<u>Automated</u> PSF measurement and homogenization in DESDM

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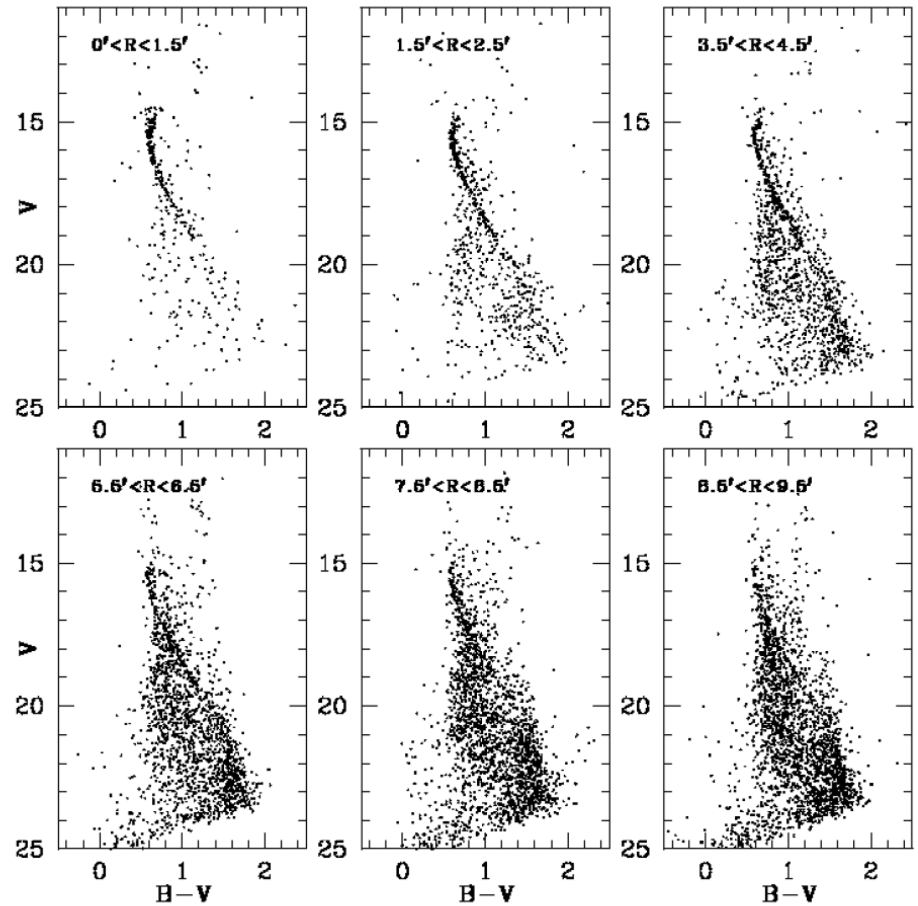
PSF homogenization

- History
- Science requirements
- PSFEX internals
  - Point source selection
  - PSF modeling
  - Modeling PSF variations
- PSFEx in the DESDM
  - specific issues
  - Built-in quality control and metadata output
  - Pending issues and forthcoming developments

History

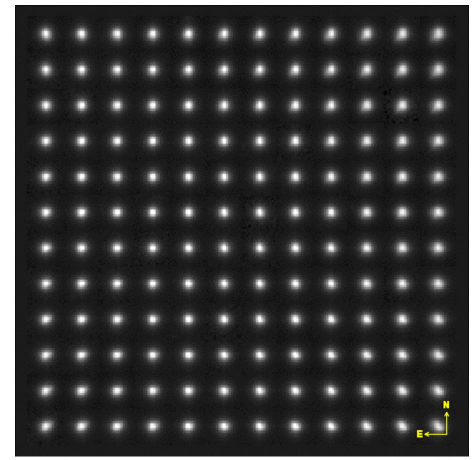
- Development started back in 1998 (!) while working on the ESO Imaging Survey
  - Originally intended to provide accurate PSF models for crowded field photometry (e.g. Kalirai et al. 2001)
- Used mostly for quality control at TERAPIX
- Modeling of PSF variations refined in the framework of the EFIGI project (galaxy morphology)
- PSF homogenization module developed for the DES project

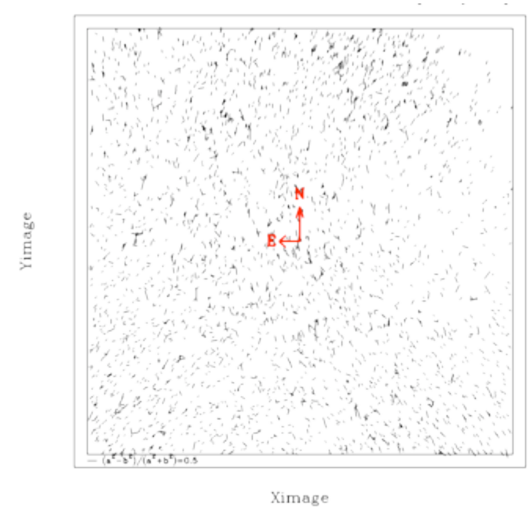


PSFEx

PSF requirements from contemporary science

- Faint galaxy morphometry
  - PSF Full-Width at Half-Maximum < 0.9''
  - PSF FWHM must be mapped with an accuracy of a few %
- Weak lensing studies
  - PSF ellipticity must be mapped at the 0.1% accuracy level
- Some existing and future wide-field imagers are undersampled: the PSF extraction software must be able to recover the PSF from aliased images.

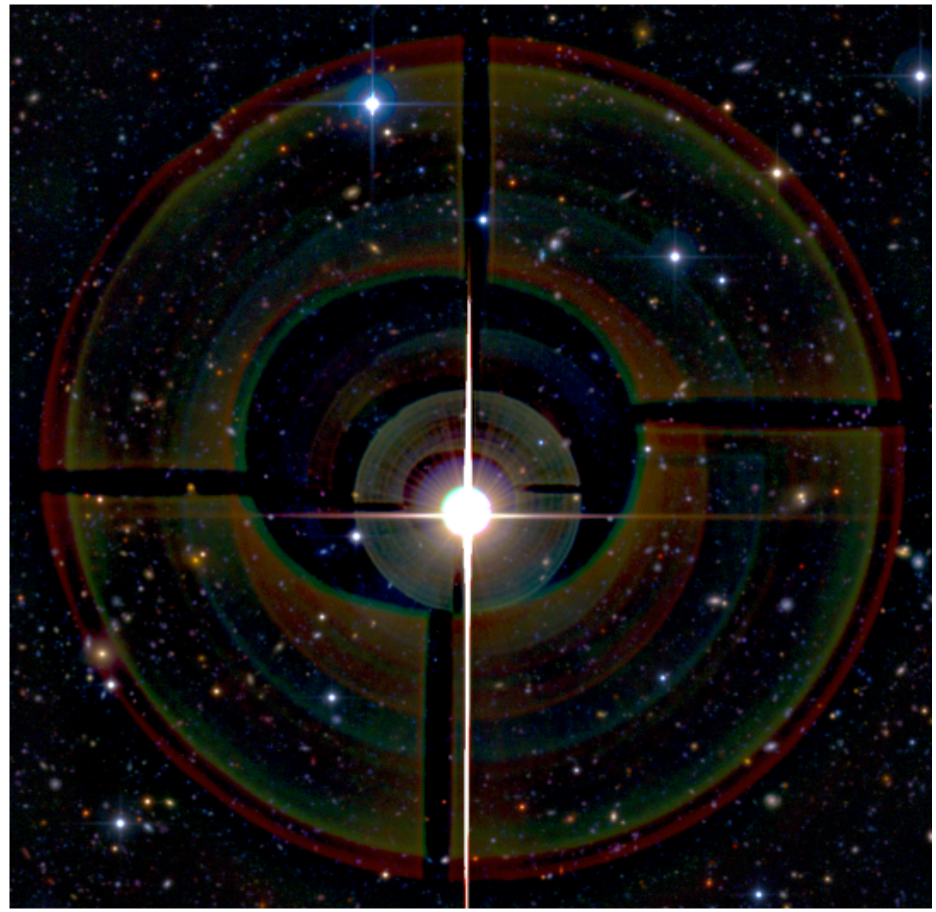




PSF image and distortion maps on a 1 sq.deg. field

PSFEx: Modeling the PSF

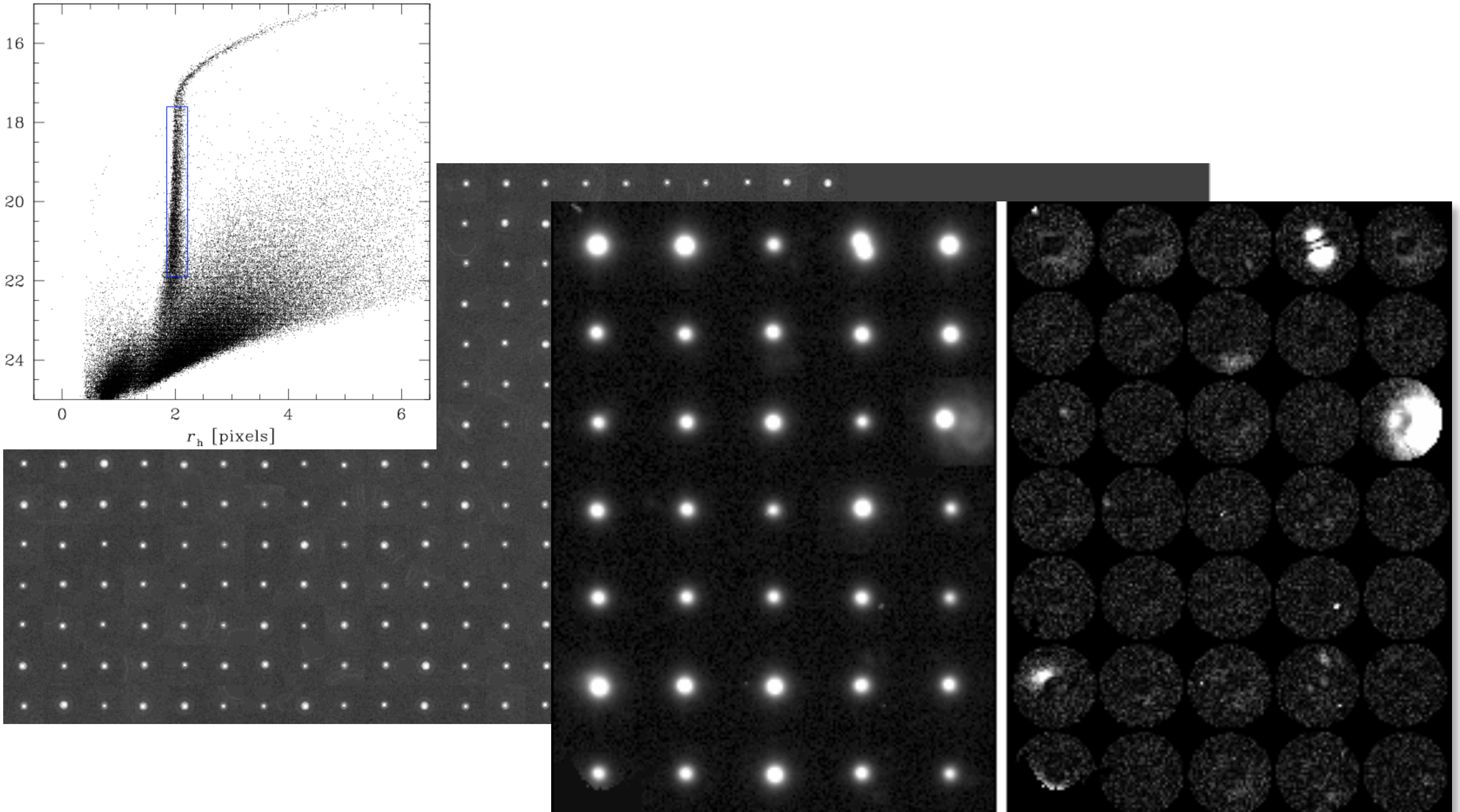
- Modern imagers behave as linear, translation-invariant systems (at least locally) and can be fully characterized by their Point Spread Function (PSF)
- Knowledge of the PSF is needed for many image analysis tasks
  - image quality control (FWHM, elongation, asymmetry, distance to best-fitting Moffat)
  - PSF homogenisation
  - matched filtering
  - profile-fitting
  - star/galaxy separation
  - galaxy morphology
  - weak-lensing analyses



DARK ENERGY SURVEY

PSFEx

Automatic point-source selection



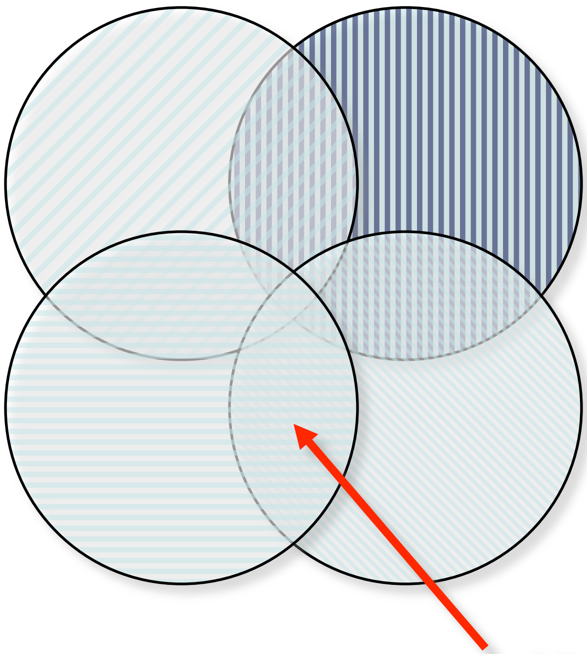
PSF modeling: Principle

- For practical reasons, PSFEx works internally with <u>rasterized</u> PSF models. PSF models are tabulated at a resolution which depends on the stellar FWHM (typically 3 pixels/FWHM)
  - Satisfy the Nyquist criterion + margin for windowed-sinc interpolation
  - Handle undersampled data by representing the PSF model on a finer grid
  - Minimize redundancy in cases of bad seeing
  - <u>Find the sample values by solving a system using point-sources located at different positions with respect to the pixel grid</u>
- The PSF is modelled as a linear combination of basis functions ψ_b
  - "Natural" pixel basis $\psi_b(\mathbf{x}) = \delta(\mathbf{x}-\mathbf{x}_b)$
    - Work with any diffraction-limited image (images are bandwidth-limited by the autocorrelation of the pupil)
  - Fourier basis
  - Gauss-Hermite or Gauss-Laguerre basis functions (aka polar *Shapelets*) $\psi_b(r, \theta)$

$$\psi_b(r,\theta) \propto r^{|m|} L^{|m|}_{\frac{n-|m|}{2}}\left(\frac{r^2}{\beta^2}\right) e^{\frac{-r^2}{2\beta^2}} e^{-im\theta}$$

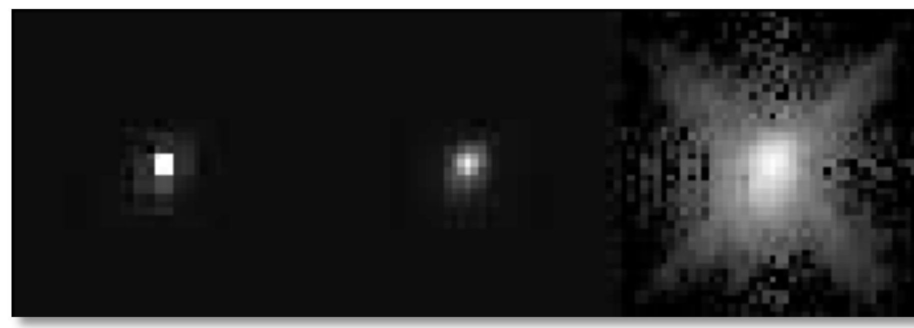
    - Scale parameter (β) adjusted to provide proper sampling
    - Should provide a more robust model for data with low S/N
  - Others (e.g. PCA components of the theoretical PSF aberration components for diffraction-limited instruments).

Solving in Fourier space



Aliased portion of the spectrum

Reconstructed NICMOS PSF



Lauer 1999

Problem: noise is seldom stationary on astronomical images!

PSFEx: solving in direct space

- A resampling kernel *h*, based on a compact interpolating function (*Lanczos3*), links the "super-tabulated" PSF to the real data: the pixel *j* of star *i* can be written as

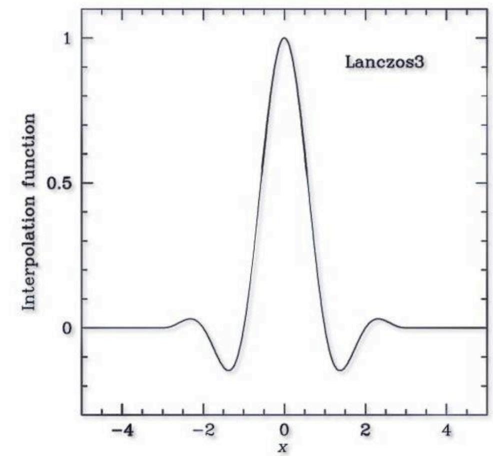
$$P_{ij} = a_i \sum_k \sum_b h(x_j - x_k) c_b \psi_{bk}$$

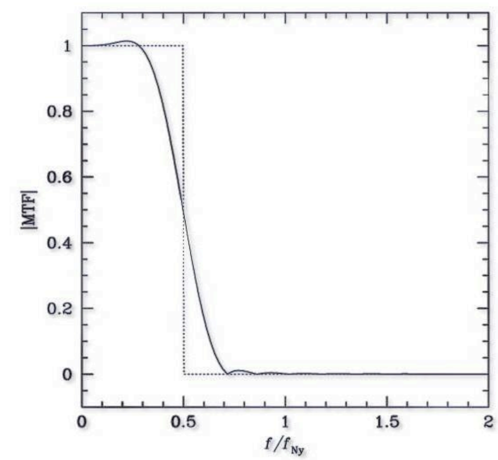
- The c_b's are derived using a <u>weighted</u> χ^2 minimization.
- The a_i's are obtained from "cleaned" aperture magnitude measurements
- Regularisation required for highly undersampled PSFs (FWHM <1.5 pixel)
  - l^2 norm (Tikhonov)
- PSF variations are assumed to be a smooth function of object coordinates
  - ☞ The variations can be decomposed on a polynomial basis X_l

$$P_{ij} = a_i \sum_l X_l(x_i) \sum_k \sum_b h(x_k - x_j) c_{lb} \psi_{bk}$$

ψ_b

$X_l =$ *cste*, x, x^2, x^3, y, xy, x^2y, y^2, xy^2, y^3

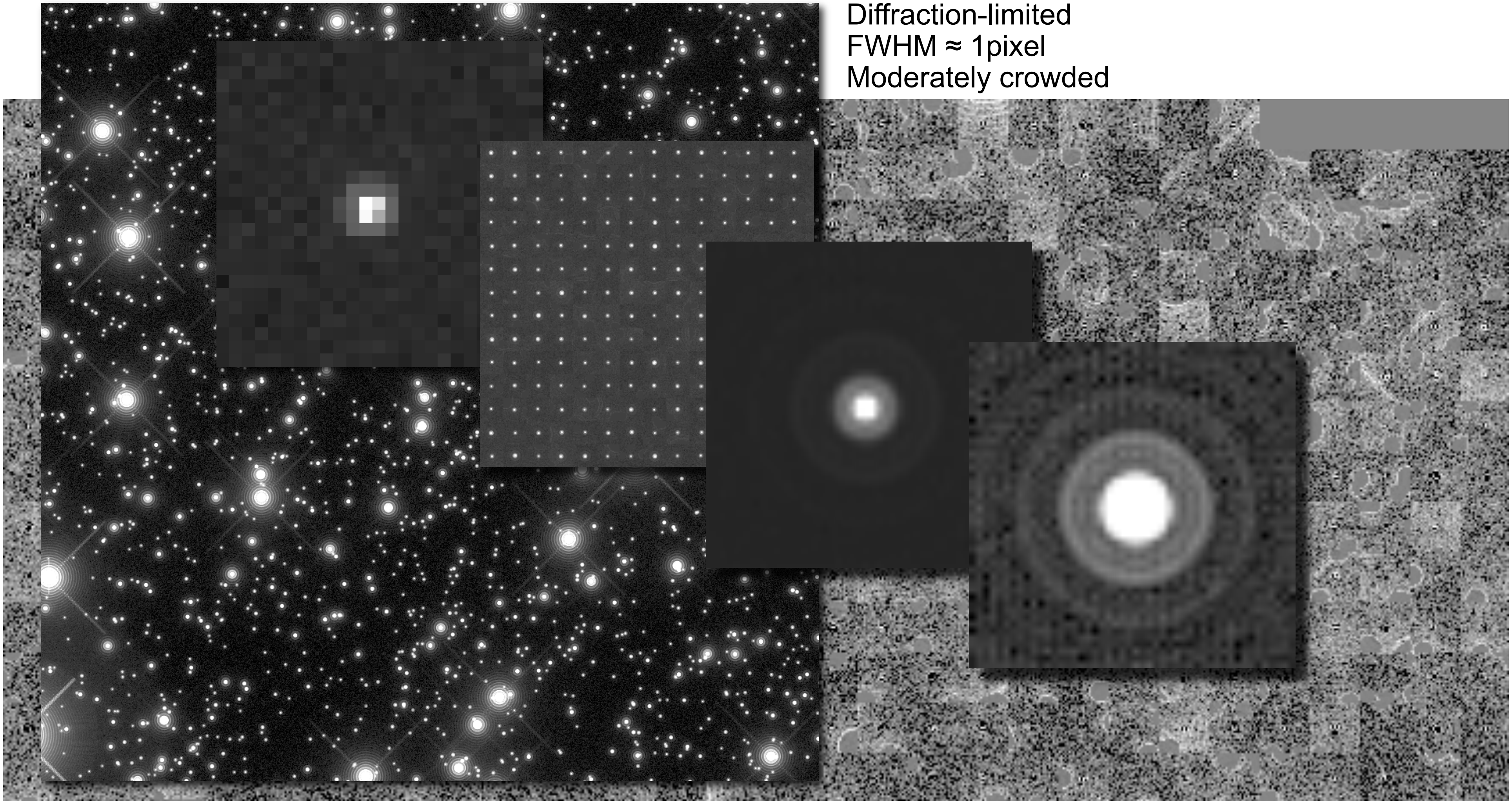




PSFEx

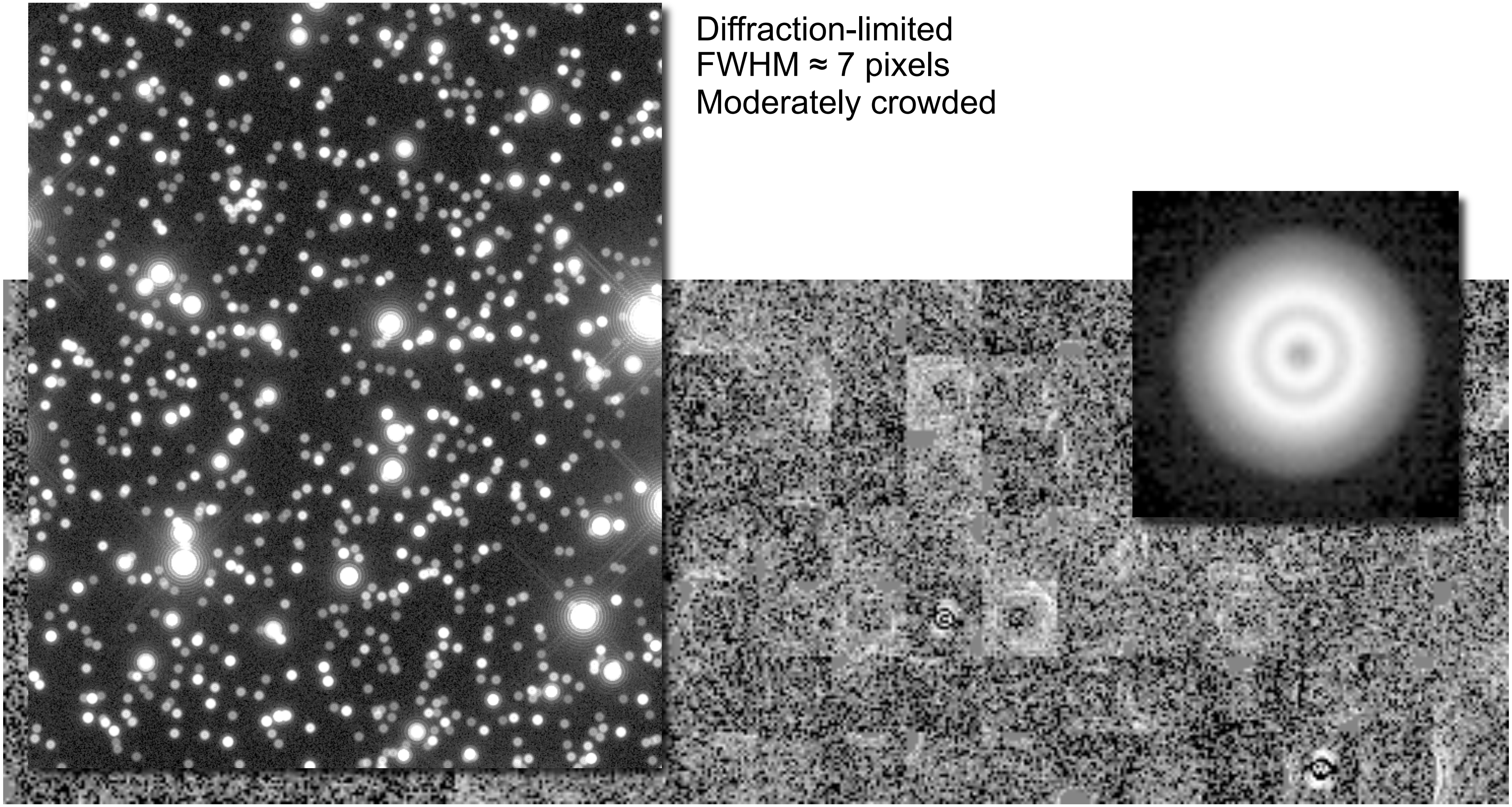
Recovered PSF with simulated, undersampled data

Diffraction-limited
FWHM ≈ 1pixel
Moderately crowded



Simulated, defocused data

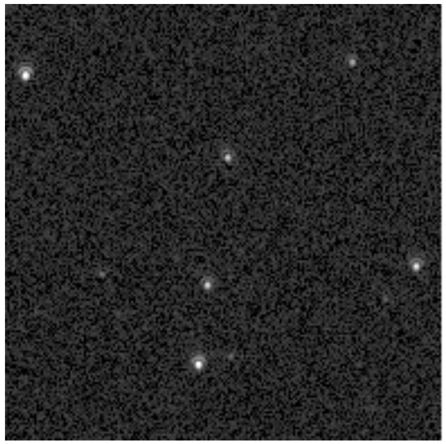
Diffraction-limited
FWHM ≈ 7 pixels
Moderately crowded



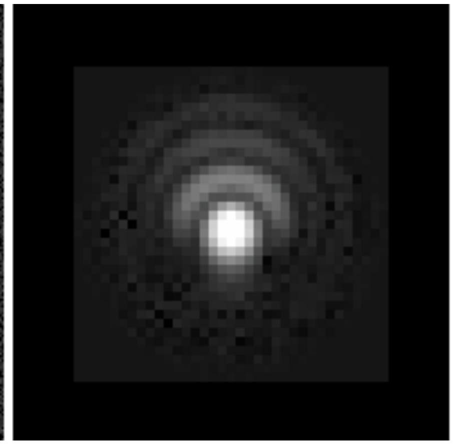
PSFEx

Gauss-Laguerre basis vs pixel basis on simulated images

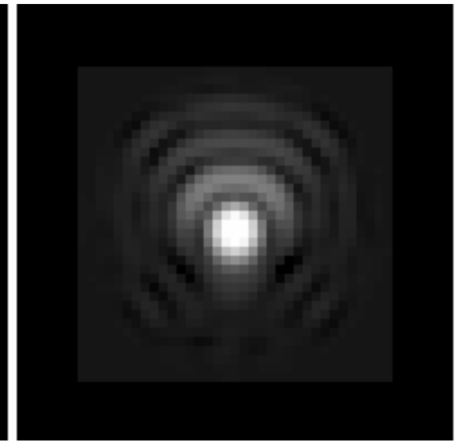
- Except for the simplest PSF profiles, shapelet decomposition does not seem to be more efficient than simple tabulation for precise modeling.
  - Typically a few hundred free parameters required in each case.



Image

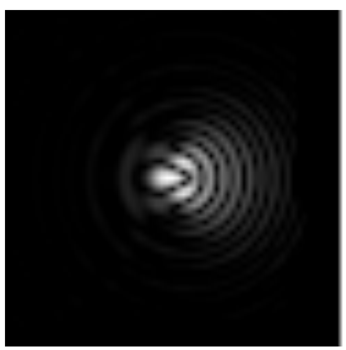


Recovered PSF: pixel basis

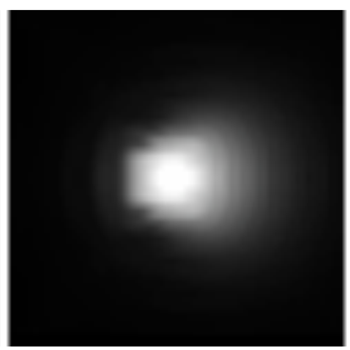


Recovered PSF: shapelet basis

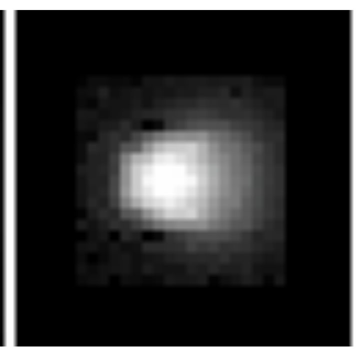
Image



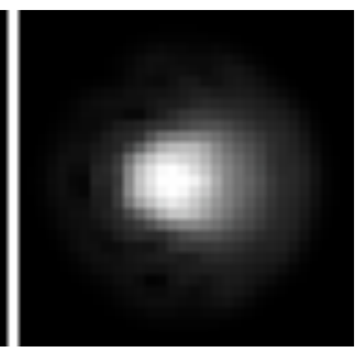
Simulated PSF



Simulated PSF with pixellation



Recovered PSF: pixel basis

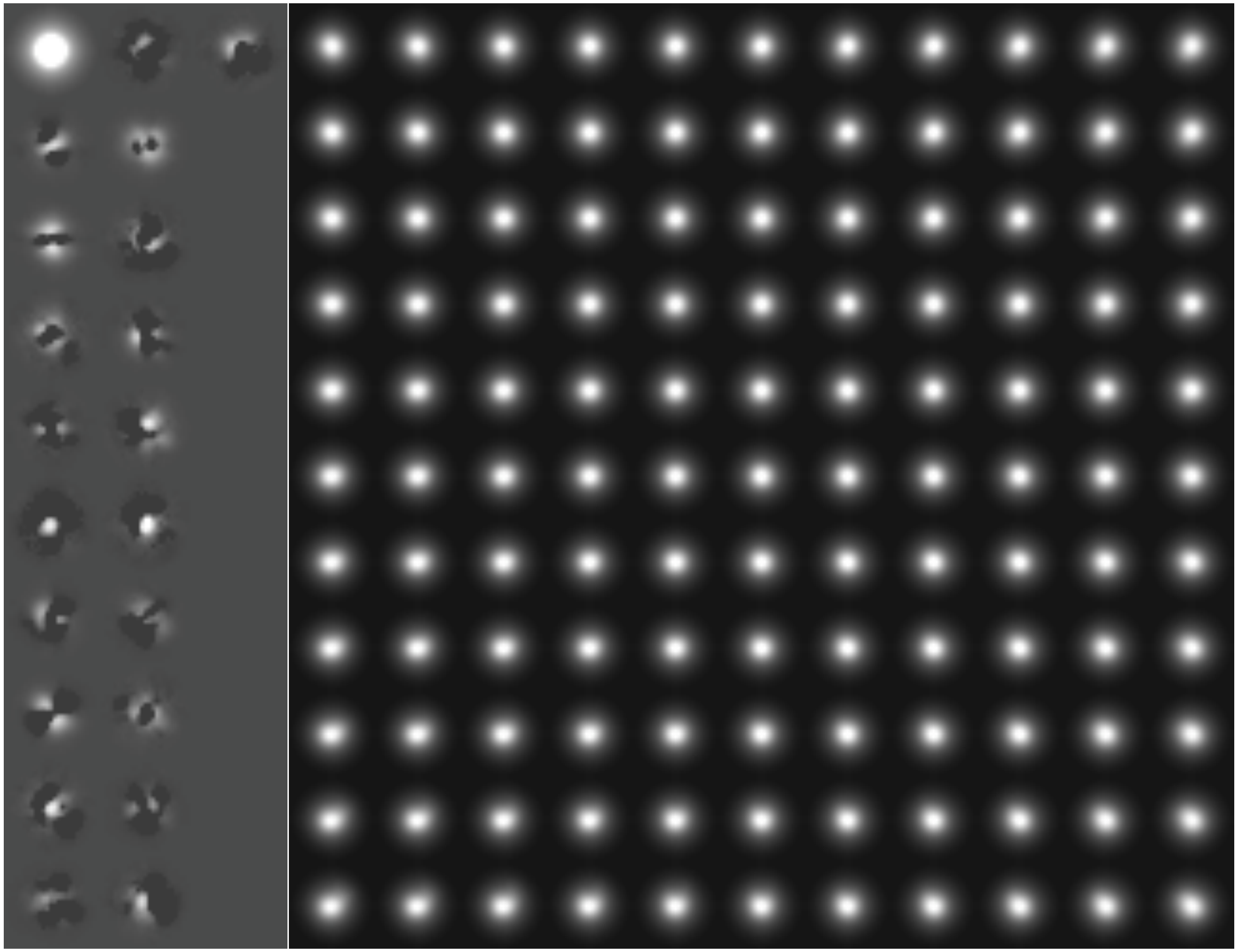


Recovered PSF: shapelet basis

PSFEx

Modelling PSF variations:
Reconstructed MEGACAM average PSF in the i-band

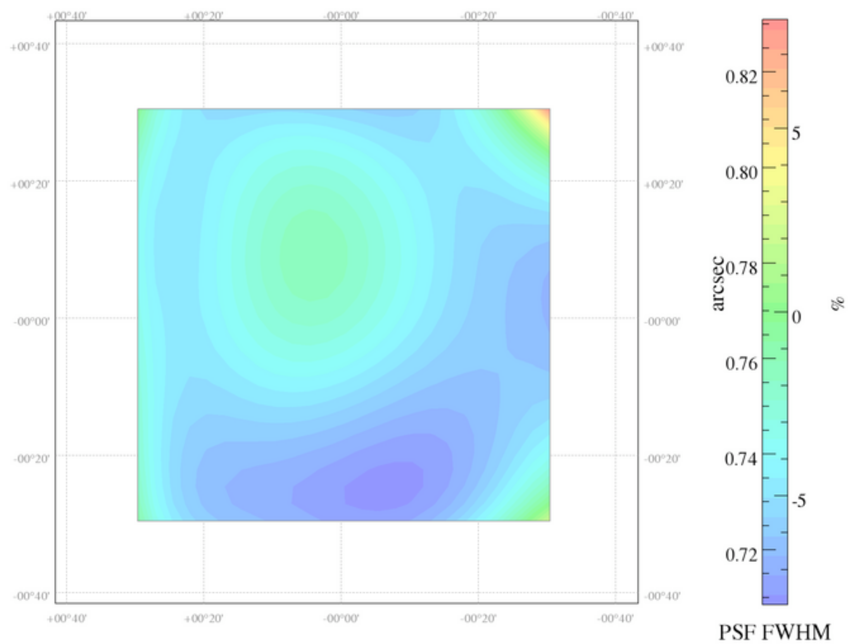
- 5^{th} order polynomial in *x*,*y*: `-PSFVAR_KEYS X_IMAGE,Y_IMAGE -PSFVAR_DEGREES 5`
- Derived from 19,000 point sources
- χ^2/d.o.f. ~ 1.3
- Processing time ~ 100s on a 2GHz processor



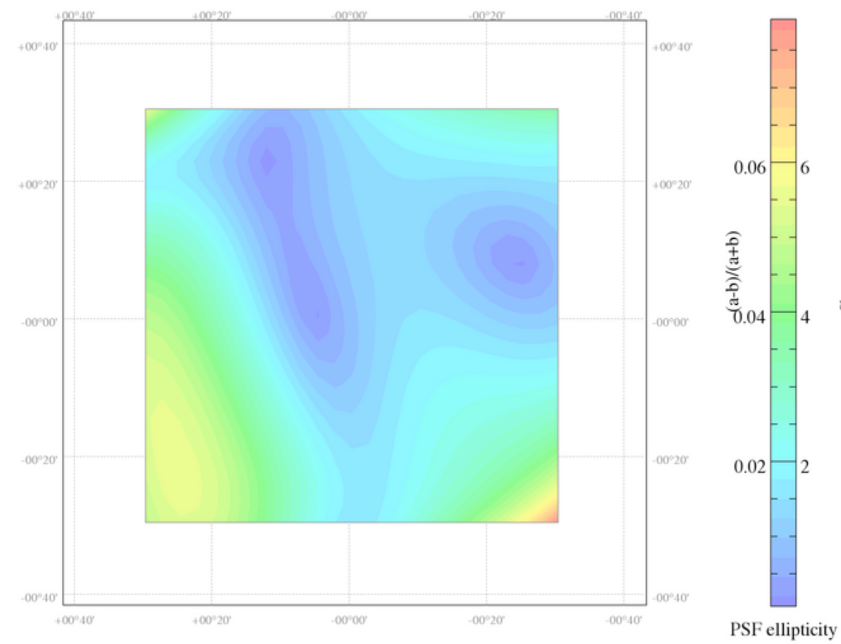
PSFEx

Reconstructed CFHTLS-D1 PSF FWHMs and ellipticities in i

CFHTLS_D-85_i_022559-042940_T0005: FWHM map



CFHTLS_D-85_i_022559-042940_T0005: ellipticity map

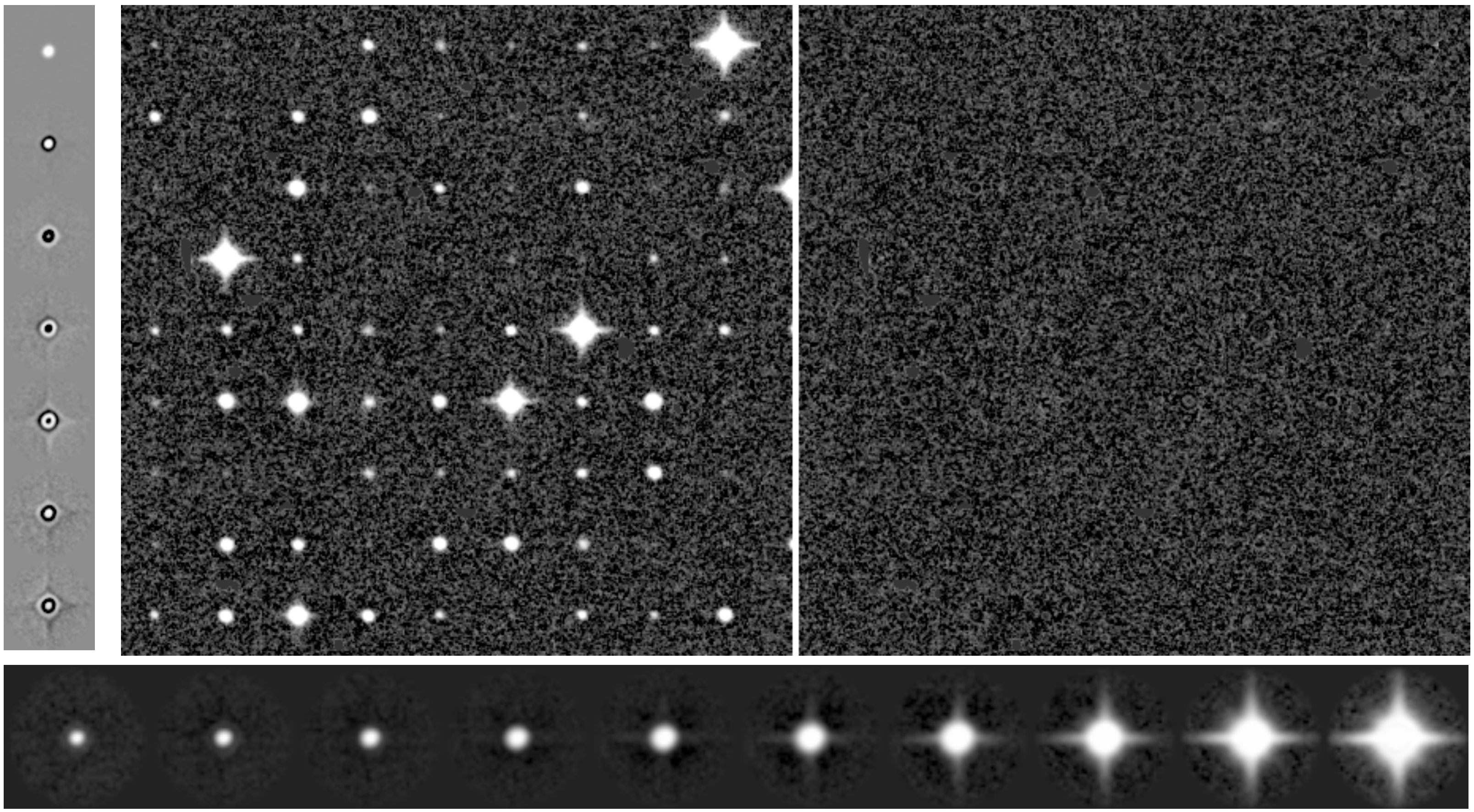


DARK ENERGY SURVEY

PSFEx

Make the PSF depend on other parameters

- 6th order polynomial in MAG_AUTO: `-PSFVAR_KEYS MAG_AUTO -PSFVAR_DEGREES 6`
- 1670 point-sources from the central 4096×4096 pixels of a photographic scan (SERC J #418 survey plate, courtesy of J. Guibert, CAI) FWHM ≈ 3pixel

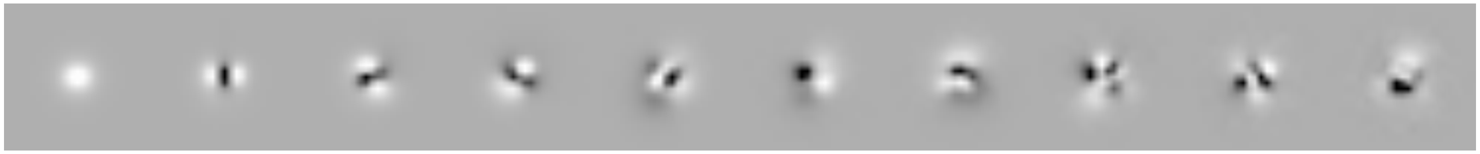


DARK ENERGY SURVEY

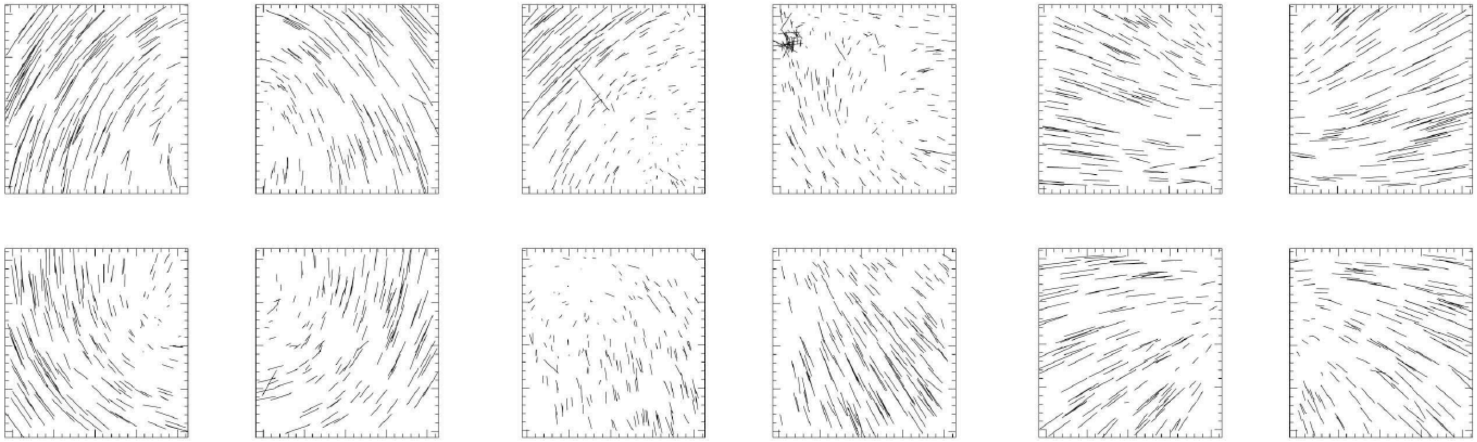
PSFEx

PSF variability mapping: advanced options

- Principal component analyses at the pixel level from PSF model variations: PSFEx offers 2 possibilities (that can be used together)
  - within an image or a series of images: find the image basis with the smallest number of vectors that fits the variable PSF at a given MSE: `-NEWBASIS_TYPE PCA_COMMON`

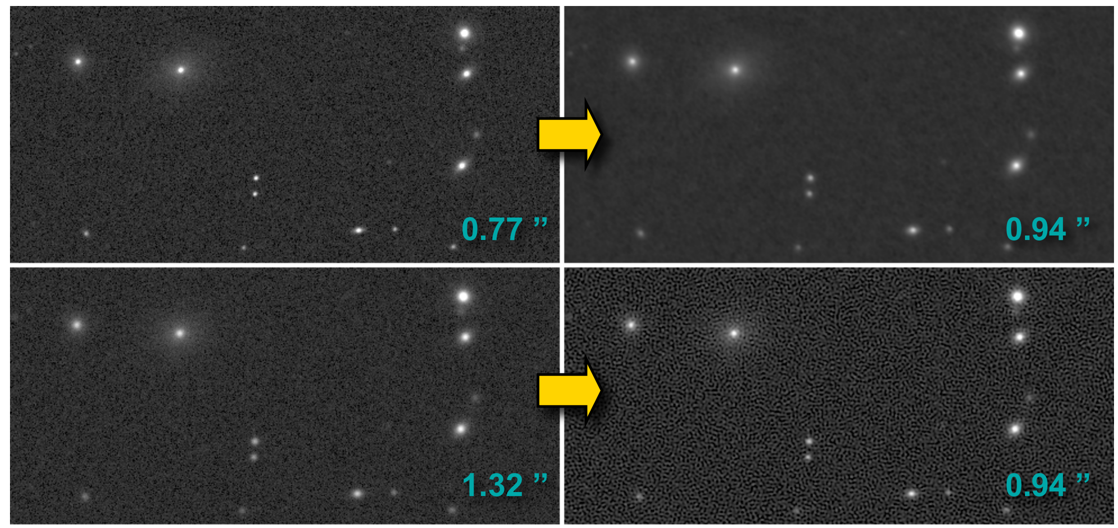


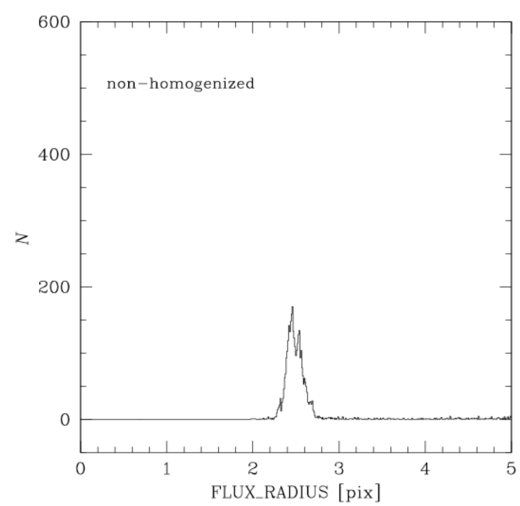
  - trace hidden dependencies of PSF variations from a series of images (Jarvis & Jain 2004); 3 steps:
    1. extract principal components of PSF variations from a series of image to obtain one set of coefficients per image
    2. use the obtained coefficients as part of a polynomial variation model and fit them to the data
    3. reconstruct the PSF model and its variations for each image: `-PSFVAR_KEYS X_IMAGE,Y_IMAGE,HIDDEN1 -PSFVAR_DEGREES 3,2`

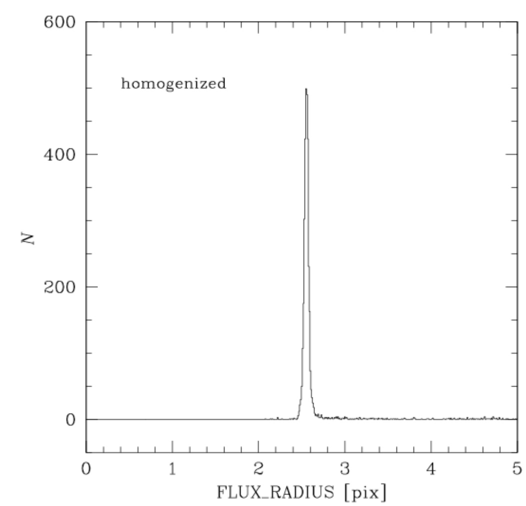


PSF homogenization

- Co-addition: large pointing offsets + small number of exposures create jumps in the PSF at image boundaries
  - ➔ PSF homogenization
    - Bring all images to the same, circular PSF, using the variable PSF models
    - DECam images are expected to be properly sampled
- R&D: Combine exposures with variable image quality
  - "Cheap" alternative to image fusion/Bayesian inference.
  - Impose the target PSF with median seeing to minimize noise correlation
  - Handle noise correlations on arcsec scales
  - Masking of artifacts is important







Darnell et al. 2009

PSFEx

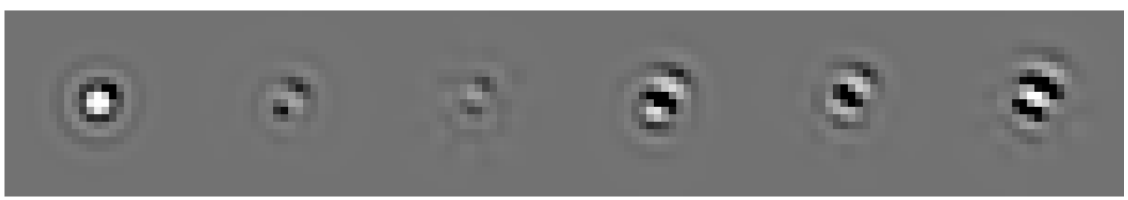
PSF homogenization: making the kernel

- We seek a convolution kernel $\boldsymbol{\kappa}(\boldsymbol{x})$ which, when applied to the model PSF, minimizes (in the χ^2 sense) the difference with a target PSF.

$$\psi' = \sum_l Y_l(x_i)\,\kappa_l * \psi(x_i) \quad \forall i$$

  - Gauss-Laguerre basis has interesting "self-regularizing" properties (Alard and Lupton 1998)
  - kernel variations handled as polynomial in *x* and *y*.
- Kernel components are saved as a FITS datacube
- All computations done are in PSFEx (`-HOMOBASIS_TYPE GAUSS-LAGUERRE` option)

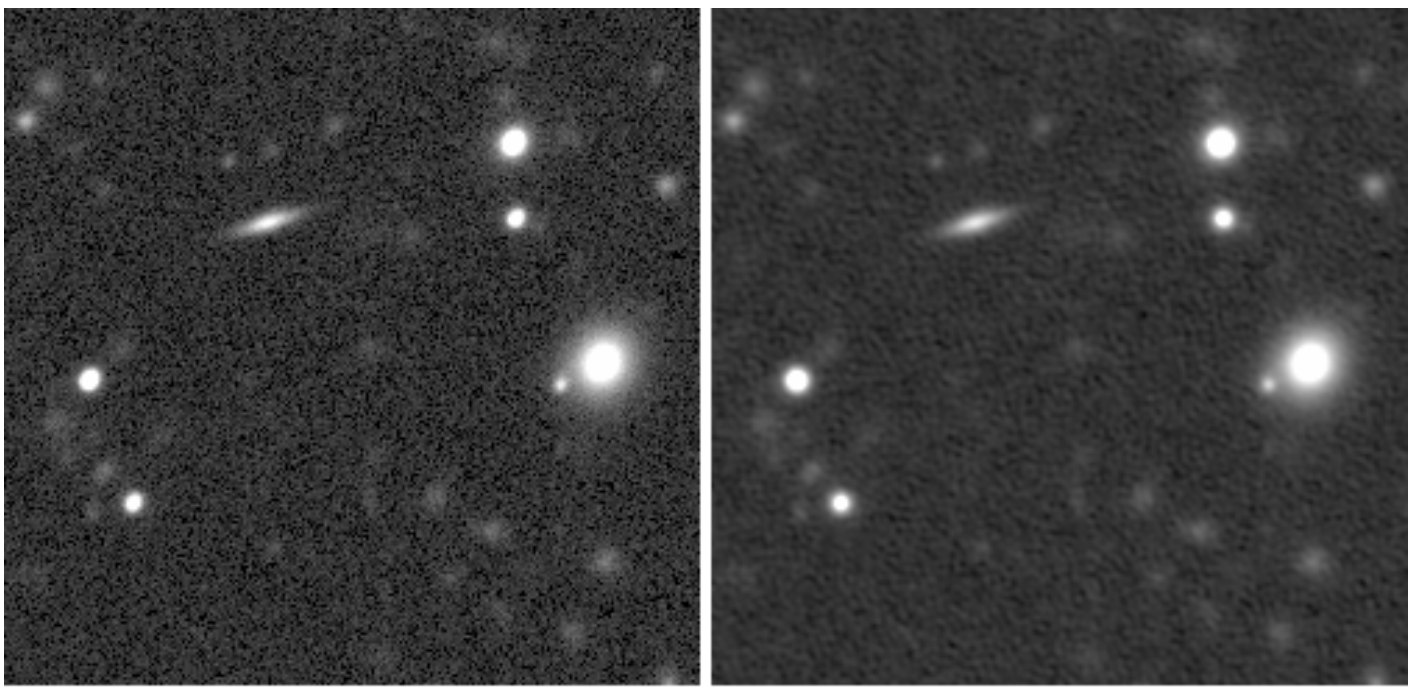
ψ_a'



$Y_l =$ $cste$ x x^2 y yx y^2

PSF homogenization: applying the kernel

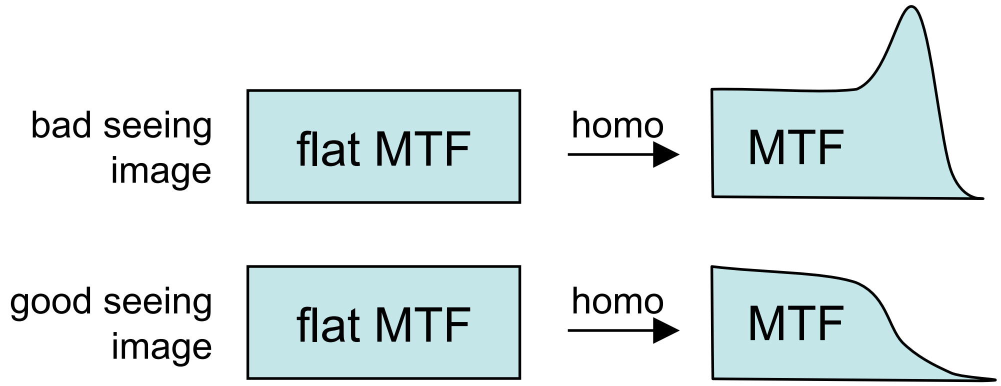
- Individual kernel components are convolved with the input image, multiplied by the corresponding polynomial term, and summed (**psfnormalize** program by Tony Darnell).
  - Very fast; convolutions done using parallelized FFTs.
  - PSF variations are assumed to be negligible on the scale of the PSF

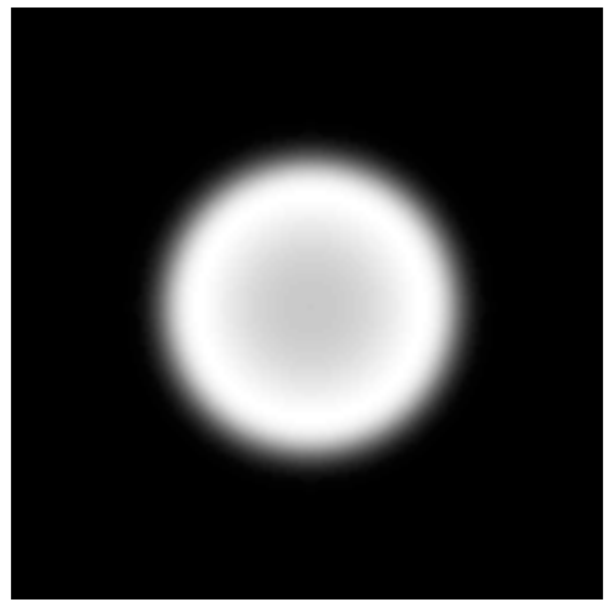


PSFEx

Noise and image weighting issues for coaddition

- Homogenized bad seeing images exhibit increased noise in a narrow spatial frequency range
  - Unweighted coaddition: S/N decreased at high frequencies because of noise contribution from bad seeing images
  - Simple weighted coaddition: S/N decreased at low frequencies because of the reduced contribution from bad seeing images
  - Multiband weighting (E.Nielsen): 2 bands might be enough

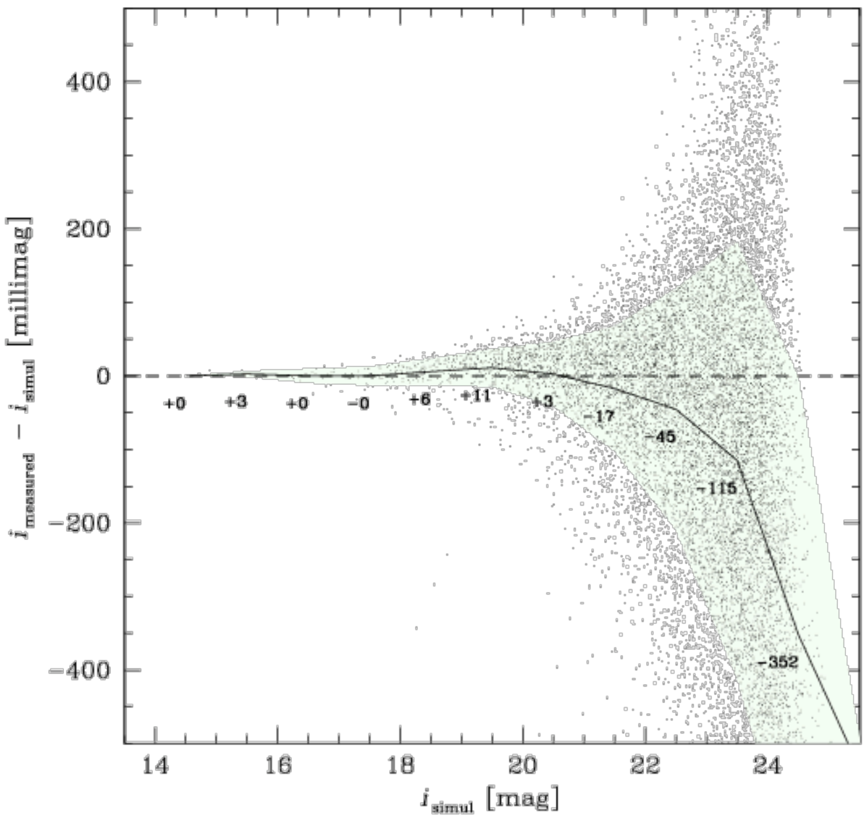


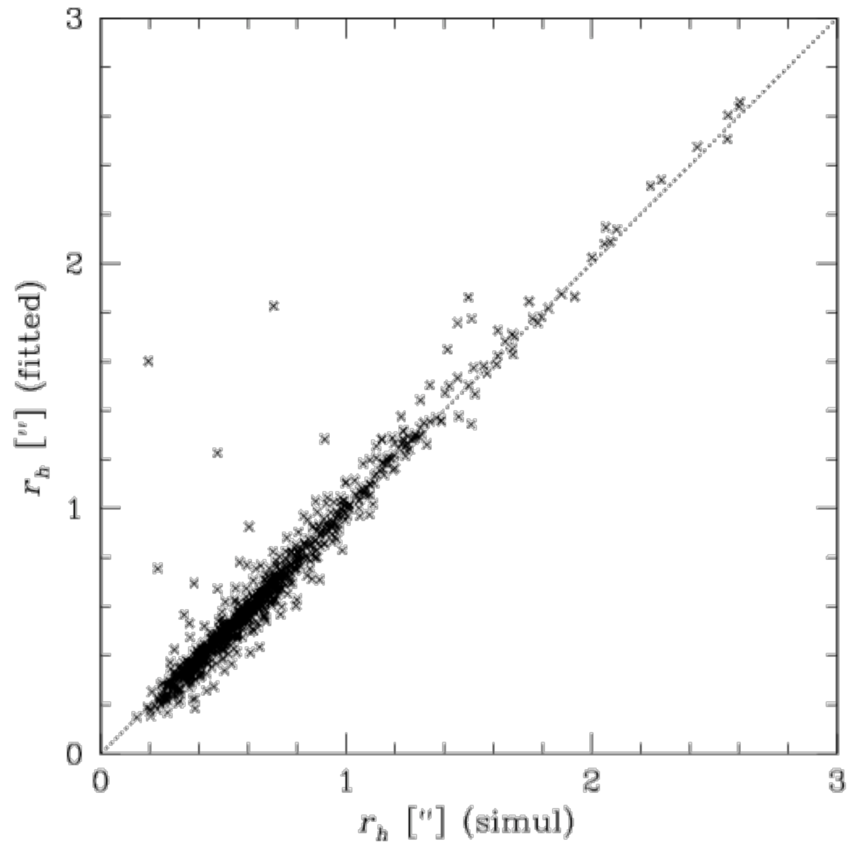


PSFEx

Galaxy measurements on homogenized simulations

Stack of 16 homogenized exposures with 0.65”<FWHM<1.3” (including ≈0.5 ” coma)





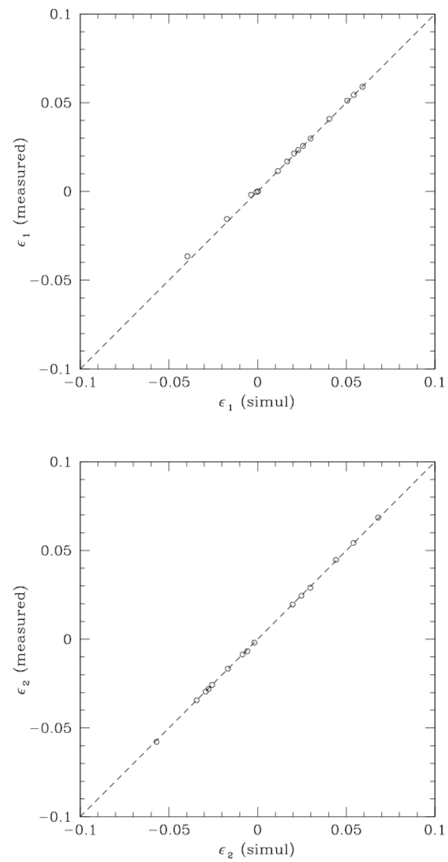
Asymptotic magnitude

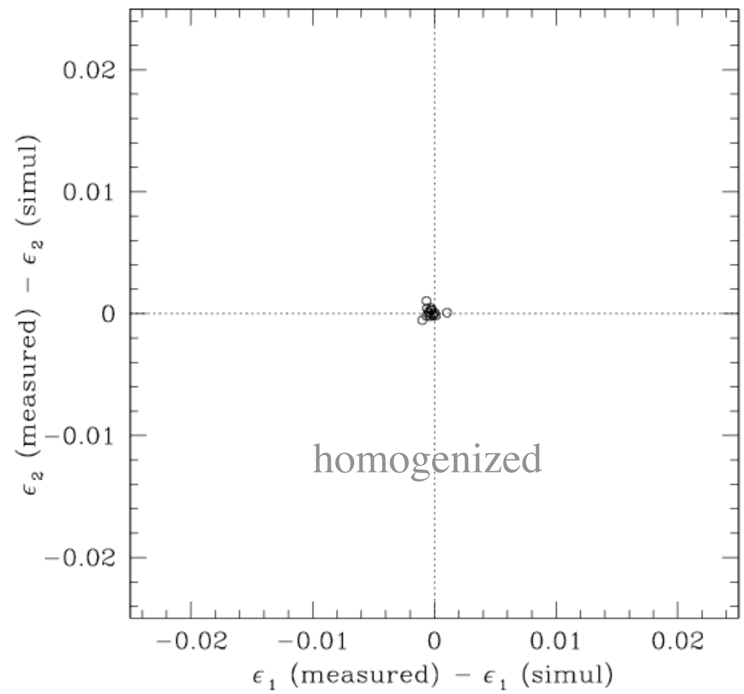
Sersic+Exponential fit

Disk scalelength (i<21)

PSF modeling and galaxy model-fitting

- Accurate enough for shear measurements?
  - Shear recovery test on Great'08 challenge data (LowNoise sample) on both homogenized and non-homogenized versions
    - |Δ**e**|<0.0005



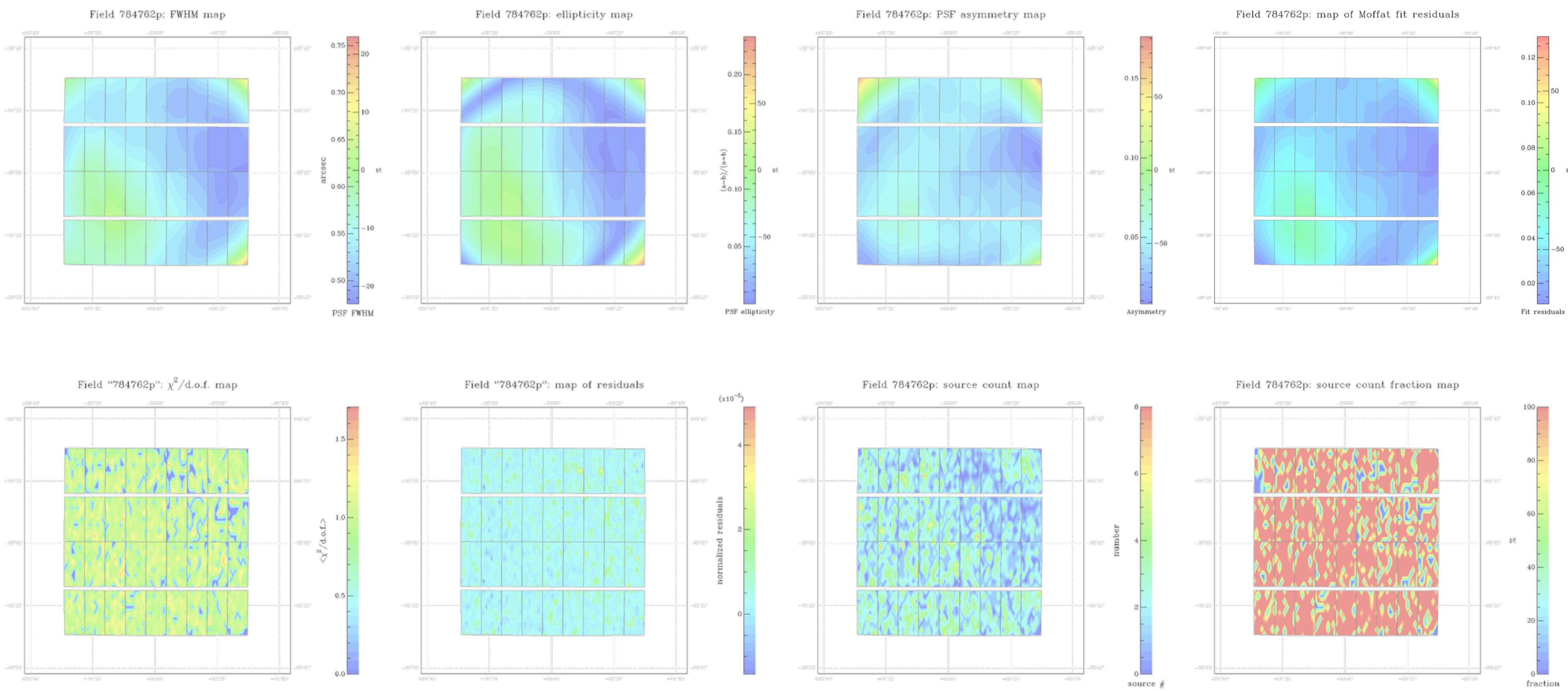


PSFEx

Built-in quality control and metadata

- PSFEx runs a variety of diagnostics
  - Various 2D histograms are produced
  - Numbers are written to a metadata file in XML-VOTable format at the end of each run.
    - An XSLT stylesheet that translates to HTML comes with the PSFEx package.
    - High level libraries such as vo.table for Python can be used to parse the VOTable
      - there are a few stability and compliancy issues (can easily be fixed)
    - More information at Astromatic.net

Built-in quality control (cont.)



PSFEx

Pending issues and future improvements

- Need to tune up the level of wings in the target PSF (Moffat beta parameter)
  - Depends on the details of the real average PSF
- Improve image weighting
- Dealing with undersampled images?
- Fit star residuals instead of rejecting them!
  - Useful in crowded fields
- Offer more customizable basis functions to describe PSF variations