“Following the Photons: Astronomical Simulations for Instruments & Telescopes”
Royal Observatory, Edinburgh, October 2011

Preparing for Some Extreme Weather

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Synoptic imaging surveys *take data all the time* - even in poor conditions

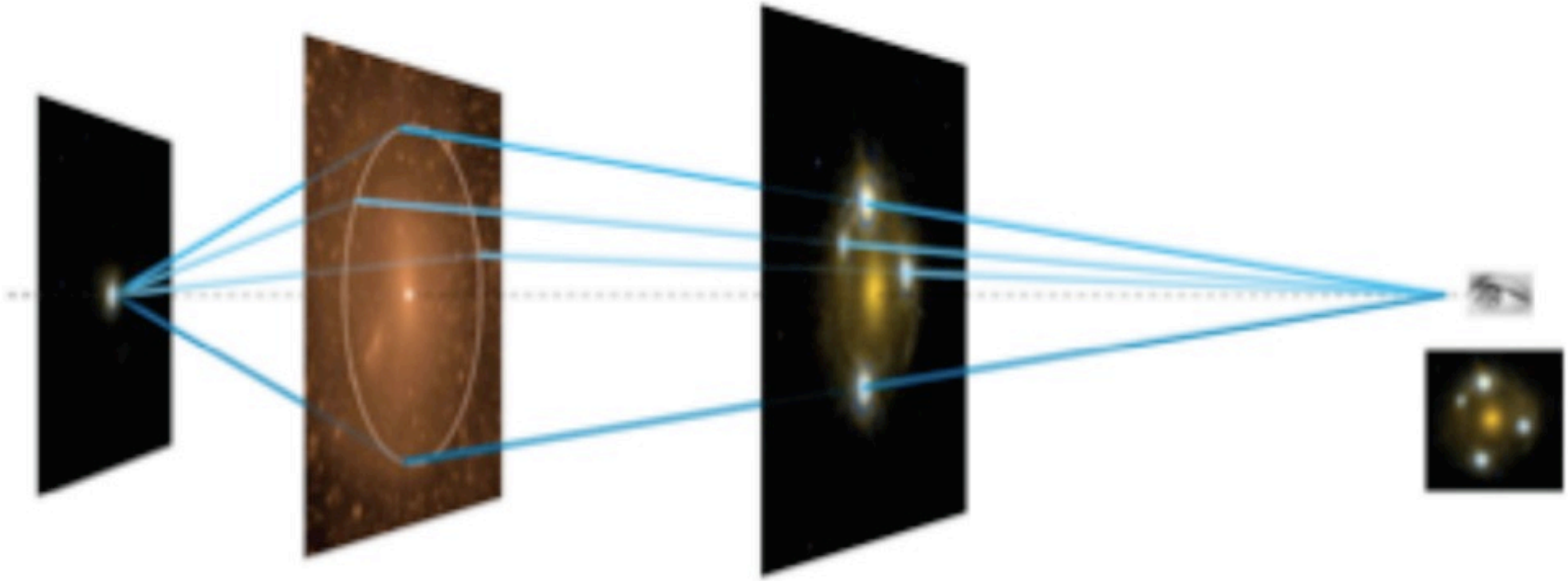
Strong lens detection:

- What will lensed quasars look like in the PS1 and LSST catalogues? How might we find them, cleanly?

Atmospheric PSF anisotropy:

- Can we predict the shape of the PSF at any given sky position, just from the stars observed in a 15 second exposure?

Strong gravitational lensing



- Massive galaxies lying right in front of distant quasars can provide 2 or more possible null geodesics that connect to our detector - all of them are followed and we see multiple, time-delayed images of the same AGN
- Science applications include: **weighing the "lens" galaxy**; quantifying the lens aberrations due to its "missing" **CDM subhalos**; measuring an **absolute distance to the lens** from the time delays; and much more...

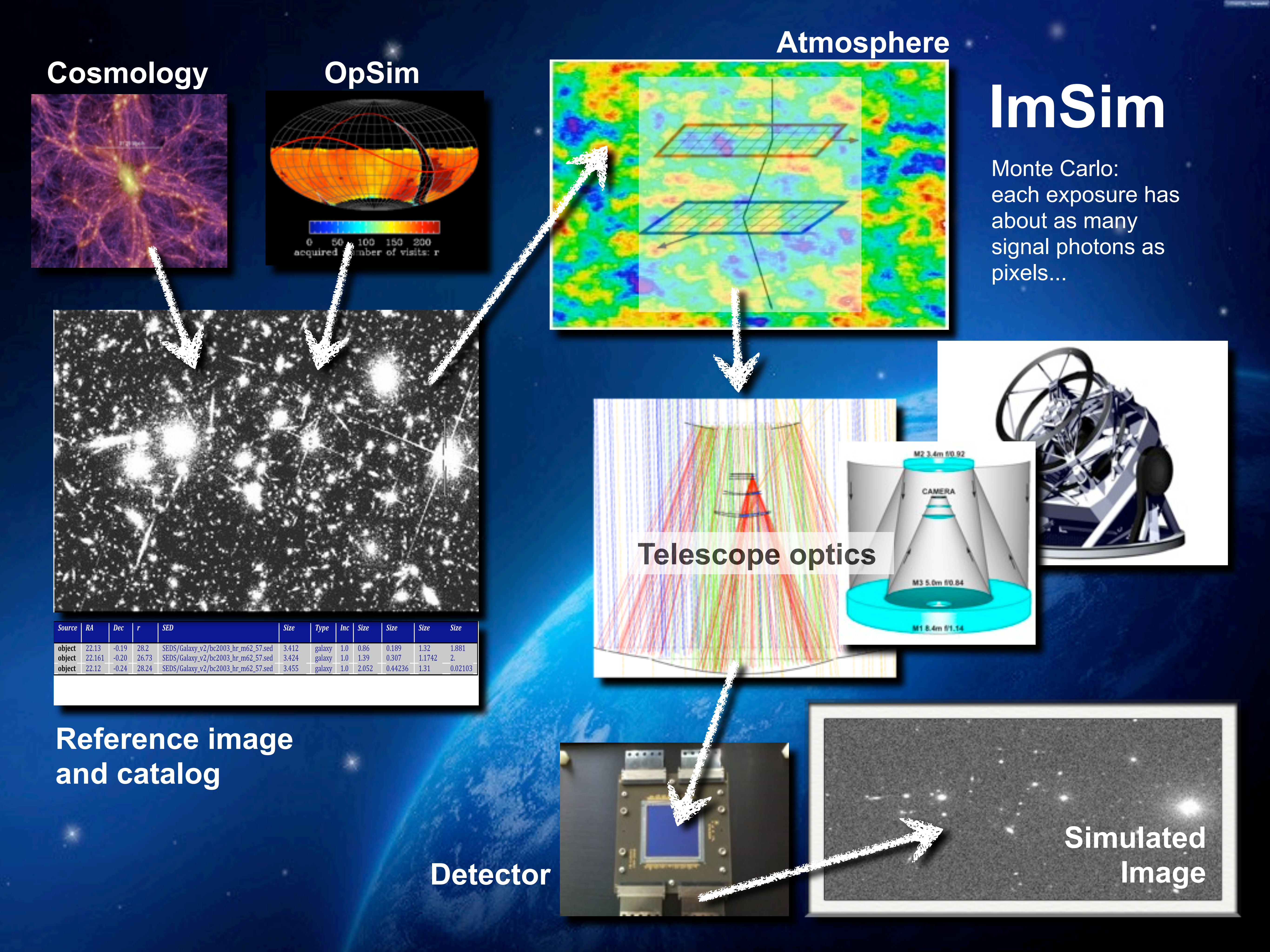
Figure: Dan Coe (2011), OMEGA Project

How many lensed quasars are there?

Survey	QSO (detected)		QSO (measured)	
	$N_{\rm nonlens}$	$N_{\rm lens}$	$N_{\rm nonlens}$	$N_{\rm lens}$
SDSS-II	1.18×10^5	26.3 (15%)	3.82×10^4	7.6 (18%)
SNLS	9.23×10^3	3.2 (12%)	3.45×10^3	1.1 (13%)
PS1/3π	7.52×10^6	1963 (16%)	...	...
PS1/MDS	9.55×10^4	30.3 (13%)	3.49×10^4	9.9 (14%)
DES/wide	3.68×10^6	1146 (14%)	...	...
DES/deep	1.26×10^4	4.4 (12%)	6.05×10^3	2.0 (13%)
HSC/wide	1.76×10^6	614 (13%)	...	...
HSC/deep	7.96×10^4	29.7 (12%)	4.30×10^4	15.3 (13%)
JDEM/SNAP	5.00×10^4	21.8 (12%)	5.00×10^4	21.8 (12%)
LSST	2.35×10^7	8191 (13%)	9.97×10^6	3150 (14%)

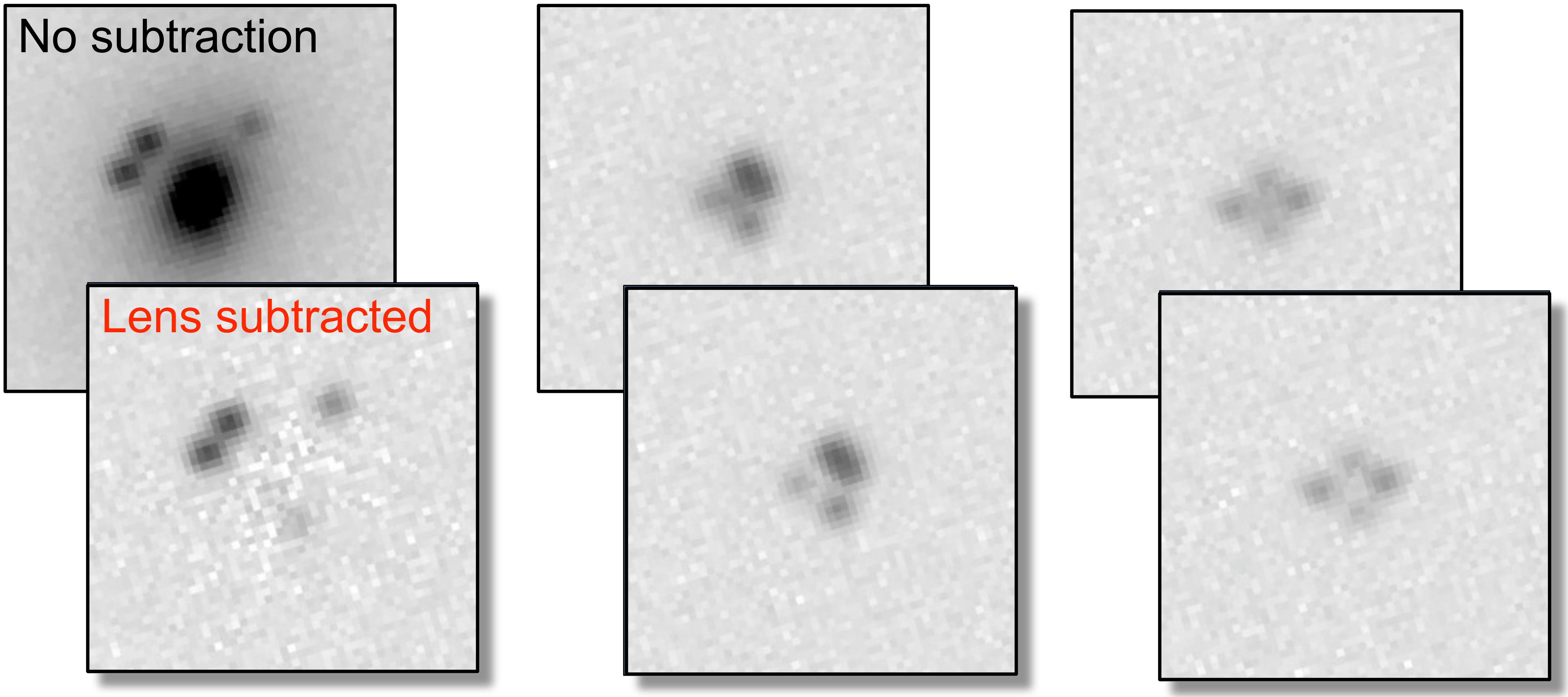
(Oguri & Marshall 2010)

- HSC+**DES**+**PS1**: ~**3000** lenses (400 quads);
- **LSST** should detect ~**8000** lenses (1000 quads)
- How are we going to find them all? **What will they look like?** In the images? *In the catalogs?*



Source	RA	Dec	r	SED	Size	Type	Inc	Size	Size	Size	Size
object	22.13	-0.19	28.2	SEDS/Galaxy_v2/bc2003_hr_m62_57.sed	3.412	galaxy	1.0	0.86	0.189	1.32	1.881
object	22.161	-0.20	26.73	SEDS/Galaxy_v2/bc2003_hr_m62_57.sed	3.424	galaxy	1.0	1.39	0.307	1.1742	2.
object	22.12	-0.24	28.24	SEDS/Galaxy_v2/bc2003_hr_m62_57.sed	3.455	galaxy	1.0	2.052	0.44236	1.31	0.02103

ImSim: LSST lensed quasars



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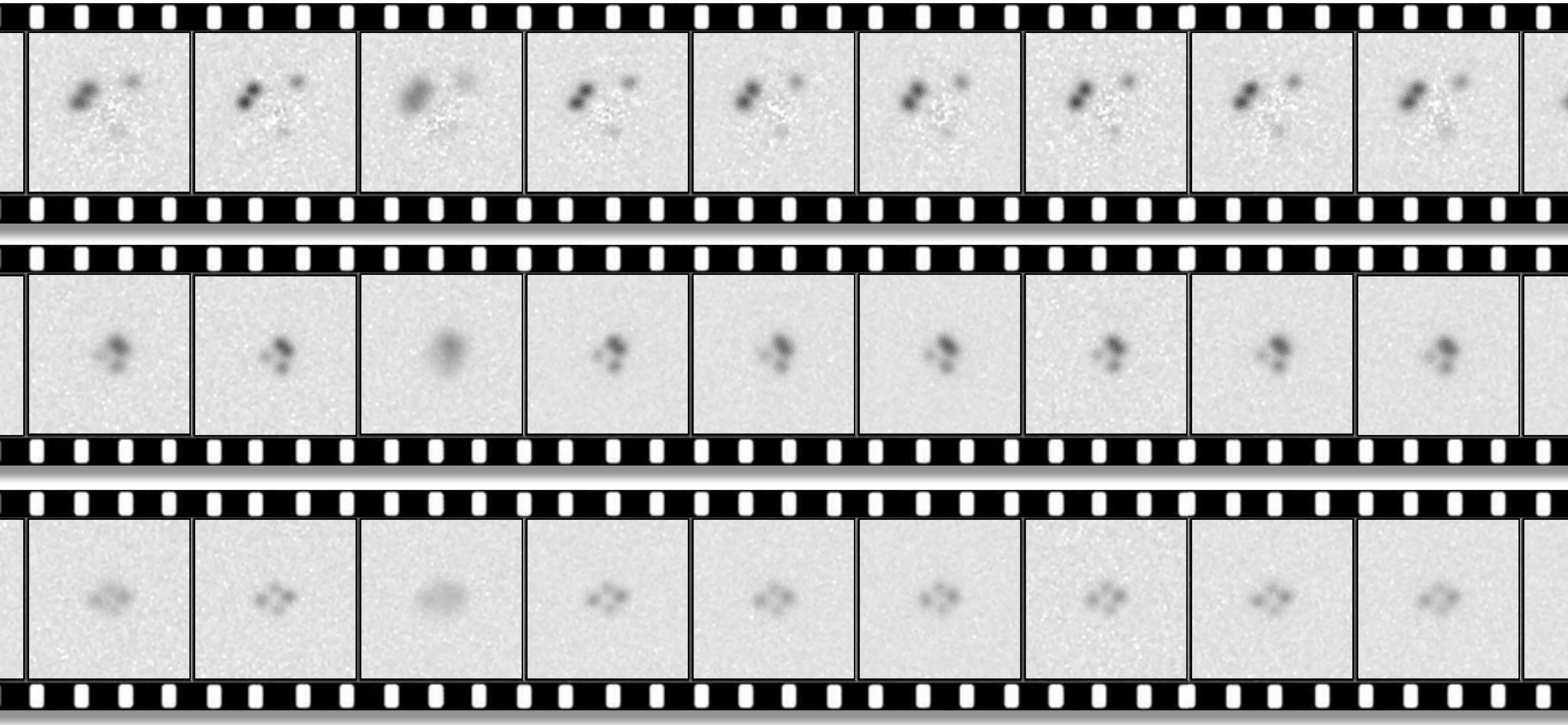

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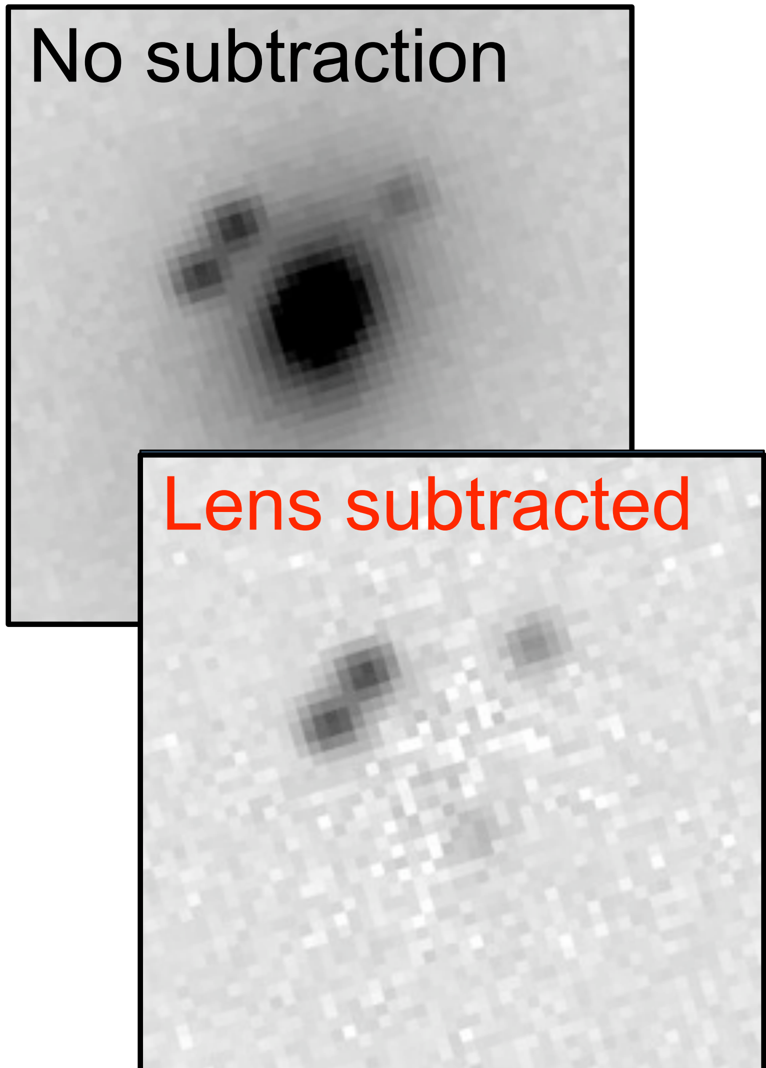
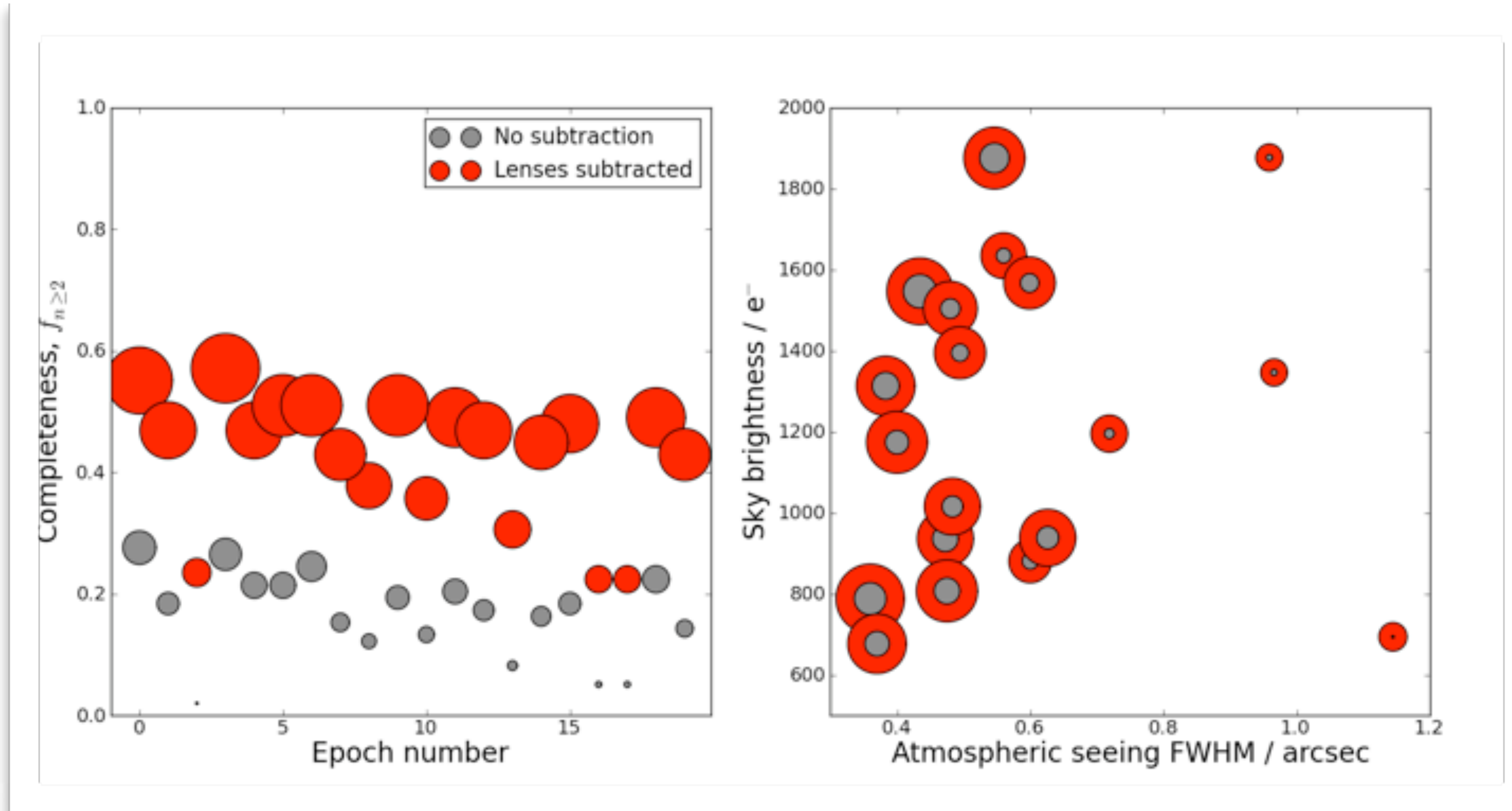
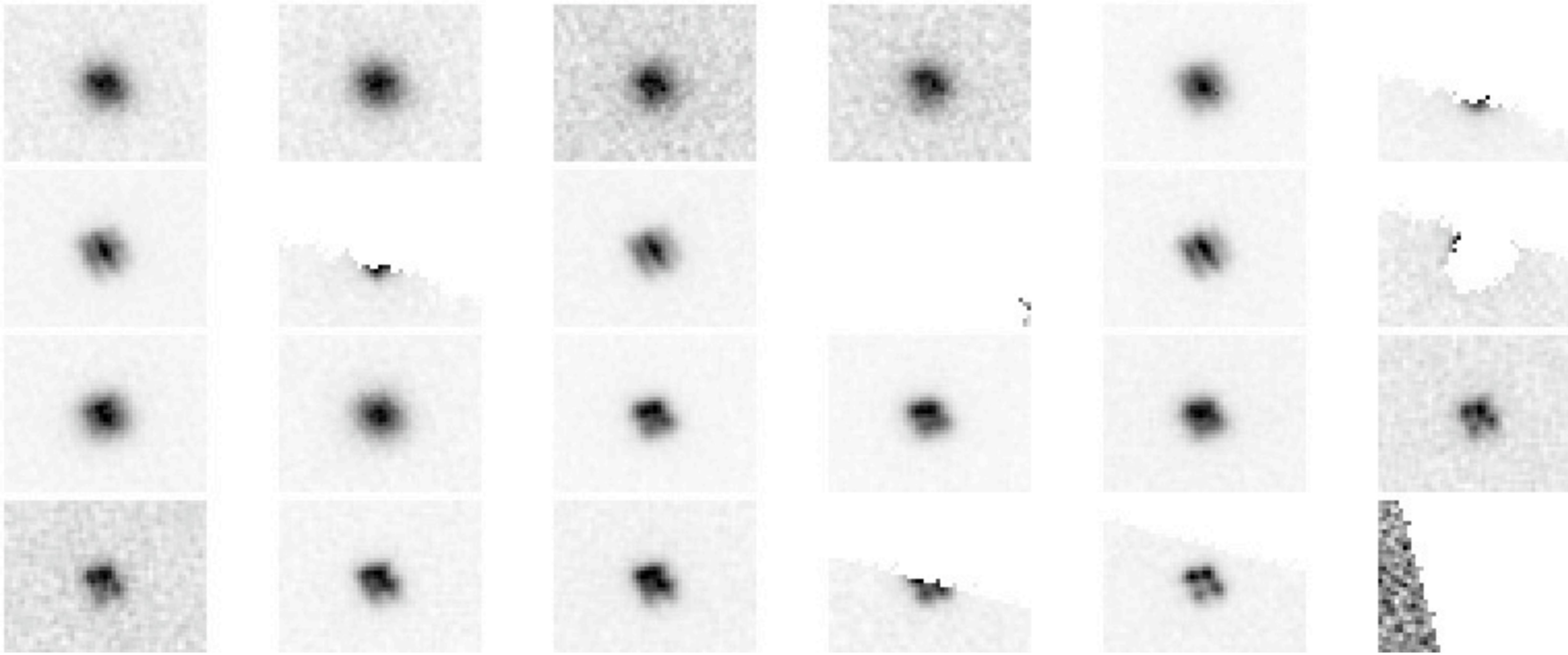




Lens completeness driven by IQ

- Basic object detection with default SExtractor, measure fraction of systems with 2 or more quasar images detected
- “Lucky imaging”: 20% complete with no lens subtraction
- Repeat with LSST DM source detector in PT1.2 - Lupton’s talk

Application: PS1 lensed quasars



- Lucky imaging with PS1: example shown is known lens **H1413+117** observed in *grizY* since 2009
- QSO identification depends on variability as well as colour: **joint modelling of data at all epochs in all filters is required.** Testing on ImSim mock lenses continues...

Conclusions: strong lens analysis

- Variable observing conditions are a plus for strong lens detection - occasionally we get a high resolution image
- **Lens candidacy requires a lens and source model:** images must be of plausibly equal colour, with lightcurves consistent with being equal but offset (modulo microlensing): joint modelling of **data at all epochs and in all filters is required.**

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- **Strong lenses are rare:** we only know a few dozen bright systems in the PS1 3pi survey area, and they were selected in a very different way

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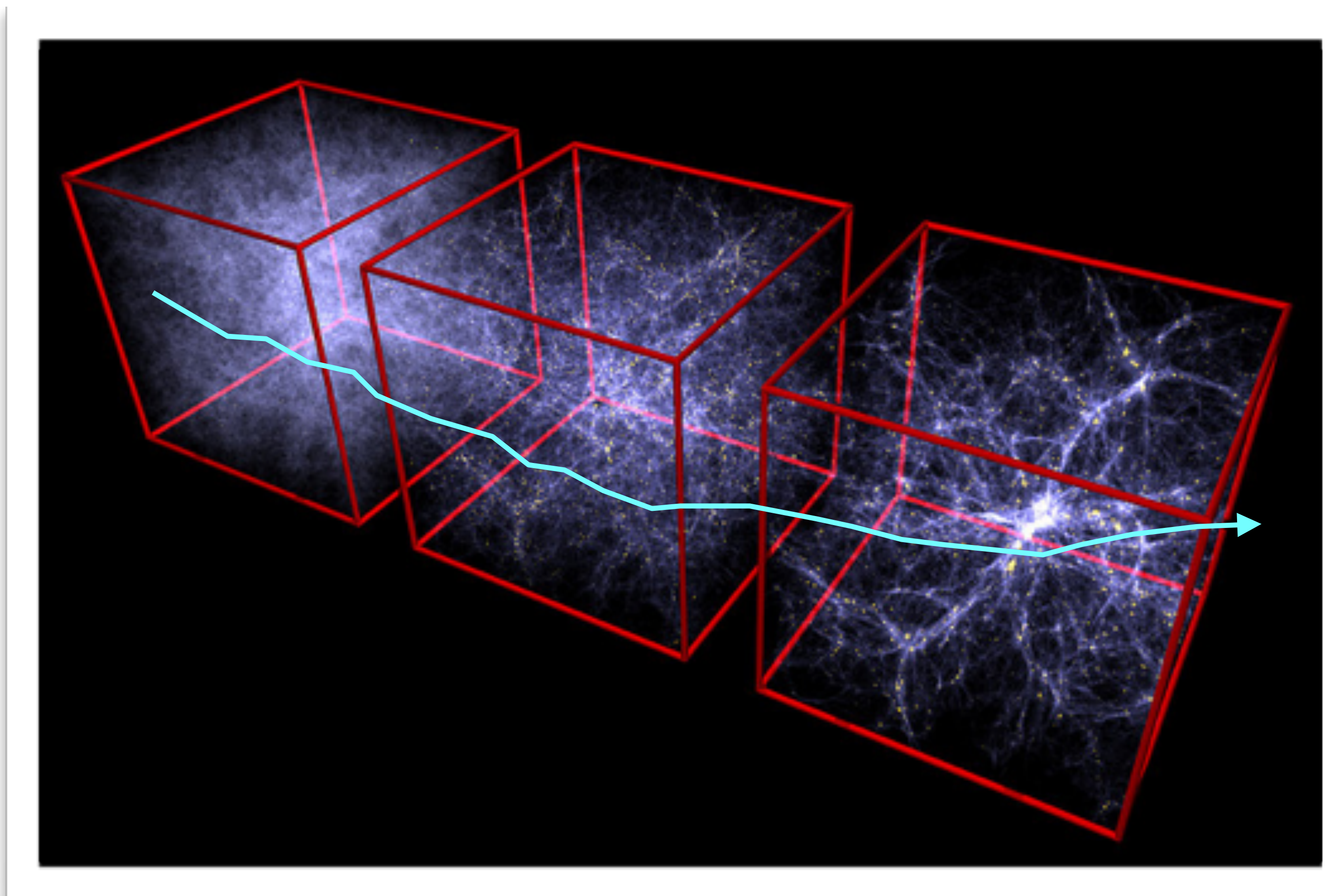
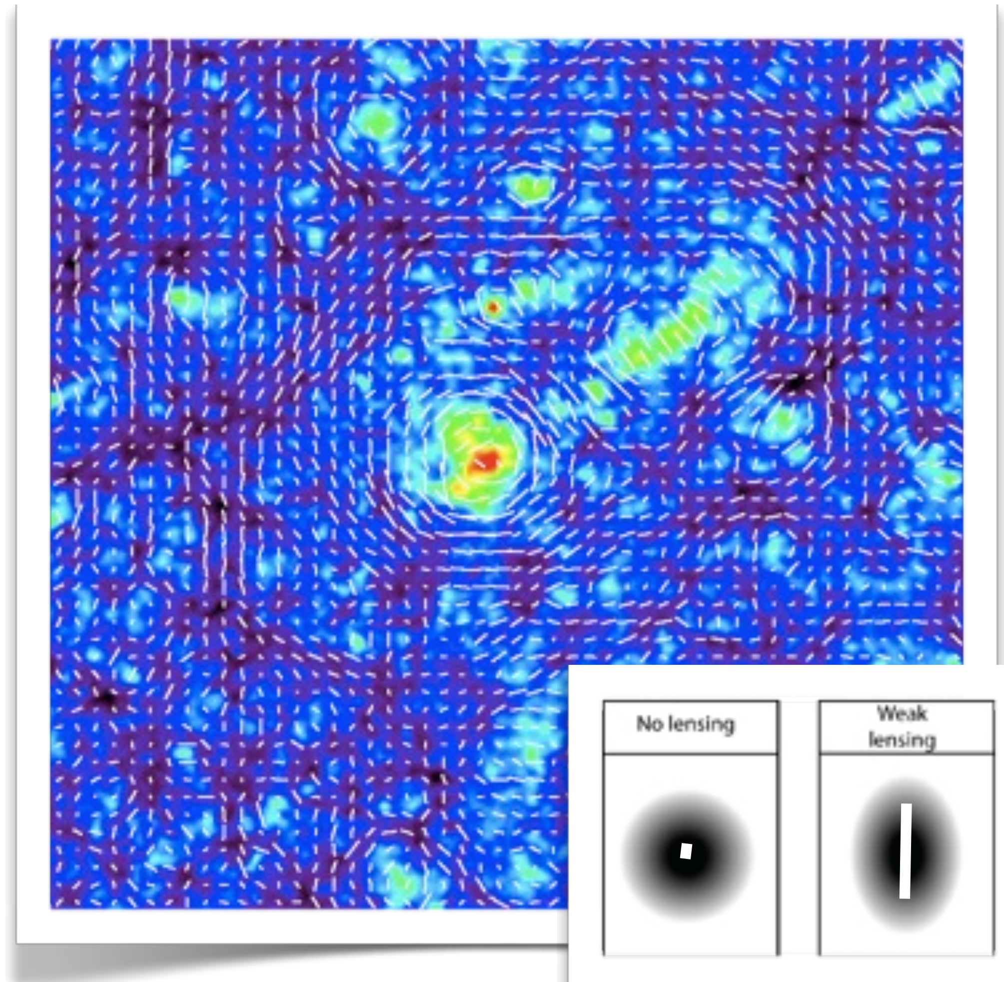
- **Strong lenses are rare:** we only know a few dozen bright systems in the PS1 3pi survey area, and they were selected in a very different way
- The ImSim systems have realistically faint images and lenses, allowing us to test detection of as yet unseen objects

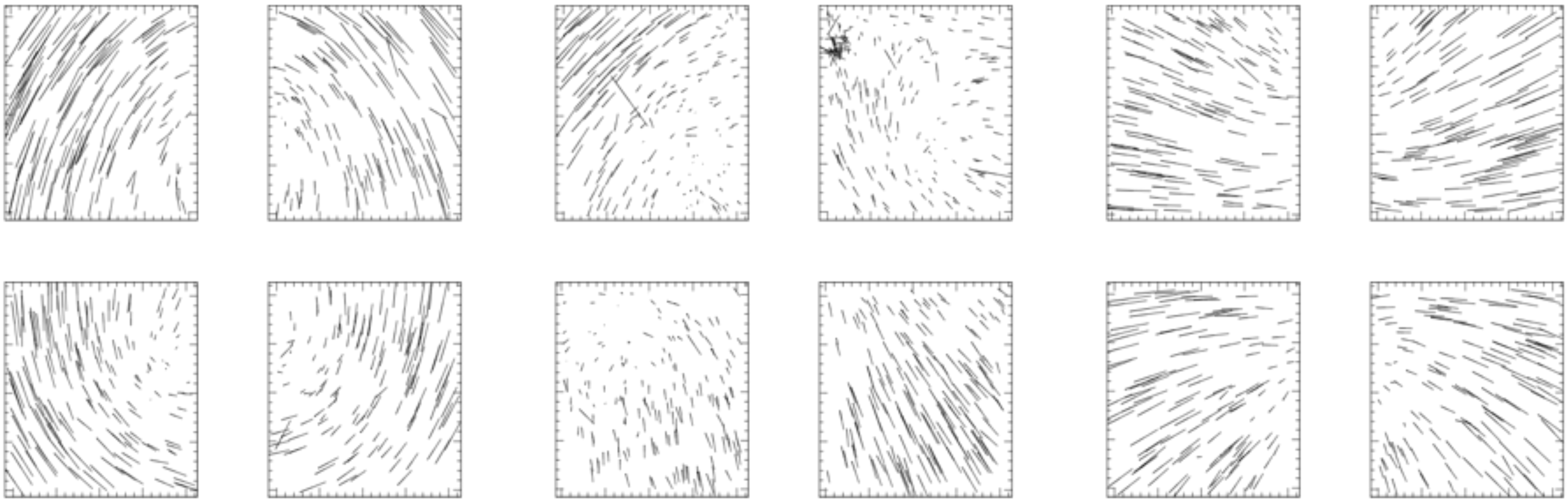
Weak gravitational lensing





- Gravitating mass is revealed by the weak, tangential distortion and alignment of images of background galaxies
- The Point Spread Function (PSF) causes ~10 times stronger "correlated ellipticity" - the PSF at each galaxy position needs to be first estimated and then deconvolved at high accuracy
- "PSF interpolation" is an *image reconstruction problem*

PSF anisotropy



Focus too low   Focus (roughly) correct   Focus too high

- Images of stars provide sparse, noisy PSF ellipticity data
- Instrumental PSF ellipticity (typically) varies on large (whole field) angular scales, and the patterns repeat: **low order polynomials** work well, and/or all images can be used to densely sample a set of basis functions to model the underlying ellipticity field (Jarvis & Jain 2008)

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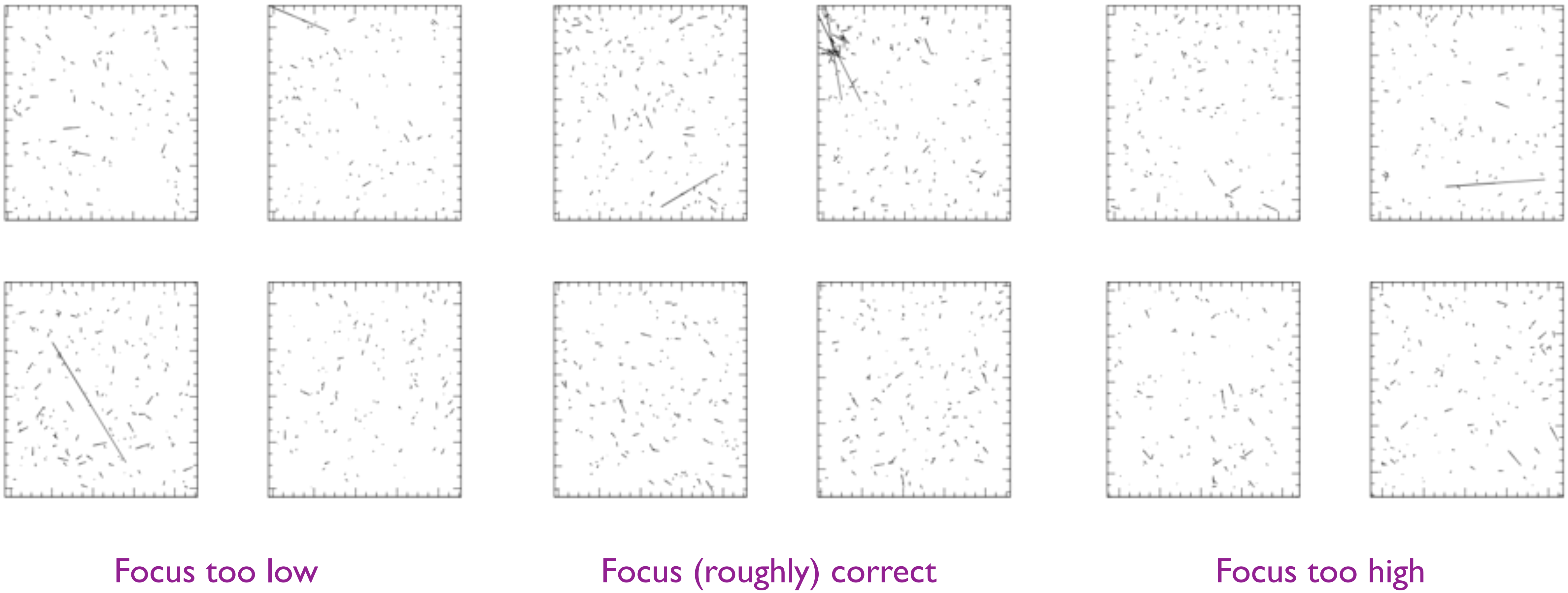

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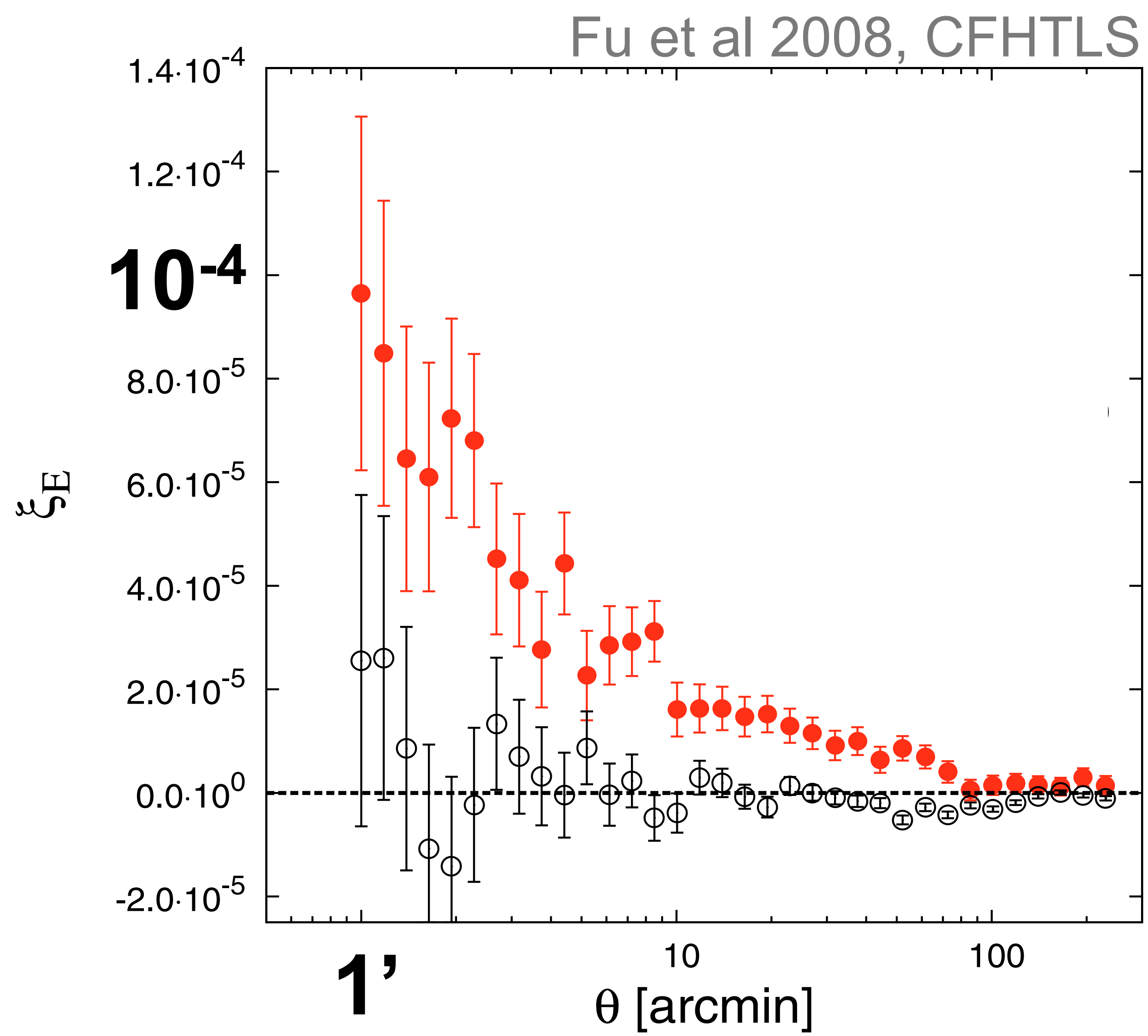
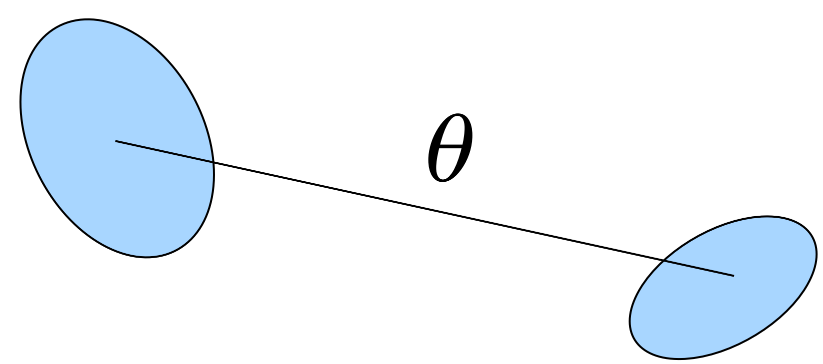
Ellipticity correlation functions



$$\langle \epsilon\epsilon \rangle \;\alpha\; \langle \gamma_G \gamma_G \rangle$$

$$\xi_{\pm}(\theta) = \langle \gamma_1(\boldsymbol{\phi})\gamma_1(\boldsymbol{\phi}+\boldsymbol{\theta}) \pm \gamma_2(\boldsymbol{\phi})\gamma_2(\boldsymbol{\phi}+\boldsymbol{\theta}) \rangle$$

$$\xi_{\times}(\theta) = \langle \gamma_1(\boldsymbol{\phi})\gamma_2(\boldsymbol{\phi}+\boldsymbol{\theta}) + \gamma_2(\boldsymbol{\phi})\gamma_1(\boldsymbol{\phi}+\boldsymbol{\theta}) \rangle$$



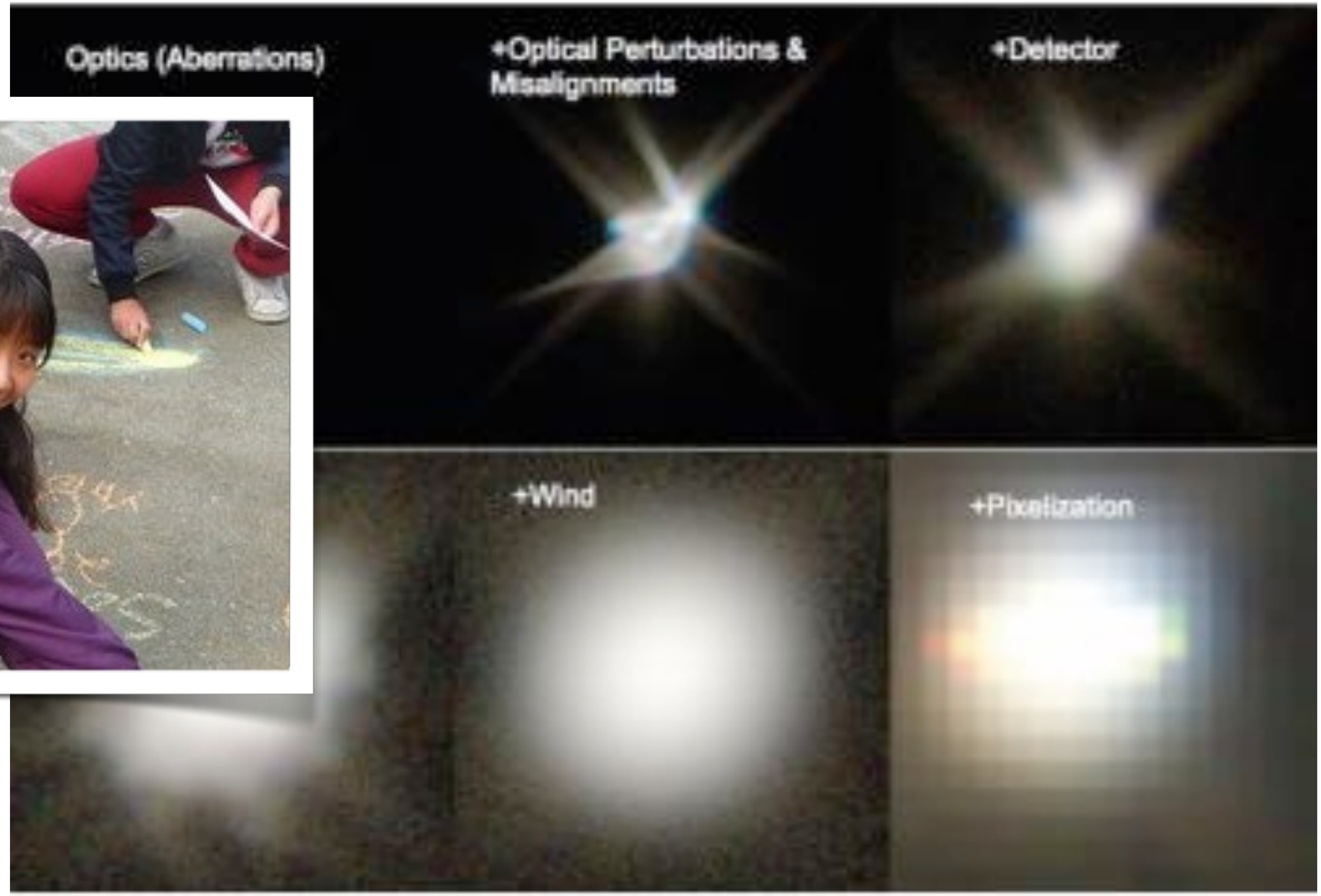
- After PSF correction, (complex) galaxy ellipticity is an estimator for the local gravitational shear: the *shear correlation function* can be predicted from cosmological models, and fitted to the observed ellipticity correlation function

What about the atmosphere?

- **Wittman (2005)** measured the stars in a **small set of 10-30s images** from Subaru, and found a residual PSF ellipticity correlation at the **$1\text{-}3\times10^{-5}$ level on scales of 1 arcmin**
- Early **simulations by de Vries et al (2007)** using frozen Kolmogorov phase screens predicted significant PSF ellipticity due to atmospheric turbulence, that **decreases with sqrt(t)**
- **Heymans et al (2011)** used archival CFHT images taken over a **wide range of observing epochs, exposure times and conditions**, and confirmed these results, noting that:

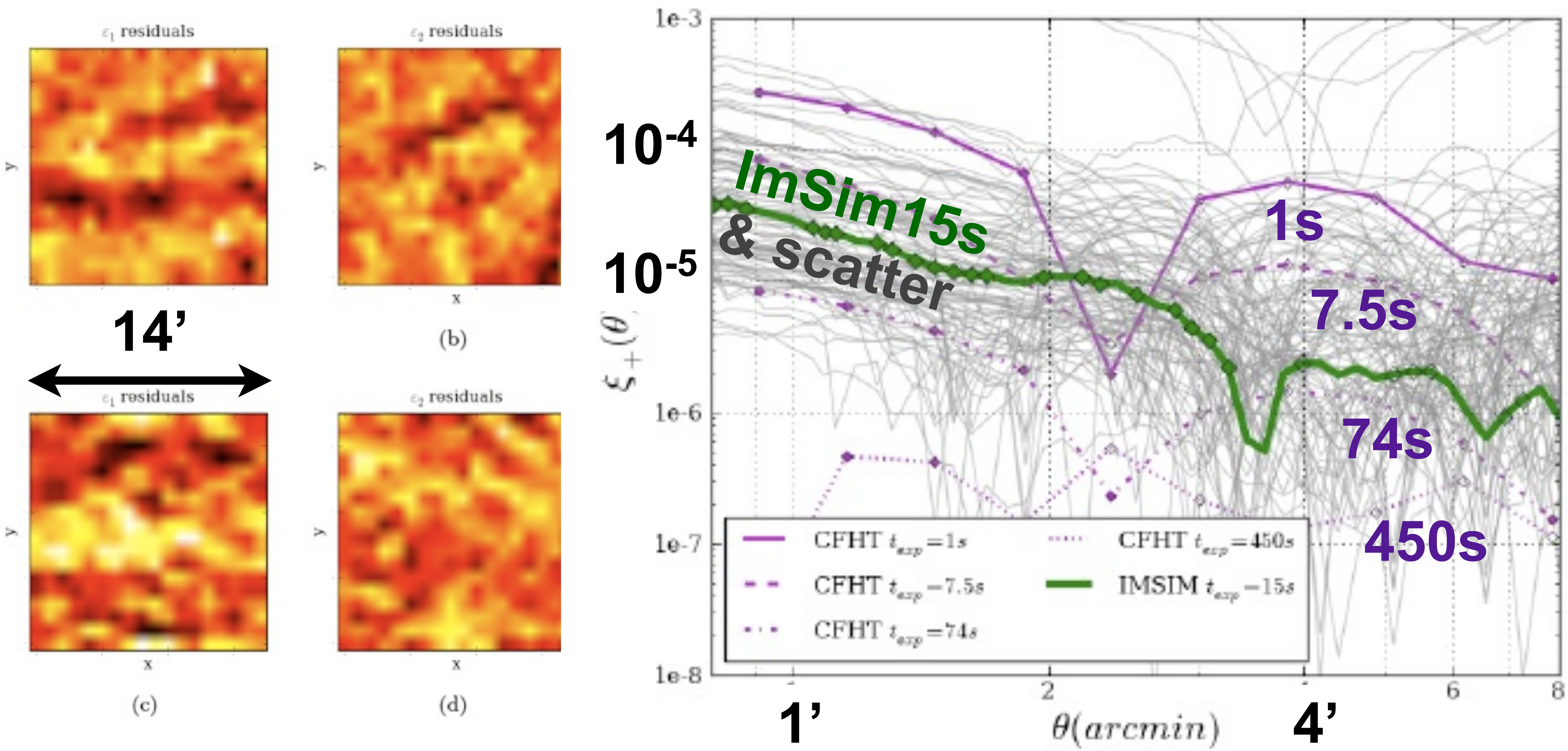
  "on these angular scales the high spatial frequency of the atmospheric aberration is too rapid to model with a typical stellar density and standard methods"
- **Use simulations to develop new PSF interpolation methods that can cope with atmospheric effects**

The LSST ImSim PSF

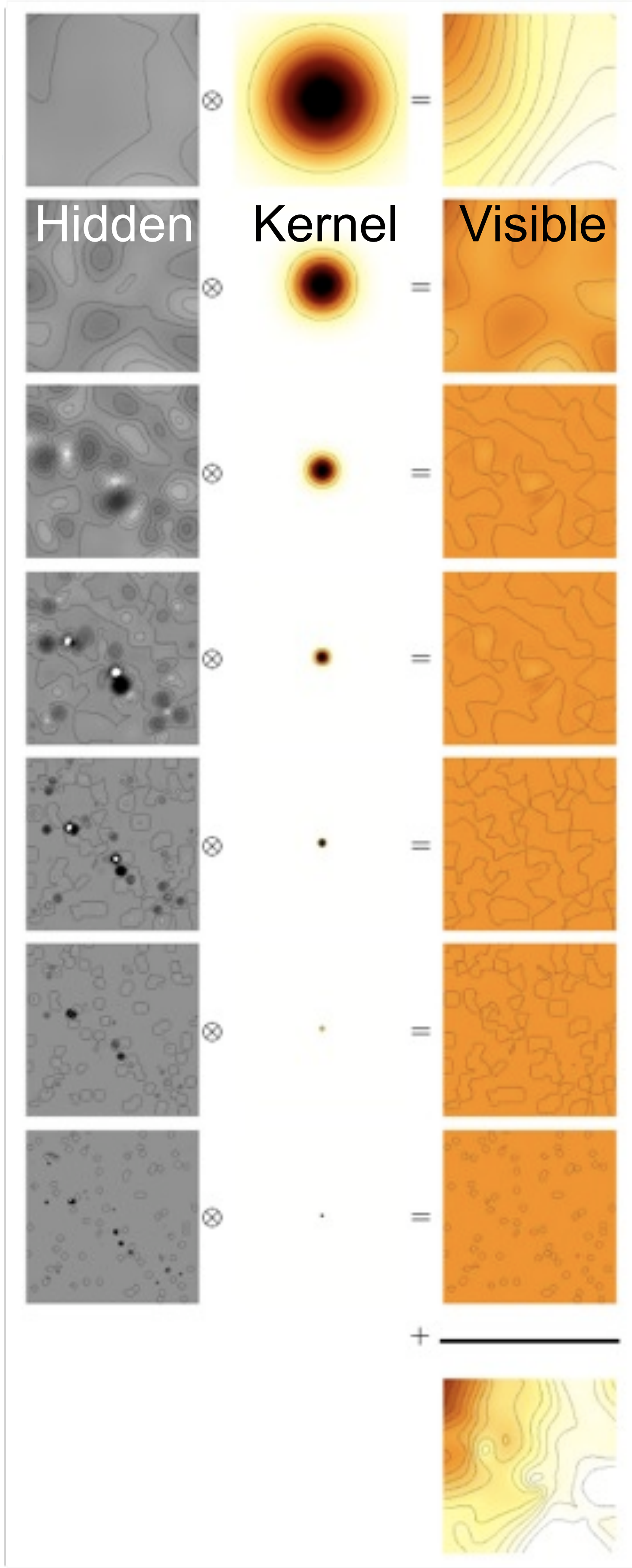


- **Chihway Chang** (KIPAC) is studying the LSST PSF - and its associated weak lensing systematic errors - using ImSim
- *Chang, Marshall et al (2011a, 2011b), Jernigan et al (2011), all in prep*

LSST ImSim - does it match the data?

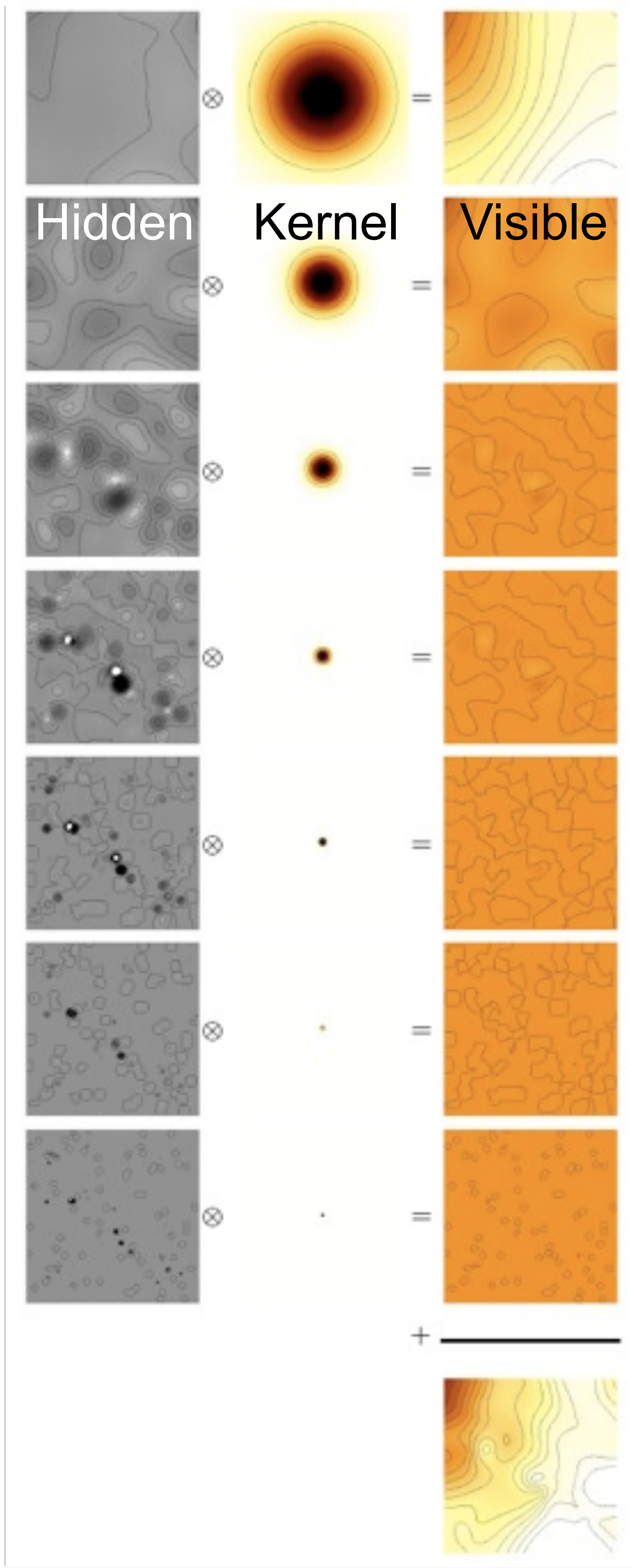


- Measure stars in real (purple) and simulated (grey/green) 15s CFHT chip images, subtract 2nd order polynomial model (for instrument)
- **Ellipticity correlation functions match well** in normalisation, slope and anti-correlation regime. *Simulations predict large scatter...*



PSFent

- Aim: **reconstruct maps of ellipticity components ε_1 and ε_2**
- Star shape data are sparse and noisy. **Inference:** Gaussian likelihood and (positive/negative) **Maximum Entropy prior, assigned to 7 hidden images**
- Each hidden image is **convolved with a different Gaussian kernel,** then summed
- **Flexible, multi-scale**: allows high frequency spatial variations to be modelled
- Different scales' **relative weight is simulation-driven**: computed from rms of hidden images in reconstructions of high S/N mock starfields. Weight ~ kernel mass
- Small scale structure only appears when the data demand it!



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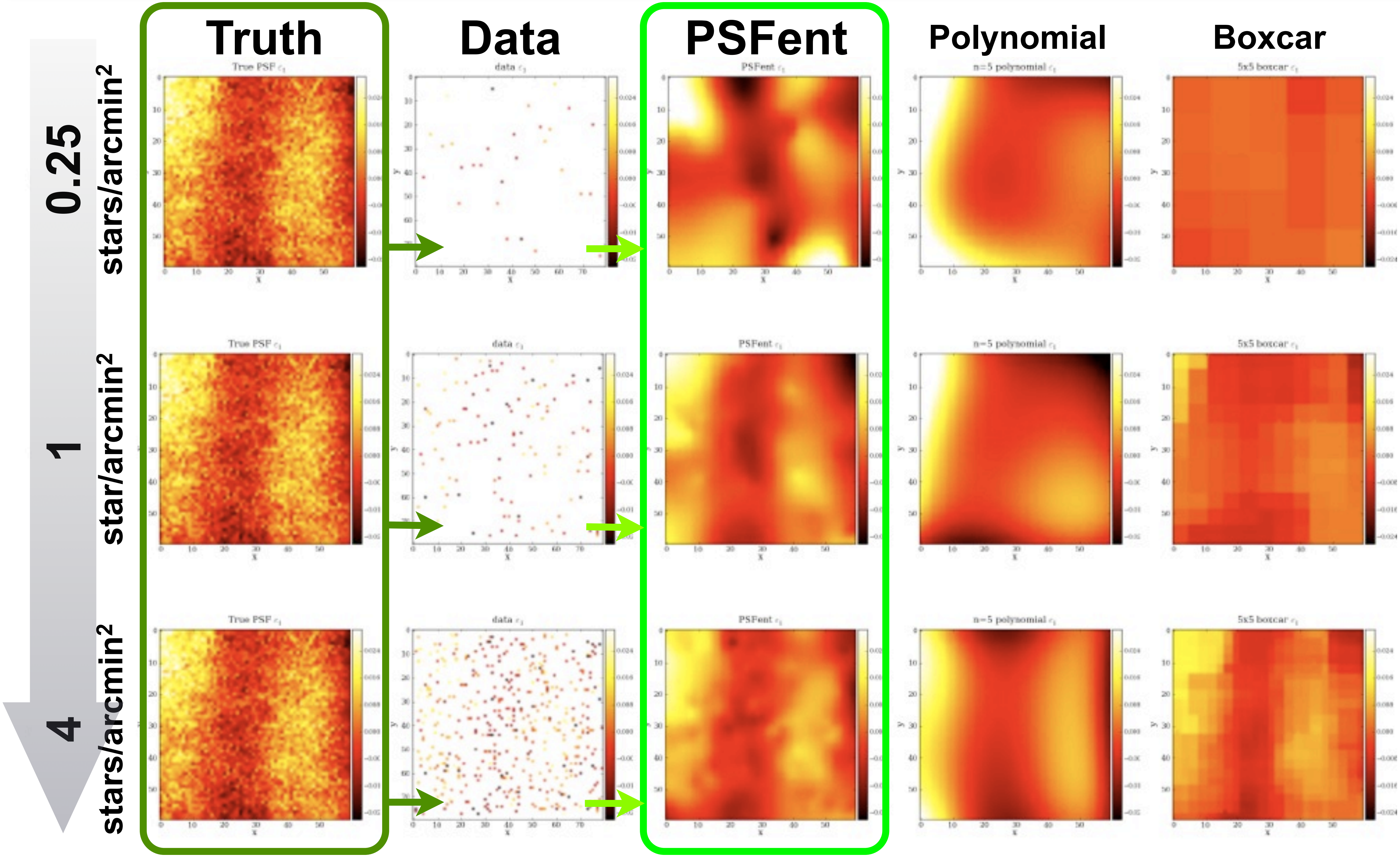
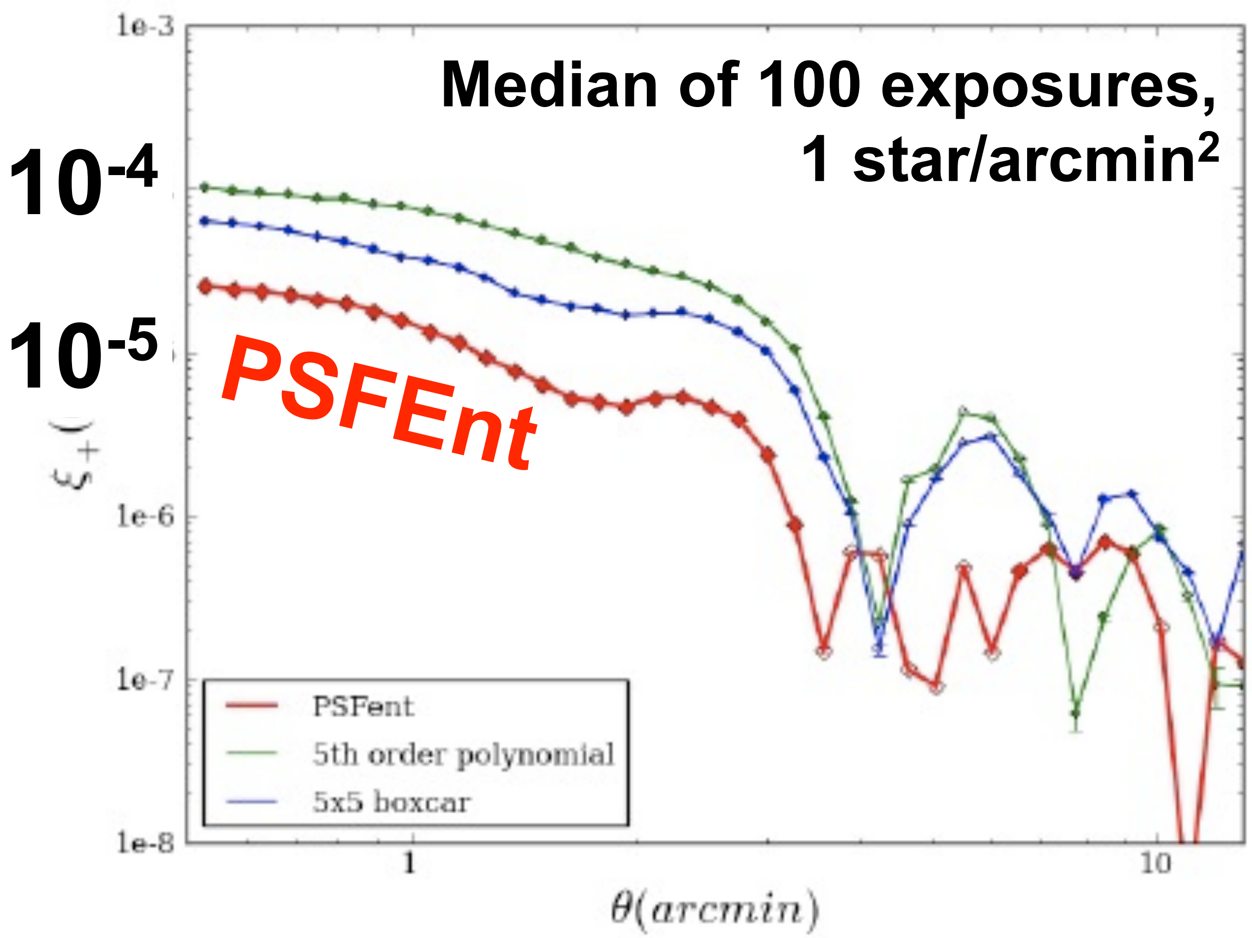
Example


Truth
Data
PSFent
Polynomial
Boxcar
0.25 stars/arcmin^2
1 star/arcmin^2
4 stars/arcmin^2

WL Systematics

- Combining ~1000 exposures, LSST statistical errors should be *very* small - need to compare residual correlations from PSF interpolation with these
- Key quantity is mean square residual additive systematic error defined by Amara & Refregier (2008): $\sigma^2_{sys} < 10^{-7}$ for LSST, **or** $\boldsymbol{\sigma^2_{sys,PSF} < 4\times10^{-8}}$
- *Simulated data allows this quantity to be estimated directly, as integral under residual (reconstruction - truth) ellipticity correlation function:*



Single exposure $\sigma^2_{sys,PSF}$

Polynomial: 10×10^{-5}
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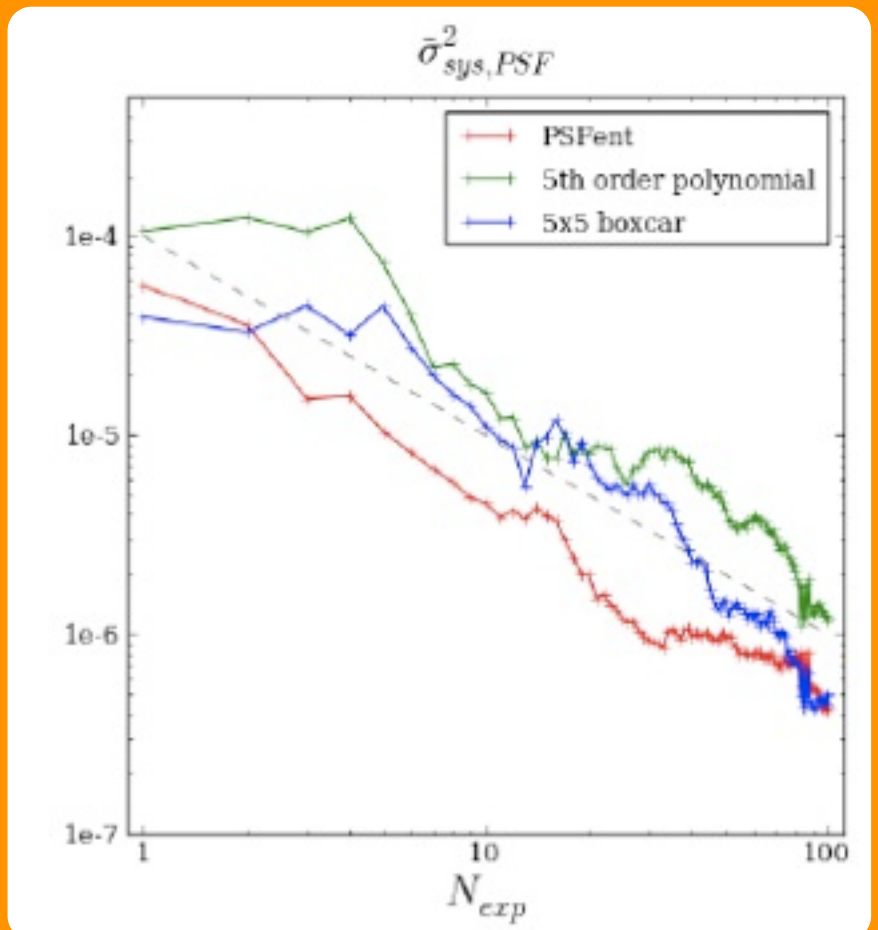

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$\sigma^2_{sys,PSF}$ scales as $1/N_{exp}$, as shown with simulations

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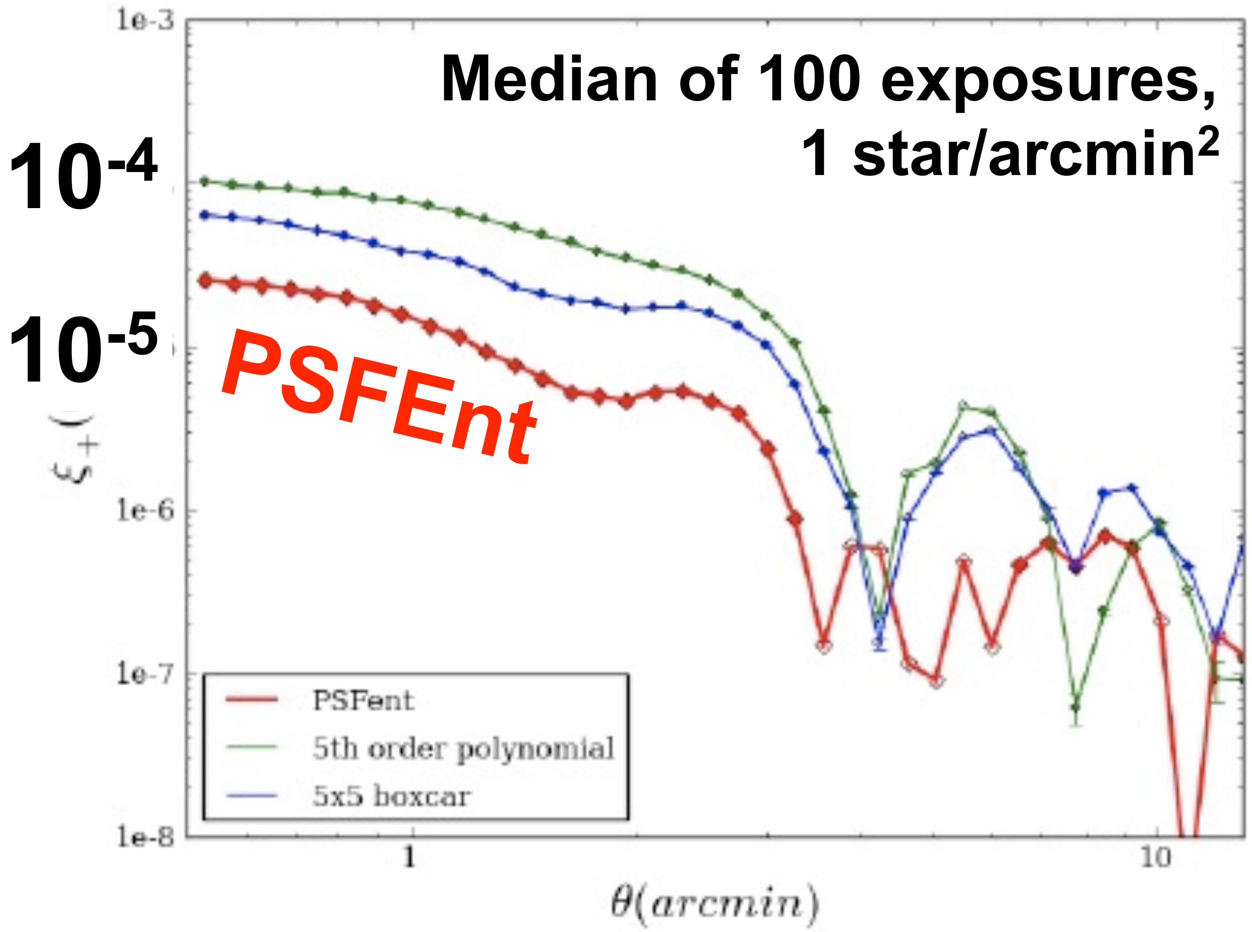


Single exposure $\sigma^2_{sys,PSF}$

Polynomial: $10\mathrm{x}10^{-5}$

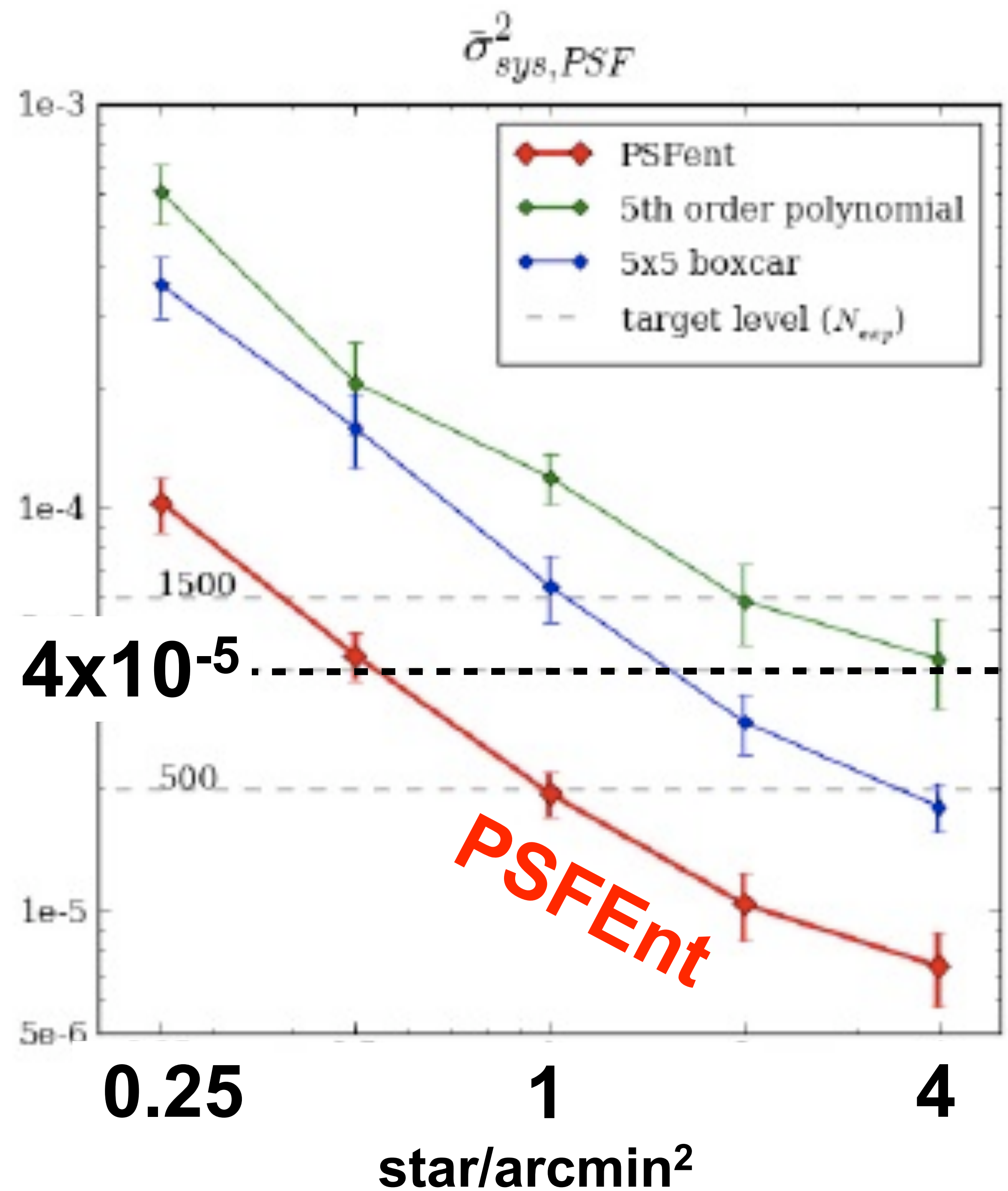
Boxcar: $6\mathrm{x}10^{-5}$

Target: $4\mathrm{x}10^{-5}$

PSFent: $2\mathrm{x}10^{-5}$

Atmospheric PSFs: conclusions

- PSFent provides **the factor of 5 improvement required** (over standard techniques) to reach the required, single exposure, residual systematic limit of $\sigma^2_{sys,PSF} < 4\times10^{-5}$, in all fields with star density > 0.5 arcmin^{-2}
- In these fields, PSF interpolation will not be the dominant source of error in the shear correlation function at arcminute scales. An additional factor of two will be required to push to half this density.



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Thanks!

Questions

Q. Do the PSF shape parameters need to be interpolated in other dimensions? LIke colour, brightness etc?
A. *Maybe, yes - current weak lensing analyses do this at some level. You could imagine interpolating spatially in bins of X, or as a function of X.*

Q. What about using PCA?
A. *The whole problem is one of finding the optimal basis set for reconstructing the ellipticity maps, and PCA is one way of deriving a basis set. Would a simulation defined set of PCs make a good basis set? The problem is that the atmospheric maps are like noise fields, so it's unlikely that a simple way of reducing the size of the PC set would be obvious. PCs, Fourier modes and so on are just rotations from real space - the key is to reduce the number of degrees of freedom in a physically motivated way. We do it by deriving a MaxEnt prior on our hidden spaces - something similar could be done for other basis sets.*

Questions

Q. PSFent sounds horribly slow. Is it?
A. *It takes ~10s to reconstruct the 2 ellipticity maps for each chip image on a standard desktop workstation, so about 200 would be needed to keep up with the LSST data rate, today. Moore's Law will help, but we will undoubtedly need to interpolate more than just two PSF shape parameters.*

Q. What about PSF size?
A. *We have not tried this yet, but I would be surprised if we cannot interpolate that in the same way: PSFent is so flexible. Whether the residual systematics due to PSF size interpolation average down in the same way is to be investigated...*