ZTF constraints on variability from intermediate-mass black hole candidates

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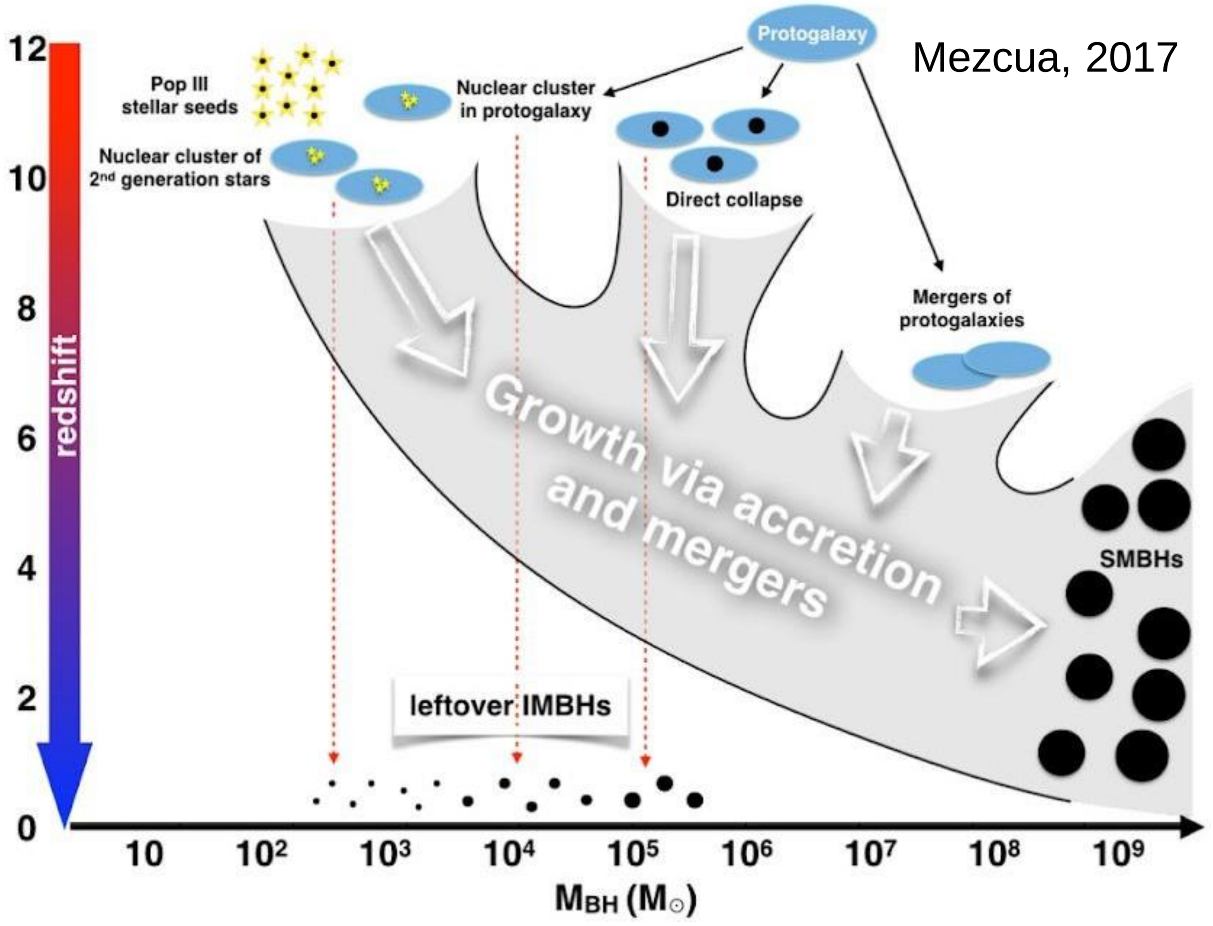
ALeRCE Automatic Learning for the Rapid Classification of Events

Motivation: why IMBH?

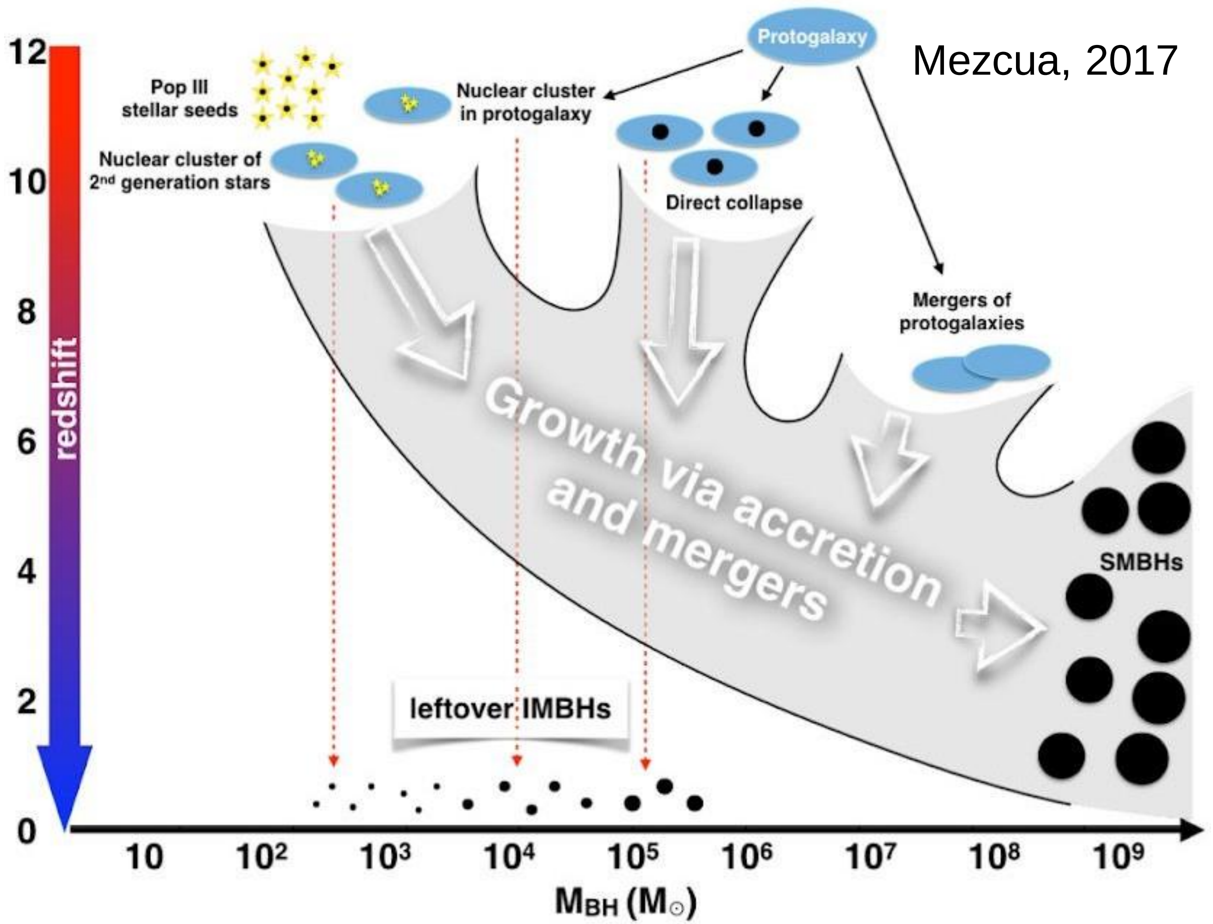
★ **Probe BH properties** at this mass regime and compare it with SMBHs.



Mezcua, 2017

Motivation: why IMBH?

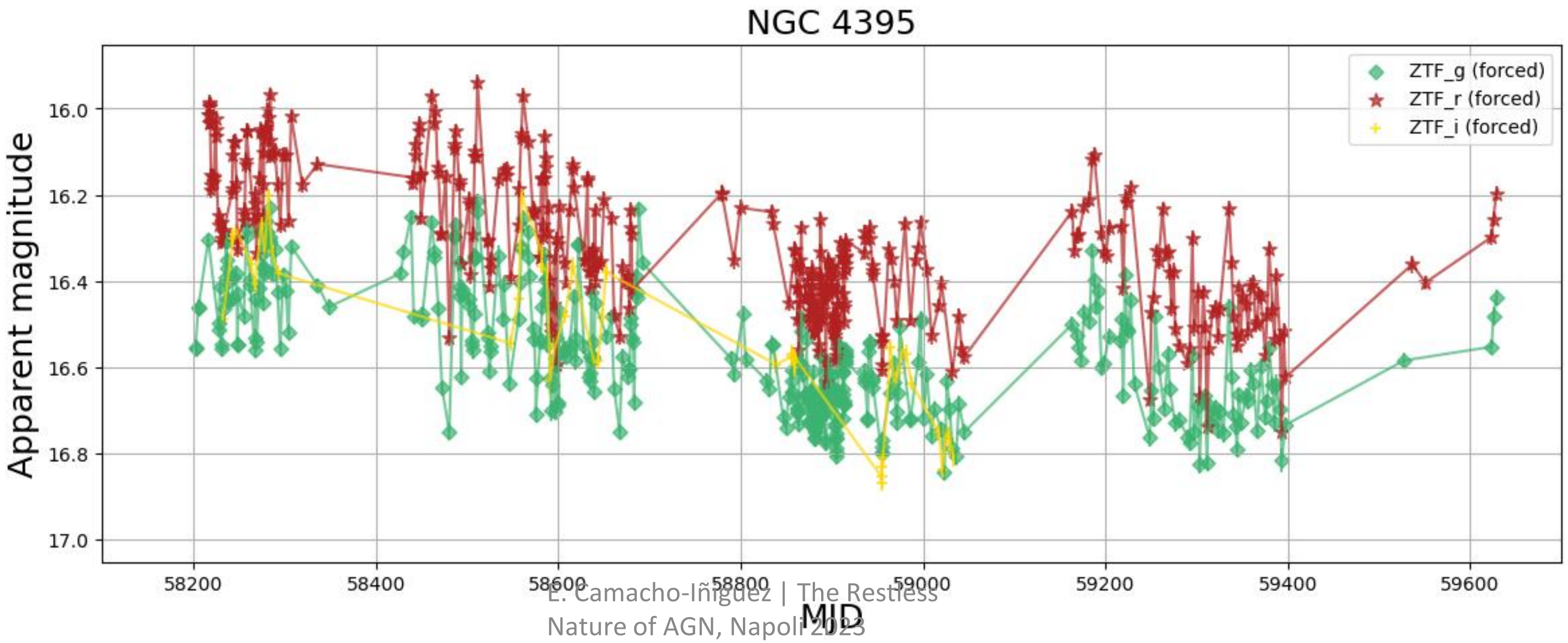
- ★ **Probe BH properties** at this mass regime and compare it with SMBHs.
- ★ **Confirm the AGN nature of IMBH candidates via variability**.
    - Pivotal for understanding <u>SMBH and galaxy growth</u>.
    - <u>Effects of BH feedback:</u> galaxy formation and SF quenching.
- ★ The sample size remains small :(



Mezcua, 2017

Motivation: why variability?

★ Variability could become a powerful tool for finding faint AGNs and characterizing them.

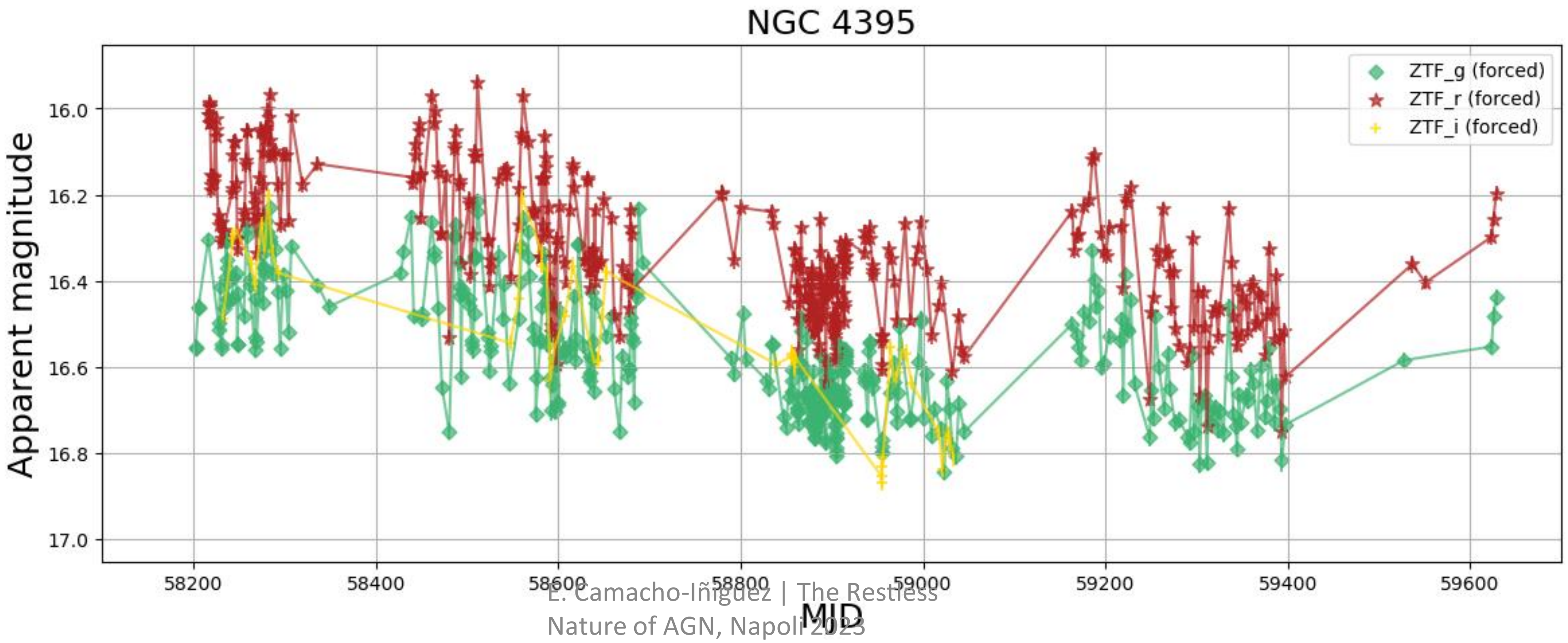


Motivation: why variability?

★ Variability could become a powerful tool for finding faint AGNs and characterizing them.

★ Is cheaper because we are in the time domain.

- ZTF
- LSST



Instrument and methods

- ★ ZTF is the most powerful optical time-domain survey operating in the present day.
  - ○ Longer LCs with g and r band obs

ZTF		LSST – Legacy Survey of Space and Time
2018-2023	→	2025-2035
1.4 TB per night	10x	**15 TB per night**
~1 billion objects		~37 billion objects
~1 trillion measurements		~7 trillion measurements
~1 million alerts per night		**~10 million alerts per night**
Public steam: *g+r* photometry		Public steam: *ugrizy* photometry
1” pixels and modest seeing (>1”-2”)		0.2” pixels and good seeing (<1”)

~2-3-day cadence
~ 1000 days baseline

Instrument and methods

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- ○ Longer LCs with g and r band obs

★ DI removes non-varying component of images by subtracting a high S/N ref image.

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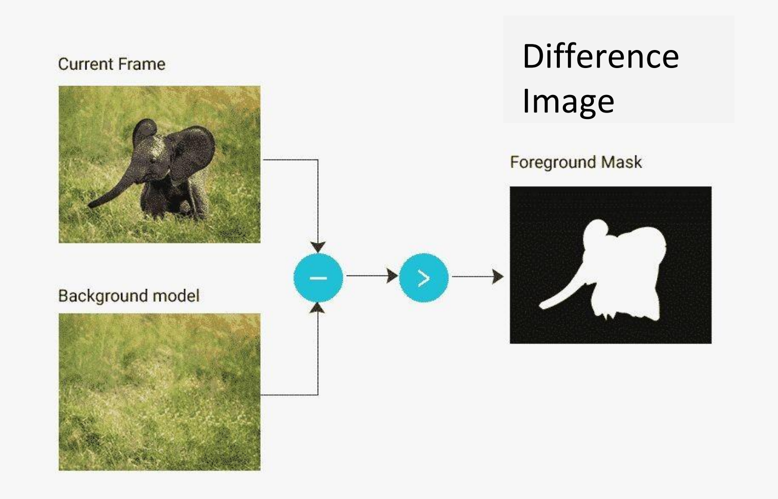
Science Image

Reference Image

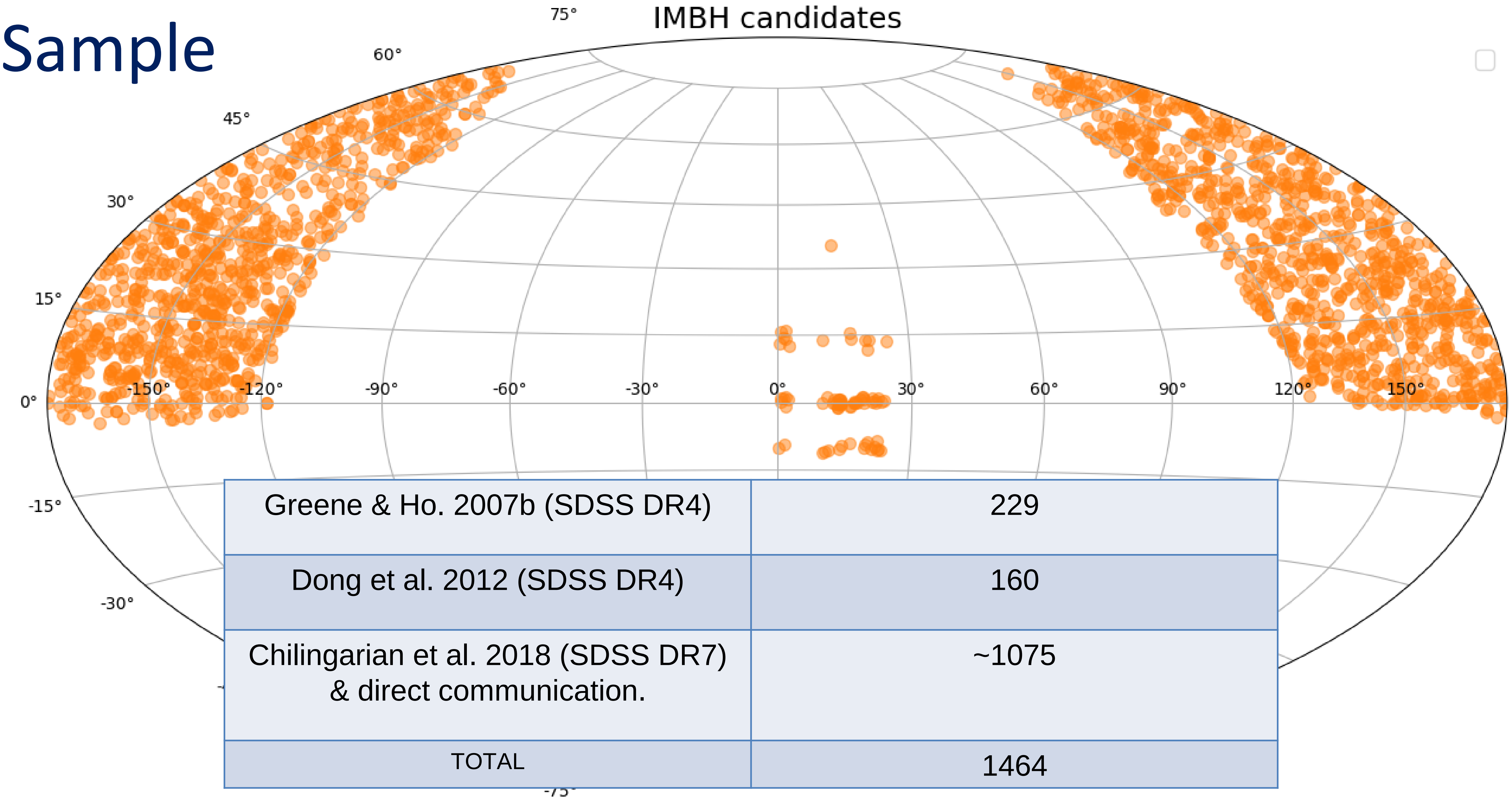


Science image

Reference image

Difference Image

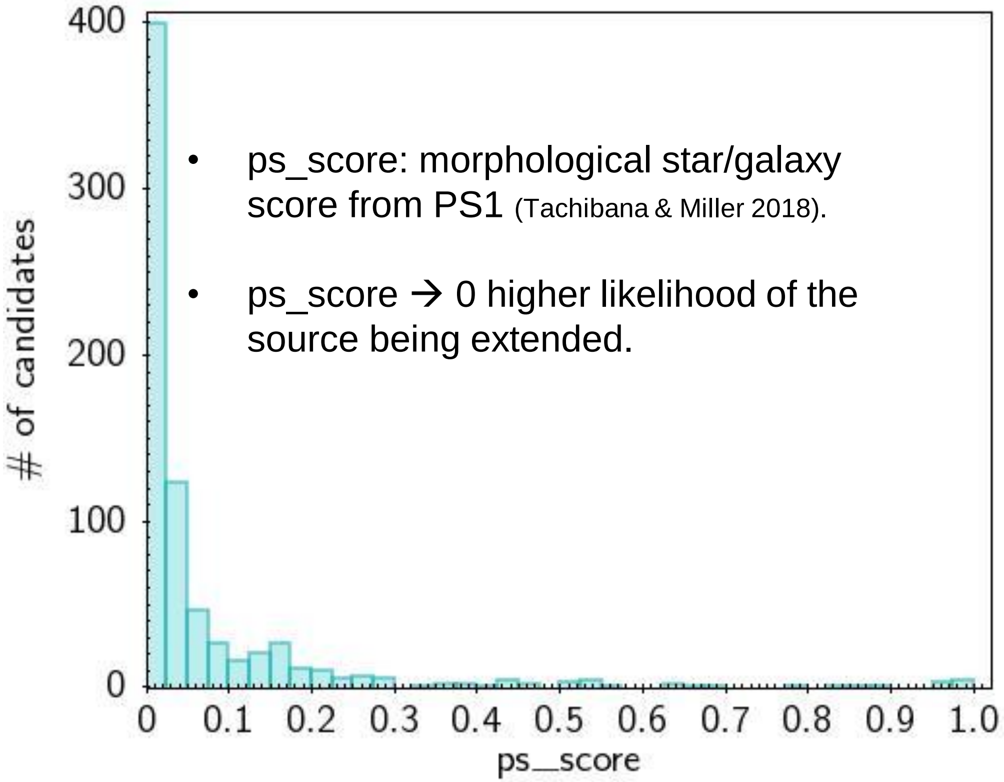
Sample

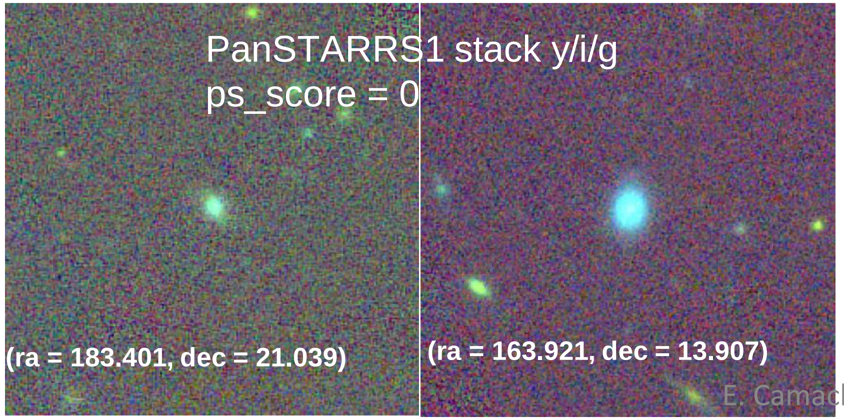


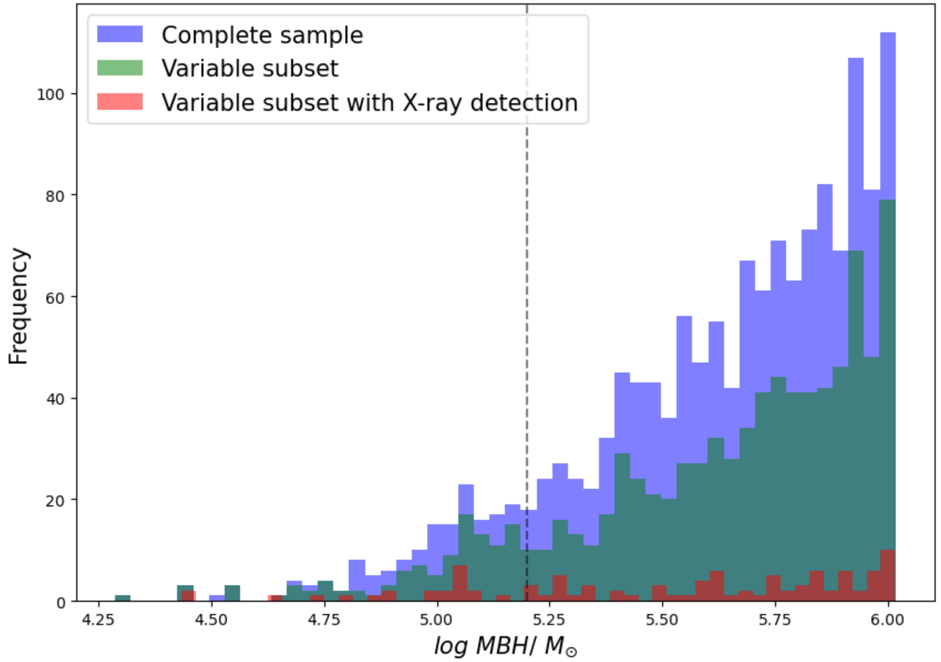
Greene & Ho. 2007b (SDSS DR4)	229
Dong et al. 2012 (SDSS DR4)	160
Chilingarian et al. 2018 (SDSS DR7) & direct communication.	~1075
TOTAL	1464

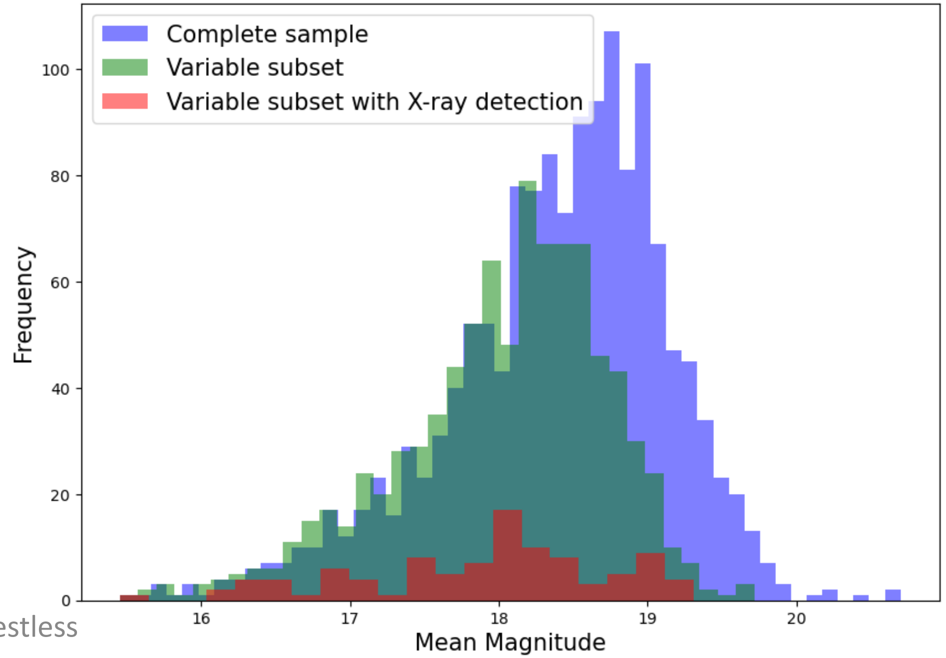
Sample

- ps_score: morphological star/galaxy score from PS1 (Tachibana & Miller 2018).
- ps_score → 0 higher likelihood of the source being extended.

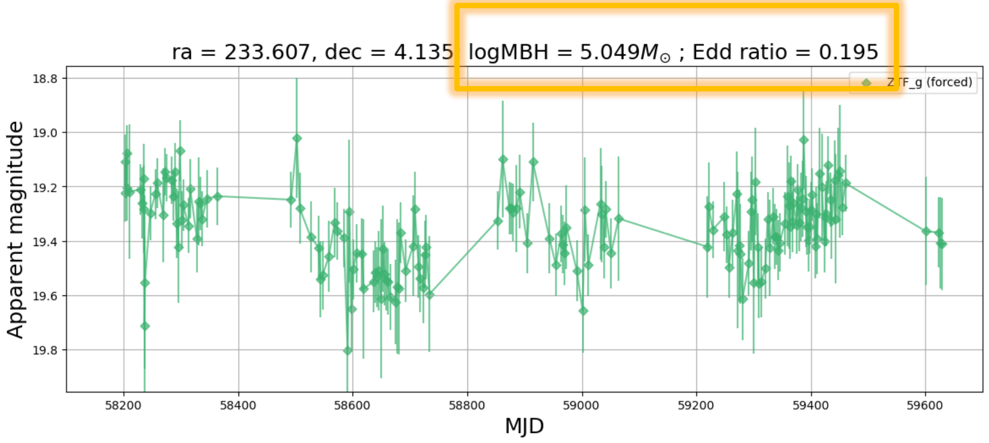


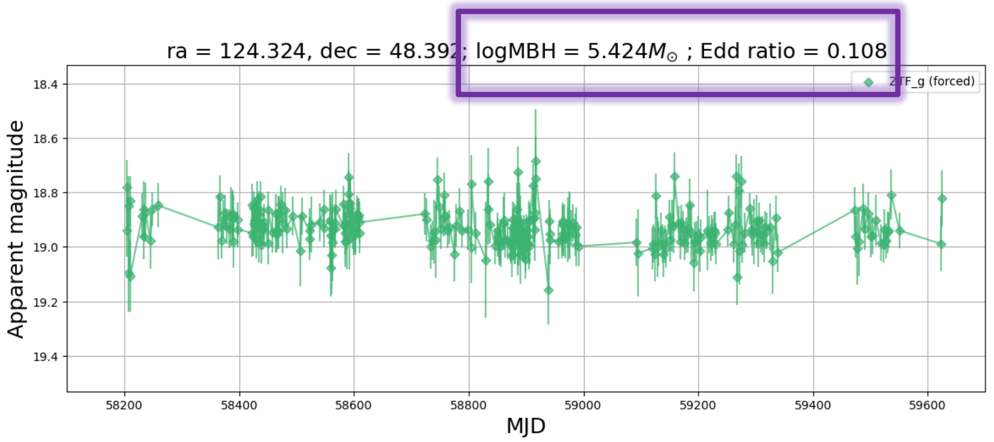


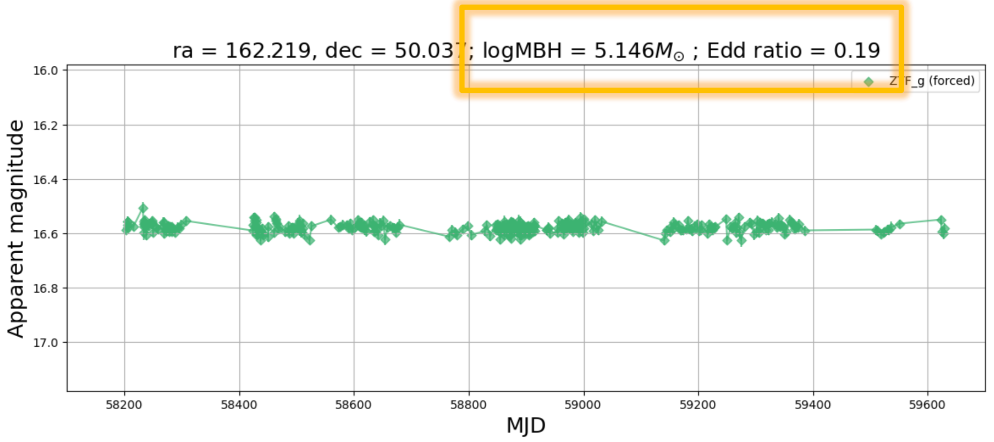


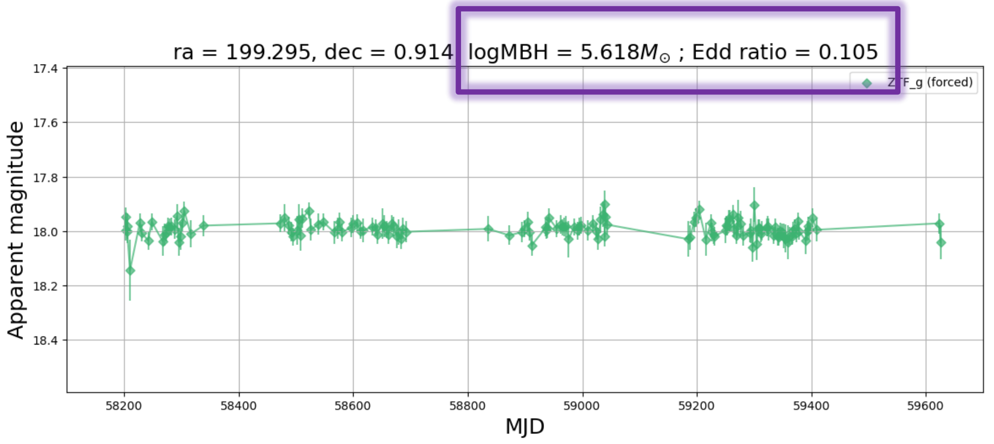


Why it’s interesting to study our sample?









Note: We have recalibrated the errors using noon-variable stars

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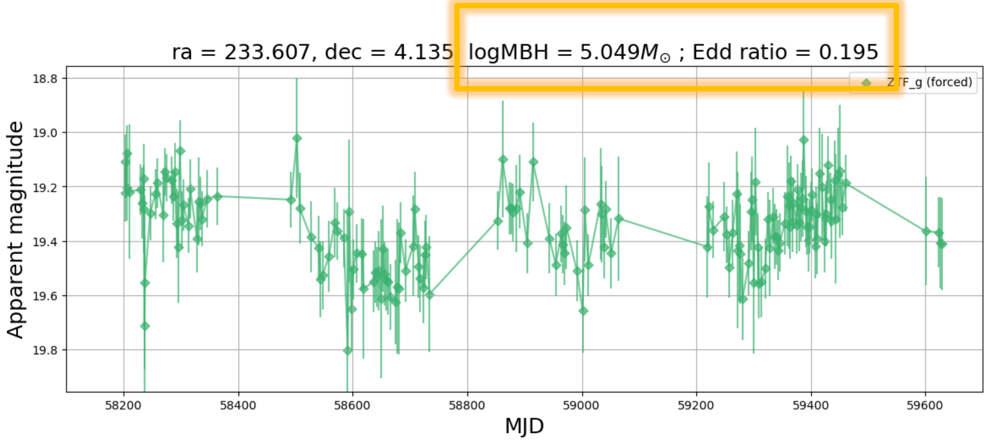
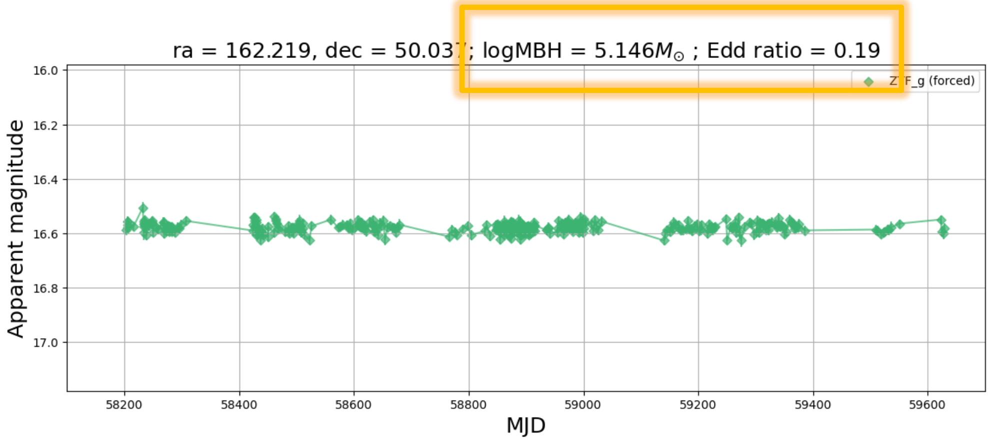


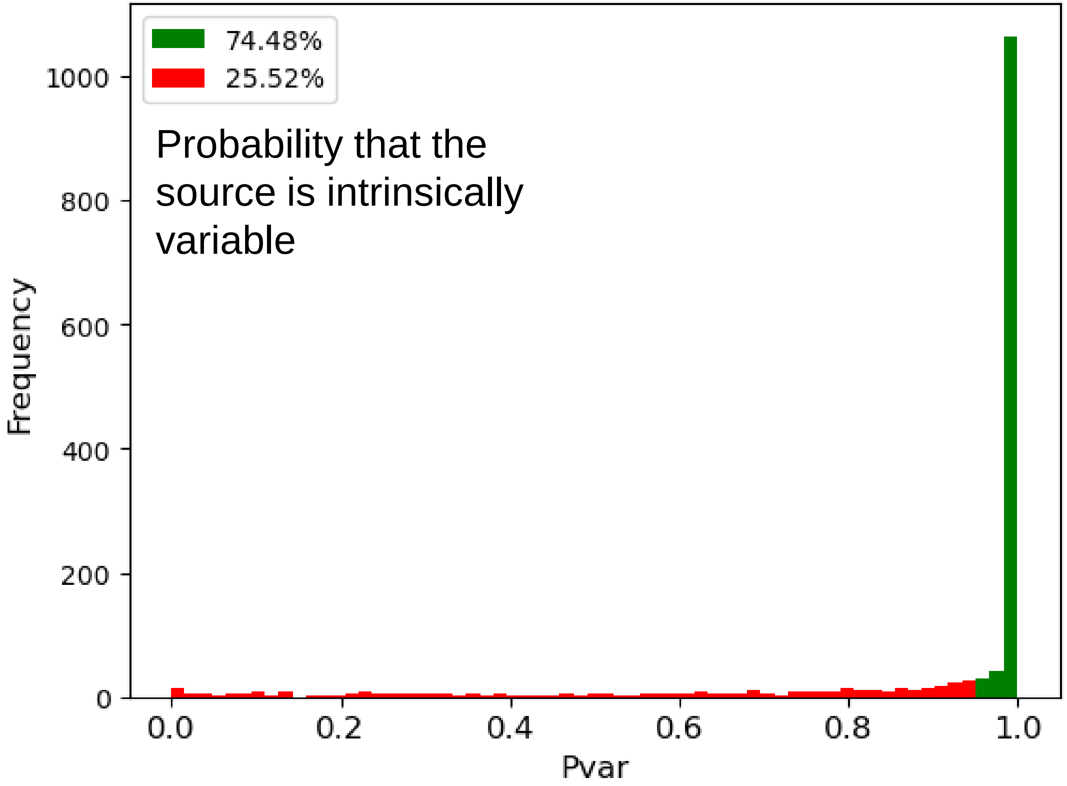


★ ExcessVar --- Allevato et al. (2013).
★ Pvar --- McLaughlin et al. (1996).
★ GP_DRW_tau --- Graham et al. (2017).
★ GP_DRW_sigma --- Graham et al. (2017).
★ SF ML amplitude --- Schmidt et al. (2010) .
★ SF ML gamma --- Schmidt et al. (2010).
★ Others

➢ **Considering the LSST Data Products Definition Document (Jurić et al. 2019), we expect that almost all these features would be measured using LSST data.**

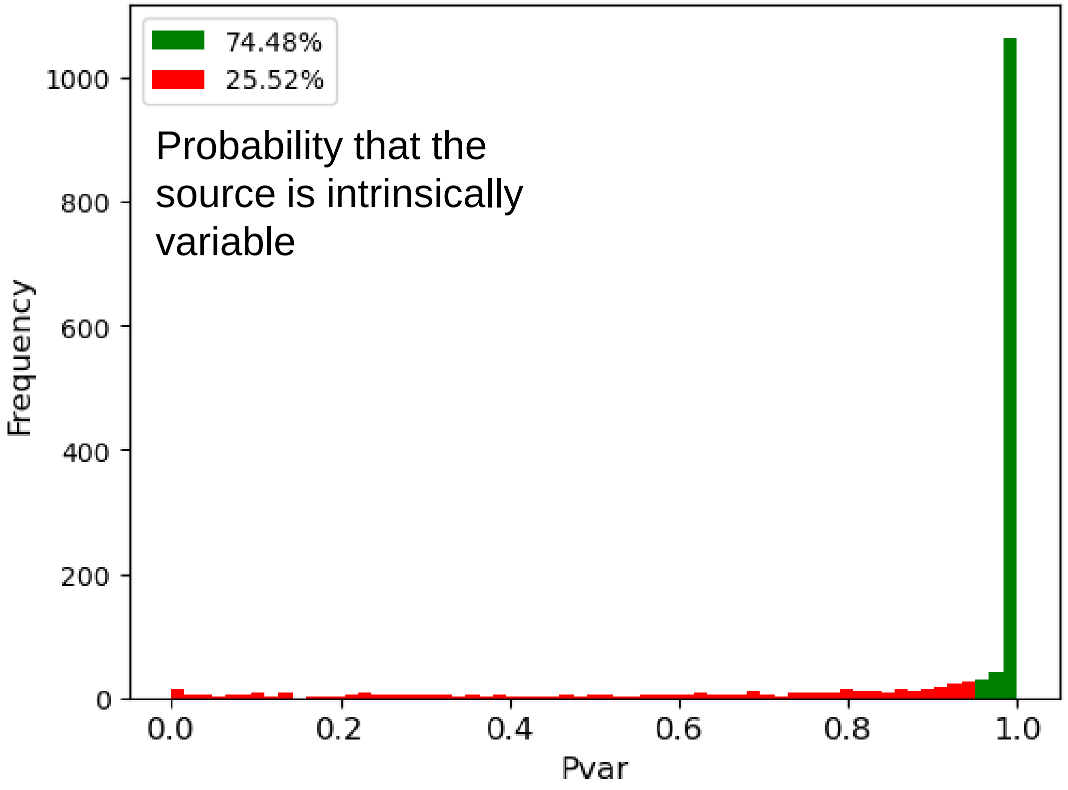
➢ Computed through FATS (Nun et al. 2015) Python package.

Data set	Number	% w.r.t total
Complete	1464	100
Pvar > 0.95 (1)	1135	74.48



$$P_{var} = P(\chi^2)$$

Data set	Number	% w.r.t total
Complete	1464	100
Pvar > 0.95 (1)	1135	74.48
ExcessVar > 0 (2)	980	64.3
(1) & (2)	919	60.3



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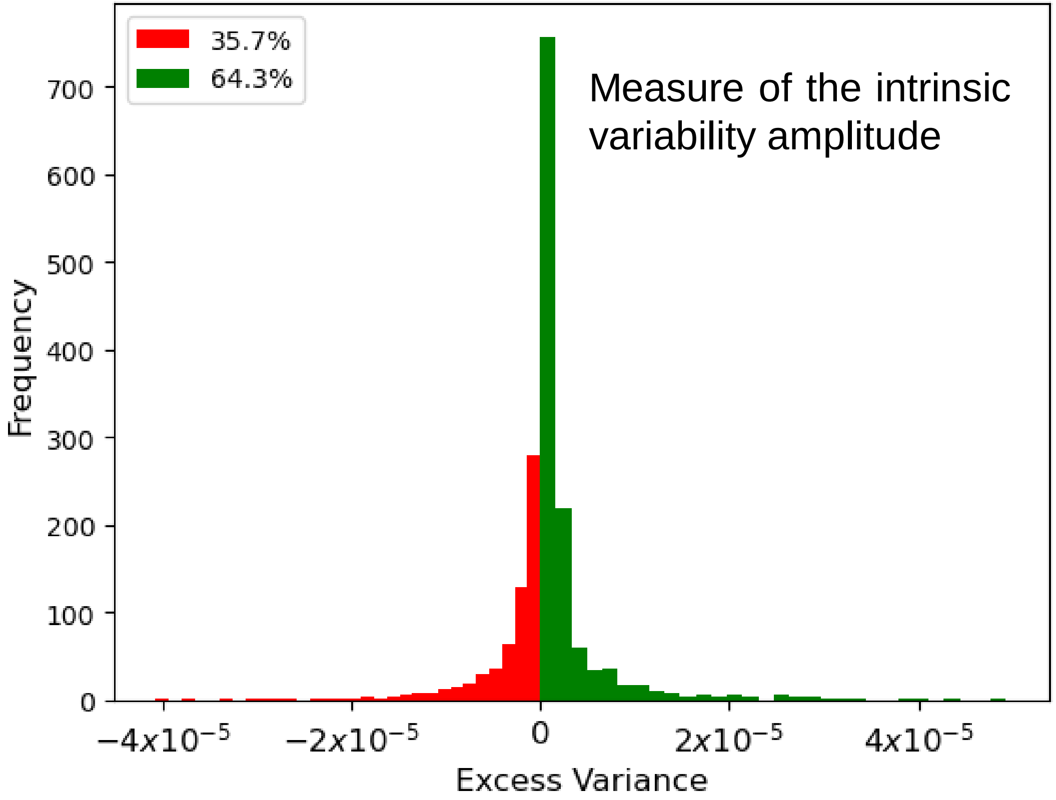


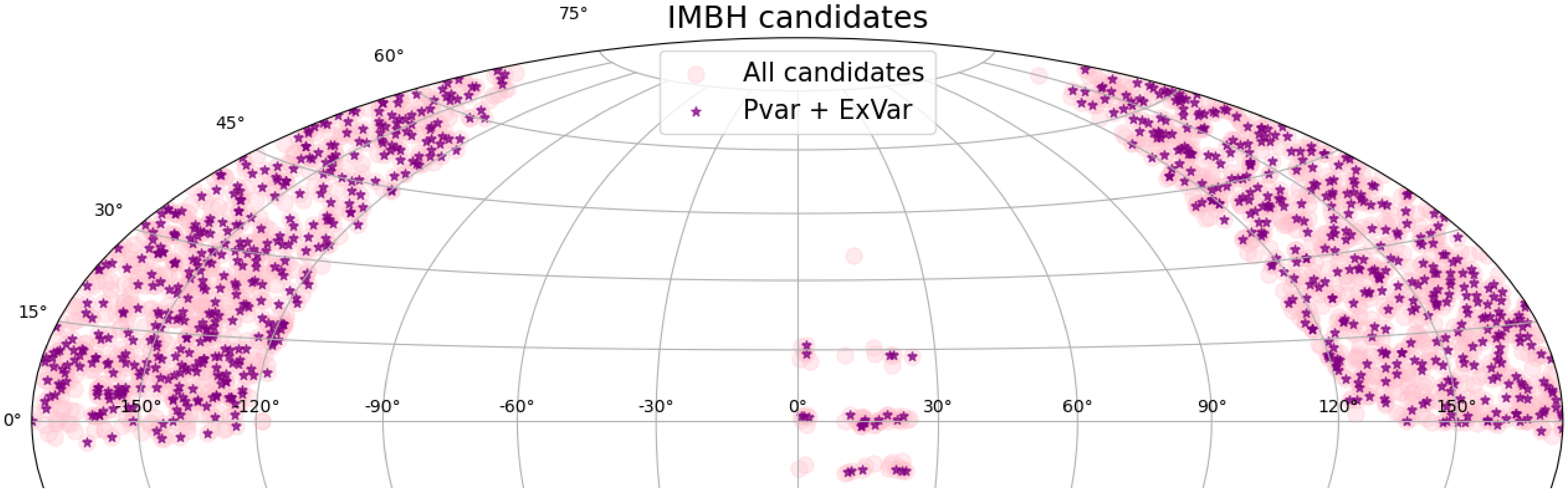
Standard deviation of the LC

Photometric error

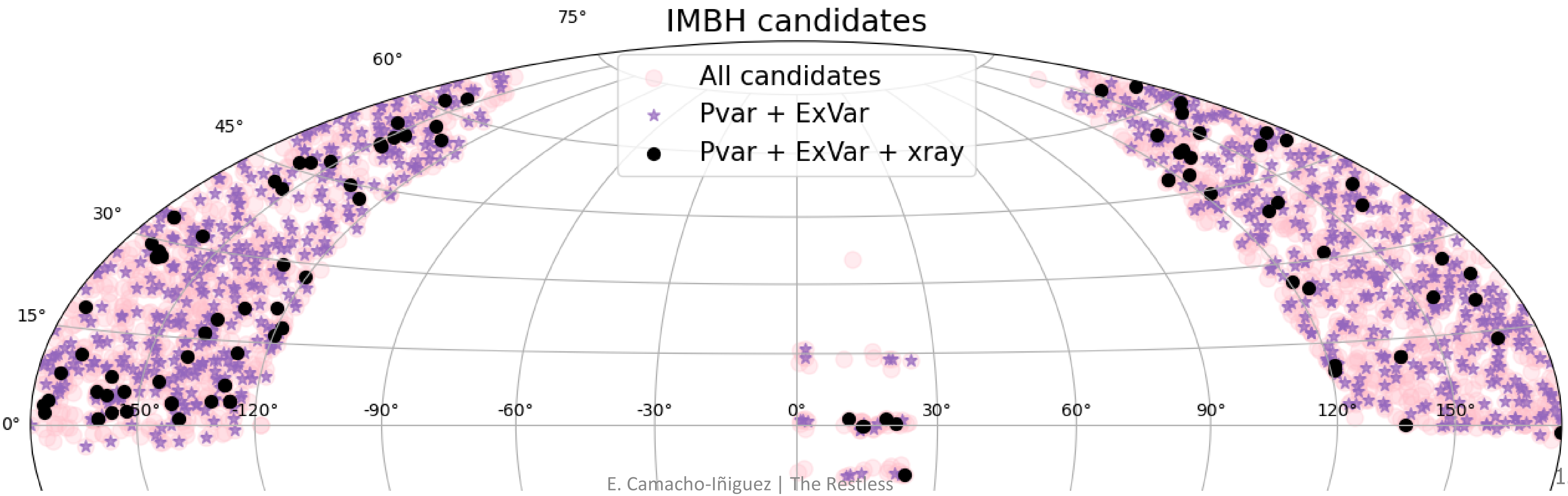
$$\sigma^2_{\rm rms} = (\sigma^2_{LC} - \overline{\sigma}^2_m)/\overline{m}^2$$

Average magnitude

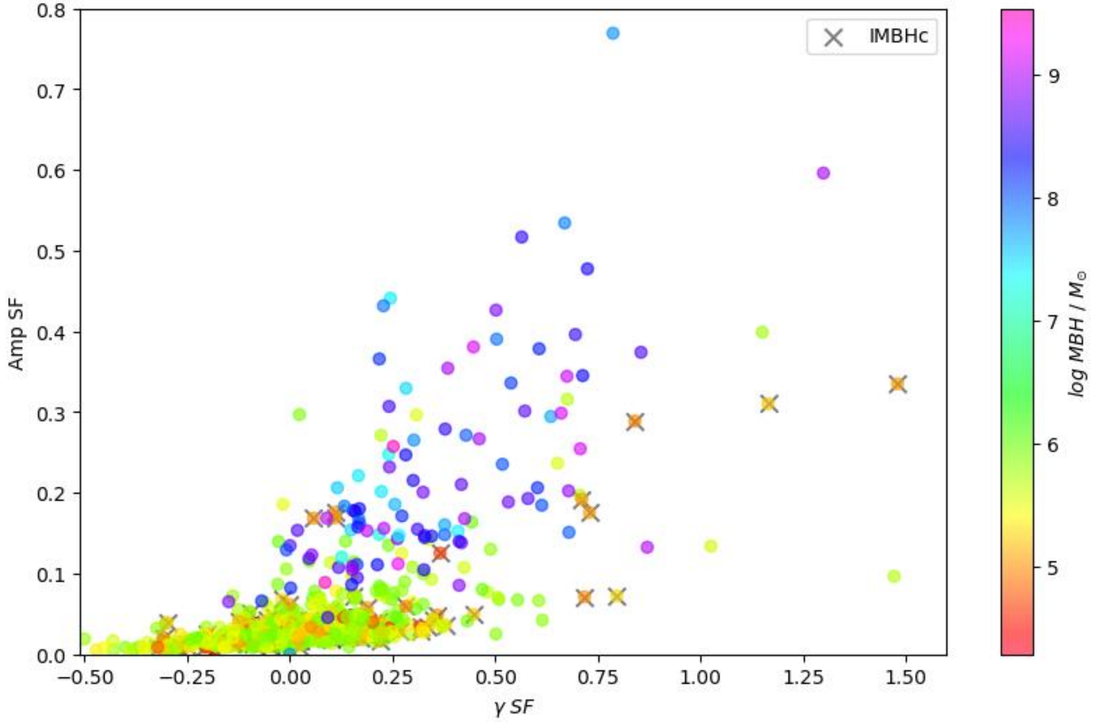
Data set	Number	% w.r.t total
Complete	1464	100
Pvar > 0.95 (1)	1092	78.54
ExcessVar > 0 (2)	931	74.59
(1) & (2)	878	63.59

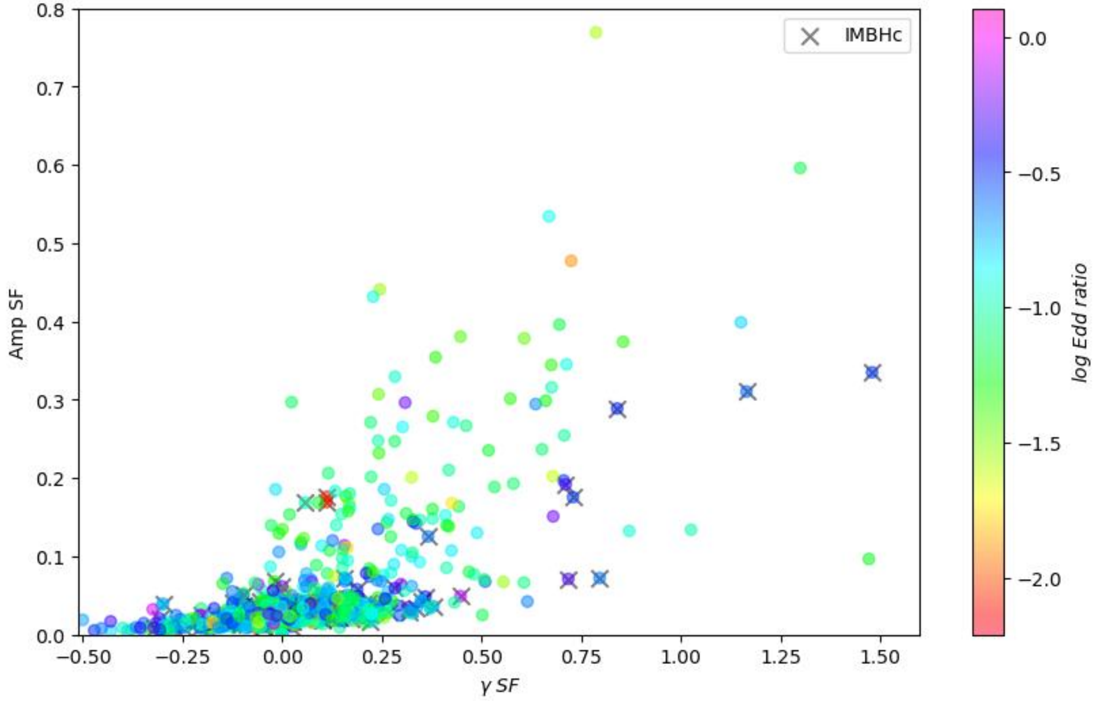


Data set	Number	% w.r.t total
Complete	1464	100
Pvar > 0.95 (1)	1092	78.54
ExcessVar > 0 (2)	931	74.59
(1) & (2)	878	63.59
X-ray detections (3)	145	-
(1) & (2) & (3)	99	6.76



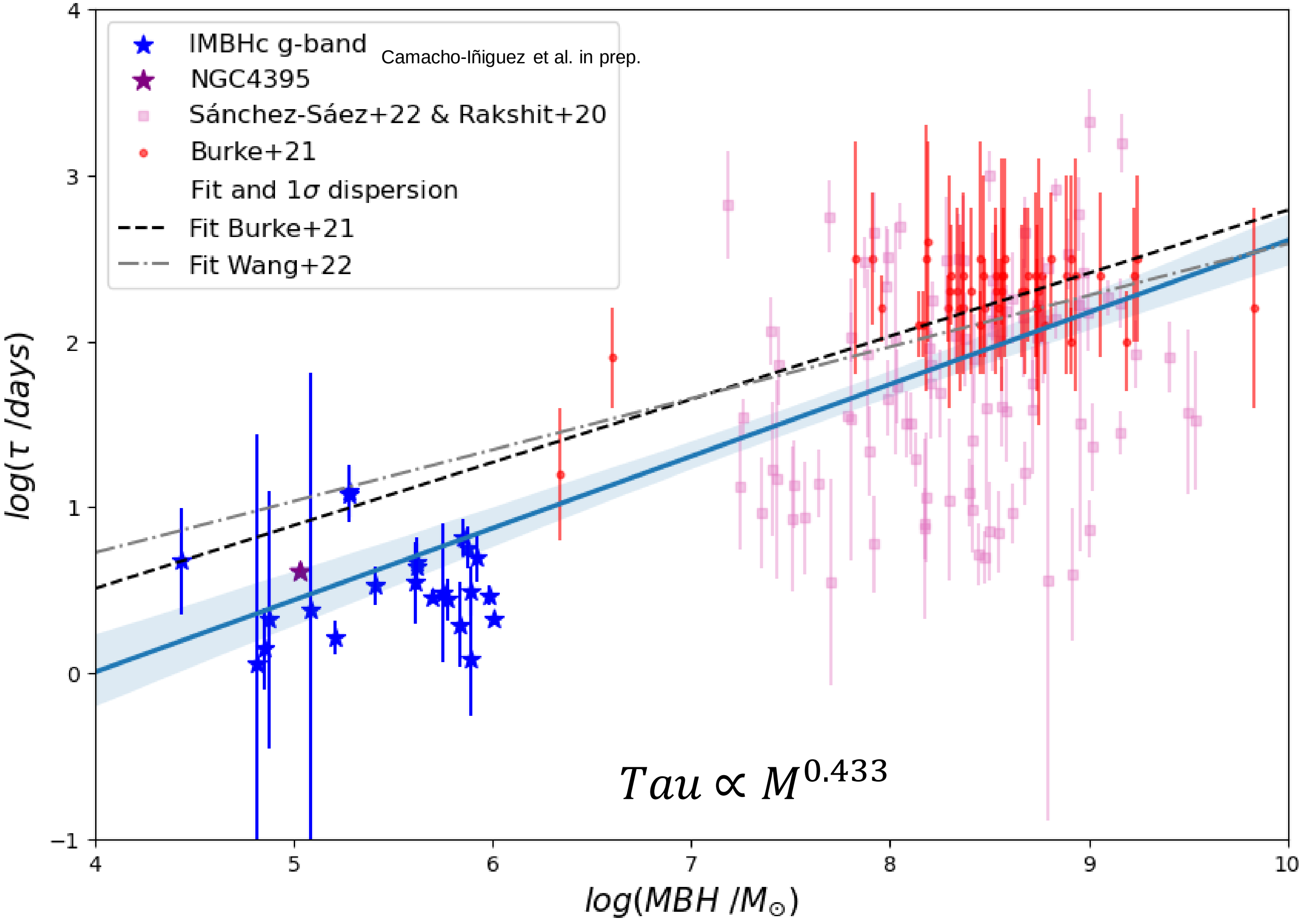
In the context of SF parameter space



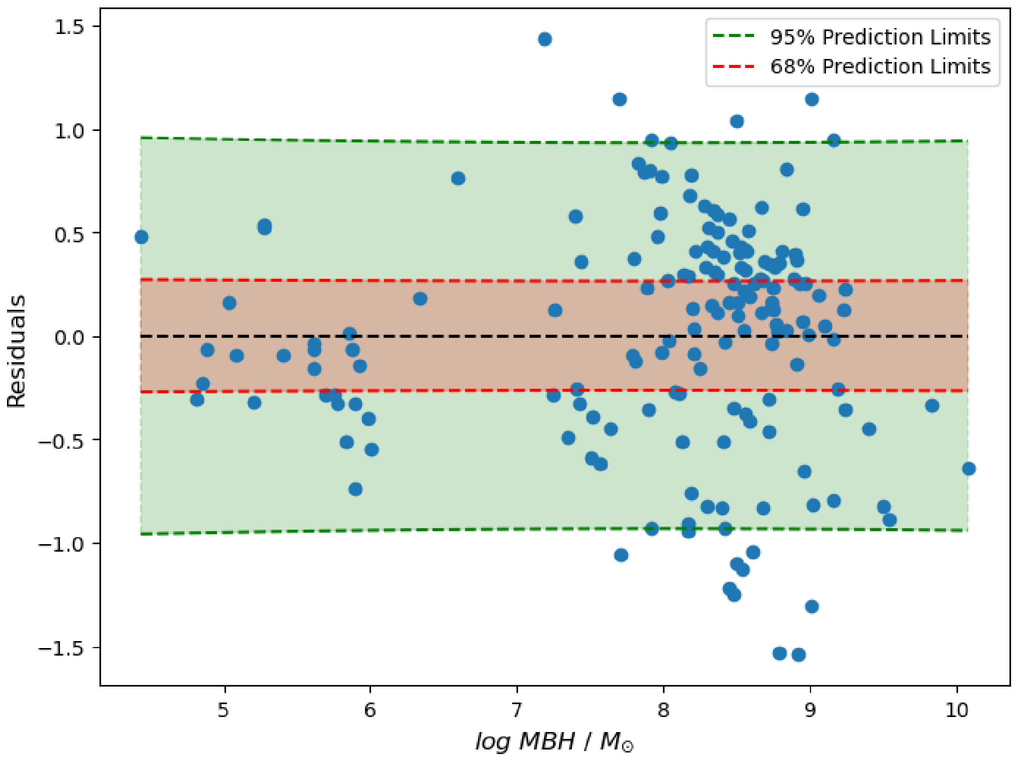


★ Even though we can find most IMBH and low-mass-SMBHs by their variability, their SF properties do not allow us to automatically select them.

★ Only a handful of the most strongly accreting ones pop up with high variability



IMBHc g-band
NGC4395
Sánchez-Sáez+22 & Rakshit+20
Burke+21
Fit and 1σ dispersion
Fit Burke+21
Fit Wang+22
Camacho-Iñiguez et al. in prep.
$Tau \propto M^{0.433}$
log(τ /days)
log(MBH /M⊙)



95% Prediction Limits
68% Prediction Limits
Residuals
log MBH / M⊙

Conclusions

★ Optical variability, even though it has its problems, is a potentially strong technique to find candidates of IMBHs and low-mass-SMBHs.

We want to use more variability features e.g. correlation of g and r bands.

Robust SMBH comparison sample

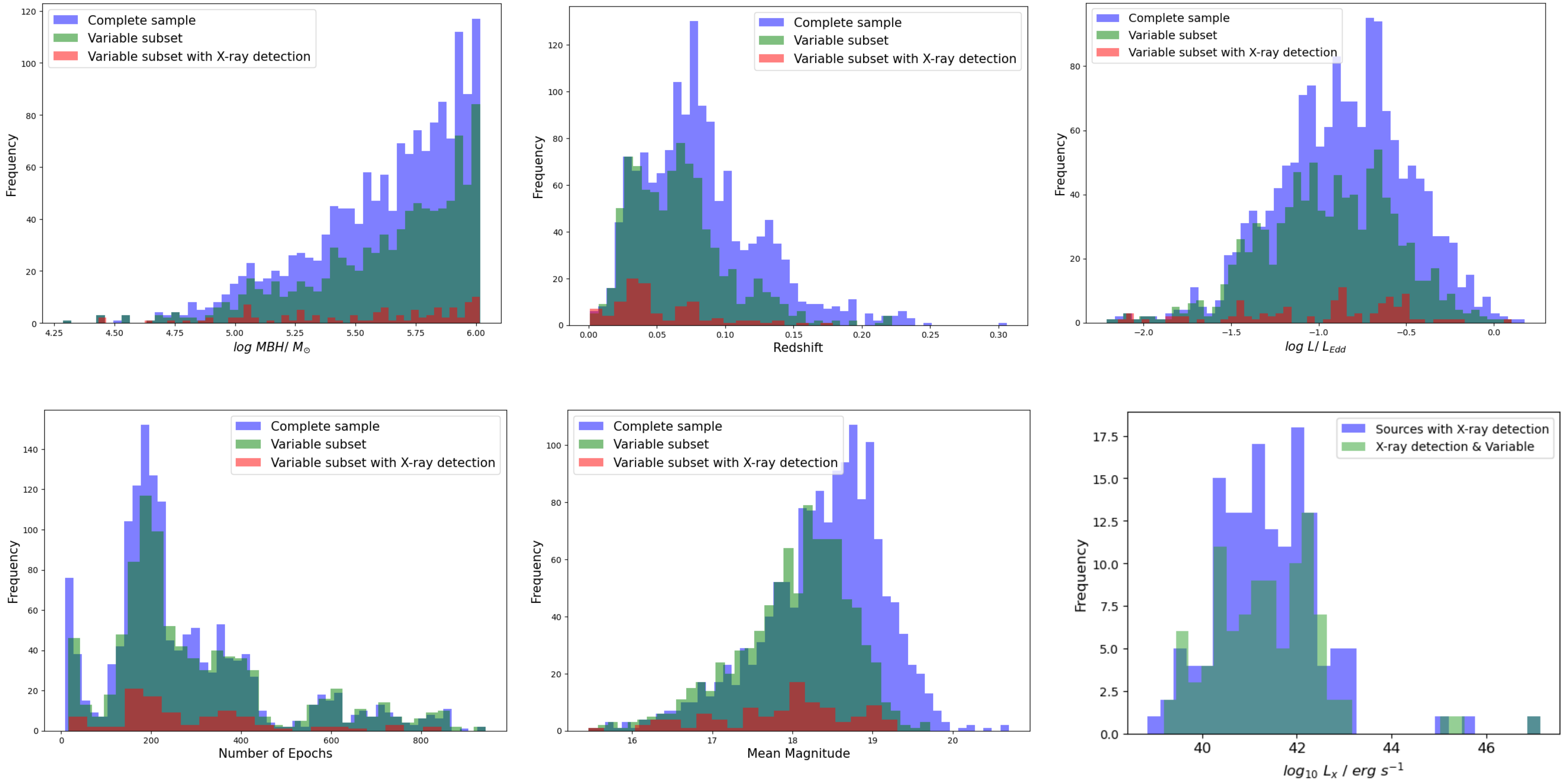
★ In the SF and DRW parameter space, IMBH and low-mass-SMBH do not stand out as we expected, it's not feasible to automatically select candidates.
Nevertheless, once the parameters are computed, they can help to filter objects.

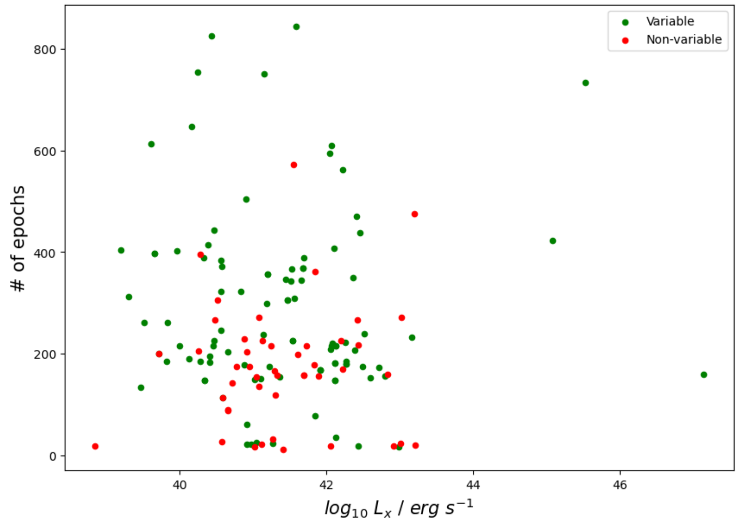
★ Among the most robust candidates, we confirm a relation between the damping timescale and the mass of the BH. BUT:

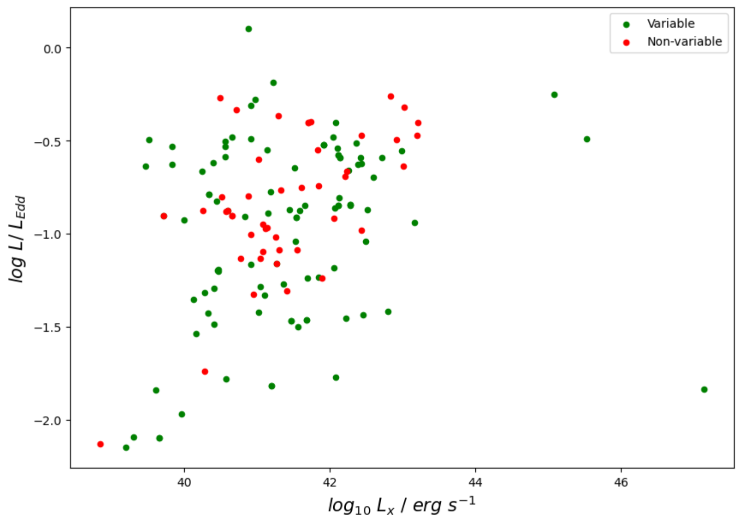
The dispersion remains large

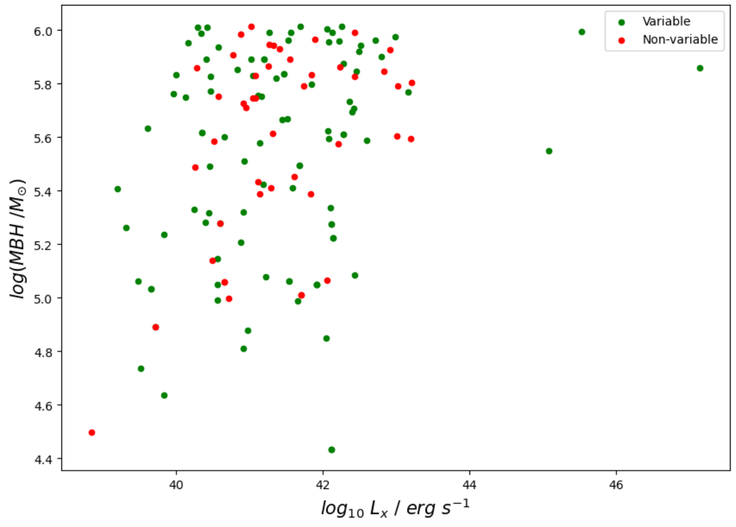
Uncertainties of tau at large masses

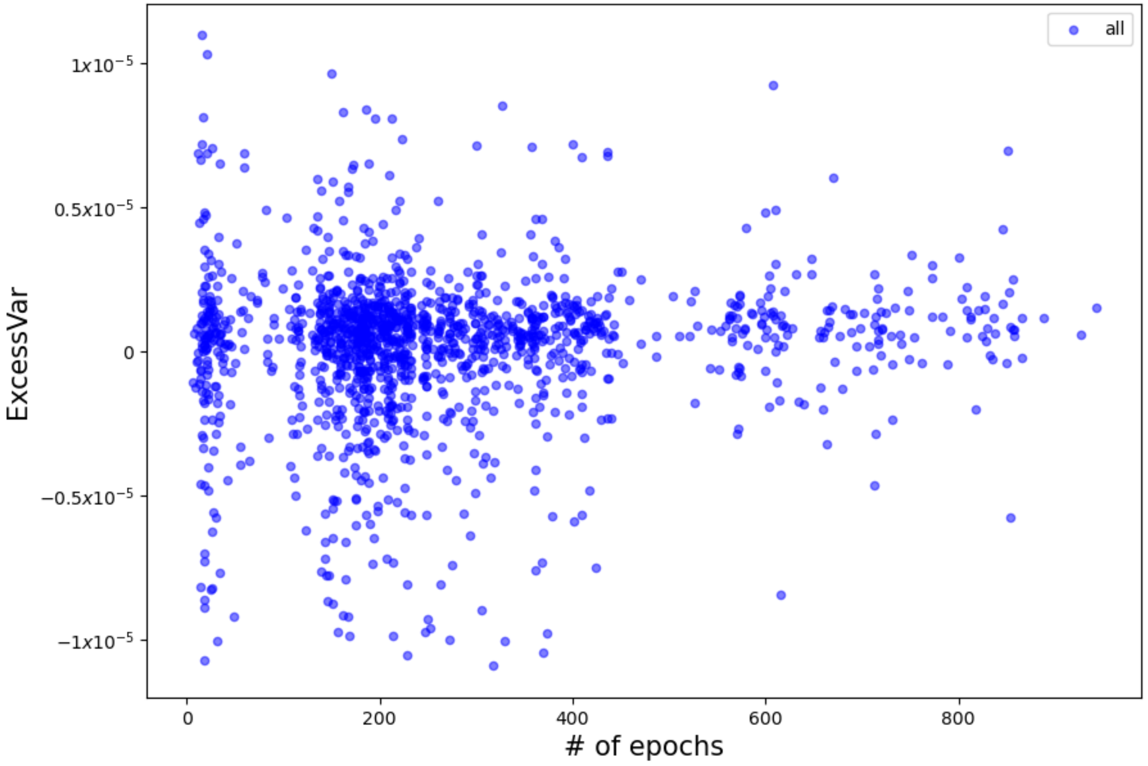
Backup slides…


Complete sample
Variable subset
Variable subset with X-ray detection
Frequency
log MBH/ M⊙
Redshift
log L/ L_Edd
Number of Epochs
Mean Magnitude
Sources with X-ray detection
X-ray detection & Variable
log10 Lx / erg s−1

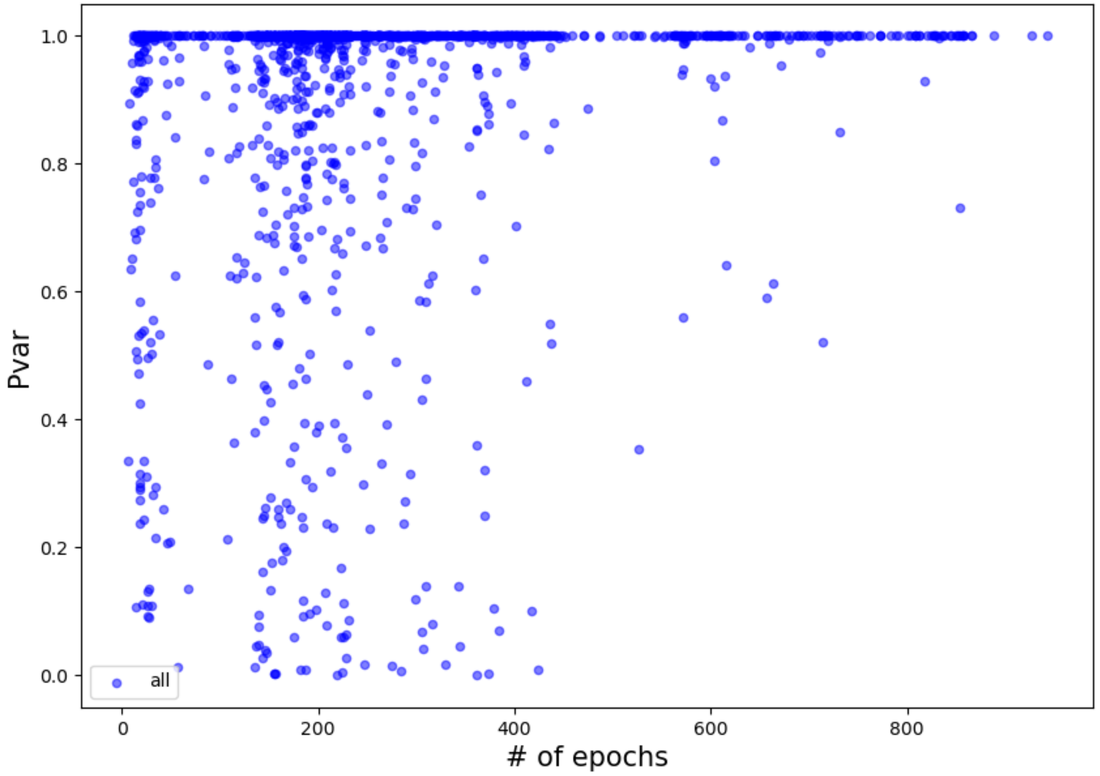

Variable
Non-variable
# of epochs
$log_{10}\,L_x\,/\,erg\,s^{-1}$


Variable
Non-variable
$log\,L/\,L_{Edd}$
$log_{10}\,L_x\,/\,erg\,s^{-1}$


Variable
Non-variable
$log(MBH\,/M_{\odot})$
$log_{10}\,L_x\,/\,erg\,s^{-1}$



all
1x10⁻⁵
0.5x10⁻⁵
0
−0.5x10⁻⁵
−1x10⁻⁵
ExcessVar
0
200
400
600
800
# of epochs



1.0
0.8
0.6
0.4
0.2
0.0
Pvar
all
0
200
400
600
800
# of epochs

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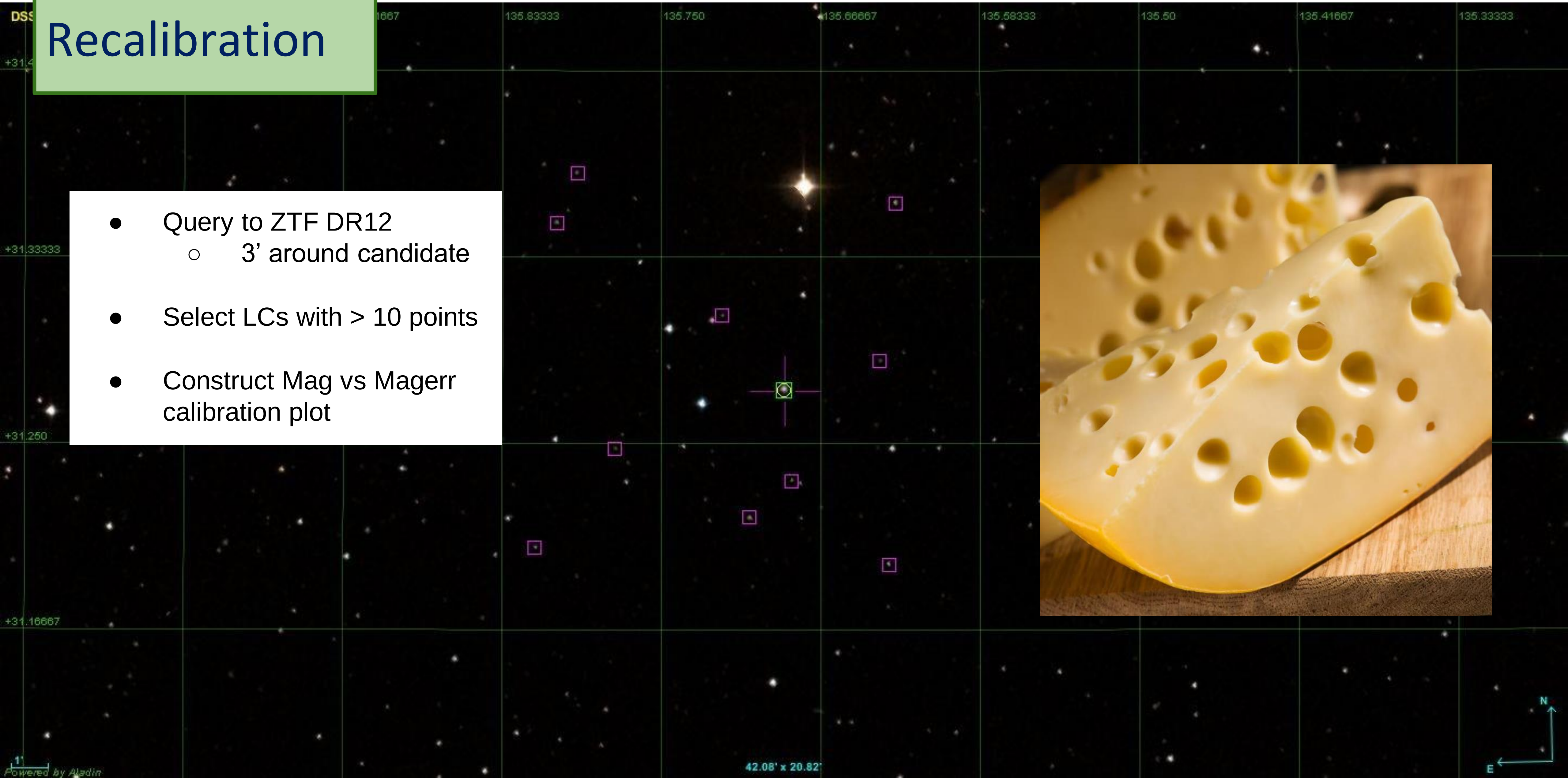
X-ray detections (3)	145	-
(1) & (2) & (3)	99	-

Data set	Number	% w.r.t total
X-ray non detections	1318	100
Pvar > 0.95 (1)	978	74.2
ExcessVar > 0 (2)	827	62.75
(1) & (2)	778	59.03

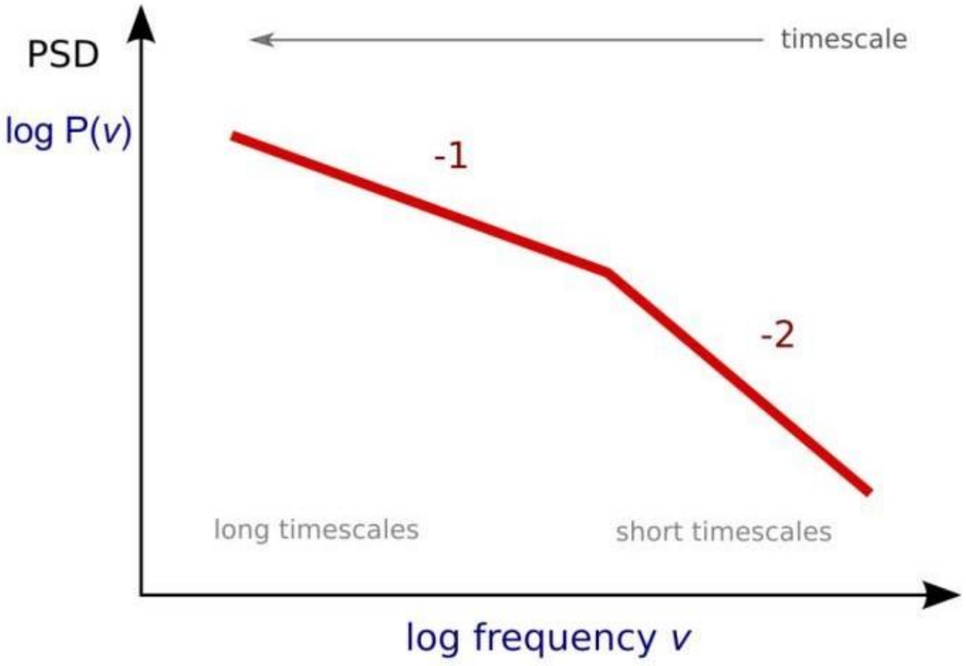
Recalibration

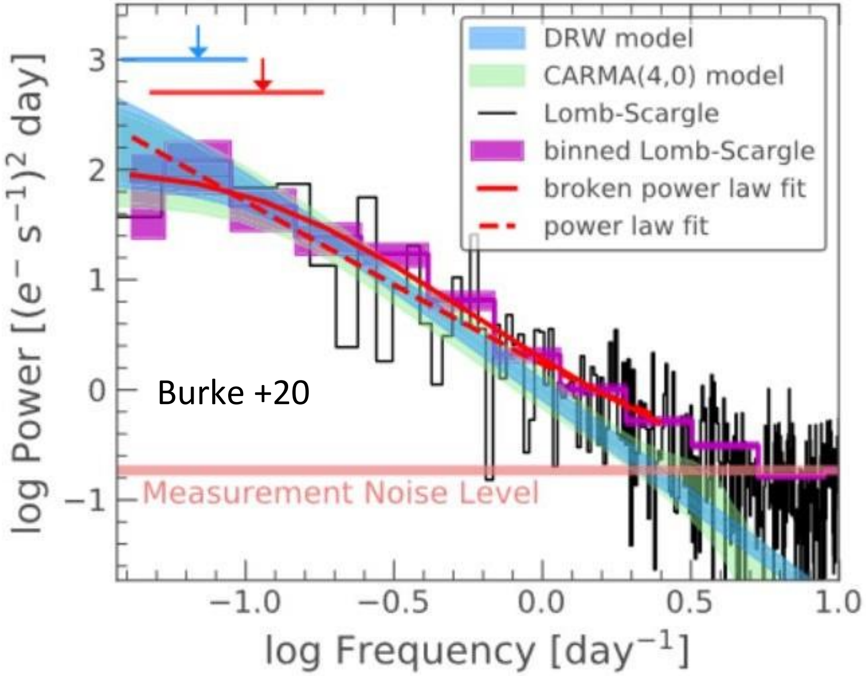
- Query to ZTF DR12
  - 3’ around candidate
- Select LCs with > 10 points
- Construct Mag vs Magerr calibration plot



Instrument and methods

★ It carries information about the strength of the physical processes driving variability at particular timescales





Why we need to clean LCs and recalibrate errors?

(MBH=10^6 M☉ and Eddington ratio of 0.3. highlights the importance of acquiring multiple AGN and MBH indicators.

z = 0.119 z = 0.0783