

Euclid Quick Data Release (Q1)

First *Euclid* statistical study of galaxy mergers and their connection to active galactic nuclei

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ABSTRACT

Galaxy major mergers are indicated as one of the principal pathways to trigger active galactic nuclei (AGN). We present the first statistical analysis of the major merger and AGN connection in the Euclid Deep Fields, and showcase the statistical power of the *Euclid* data. We constructed a stellar-mass-complete ($M_{\star} > 10^{9.8} M_{\odot}$) sample of galaxies from the quick data release (Q1) in the redshift range $z = 0.5-2$. We selected AGN using X-ray detections, optical spectroscopy, and mid-infrared (MIR) colours, and by processing I_E observations with an image decomposition algorithm. We used convolutional neural networks trained on cosmological hydrodynamic simulations to classify galaxies as mergers and non-mergers. We found a larger fraction of AGN in mergers compared to the non-merger controls for all AGN selections, with AGN excess factors ranging from two to six. The largest excess we observed was in the MIR AGN. Likewise, a generally larger merger fraction (f_{merg}) was seen in active galaxies than in the non-active controls, with the excess depending on the AGN selection method. Furthermore, we analysed f_{merg} as a function of the AGN bolometric luminosity (L_{bol}) and the contribution of the point-source component to the total galaxy light in the I_E -band (f_{PSF}) as a proxy for the relative AGN contribution fraction. We uncovered a rising f_{merg} , with an increasing f_{PSF} up to $f_{\text{PSF}} \approx 0.55$, after which we observed a decreasing trend. In the range $f_{\text{PSF}} = 0.3-0.7$, mergers appear to be the dominant AGN fuelling mechanism. We then derived the point-source luminosity (L_{PSF}) and showed that f_{merg} monotonically increases as a function of L_{PSF} at $z < 0.9$, with $f_{\text{merg}} \geq 50\%$ for $L_{\text{PSF}} \approx 2 \times 10^{43} \text{ erg s}^{-1}$. Similarly, at $0.9 \leq z \leq 2$, f_{merg} rises as a function of L_{PSF} , though mergers do not dominate until $L_{\text{PSF}} \approx 10^{45} \text{ erg s}^{-1}$. For the X-ray and spectroscopically detected AGN, we derived the bolometric luminosity, L_{bol} , which has a positive correlation with f_{merg} for X-ray AGN, while there is a less pronounced trend for spectroscopically selected AGN due to the smaller sample size. At $L_{\text{bol}} > 10^{45} \text{ erg s}^{-1}$, AGN mostly reside in mergers. We conclude that mergers are most strongly associated with the most powerful and dust-obscured AGN, which are typically linked to a fast-growing phase of the supermassive black hole, while other mechanisms, such as secular processes, might be the trigger of less luminous and dominant AGN.

Key words. Galaxies: interactions – Galaxies: evolution – Galaxies: active – Galaxies: statistics

1. Introduction

Galaxy mergers have long been considered a key driver of galaxy evolution, as they have the potential to significantly influence the growth and properties of both host galaxies and their central supermassive black holes (SMBHs; Sanders et al. 1988; Marconi et al. 2004). During such encounters, tidal forces can lead to gas inflows towards central regions (Barnes & Hernquist 1996), that feed intense nuclear star formation and active galactic nucleus (AGN) activity (e.g., Springel et al. 2005; Somerville & Davé 2015; Blumenthal & Barnes 2018). Consequently, this process can trigger AGN feedback, which can severely affect the evolution of a galaxy, for example, by driving galactic-scale outflows and suppressing or enhancing star formation (e.g., Fabian 2012; Harrison et al. 2018). Understanding the connection between mergers and AGN is therefore crucial for advancing our knowledge of galaxy evolution and the formation of large-scale structures (Alexander & Hickox 2012; Heckman & Best 2014).

Previous studies have generally shown that mergers can trigger AGN activation; however, the exact mechanisms driving this process remain poorly understood. While many simulation-based studies have suggested that mergers fuel SMBH accretion and initiate the AGN phase (e.g., Hopkins et al. 2008; Blecha et al. 2018), other simulations propose that mergers serve only

as a secondary fuelling mechanism (e.g., Di Matteo et al. 2003; Martin et al. 2018; Byrne-Mamahit et al. 2023). Similarly, mixed results have also emerged from observations. For example, multiple observational studies have reported a clear link between mergers and AGN triggering (Lackner et al. 2014; Kocevski et al. 2015; Goulding et al. 2018; Ellison et al. 2019; Gao et al. 2020; Toba et al. 2022; Tanaka et al. 2023; Bickley et al. 2024), with a possible dependency on AGN luminosity (Treister et al. 2012; Weigel et al. 2018; Pierce et al. 2022; La Marca et al. 2024), dust obscuration (Ricci et al. 2017, 2021; Donley et al. 2018), and environment (Koulouridis et al. 2006, 2024). However, other studies have highlighted that mergers are a less significant mechanism, being outnumbered by secular processes (Grogin et al. 2005; Allevato et al. 2011; Draper & Ballantyne 2012; Marian et al. 2019; Silva et al. 2021; Smethurst et al. 2024; Garland et al. 2023; Villforth 2023; Bichang’a et al. 2024). Additionally, in several studies, there has been no observed dependence on AGN luminosity (Hewlett et al. 2017; Villforth et al. 2017; Comerford et al. 2024).

The AGN triggering debate could arise from several factors. First, there are various methods to identify mergers, each with its advantages and limitations. Among the different methods, visual classification (Darg et al. 2010), close spectroscopic pairs (Knapen et al. 2015), and non-parametric morphological statistics (Nevin et al. 2019) have been widely employed in the past.

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More recently, several studies have favoured machine learning (ML), in particular deep learning (DL), techniques (e.g., Wang et al. 2020). These methods are reproducible, and once trained, they can process large samples efficiently (for a review, see Margalef-Bentabol et al. 2024a). However, their performance depends on the specific task and is constrained by the quality of the training labels. Second, as in merger detections, there is no unique method to identify AGN. Since AGN exhibit a diverse range of observational signatures and different characteristics of ongoing activity, they can be selected through a multitude of techniques, including X-ray detections, optical emission line ratios, variability, mid-infrared (MIR) colours, and radio emission (for a review, see Heckman & Best 2014). As a result, different selection methods can lead to AGN and host galaxy samples with very different characteristics (Silverman et al. 2008; Hickox & Alexander 2018). For these reasons, a panchromatic approach has emerged in order to properly investigate the merger and AGN connection, accounting for different AGN types (Li et al. 2023).

La Marca et al. (2024) exploited a large multi-wavelength dataset at $z < 1$ and estimated the AGN contribution fraction parameter, which measures the AGN light contribution to the total galaxy light, through spectral energy distribution (SED) modelling in the rest-frame wavelength range 3–30 μm . The AGN were selected with multiple diagnostics, that is, X-ray, MIR, and SED modelling and a relation was proposed between the merger fraction and the AGN fraction relation, which revealed two distinct regimes. When the AGN is not dominant (low AGN fraction), the fraction of mergers stays roughly constant, with mergers representing only a secondary AGN triggering mechanism. However, for very dominant AGN, where the AGN fraction exceeds 0.8, the merger fraction rises rapidly towards 100%. A similar picture was observed in the merger fraction as a function of the AGN bolometric luminosity. These findings could explain some of the conflicting results in the literature. Secular processes may be the principal fuelling mechanisms in non-dominant and relatively faint AGN, while major mergers are the main or only viable channel to trigger the most powerful and dominant AGN.

So far, a lack of large survey data at high redshift has limited our understanding of the merger and AGN relation and its evolution. To improve our knowledge, particularly at earlier epochs, several key ingredients are needed, including deep imaging data with high spatial resolution to perform morphological classification, large volumes to construct large statistical samples, and multi-wavelength coverage to reliably select a diverse sample of AGN and derive physical properties of AGN and their host galaxies. The advent of *Euclid* and the associated ancillary data finally offers the opportunity to investigate this problem throughout cosmic history up to ‘cosmic noon’. *Euclid* is a European Space Agency (ESA) mission (Laureijs et al. 2011) whose aim is to observe almost all of the extra-Galactic sky with two surveys. Its scientific objectives are outlined in Euclid Collaboration: Mellier et al. (2025). *Euclid* operates in the optical and near-IR in four bands (I_E , Y_E , J_E , and H_E), covering wavelengths from 0.53 μm to 2.02 μm , (Euclid Collaboration: Cropper et al. 2025; Euclid Collaboration: Jahnke et al. 2025). Although *Euclid* was designed as a cosmology mission, it will be able to detect billions of sources, of which at least 10 million are expected to be AGN detected in I_E (Euclid Collaboration: Bisigello et al. 2024; Euclid Collaboration: Selwood et al. 2025) and hundreds of thousands in the near-IR bands (Euclid Collaboration: Lusso et al. 2024). This will dramatically increase the number of known AGN with high-resolution imaging, and provide an unprecedented opportunity to study the role of mergers in the evolution of AGN.

The aim of this study is to investigate the connection between mergers and AGN using the first quick release of *Euclid* data (Euclid Quick Release Q1 2025, hereafter Q1). We constructed a stellar mass-complete sample of galaxies across the redshift range $0.5 \leq z \leq 2$, with multi-wavelength data ranging from the X-ray to the MIR. We revisited two facets of the merger and AGN connection: i) Using a binary active–non-active AGN classification, we analysed whether mergers are a viable path to trigger AGN and assessed their significance, and ii) exploring continuous AGN properties, we studied how the fraction of mergers varies with AGN dominance and absolute power. Specifically, we explored whether galaxies hosting the most dominant and luminous AGN are more likely to be mergers. We developed a convolutional neural network (CNN) to identify mergers in *Euclid* I_E images. To mitigate issues with visual classifications, we trained the CNN on mock *Euclid* observations generated from cosmological hydrodynamic simulations, which include galaxy merger histories. We used four different diagnostics to select AGN and characterised each AGN based on the central point source luminosity relative to the host galaxy and, when possible, its bolometric luminosity.

The paper is organised as follows. In Sect. 2, we first introduce the *Euclid* data products we use in this work, the ancillary multi-wavelength data, and our galaxy sample selection. Then, we describe the mock *Euclid* observations generated from cosmological hydro-dynamical simulations to train our DL classifier. In Sect. 3, we present our galaxy merger classifier and the various AGN selection methods adopted. In Sect. 4, we first explore the merger and AGN connection using a binary classification of AGN and non-AGN. Next, we analyse this connection using continuous parameters that characterise the relative and absolute AGN power. We discuss possible caveats in our analysis in Sect. 5. Finally, we summarise our main findings in Sect. 6. Throughout the paper, unless otherwise stated, we assume a flat Λ CDM Universe with $\Omega_m = 0.3$, $\Omega_\Lambda = 0.7$, and $H_0 = 70 \text{ km s}^{-1} \text{ Mpc}^{-1}$ and express magnitudes in the AB system (Oke & Gunn 1983).

2. Data

In this section, we first describe the *Euclid* data. Then, we present a brief description of the multi-wavelength ancillary data, from the X-ray to the MIR. Finally, we introduce the mock *Euclid* VIS imaging data generated from the simulations.

2.1. *Euclid* data

This work focuses on exploring Q1, comprising data from a single visit of the Euclid Deep Fields (EDFs), namely the EDF North (EDF-N), the EDF South (EDF-S), and the EDF Fornax (EDF-F), covering a total area of $\sim 63 \text{ deg}^2$. All EDFs have been observed in all four *Euclid* photometric bands, that is I_E , Y_E , J_E , and H_E . These observations have been complemented by ground-based optical photometry taken with various instruments across the wavelength range 0.3–1.8 μm . Q1 includes imaging, spectroscopic data, and value-added catalogues, including photometric redshifts (photo- z ; Euclid Collaboration: Tucci et al. 2025). Further details on Q1 can be found in Euclid Collaboration: Aussel et al. (2025), Euclid Collaboration: McCracken et al. (2025), Euclid Collaboration: Polenta et al. (2025), and Euclid Collaboration: Romelli et al. (2025). All *Euclid* data used in this work, catalogues and images, have been retrieved using the ESA Data-labs facility (Navarro et al. 2024).

Catalogues. We selected a sample of galaxies from the *Euclid* MER catalogue (*Euclid* Collaboration: Altieri et al. in prep.) removing possible contaminants using the available columns as follows. First, we required a VIS I_E detection by imposing $VIS_DET = 1$. Then, we applied the condition $DET_QUALITY_FLAG < 4$ to filter out contaminants such as bad pixels, saturation, proximity to image borders, location within VIS or NIR bright star masks, presence within extended object areas, or omission by the deblending algorithm due to large pixel size. Additional flags can be used to filter out further contaminants, such as the $SPURIOUS_FLAG$, which identifies spurious sources. We set this flag to 0 to exclude such sources from our sample. Finally, we applied constraints on source flux and size by imposing $MUMAX_MINUS_MAG > -2.6$ to filter out point-like sources and $23.9 - 2.5 \log_{10}(FLUX_DETECTION_TOTAL) < 23.5$ to exclude faint objects.

In addition to the photometric catalogue, we queried the official pipeline photo- z and stellar masses for each source (*Euclid* Collaboration: Tucci et al. 2025). We excluded objects flagged (greater than or equal to one) by PHZ_FLAGS , $PHYS_PARAM_FLAGS$, or $QUALITY_FLAG$. When available, we used photometric redshifts and stellar masses estimated by *Euclid* Collaboration: Enia et al. (2025), which complemented the *Euclid* data with public IRAC observations for an improved quality of the recovered parameters. Finally, we limited our selection to galaxies within the redshift range $0.5 \leq photo-z \leq 2.0$ and with stellar mass $M_*/M_\odot > 10^{9.8}$. These galaxy parameters are given with their probability distributions and a set of possible values, from which we adopted the median values when applying these selections. The cut on stellar mass is motivated by our requirement of selecting a stellar mass complete sample, since *Euclid* Collaboration: Enia et al. (2025) showed that at $z = 2$ the *Euclid* galaxy sample is 90% complete at $M_*/M_\odot \gtrsim 10^{9.8}$, based on the Pozzetti et al. (2010) methodology.

Images. For our task of identifying mergers, we utilised VIS imaging data, which have a pixel resolution of $0''.1$ and a signal-to-noise ratio $S/N \geq 10$ at $I_E \leq 24.5$ (*Euclid* Collaboration: Cropper et al. 2025). For each galaxy in the selected sample, we made an $8'' \times 8''$ (corresponding to a 80×80 pixel grid) thumbnail centred on the source. This size approximately corresponds to a physical scale of $50 \text{ kpc} \times 50 \text{ kpc}$ in the redshift range considered. We excluded sources for which generating an $8'' \times 8''$ cutout was not feasible because they are at the edge of the field. Additionally, we retrieved the VIS point spread function (PSF), which was used when constructing the training dataset.

Ancillary data. Q1 is complemented by ancillary multi-wavelength datasets from photometric surveys, including X-ray data from XMM-Newton, Chandra and eROSITA (*Euclid* Collaboration: Roster et al. 2025, hereafter RW25, and references therein), GALEX (Galaxy Evolution Explorer; Bianchi et al. 2017), Hyper Suprime-Cam (HSC; Miyazaki et al. 2018), Gaia (*Gaia* Collaboration et al. 2016), UNIONS (Ultraviolet Near-Infrared Optical Northern Survey; Gwyn et al. in prep.), DES (Dark Energy Survey; The Dark Energy Survey Collaboration 2005), the Dark Energy Spectroscopic Instrument (DESI; DESI Collaboration et al. 2016, 2022) Legacy Imaging Surveys (Dey et al. 2019) and spectroscopic survey, and the WISE-AllWISE DR6 survey data (Wright et al. 2010). To create multi-wavelength catalogues for each one of the EDFs, *Euclid* Collaboration: Matamoros Zatarain et al. (2025, hereafter MZ25) performed positional matches with the external surveys using the software STILTS, version 3.5–1 (Taylor 2006). The matching process was customised for each EDF to account for differences in sky coverage. For detailed information on the matching proce-

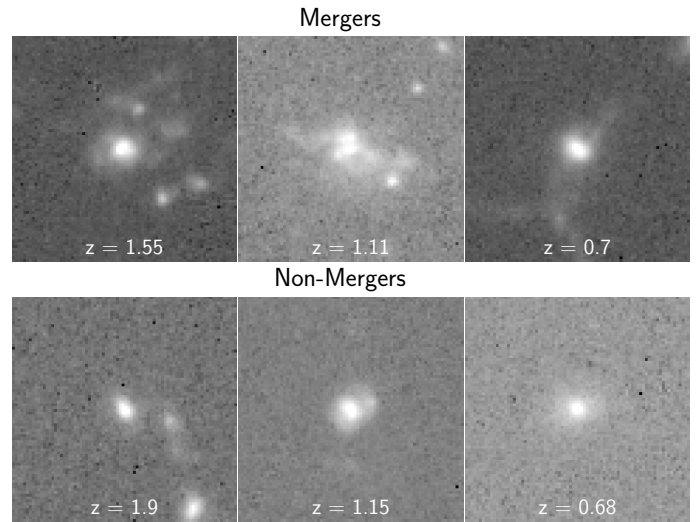


Fig. 1. Examples of mock *Euclid* VIS I_E -band observations of TNG galaxies. Galaxies were randomly selected among the TNG100 galaxies available. The images are $8'' \times 8''$ wide and log-scaled in the 1st–99th percentile range. The redshift of each galaxy is reported in each panel.

dure, including the radii used and selection criteria applied, we refer the reader to MZ25.

2.2. The IllustrisTNG galaxy sample

To train our merger identification model, we used simulated galaxies from the IllustrisTNG (hereafter TNG) cosmological hydrodynamical simulations, which provide detailed merger histories in large cosmological volumes, ensuring a large sample of galaxies. The TNG simulation consists of three different volumes varying in physical size and mass resolution (Marinacci et al. 2018; Naiman et al. 2018; Nelson et al. 2018; Pillepich et al. 2018; Springel et al. 2018). We used the TNG100 and TNG300 boxes (hereafter referred to as the TNG simulation), with their box size corresponding to 110.7 Mpc and 302.6 Mpc, respectively. The baryonic matter resolution is $1.4 \times 10^6 M_\odot$ in TNG100 and $1.1 \times 10^7 M_\odot$ in TNG300. Using both TNG suites allows us to confidently select galaxies down to $M_*/M_\odot = 10^9$ in TNG100, and to have a large sample of galaxies thanks to the TNG300 size. We required a minimum of about 1000 baryonic particles, which, for TNG100, correspond to galaxies with stellar mass $M_*/M_\odot \geq 10^9$, while for TNG300 the lower mass limit is $M_*/M_\odot > 8 \times 10^9$.

We selected galaxies within the redshift range $z = 0.5–2$, corresponding to simulation snapshot numbers 67–33. The time step between each snapshot is 150 Myr. For each galaxy, the TNG simulation provides a complete merger history (Rodríguez-Gómez et al. 2015) identified through the Subfind algorithm (Springel et al. 2001). We then define a subhalo as a merger if a merger event occurred in the previous 300 Myr or will occur within the next 800 Myr. Otherwise, the subhalo is considered a non-merger. This time window is motivated by simulation studies (e.g., Moreno et al. 2019), which show that during this period, the majority of gas is transferred between galaxies, leading to enhanced star formation and nuclear activity. Here we considered only major merger events, with a stellar mass ratio $M_1/M_2 \leq 4$. This selection includes pre-mergers (close galaxy pairs expected to merge within 800 Myr), ongoing mergers, and recent post-mergers. As such, we sample a significant fraction of the merger timescale, covering the late stages of the dynamical interaction

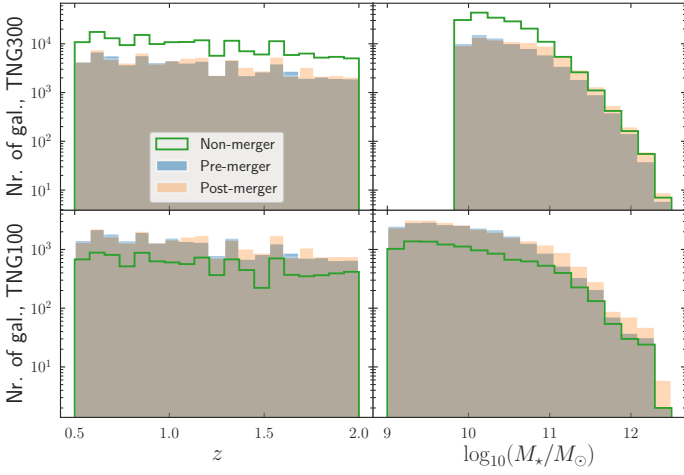


Fig. 2. Redshift (left column) and M_* (right column) distributions for pre-, post-, and non-merging galaxies in the TNG300 (top row) and TNG100 (bottom row) training sets.

and the immediate aftermath of coalescence, but excluding wide pairs that are still in the early interaction phase. It is important to note that the merger rate and its evolution in hydrodynamical simulations such as TNG depend on the underlying galaxy-halo connection implemented in the simulation. Different simulations with distinct prescriptions for galaxy formation physics can yield different merger rates (e.g., Grylls et al. 2020).

The dataset was divided into training, validation, and testing sets, corresponding to 80%, 10%, and 10% of the total sample, respectively. We ensured that galaxies involved in the same merger sequence were included in only one subset. These datasets result in 499 523 galaxies for the training sample (427 577 from TNG300 and 71 946 from TNG100), 54 911 for the validation set (46 660 from TNG300 and 8251 from TNG100), 61 697 for the testing set (52 875 from TNG300 and 8822 from TNG100). Of these, 250 142, 26 999, and 30 986 are mergers, respectively. In each set, we balanced the number of non-mergers with that of mergers. Figure 2 displays the z and M_* distributions of the training samples, split in pre-, post-, and non-mergers.

We generated mock observations for the TNG galaxies following the Margalef-Bentabol et al. (2024a) methodology. We prepared the mock VIS I_E -band observations, at the same pixel resolution of $0''.1$, as follows:

1. Each stellar particle contributes to the galaxy's SED, determined by its mass, age, and metallicity. These SEDs are derived from the stellar population synthesis models of Bruzual & Charlot (2003). The summed SED was passed through the VIS filter to generate a smoothed 2D projected map (Rodríguez-Gomez et al. 2015). The image is then cropped to $8'' \times 8''$, corresponding to approximately $50 \text{ kpc} \times 50 \text{ kpc}$ in the relevant redshift range, matching the size used for the *Euclid* galaxy images.
2. Each image was convolved with a VIS PSF, randomly chosen to account for the spatial variation of the PSF across the field of view.
3. Poisson noise was added to each image to simulate the statistical variation in photon emission from sources over time.
4. To ensure realistic merger classifications, it was essential to include observational effects (e.g., Huertas-Company et al. 2019; Rodríguez-Gomez et al. 2015). We injected the TNG galaxies into actual *Euclid* sky cutouts of $8'' \times 8''$. To prepare

the sky cutouts, we generated random coordinates within the area covered by Q1 data. We controlled the segmentation map for each coordinate, ensuring that within a $9'' \times 9''$ box, all pixels were set to zero¹. When creating the cutouts, we controlled that there were no invalid pixels (NaN values) and that the selected coordinates allowed for a perfectly square cutout without intersecting the edge of a tile.

To create a training sample that accounts for possible AGN, we added a central point source to the host galaxies. The central source intensity can be defined in relation to the host galaxy flux, given the PSF fraction (f_{PSF}):

$$f_{\text{PSF}} = \frac{F_{\text{PSF}}}{F_{\text{host}} + F_{\text{PSF}}}, \quad (1)$$

where F_{PSF} and F_{host} are the fluxes within a $0''.5$ aperture of the central source and the host galaxy, respectively. The observed VIS PSF models were used as the central point source. The f_{PSF} values were uniformly chosen in the range 0–1. This operation was performed for a randomly selected 20% of the TNG sample. We show examples of the final mock observations in Fig. 1. To see the effect of each step in the mock observations generation, we refer the reader to Margalef-Bentabol et al. (2024a).

Our mock images do not include dust attenuation, which may affect morphologies at $z = 2$, where the I_E -band probes the rest-frame ultraviolet. However, previous studies have shown that including dust attenuation via full radiative transfer calculations yields only modest changes in the overall classification performance (Bottrell et al. 2019; Rodríguez-Gomez et al. 2019; Wang et al. 2020), while being computationally prohibitive at the scale of our training sample. Moreover, modelling the effect of dust involves many assumptions (e.g. on dust composition and distribution), whose validity remains to be tested (Zanisi et al. 2021). We therefore followed previous works and used dust-free mock observations.

We normalised each image following Bottrell et al. (2019). This normalisation ensures that all images are in a hyperbolic arcsin scale within the range 0–1, maximising the contrast of the central target. A summary of the main steps applied is provided below (see Bottrell et al. 2019, for a detailed description).

- i) We took the hyperbolic arcsin of the images. Values below -7 were converted to NaNs.
- ii) We computed the median of each image, a_{min} , and the 99th percentile, a_{max} , considering a central box of side 25 pixels.
- iii) All values below a_{min} were set to a_{min} , including the NaNs. Values above a_{max} were set to a_{max} . The resulting clipped images were normalised by subtracting a_{min} and dividing by $a_{\text{max}} - a_{\text{min}}$.

This mock *Euclid* dataset was used to train, validate, and test our merger classifier, as described in the next section.

3. Methodology

Here, we present the DL classifier developed to identify mergers in *Euclid* images. Then, we describe the diagnostics used to select AGN.

3.1. Merger classification using CNNs

We developed a CNN (Lecun et al. 1998) to classify mergers and non-mergers. CNNs consist of multiple layers that apply

¹ This constraint ensures that there are no detected sources or artefacts in each image pixel. The $9''$ radius is derived from the estimated source density of the EDFs.

Table 1. Convolutional neural network architecture.

Layer type	No. param.	Output shape	Properties
Input	0	(1,80,80)	
Convolutional 32 filters (7,7)	1600	(32,80,80)	1 pixels stride, “same” padding, ReLU act.
Max Pooling	0	(32,40,40)	pool size 2
Dropout	0	(32,40,40)	30%
Convolutional 64 filters (7,7)	100 416	(64,40,40)	1 pixels stride, “same” padding, ReLU act.
Max Pooling	0	(64,20,20)	pool size 2
Dropout	0	(64,20,20)	30%
Batch Norm.	256	(64,20,20)	
Convolutional 128 filters (7,7)	401 536	(128,20,20)	1 pixels stride, “same” padding, ReLU act.
Max Pooling	0	(128,10,10)	pool size 2
Dropout	0	(128,10,10)	30%
Convolutional 128 filters (7,7)	802 944	(128,10,10)	1 pixels stride, “same” padding, ReLU act.
Max Pooling	0	(128,5,5)	pool size 2
Dropout	0	(128,5,5)	30%
Flatten	0	(32 000)	
Dense	819 456	(256)	256 units, ReLU act.
Dropout	0	(256)	30%
Dense	32 896	(128)	128 units, ReLU act.
Dropout	0	(128)	30%
Dense	129	(1)	1 unit, sigmoid act.

Notes. The columns are the name of the Keras layer (and the filters for the convolutional layers), the number of trainable parameters, the output shape, and the hyper-parameters for each layer.

learnable filters to an input image to capture features such as edges and textures. The later layers of the network are typically fully connected, combining the features from earlier layers to calculate a classification for the input image. The architecture developed in this work is presented in Table 1, for which we utilised the Keras framework for the TensorFlow platform (Chollet 2023; Abadi et al. 2016). The CNN consists of four convolutional layers and three fully connected layers. For all layers, we adopted a rectified linear unit (ReLU) as an activation function, except for the final layer, where a sigmoid activation function was used. A stride of one pixel was used for the convolutional layers. We introduced dropout layers after each processing layer to prevent overfitting. These dropout layers randomly set input units to zero at a specified rate. To further prevent overfitting, early stopping in the training phase was used. The specific hyper-parameters, listed in Table 1, include filter numbers and sizes, dropout rates, and strides, chosen based on a grid search.

We evaluated the model performance on the test set from the TNG simulations, using common metrics such as ‘precision’, ‘recall’, and ‘F1-score’. Precision measures how often the model correctly predicts a given class, while recall focuses on how complete the model is at finding objects in a given class. In other words, precision is the number of objects correctly recovered for a class divided by the total number of objects predicted in that class. Recall is the number of objects correctly recovered

Table 2. Overall performance of the CNN on the TNG test set.

Class	Precision	Recall	F1-score
Mergers	0.80	0.68	0.74
Non-mergers	0.72	0.83	0.77

Notes. Two thresholds were used for classifying galaxies as mergers (score ≥ 0.59) and non-mergers (score < 0.35).

for a class divided by the total number of objects in that class. F1-score is the harmonic mean of precision and recall. All metrics are calculated on a balanced sample (50% mergers and 50% non-mergers).

In this work, we are interested in selecting a pure sample of mergers. Hence, we followed La Marca et al. (2024) to have a higher classification precision for mergers. We searched for a threshold which maximises the F1-score to identify mergers while maintaining a precision greater than or equal to 0.80 for the merger class. According to these prescriptions, the best threshold for mergers is 0.59. Thus, all galaxies with a predicted score greater than 0.59 are classified as mergers. Similarly, to select a sample of non-mergers with low contamination levels, we searched for a threshold that ensures at least 0.70 precision for non-mergers, maximising the F1-score. We lowered the precision to 0.70, given the poorer precision of our classifier for the non-merger class. It is important to highlight that the expected number of non-mergers is much larger than that of interacting galaxies (e.g., Ferreira et al. 2020). Therefore, in real galaxies, we expect a much lower contamination of mergers in predicted non-mergers. The set threshold is 0.35, meaning all galaxies with a predicted score below 0.35 are labelled as non-mergers. Performance metrics for mergers and non-mergers are shown in Table 2. Setting a larger threshold for mergers and a lower one for non-mergers will further improve the purity of both classes, but also strongly affect their completeness, limiting the sample size of both classes.

The model performance is comparable to the performance of other recent studies. Margalef-Bentabol et al. (2024a) benchmarked several state-of-the-art methods to identify major mergers in astronomical images out to $z = 1$. Each model was trained on mock observations from cosmological hydrodynamical simulations, where mergers have been defined in a similar fashion to this work. Based on the performance metrics on the TNG-test set, the best model in Margalef-Bentabol et al. (2024a, Table 3) obtained a precision of 0.80 and a recall of 0.74 (F1-score 0.77) for the merger class, which is consistent with the performance for mergers we report in Table 2. While comparable to similar contemporary works, the model performance metrics (Table 2) indicate non-negligible levels of sample contamination and incompleteness inherent to automated classification. We quantitatively assess the impact of these classification uncertainties on our key scientific results regarding the merger-AGN connection in Section 5.3.

The *Euclid* collaboration also provides detailed morphologies (Euclid Collaboration: Walmsley et al. 2025), including possible companions and merger features, based on predictions from the Bayesian DL classifier Zoobot (Walmsley et al. 2022). However, these predictions are limited to the top 1% brightest and most extended galaxies, with the selection criteria being $\text{segmentation_area} > 1200 \text{ pixels}$ OR $I_E < 20.5 \text{ mag}$ AND $\text{segmentation_area} > 200 \text{ pixels}$. In comparison, our stellar mass-complete sample goes down to $I_E \approx 23.5 \text{ mag}$. Therefore, we developed our own classifier. We compare our model predic-

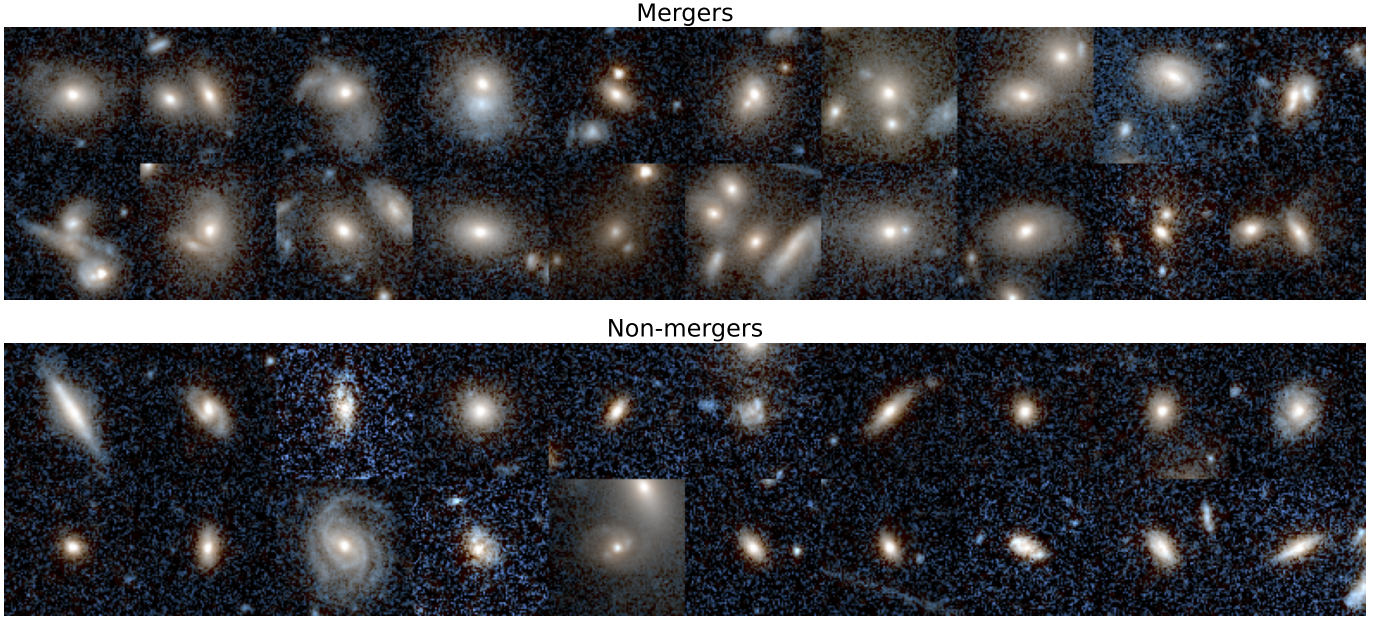


Fig. 3. Examples of galaxies classified as mergers (*top panel*) and as non-mergers (*bottom panel*) by our algorithm. The cutouts are *Euclid* composite RGB images where the R channel is Y_E , the B channel is I_E , and the G channel is the mean, following a 99.85th percentile clip and an arcsinh stretch ($x' = \text{arcsinh } Qx$, with $Q = 100$; [Euclid Collaboration: Walsley et al. 2025](#)).

tions with the Zoobot classification for the common galaxies in Appendix A.

The double threshold approach has the side effect of producing unclassified galaxies, defined as those with a predicted score between 0.35 and 0.59, inclusive. However, given the large sample size of Q1, this does not affect the analysis carried out in this work. The *Euclid* galaxy sample constructed contains 105 037 sources classified as mergers, 254 564 as non-mergers, and 204 082 unclassified objects. These values correspond to 18.6%, 45.2%, and 36.2% shares of the whole sample, respectively. The catalogue with the merger classification is available from Zenodo². Hereafter, we focus on the classified galaxies and calculate merger fractions as

$$f_{\text{merg}} = \frac{N_{\text{merger}}}{N_{\text{classified}}} = \frac{N_{\text{merger}}}{N_{\text{merger}} + N_{\text{non-merger}}}, \quad (2)$$

unless differently stated. We show some randomly selected *Euclid* merger and non-merger examples in Fig. 3. Examples of unclassified galaxies are provided in Appendix B. Most galaxies classified as mergers are pair galaxies, with close companions clearly visible in the images. In comparison, non-merger galaxies appear to be quite regular and isolated. Here, we point out that two close galaxies, if both detected, were considered individually rather than as a single system.

3.2. AGN identification

The Q1 data are accompanied by a set of multi-wavelength catalogues that allow for multiple AGN selections. This work focuses on four main AGN detection techniques: X-ray, optical spectroscopy, DL-based image decomposition, and MIR colours. The first *Euclid* AGN catalogue is presented in [MZ25](#) and includes all these AGN selections, except the DL-based image decomposition method, described in [Euclid Collaboration:](#)

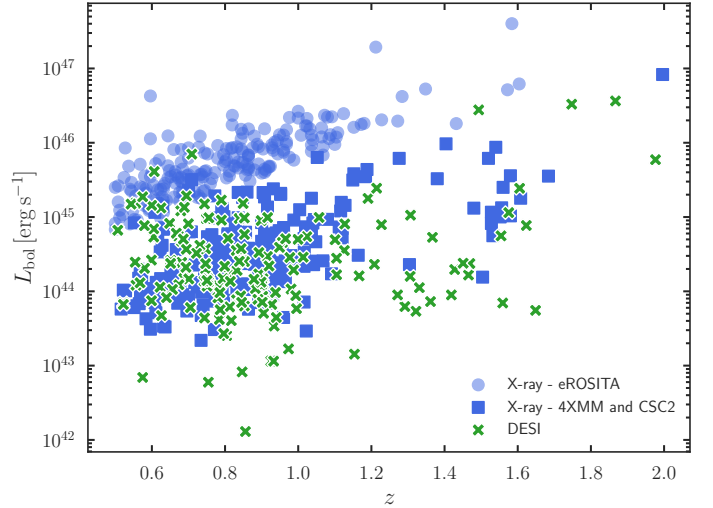


Fig. 4. AGN bolometric luminosity (L_{bol}) versus redshift for the X-ray and DESI-selected AGN.

[Margalef-Bentabol et al. \(2025, hereafter MB25\)](#). The AGN-selection techniques are detailed in these two papers. Here, we summarise the main aspects of the criteria used.

MIR colour selections defined in [Assef et al. \(2018, hereafter A18\)](#). [MZ25](#) used two different diagnostics, C75 and R90, to select MIR AGN among the sources with AllWISE fluxes. The C75 selection, focusing on achieving 75% completeness, is defined as

$$W_1 - W_2 > 0.71 \text{ Vega mag}, \quad (3)$$

while the R90 diagnostic, optimised for obtaining 90% reliability, is

$$W_1 - W_2 > \begin{cases} 0.65 e^{0.153(W_2 - 13.86)^2}, & W_2 > 13.86, \\ 0.65, & W_2 \leq 13.86. \end{cases} \quad (4)$$

² <https://doi.org/10.5281/zenodo.17087033>

Table 3. Active Galactic Nucleus counts for each selection used in this paper.

AGN selection method	Reference	Description	No.
X-ray	RW25	Extragalactic point-like X-rays sources from 4XMM-DR13, CSC2, and eROSITA surveys	437
DESI, spectroscopy	Siudek et al. (2024)	Spectroscopic diagnostics based on emission lines for the matched DESI sources (see Sect. 3)	160
DL-based	MB25	Galaxies with a predicted $f_{\text{PSF}} > 0.2$, based on VIS images	23 338
C75, AllWISE	A18	75% Completeness-optimised MIR diagnostic Eq. (3) applied to the AllWISE data	5712
R90, AllWISE	A18	90% Reliability-optimised MIR diagnostic Eq. (4) applied to the AllWISE data	556

These criteria were accompanied by some extra conditions. We only considered sources with W_1 and W_2 magnitudes fainter than the saturation limits of the survey set as $W_1 > 8$ and $W_2 > 7$ (Vega magnitudes), with $S/N_{W_2} > 5$, and not flagged as either artefacts or affected by artefacts, meaning that the `cc_flags` are equal to zero ([MZ25](#)). In the case of EDF-F and EDF-S, multiple WISE fluxes are available, including the AllWISE and the LegacyDR10 WISE fluxes. The main difference is that the latter are obtained through forced photometry at the locations of the Legacy Surveys optical sources, resulting in a larger number of matches with *Euclid* counterparts. Moreover, the extra conditions of the [A18](#) diagnostics are not easily applicable to the LegacyDR10 WISE data. Therefore, considering that the EDF-N has only AllWISE data, we decided to work with the AllWISE MIR data also for EDF-F and EDF-S.

Sources with an X-ray counterpart identified by [RW25](#). Several X-ray surveys observed the EDFs, such as the XMM-Newton 4XMM-DR13 survey ([Webb et al. 2020](#)), the *Chandra* Source Catalogue v2.0 (CSC2; [Evans et al. 2024](#)), and the eROSITA DR1 Main sample ([Predehl et al. 2021](#); [Merloni et al. 2024](#)). [RW25](#) identified Q1 counterparts from these X-ray surveys using the Bayesian algorithm NWay ([Salvato et al. 2018](#)). The final product is a catalogue of Q1 sources matched with several X-ray point-like sources. This catalogue also includes spectroscopic redshift, if available, otherwise photo- z , X-ray luminosities (L_X), and a galactic or extragalactic probability (`Gal_proba`). We refer the reader to [RW25](#) for more details about the optical-X-ray matching procedure and the catalogue generation. To select a pure sample of X-ray AGN, we selected only sources with `match_flag` = 1, `Gal_proba` < 0.5, optical signal-to-noise $S/N \geq 2$, and $L_X \geq 10^{42} \text{ erg s}^{-1}$. This soft X-ray luminosity threshold is generally sufficient for isolating AGN from other X-ray sources ([Aird et al. 2017](#)).

The [MZ25](#) multi-wavelength catalogue provided DESI spectroscopic counterparts for 42 706 galaxies, and thus allowed for spectroscopic AGN detection. We ran several diagnostics to identify quasars (QSOs) and AGN candidates based on these spectroscopic data. To select QSOs, we utilised the DESI spectral-type classification (`SPECTYPE=QSO`; [DESI Collaboration et al. 2024](#)). For sources classified as galaxies (`SPECTYPE=GALAXY`), we used several methods to identify AGN based on emission line fluxes, widths, and equivalent widths measured with FastSpecFit ([Moustakas et al. 2023](#)). [MZ25](#) reports the details of these measurements, available for 40 274 of the DESI EDR Q1 sources. This sample was accompanied by SED fitting performed by [Siudek et al. \(2024\)](#), which provided stellar masses and AGN properties. They only kept sources with

an SED fit with a reduced $\chi^2 < 17$. With these criteria, we found 160 counterparts in our stellar-mass-limited sample. This threshold for χ^2 was adopted from [Siudek et al. \(2024\)](#), who, based on extensive visual inspections (their Appendix D.2), defined it as optimal for ensuring reliable SED fits in their value-added catalogue. For our DESI-selected AGN sample, the vast majority (139 out of 160) have even higher quality fits, with $\chi^2 < 5$, and excluding the remaining 21 sources with χ^2 between 5 and 17 does not qualitatively affect our results.

[MB25](#) trained a DL-based algorithm to perform image decomposition in the VIS imaging data and provide an estimate of the PSF contribution (f_{PSF}) with respect to the total galaxy light in the observed flux. Following the same technique as in [Margalef-Bentabol et al. \(2024b\)](#), [MB25](#) fine-tuned the pre-trained DL-architecture Zoobot ([Walmsley et al. 2023](#)) to predict f_{PSF} from galaxy images. The training set consisted of mock *Euclid* observations of TNG galaxies, where central point sources were injected with randomly chosen f_{PSF} values in the range [0, 1). The resulting DL model achieves high accuracy and precision in recovering f_{PSF} , with a mean bias $\langle f_{\text{PSF}}[\text{injected}] - f_{\text{PSF}}[\text{Zoobot}] \rangle = -0.0078$, and a root mean square error of 0.051. Only about 5% of galaxies with $f_{\text{PSF}}[\text{injected}] < 0.05$ have a predicted $f_{\text{PSF}}[\text{Zoobot}] > 0.2$. Here, we labelled as DL-based AGN those galaxies with $f_{\text{PSF}} > 0.2$, which corresponds to a 4σ cut given the mean uncertainty in the f_{PSF} estimates, and ensures a high-purity sample. Although this f_{PSF} threshold aims for a high-purity selection of dominant central point sources, we acknowledge that the derived f_{PSF} may include contributions from nuclear star formation in addition to AGN, and that its completeness could be affected by heavy nuclear obscuration. A more detailed discussion of the method, its performance, validation, and comparison with traditional selection methods, is presented in [Margalef-Bentabol et al. \(2024b\)](#) and [MB25](#). We also estimate the AGN luminosity in the VIS band (L_{PSF}) by multiplying the total galaxy flux by the predicted f_{PSF} and converting it into a luminosity using the photometric redshift.

In total, our sample includes 28 670 classified galaxies hosting an AGN identified by at least one of the selection methods above.³ The number of AGN identified per selection method is reported in Table 3. Many AGN have multiple detections. We show the intersection of the AGN selections in Appendix C. The [MZ25](#) Q1 AGN catalogue includes a variety of AGN selections, among which an AGN identification diagnostic based on *Eu-*

³ Considering the whole sample, i.e. classified plus unclassified galaxies, about 39% of AGN are labelled as unclassified, similar to the non-AGN population, where the unclassified fraction is 36%.

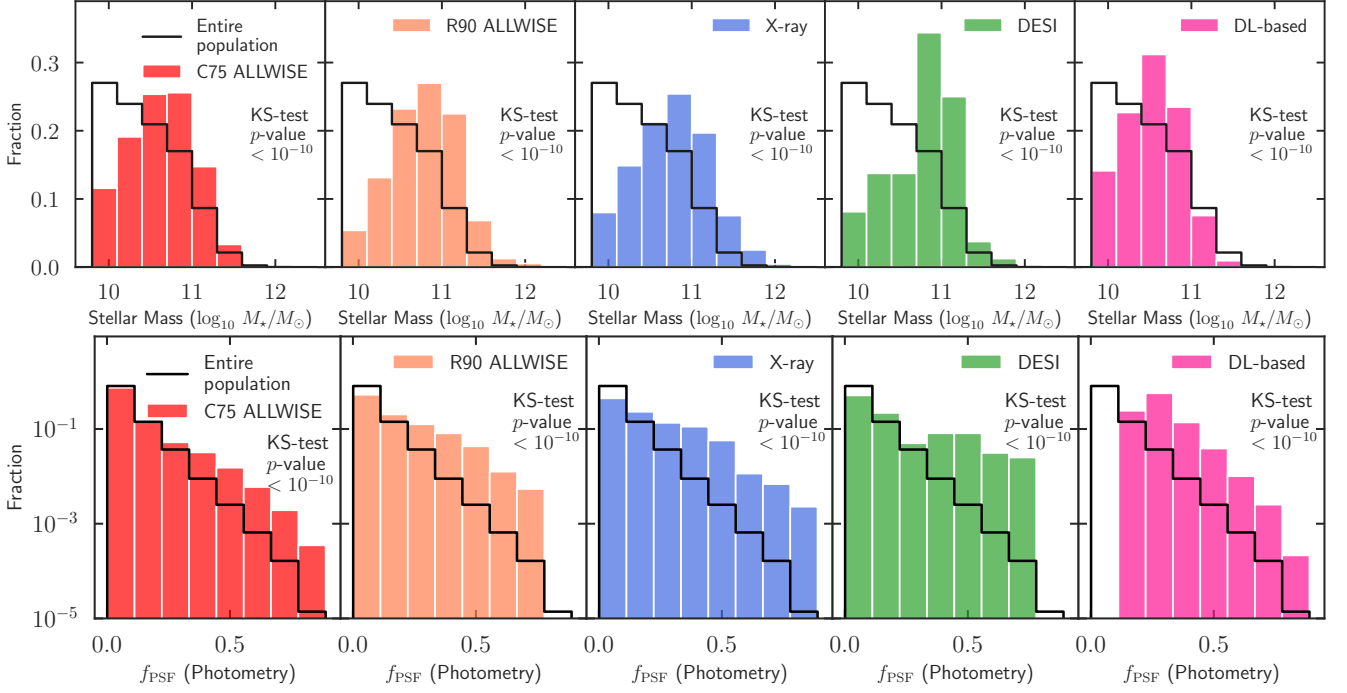


Fig. 5. Stellar mass (upper row) and point-source contribution, estimated by the PSF fraction (f_{PSF} , lower row) distributions for each AGN population. As a reference, we overlay the distribution for the entire sample of classified galaxies, including the selected AGN, in each panel. The distribution areas are normalised to unity. In each panel, we report the results of a two-sample KS test between the selected AGN and the entire galaxy sample.

clid's photometry alone (Euclid Collaboration: Bisigello et al. 2024). However, we did not consider this selection because its purity and completeness are poor in the absence of u -band observations. Moreover, this methodology is oriented towards obtaining a clean sample of quasars, which requires constraints on the point-like morphology of the source, which will bias against the detection of potential merging features.

For DESI- and X-ray-selected AGN, we computed the AGN bolometric luminosity. In the first case, we utilised the L_{bol} estimated through SED fitting by Siudek et al. (2024). The SED fitting was performed using Code Investigating GALaxy Emission (CIGALE v2022.1; Boquien et al. 2019; Yang et al. 2020, 2022), assuming for the AGN contribution the Fritz et al. (2006) templates. Siudek et al. (2024) found a close agreement between the L_{bol} derived from *Chandra* and SED fitting, with a median difference of $L_{\text{bol, SED}} - L_{\text{bol, Chandra}} \approx -0.1$ dex. For the X-ray AGN, we used the X-ray luminosities (L_X) from RW25, which we converted into bolometric luminosities using the conversion factors from Shen et al. (2020). Specifically, we used the double power law

$$\frac{L_{\text{bol}}}{L_X} = c_1 \left(\frac{L_{\text{bol}}}{10^{10} L_{\odot}} \right)^{k_1} + c_2 \left(\frac{L_{\text{bol}}}{10^{10} L_{\odot}} \right)^{k_2}, \quad (5)$$

where $c_1 = 5.712$, $k_1 = -0.026$, $c_2 = 12.60$, and $k_2 = 0.278$. We show how L_{bol} evolves with redshift for DESI and X-ray AGN in Fig. 4. X-ray sources are shown separately to highlight the difference in the survey characteristics (RW25). We note that 4XMM and CSC2 are deeper surveys compared to eROSITA, which covers a larger area but is biased towards brighter AGN ($L_{\text{bol}} \gtrsim 10^{45}$ erg s $^{-1}$).

Different AGN selections correspond to different host galaxy properties (e.g., Silverman et al. 2008). We compare the stellar mass of the AGN candidates hosts for the different AGN selections in Fig. 5, top panels. Compared to the entire galaxy sample

(active and non-active galaxies), AGN candidates reside in more massive galaxies, with their $M_{\star}$ distribution peaking at $10^{10.5} - 10^{11} M_{\odot}$. Nevertheless, we should bear in mind that the stellar masses derived by Euclid Collaboration: Enia et al. (2025) or the official *Euclid* pipeline do not consider the AGN component, which could bias the estimates of the $M_{\star}$ of AGN host galaxies. For example, the Euclid Collaboration: Enia et al. (2025) $M_{\star}$ are systematically lower by 0.07 dex compared to those derived for the DESI sample, which included an AGN component in their SED fitting (Siudek et al. 2024).

To assess the statistical difference among the AGN populations and the entire galaxy sample, we ran a two-sample Kolmogorov-Smirnov test (KS test; Hodges 1958). The KS test determines whether two samples come from the same parent distribution (null hypothesis). The p -value measures the probability of obtaining the observed difference between distributions, assuming the null hypothesis is true. If the p -value is below the significance level (here we take it to be 0.05), the difference between the two samples is statistically significant. In each panel of Fig. 5, we report the resulting p -value between each AGN selection and the entire galaxy sample. The results confirm that the $M_{\star}$ distributions of AGN candidates are statistically different from the $M_{\star}$ distribution of the entire sample (active plus non-active galaxies).

There are also some differences among the different AGN selections. DESI AGN live in extremely massive galaxies, with more than 70% of these galaxies having $M_{\star}/M_{\odot} \geq 10^{11}$. X-ray AGN and R90 MIR AGN tend to be in slightly less massive galaxies, with average $M_{\star}/M_{\odot} \approx 10^{10.8}$, in agreement with previous studies (Bongiorno et al. 2012; Mountrichas et al. 2021). A KS test run to compare the $M_{\star}$ distributions of AllWISE R90, X-ray, and DESI AGN with each other, confirms this similarity (p -value < 0.05). DL-based and C75 MIR AGN inhabit the least massive galaxies, with average $M_{\star}/M_{\odot} \approx 10^{10.5}$. Also in this

case, we found agreement with previous studies in the literature (e.g., [Bornancini et al. 2022](#)). These differences might be due to selection biases. DESI AGN are spectroscopically selected and so naturally more likely to be in brighter, hence more massive, galaxies. Similarly, the difference between the stellar masses of R90 and C75 MIR AGN candidates hosts is expected because redder colours and brighter magnitudes are required ([A18](#)) to select more reliable samples of AGN. The DL algorithm used to identify AGN components was trained using galaxies down to $10^9 M_\odot$. Thus, it is not surprising that this method allowed us to select AGN in less massive galaxies than the other methods.

In Fig. 5, bottom panels, we compare the f_{PSF} distribution for the different AGN selections. As expected, all AGN types show a larger fraction of galaxies with higher f_{PSF} values compared to the entire galaxy sample. It is not surprising that the largest fraction of $f_{\text{PSF}} \geq 0.5$ galaxies is observed in DESI AGN, these being optically selected spectroscopic AGN. However, we might be missing the extremely dominant point sources ($f_{\text{PSF}} > 0.8$) because CIGALE fails to estimate the stellar mass correctly when the AGN outshines the host galaxy. The KS tests confirm the difference between AGN candidate hosts and the entire galaxy population. This statistical difference confirms that the f_{PSF} parameter effectively isolates galaxies with a prominent central luminous component, characteristic of AGN activity, across all selection methods. It also provides an additional validation for the statistical reliability of our DL-based method in quantifying the AGN contribution. In Appendix C, we also compared the redshift distributions of each AGN selection.

4. Results

In this section, we first construct control samples of mergers and non-mergers and AGN and non-AGN galaxies. Then, we investigate the merger and AGN relation by adopting a binary AGN–non-AGN classification and exploring continuous AGN parameters. All experiments are divided into two redshift bins, which are $0.5 \leq z < 0.9$, and $0.9 \leq z \leq 2.0$, with roughly equal numbers of AGN.

4.1. Control pools

Proper control samples are crucial as AGN occurrence and the merger rate can depend on host galaxy properties such as stellar mass and redshift (e.g., [Aird et al. 2012](#); [Ferreira et al. 2020](#)). Specifically, the merger and AGN control samples satisfy the following conditions:

$$|z_{\text{control}} - z_{\text{sample}}| \leq 0.04 z_{\text{sample}}, \quad (6)$$

$$|\log_{10}(M_{\star, \text{control}}/M_{\star, \text{sample}})| \leq 0.2 \text{ dex}. \quad (7)$$

We chose these values according to the estimated normalised median absolute deviations for photo- z and $M_\star$ ([Euclid Collaboration: Enia et al. 2025](#)). These two conditions ensure that each galaxy (AGN) is compared with a sample of galaxies with similar redshift and stellar mass. For each galaxy (AGN) in the original sample, we required at least ten counterparts that satisfy these criteria. When more than ten controls were found, we randomly picked ten of them. If there were fewer than ten controls, we iteratively increased our tolerances by a factor of 1.5 for each parameter. This operation was performed up to three times; otherwise, we rejected the galaxy (AGN). When constructing controls for AGN galaxies, we sampled from all galaxies that do not host any detected AGN, a pool of 330 931 possible galaxies. Non-AGN controls were constructed independently for each AGN selection.

While matching in other physical parameters, such as star formation rate, could further refine the control samples, we have not included these in the current analysis. Specifically, star formation rate estimates available in Q1 are subject to considerable uncertainties at this stage (e.g., normalised median absolute deviations of ~ 0.45 – 0.64 dex, as detailed in [Euclid Collaboration: Enia et al. 2025](#)). Given these large uncertainties, attempting to match the star formation rate would not improve the control.

4.2. Merger and AGN relation using a binary AGN classification

In the first set of experiments, we investigated whether mergers can trigger AGN by examining the incidence rate of AGN in mergers and non-merger controls, and whether they are the primary trigger, by comparing the merger fraction in AGN and non-AGN controls.

4.2.1. AGN frequency in mergers and non-mergers

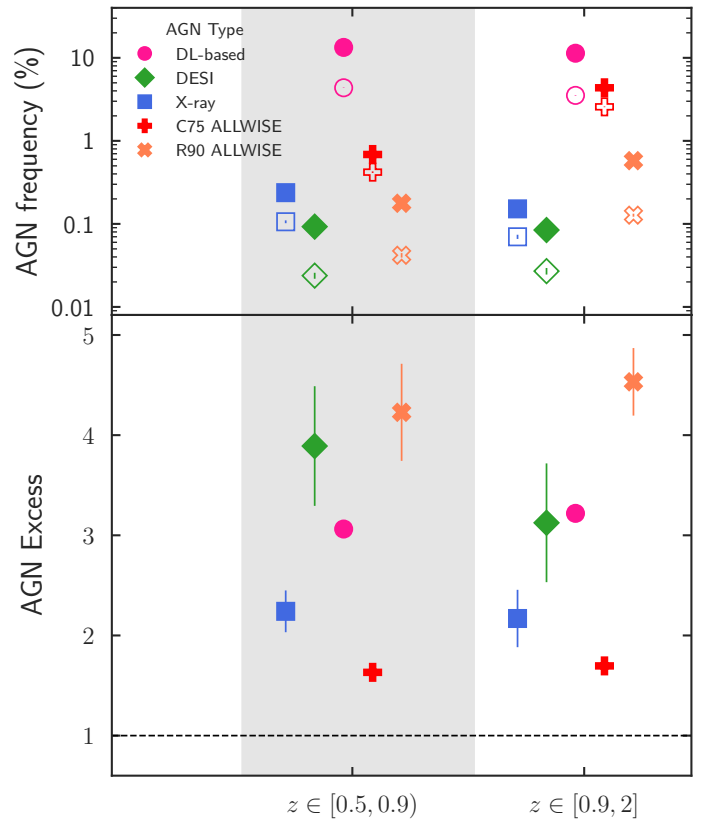


Fig. 6. Active galactic nuclei frequency (Eq. 8) in mergers and non-merger controls in two redshift bins. *Top:* Frequency of AGN in mergers (filled symbols) and non-merger controls (empty symbols). *Bottom:* AGN excess in mergers compared to non-merger controls. The excess is the AGN frequency in mergers divided by that in the relative non-mergers.

The frequency of AGN in mergers and respective non-merger controls, per AGN type, is reported in Table 4 and shown in Fig. 6. The frequencies and relative statistical uncertainties are estimated using bootstrapping with resampling (1000 samples for each population). In both classes, the AGN frequency is defined as the ratio of identified AGN in the merger class to the

Table 4. Frequency of selected AGN types in mergers and non-merger controls (Eq. 8), divided into two redshift bins.

AGN type	$0.5 \leq z < 0.9$			$0.9 \leq z \leq 2.0$		
	M	NM (control)	Excess	M	NM (control)	Excess
X-ray RW25	$0.24 \pm 0.02\%$ (146/61 393)	$0.106 \pm 0.004\%$ (652/614 411)	2.2 ± 0.2	$0.15 \pm 0.02\%$ (66/43 644)	$0.070 \pm 0.004\%$ (319/435 959)	2.2 ± 0.3
DESI Siudek et al. (2024)	$0.09 \pm 0.01\%$ (57/61 393)	$0.024 \pm 0.002\%$ (147/614 411)	3.9 ± 0.6	$0.08 \pm 0.01\%$ (37/43 644)	$0.027 \pm 0.002\%$ (118/435 959)	3.1 ± 0.6
DL-based MB25	$13.3 \pm 0.1\%$ (8196/61 393)	$4.36 \pm 0.03\%$ (26 779/614 411)	3.06 ± 0.04	$11.4 \pm 0.1\%$ (4960/43 644)	$3.52 \pm 0.03\%$ (15 387/435 959)	3.22 ± 0.05
C75 AllWISE A18	$0.69 \pm 0.03\%$ (420/61 393)	$0.420 \pm 0.008\%$ (2578/614 411)	1.63 ± 0.09	$4.4 \pm 0.1\%$ (1902/43 644)	$2.57 \pm 0.02\%$ (11 195/435 959)	1.69 ± 0.04
R90 AllWISE A18	$0.18 \pm 0.02\%$ (109/61 393)	$0.042 \pm 0.003\%$ (258/614 411)	4.2 ± 0.5	$0.58 \pm 0.04\%$ (252/43 644)	$0.127 \pm 0.005\%$ (555/435 959)	4.5 ± 0.3

Notes. M (NM) indicates mergers (non-mergers). Fractions and relative errors are calculated using bootstrapping with resampling (1000 samples for each population). In brackets, we provide the number of AGN for each type, over the total number of mergers and non-merger controls.

total number of objects in the merger class:

$$\text{AGN frequency} = \frac{N_{\text{AGN}}}{N_{\text{all}}}. \quad (8)$$

For all AGN types, we observed a higher frequency of AGN in mergers than non-merger controls in both z bins, demonstrating that mergers are a viable method to fuel accretion onto SMBHs. To show it more clearly, we calculated the AGN excess, defined as the ratio of the AGN frequency in mergers relative to non-mergers. The AGN excess is reported in Table 4 and the lower panel of Fig. 6. X-ray AGN show the same excess (2.2) relative to controls in both redshift bins. Similarly, DL-based, MIR C75 and R90 AGN have consistent excess in both z bins, showing no clear signs of redshift evolution. On the contrary, DESI AGN go from an AGN excess of 3.9 at $z < 0.9$, to 3.1 at $z > 0.9$. However, this AGN selection shows larger uncertainties. Therefore, one must be cautious in inferring any redshift trends. Interestingly, the two MIR AGN selections exhibit completely different AGN excesses, with a much higher excess in the purer R90 selection. This could indicate that the C75 selection is highly contaminated by non-AGN galaxies. While these results indicate a clear excess of AGN activity in mergers, it is important to consider the potential impact of classification uncertainties inherent to automated methods, which we rigorously assess using detailed Monte Carlo (MC) simulations in Sect. 5.3.

Our results are in agreement with previous studies that adopted the same AGN excess definition. The optical AGN excess we observed is consistent with the 3.7 AGN excess reported by Bickley et al. (2023) for similar AGN in post-mergers, but it is much higher than the upper bound of 1.5 for the optical AGN excess found by Gao et al. (2020) (sample selections in both works, $z < 0.3$ and $M_{\star} > 10^9 M_{\odot}$). Regarding the X-ray AGN, the excess we found is comparable to the 1.8 excess found by Bickley et al. (2024, $z < 0.3$ and $M_{\star} > 10^8 M_{\odot}$), the 1.9 excess found by La Marca et al. (2024, at $0.5 < z < 0.8$ and $M_{\star} > 10^9 M_{\odot}$), and the 2.2 excess reported by Lackner et al. (2014, $0.5 < z < 1$ and $M_{\star} > 10^8 M_{\odot}$). Nevertheless, La Marca et al. (2024) observed a much lower X-ray AGN excess of 1.3 at $z < 0.5$, while Secrest et al. (2020) found no statistically significant evidence for an X-ray AGN excess in post-mergers at $z < 0.2$ and $M_{\star} > 10^{9.5} M_{\odot}$. However, the latter work showed a much larger excess for MIR-selected AGN, suggesting that AGN in post-mergers are more likely to be heavily obscured. In fact, several other studies reported a larger excess of MIR AGN in mergers compared to non-merger controls, reaching a factor of 3–7 (Goulding et al. 2018;

Bickley et al. 2023; La Marca et al. 2024), which is in agreement with our results of the more reliable MIR AGN selection (R90).

Our results and previous studies allow for some robust conclusions and some speculation. These findings robustly imply that major mergers trigger and fuel AGN, independently of AGN selection and the redshift. Considering that the purest MIR AGN show a larger excess than other AGN selections, we could speculate that mergers are more strongly connected to the triggering of dust-obscured AGN. For example, a major merger could redistribute gas and dust within a galaxy, increasing the dust obscuration surrounding the central active nucleus. This obscuration, if particularly heavy, might also make the detection of optical and soft X-ray AGN more challenging, partially explaining the lower excesses for these AGN.

4.2.2. Merger fraction in AGN and non-AGN

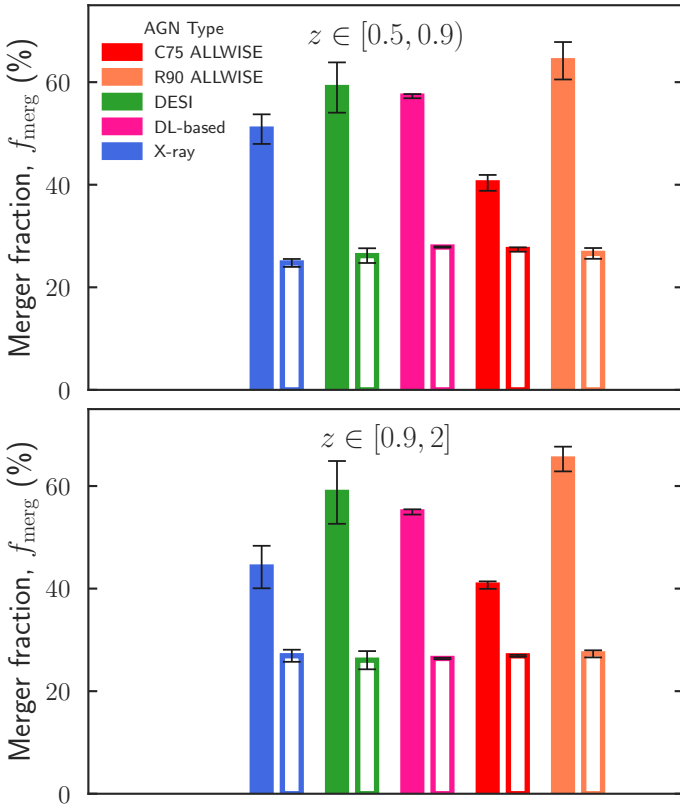
Table 5 and Fig. 7 report the merger fraction (f_{merg} , Eq. 2) in AGN and corresponding non-AGN controls, divided by AGN type. In both z bins, and for each AGN type, the fraction of mergers is higher for AGN than for non-AGN controls, reinforcing the merger-AGN connection. All AGN types, excluding the X-ray-selected ones, do not show signs of redshift evolution for the f_{merg} in AGN and non-AGN. The difference in f_{merg} for X-ray AGN at $z < 0.9$ and $z \geq 0.9$ is within 2σ uncertainty. Across the entire redshift range, X-ray, DESI, DL-based, and R90 MIR AGN predominantly inhabit merging galaxies, with f_{merg} ranging from 44% to 65%. Only in the case of C75 MIR AGN, we reported a merger fraction of 40%, which might indicate a possibly higher contamination degree in this selection. On the other hand, non-AGN controls are classified as mergers in 25–28% of the cases, about a factor of two less frequently than for the AGN host galaxies. To confirm that these findings are not an artefact of imperfections in the merger classification process, we evaluate the influence of classification uncertainties on these merger fractions through the MC analysis detailed in Sect. 5.3.

Low-redshift studies have found that the fraction of mergers in the MIR-selected AGN is a factor of 1.5–2.3 larger than that of non-AGN controls, in agreement with our results ($z < 0.8$ and $M_{\star} > 10^9 M_{\odot}$; Ellison et al. 2019; Gao et al. 2020; La Marca et al. 2024). Likewise, Donley et al. (2018) found that IR-only AGN out to $z = 5$ are more likely to be classified as irregular, asymmetric, or interacting than as regular galaxies. For optically selected AGN, Ellison et al. (2019) found a merger fraction in AGN twice as large as that in non-AGN, similar to what we ob-

Table 5. Merger fraction (f_{merg}) in active galaxies (AGN) and non-active galaxies (non-AGN controls) for different AGN selections divided into two redshift bins.

AGN type	$0.5 \leq z < 0.9$		$0.9 \leq z \leq 2.0$	
	$f_{\text{merg}}(\text{AGN})$	$f_{\text{merg}}(\text{non-AGN controls})$	$f_{\text{merg}}(\text{AGN})$	$f_{\text{merg}}(\text{non-AGN controls})$
X-ray RW25	$51 \pm 3\%$ (146/288)	$24.7 \pm 0.8\%$ (726/2935)	$44 \pm 4\%$ (66/149)	$27 \pm 1\%$ (386/1435)
DESI Siudek et al. (2024)	$59 \pm 5\%$ (57/97)	$26 \pm 1\%$ (257/982)	$59 \pm 6\%$ (37/63)	$26 \pm 2\%$ (161/618)
DL-based MB25	$57.3 \pm 0.4\%$ (8196/14 313)	$27.9 \pm 0.1\%$ (39 886/143 223)	$54.9 \pm 0.5\%$ (4906/9025)	$26.4 \pm 0.1\%$ (23 777/90 157)
C75 ALLWISE A18	$40 \pm 2\%$ (420/1041)	$27.4 \pm 0.4\%$ (2848/10 404)	$40.7 \pm 0.7\%$ (1902/4671)	$26.9 \pm 0.2\%$ (12 558/46 716)
R90 ALLWISE A18	$64 \pm 4\%$ (109/170)	$27 \pm 1\%$ (454/1705)	$65 \pm 2\%$ (252/386)	$27.3 \pm 0.7\%$ (1052/3855)

Notes. Fractions and relative errors are calculated using bootstrapping with resampling (1000 samples for each population). The numbers of AGN for each type, relative to the total number of mergers and non-merger controls in each z -bin, are provided in brackets.

**Fig. 7.** Merger fraction for all AGN types (filled bars) and relative non-AGN controls (empty bars), divided into two redshift bins. The fraction of mergers is higher in the AGN samples than in the non-AGN controls for all AGN types in both bins.

serve for the DESI AGN. In contrast, [Gao et al. \(2020\)](#) reported an excess of f_{merg} in optical AGN of a factor below 1.5. For X-ray-selected AGN, [Bickley et al. \(2024\)](#) reported an f_{merg} excess of a factor of 2, while [La Marca et al. \(2024\)](#) found an excess of 1.3 at $z \leq 0.5$ and of 1.8 at $0.5 < z < 0.8$, close to our findings. At higher redshift ($1 \leq z \leq 2$), other studies uncovered only a marginally higher fraction of mergers in X-ray AGN compared to non-AGN, comparable with no excess at all ($M_{\star} \gtrsim 10^{9.5} M_{\odot}$; [Cisternas et al. 2011](#); [Kocevski et al. 2012](#); [Marian et al. 2019](#)), although these samples are limited to intermediate AGN luminosity (X-ray luminosity $10^{42} < L_X < 10^{44} \text{ erg s}^{-1}$). Recently,

[Villforth \(2023\)](#) reviewed several studies in the literature about the merger fraction in AGN and non-AGN controls. They concluded that f_{merg} in X-ray-selected AGN are consistent with no excess over controls, in contrast with our findings, while for optically selected AGN, there is an excess over control samples, in agreement with our results for DESI AGN.

Although the elevated merger fractions observed in AGN hosts point to a connection between mergers and nuclear activity, caution is needed when interpreting the role of mergers as a primary triggering mechanism. First, a non-negligible merger fraction (25–28%) is also observed in the non-AGN control samples. Second, our analysis is limited to classified galaxies and does not include sources below our detection and classification thresholds, which may introduce biases and incompleteness. Therefore, our results do not allow us to quantify the exact contribution of mergers relative to other triggering channels.

4.3. The merger and AGN connection using continuous parameters

In this second set of experiments, we examined the merger-AGN connection using continuous parameters, which characterise either the relative or the absolute AGN power. Specifically, we first analysed the PSF fraction, f_{PSF} , which assesses the power of an AGN relative to its host galaxy. Then, we concentrated on the AGN luminosity for studying the absolute AGN power.

4.3.1. Dependence on the relative AGN power

Here we analysed the connection between mergers and the PSF fraction parameter, f_{PSF} , which measures the relative nuclear power. We reported the f_{PSF} normalised distributions for mergers and relative non-merger control galaxies in Fig. 8. Mergers show a larger fraction of galaxies in the range $0.1 \leq f_{\text{PSF}} < 0.8$ than non-merger controls, in both redshift bins. The only exception is represented by the $f_{\text{PSF}} > 0.8$ galaxies at $z \geq 0.9$. We show the results of KS tests in each panel of Fig. 8. The KS test output strongly excludes the null hypothesis, that is, the difference between the f_{PSF} distribution for mergers and non-merger controls is statistically significant, in both z bins. This hints towards a scenario where mergers fuel the accretion onto the SMBH, enhancing its accretion rate and, consequently, the point-source luminosity and contribution to the total galaxy light.

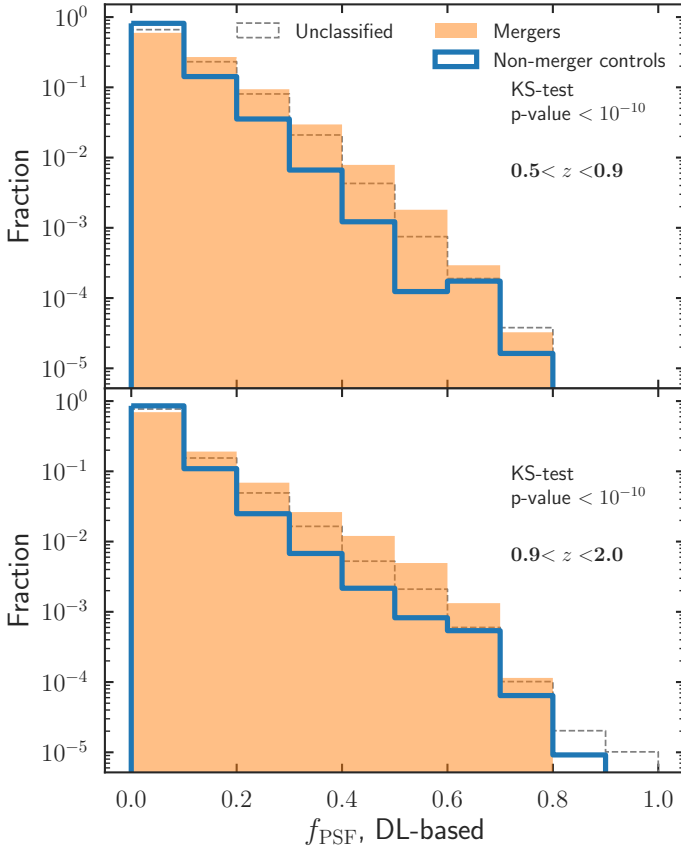


Fig. 8. Normalised distributions of the PSF fraction for mergers and non-mergers, in the two redshift bins. The results of a two-sample KS test are reported in each panel. The f_{PSF} -normalised distribution for unclassified galaxies is overlaid as a comparison.

We present the merger fraction versus f_{PSF} relationship for all galaxies in Fig. 9, divided into redshift bins. We calculated the merger fraction in N f_{PSF} bins, logarithmically spaced in the range 0–0.86 (the maximum f_{PSF} in our sample). The number

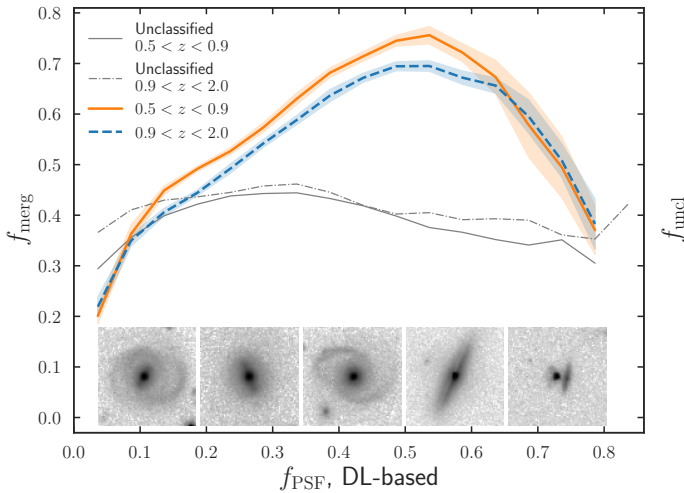


Fig. 9. Merger fraction and PSF contribution fraction relationship for the two redshift bins considered. All AGN are included. Trend lines represent the running median, while the shaded areas are one standard deviation. Examples of *Euclid* images of galaxies with increasing levels of f_{PSF} are shown at the bottom. Cutouts are $8'' \times 8''$, log-scaled in the 1st–99th percentile range. Grey lines indicate the fraction of unclassified objects as a function of f_{PSF} .

of bins N is randomly sampled between 6 and 20. Bootstrapping with resampling is used (1000 samples for each population). The trends reported represent the running median of all outcomes and the respective 1σ uncertainties, for each population. A clear trend emerges for both redshift bins. From $f_{\text{PSF}} = 0$ up to $f_{\text{PSF}} = 0.55$, the fraction of mergers monotonically increases, from $f_{\text{merg}} = 0.2$ to $f_{\text{merg}} \approx 0.7$. After this peak value, the merger fraction declines with increasing f_{PSF} , down to $f_{\text{merg}} = 0.4$ at $f_{\text{PSF}} = 0.8$. Uncertainties become larger with increasing f_{PSF} , mostly due to fewer galaxies in those bins. In the range $0.2 \leq f_{\text{PSF}} \leq 0.75$ mergers appear to be the dominant mechanism to trigger AGN ($f_{\text{merg}} > 0.5$).

The trend inversion for $f_{\text{PSF}} = 0.55$, where f_{merg} begins to decline despite increasing PSF dominance, presents a complex interpretive challenge. We specifically investigated if this decline is primarily due to the dominant PSF outshining the host galaxy’s morphological features, thereby making merger identification more difficult. To test this, we performed an experiment using a randomly selected sample of ~ 1500 galaxies without an injected PSF from our test set. Focusing on the dominant regime ($f_{\text{PSF}} > 0.55$), we re-classified simulated galaxies after injecting a prominent PSF component into the host galaxies from this sample. Our analysis revealed that only approximately 4% of simulated galaxies originally classified as mergers were re-labelled as non-mergers or unclassified after a dominant PSF was added. This indicates that while a dominant PSF can marginally hinder morphological classification, it is not the primary driver for the observed steep decline in f_{merg} at the highest f_{PSF} values. An alternative explanation might lie in the fact that f_{PSF} is a relative quantity. Although extremely dominant, a point source could be faint in absolute terms, in which case mergers might play a minor role, as we show in the next section.

To investigate possible differences among the various AGN selections, we analysed in Appendix D the f_{merg} versus f_{PSF} relation for individual AGN types. The C75 MIR AGN show a trend similar to the whole galaxy population, while the trend is less clear in the case of the DESI and X-ray AGN, probably due to the lower number statistics. R90 MIR AGN have a very high f_{merg} ($> 60\%$) for the whole f_{PSF} range.

In La Marca et al. (2024), the authors estimated the relative AGN power, the AGN fraction parameter (f_{AGN}), through SED fitting. This f_{AGN} is the fraction of light emitted by the AGN component over the total galaxy light, in the wavelength range 3–30 μm . This particular wavelength range was chosen as it robustly probes the re-emission from warm dust in the AGN torus, making it a reliable indicator of AGN activity, particularly for obscured sources (Hickox & Alexander 2018). They presented an f_{merg} versus f_{AGN} relation with two regimes, for all AGN types considered: f_{merg} is rather flat as a function of f_{AGN} for relatively subdominant AGN, then it steeply rises above 50% for the most dominant AGN ($f_{\text{AGN}} \geq 0.8$). Although we estimated the AGN relative contribution through photometry, there are some similarities. First, for less dominant AGN ($f_{\text{PSF}} \leq 0.2$), mergers are not the main AGN triggering mechanism. Second, major mergers are the principal pathway to fuel more dominant AGN. Yet, some differences exist. The f_{merg} versus f_{PSF} relation does not show any flat regime, but rather f_{merg} constantly increases, and subsequently decreases, as a function of f_{PSF} . Overall, these results support the idea that mergers can enhance AGN fuelling and are the prevailing mechanism for producing dominant AGN with respect to their host galaxy. In contrast, less dominant AGN may be primarily fuelled by other mechanisms, such as secular processes (e.g., Cisternas et al. 2011; Schawinski et al. 2011; Treister et al. 2012).

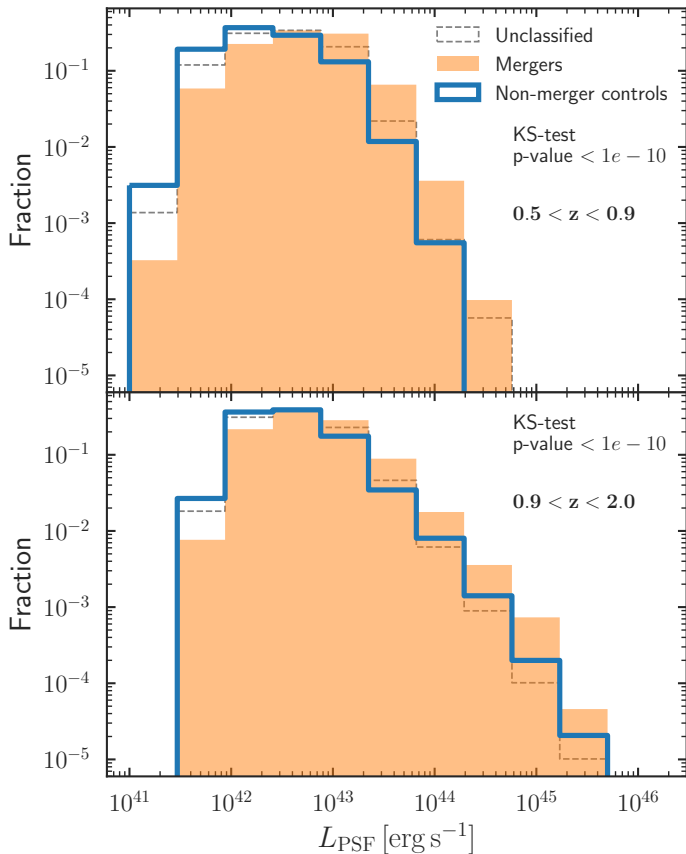


Fig. 10. Normalised distributions of the PSF luminosity for mergers and non-mergers, in the two redshift bins. The results of a two-sample KS test are reported in each panel. The f_{PSF} -normalised distribution for unclassified galaxies is overlaid as a comparison.

4.3.2. Dependence on the absolute AGN power

Next, we analysed the AGN luminosity parameters, which trace the absolute AGN power. Specifically, we focused on the point source luminosity, L_{PSF} , and the bolometric luminosity, L_{bol} , where the latter is available only for the X-ray and DESI AGN (see Sect. 3 for details on the derivation of L_{bol}).

We present the normalised distributions of L_{PSF} for mergers and non-merger controls in Fig. 10. In both redshift bins, we observed a higher fraction of mergers at $L_{\text{PSF}} > 10^{43} \text{ erg s}^{-1}$ compared to non-merger controls. Therefore, mergers are more likely to harbour a bright AGN than the relative non-merger control galaxies. We show the normalised L_{bol} distribution for mergers and non-merger controls in Fig. 11. In the case of the X-ray AGN, mergers and non-mergers have similar L_{bol} distributions, with some differences at the very bright end in both z bins. Indeed, a larger fraction of mergers host a bright AGN ($L_{\text{bol}} \geq 10^{46} \text{ erg s}^{-1}$) compared to non-mergers. The KS test confirms such a difference in both z bins. In the case of the DESI AGN, this difference emerges at lower luminosities, at $L_{\text{bol}} \geq 10^{45} \text{ erg s}^{-1}$ for the $0.5 \leq z < 0.9$ bin, and at $L_{\text{bol}} \geq 10^{44} \text{ erg s}^{-1}$ for the $0.9 \leq z \leq 2.0$ bin. For both X-ray and DESI AGN, in both redshift bins, the brightest AGN seem to inhabit almost exclusively interacting galaxies, hinting towards a picture where major mergers are responsible for fuelling the most powerful AGN. We evaluated the significance of this overabundance by performing a two-proportion z-test, comparing the fraction of bright X-ray ($L_{\text{bol}} > 5 \times 10^{45} \text{ erg s}^{-1}$) and DESI ($L_{\text{bol}} > 10^{45} \text{ erg s}^{-1}$) AGN in mergers and non-merger controls, in both redshift bins. The

results showed that these differences are statistically significant ($p\text{-value} < 0.05$) in all cases, except for the DESI AGN in the $0.9 \leq z \leq 2.0$ bin ($p\text{-value} = 0.43$).

We plot the merger fraction as a function of L_{PSF} in Fig. 12, using the same methodology as for the $f_{\text{PSF}}\text{-}f_{\text{merg}}$ relation. For both redshift bins, f_{merg} increases as a function L_{PSF} . At $z < 0.9$, f_{merg} show a steeper monotonic rise, with most of the galaxies being in mergers at $L_{\text{PSF}} \approx 10^{43.5} \text{ erg s}^{-1}$. This happens towards higher luminosities at $0.9 \leq z \leq 2.0$, when we observe a flat f_{merg} in the range $10^{43}\text{--}5 \times 10^{44} \text{ erg s}^{-1}$, and mergers become prevalent only for the very bright end of the AGN population, $L_{\text{PSF}} > 10^{45} \text{ erg s}^{-1}$. This might indicate that at higher redshift, when larger gas supplies are available within galaxies (Tacconi et al. 2010), major mergers are less important in fuelling bright AGN. At the same time, at $z < 0.9$, when less gas is available, mergers might be the sole viable path to fuel such powerful AGN. We perform the same analysis but for individual AGN selections in Appendix D.2.

To quantify the statistical significance of these apparent redshift differences in the f_{merg} versus L_{PSF} relation, we performed two-proportion z-tests comparing the merger fractions in four equally spaced L_{PSF} bins spanning the range 10^{42} to $10^{44} \text{ erg s}^{-1}$, where the data from both redshift samples overlap. In all four luminosity bins tested, we find that the merger fraction in the lower redshift bin ($0.5 \leq z < 0.9$) is significantly higher than in the higher redshift bin ($0.9 \leq z \leq 2.0$), with $p\text{-values} < 0.001$. This statistically confirms the visual impression from Fig. 12 that, at a given L_{PSF} , mergers are more prevalent at lower redshifts in our sample. However, it is important to note that when the uncertainties arising from the merger classification process are considered (as detailed in our MC simulations in Sect. 5.3), the shaded error regions for the two redshift trends show considerable overlap. This suggests that the true underlying difference might be less pronounced once the full impact of potential misclassifications is taken into account.

Finally, we present the merger fraction versus AGN bolometric luminosity relationship for DESI and X-ray AGN, and previous literature results (Urrutia et al. 2008; Treister et al. 2012; Glikman et al. 2015), in Fig. 13. As for the f_{merg} and f_{PSF} relation, we calculated the f_{merg} in N L_{bol} -bins, randomly sampled in the range $10^{42}\text{--}10^{47} \text{ erg s}^{-1}$. Bootstrapping with resampling was used to estimate uncertainties. In both cases, given that there are only a few numbers in each bin, we report large uncertainties, of the order $f_{\text{merg}} = 0.1\text{--}0.15$. These large uncertainties do not allow for strong conclusions to be drawn. X-ray AGN show a clear trend: the fraction of mergers increases with increasing luminosity. DESI AGN show a less clear trend, having an initially ($L_{\text{bol}} \leq 10^{45} \text{ erg s}^{-1}$) decreasing merger fraction followed by a steady increase with increasing L_{bol} . In both cases, major mergers appear as the dominant triggering mechanism of the most luminous AGN.

Our finding that the f_{merg} increases with bolometric AGN luminosity, particularly for the X-ray AGN sample, and that f_{merg} is particularly high for the most luminous AGN ($L_{\text{bol}} \gtrsim 10^{45.5} \text{ erg s}^{-1}$) is consistent with previous work. For instance, Urrutia et al. (2008) and Glikman et al. (2015) found very high merger fractions, $f_{\text{merg}} > 80\%$, for luminous, dust-reddened quasars. Similarly, Treister et al. (2012) found similar results and argued that major mergers are essential for fuelling the most luminous AGN. While direct comparison of absolute merger fractions is challenging due to different merger identification techniques, AGN selection methods, and redshift ranges, the qualitative trend of mergers playing an increasingly dominant role at

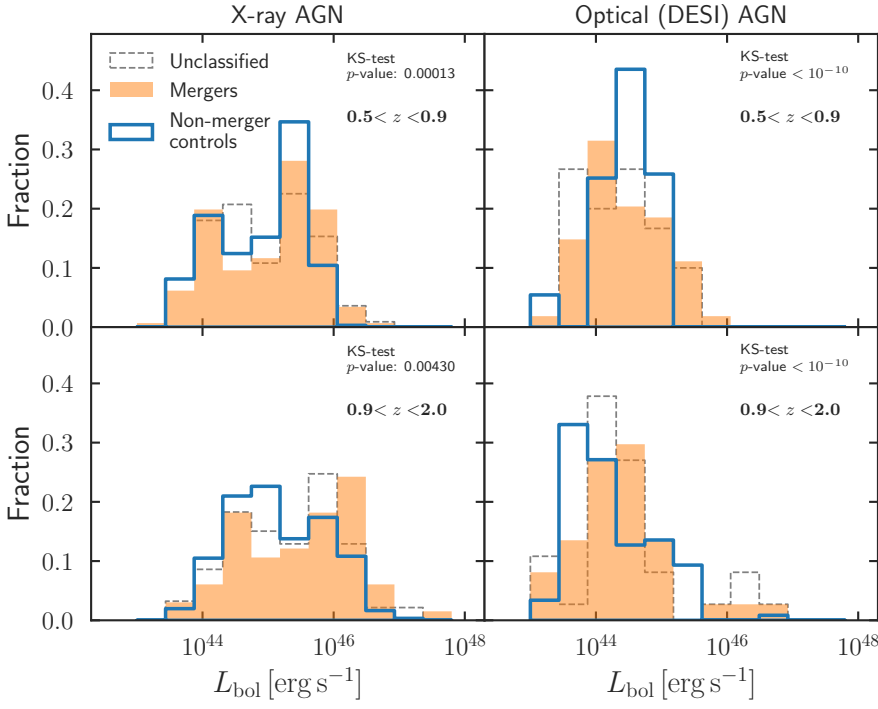


Fig. 11. Normalised distributions of the AGN bolometric luminosity for mergers and non-merger controls in the two redshift bins for the X-ray AGN (left column) and the DESI-selected AGN (right column). We report the results of a two-sample KS test in each panel. The f_{PSF} normalised distribution for unclassified galaxies is overlaid as a comparison.

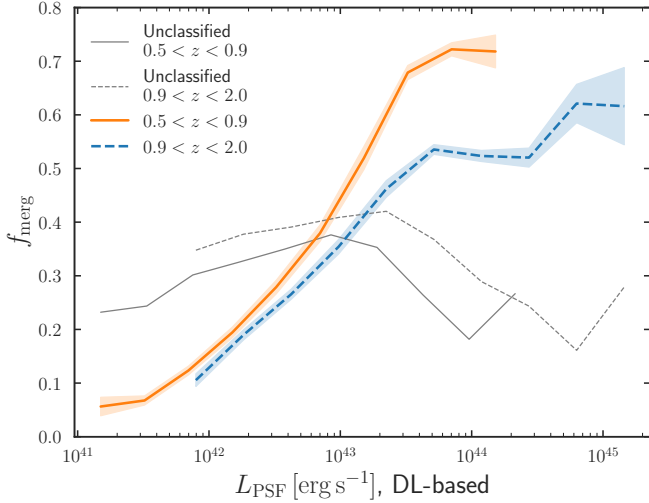


Fig. 12. Merger fraction as a function of the PSF luminosity, L_{PSF} , measured through photometry. The shaded areas show the uncertainties obtained through bootstrapping. The solid and dashed grey lines indicate the fraction of unclassified objects as a function of L_{PSF} .

higher AGN luminosities is a common theme (see also Donley et al. 2018; Ellison et al. 2019; La Marca et al. 2024). For producing such powerful emissions, a large amount of matter must be fed to the central SMBH, and major mergers are an efficient way of bringing large amounts of gas to the centres of galaxies (Blumenthal & Barnes 2018).

5. Caveats discussion

In this section, we investigate the main factors that might influence the relationship between mergers and the AGN properties characterised by the continuous parameters f_{PSF} and L_{PSF} , potentially affecting our results and conclusions. We discuss the role of unclassified galaxies, the dependency on stellar mass, and the systematics in our classification.

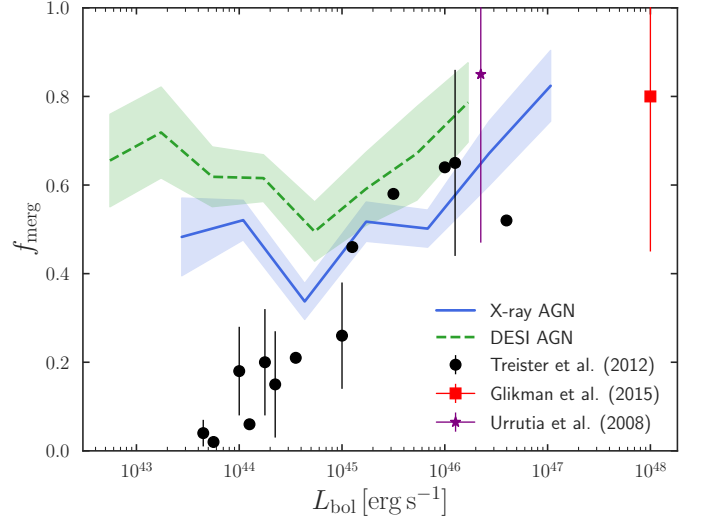


Fig. 13. Merger fraction and bolometric AGN luminosity relation for the X-ray and DESI-selected AGN. Trend lines show the running median, and shaded areas are one standard deviation. We include data from Treister et al. (2012, black circles), Urrutia et al. (2008, purple star), and Glikman et al. (2015, red square), with the associated f_{merg} uncertainties, if available.

5.1. The unclassified galaxies

First, we examined the impact of the unclassified galaxies on the observed trends. Figure 8 presents the normalised f_{PSF} distributions for the unclassified galaxies, which lie between the distributions of the non-merger controls and the mergers. This intermediate positioning likely reflects their mixed composition. However, mergers remain dominant over unclassified galaxies, with significantly higher fractions in the range $f_{\text{PSF}} = 0.1$ – 0.8 . To test whether unclassified galaxies influence the observed $f_{\text{merg}}-f_{\text{PSF}}$ trends, we analysed how the fraction of unclassified galaxies (f_{uncl}) varies with f_{PSF} . The results, shown in Fig. 9, indicate that f_{uncl} remains roughly constant in both redshift bins,

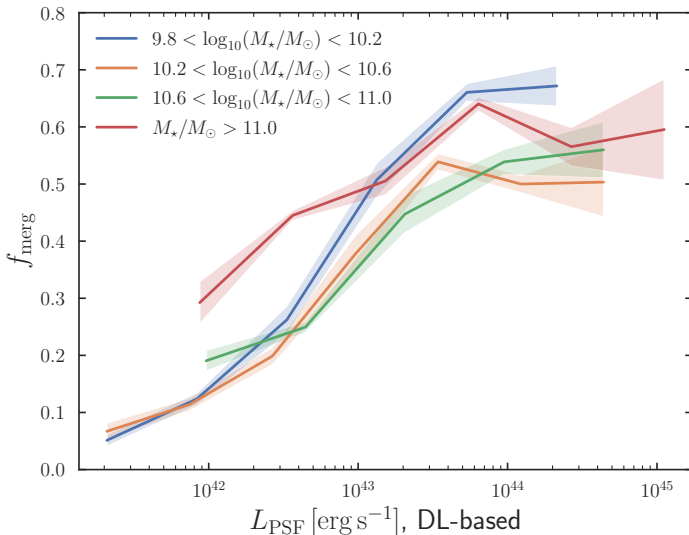


Fig. 14. Similar to Fig. 12 but with the merger fraction and PSF luminosity relation divided in stellar mass bins.

varying very mildly within the range $f_{\text{uncl}} = 0.3\text{--}0.4$. These findings suggest that unclassified objects do not significantly impact the relationship between major mergers and f_{PSF} . Indeed, this result strengthens our overall conclusion that mergers are predominantly associated with relatively bright central point sources, serving as the primary mechanism for fuelling dominant AGN.

We also investigated the role of unclassified galaxies in the mergers and AGN luminosity relation. Figures 10 and 11 overlay the normalised L_{PSF} and L_{bol} distributions for unclassified sources. These comparisons indicate that major mergers primarily trigger the most luminous AGN, since they exhibit a significant excess compared to both non-merger controls and unclassified galaxies. Furthermore, we computed f_{uncl} as a function of L_{PSF} for both redshift bins (Fig. 12). The fraction remains relatively stable at 0.25–0.35 up to $L_{\text{PSF}} = 10^{43} \text{ erg s}^{-1}$, before decreasing to 0.2 for brighter AGN. These marginal variations do not alter the main finding that mergers play an increasingly significant role in fuelling the most luminous AGN.

5.2. The effect of stellar mass

Another potential concern is whether brighter, and consequently more massive, galaxies are more likely to be classified as mergers. To assess whether the observed trends primarily arise from the galaxy stellar mass, we examined the $f_{\text{merg}}\text{--}L_{\text{PSF}}$ relation in four stellar mass bins, each containing a similar number of galaxies. The results (Fig. 14) confirm the general trend observed in Fig. 12: the merger fraction increases with L_{PSF} and then flattens for the most luminous point sources ($L_{\text{PSF}} > 10^{43.5} \text{ erg s}^{-1}$), where mergers constitute the majority of the population. The most massive galaxies ($M_* > 10^{11} M_{\odot}$) exhibit the highest f_{merg} on average, consistent with recent studies reporting a positive correlation between f_{merg} and stellar mass (e.g., Nevin et al. 2023). Thus, we conclude that stellar mass is not the primary driver of the $f_{\text{merg}}\text{--}L_{\text{PSF}}$ relation.

5.3. Systematics in the classification

A key aspect of this study relies on the automated classification of galaxies into mergers and non-mergers using a CNN. As detailed in Sect. 3.1 and Table 2, our classifier achieves per-

formance levels comparable to contemporary studies, with a precision of 0.80 and recall of 0.68 for the merger class, and a precision of 0.72 and recall of 0.83 for the non-merger class. While these metrics are robust, they inevitably imply that our classified samples contain non-negligible fractions of misclassified objects and are incomplete. Throughout our manuscript, we relied on statistical uncertainties under the assumption that our classifier perfectly distinguishes mergers from non-mergers. It is therefore crucial to assess the impact of these classification uncertainties on our main scientific findings, derived from both the binary comparisons (Sect. 4.2) and the analysis of continuous AGN properties (Sect. 4.3).

To quantitatively evaluate the robustness of our results against these misclassifications, we performed a detailed MC simulation based directly on the classifier’s performance metrics.⁴ The core simulation procedure involved 1000 independent iterations. In each iteration, we did the following:

1. We simulated the effect of contamination (finite precision). Based on the measured precision for mergers ($p_{\text{merger}} = 0.80$), a fraction ($1 - p_{\text{merger}} = 20\%$) of galaxies initially classified by our CNN as mergers were randomly selected and temporarily relabelled as non-mergers. Similarly, based on the precision for non-mergers ($p_{\text{non-merger}} = 0.72$), a fraction ($1 - p_{\text{non-merger}} = 28\%$) of galaxies initially classified as non-mergers were randomly selected and temporarily assigned to the merger class. This step yielded temporary ‘corrected’ classifications for all galaxies within that iteration.
2. We accounted for the classifier’s incompleteness (finite recall). To estimate fractions relative to the total underlying population in any given subsample (e.g., AGN hosts, specific luminosity bins), rather than just the classified population, we applied weights based on the recall values. Any galaxy temporarily labelled as ‘merger’ in the iteration received a weight $w_M = 1/\text{recall}_M = 1/0.68$. Any galaxy labelled as ‘non-merger’ received a weight $w_{NM} = 1/\text{recall}_{NM} = 1/0.83$. This weighting statistically corrects the counts for the classifier’s detection efficiency.

Using these temporary weighted classifications from each MC iteration, we recalculated our key metrics presented in Tables 4 and 5 and recomputed the $f_{\text{merg}}\text{--}L_{\text{PSF}}$ relation (Fig. 12).

5.3.1. Systematic uncertainties on the binary experiments

For each MC iteration, we recalculated the AGN frequency in mergers and non-mergers presented in Table 4, for each AGN type and in both redshift bins, using the relabelled outcomes. The ratio of the two frequencies above was calculated for each iteration, producing a distribution for the AGN excess. The results of these simulations confirm the robustness of our binary analysis findings. Across the 1000 MC iterations, the AGN frequency was consistently found to be higher in the simulated merger populations compared to the non-merger controls for all AGN types and redshift bins considered. We plot in Fig. 15 the median AGN excess derived from the 1000 iterations, alongside the 2.5th to 97.5th percentile for each AGN type and redshift bin. This range represents the central 95% interval of the simulated outcomes,

⁴ Quantitatively assessing and propagating classification systematics (contamination and incompleteness) has historically been challenging in merger studies, due to the absence of precise performance metrics. Our detailed MC simulation represents a significant step forward in rigorously assessing the impact of classification uncertainties on large statistical samples.

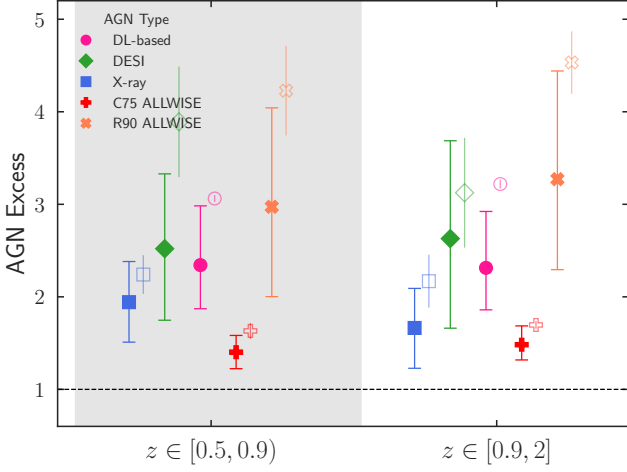


Fig. 15. Monte Carlo simulation outcomes for the AGN excess in mergers compared to non-merger controls. The symbols represent the median value of each AGN excess distribution, while the error bars cover the 2.5th-97.5th percentile range. Empty, transparent symbols represent the results presented in Fig. 6.

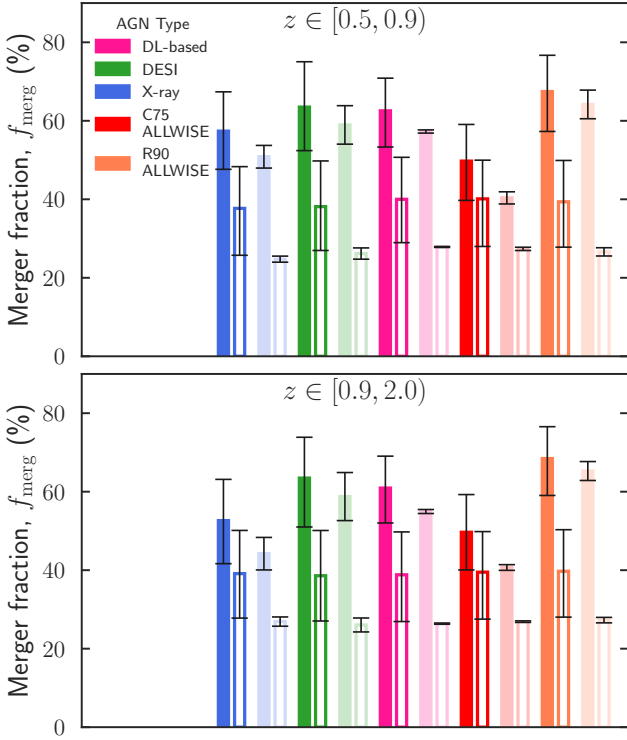


Fig. 16. Monte Carlo simulation outcomes for the merger fractions in AGN and non-AGN control sample (empty bars). The bars show the median value of the 1000 MC simulations, while the error bars display the 2.5th-97.5th percentile range. Results from Fig. 7 are reported as transparent bars.

effectively illustrating the statistically dominant parameter space explored when accounting for potential misclassifications. The median values are generally lower than the corresponding AGN excesses presented in Fig. 6, but still within the parameter space covered. As evident in Fig. 15, even considering the full extent of these uncertainties, the lower bound of the simulated AGN excess consistently remains well above unity, confirming that the observed excess is statistically significant and not merely an artefact of misclassification.

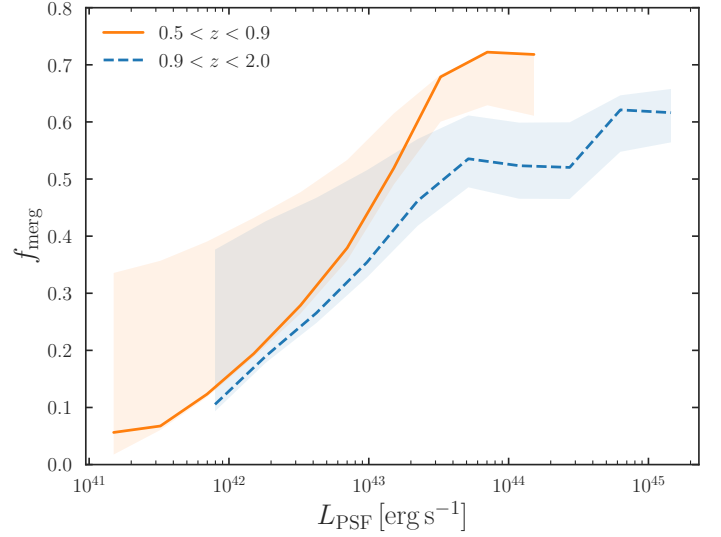


Fig. 17. Monte Carlo simulation of the merger fraction and PSF luminosity relation. The solid line trends reported are the same as in Fig. 12, while the shaded areas represent the full parameter space covered (0th-100th percentile range) by the MC simulation results.

Similarly, we calculated the weighted sum of temporary ‘mergers’ within the AGN host sample and divided it by the total weighted sum of the AGN host sample. The same was done for the non-AGN control sample, generating distributions for the merger fraction in both populations. Figure 16 illustrates the median f_{merg} from each distribution obtained through the MC simulation, alongside the 2.5th to 97.5th percentile range, divided into two redshift bins. On average, the merger fraction was found to be slightly higher in the AGN samples compared to the non-AGN controls across the MC iterations. However, the parameter space ranges for AGN and non-AGN controls overlap in most cases.

5.3.2. Systematic uncertainties on the $f_{\text{merg}}-L_{\text{PSF}}$ relation

For each MC iteration, we recalculated f_{merg} in each L_{PSF} bin using the weighted counts. Figure 17 shows that, as expected, the MC simulations yield a broader range of f_{merg} values compared to the bootstrapping uncertainties. The median trend across the 1000 MC iterations closely follows the trend derived directly from the initial classification (solid lines), while the shaded areas (0th-100th percentile range) illustrate the propagated uncertainty. The MC results demonstrate that while uncertainties introduce larger scatter, particularly at lower luminosities ($L_{\text{PSF}} < 10^{43} \text{ erg s}^{-1}$), the rising trend of f_{merg} with increasing L_{PSF} remains robust. The conclusion that mergers dominate ($f_{\text{merg}} > 50\%$) among the most luminous AGN holds true across the vast majority of the MC realisations.

In summary, our detailed MC simulations, incorporating the measured precision and recall, indicate that our classifier is sufficiently robust to establish the primary qualitative conclusions presented in Sect. 4. Both the enhanced presence of AGN in mergers found in the binary analysis and the trend of increasing merger importance for more luminous AGN seen in the continuous analysis hold even when accounting for realistic levels of misclassification inherent to automated methods in deep surveys.

6. Summary and conclusions

In this paper, we have performed the first detection of major mergers in the *Euclid* VIS I_E -band imaging data and examined the merger and AGN connection at $0.5 \leq z \leq 2.0$ in the Q1 EDFs. We constructed a stellar mass-complete sample of galaxies ($M_\star > 10^{9.8} M_\odot$) and employed a CNN trained on mock *Euclid* observations generated from Illustris-TNG simulations to identify merging galaxies. We defined mergers in Illustris-TNG galaxies with a major merger event (a stellar mass ratio ≤ 4) in the time interval spanning 800 Myr before to 300 Myr after coalescence. We exploited the rich multi-wavelength datasets for selecting AGN using four different diagnostics to select AGN via X-ray detections, optical spectroscopy (DESI data), two different MIR colour selections, and a DL-based imaging decomposition technique. We analysed the role of mergers in triggering AGN using a binary approach and a more refined approach that focuses on continuous AGN parameters. Our key findings are the following.

- i) A larger fraction of AGN in mergers than in non-merger controls, which results in an excess of AGN in mergers, regardless of the AGN selection used. X-ray and DL-based AGN show a factor of two to three excess in mergers across the whole redshift range. DESI-selected AGN show a larger excess (3.9) at $z \geq 0.9$ than at $z < 0.9$ (3.1). MIR AGN show an excess that depends on the criterion adopted. For the more reliable selection, R90, the excess is much larger (a factor of 4.2–4.5) than that of the more complete selection, C75 (1.7). This indicates that mergers can trigger all AGN types but are likely to be more connected with dust-obscured AGN.
- ii) A higher merger fraction (f_{merg}) in active galaxies, with a larger fraction in AGN by 15–25 percentage points compared to non-AGN controls, for all AGN types. However, we cannot conclude with certainty whether mergers are a primary triggering mechanism.
- iii) A rising trend in the f_{merg} as a function of the PSF relative contribution f_{PSF} , measured in the I_E -band up to $f_{\text{PSF}} \approx 0.55$ followed by a decline. This trend is independent of the redshift. In the range $f_{\text{PSF}} = 0.3$ – 0.75 , most galaxies are classified as mergers, which hints towards a scenario where mergers are the prevalent fuelling mechanism in relatively dominant AGN ($f_{\text{PSF}} > 0.5$).
- iv) A positive correlation between f_{merg} and the PSF luminosity, L_{PSF} , where mergers represent more than 50% of the galaxies at $L_{\text{PSF}} > 10^{43.5} \text{ erg s}^{-1}$ for $z < 0.9$ and at $10^{45} \text{ erg s}^{-1}$ for $z \geq 0.9$. This confirms the idea that mergers are the main channel to fuel the brightest AGN.

Moreover, we performed detailed MC simulations to assess the impact of potential misclassification and incompleteness from our merger identification pipeline. While showing much larger uncertainties, these tests demonstrated that our primary conclusions are qualitatively robust and not driven by classification systematics.

In conclusion, our results prove that mergers are closely linked to relatively dominant and bright AGN. Moreover, larger merger fractions and AGN excesses are observed for MIR AGN, which are usually linked to the dust-obscured phase of AGN lives. This suggests that mergers efficiently funnel gas to the central regions of galaxies, driving rapid accretion onto the SMBH, possibly obscuring it with dust, and making AGN more detectable in the MIR. For less dominant AGN, other fuelling mechanisms may play a more important role. Although mergers appear to be the primary – if not the sole – trigger for the most

luminous AGN at $z < 0.9$, their influence may decline at higher redshifts, where galaxies typically have larger gas reservoirs capable of sustaining AGN activity without external triggers.

A key limitation of this study is the reliance on CNN-based merger classification, which inherently has accuracy constraints despite being trained on cosmological simulations. While the main trends remain robust, some level of misclassification is unavoidable. Future improvements in classification techniques will be essential to refining merger identification. This study, although based on only 63 deg², highlights the statistical power of *Euclid* in probing mergers and AGN fuelling. With upcoming *Euclid* releases, the sample size will increase dramatically, marking a transition from being limited by statistical uncertainties to a regime dominated by systematics, which must be understood to advance the field. Complementary datasets from XMM-Newton, eROSITA, and JWST, as well as ancillary far-IR and radio observations, will further expand the AGN sample, allowing for a more precise assessment of the role of mergers in AGN evolution. Crucially, these data will allow us to map the merger and AGN connection in a multi-dimensional space and simultaneously analyse it as a function of key galaxy properties such as stellar mass, redshift, gas content, star formation rate, and environment.

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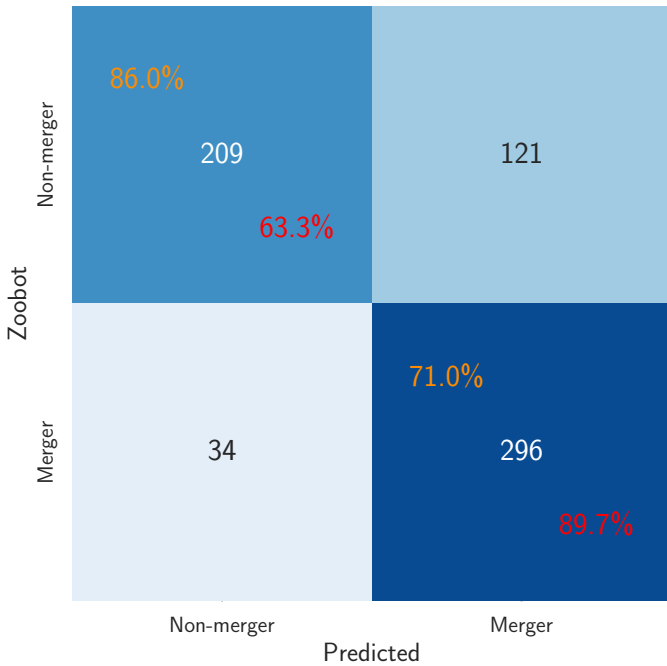


Fig. A.1. Confusion matrix comparing our model predictions with the Zoobot classifications. Along the diagonal, we report the precision (orange) and the recall (red) of each class. In black, the number of galaxies in each cell. Results are averaged over ten different balanced sets.

Appendix A: Comparison with Zoobot classification

We compared the predictions of the model trained in this work with the classification given by the Zoobot model (Euclid Collaboration: Walmsley et al. 2025) for the subsample of galaxies in common. We used two Zoobot catalogue columns to identify mergers, the merging merger fraction and the merging major-disturbance fraction, which allow us to select both pair galaxies and highly disturbed post-merging galaxies. As a first step, we removed possible artefacts from the Zoobot catalogue by setting problem artifact fraction < 0.01 AND problem star fraction < 0.01 AND problem zoom fraction < 0.01 . Then, we defined the mergers as those galaxies with merging merger fraction > 0.7 OR merging major-disturbance fraction > 0.5 , and the non-mergers as merging merger fraction < 0.2 AND merging major-disturbance fraction < 0.1 . We chose these criteria in order to obtain pure samples of mergers and non-mergers. In total, we found 40 847 galaxies in common. Of these, 27.8% are unclassified according to our model classification, which we removed to compare merger and non-merger classifications.

We created balanced samples of the Zoobot mergers and non-mergers by randomly selecting the same number of mergers among the available non-mergers. This operation was repeated ten times, and we report the average results in Fig. A.1. Our model has a precision of 71% and 86% for mergers and non-mergers, respectively, when compared to the Zoobot labels. Compared to the performance on the TNG test set, we observed a lower precision for the merger class, but an improved precision for the non-mergers. At the same time, our model classification is highly complete with respect to Zoobot mergers, with a recall of 90%, but has a much lower recall for the non-mergers, 63%. Overall, the F1-scores for both classes are the same as for the TNG test set. Considering all Zoobot mergers in the common subsample, our model classifies as mergers 90% of them (75%

if we do not exclude unclassified galaxies), demonstrating good agreement between our classification and labels obtained from a model trained on visual classification.

We visually inspected the cases where Zoobot and our CNN disagree. We observed that sometimes Zoobot misclassified mergers picked up by our CNN, but also the opposite is true (i.e., our CNN misclassified mergers correctly labelled by Zoobot). Nevertheless, we note that the comparison between our classifier and Zoobot is inherently dependent on the choice of classification thresholds in both approaches. Variations in these thresholds can significantly affect the reported merger fractions and the relative performance of the methods.

The performance of our CNN, when compared to Zoobot labels as shown in Fig. A.1, yields precision and recall values for the merger class broadly consistent with the performance achieved by our CNN on the TNG test set (Table 2). These figures, are also comparable to the typical performance levels reported for other state-of-the-art DL methods applied to merger classification in similar large, deep surveys (Margalef-Bentabol et al. 2024a). This consistency suggests that the level of accuracy, and the associated inherent uncertainties (as discussed in Sect. 5.3), are characteristic of current methodologies rather than specific shortcomings of our individual classifier.

Appendix B: Example of unclassified galaxies

We show some randomly sampled examples of unclassified galaxies in Fig. B.1. Unclassified galaxies are those objects with a predicted score between 0.35 and 0.59, inclusive. These unclassified objects appear as intermediate between mergers and non-mergers. While some look isolated and undisturbed, others appear to have close neighbours and an irregular morphology.

Appendix C: AGN sample: Additional information

We show the various intersections of all AGN selection methods used in this work in Fig. C.1 as an UpSet plot. This plot displays intersections in a matrix, with rows corresponding to the AGN selections and columns representing the intersections between these sets. The size of the sets and the intersections are shown as bar charts. The DL-based method correctly identifies about 25–30% of DESI, X-ray, and R90 MIR-selected AGN, while only about 10% of C75 MIR AGN. Relaxing the $f_{\text{PSF}} \geq 0.2$ constraint to 0.1, the DL-based model recognises many more AGN (Fig. C.2): it correctly identifies $> 50\%$ of DESI, X-ray and R90 AGN, and about 25% of C75 AGN. It is not surprising that the C75 selection method has the lowest identification ratio, as this diagnostic is also the most contaminated one.

Figure C.3 shows the normalised redshift distributions of all AGN types. X-ray and DESI AGN mostly inhabit $z < 1$ galaxies, with very few individuals at higher redshift. MIR AGN, both the C75 and the R90 selections, on average have higher redshifts, with their distributions peaking at $z \approx 1$. DL-selected AGN mostly follow the same z distribution of the full galaxy sample, which has its maximum at $z \approx 0.7$ and then monotonically decreases towards higher redshifts. This behaviour is expected because the DL-based AGN population strongly depends on the original population of galaxies.

Appendix D: f_{merg} as a function of f_{PSF} and L_{PSF} for individual AGN selections

Here, we analyse the relation of the merger fraction with the point source fraction and luminosity for individual AGN selec-

Unclassified



Fig. B.1. Examples of galaxies that we label as unclassified. The cutouts are *Euclid* RGB composite images, $8'' \times 8''$, generated as in Fig. 3.

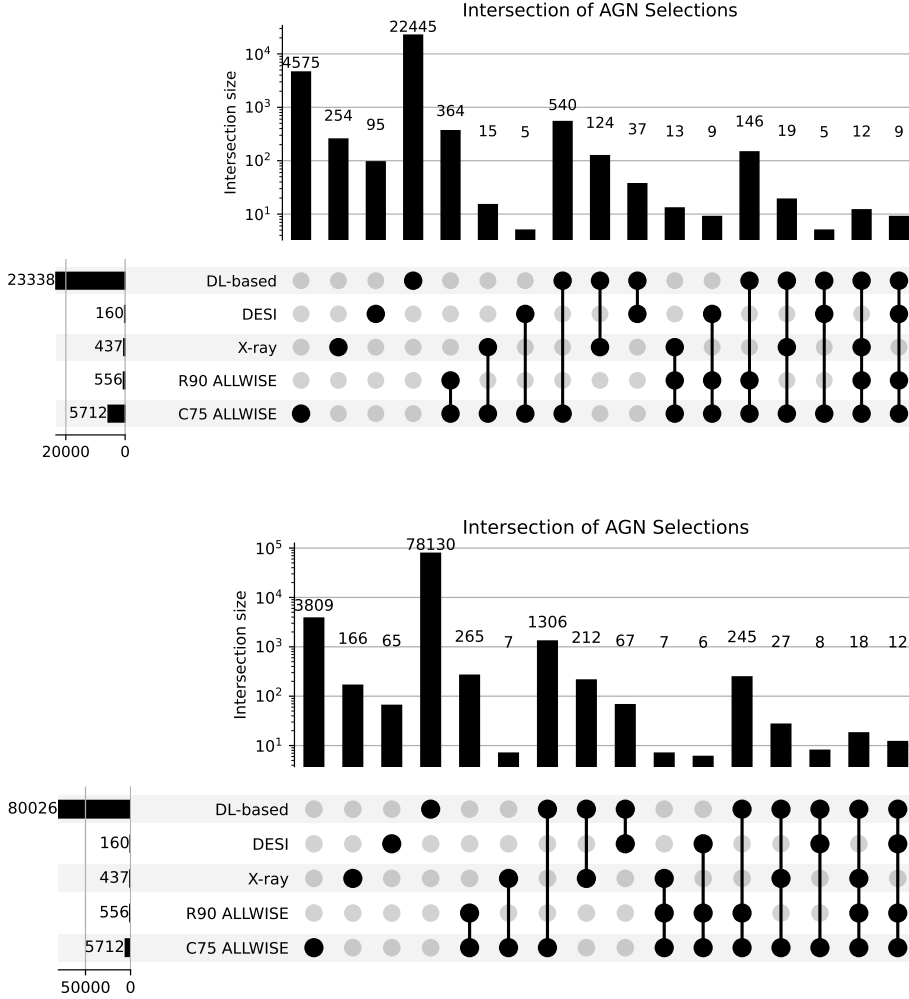


Fig. C.1. UpSet plot showing the intersections of all AGN selection methods employed. Rows correspond to the AGN selections, while columns correspond to the intersections. Numbers of each selection and intersection are displayed as bar charts. Intersections with fewer than five elements are not shown to facilitate readability.

Fig. C.2. UpSet plot showing the intersections of all AGN selection methods employed but with DL-based AGN defined as $f_{\text{PSF}} \geq 0.1$, as in Fig. C.1.

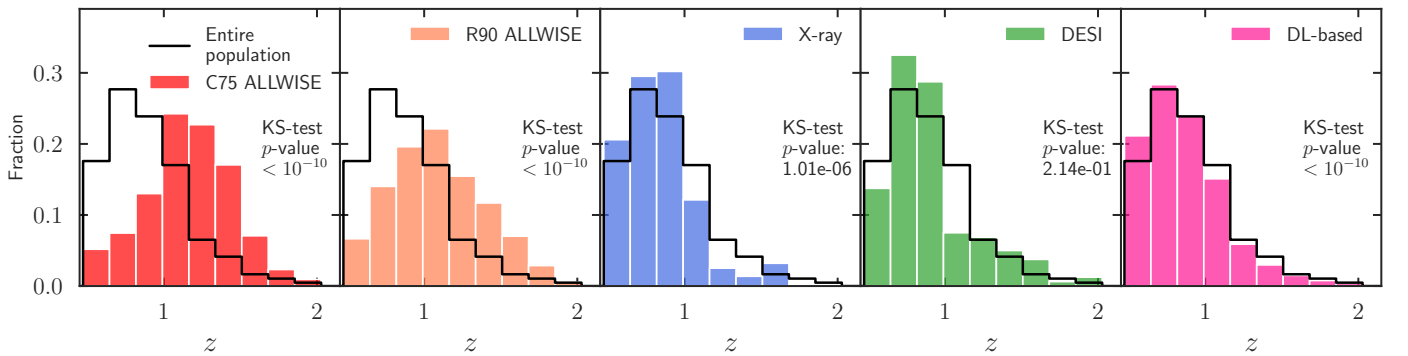
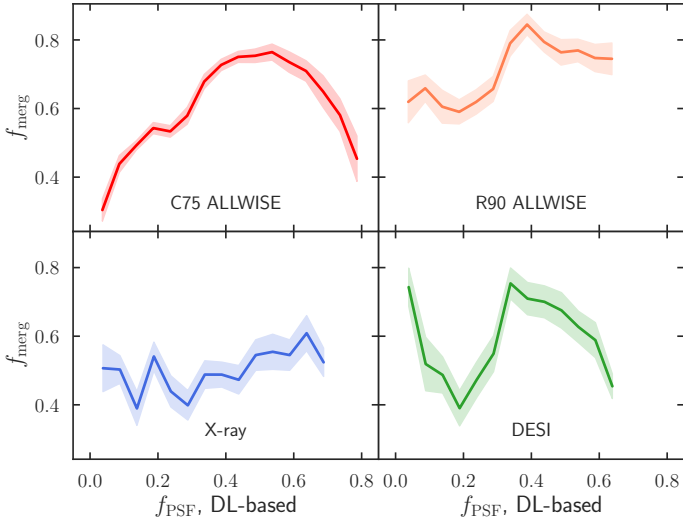


Fig. C.3. Normalised redshift distribution for each AGN population. We overlay the distribution for the entire sample of galaxies and report the results of a KS test in each panel.



brightest point sources ($L_{\text{PSF}} > 10^{43.5} \text{ erg s}^{-1}$). In this case, the trends reported are similar to those of the general AGN population in Fig. 12.

Fig. D.1. Merger fraction and PSF fraction relationship for each AGN type. Trend lines represent the running median, while shaded areas are one standard deviation. The AGN type is indicated in each panel.

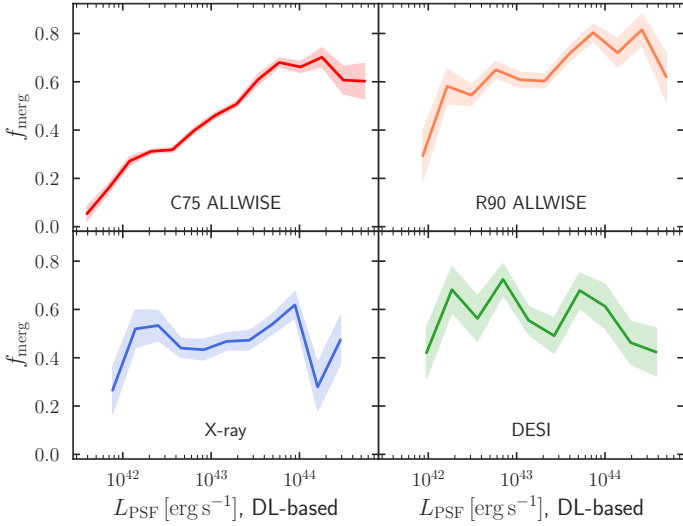


Fig. D.2. Merger fraction and L_{PSF} relation for each AGN type. Trend lines represent the running median, while shaded areas are one standard deviation. The AGN type is indicated in each panel.

tions, to study possible differences. We show the f_{merg} and f_{PSF} relation for X-ray, DESI, and MIR colour selections in Fig. D.1. X-ray and DESI AGN show larger fluctuations, mainly due to fewer objects compared to MIR and DL-based AGN selections. X-ray AGN show a rather flat trend, with a mild increase of f_{merg} as a function of f_{PSF} . Regarding the MIR AGN, the R90-selected objects show a rising f_{merg} trend with increasing f_{PSF} , centred at very high f_{merg} values (> 0.6). The C75-selected AGN have a trend similar to that of the general population reported in Fig. 9: a sharp rise in f_{merg} up to $f_{\text{PSF}} \simeq 0.55$, followed by a decreasing merger fraction.

Likewise, we show the merger fraction and point source luminosity relations for the individual AGN selections in Fig. D.2. X-ray and DESI AGN have a rather flat trend, around $f_{\text{merg}} \simeq 0.5$ and $f_{\text{merg}} \simeq 0.6$, respectively. Although their trends are significantly different from those in Fig. 12, mergers appear as a dominant fuelling mechanism for both selections. On the other hand, both MIR colour selections show monotonic rising f_{merg} as a function of L_{PSF} , with mergers becoming dominant for the