Euclid shear measurement

Martin Kilbinger, CosmoStat, CEA Paris-Saclay / IAP

Joint Euclid - CSS-OS meeting
ISSI-Beijing
November 2019

Weak lensing in Euclid: organisation

SGS

ESS: Survey planning

SCS: Instrument commanding

QLA: Quick look analysis

HMS: Scientific health monitoring

LE1: Level 1 processing

VIS: VIS image processing

NIR: NISP photometry image processing

SIR: NISP spectroscopy image processing

EXT: External data ingestion

MER: Euclid and External data merging

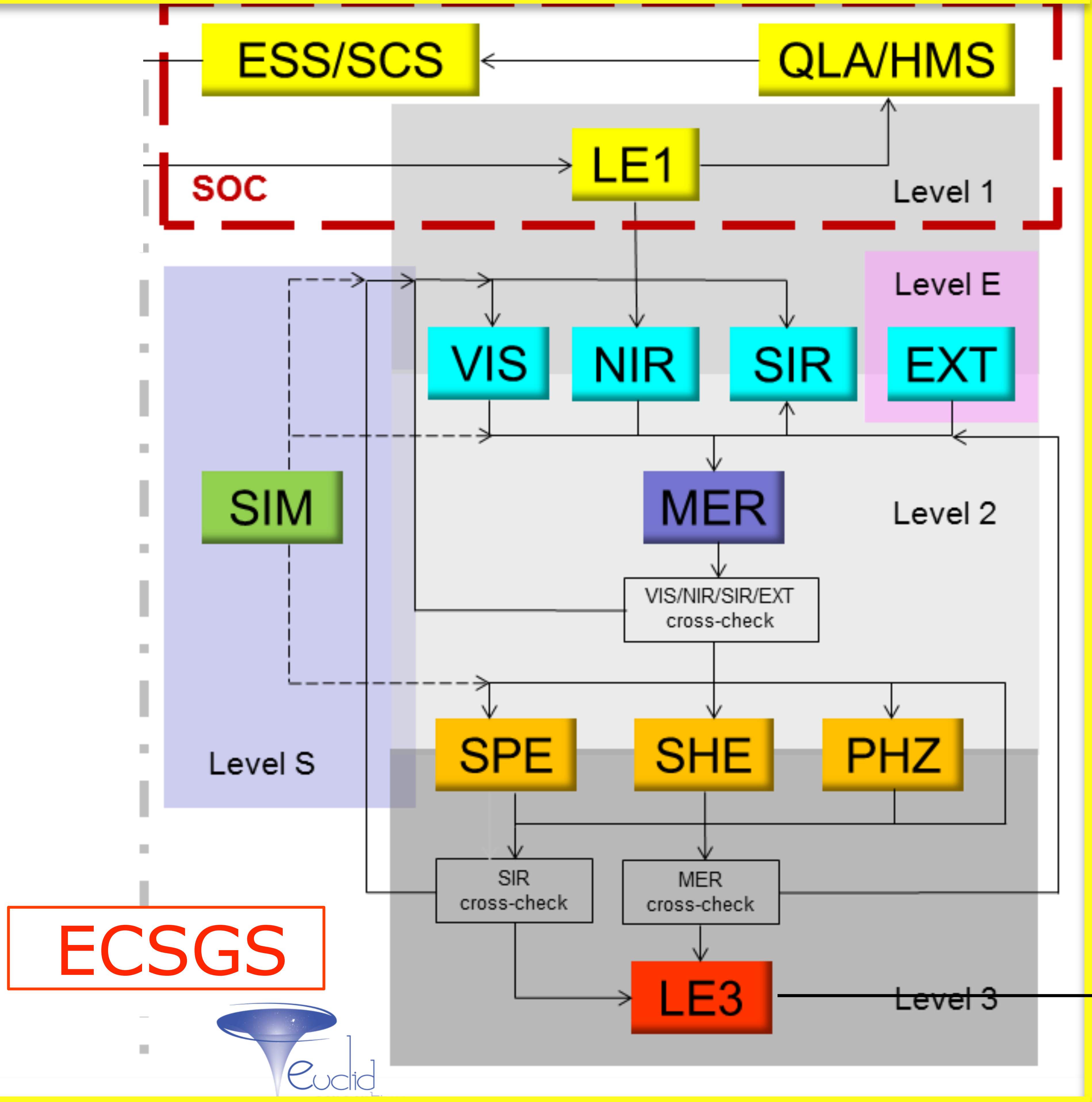
SPE: Spectroscopic redshift and spectral properties

SHE: Shear and weak lensing measurements

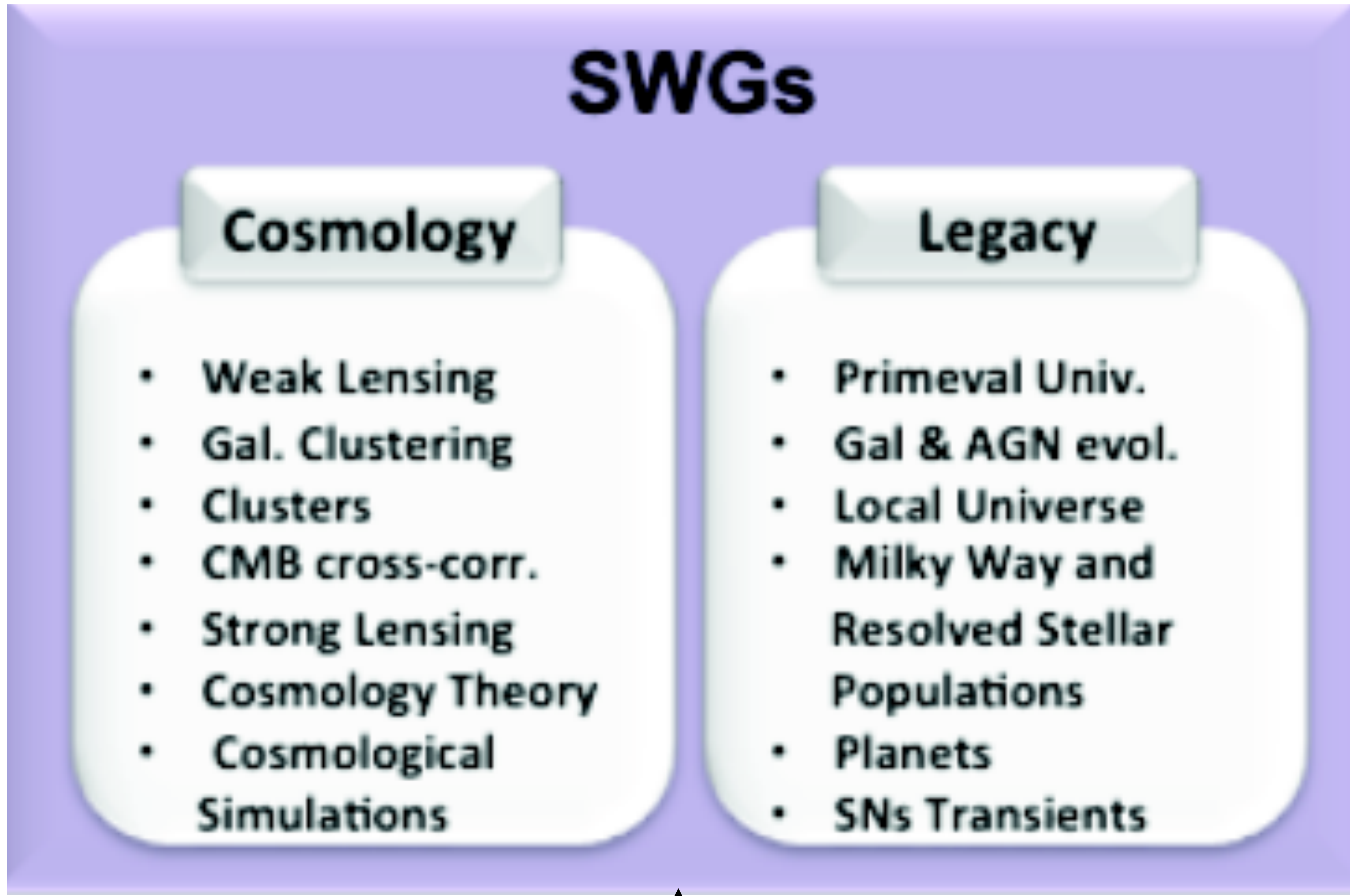
PHZ: Photometric redshift measurements

LE3: Level3 scientific processing

SIM: Image simulations



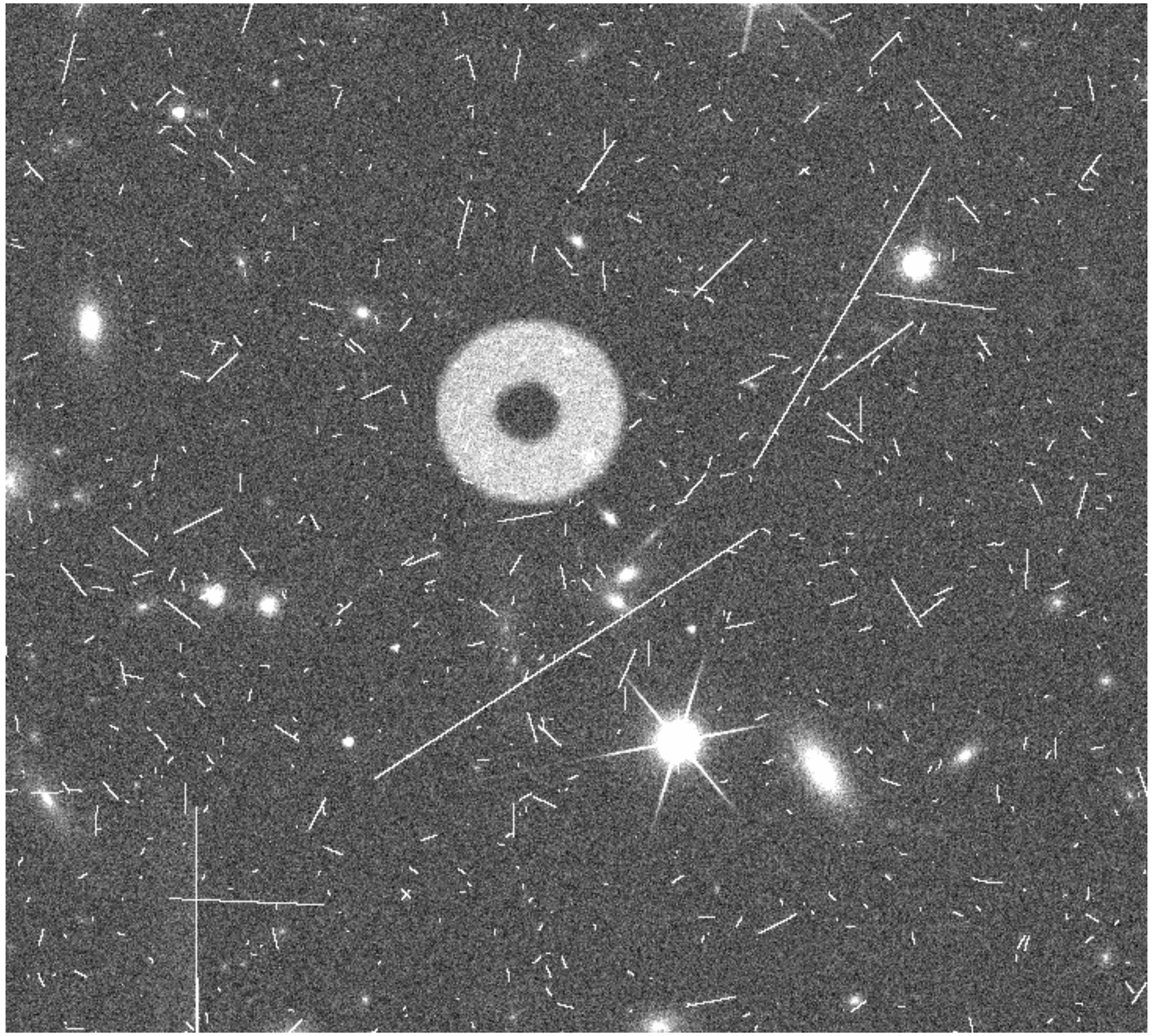
Science Ground Segment



Science Working Groups

Inter-SWG task force (IST):
- Forecasts
- Likelihood
- Non-linear

Shape measurement — instrumental effects: ghosts



VIS simulation

Reflection in the instrument (e.g. back-reflection from dichroic) of bright stars, needs to be identified and masked.

Left: simulated ghost image, from Sylvain Mottet (IAP), Real ghosts are much fainter, have complex structure.

Create multiplicative shear bias.

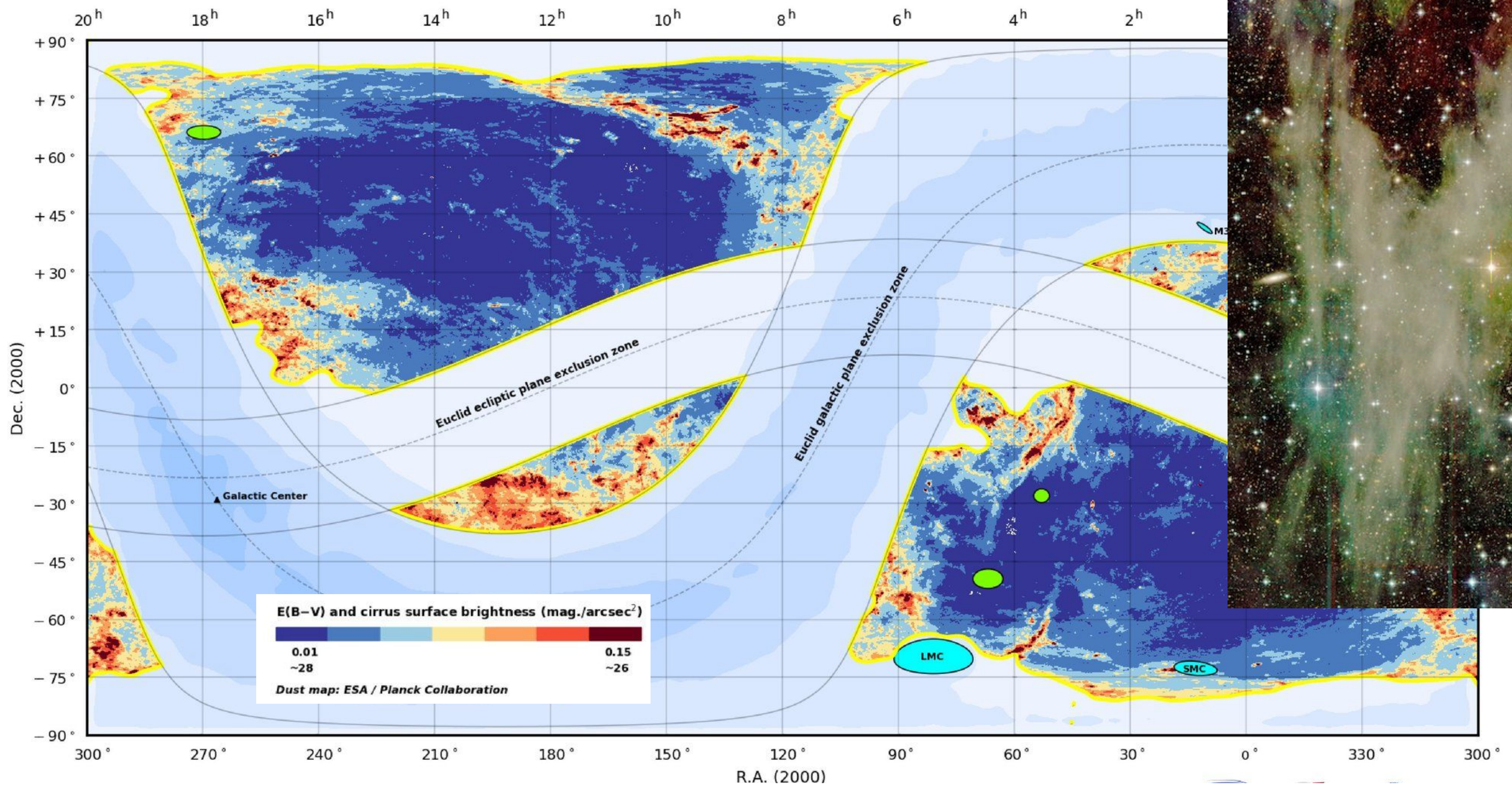
For Euclid: Within if ghosts are masked with m>16 and flux < 5x10^{-6} of PSF flux

Shape measurement — galactic cirrus

Filamentary, diffuse thermal emission and scattered light from dust grains.

- spatially varying background
- increase of noise

Multiplicative bias.
Tested with varying star density (proxy for cirrus), within requirements.

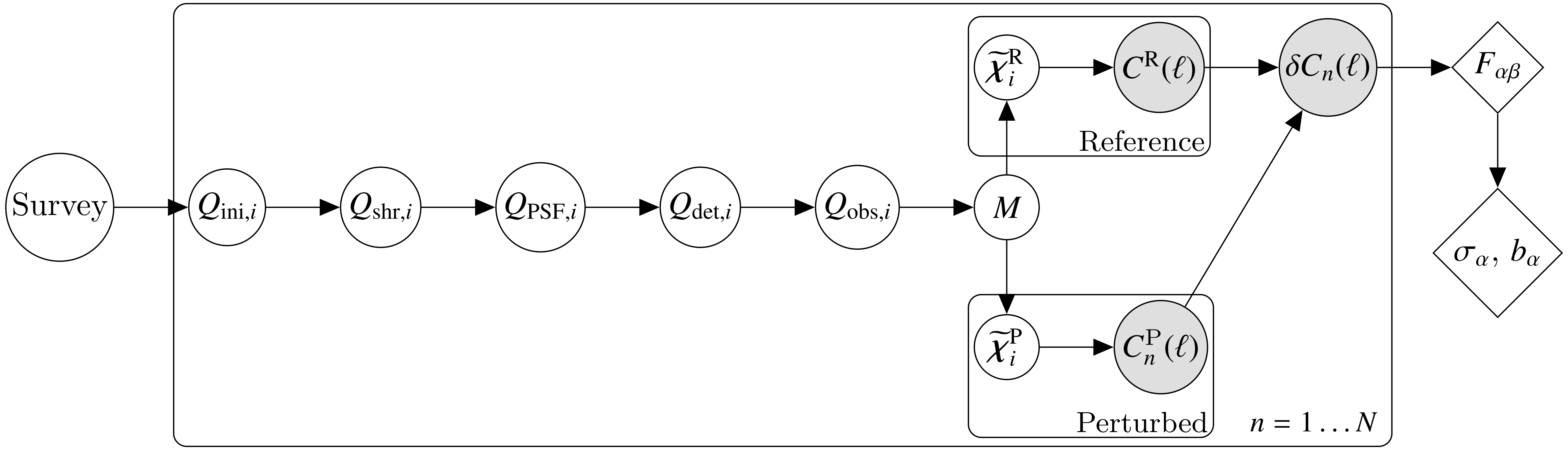


Miville-Deschênes et al. (2016)

End-to-end simulations

Catalogue-level bypass simulations. Modeling systematics on galaxy moments.
Compare reference to perturbed scenarios.
Extention of Cropper et al. (2013).

$$\chi_{\mathrm{obs},i} = \chi_{\mathrm{gal},i} + f_i\,(\chi_{\mathrm{PSF},i} - \chi_{\mathrm{gal},i}) + \chi_{\mathrm{det},i}$$



Propagation to cosmology with Fisher matrix, figure-of-merit (FoM) and bias.

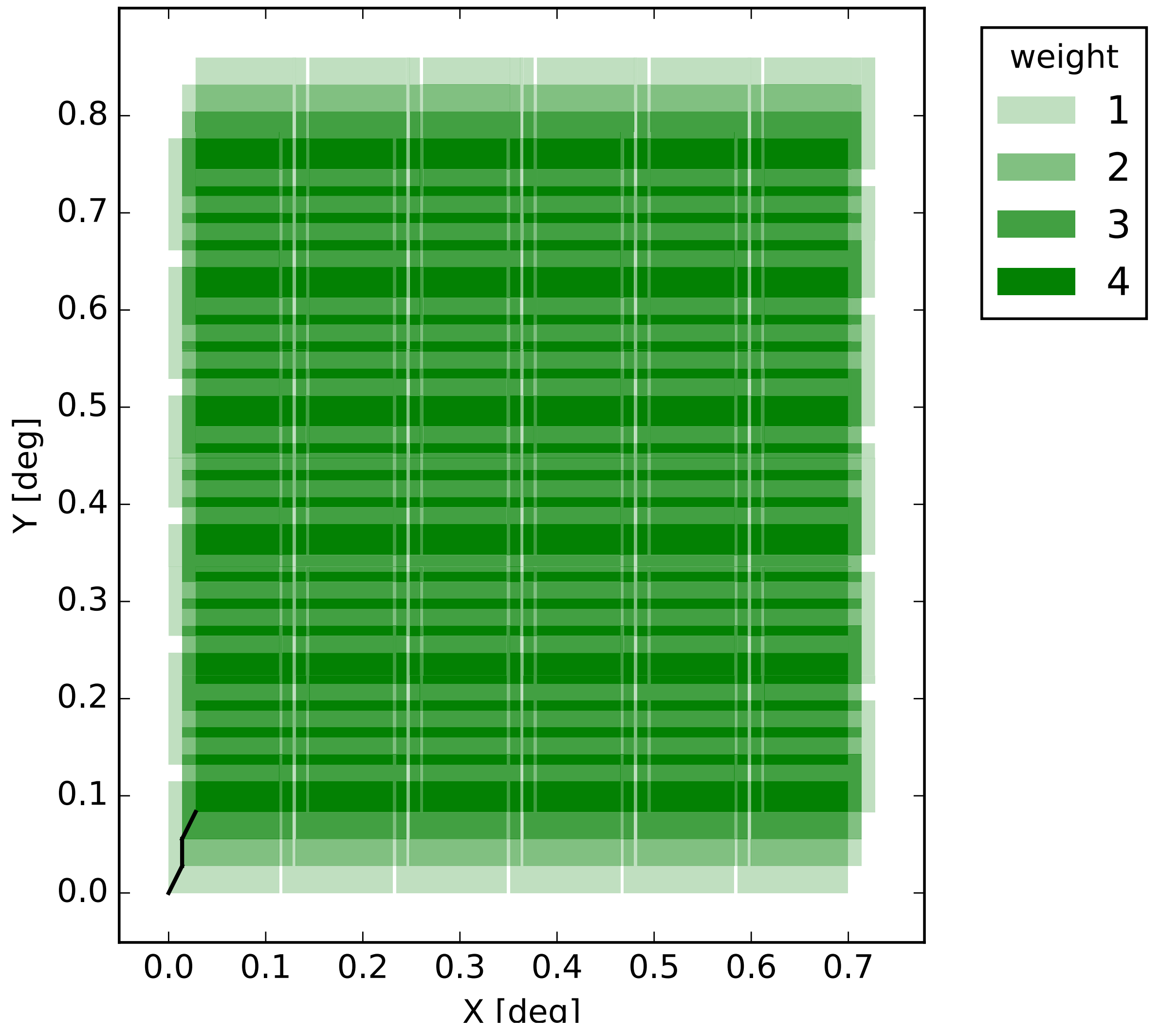
$$F_{\alpha\beta} = \sum_{jk,\ell} \mathcal{F}_{jk}(\ell)\, \frac{\partial C_{jk}(\ell)}{\partial \alpha} \frac{\partial C_{jk}(\ell)}{\partial \beta} \qquad \mathcal{F}_{jk}(\ell) = \frac{f_{\mathrm{sky}}\,(2\ell+1)}{2[C_{jk}(\ell) + N_{jk}(\ell)]^2}$$

$$b_\alpha = -\sum_\beta (F^{-1})_{\alpha\beta}\, B_\beta \qquad B_\beta = \sum_{jk,\ell} \mathcal{F}_{jk}(\ell)\, \delta C_{jk}(\ell)\, \frac{\partial C_{jk}(\ell)}{\partial \beta}$$

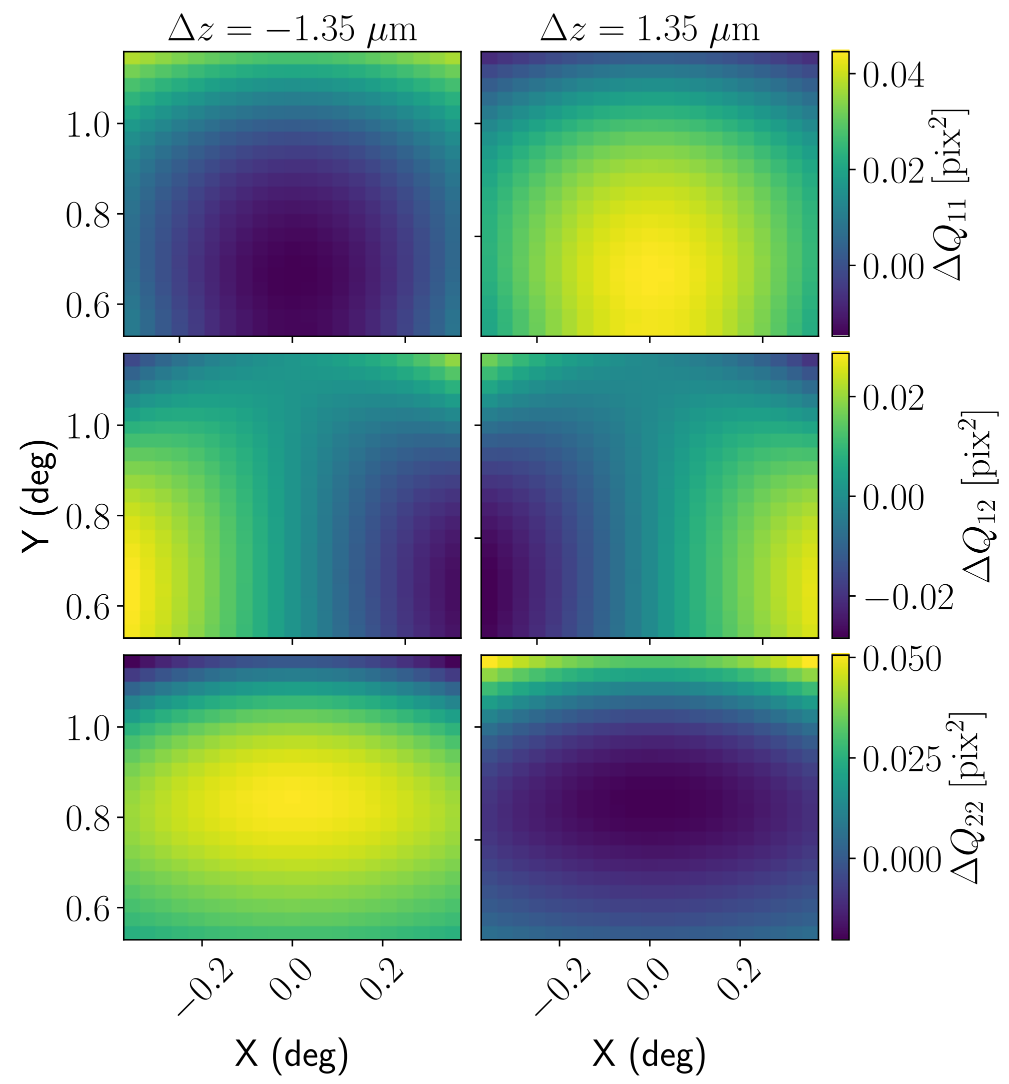
Paykari et al. (2019), arXiv:1910.105211910.10521

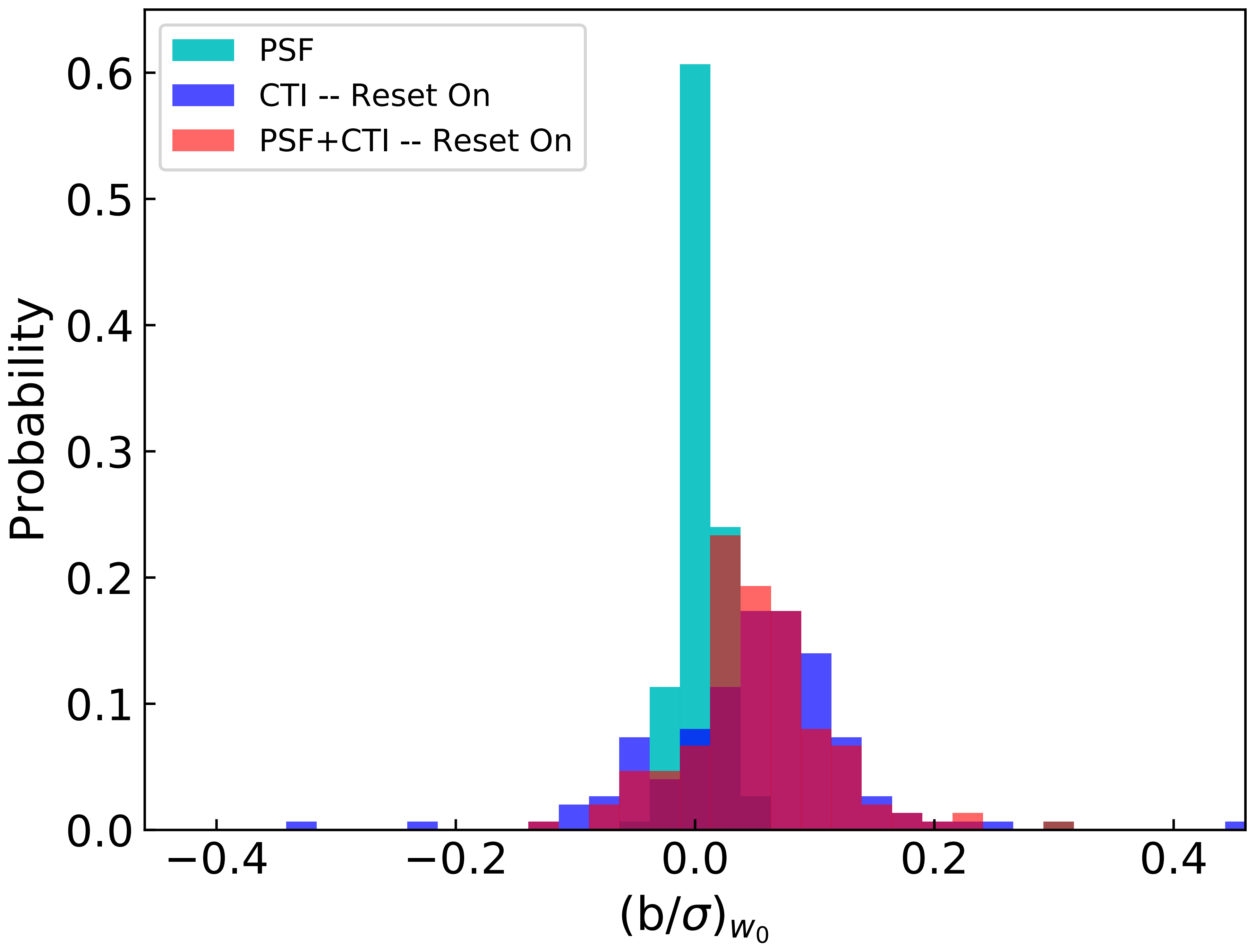
End-to-end simulations

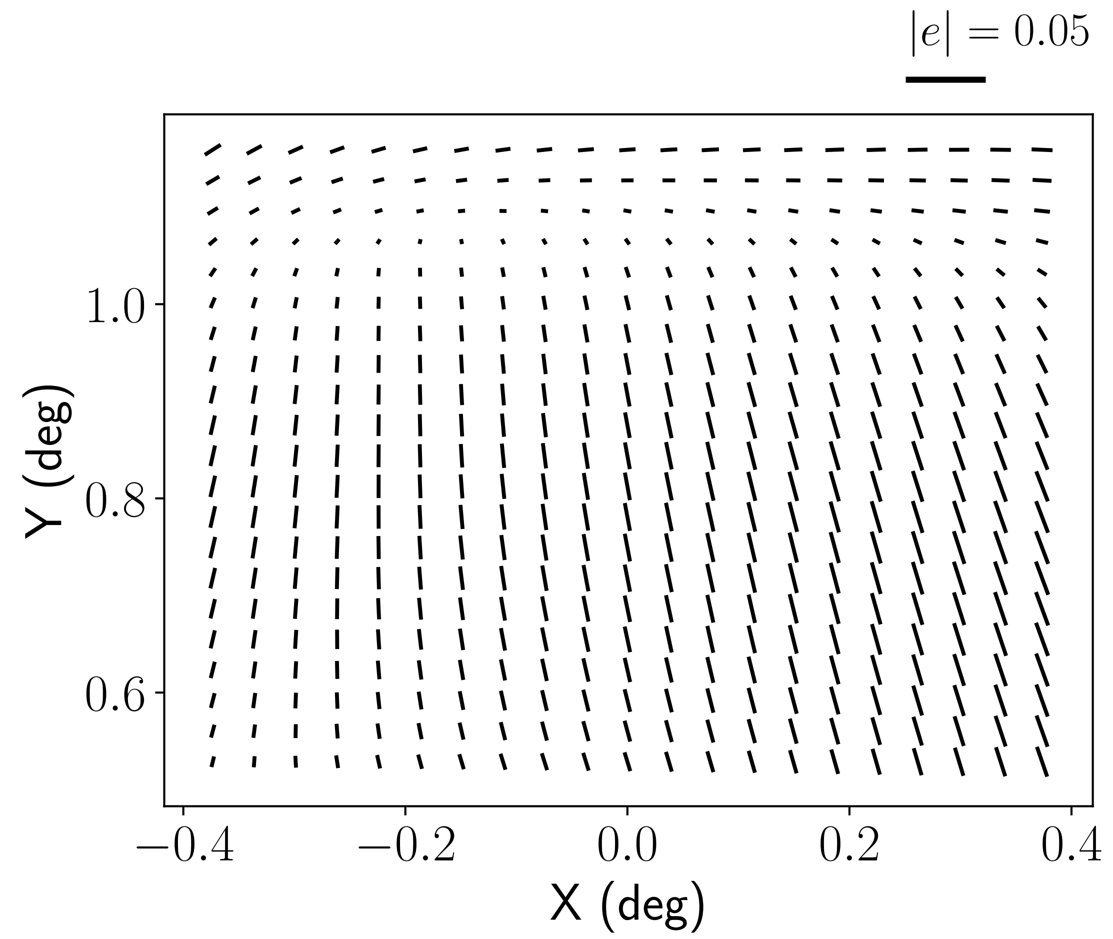
VIS field with dithers



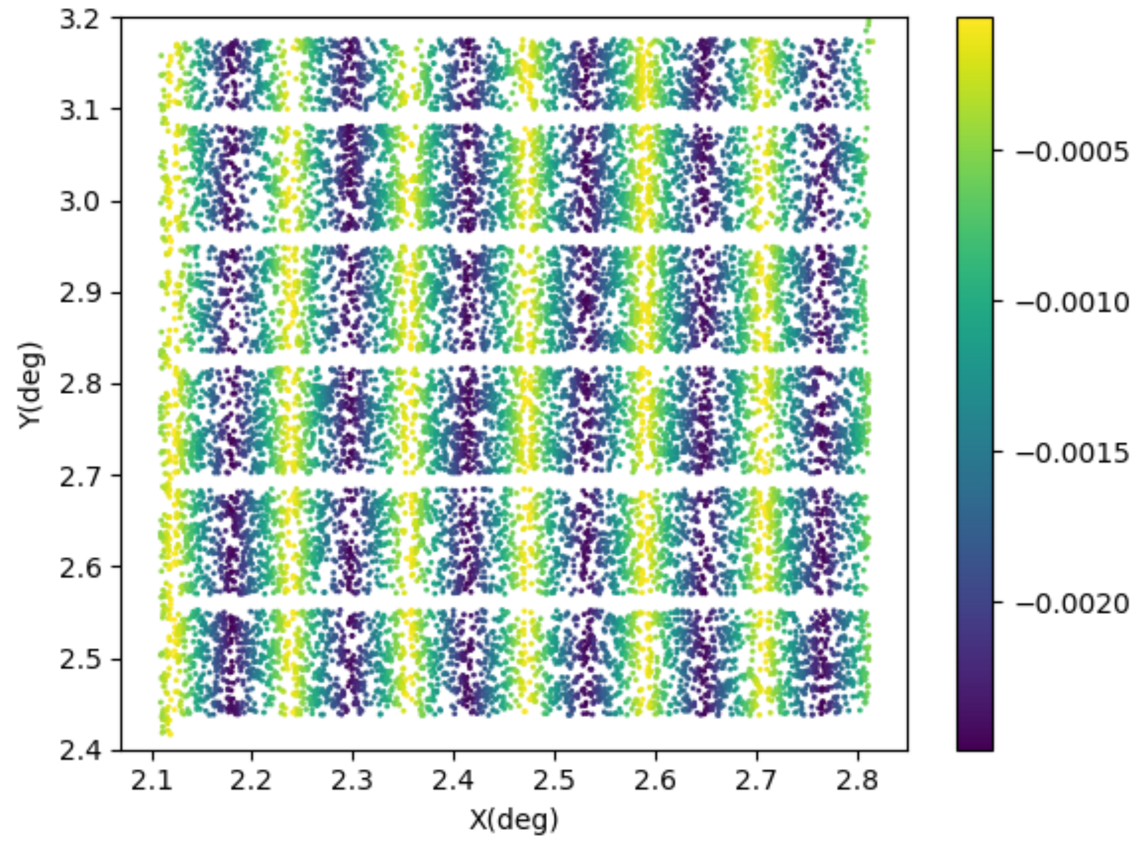
PSF moments







PSF variation across FoV



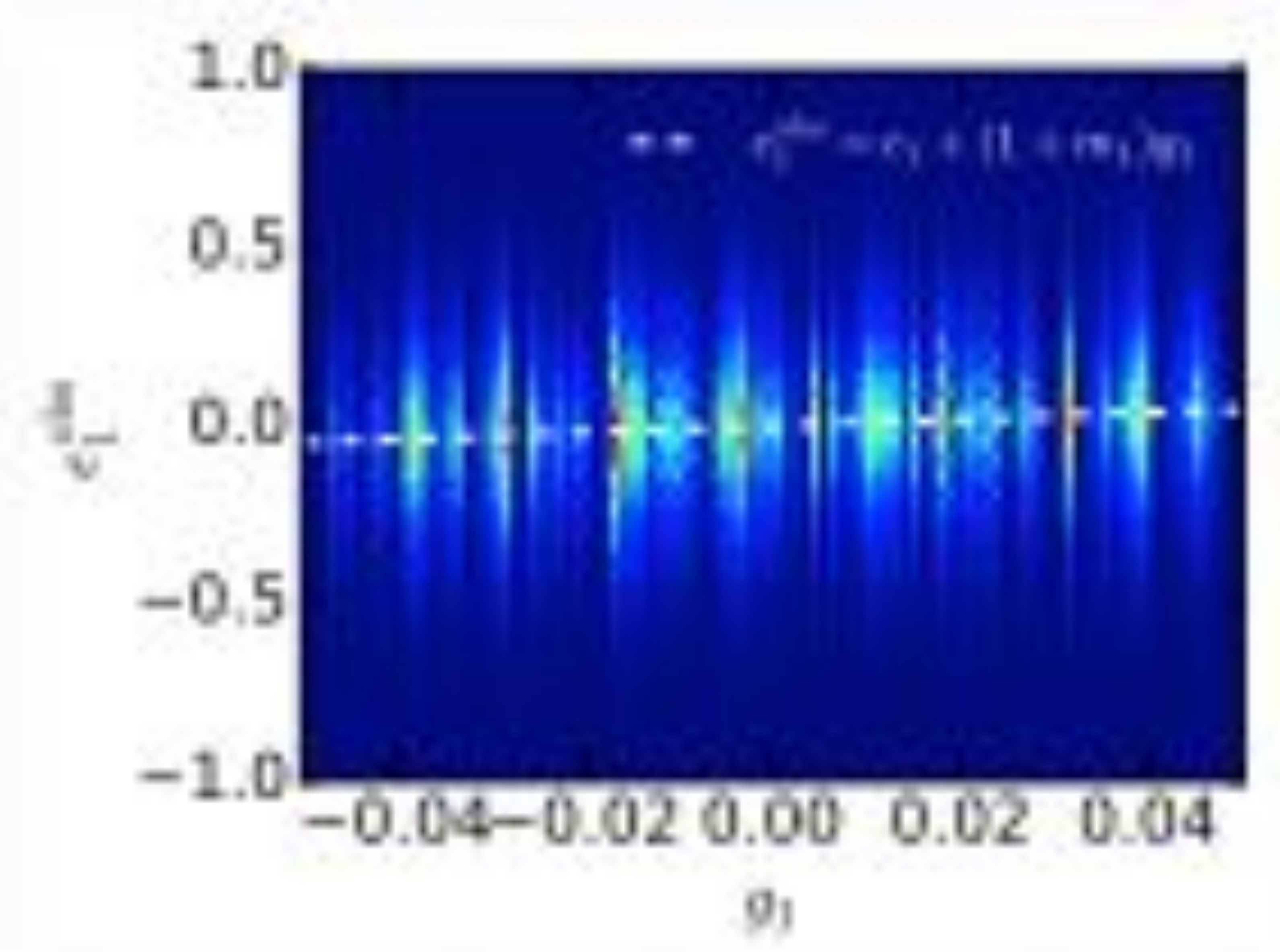
CTI effect on galaxies

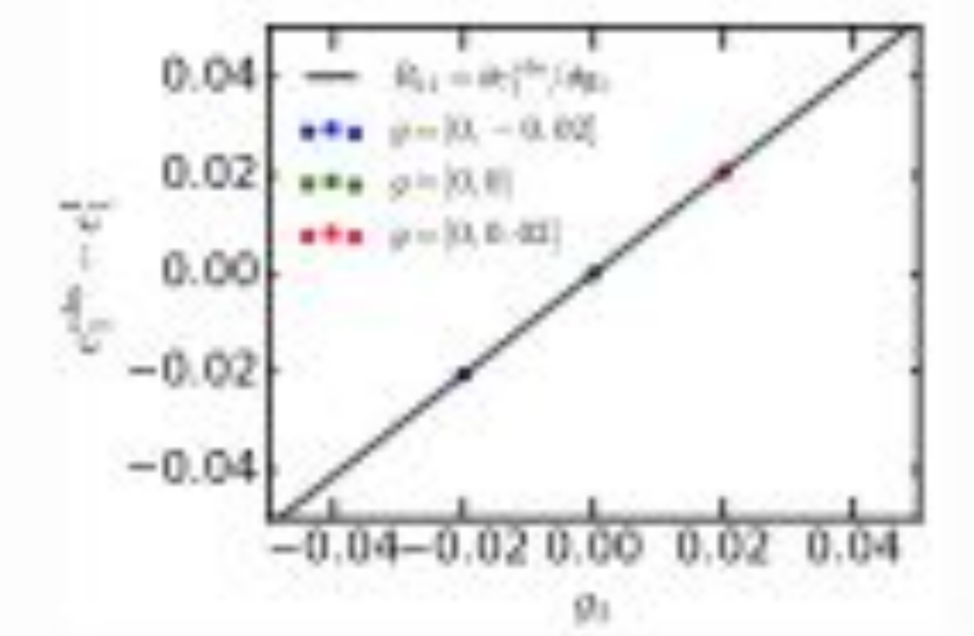
Paykari et al. (2019), arXiv:1910.105211910.10521

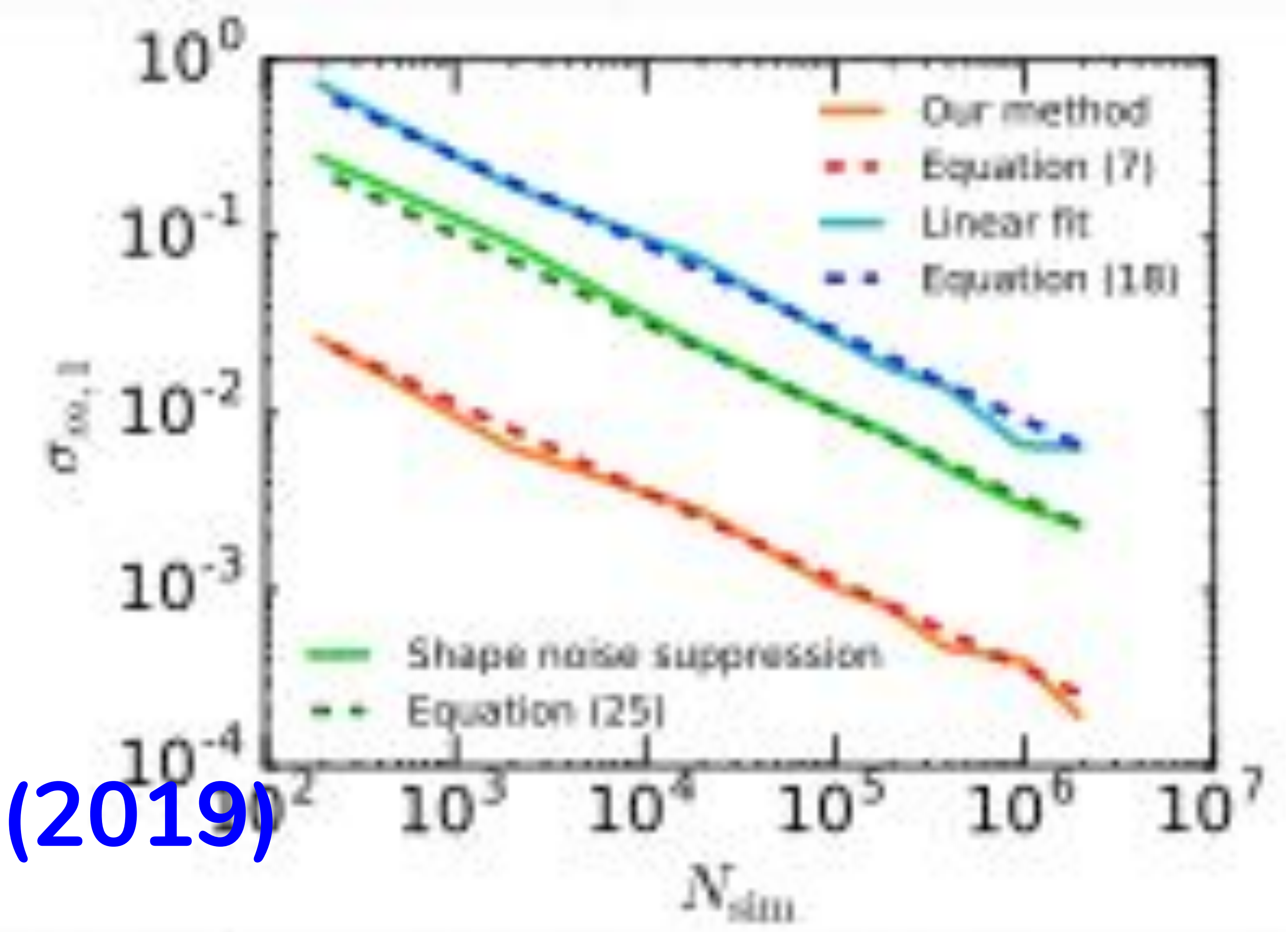
Shear calibration - simulations

Shear calibration from simulations.

$$\langle \varepsilon_\alpha^{\rm obs} \rangle = g_\alpha^{\rm obs} = (1 + m_\alpha) g_\alpha^{\rm true} + c_\alpha; \quad \alpha = 1, 2$$





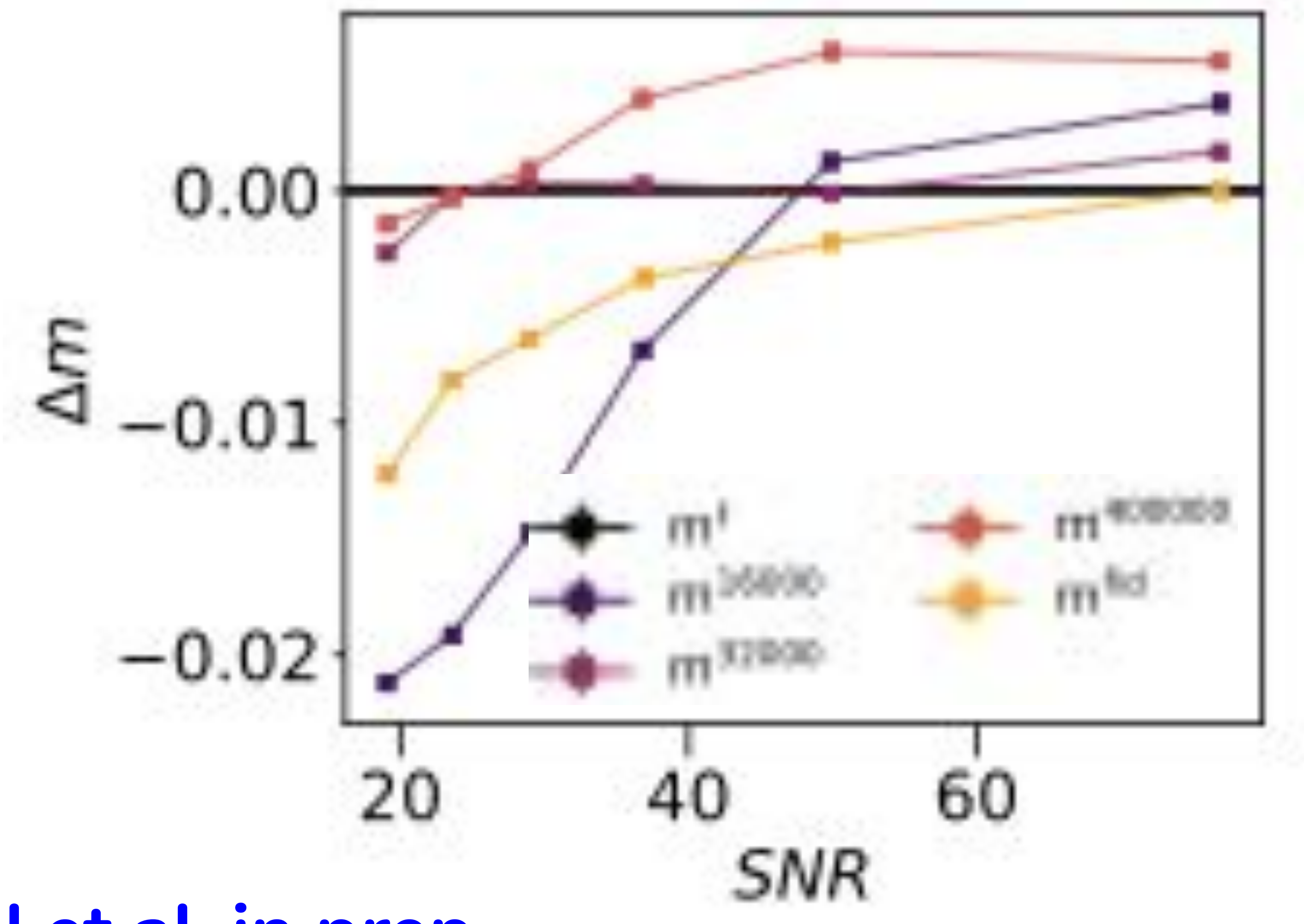


Pujol, Kilbinger, Sureau & Bobin (2019)

Deep Neural Network Regression.

Supervised training on 32 input properties (of galaxies, PSF, noise, ...) & true shear bias

4 hidden layers à 30 units, output are shear bias m_i, c_i.



Pujol et al. in prep.

Shear estimation methods

Several methods are being implemented in Euclid ground segment:

- **LensMC**
  Lance Miller, Guiseppe Congedo
  Model-fitting, lensfit extension, 3D galaxy models, MCMC sampling

- **MomentsML**
  Malte Tewes
  Machine-learning

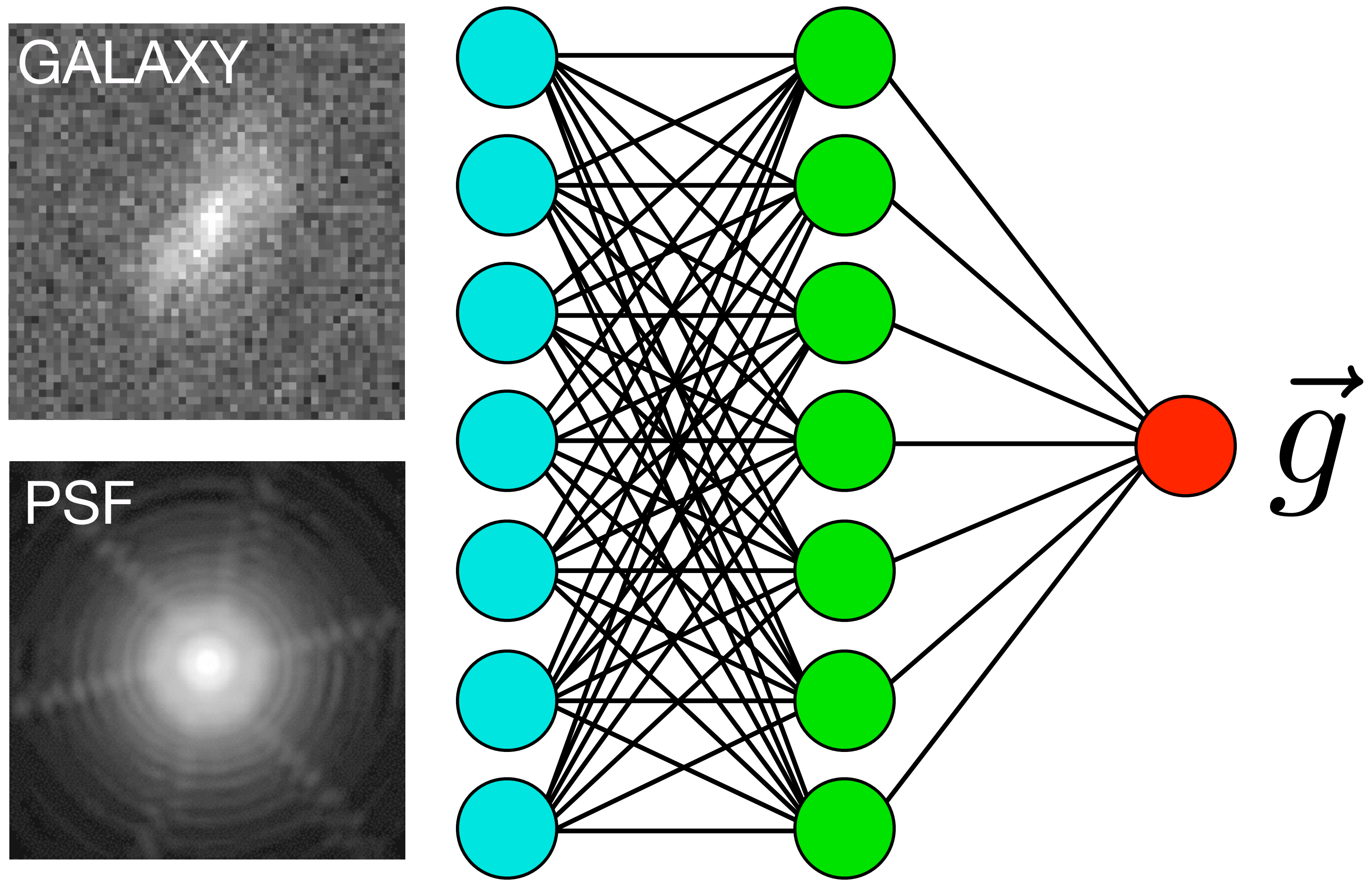
- **KSB**
  Moment-based

- **ReGauss**
  Rachel Mandelbaum, moment-based

- **BFD**
  Gary Bernstein
  Bayseian Fourier-Domain, shear estimate without individual galaxy ellipticities

Overview of MomentsML (in case this is new to somebody)

- Supervised machine learning, trained on image simulations, to predict a shear estimate for each source galaxy
- Features: measurement of moments of the galaxy image, PSF, colours, …



Motivations

- Noise propagation and complex bias effects are integrated via the training simulations
- Accuracy: calibrates as much as possible on a galaxy-by-galaxy basis, reducing *conditional* bias, i.e., the dependence on ensemble properties.
- Very fast runtime per galaxy (few ms)

Detailed description: Tewes et al. (2019), see also Euclid prep. IV / Martinet et al. (2019)

From Malte Tewes

2

Algorithm: status as implemented in SC456

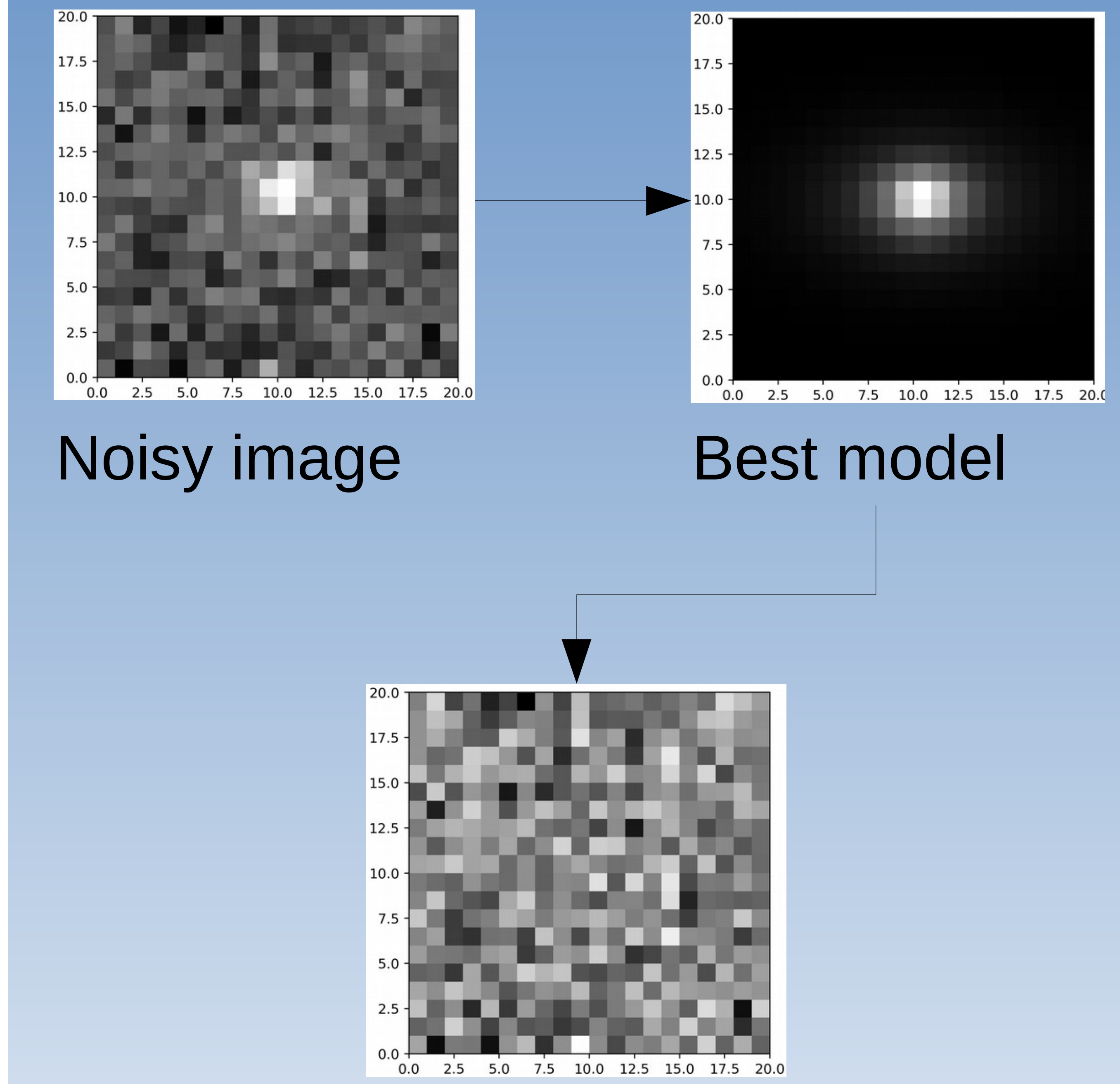
ML input	ML algorithm	ML output
• Adaptive moments (HSM) of galaxy, from single exposure • Local background noise estimate	• Ensembles of NNs trained with cost functions penalizing bias of the weighted shear estimates. • Still same own NN library (based on numpy).	• Point estimate and weight for each shear component, currently averaged over exposures.

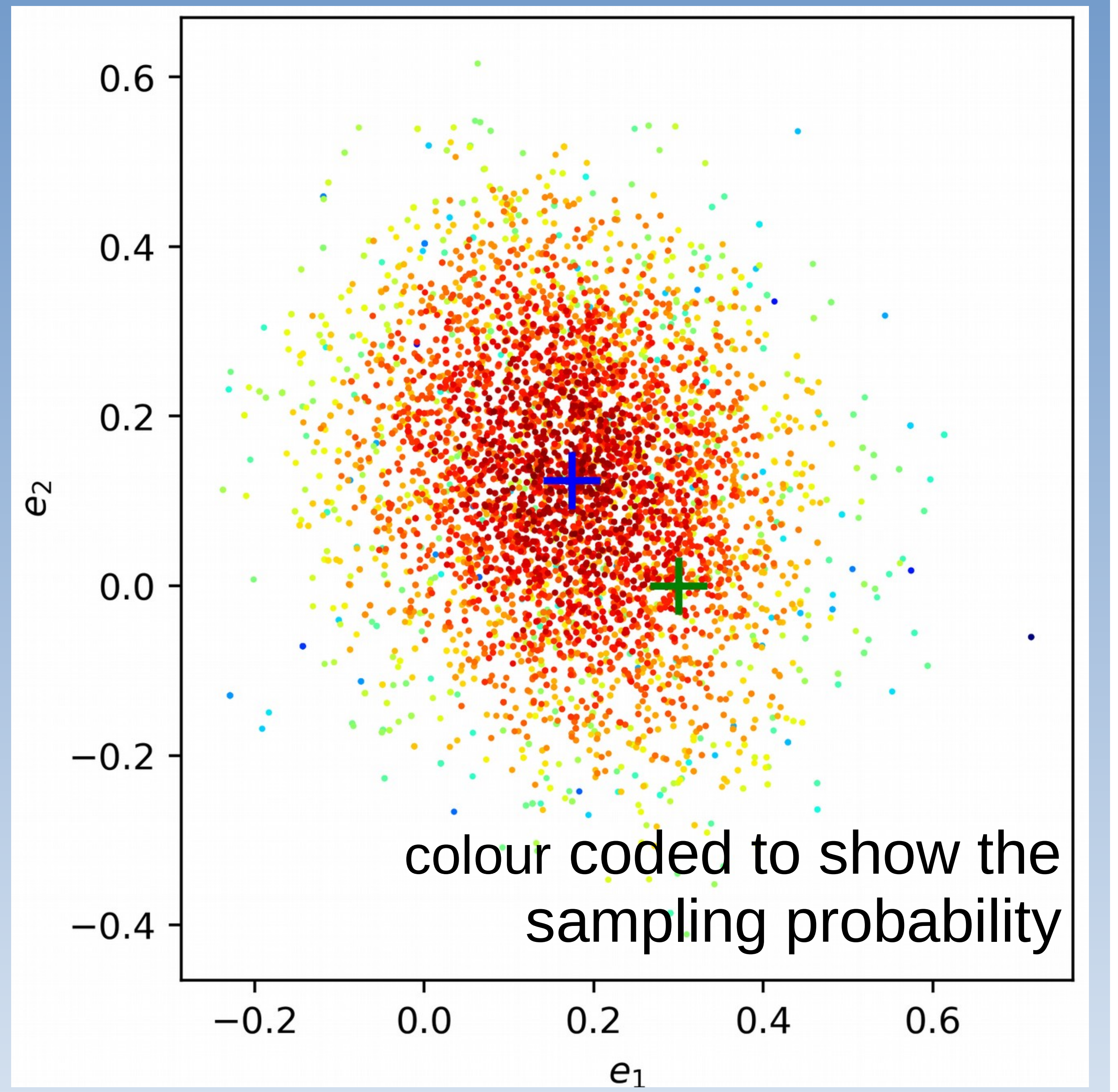
Comments

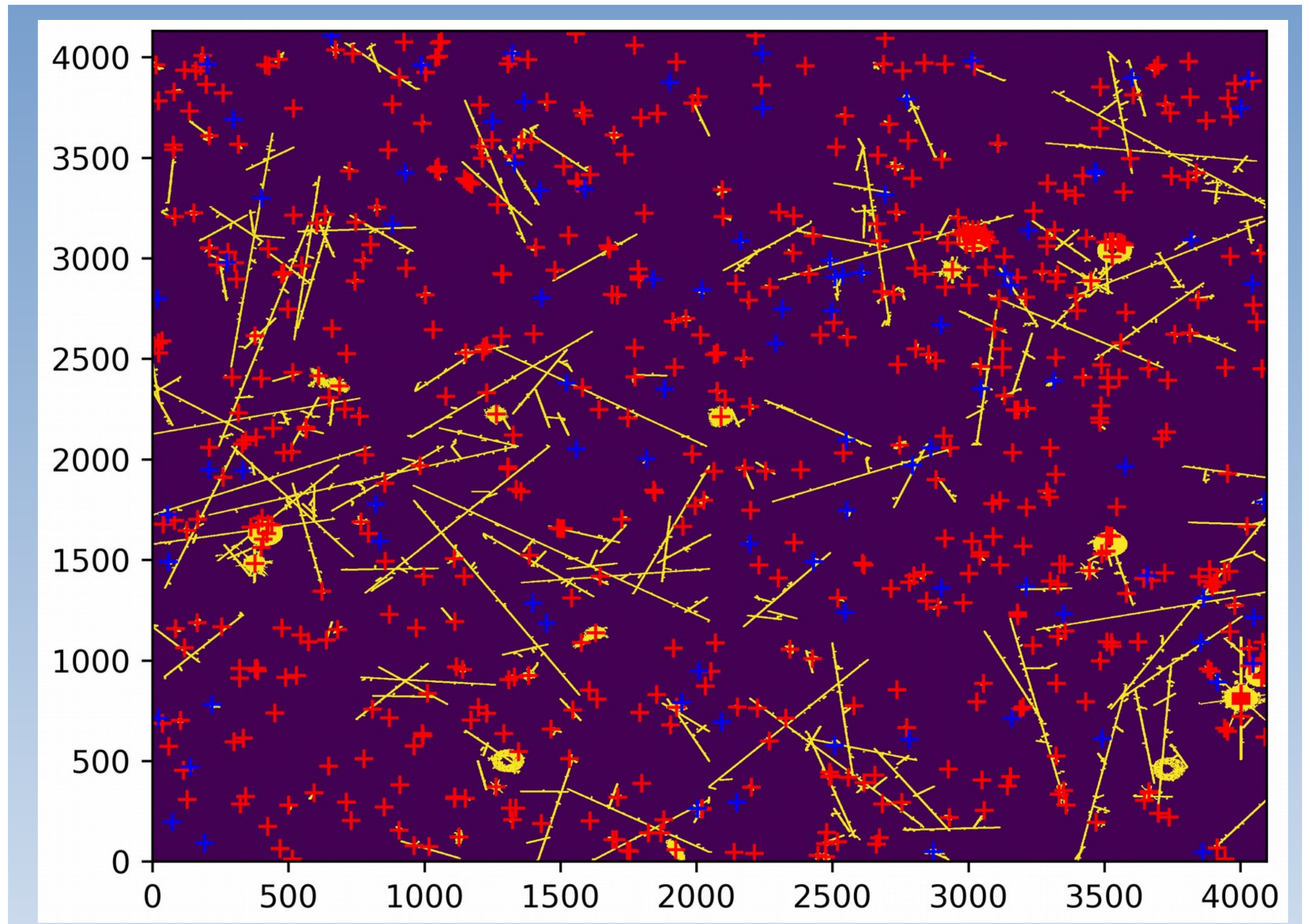
• Per-galaxy PSF information is currently *not* used: the training was done with a static PSF. Full algorithm will use moments (& colour) of the PSF, and train with diverse VIS PSFs (see Tewes et al. 2019).	• Training not parallelized, done externally. • Tensorflow in EDEN now needed!	• Keep pt-estimates and weights for SC8? (And focus on more comprehensive input features, using Tensorflow, and maybe tomographic bins instead?) Adding other outputs (PDF or uncertainty estimates) and training for 2-pt fct: after analysis of needs & decision.

From Malte Tewes

LensMC







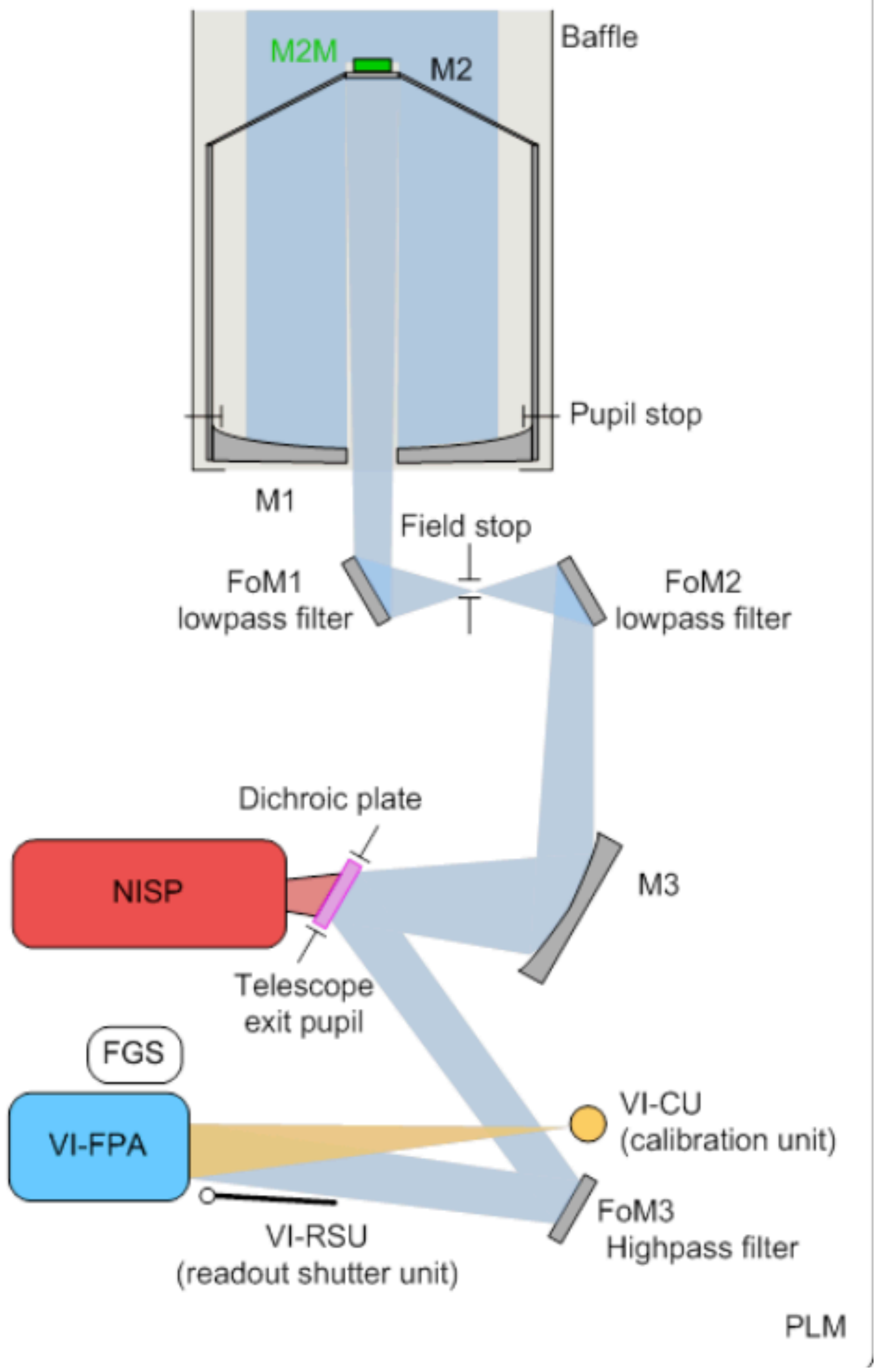
A LensMC custom-made segmentation map of a Euclid CCD image (out of 36 making a single exposure) from SC3

Model-fit to image, marginalised ellipticity samples

PSF modeling I

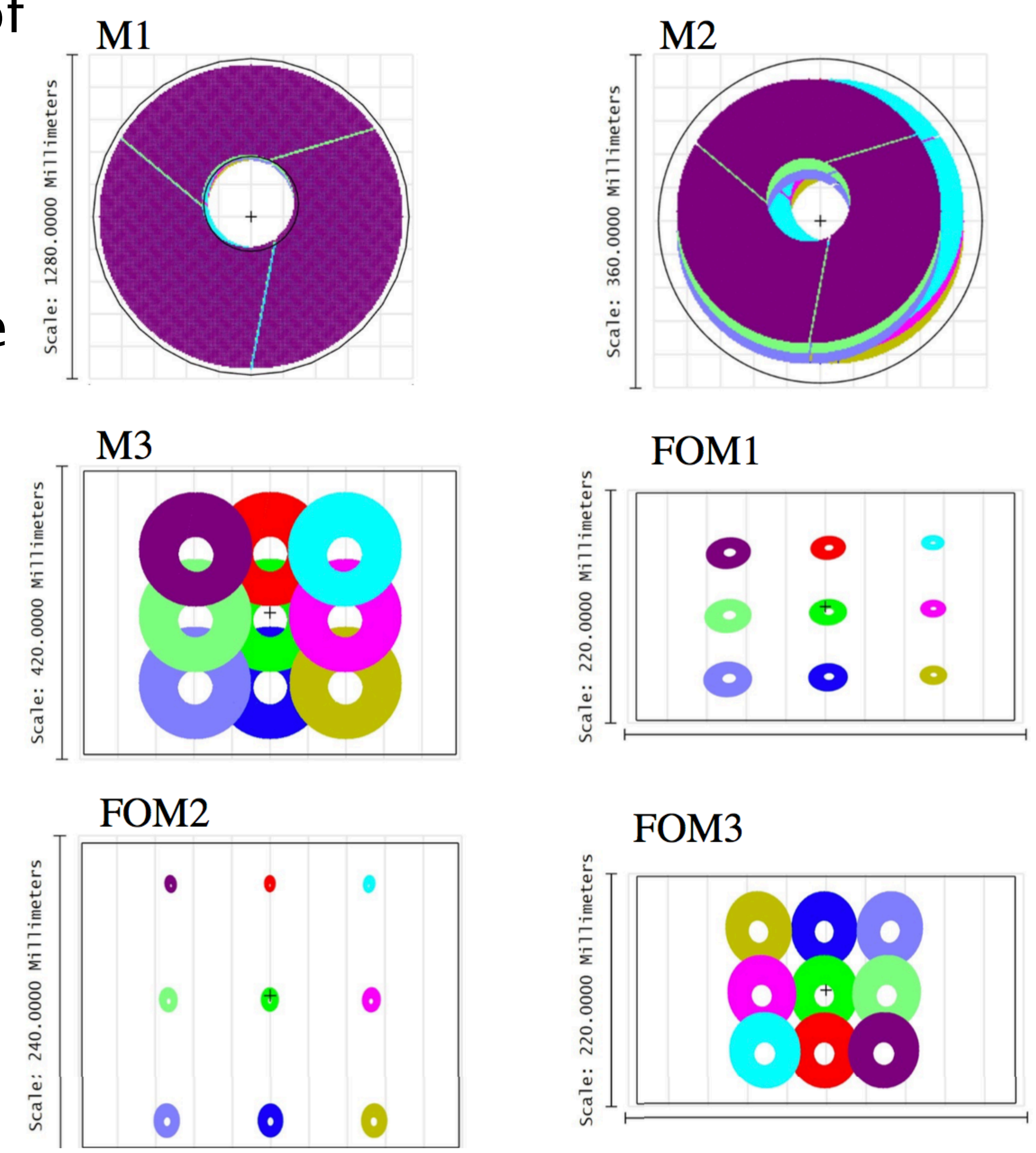
PSF from telescope system physical model.

Lance Miller, Chris Duncan,
Corentin Schreiber



FFT of wave-front at exit pupil.
SPV2 propagation of PSF errors.
Complex model: chromatic response of reflecting elements, fov variation of wavefront errors, CCD under-sampling, AOCS guiding

TBD:
Develop code to propagate surface errors. Shutter opening/closing effects. Zonal phase errors from mirror manufacturing errors, depends on fov, need lab and in-orbit calibration.



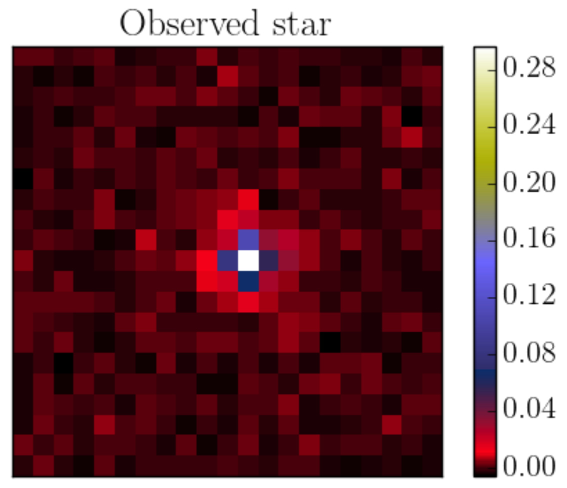
PSF modeling II

Morgan Schmitz, Fred Ngolé, Tobias Liaudat,
Jean-Luc Starck (CEA)

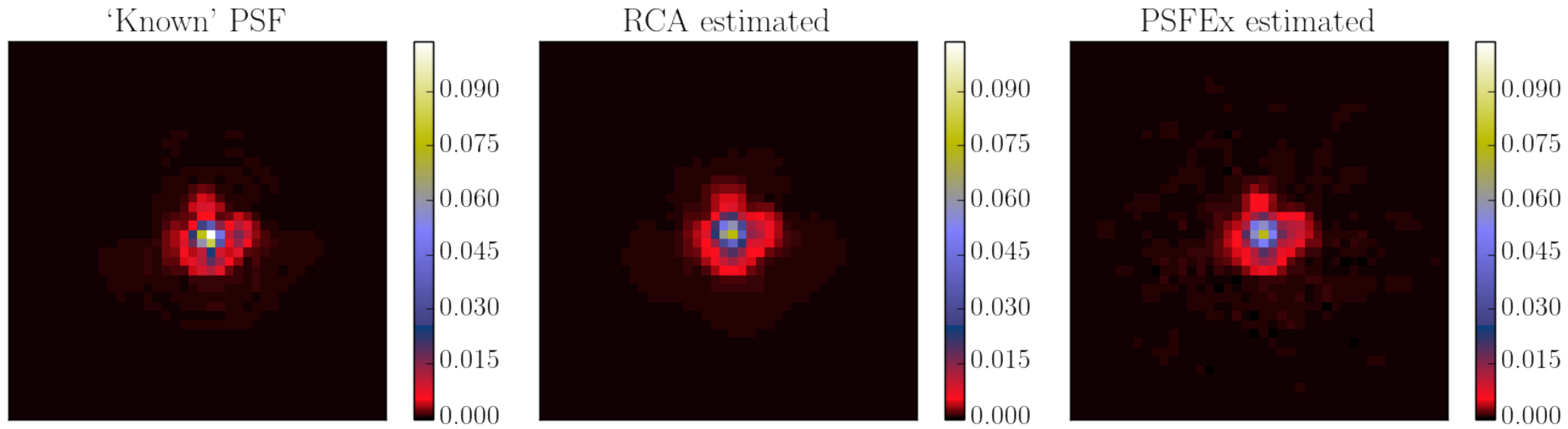
- RCA (Resolved Component Analysis).
  Super-resolution via sparsity constraints.

- Wavelength interpolation using optimal transport

- Spatial interpolation using graph constraints



Ngolé et al. (2016),
Schmitz et al. (2017, 2019)

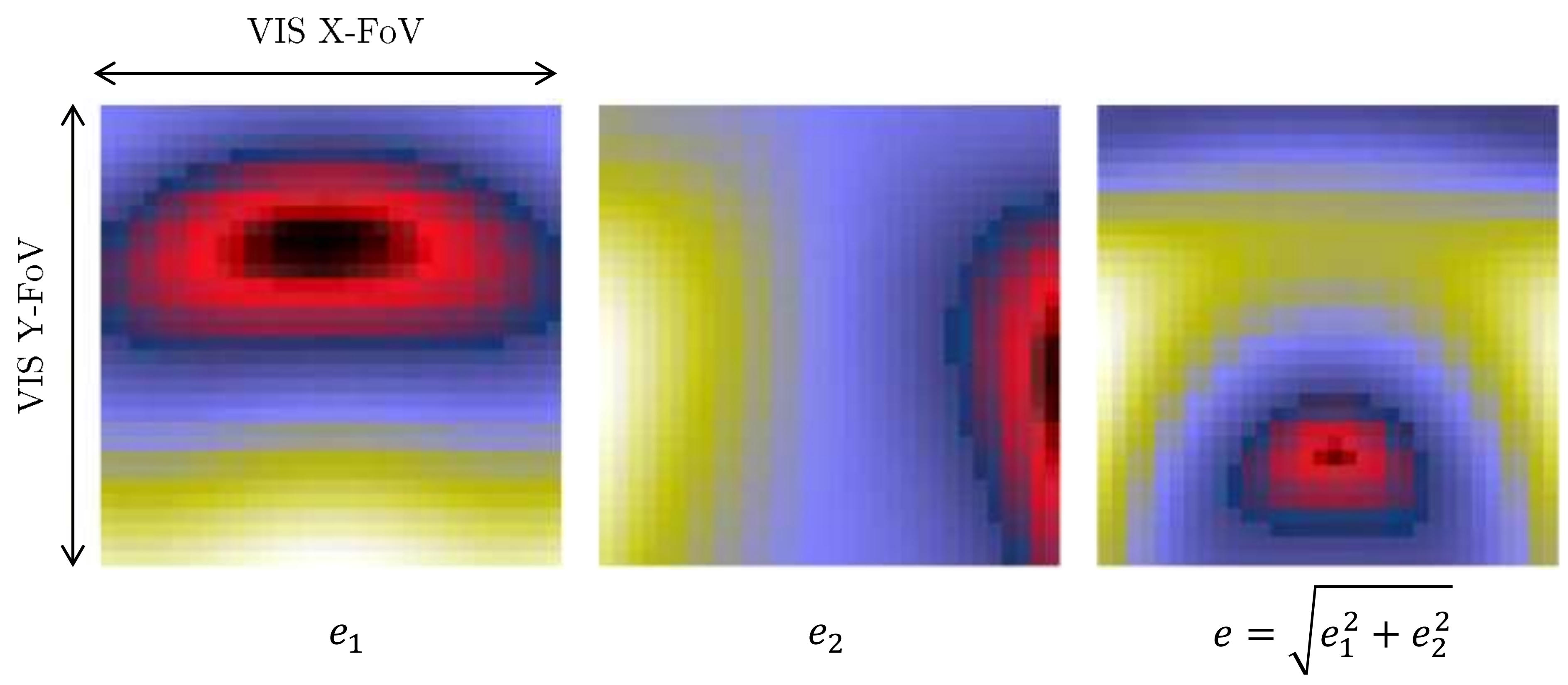


VIS PSF complete simulation

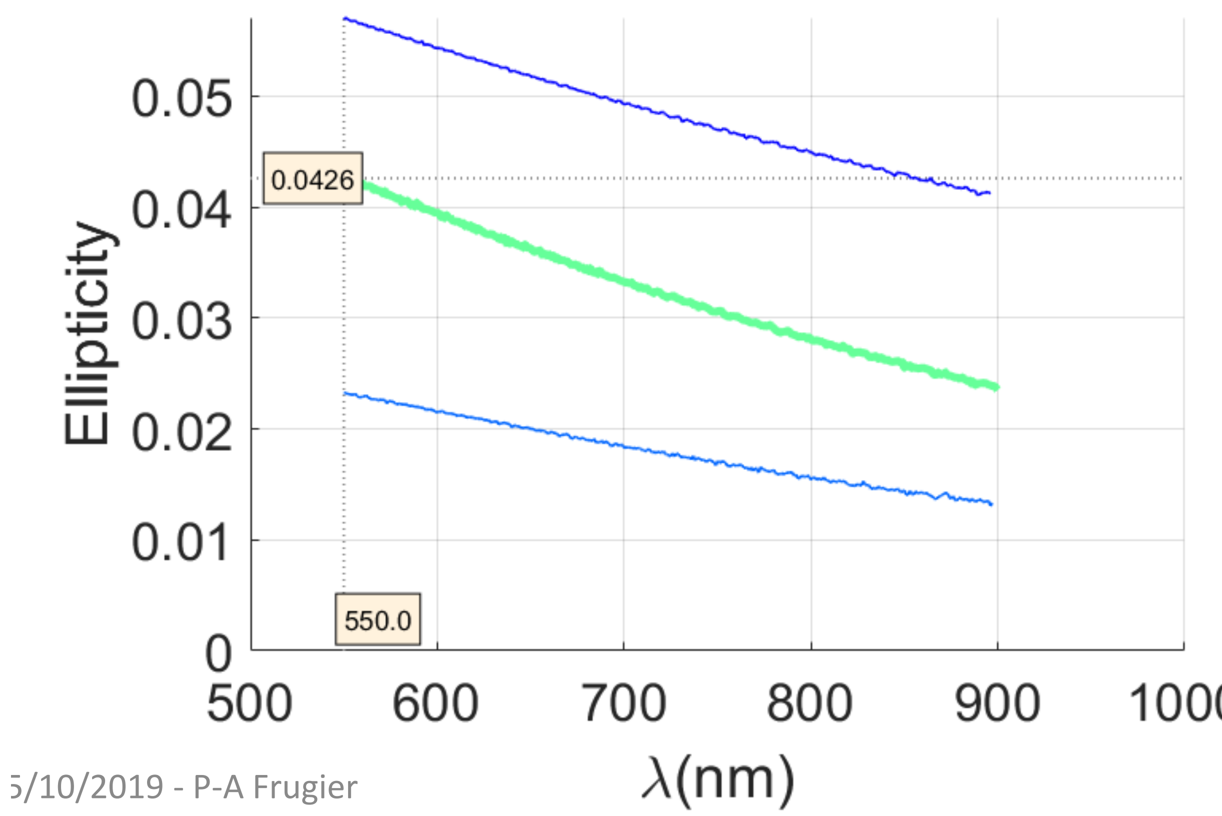
From Pierre-Antoine Frugier (CEA)

Simulating the VIS PSF

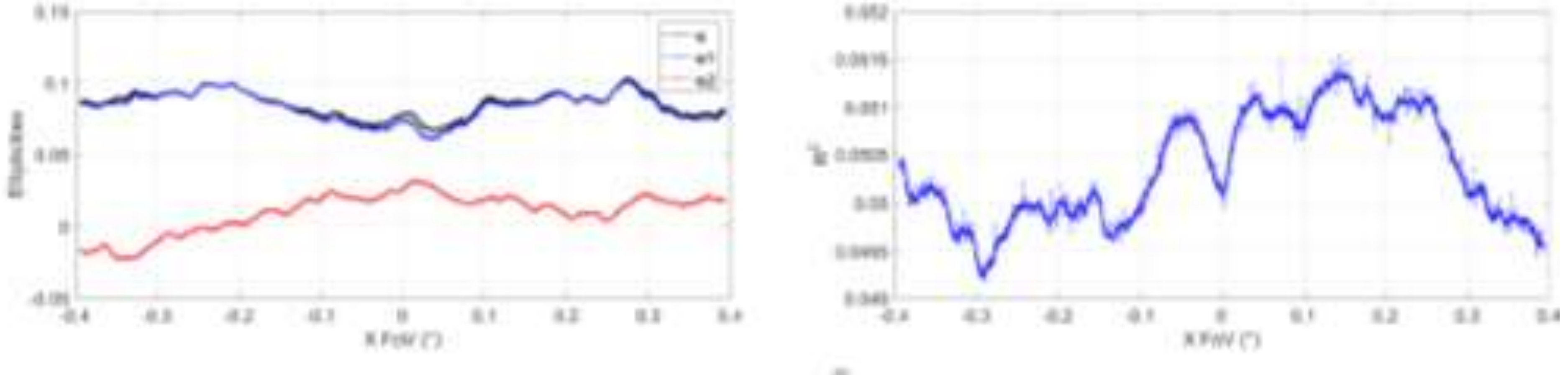
aberrations



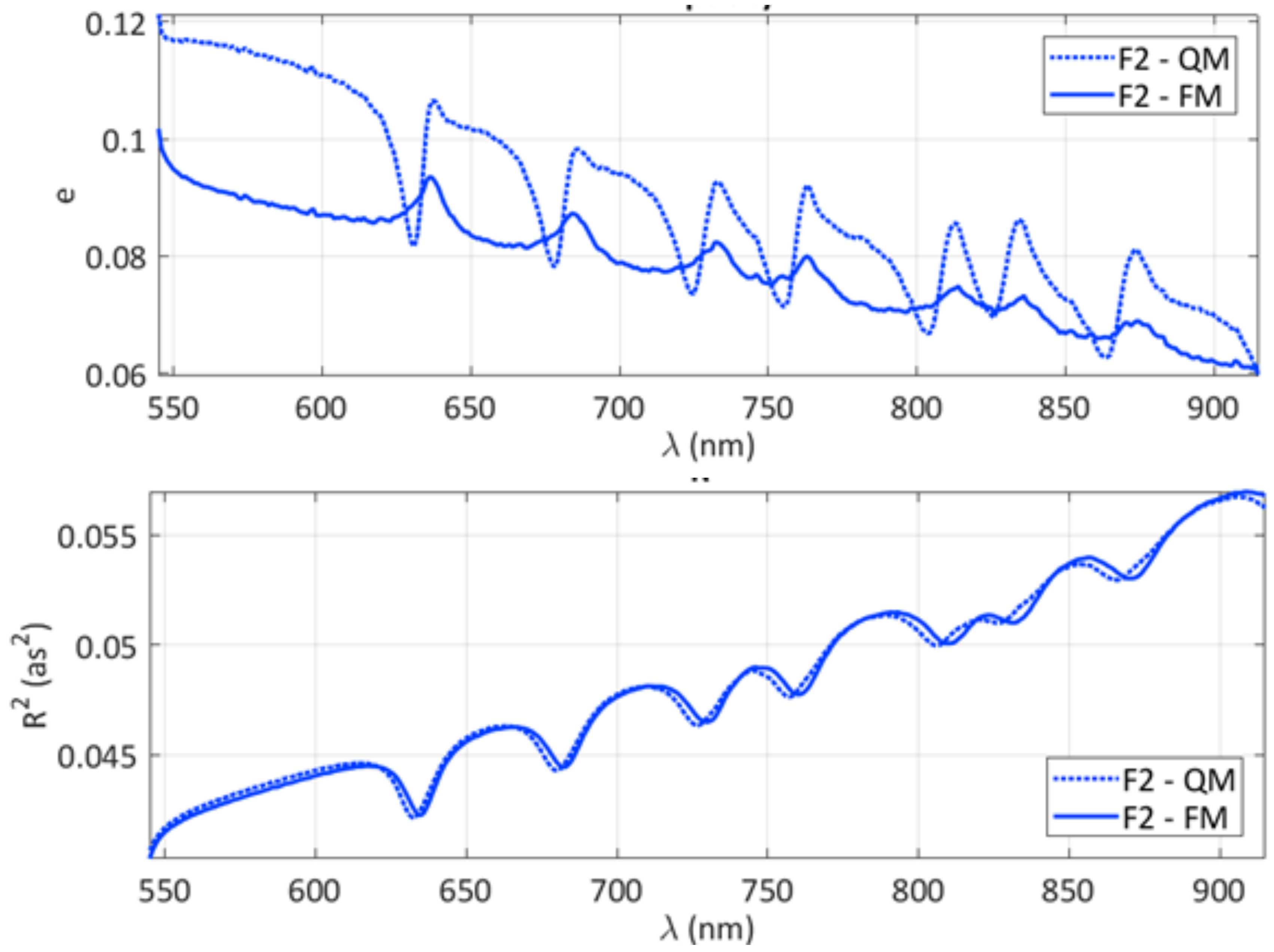
chromatic diffraction



polishing errors



dichroic coating

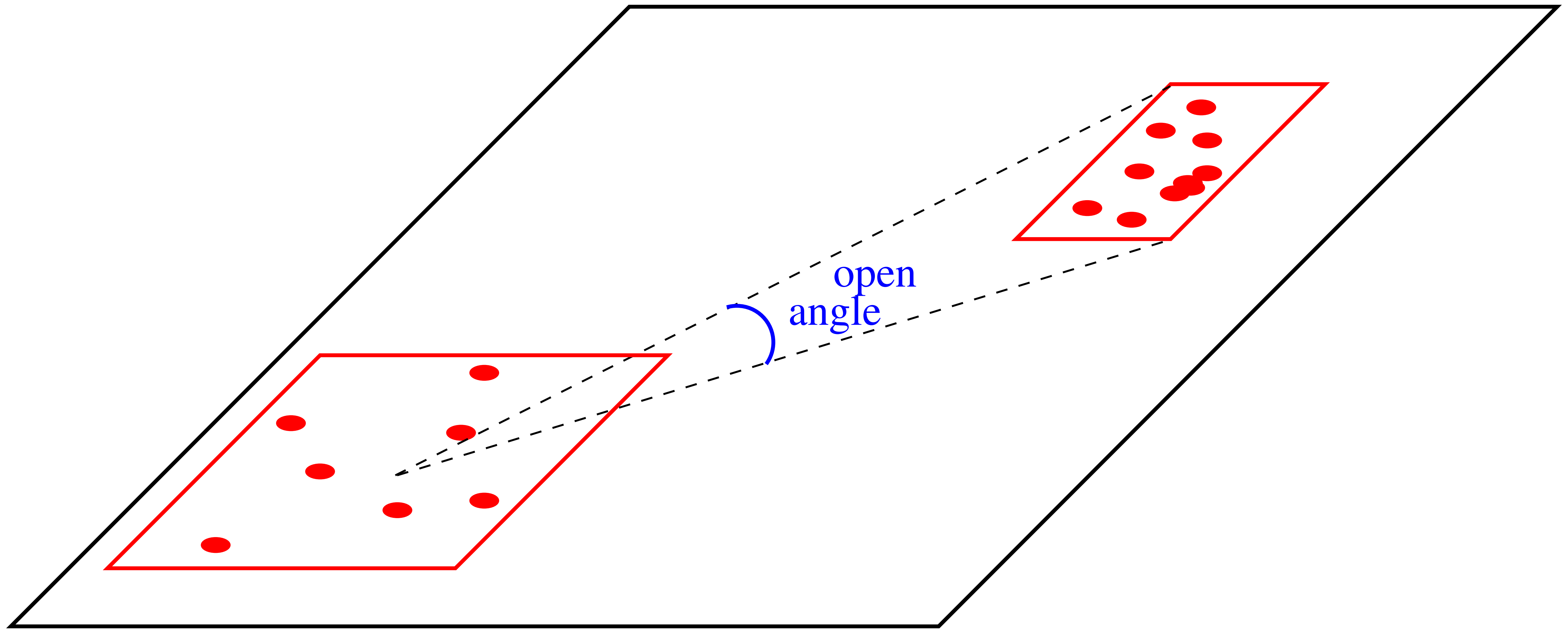


jitter

From Pierre-Antoine Frugier (CEA)

Lensing estimators

Requirements for observables: 2-point correlation function, shear power spectrum, E-/B-mode estimators. Implemented by OU-LE3.



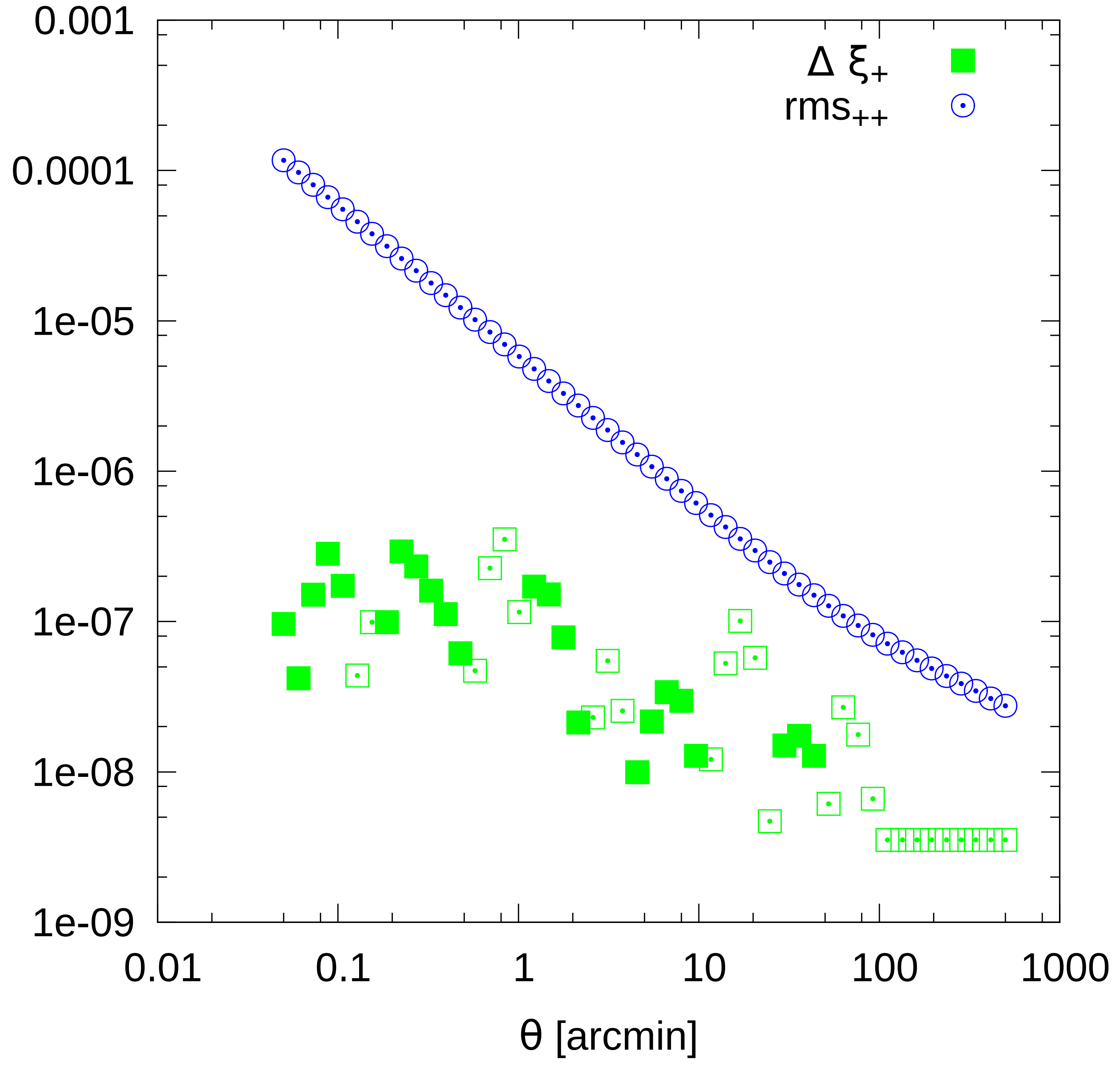
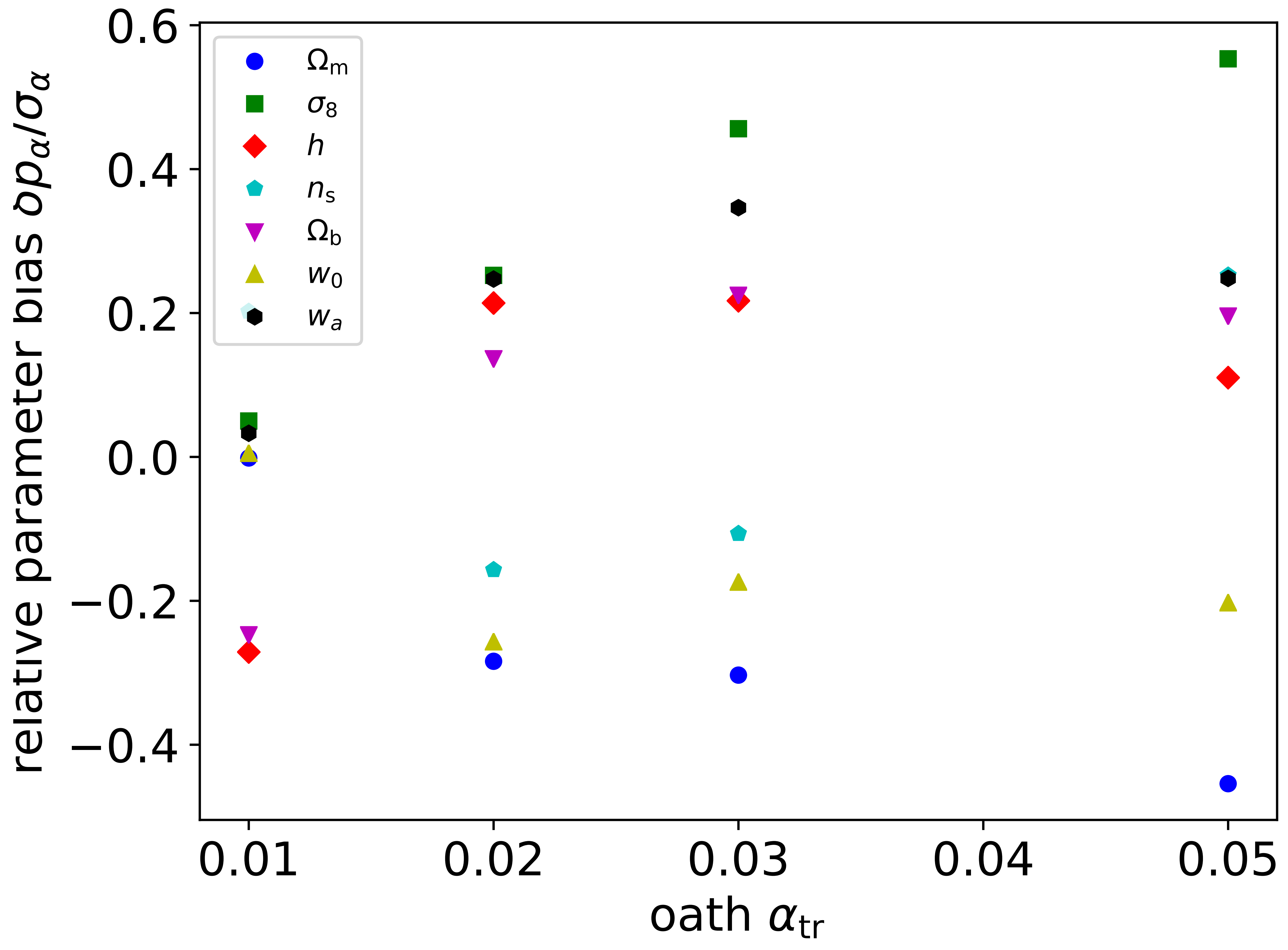


Figure 5. Example of the amplitude of the correlation function bias $\Delta\xi_+$ compared to the rms (square root of the covariance diagonal).

Lensing estimators

Propagation of LE3 algorithmic errors to cosmological parameters

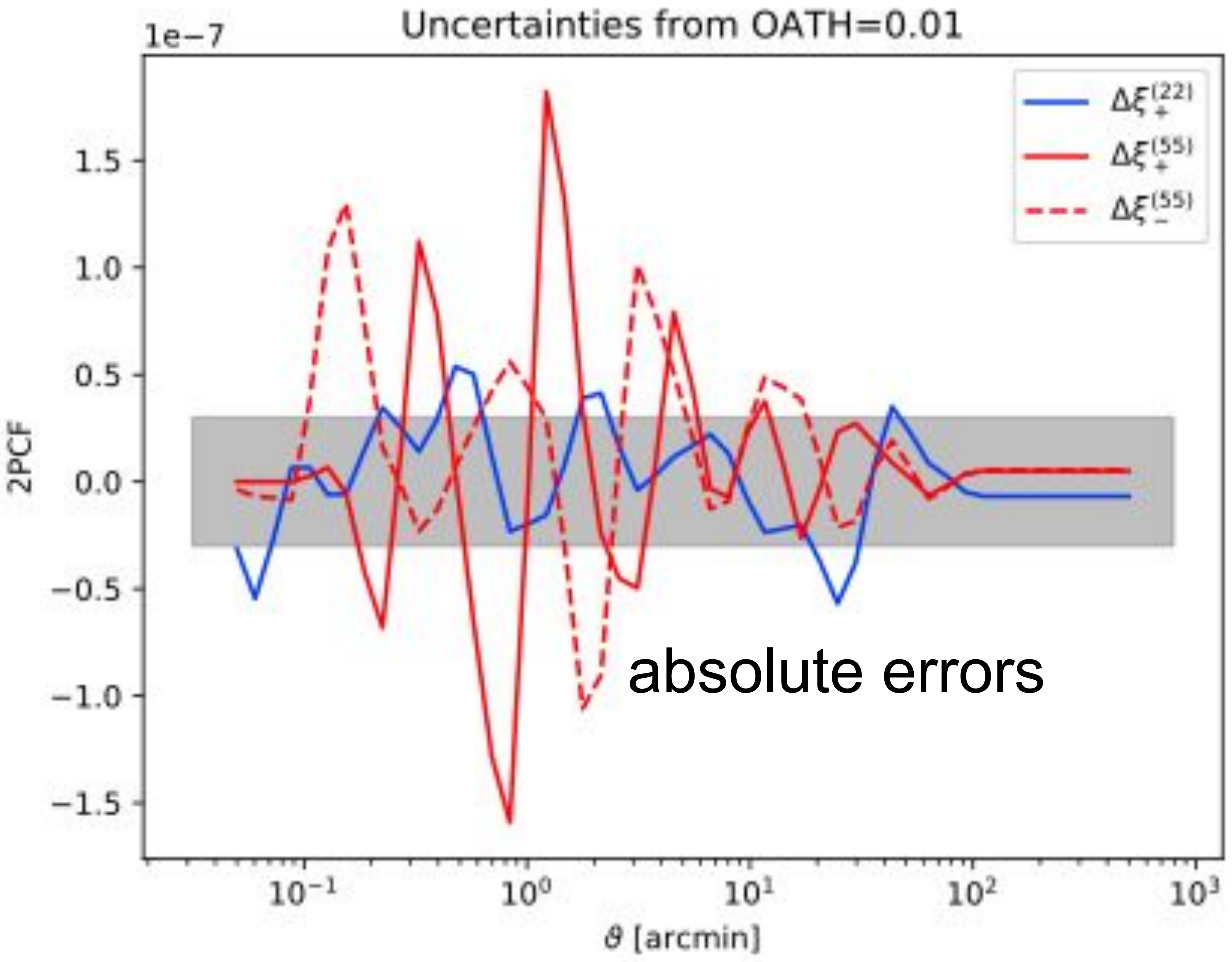


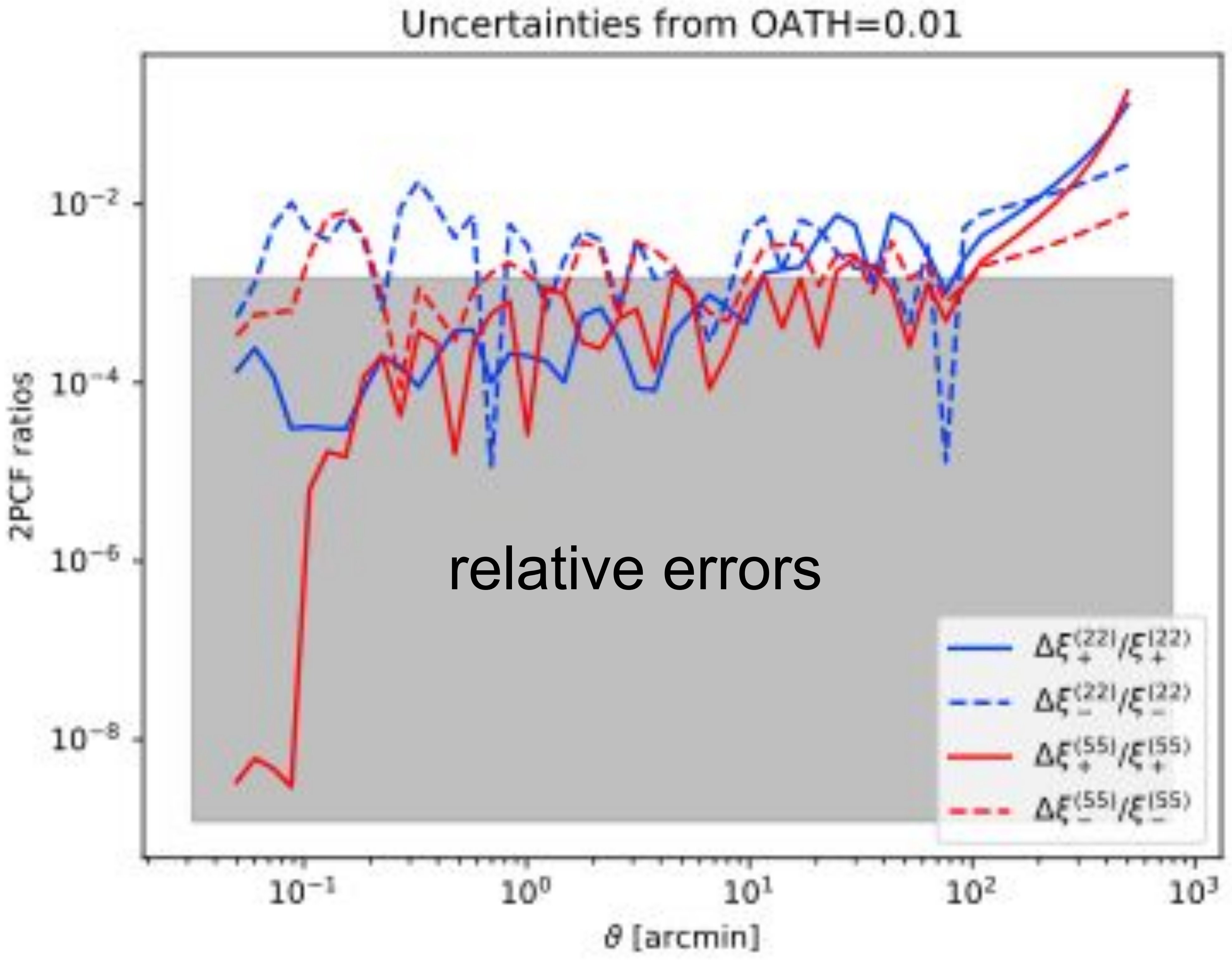
tree-code "smoothing" parameter

Kilbinger, Joachimi et al. in prep.

Lensing estimators

LE3 uncertainties for accuracy requirements





Lensing estimators

Position-position correlation function (2D clustering) as part of WL LE3 output

Estimator WP

$$w^{\mathrm{LS}}_{ij}(\theta) = A_{ij}\frac{\langle D_i D_j\rangle_\theta}{\langle RR\rangle_\theta} - \frac{B_i\langle D_i R\rangle_\theta + B_j\langle D_j R\rangle_\theta}{\langle RR\rangle_\theta} + 1$$

Number of random objects for position-position correlations, with Landay-Szalay estimator:

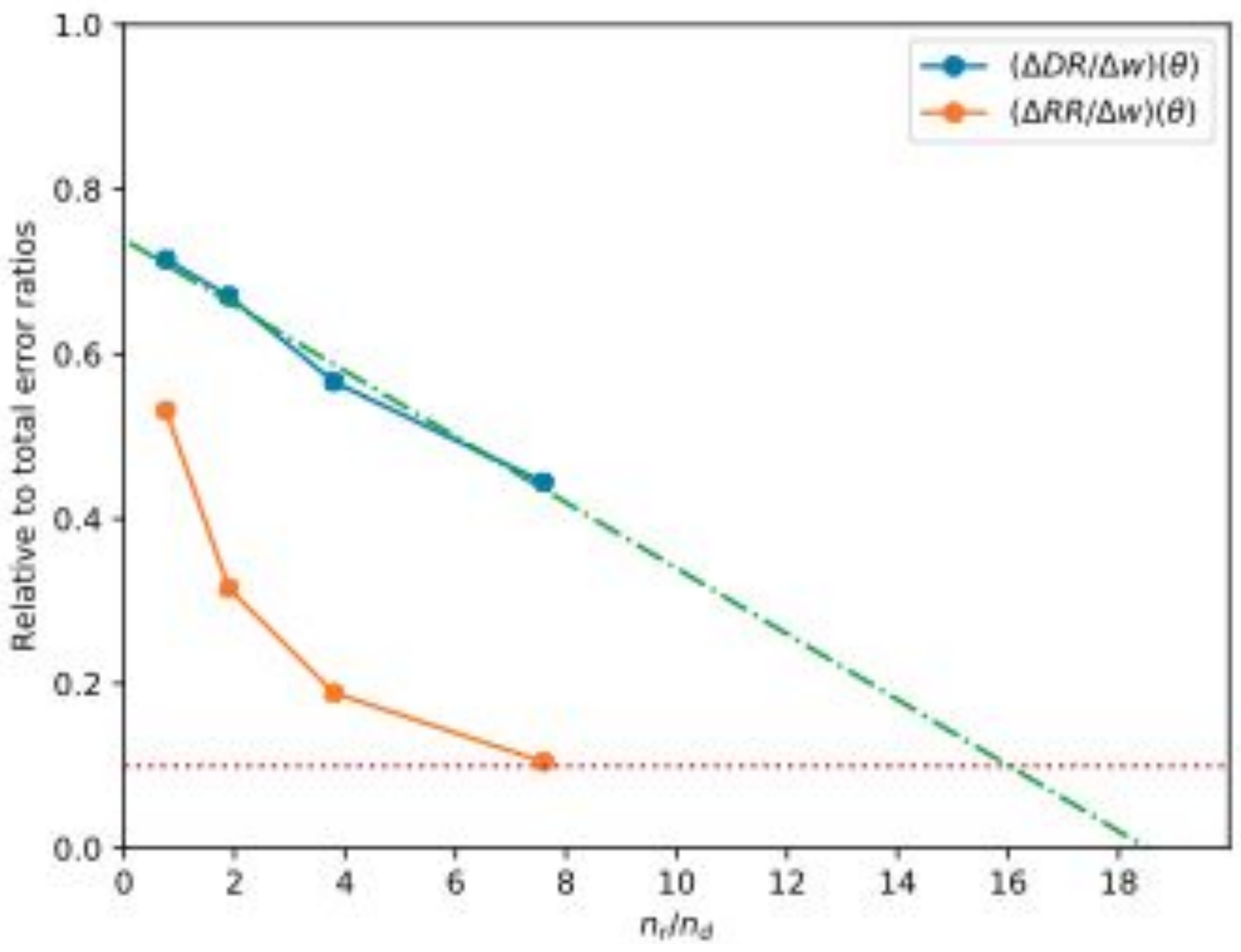
$$A_{ij} = \begin{cases} \frac{N_R(N_R-1)}{2N_i N_j} & \text{for} \quad i \neq j \\ \frac{N_R(N_R-1)}{N_i(N_i-1)} & \text{for} \quad i = j \end{cases}$$

$$B_i = \frac{N_R(N_R-1)}{2N_R N_i} = \frac{N_R-1}{2N_i}.$$

Poisson noise from <DD>, <DR>, <RR>. Random cat noise dominated by <DR>
[<RR> noise can be reduced by splitting into sub-cats, Keihänen et al. (2019)].

For <DR> contribution <= 10%:
N_R / N_D >= 16.

[cf. 3D clustering N_R / N_D = 50]



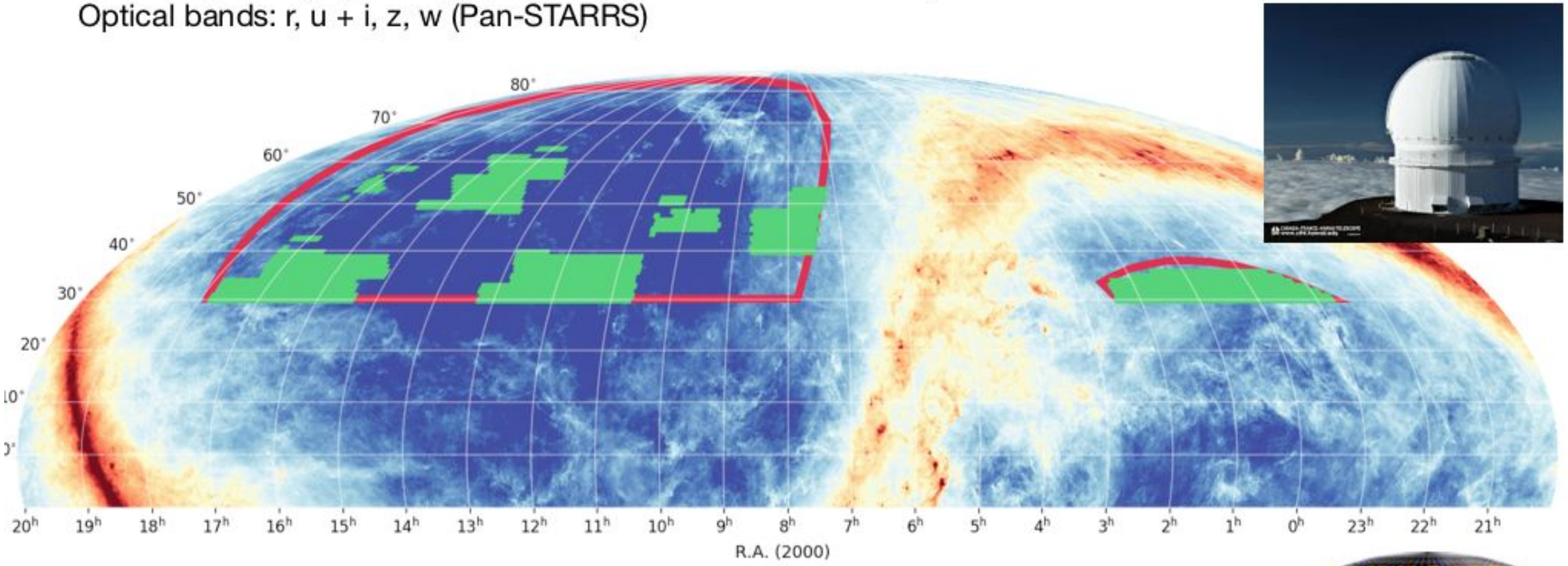
UNIONS/CFIS

Ultraviolet
Near-
Infrared
Optical
Northern
Survey

Canada-
France
Imaging
Survey

PIs Jean-Charles Cuillandre (DAp/FR), Alain McConnachie (Victoria/CA)

CFIS: Large imaging survey (5,000 deg^2) in the Northern hemisphere with the CFHT.
Optical bands: r, u + i, z, w (Pan-STARRS)



CFIS-r survey area and realized coverage as of May 2018

- Total survey area: 4.800 deg.^{2}
- Covered area: 1337 deg.^{2} (27%), left to cover: 3463 deg.^{2} (73%)

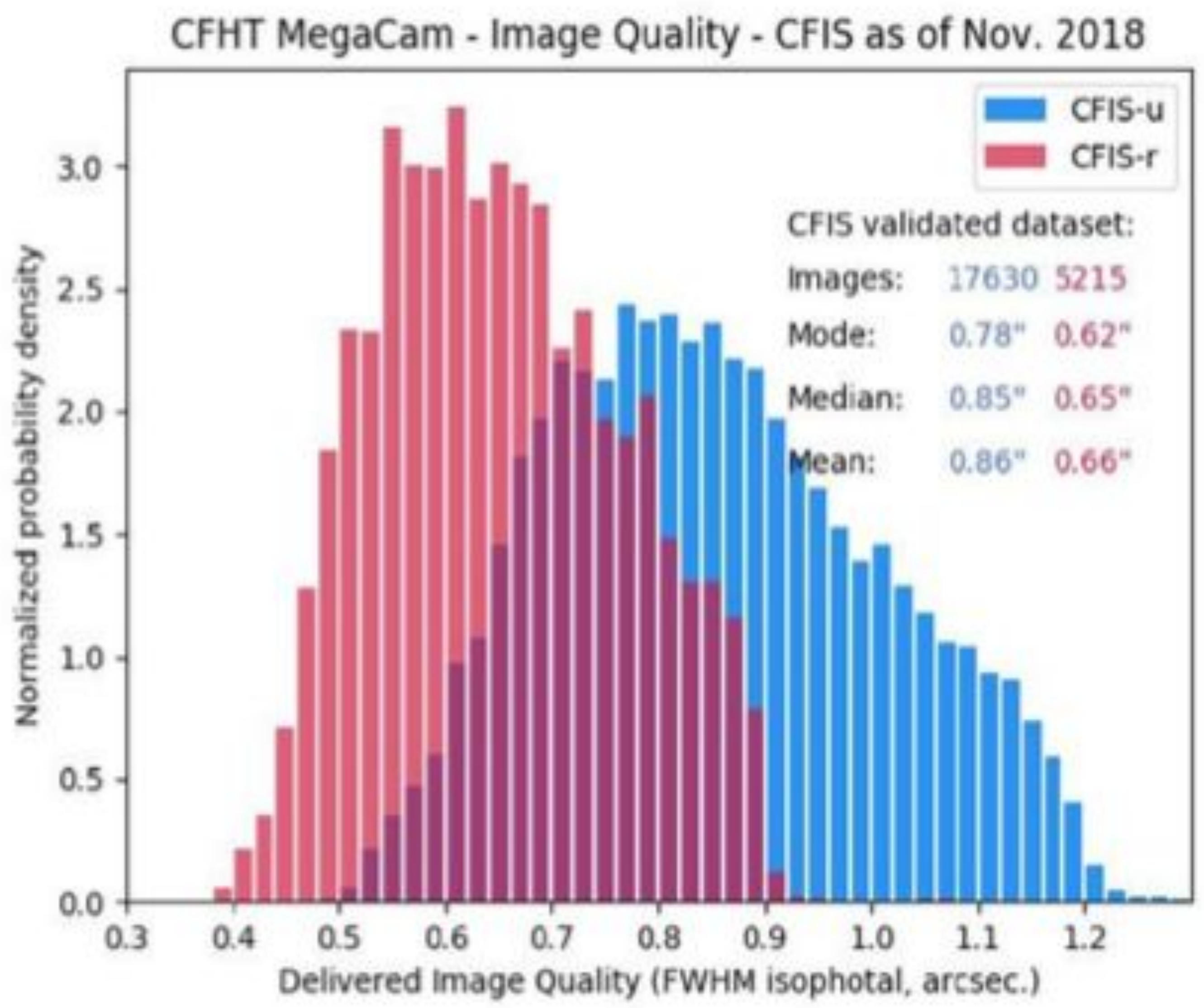
Goals:

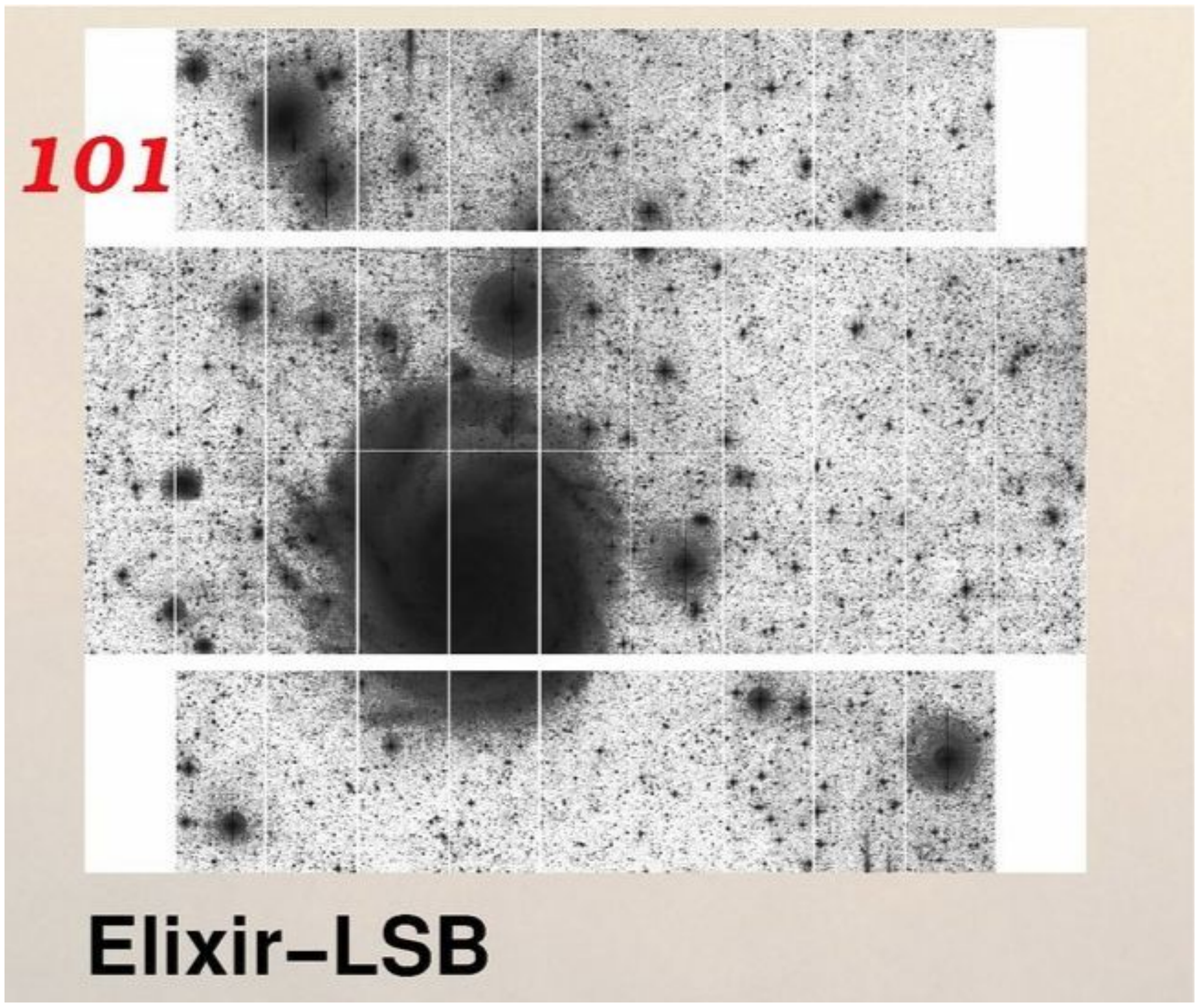
- Additional optical bands to complement infra-red bands of Euclid (for photometric redshifts for faint galaxies).
- **Weak lensing**
- Other stuff (Milky Way dynamics, large-scale structure, galaxy properties, …)

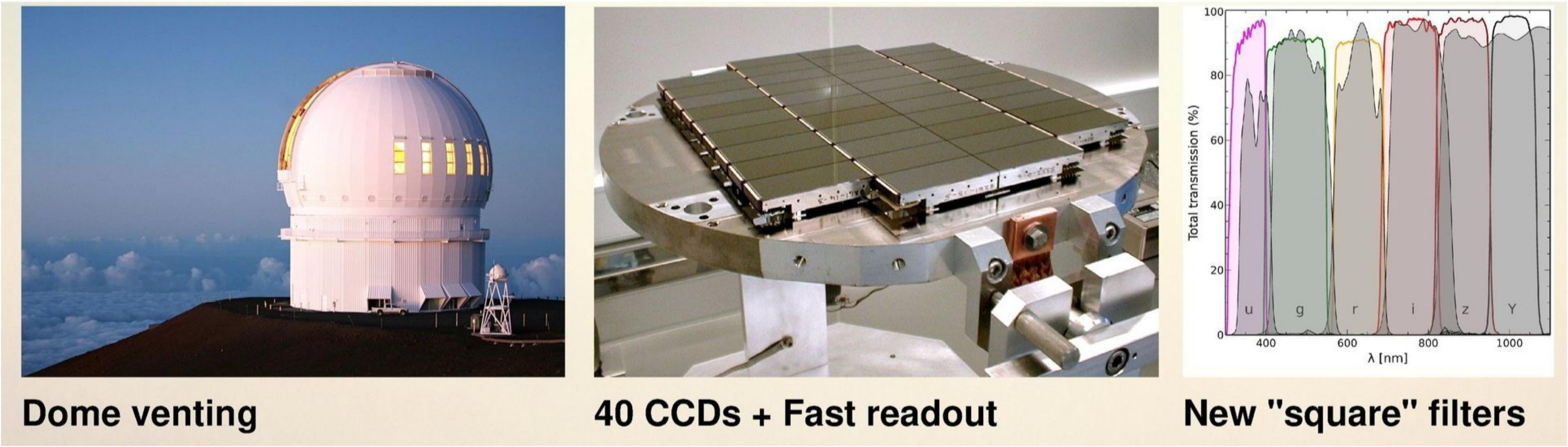
UNIONS/CFIS

Best wide-field imager on CFHT ever.

Improvements (2011 - 2014)



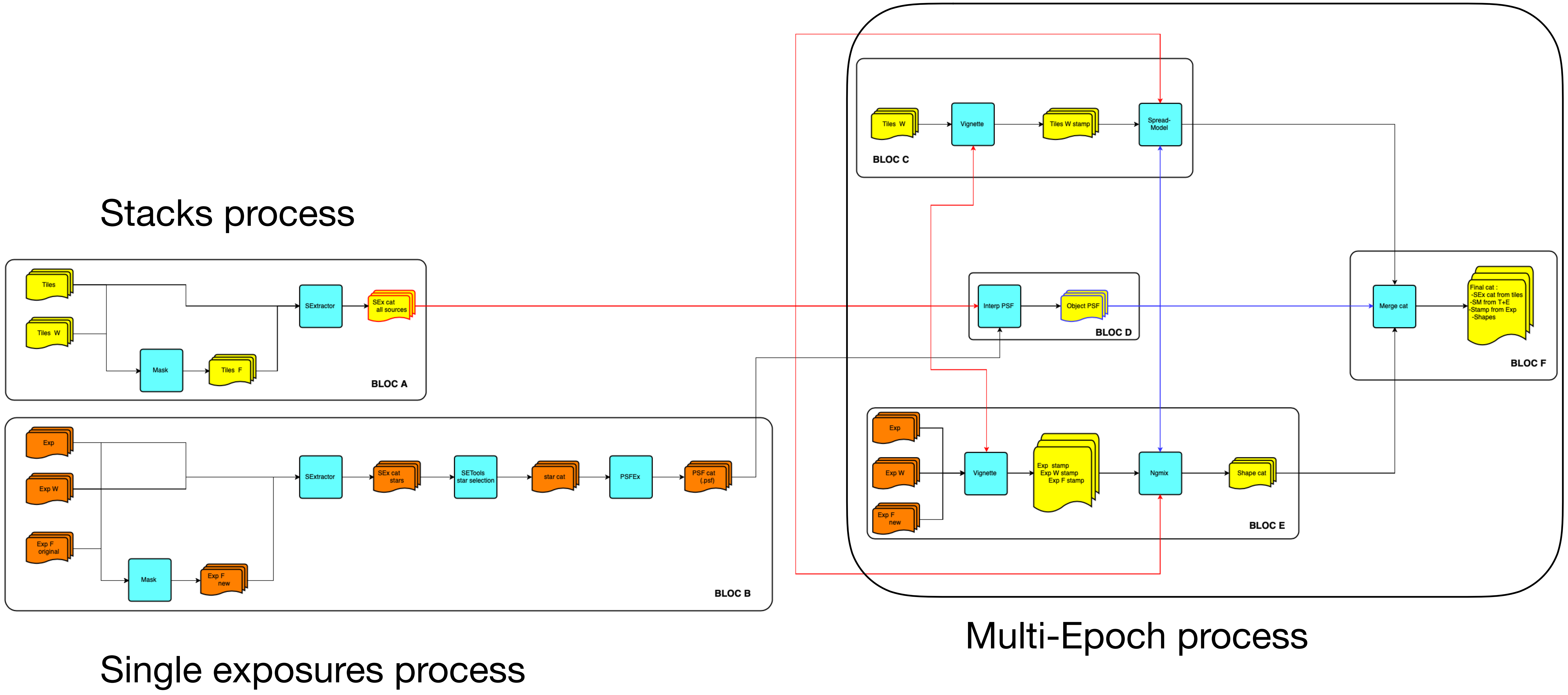




UNIONS is basically a static LSST in the North, not likely to be outdone any time soon.

CFIS weak-lensing results

ShapePipe architecture



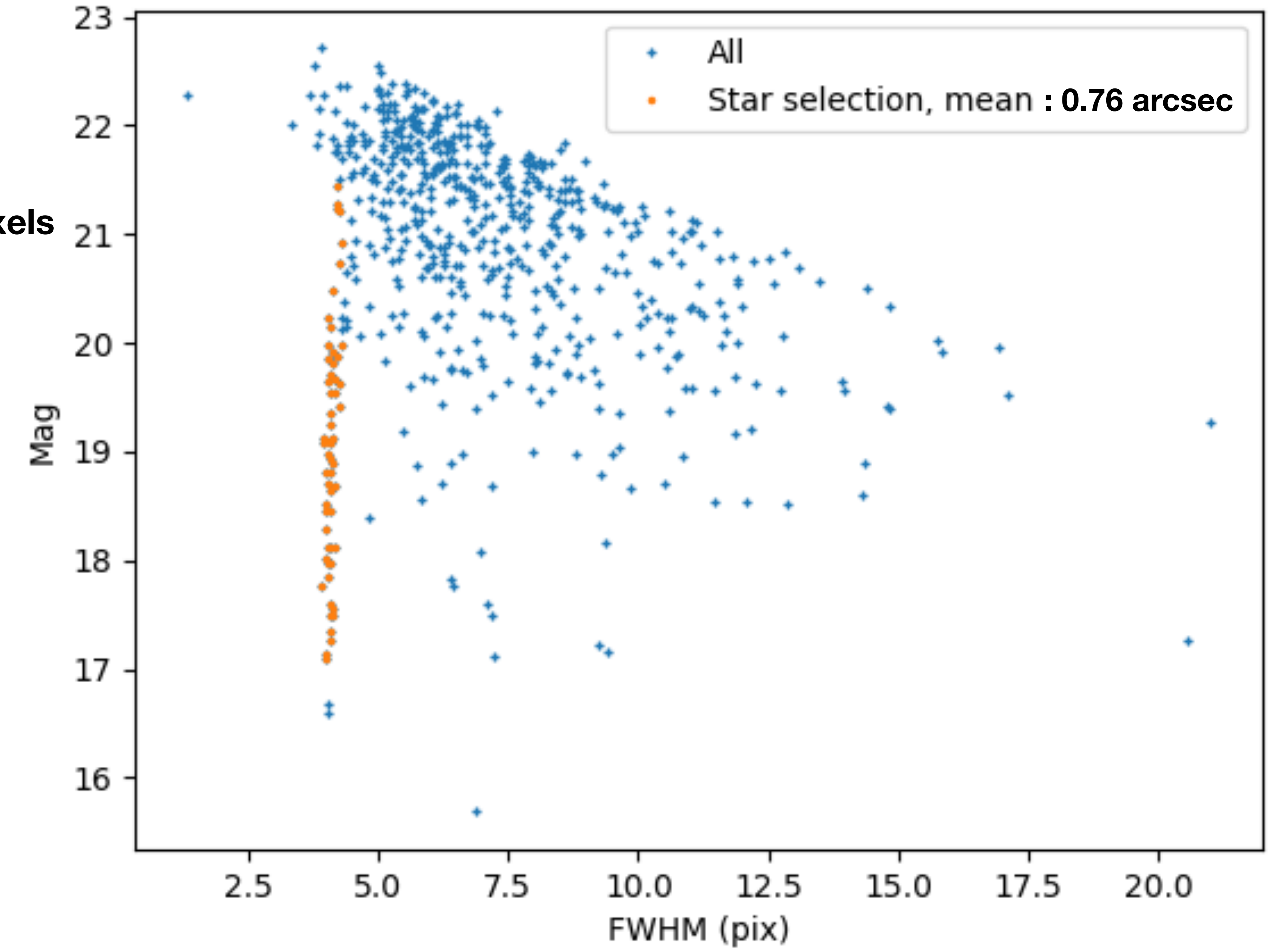
Guinot et al. in prep.

CFIS weak-lensing results

Star selection

17 < MAG < 21.5

mode(FWHM) ± 0.2 pixels

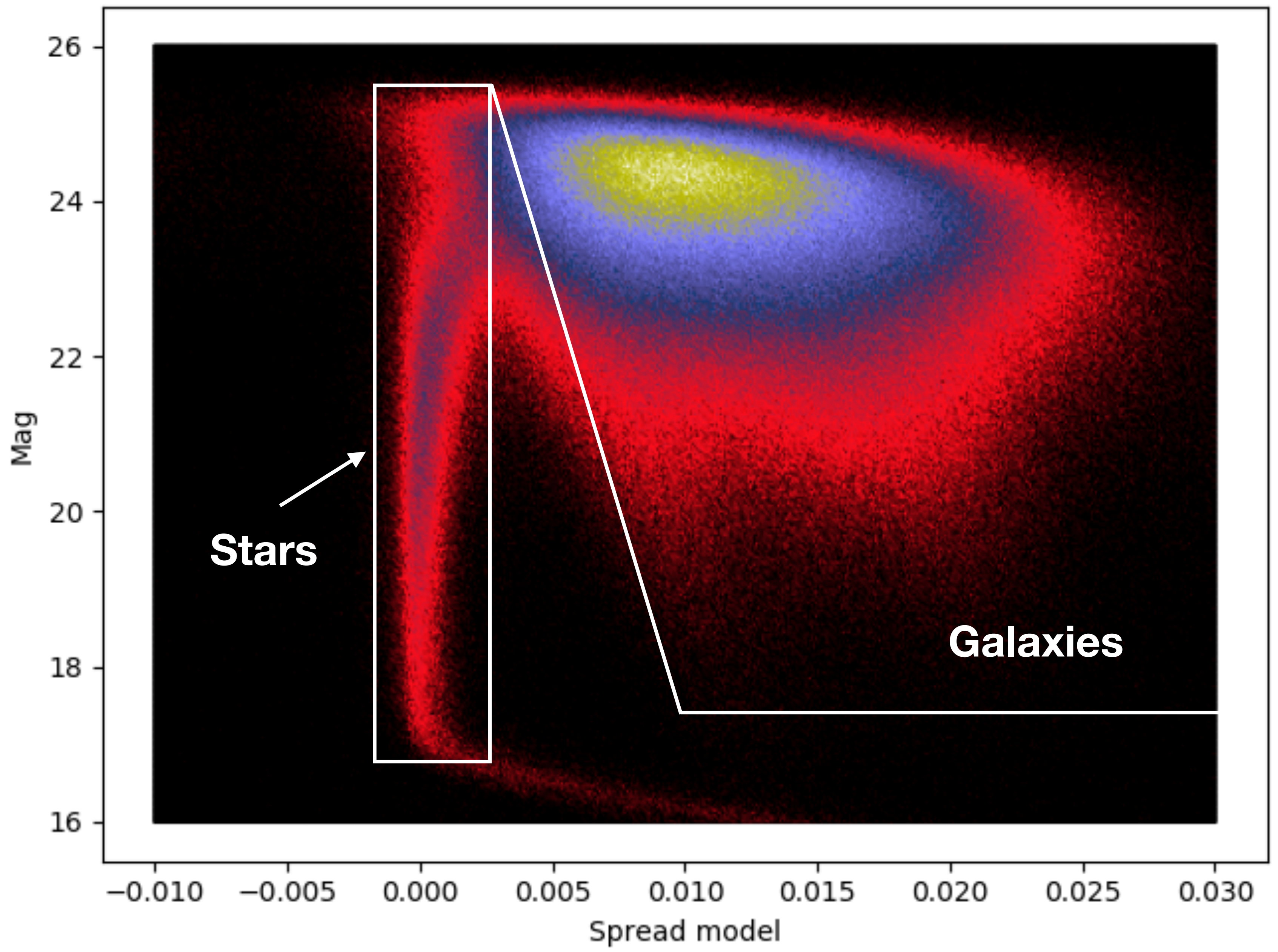


$$\mathrm{SPREAD\_MODEL} = \frac{\tilde{G}^T W p}{\tilde{\phi}^T W p} - \frac{\tilde{G}^T W \tilde{\phi}}{\tilde{\phi}^T W \tilde{\phi}},$$

G **:** galaxy model
p **:** object
Φ **:** PSF model

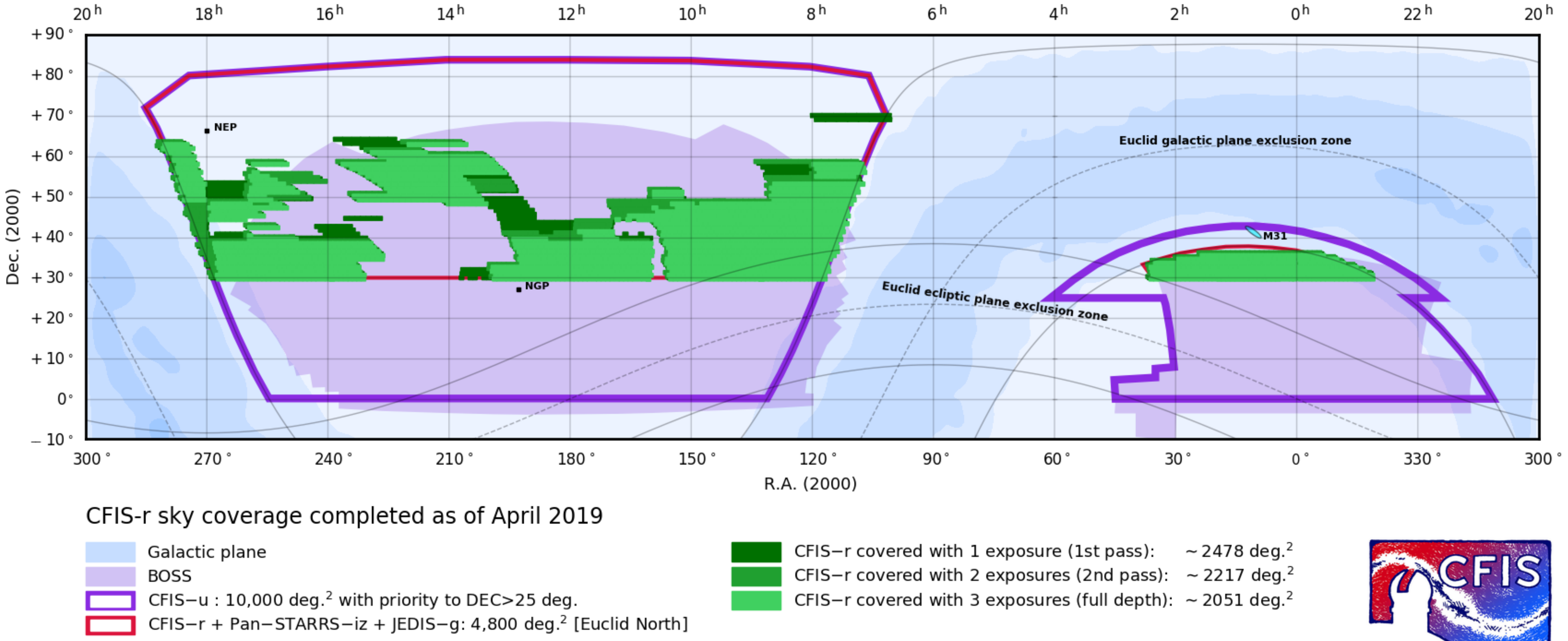
(Ref : SExtractor, E. Bertin)

Galaxy selection



Guinot et al. in prep.

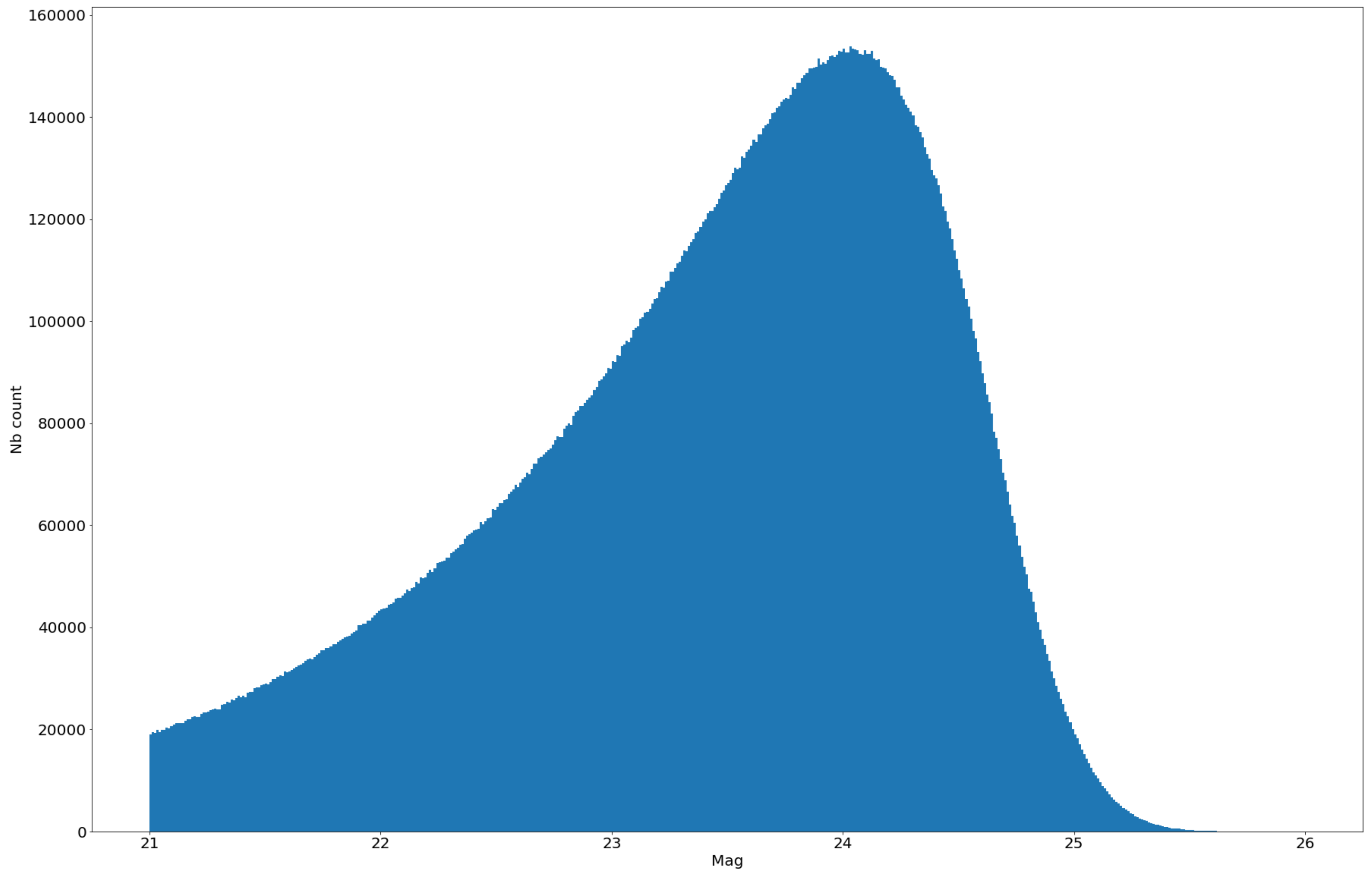
CFIS weak-lensing results



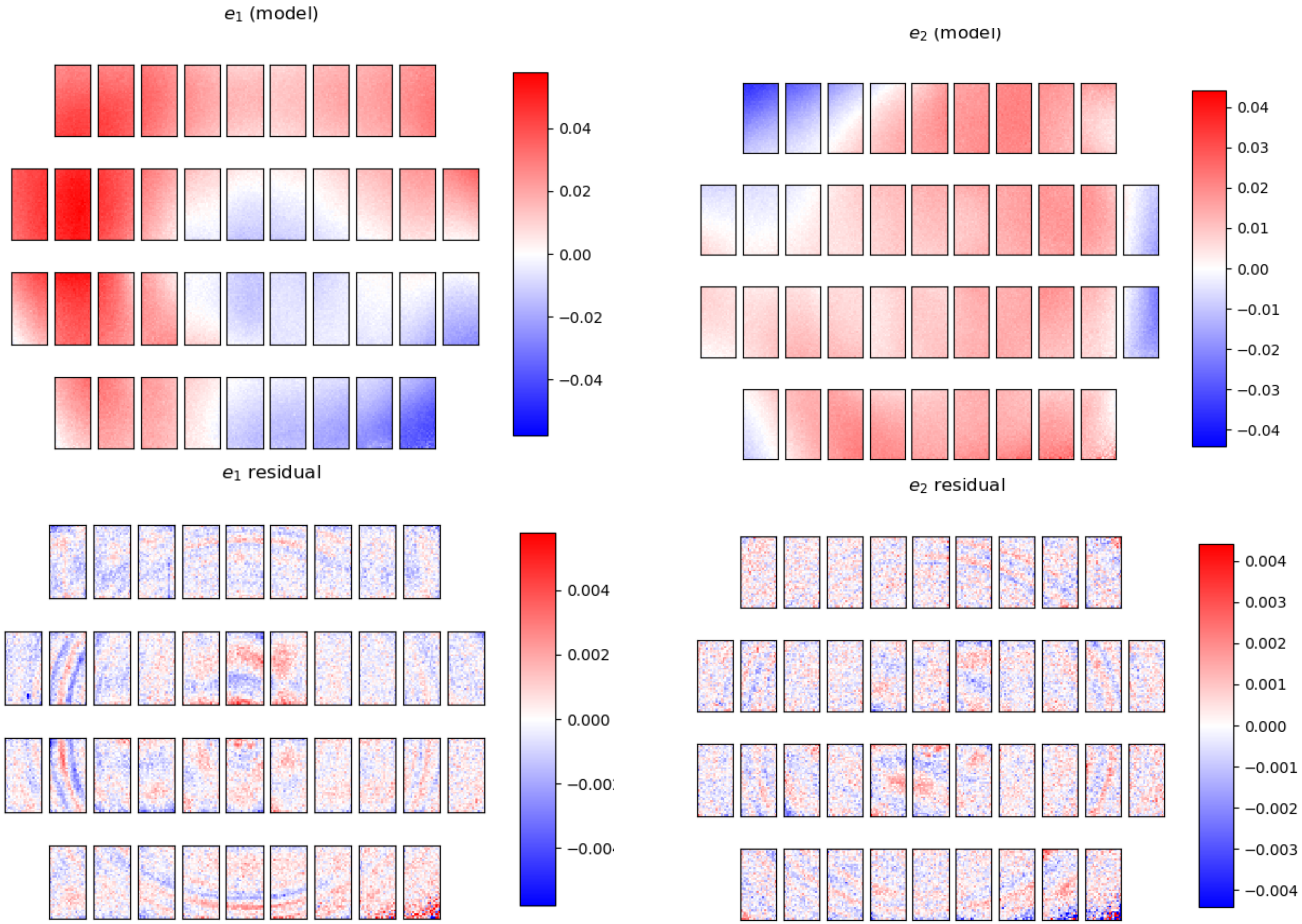
Some numbers :

- Current process ~1000 deg^2
- ~8000 single exposures and ~6000 tiles

- 50 stars on average per CCD. (2 500 stars/deg^2)
- Around 32M galaxies. (8 galaxies/arcmin^2)



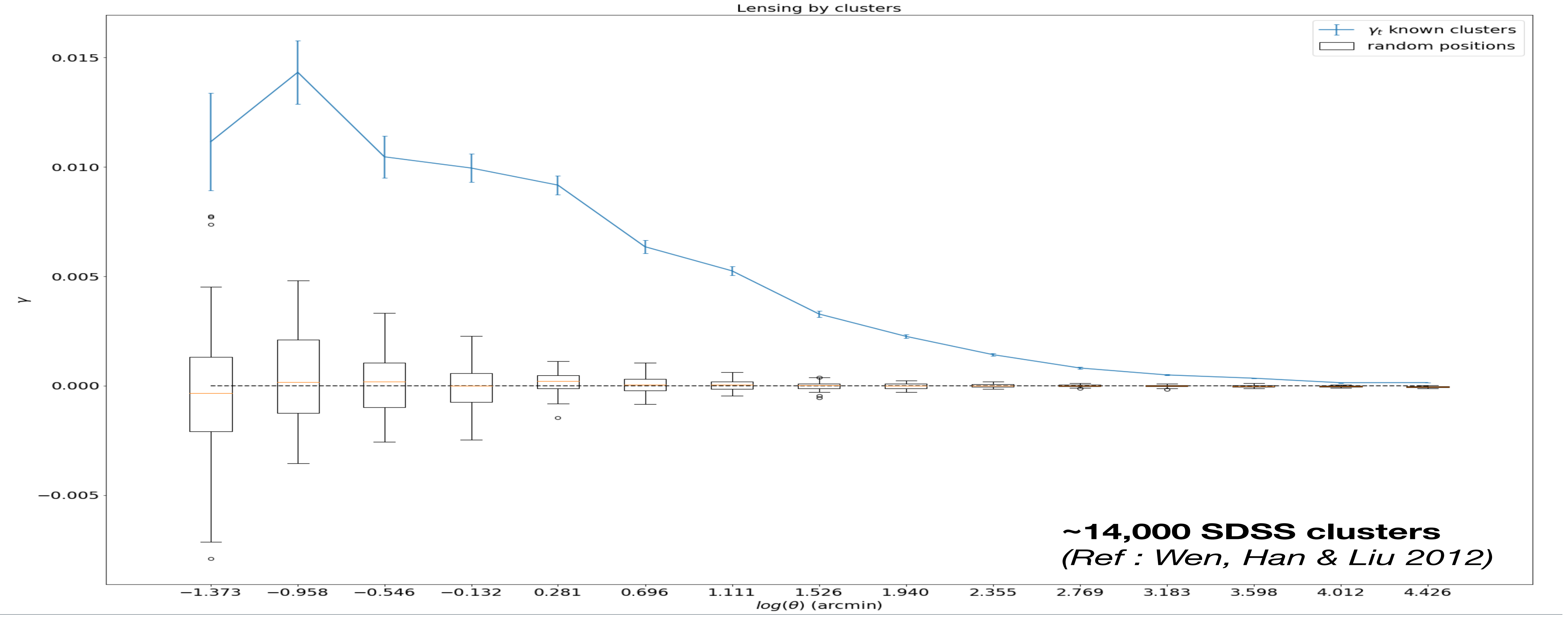
CFIS weak-lensing results

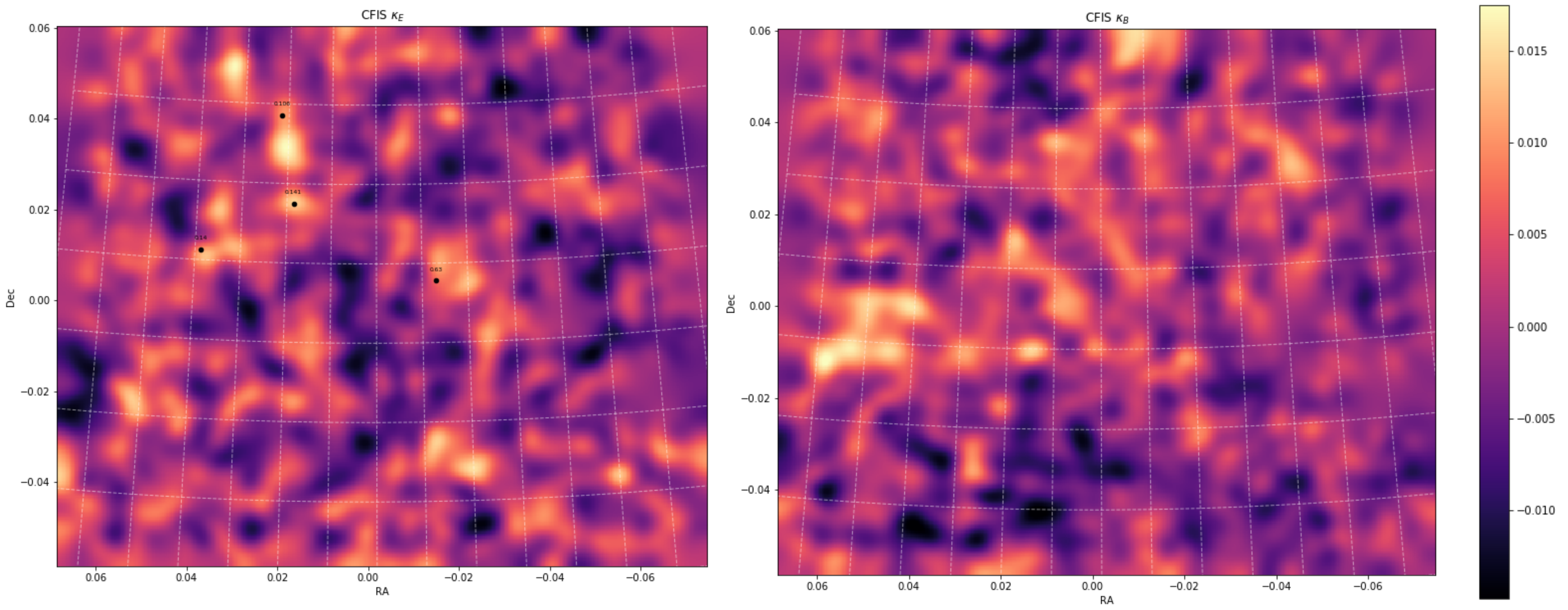


Guinot et al. in prep.

CFIS weak-lensing results

Cluster profile

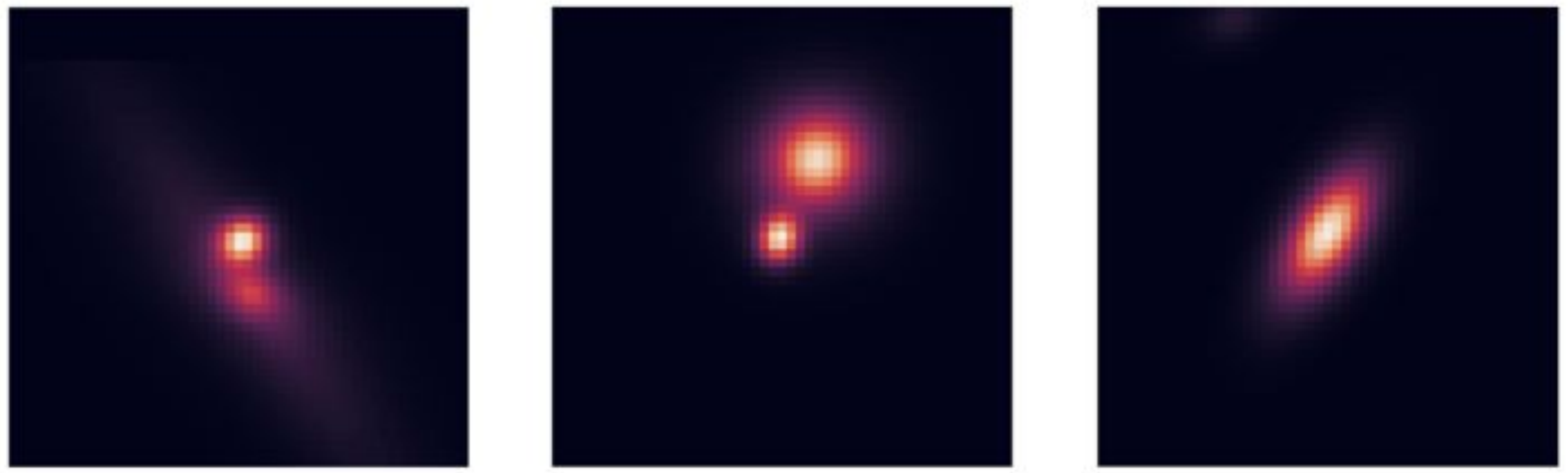




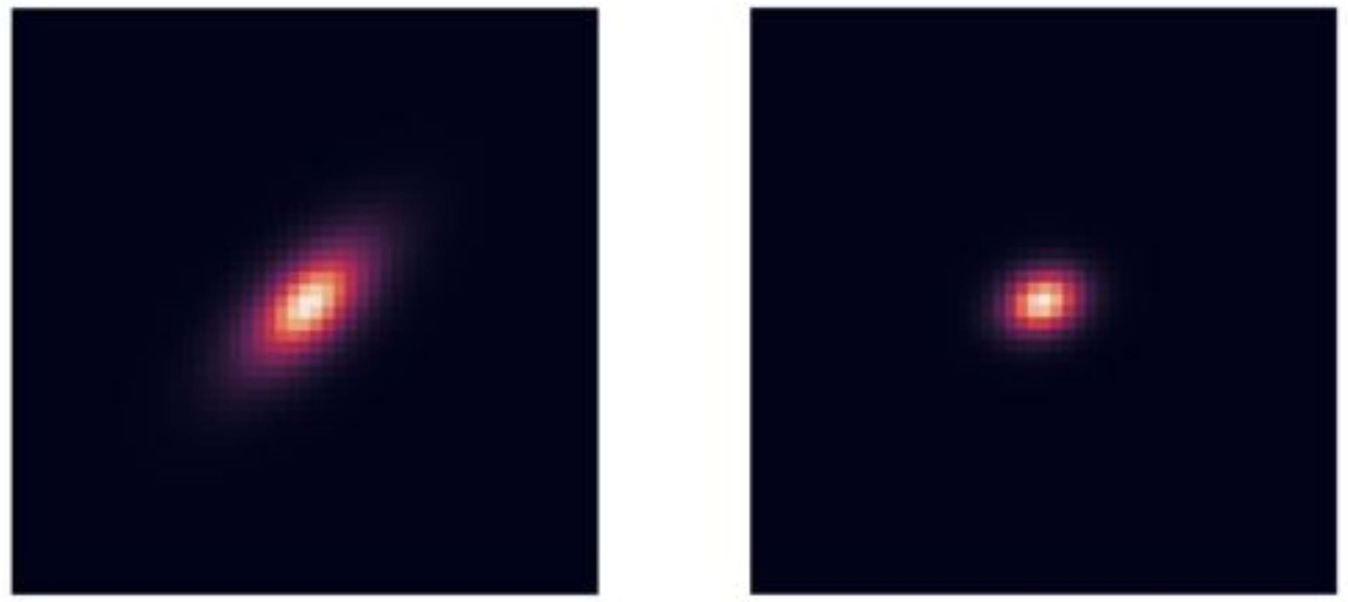
Guinot et al. in prep.

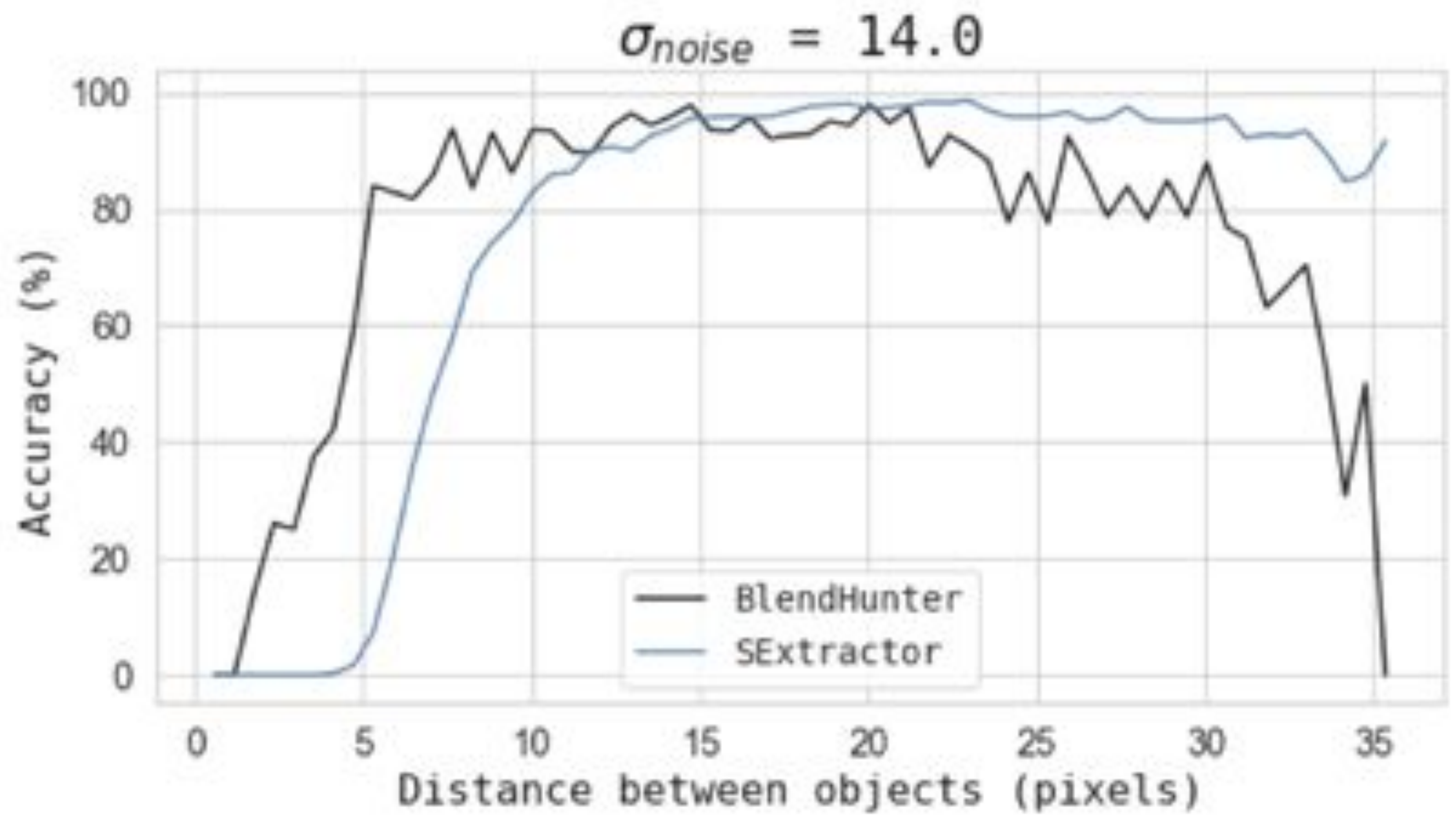
Blended galaxies detection with deep learning

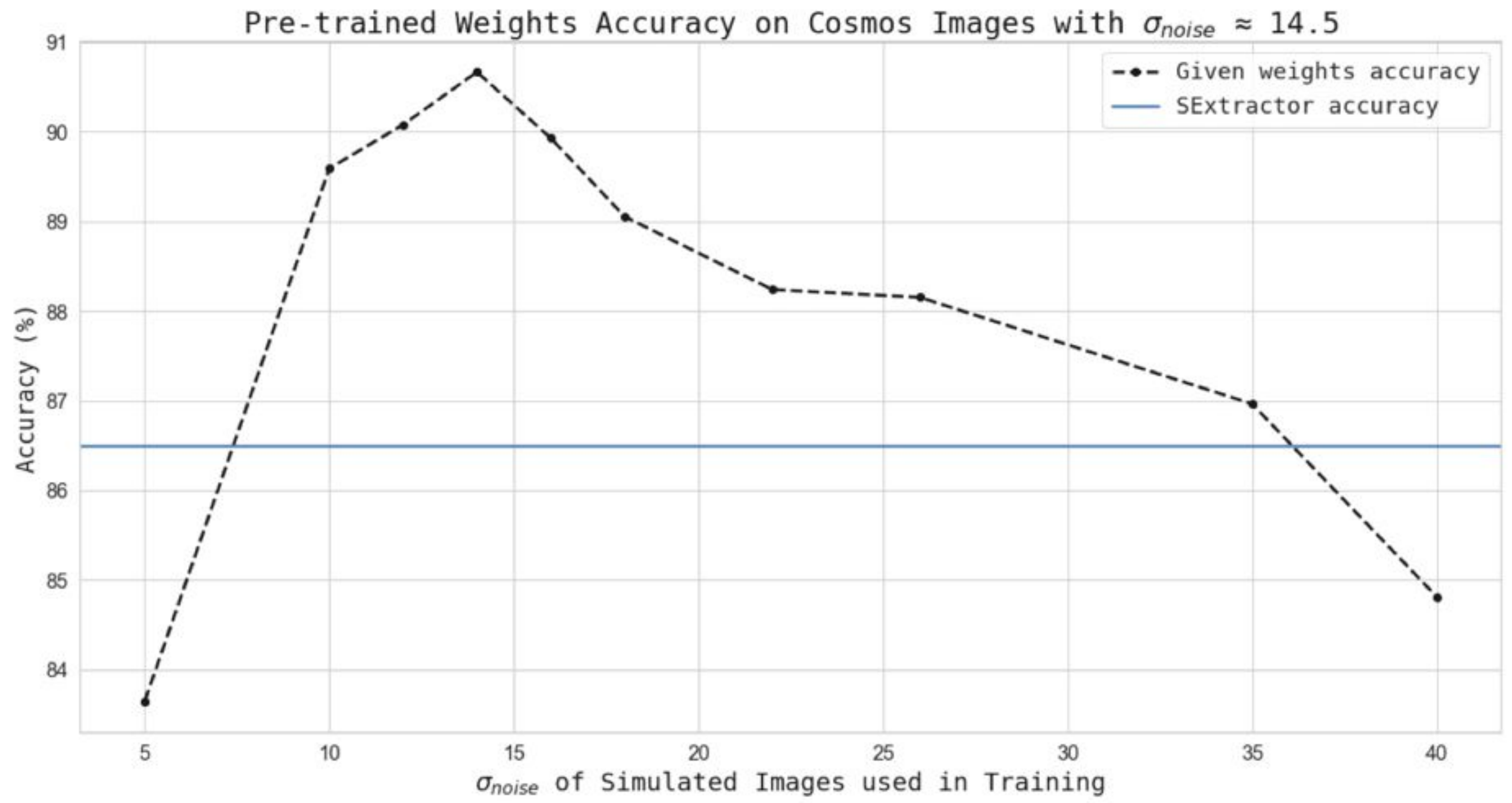
Example of blended images



Example of not blended images







From Sam Farrens

Open positions @ CEA CosmoStat

www.cosmostat.org/jobs

- PostDoc, 2 years, Deep learning and weak lensing
  with MK, Samuel Farrens, part of ANR AstroDeep (PI Eric Aubourg),
  develop methods for Euclid and LSST

- PhD positions

  - Euclid + CSST (+ UNIONS/CFIS), GW targets, weak gravitational lensing,
    funding from Chinese Science Council?
    [GW as standard sirens with host redshift → H_0]
    MK, Samuel Farrens

  - Euclid + DESI + eBOSS, cross-correlation cosmology, modified gravity
    Valeria Pettorino, MK

  - Open postdoc in China? Let me know.
    My (very good) student Axel Guinot is entering the job market…