the temperature profile represent the radial binning adopted to estimate the temperature profile.

Despite this, the errors in the values of the X-ray temperature, depicted by the error bars in the left panel of Fig. 4.9, are high ($> 10\%$). This issue can be alleviated by using the combined X-ray and SZ measurements to infer the temperature, instead of purely using X-ray spectroscopy. We notice that the density profile features a plateau in the cluster core. This, qualitatively, rules out the presence of a cool cluster core as probed by the X-ray observations.

For ACTJ0240, to estimate the combined SZ, X-ray map, T_{SZX} by following the construction procedure described earlier in this chapter, we define a mask so that we are only making temperature estimates in pixels that have reliable SZ values: $\text{SNR} > 2$. The resulting temperature map is shown in the left panel of Fig. 4.10. This map does not indicate a relaxed cluster. For a relaxed cluster, the temperature map should have a peak in the centre with a negative radial gradient. In this case, there is an extremely flat profile with temperature peaks in the Southern region of the cluster. This could point towards turbulence or shock-related temperature jumps in the ICM. To probe this further, we estimate the temperature profile $T_{\text{SZX}}(r)$ from this map. To do so, we estimate the mean values in logarithmically-spaced annuli in the map, with their associated standard deviations weighed by the number of pixels in the annuli ($1/\sqrt{n}$), as the errors. This profile is shown using red circles in the right panel of Fig. 4.10. The flat nature of the temperature profile is evident from these data points up to $r \sim 500$ kpc, after which the profile jumps to a higher temperature, corresponding to the high-temperature region in the south of the map, once again indicating that the cluster is disturbed. When comparing to the X-ray temperature profile, the combined temperature profile, barring the last data point, is consistent with the former, within their error bars. In general, the errors of the combined temperature profile are also lower than the X-ray profile data points. This serves as a reminder that such temperature sensitivity to the ICM fluctuations, for a cluster at higher redshift (0.62 in this case) is hard to achieve using X-ray spectroscopy and

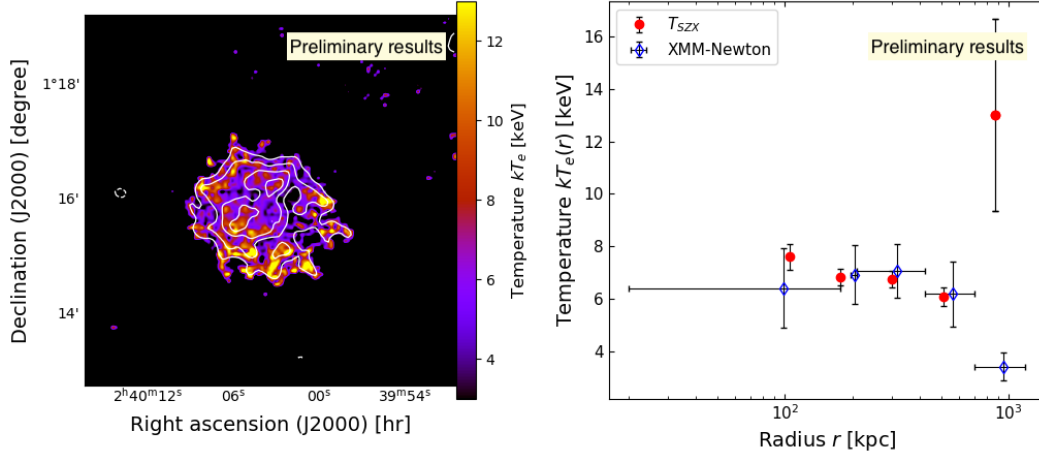


Figure 4.10 *Left:* The combined SZ, X-ray temperature map derived using a combination of SZ-derived pressure and X-ray-derived electron density. We use a mask such that this temperature is estimated only for pixels in the map where the SZ $SNR > 2$. *Right:* The temperature profile $T_{SZX}(r)$, shown using red circles, derived from the map on the left, in comparison with the X-ray only temperature profile, shown with blue empty diamond markers. The error bars in both cases show the 1σ uncertainty.

SZ observations provide an effective complementary way to map these features. It must be noted here that the central value of the combined temperature profile comes directly from the average within the annuli, of the temperature map. However, we have not estimated the errors in the individual pixels of this map. Accounting for this might change, especially for the last point with only a few pixels in its annulus, the central values and errors of the temperature profile.

4.4 Estimation of the cluster hydrostatic equilibrium mass

To estimate the cluster mass using the SZ and X-ray data, we assumed hydrostatic equilibrium (HSE) of the cluster medium, along with spherical symmetry. Under this circumstance, the mass enclosed with a spherical volume of radius r is given by the hydrostatic mass:

$$M_{\text{HSE}}(< r) = -\frac{r^2}{G\mu m_p n_e(r)} \frac{dP_e(r)}{dr}, \quad (4.23)$$

where G , μ , and m_p are the universal gravitational constant, mean molecular weight of the ICM gas, and the proton mass, respectively. Following Ettori et al. 2019, we consider $\mu = 0.61$, to be a good approximation for the ICM gas. We used the pressure profile recovered from the NIKA2 SZ maps in combination with the density profile from *XMM-Newton* observations estimated in Section 4.3.

From the obtained pressure profile distribution, $P_{\text{GNFW,NP}}$, we constructed a mass profile distribution, using Eq. (4.23). The median and the associated 16th and 84th percentile of this distribution were used as the estimates and errors on the

mass profiles.

The mass profiles inferred using the aforementioned methodology were utilised to derive the integrated quantities: mass $M(< r)$ and integrated Compton parameter $Y(< r)$ enclosed within a given radius, r . These quantities are important in the context of the LPSZ scaling relation between the two quantities. To do so, we first defined the radius at which to estimate these quantities by the density contrast Δ , defined by Eq. (2.29). Using the estimated mass profile posterior distribution and Eq. (2.29), we calculate a vector of radii corresponding to the density contrast of interest, $\Delta = 500$. Associated with this radial distribution, we estimated the posterior distribution of the integrated mass $M_{500} = M(R_{500})$ and integrated Compton parameter distribution using $Y_{500} = \frac{4\pi\sigma_T}{m_e c^2} \int_0^{R_{500}} r^2 P(r) dr$. The result of this procedure is a vector for each of the characteristic quantities R_{500} , Y_{500} , and M_{500} , where each component corresponds to the estimated quantity for the Markov chain point. The distribution of these components represents the posterior distribution sampled by the MCMC in the space of integrated quantities and was used to calculate the median values and uncertainties (percentiles) between the parameters.

4.4.1 Results

Ultimately, we want to infer the cluster mass to facilitate the calibration of the SZ-mass scaling law using the LPSZ data. We use the electron density profile presented in Section 4.3.1, in combination with the pressure profiles $P_{\text{gNFW;NP}}$ presented in Section 4.2.2, to estimate the HSE mass of ACTJ0240, using the methodology described in Section 4.4. The HSE mass profiles for both methods, where the PS is masked and where the PS is modelled, are shown in Fig. 4.11. The two NIKA2 mass profiles are compatible with each other, re-emphasising the fact that the necessary step is the addition of PS information and not the manner in which this information is included in the SZ signal modelling. The SZ profiles are also compatible, within error limits, with the HSE mass profile derived using only X-ray data. Although, the central value of the X-ray mass at R_{500} , $M_{500} = 3.67_{-0.65}^{+0.70} \times 10^{14} \text{ M}_{\odot}$ is slightly lower than the SZ, X-ray combined masses ($3.84_{-1.15}^{+1.84} \times 10^{14} \text{ M}_{\odot}$ and $4.25_{-0.45}^{+0.50} \times 10^{14} \text{ M}_{\odot}$ for the cases where the PS is modelled and masked, respectively), it is consistent with these estimates within their 1σ errors. These combined SZ, X-ray mass estimates are also consistent with the mass calibrated for a UPP in Hasselfield et al. 2013, $M_{500} = (3.3 \pm 0.8) \times 10^{14} h_{70}^{-1} \text{ M}_{\odot}$ (other parameters inferred in Hasselfield et al. 2013 are reported in Table 4.1).

The integrated quantities inferred by estimating the overdensity from the obtained HSE mass profiles are reported in Table 4.3. Again, the values for both methods are compatible with each other and previous results from Hasselfield et al. 2013. It should be noted that the integrated quantities reported here are marginalised values from the posterior distribution but, are inherently correlated. The correlation between these quantities can be estimated by calculating the covariance of the integrated quantities measured for each sample in the Markov chains. This covariance value becomes a crucial element for properly estimating the $Y_{500} - M_{500}$ scaling relation of the LPSZ (Moyer-Anin et al. 2023).

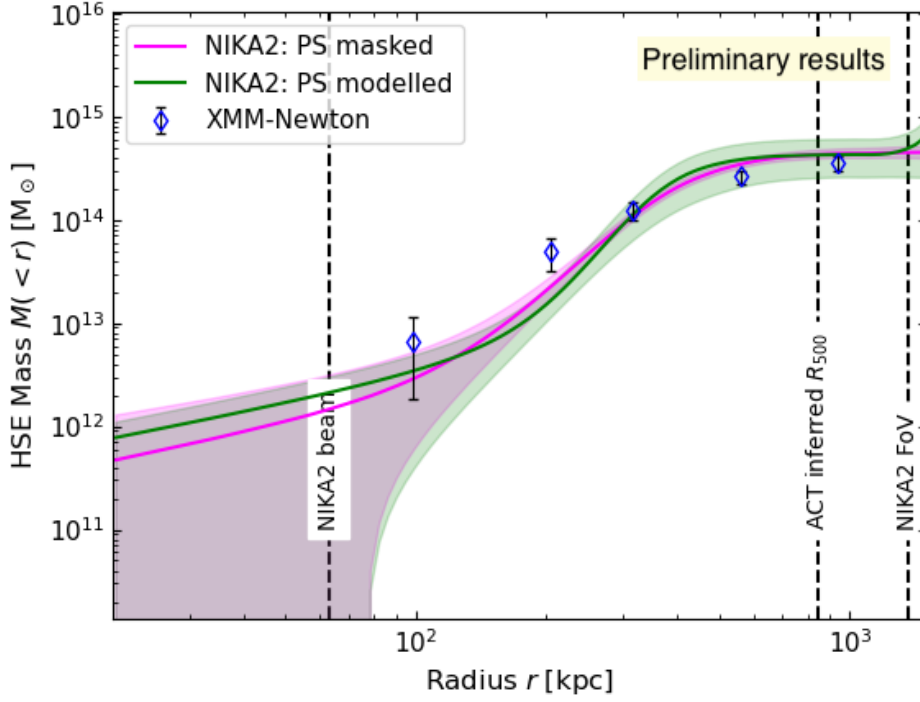


Figure 4.11 HSE mass profile estimates for ACTJ0240 inferred by NIKA2 and *XMM-Newton* data. The solid magenta and green lines are mass profiles estimated by combining the X-ray density profiles (right panel Fig. 4.9) and the NIKA2 pressure profiles $P_{\text{gNFW,NP}}$ (Fig. 4.7), in the scenarios where the PS is masked, and modelled, respectively. The shaded areas depict the 16th and 84th percentiles on these estimates. Blue, empty markers correspond to the mass profile inferred solely using the X-ray data. The error bars correspond to the 1σ uncertainties on these mass estimates.

Parameter	M_{500} [$10^{14}M_{\odot}$]	R_{500} [kpc]	$D_A^2 Y_{500}$ [kpc ²]
Analysis			
PS modelled	$3.84^{+1.84}_{-1.15}$	$897.30^{+10.62}_{-38.90}$	$47.92^{+12.28}_{-4.94}$
PS masked	$4.25^{+0.50}_{-0.45}$	$907.63^{+37.52}_{-26.66}$	$52.28^{+7.48}_{-5.64}$

Table 4.3 Median values on the integrated mass, M_{500} and radius, R_{500} at Δ_{500} , estimated via the hydrostatic equilibrium analysis using SZ and X-ray data, for cluster ACTJ0240. We also report the integrated Compton parameter Y_{500} at Δ_{500} , obtained by integrating the inferred pressure profile up to the radius R_{500} . The errors are the 16th and 18th percentiles of parameter estimate distribution.

4.5 Discussions and conclusions

In this chapter, we have produced maps and radial ICM profiles for galaxy cluster ACTJ0240 using multi-wavelength data, with a special focus on the novel, high-resolution SZ data from the NIKA2 LPSZ survey.

In Section 4.1 we provide details involved in the image processing of the SZ surface brightness, X-ray photon count and electron density, and optical galaxy number density maps (all shown in Fig. 4.6). We find synergies between the maps at the three wavelengths: they all indicate that this is a disturbed cluster system. The different centres of the cluster are not coincident. Further, the distribution of gas indicated by the X-ray and SZ data, and the galaxy distribution represented by the optical galaxy number density, are also misaligned. These features are atypical for a relaxed system. The tail structures detected in the southeast region of the SZ maps are linked with two gas clumps detected in X-ray, where we also find enhanced galaxy number density. Using this information, we speculate about the presence of matter falling onto the cluster from this direction. In this situation, the high-resolution SZ data from LPSZ allows us to probe the details of the ICM of the cluster and to investigate for signs of deviation in the radial ICM profiles, from symmetry and relaxed dynamical state.

In Section 4.2 we describe the statistical methodology to infer the cluster ICM pressure profiles and the models used to do so. We fit a NP model to the NIKA2 150 GHz map and to allow a physically meaningful hydrostatic mass estimation, we fit the binned values of the NP pressure profiles, with a gNFW model. While estimating these pressure profiles, we treat the PS contaminating the central region of the cluster in three ways: i) we completely ignore the PS, that is, we are blind to it; ii) we mask the PS while estimating the profiles; iii) we model the PS as a nuisance parameter in the pressure profile model. For the NP model, all three cases generate consistent results (within 1σ), albeit, in the first case here we understandably underestimated the pressure in the radial bin corresponding to the PS (see cyan points in Fig. 4.7), creating a noticeable dip in this pressure profile. For the gNFW fit over the NP data, owing to this dip in the pressure value, which cannot be constrained by a simple, smooth gNFW model, we do not achieve convergence for the first case of PS treatment. The gNFW fits in the other two cases are once again consistent with each other. Both, the NP profiles and their gNFW fit are consistent also with each other and fit very well, the cluster ICM up to $r \sim 500$ kpc. Beyond this point, the two do not agree and the NP profiles fall more steeply than their gNFW fits. Finally, we compare these pressure profiles with the *XMM-Newton* pressure profiles. The X-ray profile is consistent with the gNFW fits on the NP data, vouching for the complementarity of the two observable (SZ and X-ray) in mapping the cluster ICM.

Although the multi-wavelength maps of ACTJ0240 suggest that this is a disturbed system, pressure profiles do not show any obvious indications of profile jumps or features that suggest a shock or a merger. However, we compare our pressure profiles with the estimation of ACTJ0240 pressure profiles corresponding to the UPP, cool-core average profile, and the average profile of morphologically disturbed clusters in M. Arnaud et al. 2010. We find pressure profiles estimated from the SZ and X-ray data of ACTJ0240, consistent with the profile estimated for a morphologically disturbed equivalent of ACTJ0240. From this, we infer that the signs of disturbance

noticed in the multi-wavelength images are probably morphological in nature.

Section 4.3 describes the estimation process of, and presents, the cluster temperature and electron density profiles from the X-ray data. The density profile shows a flattening feature towards the core, indicating the absence of a cool core. We also estimate a cluster temperature map by combining the SZ and X-ray images which shows a rather flat temperature map for the cluster, barring the southern region where the temperature value peaks. This provides another sign of disturbance in the cluster. The radial profile corresponding to this map is consistent, at 1σ level, with the X-ray profile below R_{500} , beyond which the combined profile peaks to a higher temperature, representing the temperature peak in the southern region of the cluster. The errors of the combined temperature profile are also lower than the X-ray, serving as a reminder that SZ observations serve as a complementary tool to sensitively infer the cluster temperature, especially for clusters at high redshift, where X-ray requires a lot of integration time for spectroscopic temperature measurements. The absolute values of the combined temperature profile must be considered with the recollection that we have not estimated the errors in individual pixels of the temperature map, which should have been weighed into estimating the values and errors of the temperature profile for a more refined estimation. Finally, it is worth mentioning that this temperature map can be used to make a mask that marks the regions that show the most deviation from HSE. The resulting mask could then be used to re-estimate the cluster pressure profile and mass.

Finally, in Section 4.4 we estimate, under the HSE assumption, the hydrostatic mass of the cluster under two scenarios: masking the contaminating PS and modelling it. The HSE mass profiles are consistent with each other and the X-ray only results, within 1σ uncertainties. We estimated the integrated quantities (M_{500} , Y_{500} , and R_{500}) within the radius R_{500} , reported in Table 4.3. These values are consistent with the estimates from ACT (Hasselfield et al. 2013), calibrated for a UPP model, and the X-ray results. These values, along with their correlation matrix can be used to calibrate the $Y - M$ scaling law for the LPSZ.

In conclusion, we have created a multi-wavelength view of cluster ACTJ0240 that, along with its pressure profile and the combined SZ and X-ray temperature map indicates that the cluster is in a disturbed morphological system. We also estimated and compared various ICM profiles of the cluster but this comes with the caveat that we assume spherical symmetry. In doing so, we might be more prone to estimation bias. Further, we assume HSE for the mass estimation and this could be an additive source of bias. Having said that, our values, though slightly higher than ACT estimates for a UPP, are consistent with them, within the error limits.

Chapter 5

Validation of the point source detection pipeline of the LPSZ

We saw in Chapter 4 that the astrophysical signal measured by NIKA2 during observations of galaxy clusters is the sum of contributions from several sources along the LoS. The major contributors are the SZ effect of the ICM, which constitutes the observable of interest for our studies and the emission from PSs. This emission from PSs, being inherently positive, can partially or completely compensate for the SZ effect which is detected as a decrement in the CMB signal in the NIKA2 maps at 150 GHz. This can potentially introduce a negative bias in the reconstructed ICM pressure profile based on SZ observations. We showed an example of this effect with ACTJ0240, whose SZ signal was contaminated by a PS near its centre (see the top panel of Fig. 4.6) (for another example, see also Kéruszoré, F. et al. 2020). In considering this PS contamination while measuring the ICM properties, we concluded, in Section 4.5, that detecting the PS and including its spatial and flux information in the process is essential. A blind approach to dealing with the PS can lead to an incorrect inference of the ICM pressure and consequently the cluster HSE mass.

To account for the PS contamination, different approaches can be adopted: i) it is possible to mask the source in the SZ map, which only requires the spatial position of the source; ii) the flux information of the PS can be extracted (through its spectral energy distribution) and this can then be used to model or subtract the PS from the SZ map. For this purpose, knowing the spatial information and if required, the flux value of each source is essential. A poor estimation of this information can introduce errors in the measured thermodynamic properties. Given this context, in this chapter, we explore the PS contamination in the LPSZ and how it is dealt with, while building a framework to validate its PS detection pipeline.

5.1 Detection of point sources in the LPSZ

The LPSZ relies on accurate PS detections, firstly for creating a mask during the SZ map generation process (refer to Section 4.1.1.3), and subsequently for the analysis of the ICM from the SZ maps. This is crucial to prevent any estimation bias in the ICM properties, as mentioned earlier. The primary PS contaminants in the SZ maps are

However, for some cases, there are no PS data in pre-existing catalogs, as we saw was the case for ACTJ0240 (Chapter 4). It is also possible that not all the PSs in the cluster region are present in the catalogs. For this reason, it becomes important to have an independent and reliable method to detect PSs in the LPSZ cluster maps. For this purpose, the LPSZ uses a specific NIKA2 point source detection pipeline (Desert et al. in preparation). In brief, this pipeline uses sigma clipping to detect PSs in the NIKA2 surface brightness maps. The code first estimates the beam convolved S/N of the NIKA2 maps: the raw S/N is estimated by calculating the ratio on the NIKA2 surface brightness map (see *e.g.* the top panel of Fig. 4.6) and the corresponding noise map (see right panel of Fig. 4.5); this raw map is then convolved with a Gaussian kernel with size corresponding to the FWHM of the NIKA2 beam. Once this S/N map is obtained, the grid is traversed, pixel-by-pixel, with a kernel of the NIKA beam size and positions with S/N greater than a user-provided threshold (4 in the case of LPSZ) are marked as PSs. This procedure is performed iteratively to ensure reliable detection. The PS flux is then estimated using the detected S/N and the corresponding noise value in the variance map. This detection occurs in both bands separately and the two catalogs are merged after each entry in both of them is cross-matched and duplicate entries present in both catalogs are reduced to a single entry. For PSs that are detected only in one band, the detection position in one band is used to estimate the flux and S/N of the PS in the other band.

This catalog, providing positions, flux estimates, and S/N values for PSs within the cluster region, is crucial for accurately modelling the ICM of LPSZ clusters and estimating their mass, (extension of the work presented in Hanser et al. 2023). Additionally, the LPSZ aims to conduct a tertiary study that leverages the results obtained by applying this pipeline to the sample clusters. This study will investigate the distribution of PSs detected in sub-millimeter observations around the cluster, exploring the lensing effect of the clusters on background sources (Desert et al. in preparation). However, it is essential to note that this pipeline was originally developed for field detection of PSs, and the LPSZ primarily deals with the cluster signal in the 150 GHz band. To assess the pipeline’s effectiveness with SZ maps that contain the cluster signal, simulations are used to generate NIKA2-like maps with injected PSs. The performance of the PS detection pipeline on these maps is examined in the subsequent sections.

5.2 Validation of the LPSZ point source detection pipeline

As mentioned above, we test the performance of the NIKA2 PS detection pipeline in the context of the LPSZ using simulated NIKA2-like maps. We essentially assess the detection reliability of the pipeline as a function of detection SNR and the radial distance of the PS from the cluster centre. For this reason, we chose the random distribution of PSs in our simulations to evenly distribute them in radius and SNR. It must be kept in mind that the 150 GHz map of the LPSZ is dominated by the cluster signal. To consider this, we quantified the performance of the PS detection pipeline in two steps: i) testing the pipeline on maps that are devoid of the cluster signal and are simply made up of the expected noise in the LPSZ; ii) testing the pipeline on another set of simulations that include the cluster signal along with the LPSZ noise maps. In this section, we describe how we simulate the maps in both cases and the methodology used to quantify the performance of the PS detection code.

5.2.1 Simulating NIKA2-like maps with PS contamination

To comprehensively evaluate the performance of the PS detection pipeline with high statistics, we perform simulations involving the generation of 800 maps, each containing 20 randomly injected PSs. Two scenarios were considered: one where the maps only had noise, and the other where the cluster signal was incorporated. The process of generating these maps is schematically represented in Figure 5.1. A detailed description of this process is provided below.

The first step to creating the PS-injected maps begins with the NIKA2-like maps of the TS that have no PS contribution. In Section 3.2.1, we explained how NIKA2-like maps were simulated from the y maps of the TSs. This same process was employed to generate input maps for this analysis. In the first case, where the PS detection pipeline performance was assessed in maps without any cluster signal, the creation of the NIKA2 map was halted at the stage where the noise map for the cluster was generated. In the second case, where the cluster signal was included, the complete process described in Section 3.2.1 was utilized. To create 800 maps, we picked a cluster that was randomly selected from the three TSs to ensure an unbiased evaluation and injected it with 20 randomly sampled PSs (described below), 800 times. As already mentioned, we want to evaluate the radial dependence of the efficacy of the PS detection pipeline. Hence, instead of cropping the images to the NIKA2 LPSZ scan size, we explored a wide radial range in the maps, namely $\pm 3.5R_{500}$ from the map centre, where R_{500} comes from the AHF data of The300.

The next step involves defining the properties of the injected PSs as follows:

1. PS positions: the PS positions are randomly assigned in the (x, y) coordinates of the square grid of the image whose side is $2 \times 3.5R_{500}$. Since we eventually evaluate the PS detection efficiency as a function of radius, we need to make sure that the (x, y) coordinates of the PSs in the grid are such that the radius, $r = \sqrt{x^2 + y^2}$ does not exceed the size of the map. With map size of $2 \times 3.5R_{500}$, the largest possible radius is $3.5R_{500}$, giving us x and $y \in [-2.48...2.48]R_{500}$. We randomly draw the positions in this range to assign a pixel position to each PS. During the position assignment, it is ensured that any two given PSs are

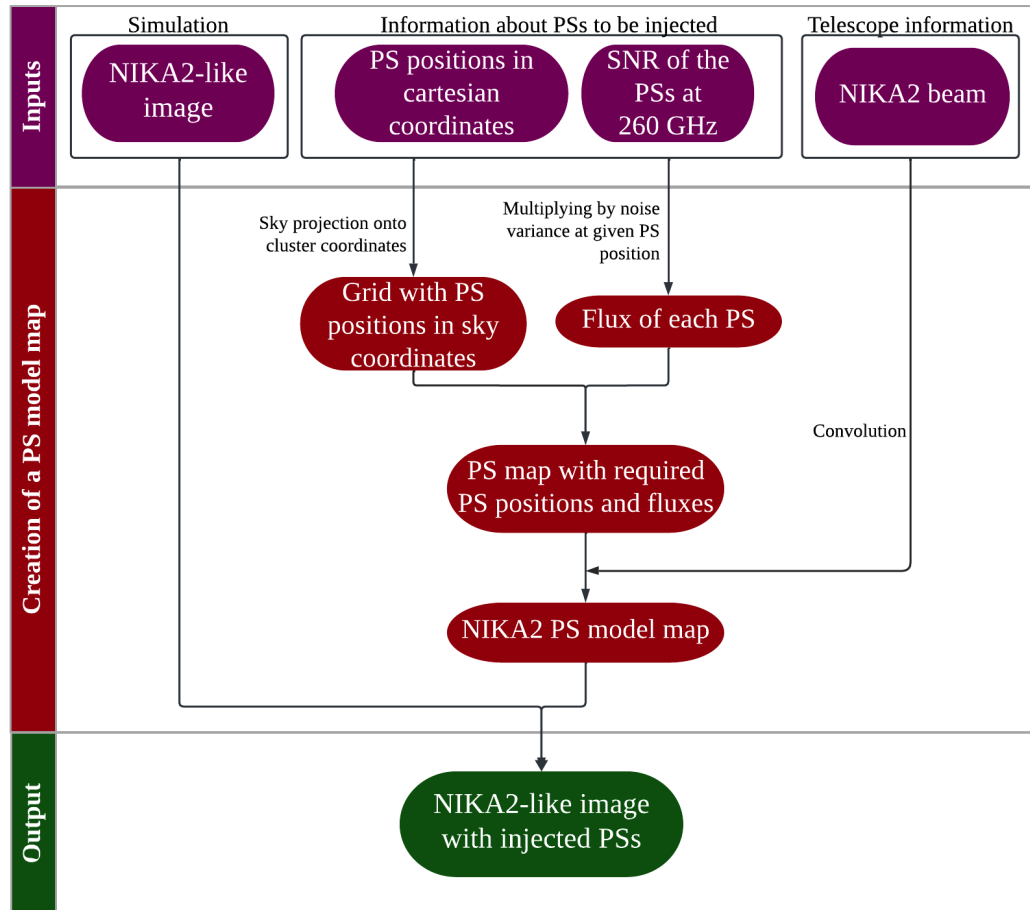


Figure 5.1 Schematic representation of the process used to create NIKA2-like maps with injected PSs, using NIKA2-like maps simulated for the TSs. The wine-coloured section represents the inputs, followed by the intermediate steps shown in maroon, and the product obtained, in green.

No. of maps	No. of PSs in each map	PS position range	PS SNR range at 260 GHz
800	20	x and y $\in [-2.48\dots 2.48]R_{500}$	$\in [2.5, 3, 3.5, 4, 4.5, 5, 5.5, 6]$

Table 5.1 A summary of the specifications of the PSs injected in the NIKA2-like maps to simulate maps for the verification of the LPSZ PS detection pipeline.

separated by at least the angular distance equivalent to the beam size. The distribution of the 16000 PSs for all the 800 maps can be seen in the top and bottom left panel of Fig. 5.2, for the case where we only use noise and the case where we include cluster signal, respectively.

2. PS SNR at 260 GHz: the pipeline identifies PSs based on SNR, and hence, we allocate SNR values, at 260 GHz to begin with, randomly in the range $\text{SNR} \in [2.5, 3, 3.5, 4, 4.5, 5, 5.5, 6]$. We justify our choice in the following discussion. A typical threshold for a significant PS detection in the LPSZ is the SNR of 3, but, we need to be careful that there is an estimation bias between our calculations of the SNR and the pipeline’s estimates (which will be demonstrated later). Hence, taking the lower limit on the threshold of SNR 3, to include this bias between our estimates, we set 2.5 as the lower limit. The upper limit is selected because, at SNR 6, the performance of the pipeline reached its maximum (completeness and purity of 1). Since we only include the SNR value of 2.5 to account for the SNR estimation bias between our values and the pipeline, but it is not a realistic SNR for PS detection, we down-weight its assignment probability compared to other values. The SNR distribution in the 260 GHz band of the 16000 PSs for all the 800 maps can be seen in the top and bottom left panel of Fig. 5.2. Once the SNR in this band is assigned, we estimate the fluxes in the 260 GHz channel, using its noise variance map. At this point, we go forward with the assumption that the main PS contaminants of the SZ maps are sub-mm galaxies. The flux ratio for such sources in the NIKA2 channel is given by $S_{150}/S_{260} = 0.2$ (Ricci 2018), using which we estimate the PS fluxes and consequently SNR in the 150 GHz band.

A summary of these PS specifications is presented in Table 5.1.

The composite of the above-mentioned PS specifications, including their positions, and SNR in both bands forms the input related to PSs in the top panel of Fig. 5.1.

In the next step, the PS positions assigned in terms of pixels in the image grid are converted to the sky coordinates associated with the cluster (taken from The300 simulation). An example of such a sky position grid can be seen in Fig. 5.3. Recall that each of these PSs already has assigned SNR values.

The third and final step to creating a PS model to be injected in the NIKA2-like maps we mentioned at the beginning, is the convolution of the PSs with the NIKA2 beam. The beams at the two frequencies are simply given by 2D Gaussians with a FWHM corresponding to $12.5''$ at 260 GHz and $18''$ at 150 GHz (Perotto, L. et al. 2020). An example of this beam-convolved PS model map is shown in the left (right) panel of Fig. 5.4 for the 260 GHz (150 GHz) bands. The difference in beam size for

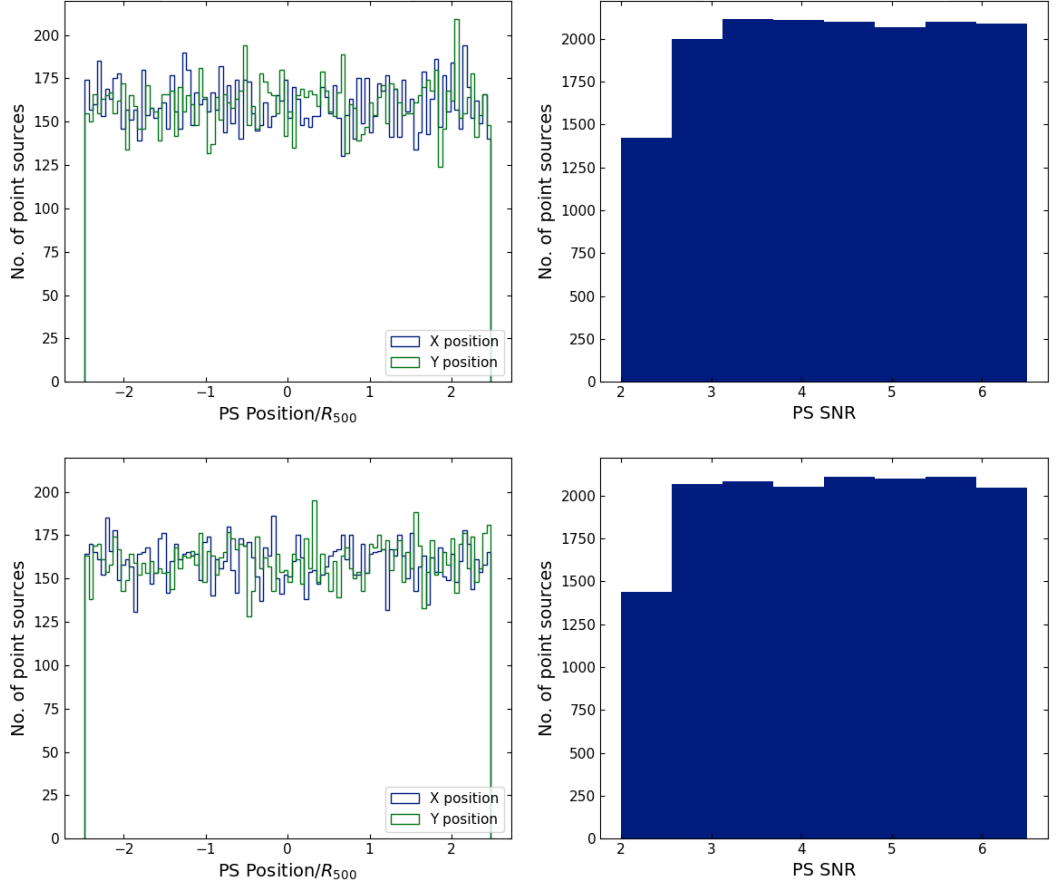


Figure 5.2 The position and SNR (at 260 GHz) distribution of the PSs injected in the simulated NIKA2-like maps shown in the left and right panels, respectively. The top panel shows the distribution for maps with only noise and the bottom panel shows the distribution of sources for maps with the cluster signal included. Noticed the random distribution of the PSs in position and SNR except at SNR 2.5.

the two frequencies is reflected by the apparent size of the PSs in both panels of the figure. Further, the flux axes of both maps have been scaled to reflect the flux ratio we have adopted: $S_{150}/S_{260} = 0.2$. This makes the PSs appear equally bright in both bands.

The final step to creating NIKA2-like images with injected artificial PSs is combining the input NIKA2-like images with the simulated PS models. For the case where we simply simulate maps with LPSZ noise, we just add the PS model to the noise map, generating an image which can then be used as input for the PS detection pipeline. On the other hand, when we include the cluster signal in the simulated image, we add the PS model map to the cluster surface brightness map, before adding the noise on top of this combined signal. This is representative of a realistic LPSZ map, albeit the PS number and distribution in the sky might actually differ from our randomly distributed sources.

We show an example of such simulated maps at 260 GHz and 150 GHz in the left

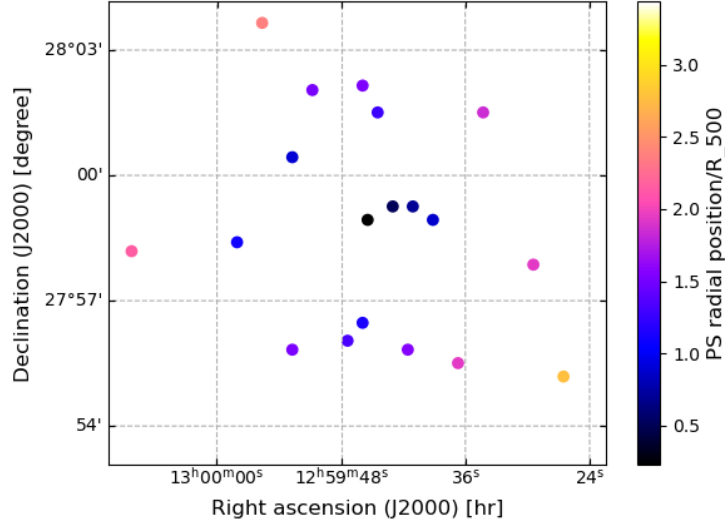


Figure 5.3 An example of the PS positions allocated to one of the 800 simulated maps showing the random PS positions of the 20 PSs converted to the sky coordinates of the cluster. The color range depicts the position of the PS with respect to the centre of the cluster (given by the centre of the cluster halo provided in The300), in terms of R_{500} .

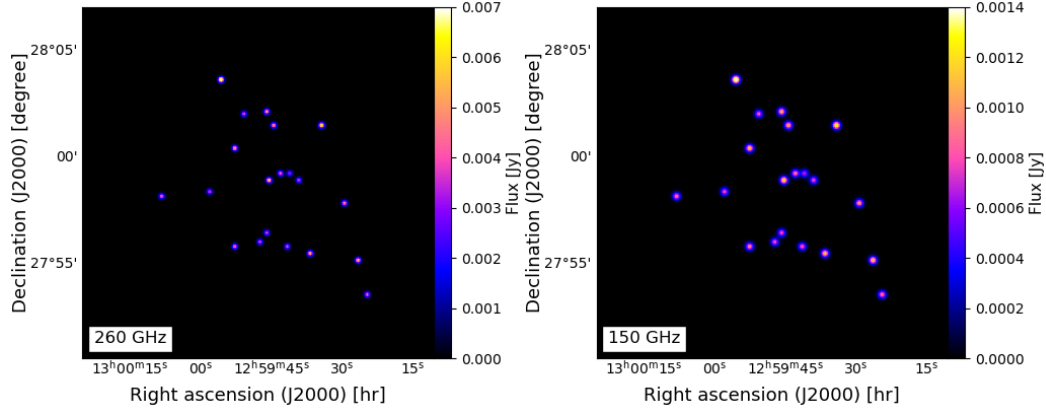


Figure 5.4 An example of one of the 800 simulated PS model maps that are injected into the NIKA2-like image to simulate maps with artificial PSs. On the left is the PS model for the 260 GHz band and on the right is the same model for 150 GHz. The difference in beam sizes can be observed by the apparent difference in the PS sizes. The flux axes of the two bands have been scaled to reflect their adopted ratio in this work ($S_{150}/S_{260} = 0.2$).

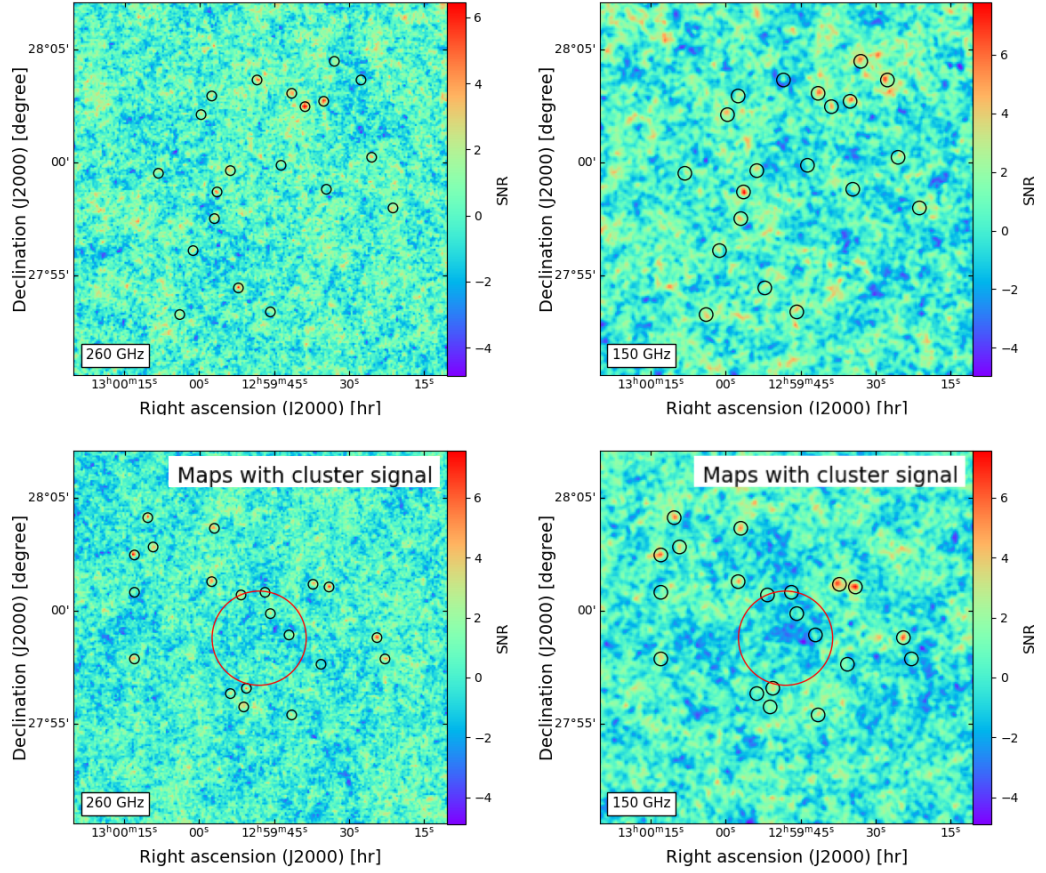


Figure 5.5 Examples of NIKA2-like simulated maps with injected PSs at 260 GHz (left) and 150 GHz (right), respectively. The maps are depicted using their SNR values and are smoothed with Gaussian kernels of $6''$ and $10''$ for the 260 GHz and 150 GHz maps, respectively, for visualisation. The injected PSs are shown using black circles, whose sizes depict the FWHM of the NIKA2 beam in the respective bands. The top panel shows the maps with only noise and the bottom panel shows the maps with the cluster signal included. The red circle in the bottom panels represents the cluster region marked by its characteristic radius, R_{500} .

and right panels of Fig. 5.5, respectively. The top panel shows the maps without the cluster signal and the bottom panel shows the maps with the cluster signal included, marked using the red circle at the R_{500} of the cluster. Notice the negative signal caused by the SZ effect of the cluster in the bottom-right panel, which is absent in the top-right panel since it only contains noise. We do not observe this effect in the left-side images because, as discussed previously, NIKA2 is unable to detect the SZ signal of the clusters in this band due to its high noise levels. We also show the injected PSs with black circles, whose sizes correspond to the FWHM of the NIKA2 beam in the respective bands. These simulated NIKA2-like maps with PSs are run through the LPSZ PS detection pipeline.

5.3 Quantifying the pipeline performance: detection purity and completeness

To validate the PS detection pipeline, we use it to run all the 1600 NIKA2-like maps, 800 with and 800 without the cluster signal, with a detection threshold of SNR 3 which then, by default, includes all sources above this SNR, *e.g.*, the sources detected with SNR 4 and above were the same in the catalogs produced with a detection threshold SNR of 3, when compared to the catalog with detection threshold SNR of 4. This enabled us to run all the maps with a single detection threshold and later segregate the detections based on their SNR. Once the simulated maps are run through the detection pipeline, we obtain catalogs of detected PSs containing their detection positions (right ascension and declination), their fluxes, and their detection SNR values. To examine how the PS detection pipeline is affected by the presence of the cluster signal, we analyze the catalogs separately for the two frequency channels. This approach allows us to specifically assess the influence of the cluster by focusing on the 150 GHz results, where the cluster signal is predominant. As previously mentioned, we utilize maps containing only noise to contrast the outcomes of the 150 GHz channel with the case where we incorporate the cluster signal. This comparison enables us to quantify the specific impact of the cluster on the pipeline.

We have established the importance of careful and reliable PS detection in the LPSZ, at the beginning of this chapter. This implies, ideally, ensuring detection of all the PSs in the cluster region and no false detections. We leverage the detection catalogs obtained from our simulated maps to quantify how many of the injected PSs are detected and how many stray detections occur. To count the fake and missing detections, we cross-match the detection catalog with the PS injection catalog for each map. To flag the detection as a ‘true positive’ (TP), each detected object is matched to entries in the injected sources and counted as a match if the angular separation of their positions differs by less than the respective beam size in the two bands. The remaining detected items that cannot be matched are marked as ‘false positives’ (FP), while all injected sources that are not detected are considered ‘false negatives’ (FN). These three quantities enable us to evaluate how well the detection pipeline works.

The determination of how many detected PSs are actual sources is given by the detection purity, defined as:

$$\text{Purity} = \frac{\text{TP}}{\text{TP} + \text{FP}}, \quad (5.1)$$

which measures the fraction of true detections out of the total number of sources detected. The ability of the pipeline to detect all the injected PSs in the maps, on the other hand, is gauged by the completeness:

$$\text{Completeness} = \frac{\text{TP}}{\text{TP} + \text{FN}}. \quad (5.2)$$

The completeness determines the fraction of PSs detected out of all the PSs we injected into the simulated maps.

We estimate the purity and completeness as a function of radial distance from the cluster centre by counting TPs, FPs and FNs in each of the 800 maps and then stacking them. To distinguish which SNR is the best in terms of these two parameters, we split the sample into the SNR ranges we discuss in the next section. Once we are able to judge how good the detection is in each of these ranges, we take the catalog of PSs detected for the real LPSZ catalog of 38 clusters and rank them in order of their detection reliability, using their detection SNR. We present these results in the following section.

5.3.1 Results

We present, in this section, the results obtained by running the PS detection pipeline on the maps simulated in Section 5.2.1, analysed using the methodology described above. The cross-matching between the injected and detected sources that we just described is purely based on the positions of the PSs. To perform an additional check to confirm that the detections marked as TPs correspond to the injected sources, we estimate the SNR difference of the PSs in the two catalogs. Ideally, this difference should be zero if the detection SNR, SNR_{det} , is actually the injection SNR, SNR_{in} . To measure this difference we define the average SNR bias as:

$$b_{\text{SNR}} = \left\langle \frac{\text{SNR}_{\text{det}} - \text{SNR}_{\text{in}}}{\text{SNR}_{\text{in}}} \right\rangle. \quad (5.3)$$

The SNR bias is calculated for each detected PS and then averaged in a given radial bin. This bias, as a function of cluster centre radial distance, is shown for the 260 GHz and the 150 GHz channels, in the left and right panel of Fig. 5.6, respectively. The average bias at a given radial point, for maps with only noise, is shown using a red solid curve while that for the maps with cluster signals, is shown using blue solid curves. The shaded regions correspond to 1σ uncertainties of the average biases and correspond to the standard deviation in the corresponding radial bin, divided by the square root of the number of PSs in that bin. We see that the bias (~ 0.1) is consistent with zero in both cases and both bands, confirming the cross-matching of the detection catalogs with the injected catalog and the consistency in the SNR estimation method we adopted and the method used in the detection pipeline. There is also no noticeable significant variation in this bias as a function of radius. We also notice that for the case where simulated maps include the cluster signal, the PSs are detected only beyond $0.6R_{500}$ because within this region the clusters, by simulation design have $\text{SNR} > 3$, to match the LPSZ survey design. This creates a blind spot for the PS detection pipeline.

After ensuring that the sources are detected with the correct SNR we finally validate the performance of the PS detection pipeline by determining the purity and completeness in each band, using Eq. (5.1) and Eq. (5.2). In the case of purity, since we only have the detection SNR for the FP detections, we use SNR_{det} for calculations. On a similar note, FN detections do not have any corresponding detected SNR and hence, we use SNR_{in} for estimating the completeness. We find that the purity and completeness below SNR 3.5 are extremely low (almost zero), while for a threshold above SNR of 5, these values get saturated to unity, the best possible value for purity and completeness. Based on this, we decided to break our validation analysis

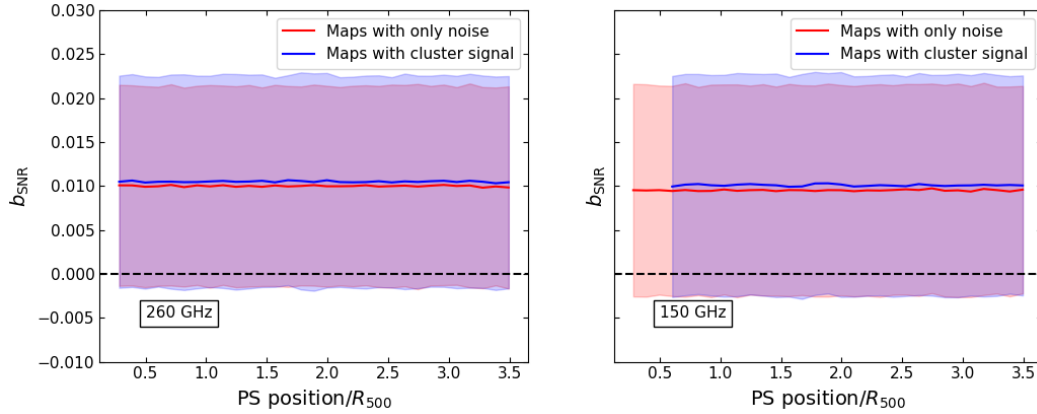


Figure 5.6 Radial variation of the average bias between the SNR of the sources detected by LPSZ pipeline, with respect to the injection SNR, at 260 GHz (left) and 150 GHz (right), respectively. The solid curves in red represent the results for maps with only noise whereas the solid blue curves depict the results for the maps simulated with the inclusion of the cluster signal. The shaded regions represent the 1σ uncertainties of these values. Notice that for the 150 GHz band, the blue curve starts beyond $0.5R_{500}$, see text for further explanation.

between these SNR values: we evaluate the purity and completeness as a function of radial distance from the cluster centre, in a SNR range starting from 3.5 and going up to 5, in increasing steps of 0.5.

If Fig. 5.7, we show the result in the case where we only simulate noise. The top panels show results for the 260 GHz and the bottom panels, for the 150 GHz channel, respectively. First, we examine the purity curves shown on the left side of the image. The purity is saturated at unity for SNR value of five (blue, solid curves) in both bands. It is the lowest for SNR values less than 3.5 (dotted-dashed yellow curves), at about 0.2, implying that only 20% of the sources detected with an SNR below this value, are true detections. In general, the purity levels for the same detection threshold are higher in the 150 GHz band. This is explained by the fact that this band has lower noise compared to the 260 GHz, channel, reducing the chance of noise manifesting as a fake PS detection. This nature is also reflected in the completeness value (right side of both panels), with 150 GHz, showing higher completeness values than the 260 GHz. Once again, lower noise enables better detection of real PSs. As opposed to purity, completeness reaches high values of 0.8 and above in both bands as soon as the SNR goes above 3.5. Other than variation around their average radial values, no significant radial trend is observed in the purity and completeness curves in either of the two channels. To provide a quantitative view of the features of the purity and completeness that we just discussed, the median values along the radius, along with their percentile errors (16th and 84th), of the purity and completeness in both the bands, are presented in Table 5.2.

For the case more relevant for the LPSZ, where the simulated maps include the cluster SZ signal, the purity and completeness curves are shown in the top and bottom panels of Fig. 5.8, for the 260 GHz and the 150 GHz channel, respectively. Once again, the purity curves (left panels) saturate at unity for the SNR value of 5

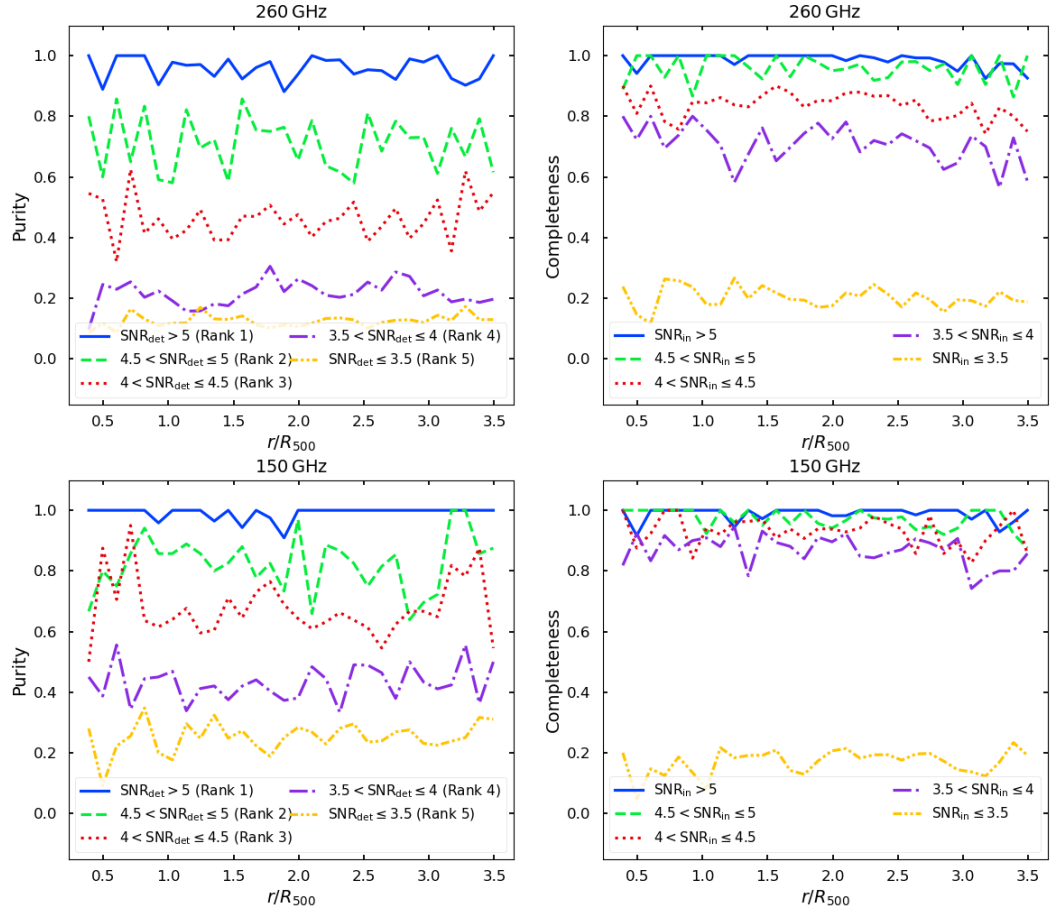


Figure 5.7 Performance quantification of the LPSZ PS detection pipeline using simulated maps devoid of the cluster SZ signal. The purity (completeness) curves for different detection thresholds are shown in the left (right) panels, using different colours and patterns depicted in the plot. The top panel corresponds to the results of the PS detection analysis performed for the 260 GHz band and the bottom panel corresponds to the results of the 150 GHz band, respectively.

Channel	Detection thresholds	Maps with only noise		Maps with cluster signal	
		Purity	Completeness	Purity	Completeness
260 GHz	SNR > 5	$0.97^{+0.05}_{-0.03}$	$0.99^{+0.01}_{-0.03}$	$0.99^{+0.01}_{-0.05}$ (rank 1)	$0.99^{+0.01}_{-0.01}$
	$4.5 < \text{SNR} \leq 5$	$0.73^{+0.12}_{-0.08}$	$0.97^{+0.03}_{-0.06}$	$0.74^{+0.06}_{-0.07}$ (rank 0.74)	$0.98^{+0.02}_{-0.03}$
	$4 < \text{SNR} \leq 4.5$	$0.46^{+0.07}_{-0.06}$	$0.84^{+0.03}_{-0.05}$	$0.46^{+0.07}_{-0.03}$ (rank 0.46)	0.85 ± 0.4
	$3.5 < \text{SNR} \leq 4$	$0.21^{+0.03}_{-0.04}$	$0.72^{+0.05}_{-0.07}$	$0.23^{+0.02}_{-0.04}$ (rank 0.23)	$0.68^{+0.07}_{-0.05}$
	SNR ≤ 3.5	$0.13^{+0.02}_{-0.01}$	$0.20^{+0.04}_{-0.02}$	$0.12^{+0.02}_{-0.03}$ (rank 0.12)	$0.22^{+0.02}_{-0.05}$
150 GHz	SNR > 5	$0.99^{+0.01}_{-0.01}$	$0.99^{+0.01}_{-0.03}$	$0.99^{+0.01}_{-0.07}$ (rank 1)	$0.99^{+0.01}_{-0.03}$
	$4.5 < \text{SNR} \leq 5$	$0.84^{+0.05}_{-0.11}$	$0.98^{+0.02}_{-0.04}$	$0.80^{+0.16}_{-0.09}$ (rank 0.8)	$0.95^{+0.05}_{-0.12}$
	$4 < \text{SNR} \leq 4.5$	$0.64^{+0.12}_{-0.04}$	$0.94^{+0.04}_{-0.07}$	$0.62^{+0.08}_{-0.05}$ (rank 0.62)	$0.92^{+0.05}_{-0.13}$
	$3.5 < \text{SNR} \leq 4$	$0.43^{+0.06}_{-0.05}$	$0.88^{+0.04}_{-0.06}$	$0.41^{+0.01}_{-0.04}$ (rank 0.41)	$0.89^{+0.06}_{-0.08}$
	SNR ≤ 3.5	$0.25^{+0.05}_{-0.03}$	$0.18^{+0.02}_{-0.05}$	$0.25^{+0.06}_{-0.04}$ (rank 0.25)	0.17 ± 0.4

Table 5.2 The median value along the radius, for the purity and completeness of PS detection in the two NIKA2 frequency bands, for the case where only noise is simulated in the PS maps and for the case where the cluster signal is included in the map construction. The SNR in case of purity and completeness referees to SNR_{det} and SNR_{in} , respectively (see the text for more information on this). The ‘rank’ mentioned below the purity values are the ranks used to assign reliability to PSs detected in the real LPSZ clusters.

(blue, solid curves) in both the bands and fall below 0.25 for SNR values less than 3.5 (dotted-dashed yellow curves). Similar to the previous analysis, the purity levels for the same detection threshold are higher in the 150 GHz band. However, in this band, we observe that the purity for every SNR threshold peaks within the cluster region (grey-shaded area) and then decreases until it reaches the almost constant behaviour seen in the case without the cluster. This is intuitive since the presence of cluster drowns out most of the noise, reducing the number of fake detections in a higher proportion than reducing the detection of real sources. Corresponding to this peak in the purity, we see a fall in the completeness in this region (see bottom right panel of Fig. 5.2). This reiterates the dominance of the cluster signal over the PSs, suggesting that the cluster region is almost a blind spot for the PS detection pipeline, specifically in the 150 GHz band. The radial median values of the purity and completeness in both the bands, for this case, can be found in Table 5.2.

5.3.2 Application to real LPSZ clusters

Eventually, as mentioned in Section 5.1, the PS detection pipeline must be able to provide reliable PS detections for the reasons we previously outlined.

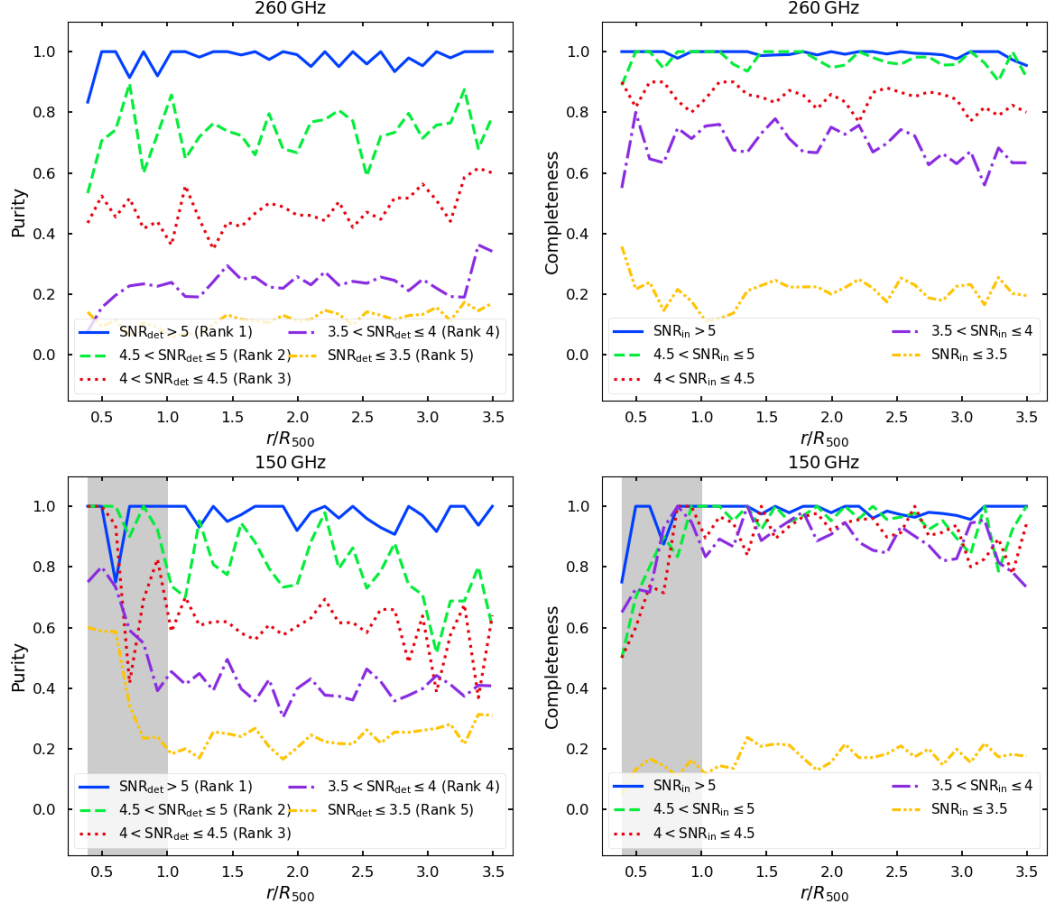


Figure 5.8 Performacne quantification of the LPSZ PS detection pipeline using simulated maps with the inclusion of the cluster SZ signal. The purity (completeness) curves for different detection thresholds are shown in the left (right) panels, using different colours and patterns depicted in the plot. The top panel corresponds to the results of the PS detection analysis performed for the 260 GHz band and the bottom panel corresponds to the results of the 150 GHz band, respectively. The shaded grey region in the 150 GHz plots depicts the region where the cluster SNR is higher than 3, by the simulation design. There is no significant radial trend in the purity or the completeness functions, except in the grey regions where sudden anomalies in the curves (peak in purity and dip in completeness) can be noticed.

To assign a reliability score to the PSs detected in the LPSZ maps, we utilise the purity curves that we obtained in our analysis with simulated NIKA2-like maps. Since the detection is always (almost) complete above SNR 3.5 (see results in the previous section), we use purity as the quantifier of the reliability of a detected PS. The median purity values at a given SNR are used as the probability of detection to be a real source, i.e. to be reliable. We call these median purity values that we use as a probability, the ‘rank’ of the PS detection. Where a value of 1 implies that the detected source is highly reliable in terms of being a true detection and the reliability decreases as the rank moves towards zero. These ranks can be found under the median purity values for the results of this set of simulations, in Table 5.2.

To apply this ranking system to the real LPSZ clusters, we first talk about the PSs in the LPSZ. As a part of the analysis looking to detect the cluster lensing effect using PSs detected in the sub-mm band, underway for the LPSZ (Desert et al., private communication, also briefly discussed in Section 5.1), the PS detection pipeline was applied to the real LPSZ maps with a detection threshold SNR of 4. Approximately 270 sources were detected across the 38 clusters. We first individually assign the ranks to these PSs in the two bands (namely, Rank₂₆₀ and Rank₁₅₀) and then, to get an overall view of the detection reliability, we estimate a combined rank using a simple average formula:

$$\text{Combined rank} = \frac{\text{Rank}_{260} + \text{Rank}_{150}}{2}. \quad (5.4)$$

The distribution of the real PSs detected in the LPSZ, in terms of their (three) ranks, is shown in Fig. 5.9. We can see from these distributions that the 260 GHz detections (shown using blue histogram) are highly skewed towards a higher rank (one), or a more reliable detection quality, while the 150 GHz detections (in green) are skewed towards lower reliability with the distribution peaking at rank 0.2. When combining the two ranks of a given detection, it must be kept in mind that a PS with rank 1 in either of the two bands might not necessarily have a high rank in the other band, meaning that the distribution of the combined rank in a given bin will not simply be the mean of bin values in each band but rather a reflection of the distribution of the unique combined ranks of the individual PSs. This is reflected by the red curve in the plot which shows the combined rank of the PSs, which peaks at a rank ~ 0.6 . This indicates that judging a PS detection using its 260 GHz gives a purer, more reliable catalog, than when using the rank in the 150 GHz or the combined rank. As a results it would be better to give the 260 GHz rank a higher weight than the 150 GHz rank in Eq. 5.4. These results help identify, for the LPSZ, the significance associated with each of the PSs and this information can be included in the PS model for the ICM pressure profile estimation. The practical details of such PS modelling and its impact on pressure profile recovery are beyond the scope of this work. Further, this information can also be useful to associate the reliability of the PSs, around each cluster in the LPSZ catalog, to study the lensing effect by clusters that we have mentioned above.

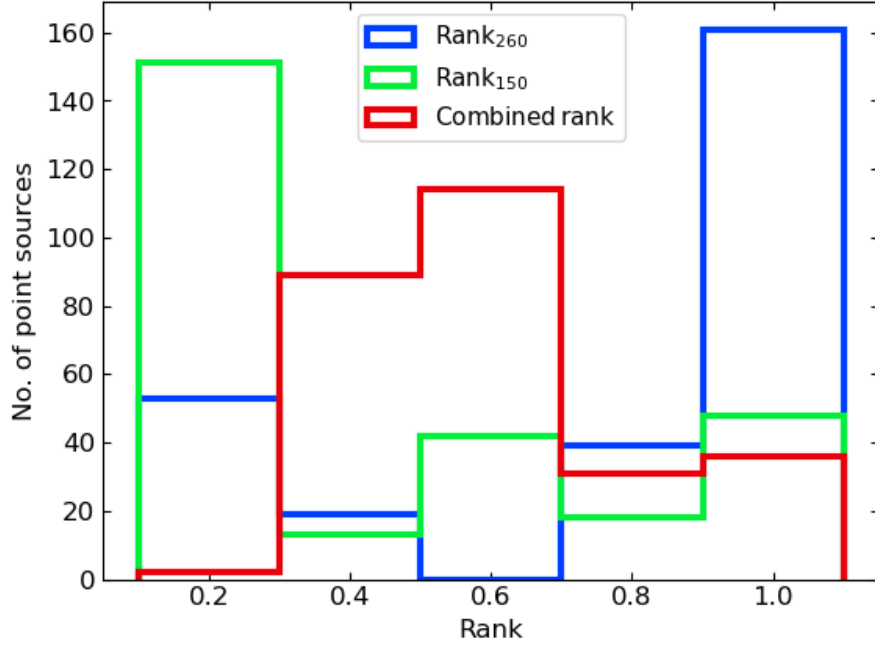


Figure 5.9 The distribution of rank values of the PS detections in the real LPSZ sample. The blue, green, and red distributions represent the rank of the 260 GHz detections, the 150 GHz detections, and the combined rank, respectively. Rank 1 depicts the highest reliability of detection while rank 0 depicts the lowest.

5.4 Discussions and conclusions

In this chapter, we have validated, using simulations, the PS detection algorithm of the LPSZ. Then, we used these results to rank the PSs detected in the real LPSZ cluster maps.

To validate the algorithm, we first simulated 2 band maps devoid of the cluster signal to analyse how the algorithm works in the noise field of the LPSZ. Later we simulate another realisation of such maps with cluster SZ signal reintroduced into the simulation. We successfully produced 800 maps for both cases, with 20 PSs, mimicking submillimeter galaxies, with randomly distributed SNR and positions, injected in each of these maps. The maps were then analysed following the procedure described in Section 5.3.

For the case where we only simulated noise in the PS maps, we find the purity drops from unity to around 0.2 as we lower the detection SNR from 5 to 3.5. The completeness, on the other hand, is approximately 0.2 for SNR value of 3.5 and below and quickly rises to above 0.8 (0.6) for $\text{SNR} > 3.5$ in the 150 GHz (260 GHz) band. We find no effective radial trends in the purity or completeness in either band. Their statistical values along the radius are reported in Table 5.2. In general, due to lower noise and hence lower probability of noise manifesting as a false detection, the purity and completeness value in the 150 GHz are higher than the other band, for the same SNR range. For the case closer to the real LPSZ, where we include the cluster signal in our simulation, we find the same result as in the former case except,

in the cluster region ($r < R_{500}$), the purity suddenly jumps and the completeness suddenly drops, making this an almost blind spot for the detection pipeline. This results in the 260 GHz band being a preferred choice to detect PSs in the cluster region.

Finally, we used the purity curves in the case where we include the cluster signal, to create a ranking system for the detections generated by the LPSZ pipeline. We simply took the purity values at a given SNR as probabilities that the detection in question is reliable or real. In doing so, the SNR value with the highest purity level was assigned rank 1 and the rank decreased as the purity (and hence SNR) decreased. These ranks were assigned separately for the two NIKA2 bands. We allotted these ranks to the real LPSZ sample PSs in each band, using their detection SNR and then calculated a simple combined rank using Eq. (5.4). We found that the detection in the 260 GHz are more reliable, being biased towards higher ranks while the 150 GHz detections are poor with the PS distribution skewed to a lower rank. Once again, this makes the former observation band a preferable one for reliable PS detection. Consequently, we found that lower weight should be given to the PS rank of the 150 GHz channel, in estimating the combined rank, to prevent the detections from being biased towards low-reliability ranks.

In conclusion, we have used simulations and successfully developed a framework to quantify the performance of the LPSZ PS detection pipeline and associated a reliability score to the PS detections in the real sample. It must be kept in mind that these results rely on the valid assumption that the primary contaminants of the SZ observations are submillimetric galaxies.

Chapter 6

Recovery of 3D ICM profiles of The300–NIKA2 twin samples

In the preceding chapters, we have established that the accurate characterization of the pressure profile of galaxy clusters is crucial for cosmological analyses. In the context of SZ surveys, understanding the shape and intrinsic scatter of the pressure profile and consequently, the mass profile, is essential to address biases and systematic effects that currently hinder precise and unbiased cosmological constraints based on SZ surveys like the LPSZ. In this chapter, we deploy The300–NIKA2 twin samples to investigate how well we can recover these profiles from the 2D maps of the clusters by comparing them to the true 3D radial profiles from the simulation and examining the associated systematic effects. We also investigate if the cluster dynamical state is related to the possible biases in the recovery of these profiles.

6.1 Dataset and the cluster dynamical state

Simulations play a pivotal role in examining the extraction of 3D profiles from 2D cluster maps. Spherical symmetry is assumed for de-projection but, the validity of this assumption relies heavily on the morphological and dynamical state of the cluster. Using simulations we can leverage our understanding of physical processes within the ICM to examine what process might invalidate this assumption. By comparing simulated 2D projections with observed cluster maps, we can refine our models by including details that are ignored in a simple de-projection, to achieve a consistent match between the two. This then enables an informed deconvolution of the projection effects for reconstructing accurate 3D profiles of the cluster. This makes simulations crucial for advancing our comprehension of the cluster ICM studied by observation data.

In Section 3.2.1, we produced three distinct TSs representing the LPSZ clusters for their total mass, hydrodynamical mass, and integrated Compton parameter. We aim to utilize NIKA2 SZ maps generated from these samples to investigate the recovery of the 3D ICM (pressure and mass) profiles from them while testing the impact of the dynamical state of clusters under consideration, as we will later see in the analysis. To determine this state we use the relaxation parameter χ , first introduced, to estimate the dynamical state of The300 clusters, in Hagger et al. 2020.

However, we adopt the definition of this parameter, defined in De Luca et al. 2021:

$$\chi = \sqrt{\frac{2}{\left(\frac{\Delta_r}{0.1}\right)^2 + \left(\frac{f_s}{0.1}\right)^2}}, \quad (6.1)$$

which is the inverse square root of the normalized quadratic mean of the indicators Δ_r and f_s . The parameter Δ_r gives the offset of the centre of mass from the theoretical centre of the cluster in the simulation and f_s is the ratio between the sum of all the sub-halo masses and the main cluster mass within a given volume. In De Luca et al. 2021, the clusters are defined to be dynamically relaxed (disturbed) for $f_s < 0.1$ and $\Delta_r < 0.1$ ($f_s > 0.1$ and $\Delta_r > 0.1$). By definition then, values of χ much higher than 1 represent relaxed clusters and vice versa.

In the left panel of Fig. 6.1, we show the distribution of the relaxation parameter for the three distinct types of TS: TS_{TM}, TS_{HSE}, and TS_Y represented by blue, cyan, and magenta histograms, respectively. Solid and dotted vertical lines mark the median, 16th, and 84th percentiles of each distribution. Notably, the median and inter-percentile range for TS_Y (magenta lines) are shifted towards lower χ values, indicating a bias towards disturbed clusters within this sample.

Since, in our analysis, the focus is on statistically analysing the recovery of 3D profiles, we combine all three TSs into one ‘unified sample’. This improves our statistical analysis in terms of precision and reliability, leading to more robust and accurate insights. This combined TS consists of 120 unique clusters instead of 135 since some of the clusters were common to two samples and must only be considered once in the combined list. In the right panel of Fig. 6.1, we see the distribution for the relaxation parameter for the complete sample. Its median is indicated by a vertical solid black line, aligning well with the zero value. This alignment implies an unbiased distribution of χ within this complete sample. The left and right vertical dotted lines represent the 16th and 84th percentiles, respectively. We categorize clusters with χ values below the 16th percentile as the most disturbed (shaded red region) and those above the 84th percentile as the most relaxed (green shaded region). By using the combined sample for this analysis, besides increasing statistical reliability, we also ensure the usage of a representative population of clusters in terms of their dynamical state.

In the following sections, we use this ‘unified sample’ for our analysis. In particular, we use one projection of the y map of each cluster in the sample. This projection is selected randomly among the 29 available projections, and hence it is randomly oriented with respect to the inertial axes of the cluster. As given by Eq. (2.39), y is a LoS integral of the pressure of the cluster. For The300 this integration is performed as a summation over gas particles along the LoS. For our purpose, we adopt a summation depth of $4R_{200}$ since we examine overdensities ~ 100 and want to avoid any artefact in our analysis caused by edge effects. This summation is given by Cui et al. 2018:

$$y = \frac{\sigma_T k_B}{m_e c^2 d A} \sum_{i=0}^N T_i N_{e,i} W(r, h_i), \quad (6.2)$$

where N_e is the number of electrons in a given gas particle and substitutes the electron number density n_e in this calculation. The two quantities are related within

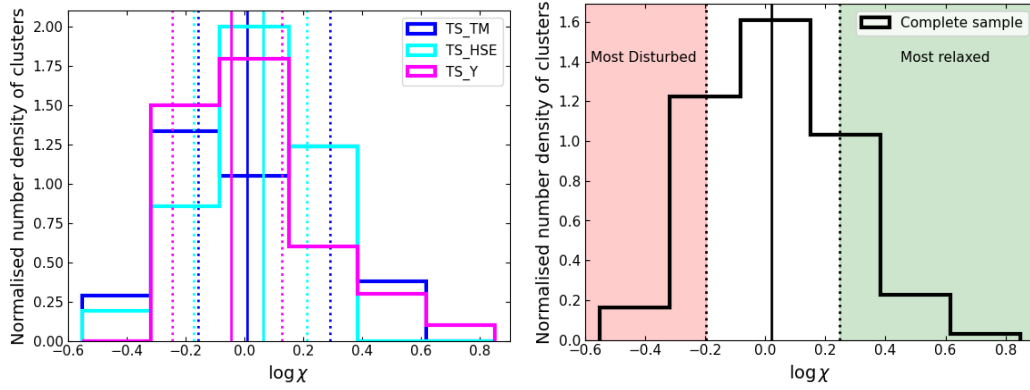


Figure 6.1 Distribution of the dynamical state indicator, namely, the relation parameter χ for the TSs. On the **left** are the distributions for TS_{TM} , TS_{HSE} , and TS_{Y} samples shown using blue, cyan, and magenta histograms, respectively. The median of each distribution and their corresponding 16th and 84th percentiles are shown using solid and dotted vertical lines. The median and the inter-percentile range for TS_{Y} , shown using magenta vertical lines, are shifted towards lower χ values, implying that this sample is biased to disturbed clusters. On the **right** is the distribution for the unified sample with its median shown using a vertical, solid black line. The left vertical dotted line represents the 16th percentile and clusters with χ below this value are classified as the most disturbed (shaded red region), whereas the vertical dotted line on the right is the 84th percentile and clusters with χ above this value are marked as the most relaxed (green shaded region).

a given volume (dV) as $n_e = N_e/dV = N_e/dA/dl$. $W(r, h_i)$ represents the SPH smoothing kernel which, using the smoothing length h_i , distributes the signal from each particle to the projected pixels. The projected y map obtained this way is used to create NIKA2-like maps for our combined sample, as described in Section 3.2.1. These maps are utilised for inferring the cluster ICM properties.

6.2 Recovery of the 3D profiles

Having defined the sample we use in this analysis, we employ this dataset to estimate the ICM pressure and mass profiles from their simulated SZ maps. We determine both quantities through a variety of methods, which we summarise in Table 6.1 and describe throughout the course of this section. For all the estimates, we use the radial range $0.05 - 1.8 R_{500}$ since it is representative of the radial range in between the NIKA2 beam size and its FoV (see Chapter 4 for an example with a real cluster) and also roughly the range in which the PANC02 software estimates the pressure profiles by default. This allows us to also verify the performance of PANC02 with realistically simulated clusters, using our analysis. The distance R_{500} is determined using the 3D radial mass profile of the cluster and Eq. (2.29).

6.2.1 Pressure profiles

We discussed in Section 3.1.2 that a part of the primary goals of the LPSZ entails the characterisation of clusters using their pressure profile inferred from their NIKA2 SZ

Variable	Description
R_Δ	Radius at a given spherical overdensity derived from the radial 3D mass profiles of the cluster obtained from The300
P_{true}	3D ICM pressure profile from the simulation
$P_{\text{gNFW,true}}$	gNFW fit to the true 3D pressure profile P_{true}
P_{NP}	best-fitting NP model to the NIKA2-like SZ maps of the TSs
$P_{\text{gNFW,NP}}$	3D gNFW fit to the binned data of the NP model P_{NP}
P_{gNFW}	best fit of the projection of the gNFW profile to to the NIKA2-like SZ maps of the TSs
M_{sph}	3D radial mass profile from the simulation
$M_{\text{HSE,true}}$	3D Hydrostatic equilibrium mass profiles derived using the 3D gas density profiles and P_{true}
M_{HSE}	3D Hydrostatic equilibrium mass profile derived using the gas density from the simulation and the estimated pressure profile $P_{\text{gNFW,NP}}(r)$

Table 6.1 A summary of the quantities used or estimated in this chapter, along with their descriptions. The various pressure and mass estimates are used to quantify how well the pressure and mass profiles are recovered from the simulated SZ maps of the TS clusters.

maps and creating a universal pressure profile using independent SZ measurements at high redshift. We saw in Section 4.2.2, the pressure profile analysis of the LPSZ cluster ACTJ0240. We classified this cluster as morphologically disturbed by comparing its profile to the UPP from M. Arnaud et al. 2010. This case makes it clear that the knowledge of the shape and scatter of the pressure profile is important. To this end, we use NIKA2-like maps of our combined sample to infer 3D profiles from projected data and quantify how well they are recovered by comparison with the true pressure profiles from the simulation. In the following discussion, we describe the various ways we estimate the pressure profiles:

1. **Theoretical ICM pressure profile (P_{true}):** this variable is the true 3D pressure of the ICM as a function of radius, this represents the baseline with which all other results are compared.
2. **The gNFW fit of the theoretical ICM pressure profile ($P_{\text{gNFW, true}}$):** this estimate refers to the pressure of the ICM at a given radius, estimated from the gNFW fit (Eq. 4.8) to the true 3D pressure profile (P_{true}). It serves as a modelled representation of the true pressure distribution, facilitating model accuracy assessments. We used MCMC analysis to perform this fit. Particularly, we used a Python implementation called `emcee` (Foreman-Mackey et al. 2019) to execute the fitting with the use of 50 walkers, with a burn-in of 4000 steps and ran the chain until convergence (see Section 4.2 for convergence criteria). Even though we have fixed our radial range of comparison, we want to test how well the gNFW model fits the theoretical profiles in our range in comparison to other values. In Fig. 6.2 we show a comparison of the 3D pressure profile and its gNFW fit. The median profile of the entire sample is shown using a solid, muted blue curve. The gNFW model is fit to each individual cluster and the medians of these fits are shown for different radial ranges of fitting. The dotted red, dotted-dashed green, and dashed blue curves correspond to the range of fitting $0.05 - 1.8 R_{500}$, $0.1 - 1.8 R_{500}$, and $0.1 - 1.2 R_{500}$, respectively. We can see, through the ratio of the true median profile and the median of the gNFW fits in the bottom panel that we get the worst results with maximum deviation when using the radial limits $0.05 - 1.8 R_{500}$ (red curve). For $0.1 - 1.8 R_{500}$ (green curve), and $0.1 - 1.2 R_{500}$ (blue curve), the results show improvements, with lower deviation but there is no improvement between the two. This makes either of these two fitting ranges suitable to fit the true 3D profile. Recalling that we chose the radial range $0.05 - 1.8 R_{500}$, we see that a gNFW model is not suitable for the true profiles in this range. For this reason, we always compare our estimates directly to the true profile instead of its gNFW fit.
3. **Pressure profile derived from PANC02 (P_{NP}):** we calculate the pressure profile (using PANC02) from the NIKA2 SZ maps generated for our sample by fitting a projected NP model to the simulated maps. The entire fitting process, detailed in Section 4.2, is closely followed, including the generation of the noise covariance matrix used in the likelihood function (Eq. 4.10) and the adherence to convergence criteria of the MCMC analysis. It's important to note that, in this case, the noise power spectrum employed for simulating SZ maps is the

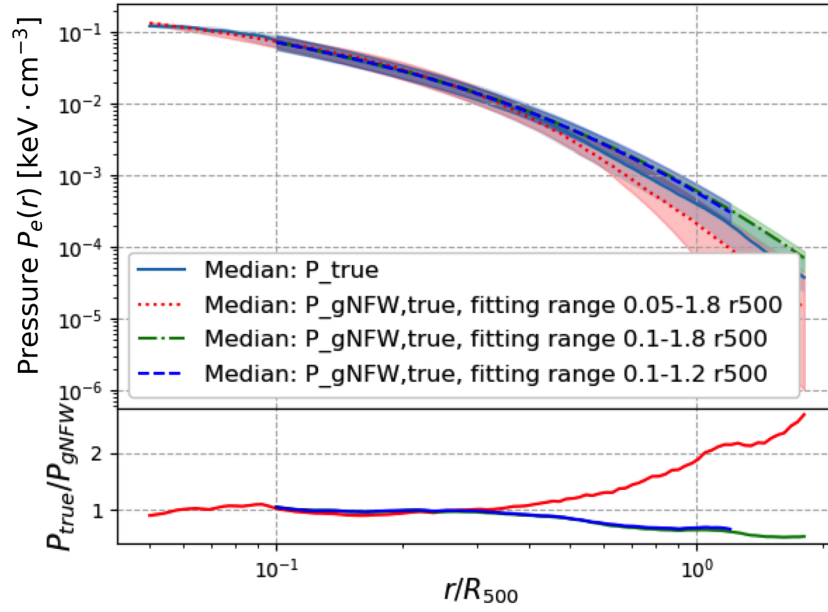


Figure 6.2 The median 3D pressure profile for the combined sample shown with a solid muted blue curve, along with the medians of the gNFW fits with the dotted red, dotted-dashed green, and dashed blue curves. These curves correspond to the range of fitting $0.05 - 1.8 R_{500}$, $0.1 - 1.8 R_{500}$, and $0.1 - 1.2 R_{500}$, respectively. The shaded regions depict the 16th and 84th percentile of the profile distribution of the 120 clusters in the sample. At the bottom, we show the ratio of the true median profile and the median of the gNFW fits.

same as the one used to create noise realizations for the covariance matrix. Moreover, it's worth mentioning that we lack observational estimates of Y_{500} to set constraints on the pressure profile in the cluster outskirts (last term of the likelihood function, Eq. 4.10). To address this, we substitute Y_{500} with values obtained from the simulation y maps through aperture integration within R_{500} . For the NP profile modelling, we adopt a binning scheme comprising six logarithmically spaced bins in units of R_{500} , with the first and last bin centres set at 0.05 and 1.8 R_{500} , respectively. This binning in R_{500} units standardizes the bin size, accounting for the unique physics of each cluster.

4. **ICM pressure derived by fitting a gNFW model to the NP profile ($P_{\text{gNFW, NP}}$):** as we mentioned in Section 4.2, the NP model cannot directly be used to infer the cluster mass because of its irregular form and non-negative derivative values. For this reason, following the same procedure as previously described in Section 4.2, we fit a gNFW model to the binned data of the NP pressure profile $P_{\text{gNFW, NP}}$.
5. **ICM pressure derived by fitting a gNFW model directly to the SZ maps (P_{gNFW}):** to obtain an independent estimate of the projected pressure profile, avoiding direct or indirect dependencies on PANC02 results, we opt for a direct fit of the gNFW model to the SZ maps. We project the gNFW model along the (LoS) through numerical integration, producing a ‘model’ for the projected pressure profile. We use our simulated maps to estimate a projected pressure profile from them simply by estimating the average signal within concentric annuli as a function of increasing radius from the cluster centre. This profile is then fit with the projected one to obtain a direct gNFW fit. We implement the fit using Bayesian analysis with the same MCMC software and convergence criteria detailed in Section 4.2.

In the following section, we compare the results obtained from each of these methods. We also provide a comparison between the three-dimensional (3D) and projected profiles to discuss how well we can recover 3D profiles from the (2D) maps.

6.2.1.1 Results

3D pressure profiles

A part of the primary objective of the LPSZ, with the pressure profiles, is to thoroughly analyse each of its clusters (ICM) by examining its 3D radial profile. This involves utilizing the profile for an unbiased determination of the value of M and Y . This estimate also serves as an ingredient for calibrating the $Y - M$ scaling laws at high redshift. For this reason, we begin with a comparative analysis of the previously estimated 3D pressure profiles.

In Fig. 6.3, we present the sample median, along with the 16th and 84th percentiles, for the 3D pressure profiles obtained from the various pressure estimation methods discussed earlier. The solid blue line represents the true pressure profiles of the clusters. The corresponding gNFW fit denoted as $P_{\text{gNFW, true}}$ is illustrated by the dotted red curve. As demonstrated previously in this chapter (refer to Fig. 6.2), the gNFW model struggles to accurately capture the shape of the true profiles when

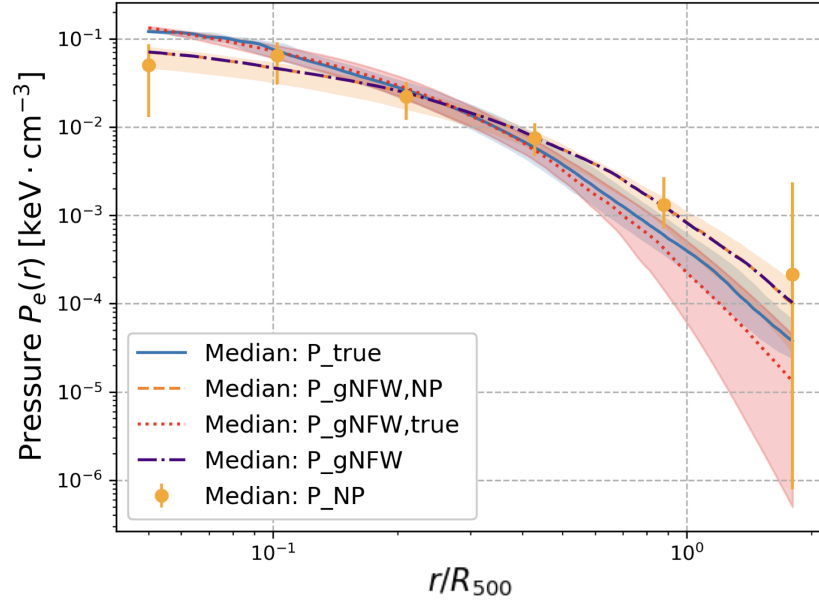


Figure 6.3 Comparison of the 3D pressure profiles estimated using different methods.

The plot shows the sample median with curves (marker), along with the 16th and 84th percentiles shown using the shaded regions (error bars). The true pressure profiles of the clusters are represented by a solid blue line, and the corresponding gNFW fit $P_{\text{gNFW,true}}$ is shown with a dotted red curve. The median of the NP model (P_{NP}) fit to the simulated SZ maps is shown using orange markers and the corresponding gNFW fit to these NP profile binned data points, $P_{\text{gNFW,NP}}$, is illustrated by an orange dashed line. The dotted-dashed indigo line represents the sample median of the direct gNFW fit to the SZ map P_{gNFW} . The errors on P_{gNFW} have been omitted for clear visualisation.

fitted over the entire radial range, particularly beyond R_{500} , as evidenced by the deviation of the red curve from the blue curve.

Next, we examine the profiles P_{NP} . The orange dots in the plot showcase that the median NP model, derived from individual clusters, tends to underestimate the pressure in the inner regions ($r < 0.1 R_{500}$) while overestimating it in the outskirts ($r > R_{500}$). The corresponding median of the gNFW fit to these NP profile binned data points, labelled as $P_{\text{gNFW,NP}}$ and depicted using an orange dashed line, consistently exhibits the same behaviour of underestimation in the core and overestimation in the outskirts. Finally, the dotted-dashed indigo line represents the sample median of deprojected gNFW fitted directly on the SZ maps, and is denoted as P_{gNFW} . This provides an independent estimate of the pressure and demonstrates consistency with P_{NP} (orange dot) and $P_{\text{gNFW,NP}}$ (dashed orange curve). We also performed this analysis for individual TSs created in Section 3.2.1. They show the same behaviours as the complete sample, except for TS_{Y} which is biased to disturbed clusters. The plots can be found in Appendix B.

Ultimately, we observe that different methods for estimating the pressure profile from SZ maps exhibit consistency with each other, but not with the true 3D profile from the simulation. It is also noteworthy that our results are compatible with those of PANC02, implying that any discrepancies in recovery are systematic and not related to the software algorithm. Moving forward, as all estimates from the

simulated NIKA2-like maps align with each other, we proceed with further analyses using a single estimate, namely, $P_{\text{gNFW,NP}}$. To quantify the difference between the true profile and the estimate from the SZ maps, we calculate the bias in the pressure profiles as:

$$b_P = \frac{P_{\text{true}} - P_{\text{gNFW,NP}}}{P_{\text{true}}}. \quad (6.3)$$

The sample median of this bias is presented in the left panel of Fig. 6.4. The black curve illustrates its behaviours for the complete sample, while the dashed green and dashed-dotted red curves show the bias for the most relaxed and most disturbed, respectively. The shaded region represents the 16th and 84th percentiles. Notably, the bias for the complete sample is approximately zero around the radius $0.2 R_{500}$ and positive below this point, turning negative above it. There is no notable difference in the bias value behaviour based on the dynamical state of the cluster. The bias rises rapidly at the cluster outskirts, and the median value nearly reaches -1.5 , for the complete sample and the disturbed clusters. This can be particularly critical for mass estimation at R_{500} . Eq. (4.23) shows that it is, in fact, the slope of the mass that impacts mass estimation. For this reason, we also define the bias of the slope of the reconstructed profiles relative to the true one:

$$b_{\text{slope}} = \frac{\frac{dP_{\text{true}}}{dr} - \frac{dP_{\text{gNFW,NP}}}{dr}}{\frac{dP_{\text{true}}}{dr}}. \quad (6.4)$$

We calculate our slope values analytically for $P_{\text{gNFW,NP}}$

The right panel of Fig. 6.4 shows the median bias in the slope for the complete sample (black curve), the most disturbed (red dotted-dashed curve) and the most relaxed clusters (green dashed curves). Notably, the bias in the slope is lower than the pressure itself. We observe a decreasing trend until we reach a minimum, around $0.3 - 0.4 R_{500}$, and then a small upturn until stabilising around the value 0.25 . However, we can see that the disturbed clusters show a lower bias in the inner regions, albeit with a higher variability, whereas for the relaxed ones, the bias is smaller in the outskirts.

In the end, we find discrepancies between the true 3D profile and those derived from their SZ maps. Especially in the core and cluster outskirts. In the next section, we explore the comparison in the 2D space to understand the nature of these discrepancies.

Projected 2D pressure profiles

Up to now, we have used the theoretical 3D pressure profile as a baseline. However, the discrepancies encountered with the profiles recovered through the different methodologies (described in the previous sections) force us to take a step back and analyse the goodness of fit with respect to the data, i.e. the y maps used to create the SZ map.

The comparison of the median of our fits, $P_{\text{gNFW,NP}}$ and P_{gNFW} with the median of the data, which refer to the profiles obtained by taking averages in the annuli of the NIKA2-like maps, is shown in the left panel of Fig. 6.5, using orange dashed, indigo dashed-dotted, and blue solid curves, respectively. These profiles are then binned values of the projected profiles with the same radial binning as adopted for

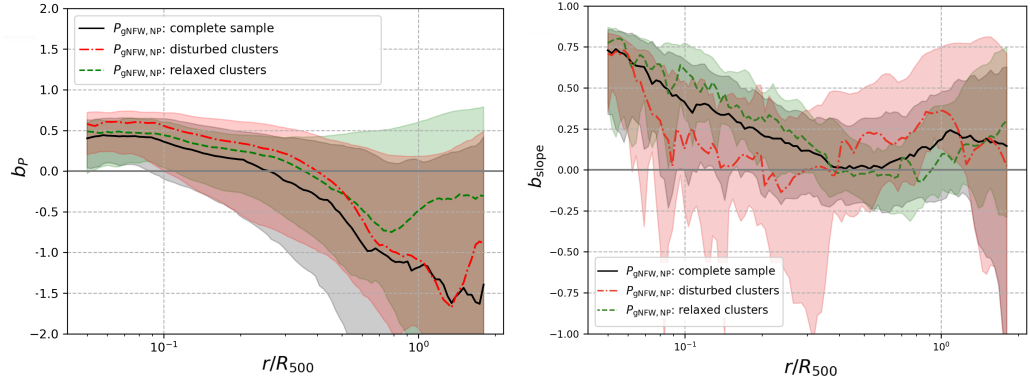


Figure 6.4 *Left:* The median bias of the pressure estimate from the 2D maps, with respect to the true 3D profiles, along with their 16th and 84th percentiles shown using shaded regions. We show the median bias for the entire sample (black curve), with specific curves for the most disturbed (red dotted-dashed) and most relaxed clusters (green dashed). *Right:* Using the same colour and pattern scheme, we show the bias in the slope of the pressure profile recovered from the 2D maps, relative to the slope of the true 3D pressure profile.

P_{NP} . Unlike the 3D profiles, the 2D equivalents are in complete agreement without any discrepancies in the core or the cluster outskirts. This is also reflected by the bias in the pressure profiles that we define in the same way as Eq. (6.3). The right panel of Fig. 6.5 show the median bias for the complete sample (black curve), the disturbed clusters (red curve), and the relaxed clusters (green curve). All the biases are always less than 0.1 and this value is independent of the cluster dynamical state. The only noticeable feature of the bias is that the uncertainty on the bias, shown using the shaded regions, blows up at approximately R_{500} . A comparison of the projected profiles for the individual TSs can be found in Appendix B.

The observed consistency in the 2D pressure profiles, as opposed to the observed discrepancies in the 3D pressure profiles, prompts potential de-projection effects. When de-projecting 2D profiles to 3D, the assumption of spherical symmetry could introduce differences between the true 3D profile and the de-projected counterpart, especially if the 2D maps do not truly represent a spherical cluster or are aligned with a specific projection axis that is elongated or shortened with respect to the spherical cluster halo. However, as the SZ maps are generated from random projections of the cluster y maps, there is no preferential alignment that would systematically affect the de-projected pressure profile.

Another aspect to consider is that in 3D space, we make a comparison between our fits and the true 3D profile while in the 2D space, we make a comparison with respect to the profile directly measured on the y maps and not a projection of P_{true} . To assess the difference between the two latter quantities, we examine the LoS integration equation (Eq. 6.2) used in the simulation to project the pressure onto a map. Here the quantity differentiating the 3D from projection is the smoothing kernel $W(r, h_i)$. To quantify the impact of this kernel, we compare y maps produced for a randomly selected cluster with and without this smoothing kernel. The difference map, shown in the left panel of Fig. 6.6, exhibits differences an order of magnitude lower than the y values of the map, suggesting minimal impact on the pressure profiles. Regardless,

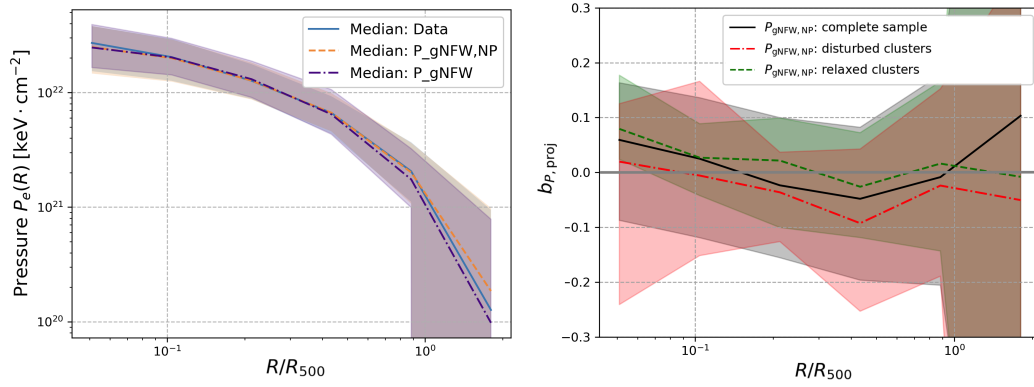


Figure 6.5 A comparison of the median values of the binned projected pressure profiles. On the right are the median values of the projected profiles $P_{\text{gNFW,NP}}$ (orange dashed curve), P_{gNFW} (dashed-dotted indigo curve), and the profile of the NIKA2-like SZ map (solid blue curve), respectively. The shaded regions depict the 16th and 84th percentile uncertainties of the median. These profiles are consistent with each other. This consistency is shown in the bias plot for $P_{\text{gNFW,NP}}$ in the right panel, where we show the median bias in the 2D profile $P_{\text{gNFW,NP}}$ respective to the data. The black, the dashed green, and the dashed-dotted red curve represent the complete sample, relaxed clusters, and disturbed clusters, respectively.

we perform a fit to obtain the pressure profile from both maps. The results for $P_{\text{gNFW,NP}}$ are shown in the right panel of Fig. 6.6, where the green dotted-dashed curve represents the profile in the case without the smoothing kernel and the orange dashed curve represents the case where the smoothing kernel is included. Although there is a minor difference in the two profiles, they are compatible within their errors, and the variance is insufficient to account for the observed discrepancy between the fit and the true 3D profile. Since no discernible trends in profile biases based on cluster dynamical state are observed, we attribute the discrepancies in the 3D profiles to a combination of the smoothing kernel and the assumption of spherical symmetry during de-projection, with the latter being the more dominant effect.

Finally, in terms of the pressure profile analysis, keeping in mind that one of the primary goals of the LPSZ is to derive a UPP at higher redshifts than before, we compare our fits $P_{\text{gNFW,NP}}$ with the UPP from M. Arnaud et al. 2010. In Fig. 6.7, we see the normalised pressure profiles for individual clusters shown with black lines. We also show the mean of all the profiles using a dashed cyan line. In comparison to the UPP from M. Arnaud et al. 2010 (solid yellow line), we have a higher normalisation and a shallower slope. Since we use a sample with even distribution in terms of dynamical state, we speculate that this change in normalisation and slope could be indicative of redshift evolution in these parameters. This evolution in slope and normalisation is in line with results in Ghirardini et al. 2017 for the redshift ranges $[0.4, 0.52]$ and $[0.52, 0.77]$, the closest redshift range to our sample. The evolution can be interpreted as a reflection of redshift variation of the number of different types of clusters based on properties like the cluster core temperature, since such properties can directly alter the pressure profile. Alternatively, this could point at SZ tracing the pressure in a different way than X-ray which is used to derive the UPP that we compare ours with.

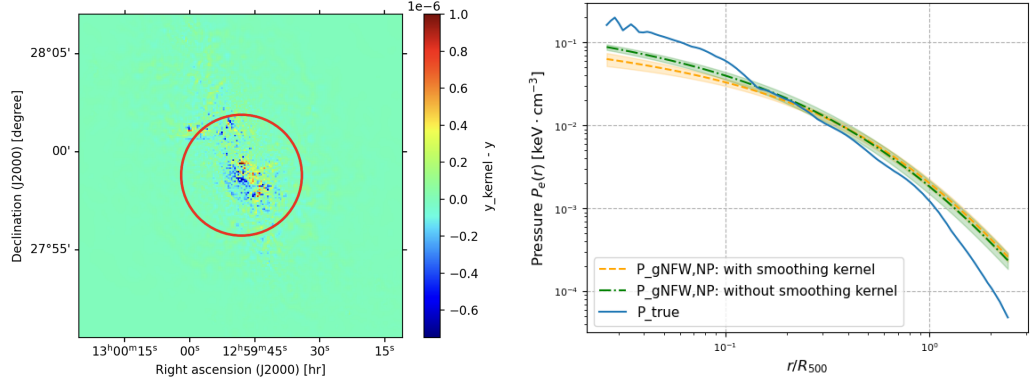


Figure 6.6 *Left:* the difference in the y maps, of a random cluster in the sample, generated with and without applying a smoothing kernel in the LoS integration Eq. 6.2. *Right:* the pressure profiles $P_{\text{gNFW,NP}}$ derived from the simulated SZ maps of y maps with (orange curve) and without (green curve) simulation smoothing kernel, shown in comparison with the trued 3D pressure profile (blue curve).

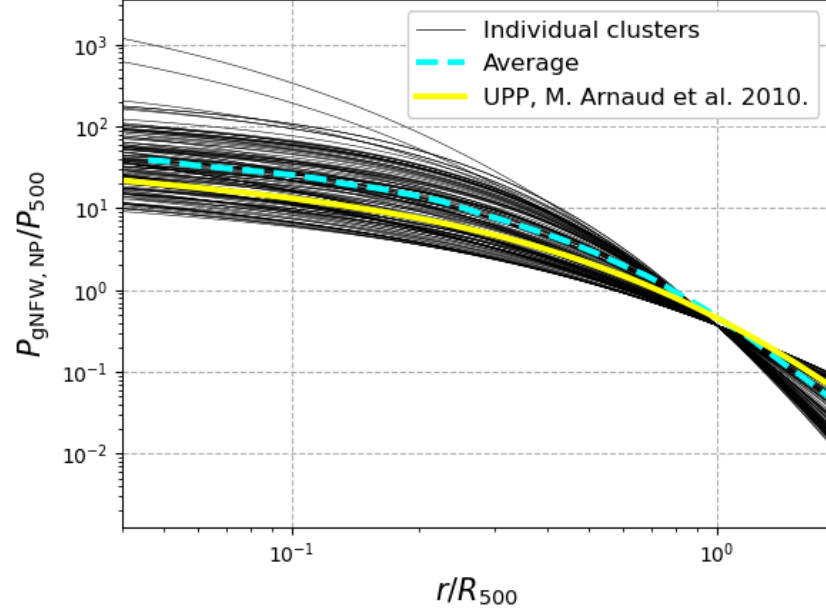


Figure 6.7 The normalised pressure profiles of our sample are shown using black lines. The mean is shown using a dashed cyan line, in comparison with the UPP from M. Arnaud et al. 2010, shown using a yellow line.

6.2.2 Mass profiles

In Section 3.1.2, we emphasized the significance of mass estimation as one of the key results of the LPSZ survey analysis, a process achieved through the integration of its data with electron density information derived from X-ray observations. We showed an example in Chapter 4. Building upon this, we perform a detailed examination and comparison of the HSE mass estimates we have computed for clusters within the TSs, and compare them to the true mass of these clusters.

Since the goal of this analysis is to test how well the methodology used in the LPSZ can recover the cluster pressure and mass profiles, when using the TSs, we note that we do not have simulated X-ray data with instrumental effects taken into account. As a substitute for the X-ray derived electron density profile $n_e(r)$, we consider the simulation gas density profile $\rho_{\text{gas}}(r)$ and use the following relation:

$$\rho_{\text{gas}}(r) = n_{\text{gas}}(r) \mu m_p \sim 1.8 n_e(r) \mu m_p, \quad (6.5)$$

where m_p is the proton mass and $\mu = 0.61$ is the mean molecular weight of proton. By definition $n_{\text{gas}} = n_e + n_p$, and $n_p = 0.8 n_e$. This gives us $n_{\text{gas}} = 1.8 n_e$, which results in the second equality in the above equation. Using the electron density profile derived from this relation and the pressure profiles in the previous section we determine the following HSE mass values, using Eq. (4.23):

1. **Theoretical HSE mass estimate** ($M_{\text{HSE,true}}$): we combine the numerically estimated derivative ($dp/dr = \Delta P/\Delta r$) of the true pressure profile P_{true} with the afore-derived electron density profile to estimate the HSE mass as it would be estimated from the 3D profiles of the simulation. This calculation is done in the same radial range as the pressure profiles in the previous section: $0.05 - 1.8 R_{500}$.
2. **HSE mass derived from reconstructed pressure profiles** (M_{HSE}): by employing the fitted pressure profiles $P_{\text{gNFW,NP}}$ and integrating these profiles with the corresponding theoretical electron density profiles, we calculated the corresponding HSE mass. This methodology closely aligns with the approach used for estimating mass in a real LPSZ cluster, barring the electron density profile estimate, which is obtained from real, projected X-ray data in the case of the LPSZ.

6.2.2.1 Results

We now compare the two mass estimates (defined above) with respect to the total mass profile from the simulation and put these results in the context of the LPSZ.

In Fig. 6.8 we show the median total mass (M_{sph}) in blue, in comparison to the medians of the mass profiles $M_{\text{HSE,true}}$ and M_{HSE} , depicted using green dotted-dashed and orange dashed lines, respectively. As expected, the HSE mass estimates are biased low in comparison to the total mass of the cluster. Additionally, the closest representative of HSE mass derived from real observations is our estimate M_{HSE} , which shows a larger mass bias than $M_{\text{HSE,true}}$, relative to the true mass. This implies that our methodology does not perfectly recover the 3D HSE mass profile.

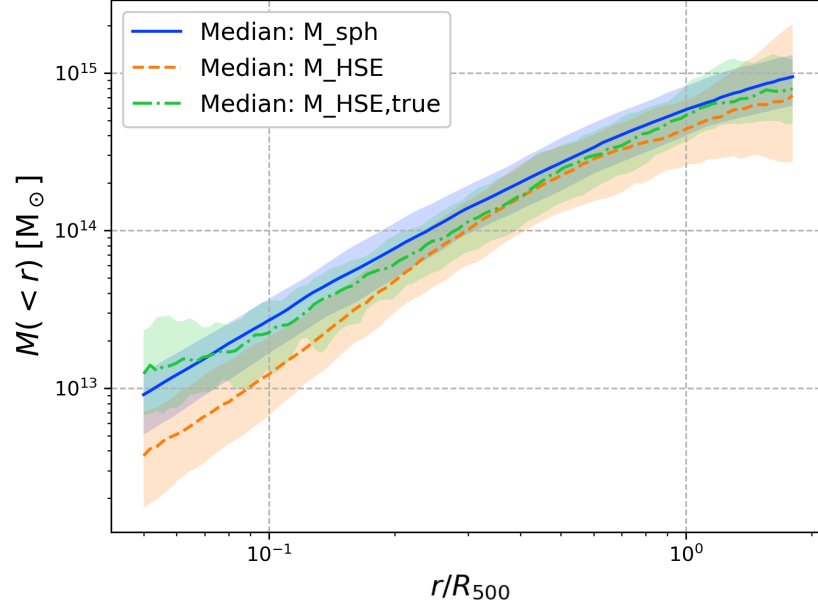


Figure 6.8 A comparison of various median mass profiles shown along with their 16th and 84th percentiles (shaded regions). The solid blue curve represents the total mass of the cluster given by the 3D mass profiles of the simulation. The green dotted-dashed and orange dashed lines represent the theoretical and the SZ map-derived HSE mass estimates, respectively.

To quantify the differences between both estimations of the HSE mass, *i.e.*, how far the HSE mass estimates from the data, we define an estimation bias as follows:

$$b_{M_{\text{HSE,est}}} = \frac{M_{\text{HSE,true}} - M_{\text{HSE}}}{M_{\text{HSE,true}}}. \quad (6.6)$$

In the left panel of Fig. 6.9, we present the median bias for the complete sample (black curve), the dotted-dashed red curve for disturbed clusters, and the dashed green curve for relaxed clusters. As expected, we obtained a result identical to that observed in Fig. 6.4 for the slope of the pressure profiles, since the HSE mass is directly proportional to the derivative of the pressure itself. Furthermore, in the right panel of Fig. 6.9, we highlight the bias in the region between $0.2 - 1.8 R_{500}$, in this case as a function of overdensity, which contains the overdensities at which mass is typically given: 2500, 500, 200. Notably, we find that the HSE mass estimation bias is lowest at $\Delta = 2000$ and reaches approximately 0.2 at $\Delta = 500$. This suggests that, at the typical density used for mass estimation in the LPSZ ($\Delta=500$), the HSE mass profile is not perfectly recovered, introducing an additional bias in the mass estimation, which must be accounted for when calibrating the $Y - M$ scaling laws.

Ultimately, cluster-based cosmological studies have in them, the bias between the recovered and the true mass, namely the hydrostatic mass bias, as a key parameter. So we finally quantify the bias of the HSE mass estimates with the true spherical mass of the cluster. We define the hydrostatic mass bias as:

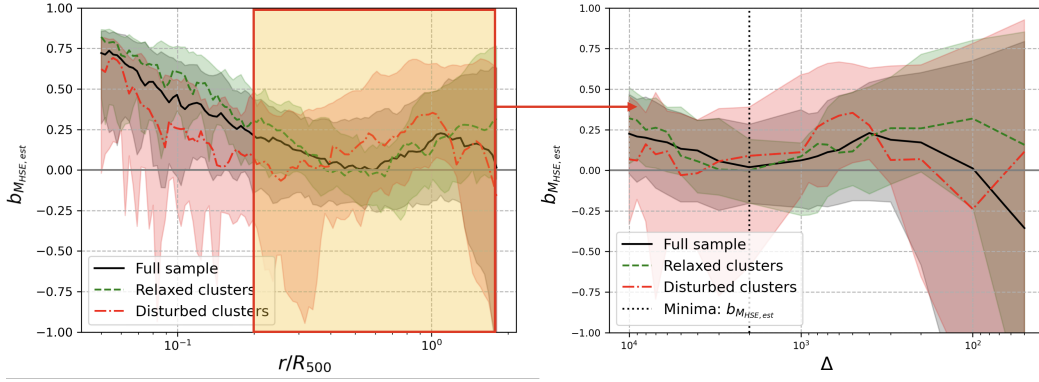


Figure 6.9 The median bias of the HSE mass estimation is depicted in the left panel as a function of radius using a black curve, dotted-dashed red curve, and dashed green curve for the complete sample, disturbed clusters, and relaxed clusters, respectively. The yellow highlighted region depicts the radial range for which the bias is below 0.25. This region is depicted as a function of overdensity in the right panel, where the dotted vertical black line represents zero estimation bias. The sampling in radius and overdensity are slightly different, resulting in slightly different features in both maps.

$$b_M = \frac{M_{\text{sph}} - M_{\text{HSE}} \text{ (or } M_{\text{HSE,true}})}{M_{\text{sph}}}. \quad (6.7)$$

Fig. 6.10 depicts the sample median of the HSE mass bias for the estimates M_{HSE} using an orange dotted line and the estimates $M_{\text{HSE,true}}$ using a green dotted-dashed line. We can see here the relative bias of the two, with the bias of M_{HSE} being higher than $M_{\text{HSE,true}}$, except at $\Delta = 2000$ where the mass bias is the same (~ 0.15) as result of corresponding zero bias in the HSE mass estimation. At the LPSZ relevant overdensity $\Delta = 500$, the HSE mass bias for M_{HSE} is 0.23 and that for $M_{\text{HSE,true}}$ is 0.1. We also show theoretically derived mass biases (similar to our $M_{\text{HSE,true}}$ values) for the complete The300 sample at $z = 0$ (Gianfagna et al. 2021) using red markers and find compatibility between our values.

To summarise the discussion in estimating the HSE mass from the simulation 3D profiles in contrast to estimating it from simulated NIKA2-like SZ maps, we present the estimation bias and HSE mass bias values for relevant overdensities, in Table 6.2.

Bias Type	Overdensity (Δ)	Bias Value
Estimation bias	500	0.20
Estimation bias	2000	0
HSE mass Bias (M_{HSE})	500	0.23
HSE mass Bias ($M_{\text{HSE,true}}$)	500	0.10
HSE mass Bias (M_{HSE})	2000	0.15
HSE mass Bias ($M_{\text{HSE,true}}$)	2000	0.15

Table 6.2 Summary of bias values related to the recovery of mass profiles. Estimation bias is define by Eq. (6.6) and HSE mass bias is defined by Eq. (6.7).

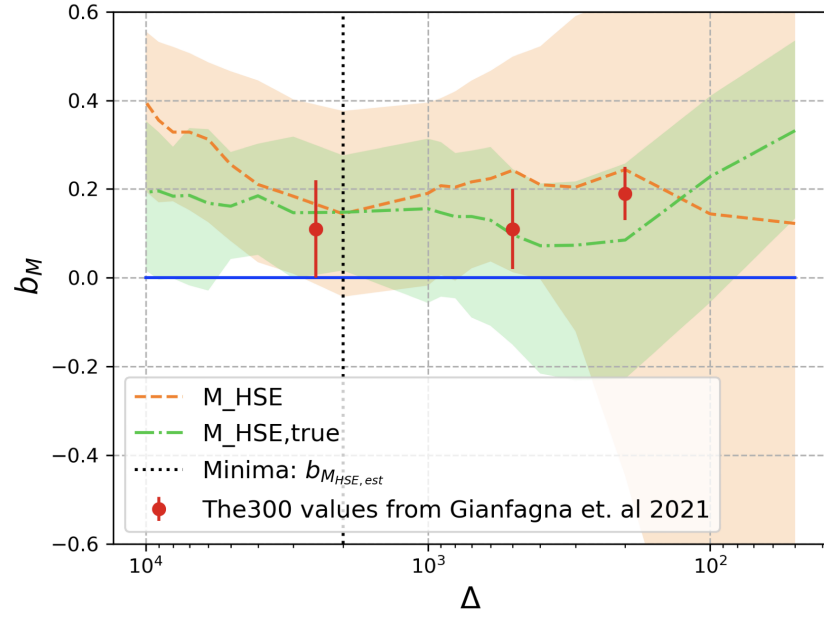


Figure 6.10 The sample median of the HSE mass bias, shown for the theoretical HSE mass using a green dotted-dashed line and for HSE mass derived from NIKA2-like maps, using an orange dashed line. Shown using red markers are the theoretically derived HSE mass bias values from Gianfagna et al. 2021, where they determine this bias for the entire The300 sample at $z = 0$. The dotted vertical black line represents the point where the estimation bias for the HSE mass is zero.

6.3 Discussions and conclusions

In this chapter, our focus has been on recovering pressure and mass profiles by fitting various models to simulated SZ maps. Moreover, we assess whether the cluster’s dynamical state has any impact on this recovery

In Section 6.1, we describe the unified sample obtained by combining the three TSs, used in this analysis, ensuring a uniform distribution of dynamical states quantified by the relaxation parameter χ . This unified sample provides statistical robustness as compared to using individual TSs.

Moving on to Section 6.2.1.1, we derived 3D pressure profiles for the clusters using three different techniques. While these estimates were consistent with each other, discrepancies emerged when comparing them to the true 3D profile. The bias analysis indicated its rapid rise towards the cluster outskirts, reaching a median value of approximately -1.5 . On the other hand, the bias in the slope of these profiles remained more moderate at 0.25 in the radial range $0.2 - 1.8 R_{500}$.

When comparing the same estimated profiles after projecting them, with the pressure from the SZ map of the clusters, we found complete agreement. We conducted investigations into why our estimates agree with simulations in the projected space but not in the 3D. One of these included testing the effect of the simulation smoothing kernel applied when projecting the cluster pressure onto a y map. We found that the impact of this kernel is minor and insufficient to account for the observed discrepancies in the 3D profiles. Ultimately, we attribute this

discrepancy to a combination of assuming spherical symmetry during de-projection and the impact of the smoothing kernel in line-of-sight integration in the simulations.

In the context of one of the primary goals of the LPSZ to derive a UPP at higher redshifts, we compared our fits with the UPP from M. Arnaud et al. 2010. The comparison of our median profile with the UPP revealed higher normalization and shallower slope in our profile, suggesting a possible redshift evolution in these parameters or differences in the way SZ and X-ray trace the ICM.

In Section 6.2.2, we investigated HSE mass estimates for clusters. Using simulated gas density profiles as a substitute for X-ray-derived electron density profiles, we compared theoretical HSE mass ($M_{\text{HSE,true}}$) with the HSE mass derived from NIKA2-like maps (M_{HSE}). Results showed an estimation bias of 0.2 at overdensity 500, while this value was zero at overdensity 2000. On the other hand, the HSE mass bias (with respect to the total 3D mass of the cluster) for both quantities was 0.15 at overdensity 2000, and at overdensity 500, the bias was 0.10 and 0.23 for $M_{\text{HSE,true}}$ and M_{HSE} , respectively.

Throughout the analysis, we assessed the estimation biases for clusters marked as most disturbed and relaxed in our sample, but we did not observe any clear indication that the bias is ruled by either of the sub-samples.

In conclusion, we find that the reconstruction of the 3D pressure and mass profiles from the SZ maps is not perfect. While the projected profiles show agreement between the simulation and our best-fits, there is an underestimation of pressure in the core ($r < 0.2 R_{500}$) and overestimation in the outskirts ($r > 0.8 R_{500}$) for the recovered 3D profile. The mass is underestimated in both of these regions. We found this estimation bias to be minimum (zero) at the overdensity 2000, and it increases to 0.2 at the overdensity 500. This additional estimation bias must be taken into account when estimating Y and M and when calibrating the $Y - M$ scaling laws for the LPSZ. These results come with the caveat that we derived them with a gNFW model and the LPSZ SNR definition used in its proposal (explained in Section 3.2.1). A change in the model and the real SNR of the LPSZ varying from its proposal values can change the position and value of the minimum estimation bias. To improve this result to be more realistic, we plan to use the real noise power spectra and transfer functions from the LPSZ data to reflect reality.

Chapter 7

Scaling relations in The300-NIKA2 twin samples

Throughout the course of this work, we have repeatedly emphasised careful considerations to be given while recovering the cluster ICM properties and consequently its mass from 2D cluster maps. In Chapter 4, we analysed the LPSZ observations of ACTJ0240 along with X-ray and optical data to infer its HSE mass at R_{500} , while emphasising the importance of accounting for PS contamination. In Chapter 5 we develop a framework to quantify the (sub-mm) PS detection efficiency, to assist mitigation of the contamination caused by them in the cluster signal, which may result in biased estimates of the ICM properties. Finally, in Chapter 6, we use simulations to test how well 3D radial pressure and mass profile are recovered from their SZ map and how the cluster dynamical state impacts this recovery. All these analyses aimed wholly or partially, towards refining the cluster mass estimates and understanding the systematic effects involved in the process. All this is done because the cluster mass is a key parameter for the calibration of observable-mass scaling laws that aid cluster-based cosmological studies. In this direction, as we have mentioned before, one of the main objectives of the LPSZ is to quantify the scaling relation between the SZ observable and the mass of galaxy clusters. This chapter addresses the estimation of theoretical $Y - M$ scaling laws at different overdensities, by utilising the information we have deduced in the previous chapters, in the context of the NIKA2 LPSZ, by deploying The300-NIKA2 TSs generated in Section 3.2.1.

The observable-mass scaling laws are limited by their reliance on a single projection available for the observables involved. This often necessitates assuming spherical symmetry for de-projection into 3D quantities, introducing increased variability in mass estimates (for an example from The300 data, see Muñoz-Echeverría et al. 2023a). Furthermore, these mass estimates are commonly determined at a fixed radius corresponding to overdensities $\Delta = 2500$, $\Delta = 500$ or $\Delta = 200$ (see, for example, Lovisari, Reiprich, and Schellenberger 2015; Bulbul et al. 2019; Planck Collaboration et al. 2016e). We have seen that state-of-the-art N-body hydrodynamical simulations, such as those discussed in Cui et al. 2018; Sembolini et al. 2013, have enhanced our theoretical comprehension of the observation-related effects that limit the calibration of the true underlying scaling law of a cluster population. Hence, we use The300-NIKA2 TSs to explore the variability induced on mass (M)

and integrated SZ Compton parameter (Y) estimates due to projection. Taking this scatter into account, we aim to establish scaling laws ($Y - M$) at different overdensities (Δ) and possibly identify the optimal overdensity at which the scatter resulting from projection effects is minimized. Note that since the scaling law must truly represent the LPSZ, in this chapter, unlike Chapter. 6, we perform our analyses separately for the three TSs (described in Section 3.2.1), instead of clubbing them into one super sample. The details of the analysis are provided in the following sections.

7.1 Inference of integrated quantities

The determination of the $Y - M$ scaling relation requires a measure of the central value and related uncertainties, within a given radius, of the integrated Compton parameter and the mass of a cluster. We define several estimates of both quantities to determine a variety of scaling laws and compare them. A short descriptive summary of the parameters used or estimated in this chapter is provided in Table 7.1 and the estimation process is described in the sections below.

7.1.1 Integrated Compton parameter

To allow the calibration of a scaling-law $Y - M$, the first ingredient we need is an estimate of the integrated Compton parameter Y . First, we define the radial apertures at which we determine these values. A range of radii R_Δ is used, corresponding to overdensity Δ , ranging between 100 and 1000. The cluster 3D radial mass profile from simulations is used to calculate the R_Δ values, using Eq. (2.29), described in Section 2.1.3.1. While making these calculations, consistently with The300 simulation, we adopt the cosmology constrained in Planck Collaboration et al. 2016b. Once the radii are determined, we use the simulation y maps generated for 29 random projections (with respect to the inertial axes in the cluster simulation) and the pressure profiles $P_{\text{gNFW,NP}}$ estimated in Chapter 6, to calculate the Y value. The size and the integration depth of the y maps used for this analysis are $4 R_{200}$ each, where the size is taken to avoid edge effects, as explained in Chapter 6. We essentially determine two estimates of Y , as follows:

1. **Theoretical cylindrical integrated Compton parameter (Y_{cyl}):** it is the cylindrical Y within a given aperture R_Δ , estimated by simply integrating the y signal of the simulated map within a given area:

$$Y_{\text{cyl}} = \sum_{i=1}^{R_\Delta} y_i \, dA, \quad (7.1)$$

where y_i is the value of y in the pixel i of the map, which satisfies $r < R_\Delta$ and dA is the area of the pixel.

2. **Spherical integrated Compton parameter (Y_{SZ}):** refers to the Y value inferred from the pressure profiles estimated from the NIKA2-like images of

Variable	Description
R_{Δ}	Radius at a given spherical overdensity derived from the radial true 3D mass profiles
Y_{cyl}	Cylindrical Y obtained from aperture-integration of the projected y maps of the simulated TSs
Y_{SZ}	Spherical Y obtained by integration of the pressure profiles $P_{\text{gNFW,NP}}(r)$ (see Section 4.2 for description) inferred from the NIKA2-like maps
M_{sph}	Spherical mass enclosed within a given radius, obtained via the simulation 3D radial mass profiles
$M_{\text{HSE,true}}$	Spherical mass obtained using the 3D radial pressure and gas density profiles from the simulations, under the assumption of HSE
M_{cyl}	Cylindrical mass enclosed within a cylinder of a given radius, obtained by the aperture integration of The300 total mass surface density maps
$M_{\text{sph,NFW}}$	The de-projected spherical mass enclosed within a given radius, obtained by fitting projected NFW mass density profiles to the projected mass density maps from the simulation
M_{HSE}	Spherical mass enclosed within a given radius, estimated under the HSE assumption, using the pressure profiles $P_{\text{gNFW,NP}}(r)$ inferred from the NIKA2-like maps and the theoretical and electron density profiles from simulations

Table 7.1 A summary of the quantities used or estimated in this chapter, along with their descriptions. The various Y and M estimates are used to calculate the LPSZ $Y - M$ scaling law using the three TSs.

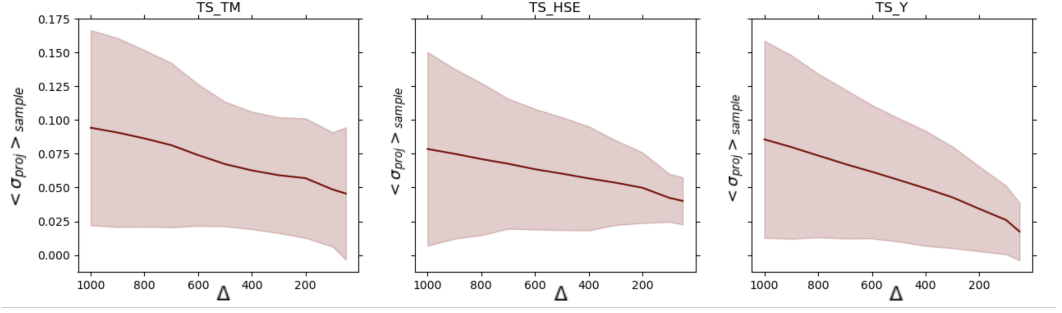


Figure 7.1 The projection-induced scatter on the logarithmic value of the cylindrical integrated Compton parameter, depicted for all three TSs. The shaded areas represent 1σ of the scatter distribution for all 45 clusters in each sample.

the TSs. We used the pressure profiles $P_{\text{gNFW,NP}}$ estimated in Chapter 6 to calculate the integrated Compton parameter

$$Y_{\text{SZ}} = \frac{4\pi\sigma_{\text{T}}}{m_e c^2} \int_0^{R_\Delta} r^2 P_{\text{gNFW,NP}}(r) dr, \quad (7.2)$$

where σ_{T} , m_e , and c hold their usual meanings and r is the radius of the pressure profile.

While Y_{SZ} only has one estimate for each cluster, the estimate of Y_{cyl} can change for each of the 29 random projections of the Compton parameter maps. We use these values for different projections to assess the variation induced on Y due to projection, at different apertures. We measure the scatter in the logarithmic values of Y_{cyl} along the 29 LoS for each cluster. The average of this scatter value for the 45 clusters in each sample is then utilized as the scatter for the entire sample. The plots in Fig. 7.1 depict the average scatter induced by projection on the common logarithmic values of Y_{cyl} as a function of overdensity. The scatter diminishes as the overdensity decreases (or the distance from the cluster centre increases), emphasizing the convergence of the integrated quantity at greater distances from the cluster centre, regardless of the viewing direction. This suggests, at least theoretically, that there is no special or preferred overdensity at which the scatter on Y induced by the projections minimises.

7.1.1.1 Cluster dynamical state and projection-induced scatter in Y

It is intuitive to expect that when viewed from different LoS, *i.e.*, when considering different cluster projections, a relaxed, spherically symmetric cluster would appear the same while a disturbed cluster with spherical asymmetry would look different. This could imply that the observable Y might also show this behaviour.

To verify the impact of projection, we use the dynamical state indicator called relaxation parameter (χ), introduced in Chapter 6 (Eq. 6.1). We look for correlation between the scatter in Y_{cyl} ($\sigma_{\text{proj},Y}$) and χ at $\Delta = 500$. Since lower values of χ imply more disturbed clusters, we would expect a negative correlation between the two. We show the distribution of clusters, in each TS, in the $\sigma_{\text{proj},Y} - \chi$ space, in Fig.

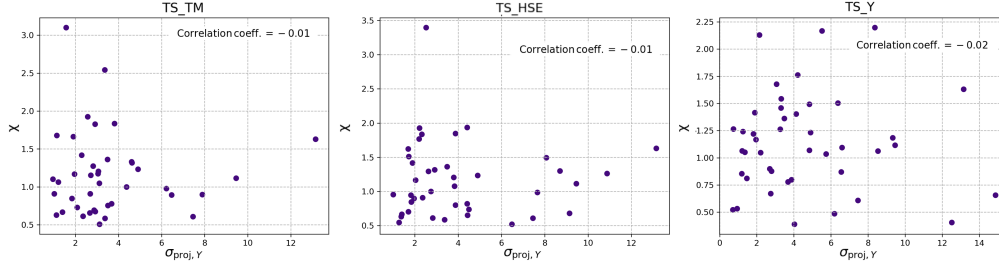


Figure 7.2 The distribution of the TS clusters in the $\sigma_{\text{proj},Y} - \chi$ space, at $\Delta = 500$. The correlation coefficient between the two parameters, for each TS, is mentioned in their respective plots.

7.2. Contrary to expectation, the clusters are scattered over this space, with no correlation between the two parameters. We calculated the correlation coefficients to be -0.01 , -0.01 , and -0.02 for TS_{TM} , TS_{HSE} , and TS_Y , respectively. To assess whether the integration of the y signal contributes to the observed negligible correlation, we additionally examine the correlation between the scatter in y and χ , where y is simply the average value of the Compton parameter at overdensity 500, estimated from the y map. As expected, a significant correlation is detected, with correlation coefficients estimated at -0.66 , -0.65 , and -0.65 for TS_{TM} , TS_{HSE} , and TS_Y , respectively. This tells us that integrating the signal wipes out the differences in different cluster projections, at least for $\Delta = 500$.

7.1.2 Mass estimation

The second ingredient towards the calibration of a cluster $Y - M$ scaling law is the estimates of cluster mass. In this case, we use the spherical mass from the simulation 3D radial mass profile as the baseline reference to compare our estimates. This value of mass, referred to as M_{sph} throughout the analysis, is calculated at the same radii R_{Δ} used to estimate the Y values in the previous section. Throughout the analysis, the radii R_{Δ} of these theoretical mass values, are used as reference points for estimating and comparing masses from other estimates. For instance, when we compare the different mass values at $\Delta = 200$, we are referring to mass inferred at the theoretical value of R_{200} , for all the mass profiles in question. We reiterate that since we aim to quantify the effect of projection on integrated quantities, we use the same 29 projections as the y maps, of the simulated cluster maps available, to infer the cluster mass from the observable. The only exception is the case of estimating hydrostatic mass from NIKA2-like images, where due to high computational time, we limit our analyses to a single projection, mentioned in Chapter 6. Both, the size and the integration depth of the projected mass density maps used in this section, are once again, $4 R_{200}$ each. To infer the cluster mass we use the following four methods:

1. **Theoretical cylindrical mass (M_{cyl}):** refers to the mass enclosed within a cylinder of a given radius. To estimate this value, we integrate the total projected mass density maps, from the simulation, within the specified

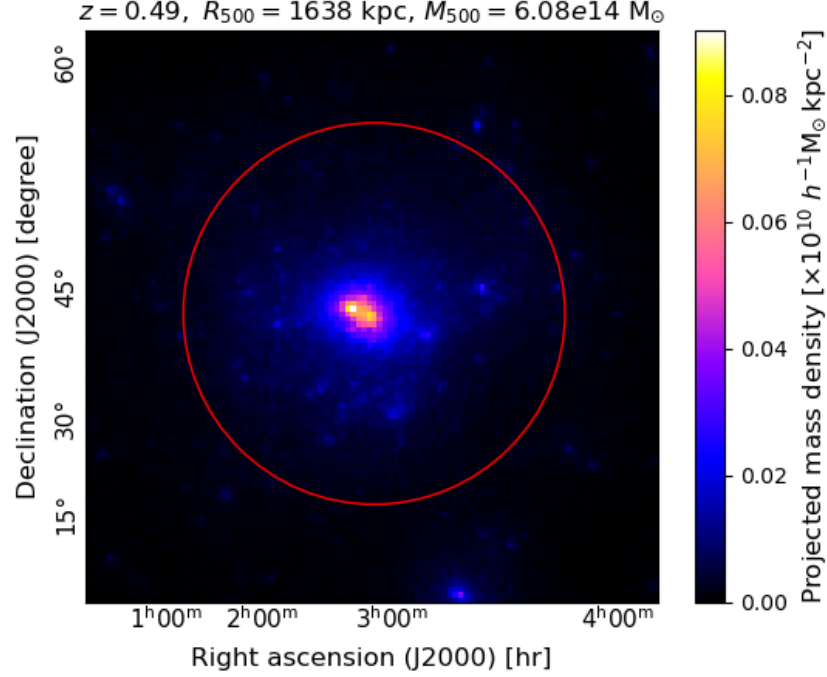


Figure 7.3 Projected mass density map of one projection out of the 29 available, for a cluster in The300-NIKA2 TSs. The red circle represents the R_{500} inferred from the 3D radial mass profile of the cluster.

apertures:

$$M_{\text{cyl}} = \sum_{i=1}^{R_{\Delta}} \Sigma_i dA, \quad (7.3)$$

where Σ_i is the value of the projected mass density in pixel i and only pixels of the map where $r < R_{\Delta}$ are considered, and dA is the area of each pixel. We show an example of the projected mass map of one of the TS clusters, in Fig. 7.3. This represents one of the 29 projections of the projected mass map available to us.

By the geometrical design, we know that the volume contained within a sphere of a given radius is less than that of the cylinder with the same radius. This implies that the cylindrical masses within a given radius must be higher than the spherical ones. To quantify this, we estimate the ratio of M_{cyl} and M_{sph} for each of the TS clusters at a given Δ and then compute the average for all 29 LoS of each cluster. For the entire TS, the ratio is estimated by taking the average value of that ratio of all clusters and the error on this average is given by $\sigma_{\text{tot}} = \sqrt{\sum \sigma_i^2 / n}$, where i represents each cluster and n is the number of clusters (45) in each twin sample. This average ratio is shown in Fig. 7.4. As expected, the cylindrical masses are higher than the spherical ones and this ratio drops with decreasing overdensity (increasing distance for cluster centre), since the farther out one goes from the centre, the lesser is the difference between the volume a sphere of radius R_{Δ} and a cylinder of radius R_{Δ} and

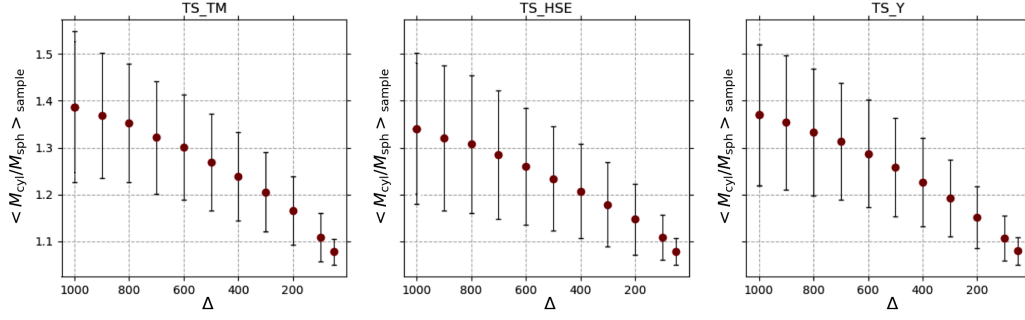


Figure 7.4 The average ratio of the theoretical cylindrical to spherical mass of the cluster as a function of overdensity, for all three TSs. The error on each point depicts the combined deviation of the complete sample.

height equal to the integration depth ($4 R_{200}$) of our projected mass density maps. This behaviour is shown consistently in all three samples.

2. **De-projected spherical mass** ($M_{\text{sph,NFW}}$): these are the spherical masses estimated by fitting the data from the projected mass density maps to a projected mass density model and de-projecting it. For this purpose, the surface mass density profiles $\Sigma(r)$ are estimated using mean values within given annuli from the projected mass maps. These profiles, with the dispersion in each annulus as the error, are fitted with the projected Navarro–Frenk–White (NFW) mass profiles (Łokas and Mamon 2001):

$$\Sigma(x) = \begin{cases} \frac{2\rho_s r_s}{x^2-1} \left(1 - \frac{2}{\sqrt{x^2-1}} \arctan \sqrt{\frac{x-1}{x+1}}\right) & (x > 1) \\ \frac{2\rho_s r_s}{x^2-1} \left(1 - \frac{2}{\sqrt{1-x^2}} \operatorname{arctanh} \sqrt{\frac{1-x}{1+x}}\right) & (x < 1) \\ \frac{2\rho_s r_s}{3} & (x = 1) \end{cases} \quad (7.4)$$

using the **COLOSSUS** software (Diemer 2018). Here, ρ_s and r_s are model parameters. The parameter $\rho_s = \delta_c \rho_{\text{crit}}$, is related to the concentration parameter c , via the relation

$$\delta_c = \frac{200}{3} \frac{c_{200}^3}{\ln(1 + c_{200}) - c_{200}/(1 + c_{200})}. \quad (7.5)$$

On the other hand r_s is the characteristic cluster radius and is related to the independent model variable x , by $x = r/r_s$. We show an example of the projected NFW fits to data, for all projections of a random TS cluster in Fig. C.1, with its details mentioned in Appendix C. Then we use the best-fit parameters within the classical 3D NFW framework to obtain the de-projected mass profile (Navarro, Frenk, and S. D. M. White 1997):

$$M_{\text{sph,NFW}}(< r) = 4\pi\rho_s r_s^3 \left[\frac{1}{1 + r/r_s} + \ln \left(1 + \frac{r}{r_s} \right) - 1 \right]. \quad (7.6)$$

The de-projected mass profiles corresponding to the best-fit projected density profiles in Fig. C.1, are shown in Fig. C.2, which shows that the NFW model does not complement the shape of the true 3D mass profiles. This behaviour

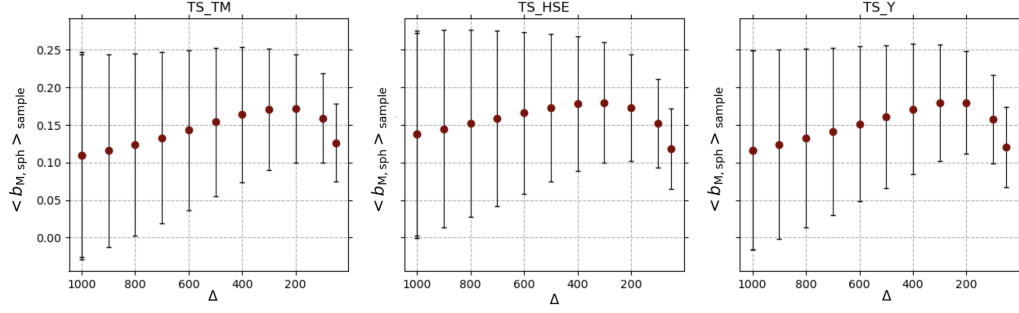


Figure 7.5 The average mass bias of the de-projected mass inferred by fitting a projected NFW profile to profiles from projected mass maps, with respect to the true spherical masses of the cluster. The bias is shown as a function of overdensity for all three TSs.

can be highlighted by visualising the mass bias between the true spherical mass and this de-projected spherical mass obtained by fitting a projected NFW model

$$b_{M,\text{sph}} = \frac{M_{\text{sph}} - M_{\text{sph,NFW}}}{M_{\text{sph}}}, \quad (7.7)$$

as a function of overdensity (or radius). The bias for the complete sample, at a given radius, is estimated by taking the average of the bias of each cluster, which itself is the mean value for all 29 projections. Once again the error on the sample is given by $\sigma_{\text{tot}} = \sqrt{\sum \sigma_i^2 / n}$, as described in the previous point. We see, in Fig. 7.5, the average bias of the de-projected spherical mass with respect to the true spherical mass. We observe the same qualitative behaviour for all three TS, with an increasing value of the bias till $\Delta = 200$ and then going through a drop. The average value of this bias is $\sim 10\%$, a typical mass bias value for mass estimated using projected mass observables (gravitational lensing) (see, *e.g.*, M. R. Becker and Kravtsov 2011).

3. **Theoretical HSE mass ($M_{\text{HSE,true}}$):** this is the theoretical estimation of the HSE mass of the cluster. We use the HSE mass (Eq. 4.23) and the 3D gas density and pressure profiles from the simulations to estimate this mass at different radii. This estimate is borrowed from Chapter 6. Refer to Section 6.2.2 for details.
4. **The HSE mass derived from the NIKA2-like images of the TSs (M_{HSE}):** refers to the HSE mass of the cluster estimated using the NIKA2-like SZ image simulated for the TSs and the theoretical density profile from the simulation. Once again we use the same estimates as derived in Section 6.2.2. Due to the high computational time required, we use a single, randomly oriented projection of the NIKA2-like image to estimate this mass.

Like with Y values, we want to measure the scatter that projection induces on the M value. The variation in mass, along the different LoS is gauged by the normalized percentile range (NPR), defined as:

$$\text{NPR} = \frac{\text{LoSP}_{84} - \text{LoSP}_{16}}{\text{LoS}_{\text{median}}}, \quad (7.8)$$

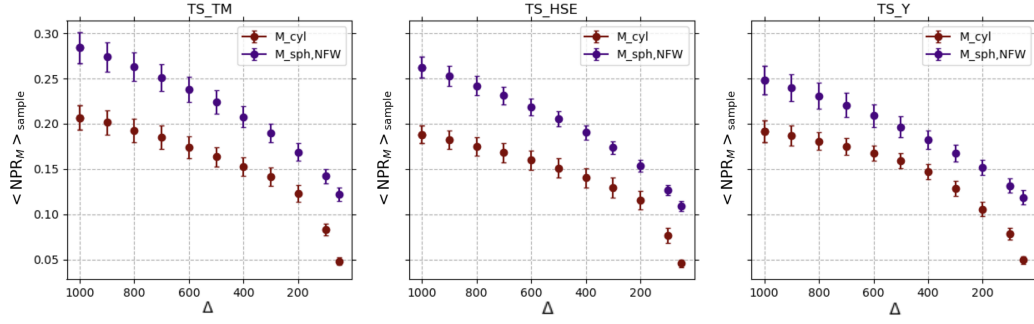


Figure 7.6 The projection-induced scatter on cylindrical mass and de-projected spherical mass, shown using maroon and indigo circles. the error represents the deviation in the NPR values of all 45 clusters in each sample.

where P84, P16, and median are the 84th percentile, 16th percentile, and median of the mass distribution along different lines of sight. Projection-induced scatter (NPR) for individual clusters is evaluated at various apertures and then averaged to determine the NPR of the entire sample. The plots in Fig. 7.6 illustrate the average NPR for each TS across different apertures. Similar to the behaviour observed in the integrated Compton parameter, the projection-induced scatter diminishes as the radial distance from the cluster centre increases. Additionally, it's worth noting that the scatter in the cylindrical mass, deduced from the projected map, is less than that observed in the de-projected spherical mass values.

7.2 Determining the Y-M scaling law at different overdensities

The preceding section provides us with the key ingredients required to determine a $Y - M$ scaling law. In this section, we understand the origin of the scaling law between these two quantities and describe how we use them in the context of LPSZ.

7.2.1 The origin of the Y-M scaling law

In terms of an observational study, the integrated Compton parameter Y was introduced as an observable strongly correlated with the cluster mass by Kravtsov, Vikhlinin, and Nagai 2006. Indeed, under the assumption of self-similarity (Kaiser 1991), it is possible to analytically relate the integrated Compton parameter to the mass of a cluster. Considering a sphere containing a perfect gas with density ρ , at temperature T , the HSE Eq.(4.23) can also be written as:

$$\frac{r^2}{\rho} \frac{d\rho}{dr} = -\frac{4\pi Gm}{k_B T} \int_0^R r^2 \rho(r) dr, \quad (7.9)$$

where m is the mass of the particles constituting the gas. The spatial derivative of this equation is then given by

$$\frac{d}{dr} \left(r^2 \frac{d \ln \rho}{dr} \right) = -\frac{4\pi Gm}{k_B T} r^2 \rho(r), \quad (7.10)$$

which is a differential equation with a power-law solution of the form $\rho(r) = \alpha r^{-\beta}$, where $\beta = 2$ and $\alpha = k_B T / (2\pi G m)$. This gives us:

$$\rho(r) = \frac{k_B T}{2\pi G m r^2} \quad (7.11)$$

Plugging this functional form of density in the integral equation relating mass and density, we get

$$M(< r) = 4\pi \int_0^r r^2 \rho(r) dr = \frac{2k_B T r}{G m}. \quad (7.12)$$

This implies that the mass within a radius r is proportional to that radius, demonstrating the self-similarity of galaxy clusters.

The characteristic radius R_Δ , as previously mentioned, is defined using Eq. (2.29). Using this in combination with the definition of critical density of the Universe (Eq. 2.5), and the above equation, leads to the expression

$$k_B T = m \Delta^{1/3} \left[\frac{G M_\Delta H(z)}{4} \right]^{2/3}. \quad (7.13)$$

Next, we estimate the analytical expression for the cluster observable Y_Δ . It has previously been described using Eq. (7.2). The electron pressure profile in this equation can be re-written using the equation of state for the perfect gas:

$$P_e(r) = n_e(r) k_B T_e = \mu m_p n_e(r) \Delta^{1/3} \left[\frac{G M_\Delta H(z)}{4} \right]^{2/3}, \quad (7.14)$$

where we use Eq. (7.13) to get the second equality. The parameter μ is the mean molecular weight of the gas and m_p is the mass of the proton and the two are related as $m = \mu m_p$. This form of the pressure profile allows the expression of the integrated Compton parameter in the following way (using Eq. 7.2):

$$Y_\Delta = 4\pi \frac{\sigma_T}{m_e c^2} \mu m_p \Delta^{1/3} \left[\frac{G M_\Delta H(z)}{4} \right]^{2/3} \int_0^{R_\Delta} n_e(r) r^2 dr. \quad (7.15)$$

To connect this with the cluster mass, we introduce the cluster mass gas fraction, $f \equiv M_\Delta^{gas} / M_\Delta$, where the gas mass is given by

$$M_\Delta^{gas} = 4\pi \mu_g m_p \int_0^{R_\Delta} n_e(r) r^2 dr, \quad (7.16)$$

where μ_g is the mean molecular weight of the gas.

Finally, using the gas mass and the cluster gas mass fraction we can re-write Eq. (7.15):

$$Y_\Delta = \frac{\sigma_T}{m_e c^2} \left(\frac{G}{4} \right)^{2/3} f \frac{\mu}{\mu_g} \Delta^{1/3} H^{2/3}(z) M_\Delta^{5/3}. \quad (7.17)$$

This equation gives us the analytics scaling relation between the cluster observable Y and its mass M under a self-similar evolution scheme, for an isothermal ICM. It takes the form of a power law where Y is proportional to $M^{5/3}$ and the proportionality coefficient is given by Δ . In reality, or in the case of a realistically simulated cluster,

we might encounter deviations from self-similarity. To take this into account, we re-write Eq. (7.17) to accommodate clusters deviating from isothermal and self-similar evolution, by allowing the slope and normalisation of the power-law to be free parameters as in this equation:

$$E(z)^{-2/3} \left[\frac{D_A^2 Y_\Delta}{10^{-4} \text{ Mpc}^2} \right] = A \left[\frac{M_\Delta}{3 \times 10^{14} \text{ M}_\odot} \right]^B. \quad (7.18)$$

This is the form of the $Y - M$ scaling law used in Planck Collaboration et al. 2014. Later, we will describe how we use this equation to infer scaling laws using this functional form as the model.

7.2.2 Intrinsic scatter in the scaling law

The aforementioned derivation of the scaling law gives us a perfect power law scaling relation between Y and M . In reality, the mass-observable relation does not perfectly follow a power-law. There are physical processes that might alter the cluster thermal energy (and therefore, Y), without resulting in a change in the cluster mass. Thus, Eq. (7.17) is only the statistical trend and not a relationship strictly followed by all galaxy clusters. This inherent difference in the observable-mass relation of each cluster based on its own structure and properties is referred to as the intrinsic scatter around the relation.

It is critical to be able to determine this intrinsic scatter because it is crucial in the cosmological exploitation of a sample of galaxy clusters. A highly scattered mass-observable relation indicates an observable that is weakly correlated with mass. The mass calibration of clusters is then imprecise, and constraints on cosmological parameters, are consequently weak. As a result, the value of intrinsic scatter can be interpreted as a measure of the quality of an observable as a proxy for mass. Thus, for studies of real clusters, the value of intrinsic scatter is a parameter of interest in fitting a scaling relation, and not just the slope and normalisation of the power law.

The intrinsic scatter, however, is not a trivial quantity to estimate. It cannot be obtained simply by generalizing a χ^2 estimator. To understand why, consider the example of fitting a set of points x_i, y_i with uncertainties $\sigma_{y,i}$, where $i \in [1...N]$ with a model of a straight line, given by $f(x) = \alpha + \beta x$. The χ^2 estimation tells us that the values of the parameters α and β , that make up a line closest to the data can be estimated by minimizing:

$$\chi^2 = \frac{1}{N} \sum_i \frac{(y_i - (\alpha + \beta x_i))^2}{\sigma_{y,i}^2} \quad (7.19)$$

To account for intrinsic scatter around the relation, we can say that the uncertainty in y_i , indeed, is a combination of the intrinsic scatter and the actual uncertainty on the value, $\sigma'_{y,i}$:

$$\sigma_{y,i}^2 = \sigma_{y,i}'^2 + \sigma_{\text{int.}}^2. \quad (7.20)$$

Although this consideration will account for the intrinsic scatter, we still cannot untangle the intrinsic scatter from the observed uncertainty on y_i because, it is the combined uncertainty that is used to minimise the χ^2 in Eq. (7.19). There is a

way to deal with this intrinsic scatter by modelling the scaling laws as probabilistic distributions instead of strict relations, which we describe later in this section.

7.2.3 Modeling the scaling law for The300-NIKA2 TSs

Since there is an inherent variability in the $Y - M$ relation due to the intrinsic scatter we discussed in Section 7.2.2, we adopt probabilistic modelling of the scaling relation that considers the intricacies involved in this relation. We follow the work by Sereno 2016, which provides a probabilistic framework for studying linear relations in the context of astronomy. Particularly, we focus on the general framework of an errors-in-variable model (see Dellaportas and Stephens 1995 and Chapter 4.3 of Feigelson and Babu 2012). This model is based on a hierarchical Bayesian approach to linear regression, where the model is divided into several sub-models, each characterized by its own probability distribution.

In the statistical literature on linear regressions mentioned above, a linear relation evolving with redshift is given by:

$$Y = \alpha_{Y|Z} + \beta_{Y|Z}Z + \gamma T(z) + \delta T(z)Z, \quad (7.21)$$

where $T(z) = \log_{10} E(z)$, with $E(z)$ is defined as in Eq. 2.10, Z is called the latent or independent variable, while Y is called the response variable. Please take note not to confuse the integrated Compton parameter with the variable Y used in the description of this statistical framework. The parameters $\alpha_{Y|Z}$, and $\beta_{Y|Z}$ are the intercept and slope of the relation, respectively, and γ and δ parameterize the redshift evolution of the normalization and slope of the relation.

Putting this general equation in the context of the $Y - M$ scaling law in Eq. (7.18), which we use as the model to determine the mass-observable relation: Y is the logarithmic value of the observable, and Z is the logarithm of the mass. More precisely:

$$Y \equiv \log_{10} \left(\frac{Y_{500}}{10^{-4} \text{ Mpc}^2} \right); \quad Z \equiv \log_{10} \left(\frac{M_{500}}{3 \times 10^{14} M_{\odot}} \right). \quad (7.22)$$

The redshift evolution of the normalisation, then becomes a fixed value $\gamma = 2/3$, for our purpose. Since there is no assumed redshift evolution of the slope in Eq. (7.18), we have $\delta = 0$.

There are several features of the data and the model that make this fitting of the linear form to data, complex. These features constitute the sub-models (that we previously mentioned) of the hierarchical Bayesian modelling. We briefly describe them below:

1. Intrinsic scatter: it is possible to consider the non-deterministic nature of the mass-observable relation by modelling it not as a strict relationship but as a probability distribution. One can consider a Gaussian distribution:

$$P(Y|Z) = \mathcal{N}(\alpha_{Y|Z} + \beta_{Y|Z}Z, \sigma_{Y|Z}^2), \quad (7.23)$$

where $\mathcal{N}(\mu, \nu)$ is the normal distribution with mean μ and variance ν . Here, $\sigma_{Y|Z}$ is the intrinsic scatter of the scaling relation, encapsulating the variability of observable values Y that can be associated with a mass value Z . Eq. (7.23) serves as a sub-model of the hierarchical model, for the intrinsic scatter.

2. Measurement uncertainties: in the study of mass-observable scaling relations, the nature of the data introduces complications in the fitting process since both, the measured observable and the mass values have associated uncertainties. The errors-in-variable model accounts for measurement uncertainties on both axes of the scaling relation and their potential correlation by modelling each data point as a multivariate probability distribution. For a galaxy cluster i , this can be expressed as

$$P(x_i, y_i | X_i, Y_i) = \mathcal{N}_{2D}(\{X_i, Y_i\}, V_i), \quad (7.24)$$

where x_i and y_i are the measured values of the mass estimate and observable, with X_i and Y_i representing the true values of these quantities. The parameter V_i is the covariance matrix of uncertainties on x_i and y_i . Thus, in this scaling relationship model, the actual values of the mass and observable estimators are nuisance parameters of the model. This probability distribution for each data point i , is another sub-model for the hierarchical model. In our case, for simplification, we assume no correlation between the uncertainties of the mass and the observable. For a more thorough evaluation, this correlation matrix can be estimated from the posterior distribution of the integrated quantities, as mentioned in Section 4.4.1.

3. Mass estimators: no mass estimator is perfect. While the hydrostatic mass is a biased but less scattered estimator; conversely, mass estimates through gravitational lensing are less biased but more scattered (see, *e.g.*, Sommer et al. 2022; Grandis et al. 2021). A review of galaxy cluster mass estimators, discussing their accuracy and intrinsic precision, can be found in Pratt et al. 2019. It is imperative to account for the biases and dispersion inherent to the mass estimators when determining an observable-mass scaling relation since a scaling relation calibrated with a biased mass estimator will lead to a biased cosmological analysis. On the other hand, a dispersed mass estimator induces a bias on the slope of the scaling relation, an effect known as Eddington bias (Eddington 1913). Once again, to account for the imperfections of the mass estimator used, the mass estimator X can be defined, which is related to the true cluster mass Z via a probability distribution:

$$P(X|Z) = \mathcal{N}(\alpha_{X|Z} + \beta_{X|Z}Z, \sigma_{X|Z}^2) \quad (7.25)$$

Here, $\alpha_{X|Z}$ is the bias of the mass estimator, $\beta_{X|Z}$ quantifies the evolution of this bias with the cluster mass, and $\sigma_{X|Z}$ is the dispersion of the estimator. In the context of this work, $\alpha_{X|Z}$ represents the hydrostatic mass bias b_M when dealing with HSE mass estimates and is fixed to the values we determine in Section 6.2.2

This list provides us with a description of the probabilistic modelling of the scaling relation adopted in this work. The ultimate goal of this modelling is to obtain the probability distribution of the parameters of interest for the scaling relation conditioned on the data, $P(\theta|D)$. Just like for the pressure profiles in the previous

chapters, this distribution can be derived from Bayes' theorem:

$$P(\theta|D) = \frac{P(D|\theta) \cdot P(\theta)}{P(D)}, \quad (7.26)$$

where θ is a vector representing the analysis parameters, D represents the data, i.e. the values of (x_i, y_i) and their covariance V_i , and $P(D|\theta)$ represents the likelihood function comparing the model to the data. In this case, the likelihood is a combination of the sub-models given by probability distributions 7.23, 7.24, and 7.25. The terms $P(\theta)$ represents the prior distribution of parameters, and $P(D)$ is a normalization constant.

In Chapter 4, we showed that a MCMC analysis allows obtaining a sample from the posterior probability distribution $P(\theta|D)$ in the parameter space using a simple algorithm like the Metropolis-Hastings algorithm. For fitting a scaling relation, as described in the second point of the list above, the use of errors-in-variable modelling involves treating each quantity X_i and Y_i as nuisance parameters. Thus, for a sample of N clusters, the analysis involves $2N$ nuisance parameters, in addition to those of the model. It then becomes necessary to employ a different sampling technique that performs well in a high-dimensional space. To address this need, many software dedicated to scaling relation fitting employ Gibbs sampling (see Chapter 11 of Gelman et al. 2013). The main difference from the Metropolis-Hastings algorithm is that the movement in the parameter space is not done for all parameters simultaneously but by groups of parameters. A parameter vector θ with N dimensions can be divided into d groups of dimension n . The iterative procedure of generating a Markov chain is then applied. The peculiarity of Gibbs sampling is that, at each iteration, the sampler iterates over the d groups to propose a movement in the parameter space group by group, rather than for all parameters simultaneously. Moreover, the movement of a group of parameters is conditioned by that of the other parameters to account for correlations between parameters from different groups. In the case of the hierarchical Bayesian model used here, parameter groups are defined based on the sub-model to which they belong. For instance, one group consists of the parameters of interest for the scaling relation (Equation 7.24); and so on. Marginalizing over the nuisance parameters allows obtaining the probability distribution of the parameters of interest, given the data.

Clearly, the statistical model of the scaling relation is complex. Therefore, we use the python wrapper¹ of an existing library called LIRA (Linear Regression in Astronomy, Sereno 2016). This software allows adjusting the probabilistic model detailed in this section using Gibbs sampling. Using LIRA and the estimates described in Section 7.1, we calibrate the following scaling laws:

1. $Y_{\text{cyl}} - M_{\text{cyl}}$: where the data uncertainties correspond to the scatter induced by projection.
2. $Y_{\text{cyl}} - M_{\text{sph,NFW}}$: here also, like the $Y_{\text{cyl}} - M_{\text{cyl}}$ scaling relation, uncertainties correspond to the projection-induced scatter.

¹<https://github.com/fkeruzore/pylira>

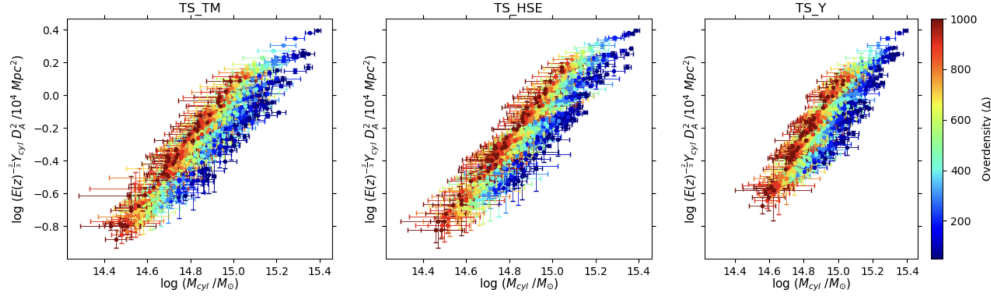


Figure 7.7 The $Y_{\text{cyl}} - M_{\text{cyl}} - \Delta$ distribution for all the TSs. These data points are used to fit the scaling law $Y_{\text{cyl}} - M_{\text{cyl}}$. The errors depicted here are the projection-induced scatters on the estimated log values of Y and M . The different colours represent different overdensities.

3. $Y_{\text{SZ}} - M_{\text{HSE}}$: in this case, the uncertainties come from the sample of the posterior distribution used to infer the quantities (see Chapter 4 and Chapter 6 for details).
4. $Y_{\text{cyl}} - M_{\text{HSE,true}}$: is another theoretical estimate of the scaling and the error is limited to the one induced by projection.

We show an example of the data points of the $Y_{\text{cyl}} - M_{\text{cyl}}$ estimates, to which we fit a scaling law, in Fig. 7.7. The distinct evolution of the scaling law with overdensity is evident.

The four scaling laws mentioned above are determined using the probabilistic modelling of Eq. (7.18) that we have provided in this sub-section. As mentioned, we assume a fixed redshift evolution of the normalisation with $\gamma = 2/3$, and no redshift evolution is assumed for the slope with $\delta = 0$. Further, we assume no prior correlation between the uncertainties of the mass and the observable. We treat the parameters as independent variables, allowing the prior distribution to be expressed as the product of the distribution for each parameter. For all parameters, we use uniform priors described by

$$\mathcal{U}(x_1, x_2) = \begin{cases} 1/|x_1 - x_2| & \text{between } x_1 \text{ and } x_2, \\ 0 & \text{elsewhere.} \end{cases} \quad (7.27)$$

We use the arbitrary value of the intervals x_1 and x_2 . These are set to $[-10^3, 10^3]$ for the normalisation (A) and $[0, 10^3]$ for slope (B) and intrinsic scatter (σ_{int}), which must strictly be positive values. The chosen distributions are intentionally sufficiently wide in order to be uninformative, ensuring that the results are not affected by errors resulting from incorrect prior knowledge.

7.2.4 Results

Following the aforementioned methodology, we were able to determine the four scaling laws mentioned in Section 7.2.3. In this section, we report and compare the various results.

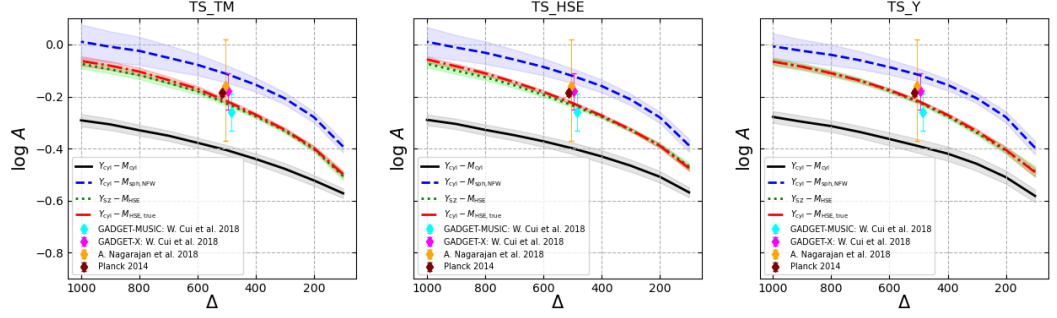


Figure 7.8 The best-fit values of the scaling law normalisation at different overdensities. The shaded regions of the curves represent the dispersion in the posterior distribution of the parameter. The solid black curve represents the values for $Y_{\text{cyl}} - M_{\text{cyl}}$, the dotted green curve represents the scaling law $Y_{\text{SZ}} - M_{\text{HSE}}$, the dotted-dashed red curve stands for $Y_{\text{cyl}} - M_{\text{HSE,true}}$, and the dashed blue curve symbolises the scaling relation $Y_{\text{cyl}} - M_{\text{sph,NFW}}$. The cyan, magenta, orange and brown diamonds represent the normalisation values from The300 GADGET-MUSIC run, The300 GADGET-X run (Cui et al. 2018), Nagarajan et al. 2019, and Planck Collaboration et al. 2014, respectively. The markers are displaced in their horizontal position for visualization purposes.

The outcomes depicting the best-fit values for the normalisation parameter (A) of the scaling laws, along with their uncertainties are shown in Fig. 7.8, for all four datasets. Given that cylindrical mass values are always higher than spherical mass estimates, we observe a consistent trend: the normalization for M_{cyl} (black solid curve) is lower than that of the spherical mass estimates, $M_{\text{sph,NFW}}$ (blue dashed curve), M_{HSE} (green dotted curve), and $M_{\text{HSE,true}}$ (red dotted-dashed curve); further the higher normalisation value for $M_{\text{sph,NFW}}$ in comparison with M_{HSE} and $M_{\text{HSE,true}}$ reflects the relative nature of the bias for both mass estimators. For $M_{\text{sph,NFW}}$, we did not include the mass estimator bias (sub-model 7.25) in the scaling relation model and hence its bias with respect to the true mass (of the order of $\leq 10\%$, see Section 7.1.2) is still present in the scaling law. On the other hand, for M_{HSE} and $M_{\text{HSE,true}}$, we include the mass estimator bias in the model and the mass values are adjusted accordingly. This makes the bias-corrected mass values for them, slightly higher than the uncorrected mass values for $M_{\text{sph,NFW}}$. As a result, the normalisation for the latter is higher than those of the former two. In all cases, since the mass increases with decreasing overdensity, the normalisation decreases in that direction. These trends are consistently observed for all the TSs.

Next, we examine the best-fit values of the slope of the scaling laws, shown in Fig. 7.9. No significant evolution with radius is noted in the slope for either of the scaling laws. All the values remain consistent, within their 1σ uncertainties, with the self-similar value of the slope ($5/3$), depicted with a dashed yellow line in the plots. The only exception is TS_Y , where the slope values for scaling laws calibrated using the HSE mass estimates M_{HSE} and $M_{\text{HSE,true}}$ (green dotted and red dotted-dashed curve, respectively) deviate slightly from self-similarity. This can be explained by the fact that we saw in Chapter 6, this TS is slightly biased in terms of the sample having more disturbed clusters than the other two samples. In this case, the HSE assumption fails and the results show a clear indication of deviation

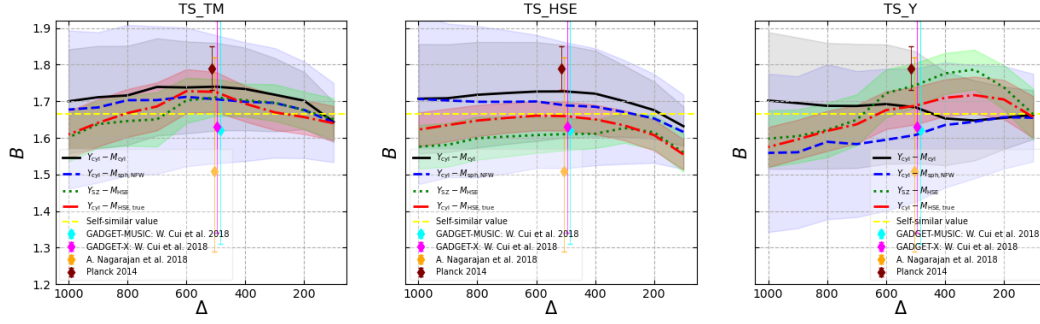


Figure 7.9 The best-fit values of the scaling law slope at different overdensities. The shaded regions of the curves represent the dispersion in the posterior distribution of the parameter. The solid black curve represents the values for $Y_{\text{cyl}} - M_{\text{cyl}}$, the dotted green curve represents the scaling law $Y_{\text{SZ}} - M_{\text{HSE}}$, the dotted-dashed red curve stands for $Y_{\text{cyl}} - M_{\text{HSE,true}}$, and the dashed blue curve symbolises the scaling relation $Y_{\text{cyl}} - M_{\text{sph,NFW}}$. The cyan, magenta, orange and brown diamonds represent the slope values from The300 GADGET-MUSIC run, The300 GADGET-X run (Cui et al. 2018), Nagarajan et al. 2019, and Planck Collaboration et al. 2014, respectively. The markers are displaced in their horizontal position for visualization purposes. The self-similar value of the slope is marked using a horizontal, dashed yellow line.

from self-similarity.

Looking at the intrinsic scatter of the scaling laws in Fig. 7.10, we notice that in the case of using M_{cyl} (solid black curve), $M_{\text{sph,NFW}}$ (dashed blue curve), and $M_{\text{HSE,true}}$ (dotted-dashed red curve) it decreases with decreasing overdensity. This suggests that it is better to integrate the signal as far out as possible to minimise the intrinsic scatter of these scaling laws. The decreasing scatter trend observed here is similar to what is observed for the projection-induced scatter discussed for M and Y in Section 7.1: they also diminish with decreasing overdensity. Additionally, like the scatter induced by projection on mass, the intrinsic scatter in scaling relations is lower for the scaling law estimated using M_{cyl} compared to those calibrated using $M_{\text{sph,NFW}}$. Whereas, the scaling law calibrated using $M_{\text{HSE,true}}$ has the highest intrinsic scatter. A special mention must be made in the case where we use the HSE inferred mass from NIKA2-like images, namely, M_{HSE} (green dotted curves). In this case, the scatter, like all other cases, falls with decreasing overdensity but beyond $\Delta = 400$ it starts to rise again. The simulation design of the NIKA2-like maps defines the noise in the maps such that the average SNR of the SZ profiles at R_{500} is three. So around $\Delta = 400$ is where the noise starts really increasing in these maps, increasing the uncertainties in the M and Y values inferred from these maps. Thus, the radial trend in the intrinsic scatter observed in this case suggests that employing a probabilistic model (sub-model 7.23 in hierarchical modelling) instead of a strict scaling law may not have completely untangled the observational and intrinsic uncertainties. We also take note of the fact that the values of projection-induced scatter on Y and intrinsic law scatter values are compatible within their error bars, making the former a non-negligible source of error for Y .

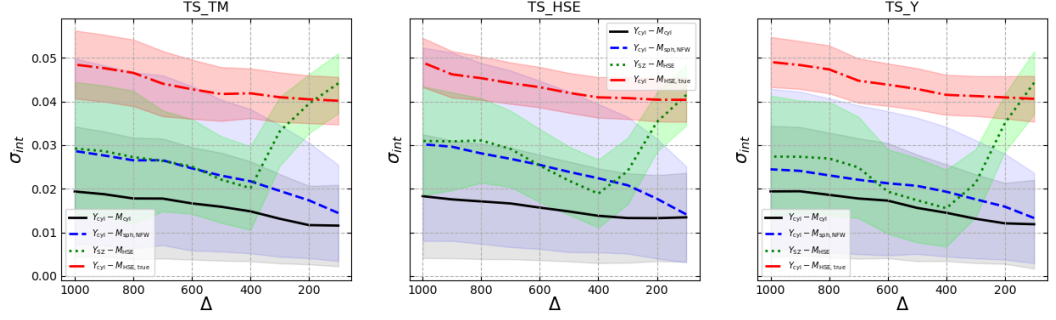


Figure 7.10 The best-fit values of the scaling law intrinsic scatter at different overdensities. The shaded regions of the curves represent the dispersion in the posterior distribution of the parameter. The solid black curve represents the values for $Y_{\text{cyl}} - M_{\text{cyl}}$, the dotted green curve represents the scaling law $Y_{\text{SZ}} - M_{\text{HSE}}$, the dotted-dashed red curve stands for $Y_{\text{cyl}} - M_{\text{HSE,true}}$, and the dashed blue curve symbolises the scaling relation $Y_{\text{cyl}} - M_{\text{sph,NFW}}$.

7.2.4.1 Comparison to literature

In this section, we compare and validate our results with the literature. Considering the different mass and observable estimates used in the above-mentioned work, we choose the scaling law $Y_{\text{cyl}} - M_{\text{sph,NFW}}$ in this work, the most suitable for comparison. We essentially refer to four sources:

1. The theoretical scaling laws from the **GADGET-X** and **GADGET-MUSIC** simulations, derived in Cui et al. 2018. Their best-fit values (scaling laws) are shown using magenta and cyan diamonds (lines) for both simulations, respectively, in all our plots. We recall that the TSs in this work are generated from the **GADGET-X** simulation of The300.
2. The observational scaling law from Nagarajan et al. 2019, where the authors calibrate the weak lensing mass and the Y observable for clusters in a similar redshift and mass range to ours. The best-fit values (scaling laws) for this work are shown using orange diamonds (line) in all our plots.
3. The scaling law from Planck Collaboration et al. 2014, where the observable Y is calibrated with the mass derived through an X-ray mass proxy. We show the best-fit values (scaling law) for this case, using brown diamonds (line) in our plots.

The slope and normalisation values for the references are shown in Fig. 7.8 and Fig. 7.9, respectively, using the marker scheme described above. The scaling laws themselves are shown in Fig. 7.11, where we also show in blue, the data points and the corresponding best-fit scaling law for $Y_{\text{cyl}} - M_{\text{sph,NFW}}$, at $\Delta = 500$. When comparing our slope and normalisation values, we are consistent with the **GADGET-X** runs of The300 (magenta diamonds/line), from which the TSs are derived and with Nagarajan et al. 2019 (orange diamonds/line), who also have a cluster sample at high redshift and similar mass range as ours. However, there is a discrepancy in the normalization values with **GADGET-MUSIC** runs of The300 (cyan diamonds/line). This

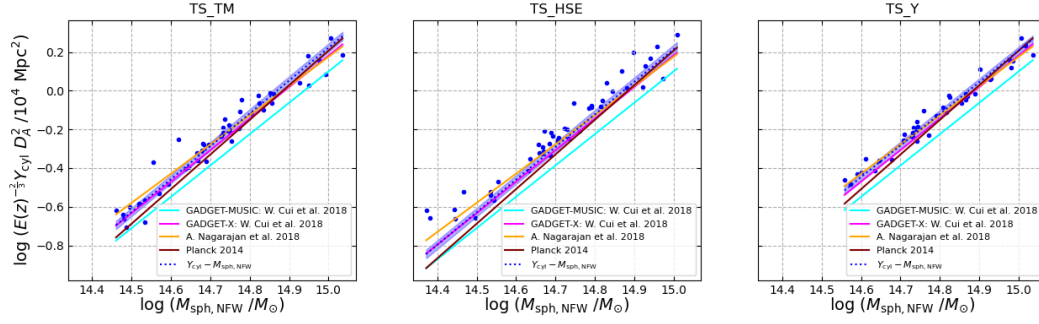


Figure 7.11 The data points and the corresponding best-fit scaling law $Y_{\text{cyl}} - M_{\text{HSE, true}}$ estimated in this work, at $\Delta = 500$, shown in blue. The errors on these data points are omitted for clearer visualisation. The cyan and magenta lines correspond to the scaling laws of the GADGET-MUSIC and GADGET-X simulations of Cui et al. 2018, respectively. The orange line corresponds to the scaling law from Nagarajan et al. 2019 and the brown line is from Planck Collaboration et al. 2014.

is expected due to the use of a different hydrodynamical code in these simulations, compared to the ones used in our TSs. Considering a completely different mass estimator and the fact that their sample is at a lower redshift and different mass range than ours, we find no concordance between our results and those of Planck Collaboration et al. 2014 (brown diamonds/line), except in the high mass end.

7.3 Discussions and conclusions

We have investigated in this chapter, using The300-NIKA2 twin samples, varied scaling laws between the integrated quantities Y and M at different overdensities and the impact that projection has on the inference of these quantities.

In Section 7.1, we infer the integrated quantities Y and M through various methods, summarised in Table 7.1. Using the 29 projections of the y maps and the projected mass density maps, we find that the projection-induced scatter on Y and M consistently decreases with decreasing overdensity. Comparing the spherical de-projected mass with its cylindrical counterpart, the former suffers more from projection effects.

After describing the origin of the $Y - M$ scaling and the inherent intrinsic scatter in this relation, we discuss the hierarchical probability model used to fit our estimates of the integrated quantities with the scaling law in Eq. (7.18), in Section 7.2.3. In doing so, we assume a fixed redshift evolution of the normalisation and no redshift evolution of the scaling law slope. Further, we consider no correlation in the uncertainties of Y and M and determine four scaling laws with our varied estimates of the integrated quantities.

The results of the fitting procedure are discussed in Section 7.2.4. The normalisation values are as expected: lower for higher mass estimates and vice versa, and decrease with decreasing overdensity. The slope values are consistent within their uncertainties, with the self-similar evolution value (5/3) except for the HSE mass scaling laws of the TS_Y but, this is understandable since the sample is biased to disturbed clusters and in this case the HSE mass estimation can be biased, resulting

in signs of deviation from self-similar evolution. The intrinsic scatter of the scaling law, like the projection-induced scatter, decreases with decreasing overdensity and is the lowest for the scaling law calibrated with the cylindrical mass estimate. The only exception to this trend is the scaling law determined using the integrated quantities inferred from the NIKA2-like maps. In this case, the intrinsic scatter diminishes till $\Delta = 400$ and then rises again. This overdensity corresponds to the range in the simulated maps where the noise explodes, indicating that we have perhaps not properly untangled the intrinsic scatter from the observational one. We also note that the intrinsic scatters of all scaling laws, within their uncertainties, are compatible with the projection-induced scatter on Y .

From this analysis, we conclude that theoretically, there is no preferred overdensity at which the projection-induced scatter on Y and M or the intrinsic scatter of the $Y - M$ scaling law is minimised. So, it is best to observe the cluster as far out as possible to minimise these scatters. From an observational aspect, we find that in the context of the LPSZ, the intrinsic scatter of the $Y - M$ scaling is minimum at $\Delta = 400$. We also observe that the projection-induced scatter and the scaling law intrinsic scatter are higher when using the spherical mass estimates as compared to when using the cylindrical mass estimates, making the latter a preferred quantity for calibrating the scaling laws. Finally, we conclude that since the projection-induced scatter on Y and the intrinsic scatter of the $Y - M$ scaling law are comparable (compatible within their uncertainties), the former can not be ignored when making an error budget for Y . Our results provide a reasonable estimation of the $Y - M$ scaling law at different overdensities in the context of the LPSZ, while taking into consideration the projection effect. In practice, these scaling laws at different radial points can be used to optimise the overdensity at which the LPSZ should calibrate its scaling laws, to minimise the associated intrinsic scatter. Alternatively, the scaling law can be estimated at an overdensity that provides sufficient SNR for the LPSZ data and our results can be used to propagate this scaling law to an overdensity more commonly used in other works, such as $\Delta = 500$ or $\Delta = 200$. To enhance our results and make them more realistic, the correlation between the uncertainties of the mass and the observable can be included in the scaling law and the redshift evolution of slope and normalisation can be set as free parameters in the model. Additionally, we have not accounted for the box selection function of the LPSZ, whose careful consideration can be used to improve our results.

Chapter 8

Summary and outlook

In this thesis, we have addressed the fundamental challenge of accurately estimating galaxy cluster masses, a crucial parameter for cosmological studies. Our approach combines high-angular-resolution observations from the NIKA2 LPSZ with detailed N-body hydrodynamical simulations from The300 by creating the so-called ‘twin samples’ among the two. We use the case study of a real cluster to motivate the refinement of the inference of cluster properties by using simulations to enhance the theoretical understanding of the systematic effects involved in the process. In this chapter, we summarise our analyses while outlining the wider significance and implications of our results, in the context of the LPSZ collaboration and The300 collaboration, and cluster-based cosmological studies at large.

Study of cluster ACTJ0240

We conducted a detailed analysis of an LPSZ survey member cluster, ACTJ0240, using a multi-wavelength approach, with a primary focus on high-resolution SZ observations obtained under the LPSZ. Our investigation involved creating composite images from NIKA2 bands, X-ray surface brightness, and an optical galaxy number density map. The results revealed distinct signs of disturbance within the cluster, with non-aligned gas and member galaxies, indicating an atypical dynamical state. In particular, the analysis detected two tail-like structures in the southeastern region of the cluster in the 150 GHz SZ map. These structures aligned with gas clumps identified in X-ray observations and an optical overdensity of galaxies, suggesting an inflow of matter onto the cluster and reinforcing the case for it being a disturbed, interacting system.

During our analysis, we identified a contaminating PS in the cluster via its 260 GHz SZ map. We applied three approaches to address this PS while determining the pressure and mass profile of the cluster from its SZ data. Our findings highlighted the importance of including the PS in the estimation, as both modelling and masking did not significantly alter the results. The pressure profiles obtained in cases where the PS was modelled and masked exhibited consistency, emphasizing the robustness of our approach. Additionally, we compared our results to the UPP for disturbed clusters, confirming the disturbed nature of the cluster. The mass estimates $3.84^{+1.84}_{-1.15} \times 10^{14} M_{\odot}$ and $4.25^{+0.50}_{-0.45} \times 10^{14} M_{\odot}$ for the cases where the PS

was modelled and masked, respectively, were found to be consistent with X-ray estimates and those from previous studies. The creation of a combined SZ and X-ray temperature map further supported the conclusion of a disturbed system, revealing a relatively flat temperature profile except for the southern region of the cluster. Mapping the ICM temperature for a cluster at a high redshift ($z = 0.62$) through this amalgamation of observations proves more sensitive compared to X-ray spectroscopic measurements. X-ray emissions decline with redshift, making them less reliable when integration time is not exceptionally high.

In conclusion, our findings strongly suggest that ACTJ0240 is a disturbed cluster system, and the detailed observations and derived values serve as a compelling case study for the capabilities of the LPSZ in mapping the cluster ICM with high precision. The pressure, integrated Compton parameter, and mass values inferred in this study contribute valuable data for scaling relations in the LPSZ (see Moyer-Anin et al. 2023).

Validation of the LPSZ PS detection pipeline

In examining the analysis of ACTJ0240 and referring to previous LPSZ studies (see K  r  z  r  , F. et al. 2020), we recognized the critical importance of accurately detecting and addressing PS contamination in resolved SZ observations. Additionally, studying the distribution of PSs in the cluster region can unveil information about the lensing impact of clusters on background sources. The detection of these PSs for real observations is done by the LPSZ PS detection pipeline. To verify its performance, we utilized NIKA2-like maps of twin samples injected with PSs in both NIKA2 bands.

Initially, we simulated maps containing only noise to assess how effectively the pipeline works in the field. Subsequently, we simulated maps including the cluster signal to evaluate how the cluster signal affects the pipeline’s ability to reliably detect PSs. We measured the performance of the pipeline by estimating the completeness and purity of detections as a function of radius. By using purity in each NIKA2 band as a probability indicator that the detected PS is reliable, we established a ranking system to assign reliability scores to PSs detected by the pipeline. Using this ranking system, we assigned each PS detected in the actual LPSZ sample a reliability score, quantified by this rank (refer to Table 5.2 for a summary of the rank associated with a given SNR of a detected PS). These findings are crucial for effectively mitigating PS contamination in the LPSZ and for ongoing studies to detect and analyze the lensing effect of clusters in the LPSZ. This involves examining the distribution of PSs detected in the sub-millimeter (LPSZ) observations of the clusters. The results also underscore the effectiveness of The300 simulations in providing realistic cluster maps for enabling such studies.

Recovery of 3D pressure and mass profiles from SZ maps of clusters

The 3D profiles of clusters, encompassing mass and pressure profiles, serve as crucial elements for estimating their properties used in cosmological studies. When derived

from projected data, such as maps, the assumption of spherical symmetry is made to de-project the information into 3D profiles. However, this assumption becomes precarious, especially for disturbed or spherically asymmetric clusters. In our results for ACTJ0240, where disturbance in the cluster was evident, we employed spherical symmetry in estimating its properties, introducing potential bias into the analysis. Understanding the sources of error and the impact of the dynamical state in the de-projection process is essential.

To assess how well 3D profiles are recovered from their projected SZ data, we simulated NIKA2 SZ maps of the TSs and used them to estimate the pressure and hydrostatic HSE mass profiles of the cluster in various ways (see Chapter 6). The estimates of pressure profiles in 2D space were consistent at the 1σ level with the 2D pressure profile directly estimated from simulated SZ maps. However, discrepancies were observed in the cluster core ($r < 0.2 R_{500}$) and outskirts ($r > 0.8 R_{500}$) between our estimates and the true 3D pressure profile from the simulation. Similar discrepancies were found in the HSE mass profiles. We attribute this discrepancy to the combination of assuming spherical symmetry during de-projection and the smoothing kernel adopted in the simulation to obtain y maps from the 3D sphere of the cluster. Notably, the bias between the 3D profiles recovered from 2D data and the true 3D profiles is minimized at overdensity 2000. For the HSE mass, the estimation bias increases to 0.2 at overdensity 500. The hydrostatic mass bias for our estimate is 0.15 at overdensity 2000 and 0.23 at overdensity 500. Furthermore, a comparison of the median of the scaled pressure profiles we recovered from simulated SZ maps with the UPP calibrated for a sample with $z < 0.2$ (M. Arnaud et al. 2010) suggests a higher normalization and shallower slope in our case, hinting at a potential redshift evolution in the UPP. Importantly, no isolated trend was observed for the most disturbed or most relaxed clusters in our sample, indicating that the recovery is seemingly unaffected by the cluster dynamical state.

In conclusion, we suggest that, ideally, measuring quantities at $\Delta = 2000$ is better than at $\Delta = 500$ for the LPSZ. However, when using $\Delta = 500$ for evaluation, attention must be given to account for the additional error estimated in this work. Our analyses were performed by fixing our pressure profile model to gNFW and the SNR definition in our maps to the one in the LPSZ proposal. Realistically, it is possible that gNFW may not accurately describe the profiles of the LPSZ (or The300) clusters, and the final SNR in the real LPSZ may differ from the one in the proposal. To enhance our results in terms of SNR definition, it would be beneficial to use real noise maps and transfer functions from the LPSZ and incorporate them into the clusters in The300 twin samples. This would ensure that the noise and filtering precisely replicate the LPSZ. Additionally, other pressure profiles can be explored to test their impact on these results. In a broader context, this analysis underscores the importance of using simulations as test beds for results obtained from sensitive observational data that is accessible only as a projection.

The $Y - M$ scaling laws at different overdensities

After analysing various aspects of details involved in the estimation of Y and M we used our TSs to estimate a scaling between the two quantities at different

overdensities and varied estimates of the two (see Chapter 7 for details).

We account for the projection effect by estimating and including the projection-induced scatter on Y and M in the estimation of the scaling laws. From our analysis, we deduce that there is no theoretically preferred overdensity at which the projection-induced scatter on Y and M or the intrinsic scatter of the $Y - M$ scaling law is minimized. Hence, it is advisable to observe the cluster as far out as possible to mitigate these scatters. On the observational front, within the context of the LPSZ, we observe that the intrinsic scatter of the $Y - M$ scaling is minimized at $\Delta = 400$. Additionally, we note that the projection-induced scatter and the intrinsic scatter of the scaling law are higher when using spherical mass estimates compared to cylindrical mass estimates, making the latter a preferable quantity for calibrating the scaling laws. We also find that the projection-induced scatter on Y and the intrinsic scatter of the $Y - M$ scaling law are compatible within their uncertainties, implying that the former cannot be ignored when establishing an error budget for Y . In terms of normalisation and slope of the scaling law, we recover the expected value and the slope agrees with the self-similar value of $5/3$, with typical error bars ranging between ± 0.05 and ± 0.15 for the different scaling laws that we estimate in this work.

While the results concerning the behaviour of various scatters with overdensity for different Y and M estimates align, providing valuable insights into suitable overdensities for the LPSZ, our analysis rests on certain assumptions that warrant further refinement. Initially, we assumed zero correlation of uncertainties between mass and the observable; however, incorporating this correlation in estimating the scaling law could enhance the accuracy of our results. Additionally, we constrained the redshift evolution of our normalization to $2/3$ and the slope to zero. Allowing these parameters to vary freely, especially in the high redshift range of the LPSZ, could provide more meaningful outcomes. Another crucial refinement involves considering the box selection function of the LPSZ, a factor that has not been accounted for in our analysis and may influence the results.

Final comments

In summary, our integration of The300 and the LPSZ has provided a synergistic approach, elevating the theoretical understanding of interpreting cluster science from detailed and sensitive SZ data on the one hand, and exploring the richness of the simulations by putting them in observational context, on the other. By delving into the intricacies of issues like point source contamination and the recovery of 3D profiles from projected data, our results not only hold significance for both collaborations but also bear implications for the broader field of cluster cosmology using the SZ effect. As SZ surveys continue to generate increasingly sensitive data, the insights gained from our exploration become pivotal for accurately interpreting and utilizing such detailed observations of clusters in the SZ. Additionally, it's worth noting that our results can be further refined and adapted with considerations we have earlier provided in this chapter.

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Appendix A

List of twin samples

Redshift	Snapshot	Region ID
0.490	110	18
0.490	110	39
0.490	110	110
0.490	110	24
0.490	110	36
0.490	110	202
0.490	110	67
0.490	110	48
0.490	110	198
0.490	110	194
0.490	110	128
0.490	110	54
0.490	110	97
0.490	110	290
0.490	110	50
0.490	110	309
0.490	110	123
0.592	107	30
0.592	107	128
0.592	107	97
0.592	107	282
0.592	107	53
0.592	107	249
0.592	107	94
0.592	107	180
0.700	104	17
0.700	104	159
0.700	104	153
0.700	104	129
0.700	104	115
0.700	104	46
0.700	104	27
0.700	104	59
0.700	104	38
0.700	104	21
0.700	104	166
0.700	104	42
0.700	104	145
0.700	104	71
0.817	101	41
0.817	101	27
0.817	101	95
0.817	101	152
0.817	101	33
0.817	101	211

Table A.1 List of The300 clusters in TS_{TM} , with their redshift, snapshot and regions ID specified.

Redshift	Snapshot	Region ID
0.490	110	30
0.490	110	18
0.490	110	39
0.490	110	46
0.490	110	68
0.490	110	24
0.490	110	27
0.490	110	102
0.490	110	120
0.490	110	285
0.490	110	4
0.490	110	324
0.490	110	38
0.490	110	246
0.490	110	61
0.490	110	291
0.490	110	180
0.592	107	21
0.592	107	135
0.592	107	84
0.592	107	181
0.592	107	234
0.592	107	322
0.592	107	145
0.592	107	167
0.700	104	9
0.700	104	17
0.700	104	159
0.700	104	95
0.700	104	128
0.700	104	72
0.700	104	160
0.700	104	56
0.700	104	299
0.700	104	282
0.700	104	110
0.700	104	242
0.700	104	117
0.700	104	140
0.817	101	129
0.817	101	41
0.817	101	141
0.817	101	19
0.817	101	221
0.817	101	16

Table A.2 List of The300 clusters in TS_{HSE} , with their redshift, snapshot and regions ID specified.

Redshift	Snapshot	Region ID
0.490	110	21
0.490	110	18
0.490	110	39
0.490	110	52
0.490	110	17
0.490	110	75
0.490	110	95
0.490	110	33
0.490	110	101
0.490	110	153
0.490	110	35
0.490	110	271
0.490	110	67
0.490	110	156
0.490	110	5
0.490	110	25
0.490	110	268
0.592	107	30
0.592	107	27
0.592	107	127
0.592	107	59
0.592	107	128
0.592	107	34
0.592	107	44
0.592	107	179
0.700	104	129
0.700	104	41
0.700	104	195
0.700	104	36
0.700	104	137
0.700	104	56
0.700	104	299
0.700	104	107
0.700	104	48
0.700	104	97
0.700	104	4
0.700	104	26
0.700	104	70
0.817	101	120
0.817	101	29
0.817	101	46
0.817	101	84
0.817	101	306
0.817	101	216

Table A.3 List of The300 clusters in TS_Y , with their redshift, snapshot and regions ID specified.

Appendix B

Recovery of 3D profiles for individual twin samples

In this Chapter, we have provided supplement plots for Chapter 6. In the main chapter, we show plots for the unified TS and here we show the same plots for individual TSs.

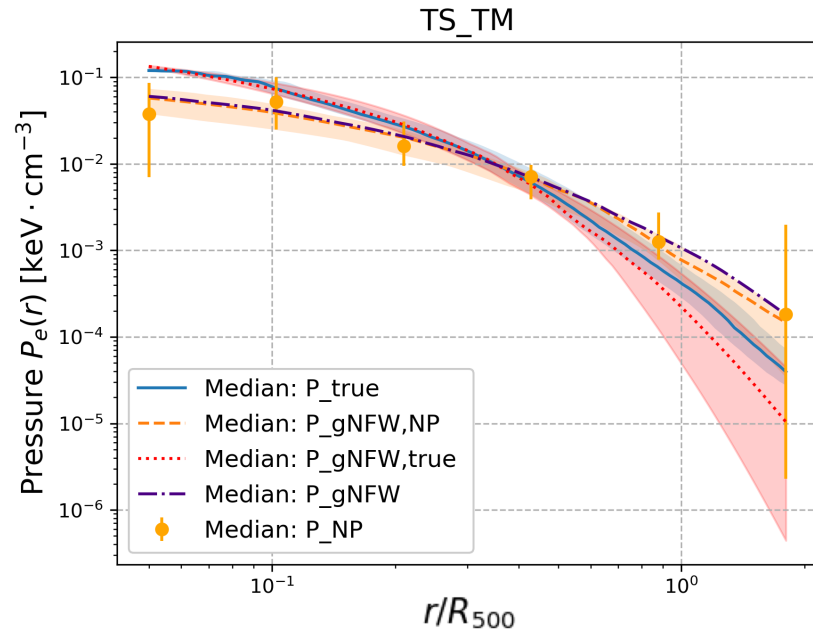


Figure B.1 Same as Fig. 6.3 but for TS_{TM}

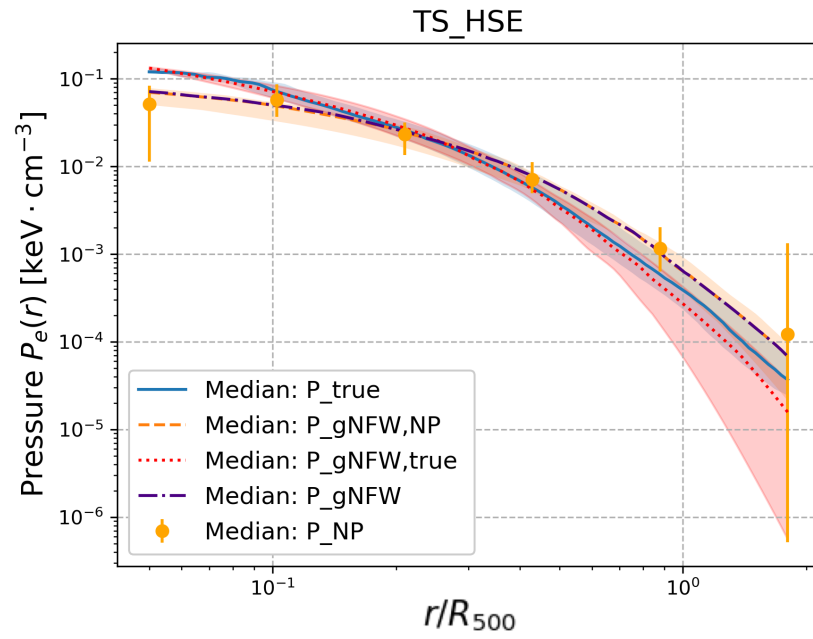


Figure B.2 Same as Fig. 6.3 but for TS_{HSE}

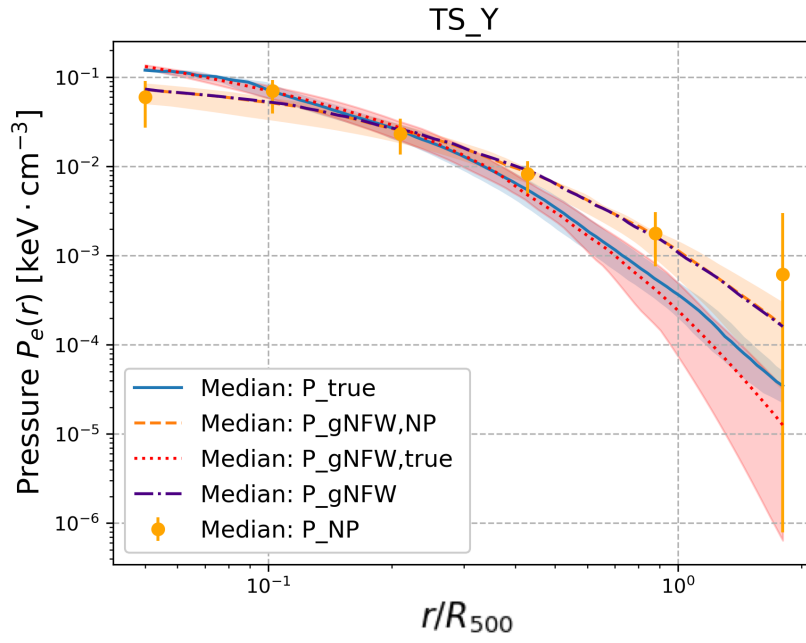


Figure B.3 Same as Fig. 6.3 but for TS_Y

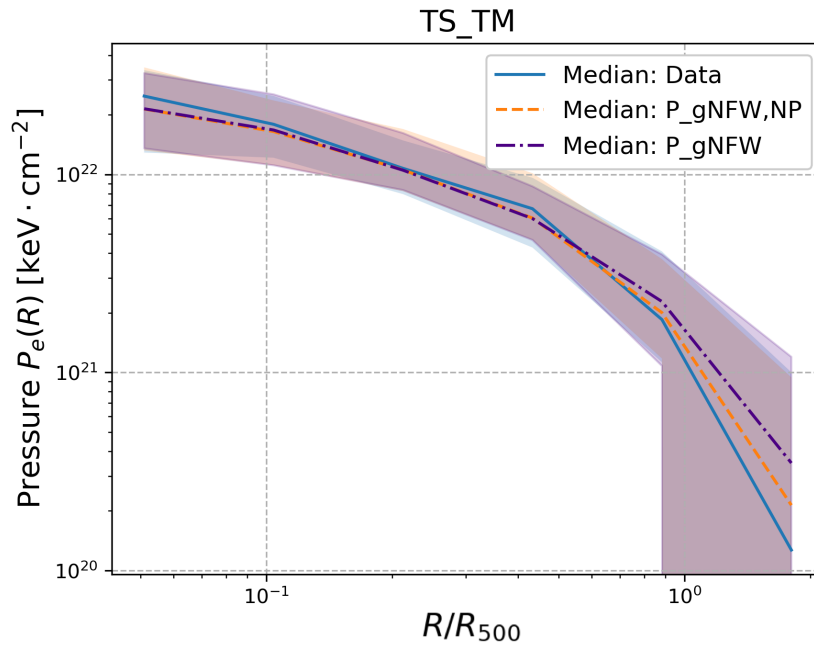


Figure B.4 Same as left panel of Fig. 6.5 but for TS_{TM}

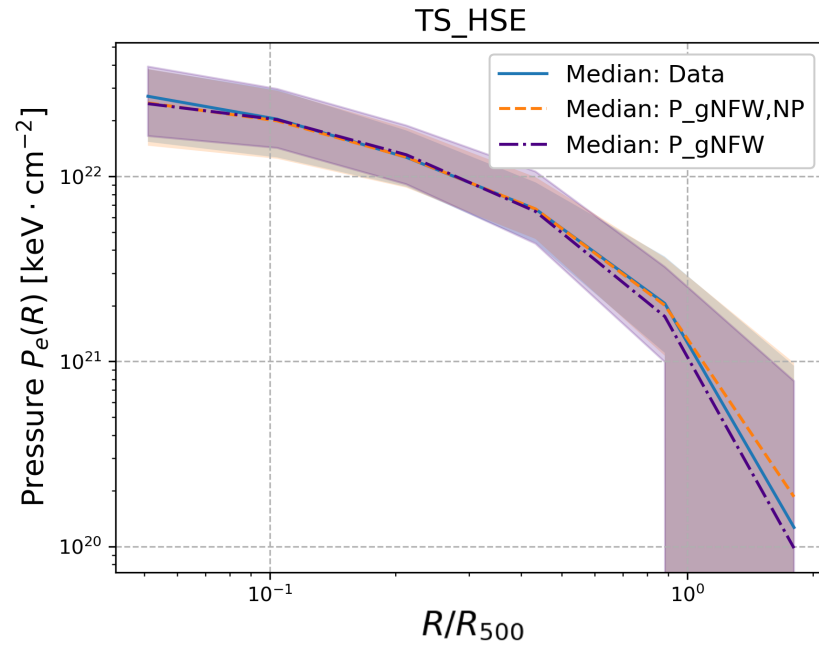


Figure B.5 Same as left panel of Fig. 6.5 but for TS_{HSE}

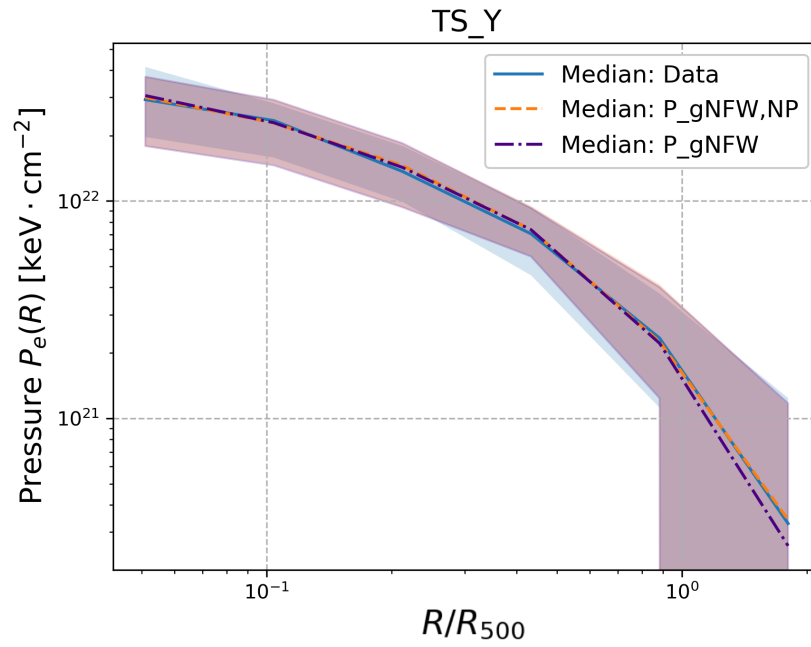


Figure B.6 Same as left panel of Fig. 6.5 but for TS_Y

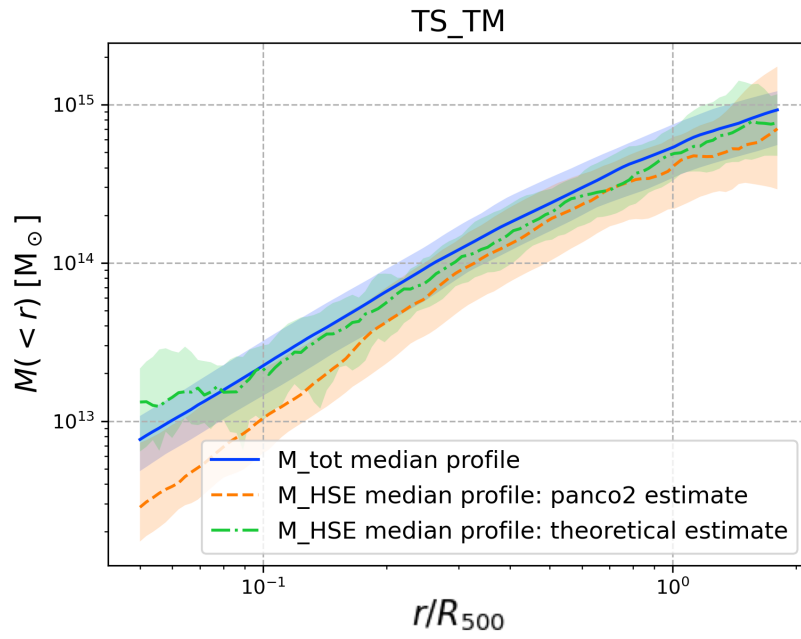


Figure B.7 Same as Fig. 6.8 but for TS_{TM}

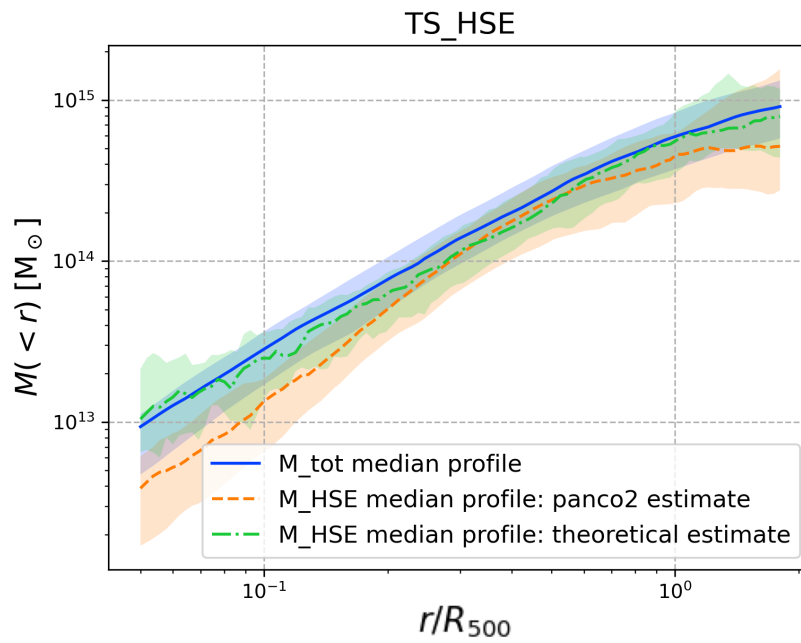


Figure B.8 Same as Fig. 6.8 but for TS_{HSE}

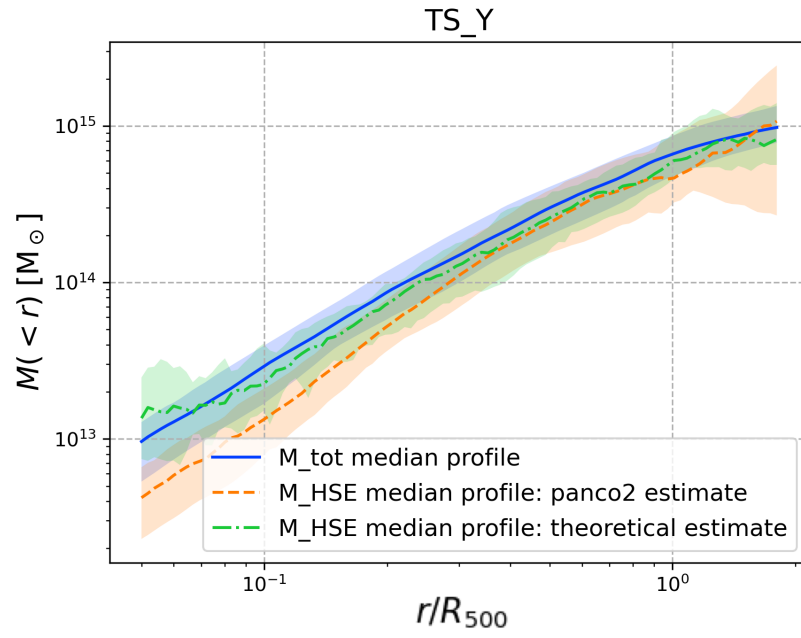


Figure B.9 Same as Fig. 6.8 but for TS_Y

Appendix C

Fit of projected NFW profiles to projected mass maps from simulation

In Chapter 7, we perform the fit of a projected NFW model to projected mass maps from the simulation to obtain their de-projected density and mass profiles. We show here, an example of these fit for all available projections one of the of the TS clusters, namely cluster 27 of snapshot 101 of the simulation.

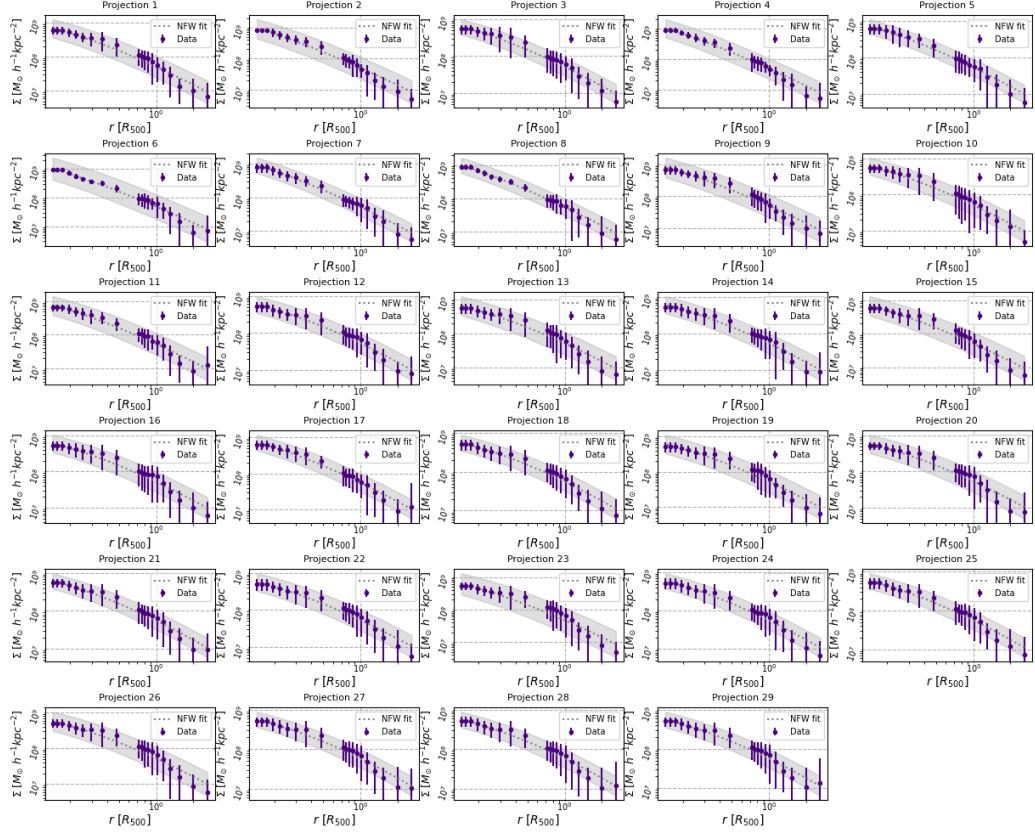


Figure C.1 Fit for the projected NFW profile (in grey), to the profile inferred from the projected mass map from simulation (indigo data points). This profile was inferred by taking the mean value of equally spaced annuli in the projected maps and using the deviation in the respective annuli as the error on the mean value. The shaded grey region depicts the 1σ uncertainty of the NFW fit.

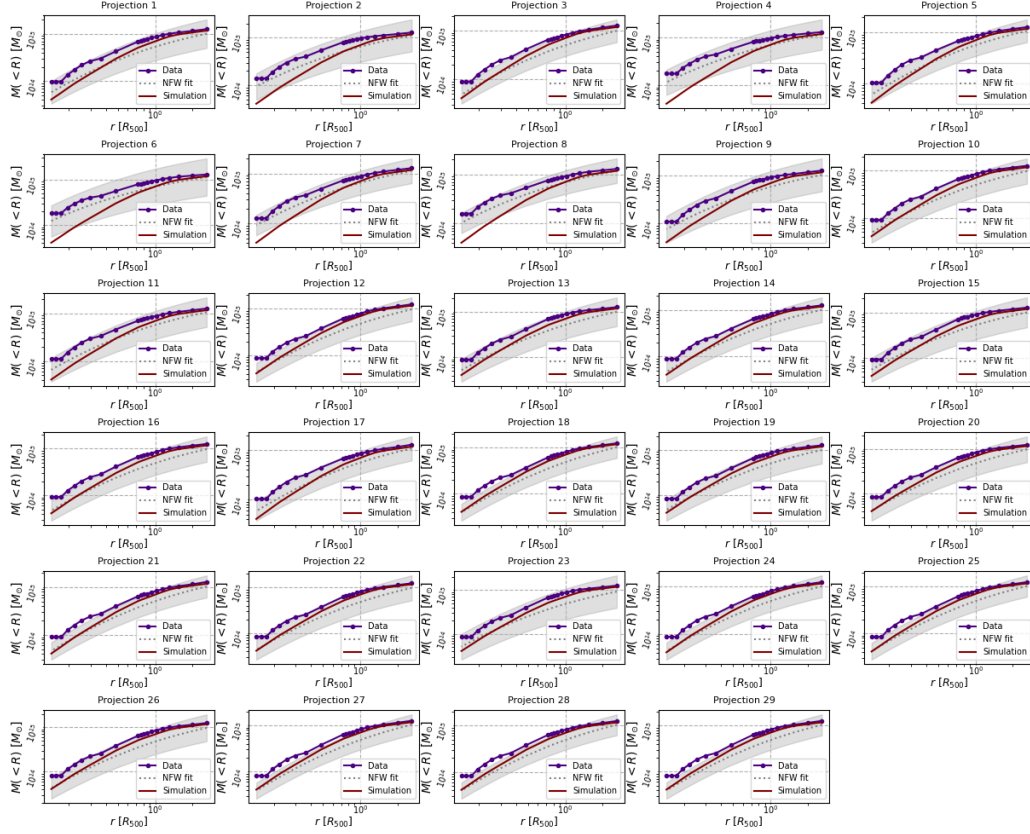


Figure C.2 Fit for the de-project mass profile (in grey), obtained from the projected density profile model fitted to the projected mass maps (grey lines in Fig. C.1). The indigo data points correspond to the mass inferred directly from the projected mass maps by integrating them within a given aperture. The maroon solid curve correspond to the 3D mass profiles from the simulation.

Acronyms

ACT Atacama Cosmology Telescope. 28, 33, 34, 37, 38, 40, 47, 57, 62, 65–67, 73, 75, 83, 175–177

CDM cold dark matter. 6

CIB cosmic infrared background. 50

CM Common Mode. 52–57

CMB cosmic microwave background. 3, 5, 6, 10, 13–16, 18–24, 30, 50, 64, 85, 173, 174

EDS Einstein-de Sitter. 12

FN false negative. 93

FP false positive. 93

FWHM full-width at half-maximum. 33, 44, 89

gNFW generalized Navarro-Frenk-White. 66–68, 70–73, 75, 82, 106, 107, 109, 119, 177, 185

HSE hydrostatic equilibrium. 1, 83, 115

ICM intracluster medium. 16–23, 25–27, 36, 85, 103, 106, 107, 109, 173, 174

KID kinetic inductance detector. 33–36, 50, 52, 175

kSZ kinetic Sunyaev–Zeldovich. 20, 23–25, 174

LoS line of sight. 19, 85, 104, 109

LPSZ NIKA2 SZ Large Program. 3, 105, 141

MCMC Markov chain Monte Carlo. 64, 107

NIKA2 New IRAM KID arrays 2. 3, 141

NP non-parametric. 65–68, 70, 71, 73, 75, 82, 106, 177

PS point source. 57, 60, 61, 66, 71–73, 80–82, 85, 87, 142, 177, 178

PSF point spread function. 76

rSZ relativistic Sunyaev–Zeldovich. 25

SDSS Sloan Digital Sky Survey. 47

SNR signal-to-noise ratio. 44, 87, 89, 94

SPH smooth–particle–hydrodynamic. 39, 105

SZ Sunyaev–Zeldovich. 1, 3, 13, 85, 103, 106

The300 THE THREE HUNDRED project. 3, 87, 103, 141

TOI Time-Ordered Information. 49–56, 58, 59, 176

TP true positive. 93

TS twin sample. 87, 103, 105, 106, 110, 115, 180, 185

tSZ thermal Sunyaev–Zeldovich. 20–27, 174

UPP universal pressure profile. 28, 29, 38, 107, 114, 141, 174, 181

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