

Enabling Early Rubin Science with Robust Cross-Matches in the Crowded LSST Sky

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Photometric Observations

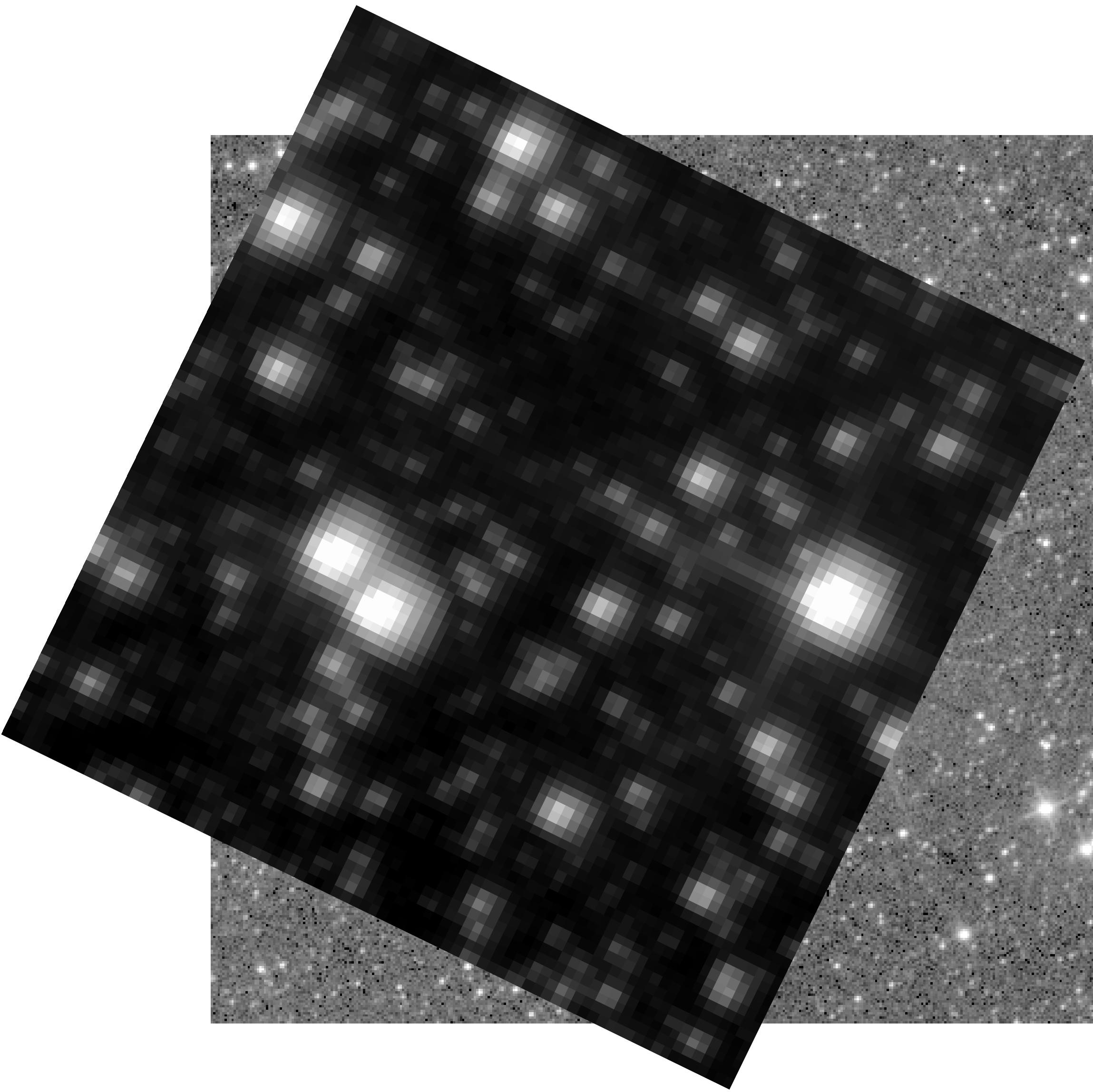


WISE - Wright et al. (2010)

WISE W1

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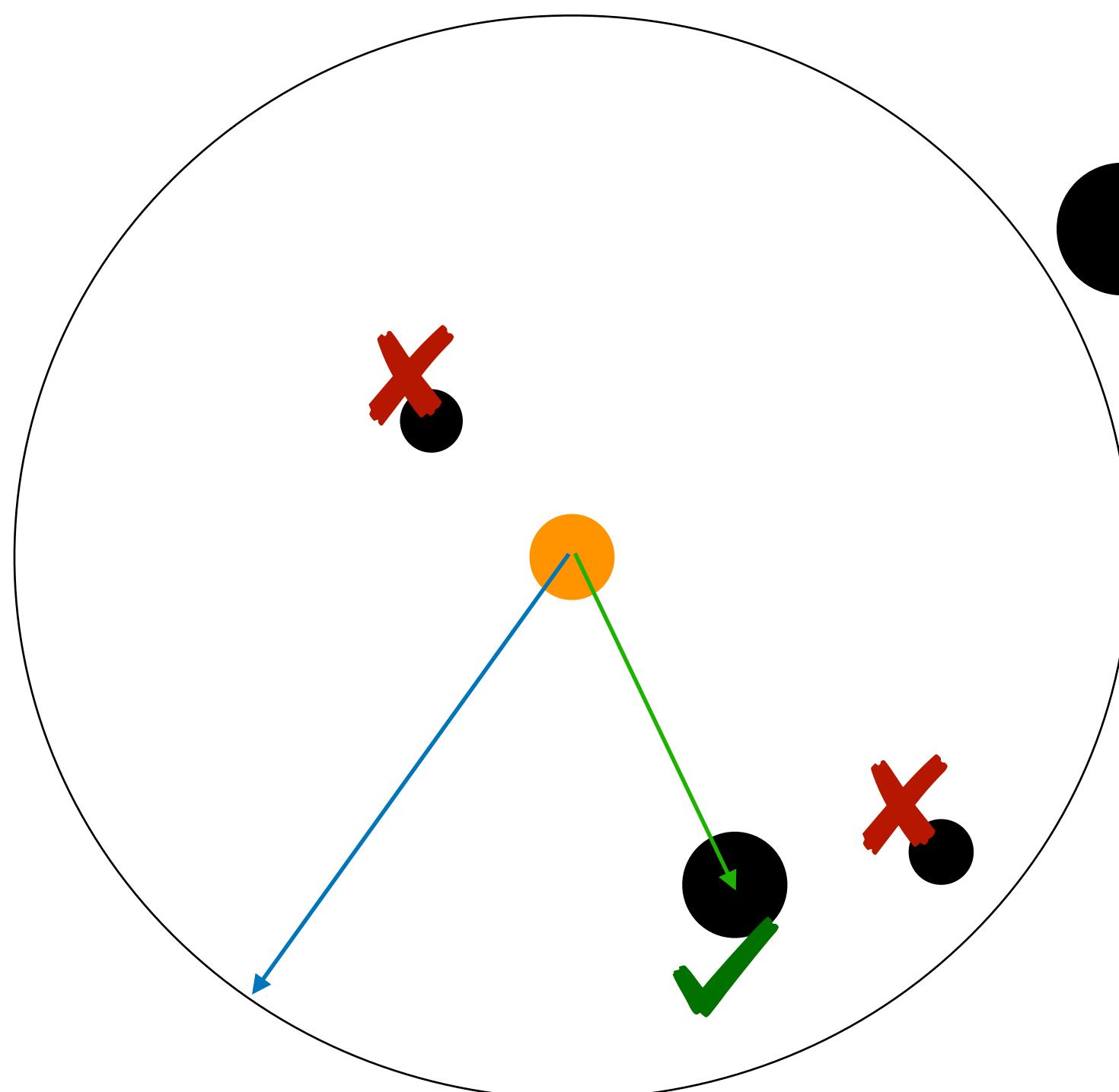
Photometric Observations



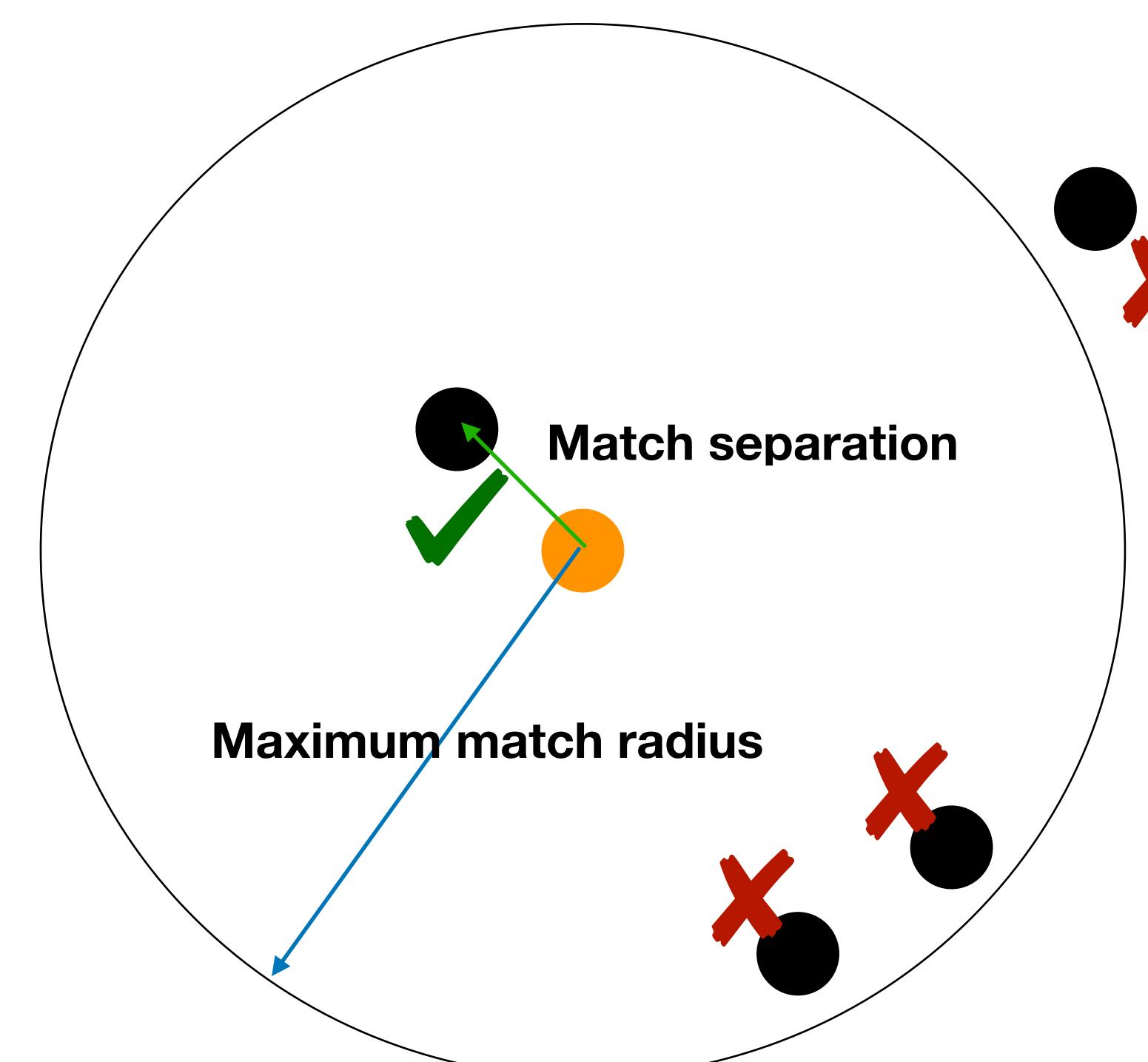
WISE - Wright et al. (2010)
TESS - Ricker et al. (2015)

TESS T
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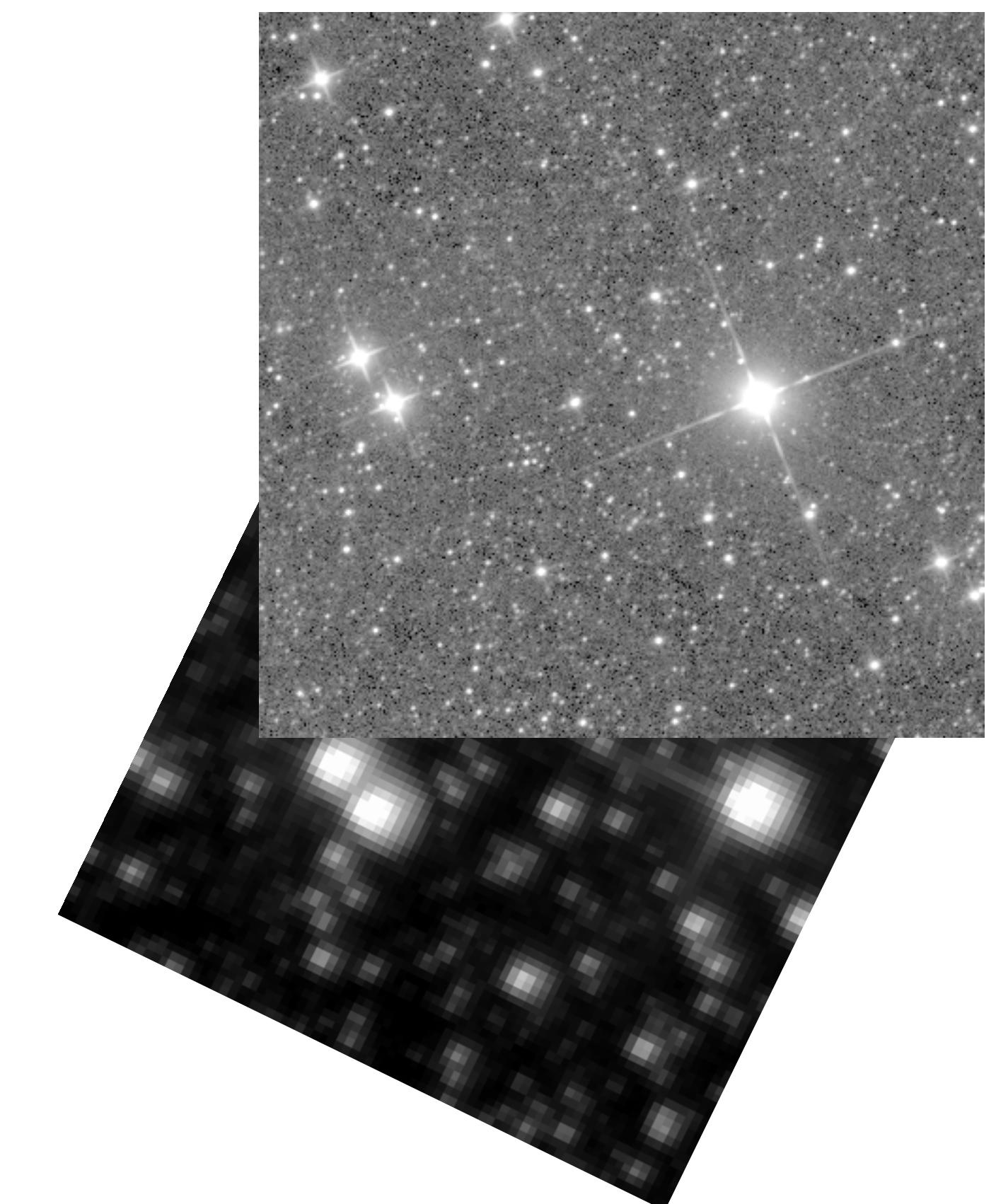
“Traditional”/“Simple” Cross-Matching



Declination / degrees

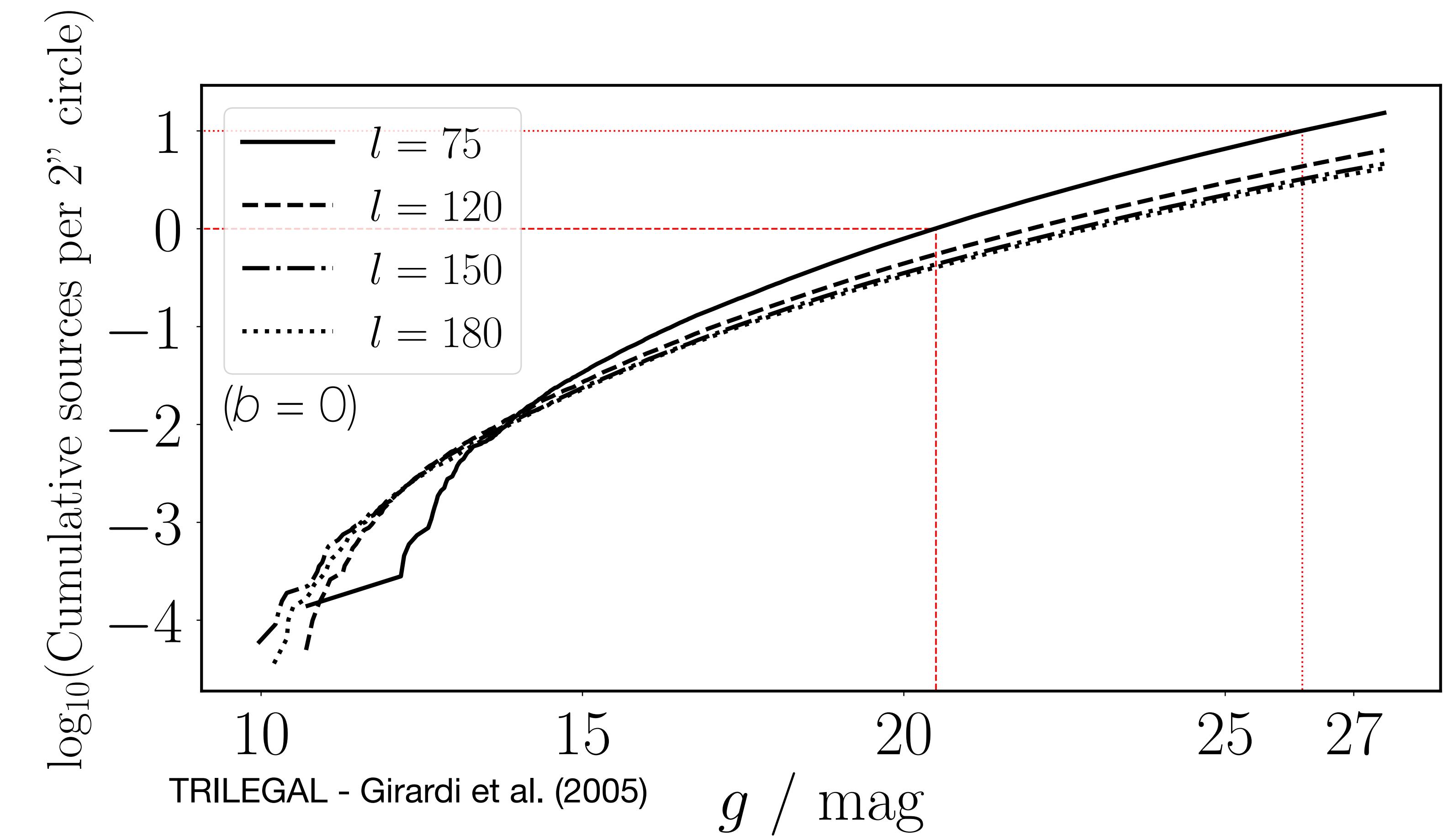
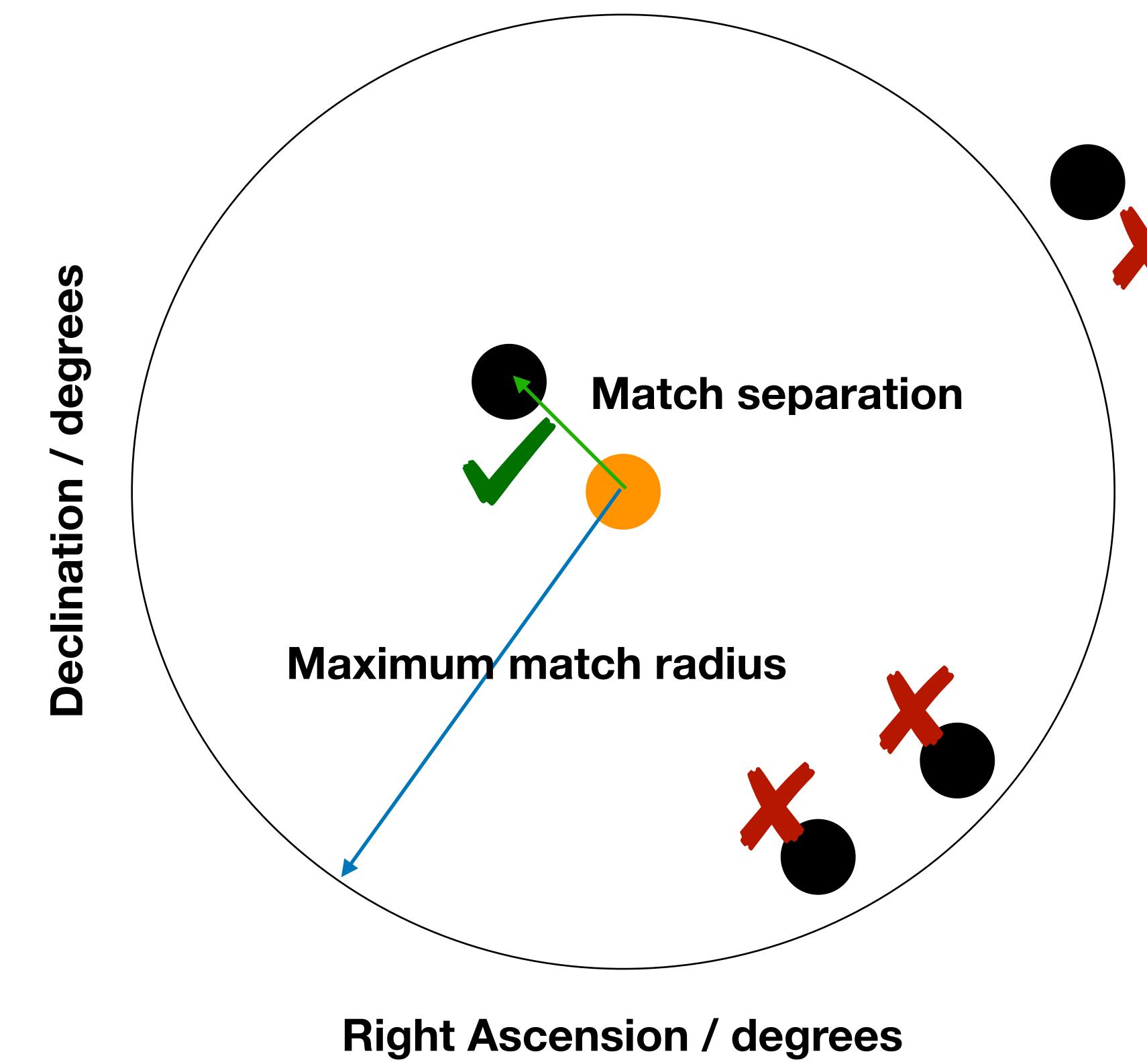


Right Ascension / degrees

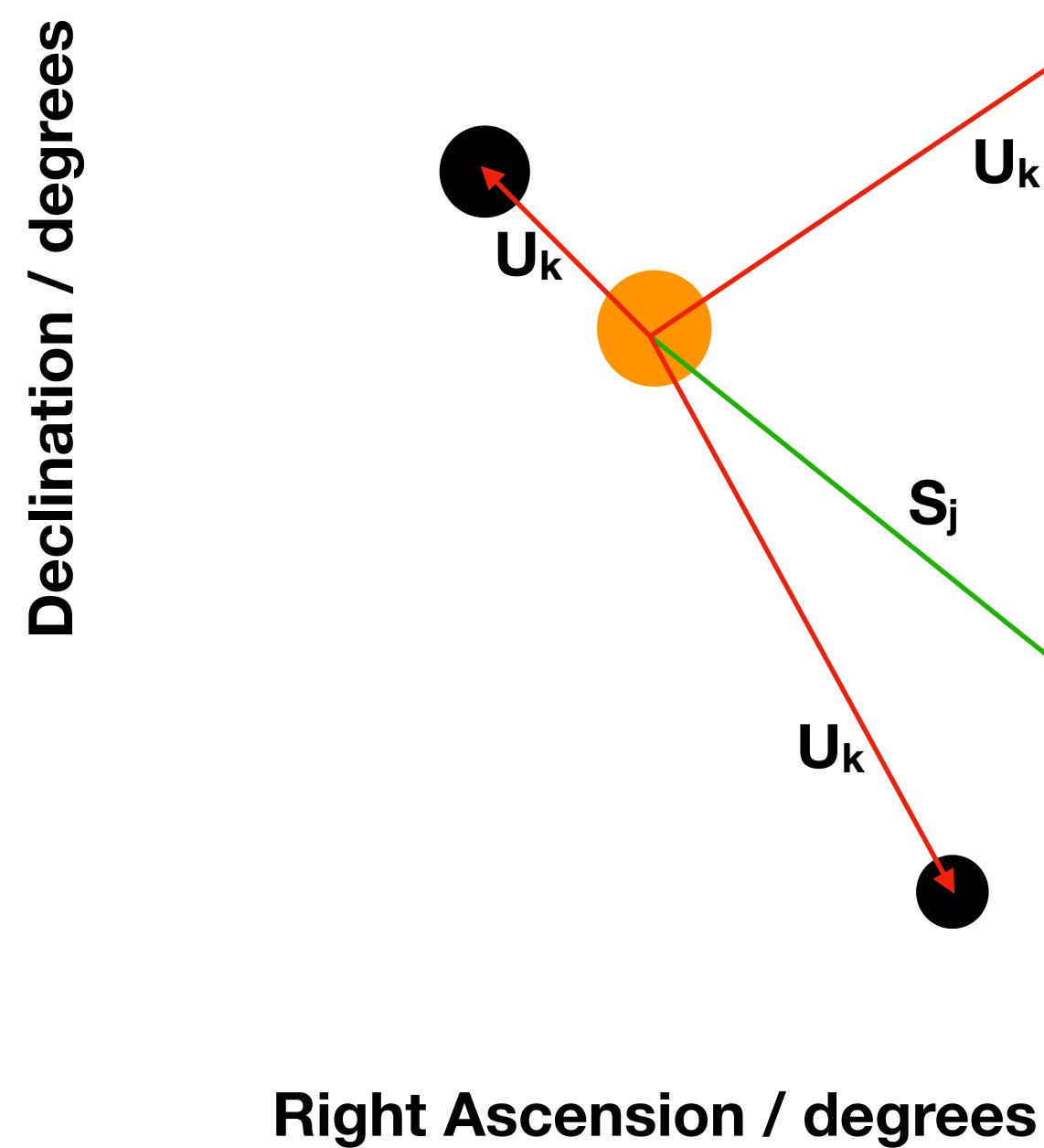


The Problem With Rubin Obs.'s LSST

**Nearest neighbour/
proximity matching**



Probabilistic Cross-Matching



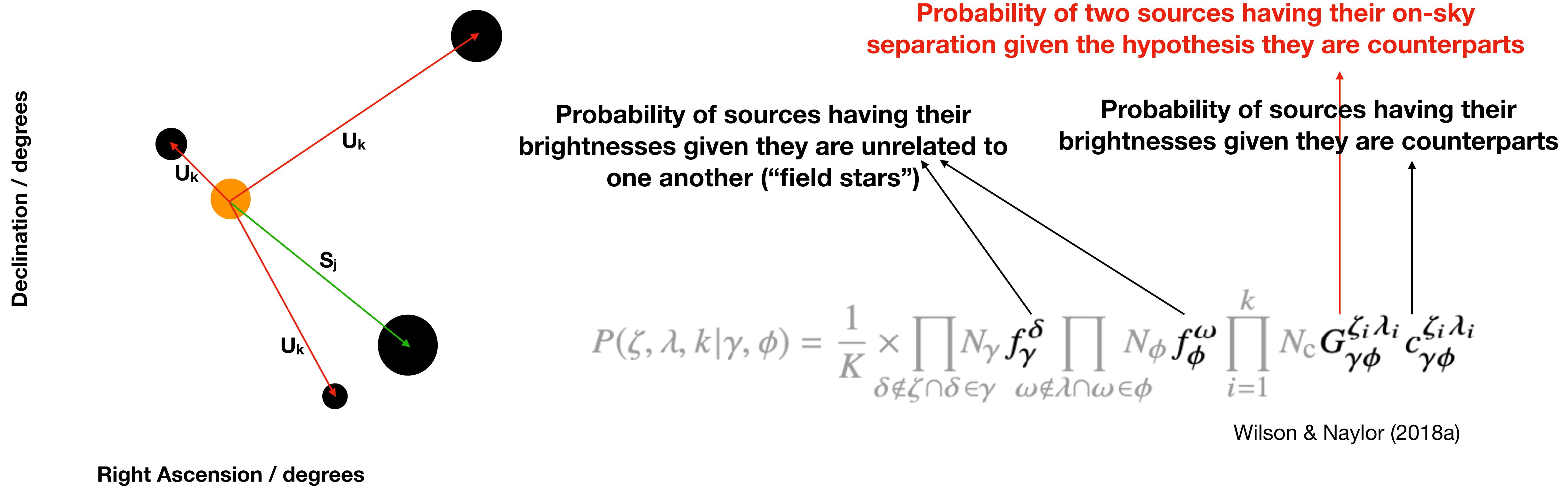
$$R_j = \frac{\Pr\left[S_j \cap \left(\bigcap_{k \neq j} U_k\right) \cap \left(\bigcap_{k'} E_{k'}\right)\right]}{\sum_i \Pr\left[S_i \cap \left(\bigcap_{k \neq i} U_k\right) \cap \left(\bigcap_{k'} E_{k'}\right)\right] + \Pr\left[(m_s > m_{\text{lim}}) \cap \left(\bigcap_k U_k\right) \cap \left(\bigcap_{k'} E_{k'}\right)\right]} = \frac{\frac{q(m, c) f(x, y)}{n(m, c)}}{\sum_i L_i + (1 - Q)} = \frac{L}{L_j}$$

Sutherland & Saunders (1992)

$$P(\zeta, \lambda, k | \gamma, \phi) = \frac{1}{K} \times \prod_{\delta \notin \zeta \cap \delta \in \gamma} N_\gamma f_\gamma^\delta \prod_{\omega \notin \lambda \cap \omega \in \phi} N_\phi f_\phi^\omega \prod_{i=1}^k N_c G_{\gamma\phi}^{\zeta_i \lambda_i} c_{\gamma\phi}^{\zeta_i \lambda_i}$$

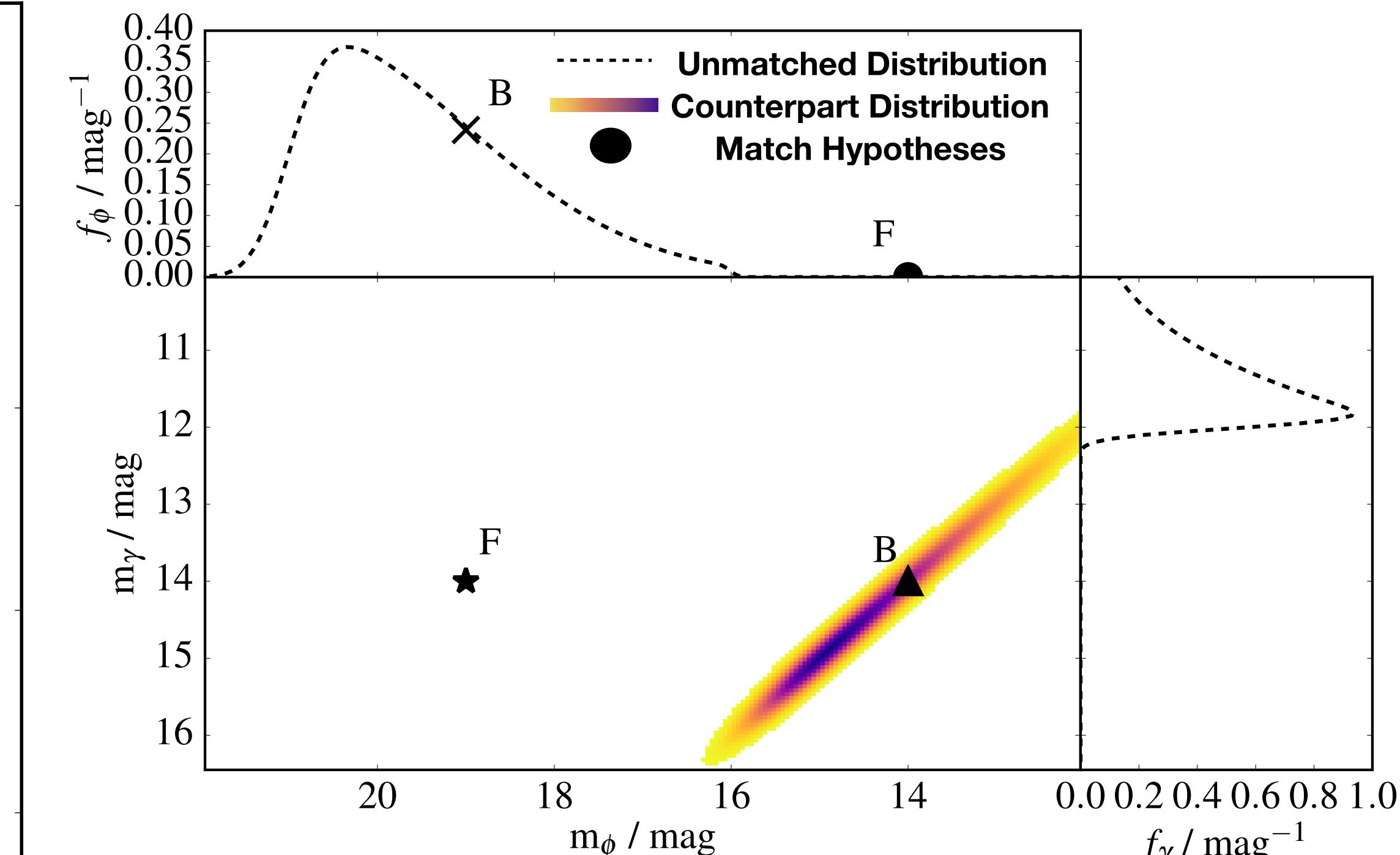
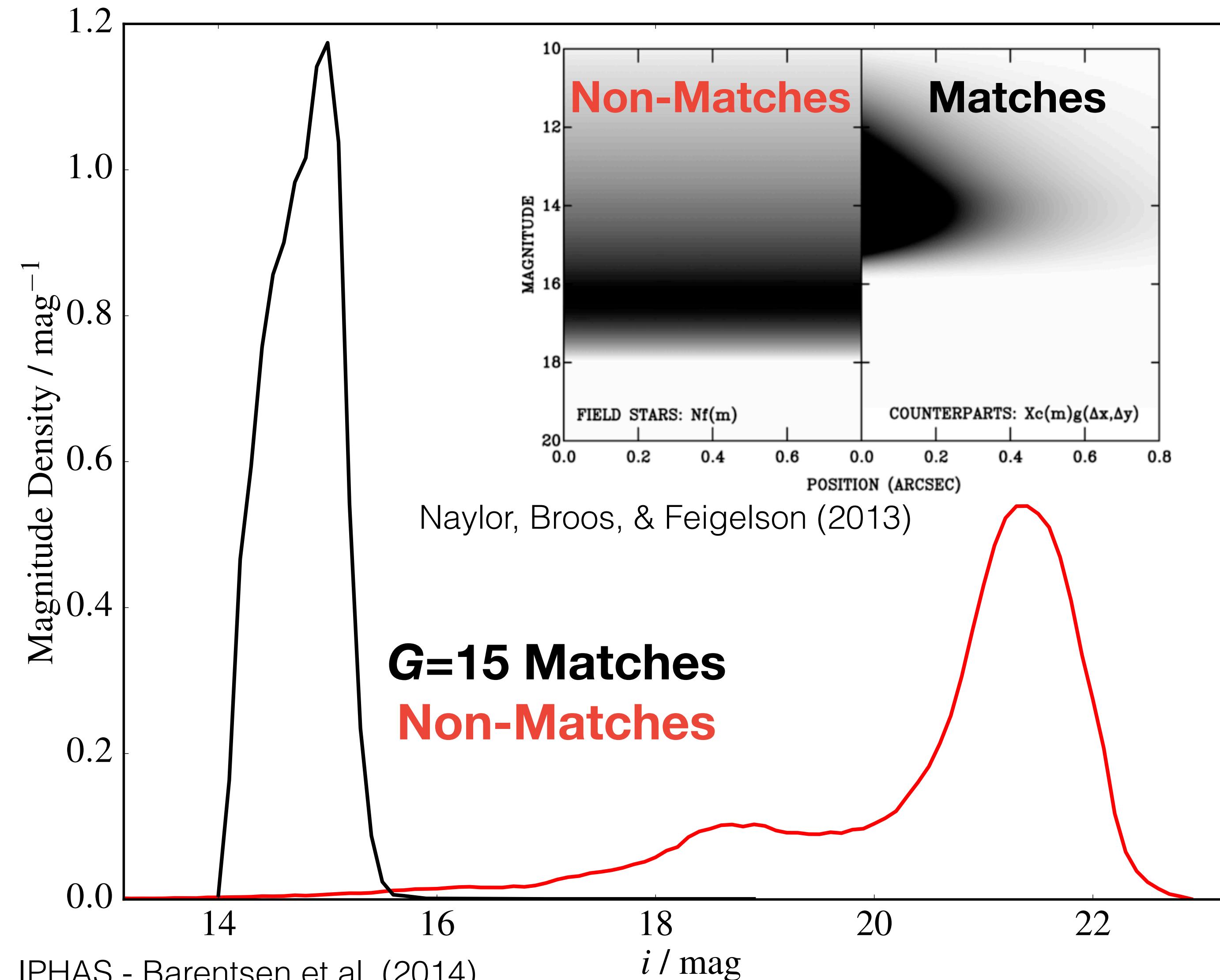
Wilson & Naylor (2018a)

Probabilistic Cross-Matching



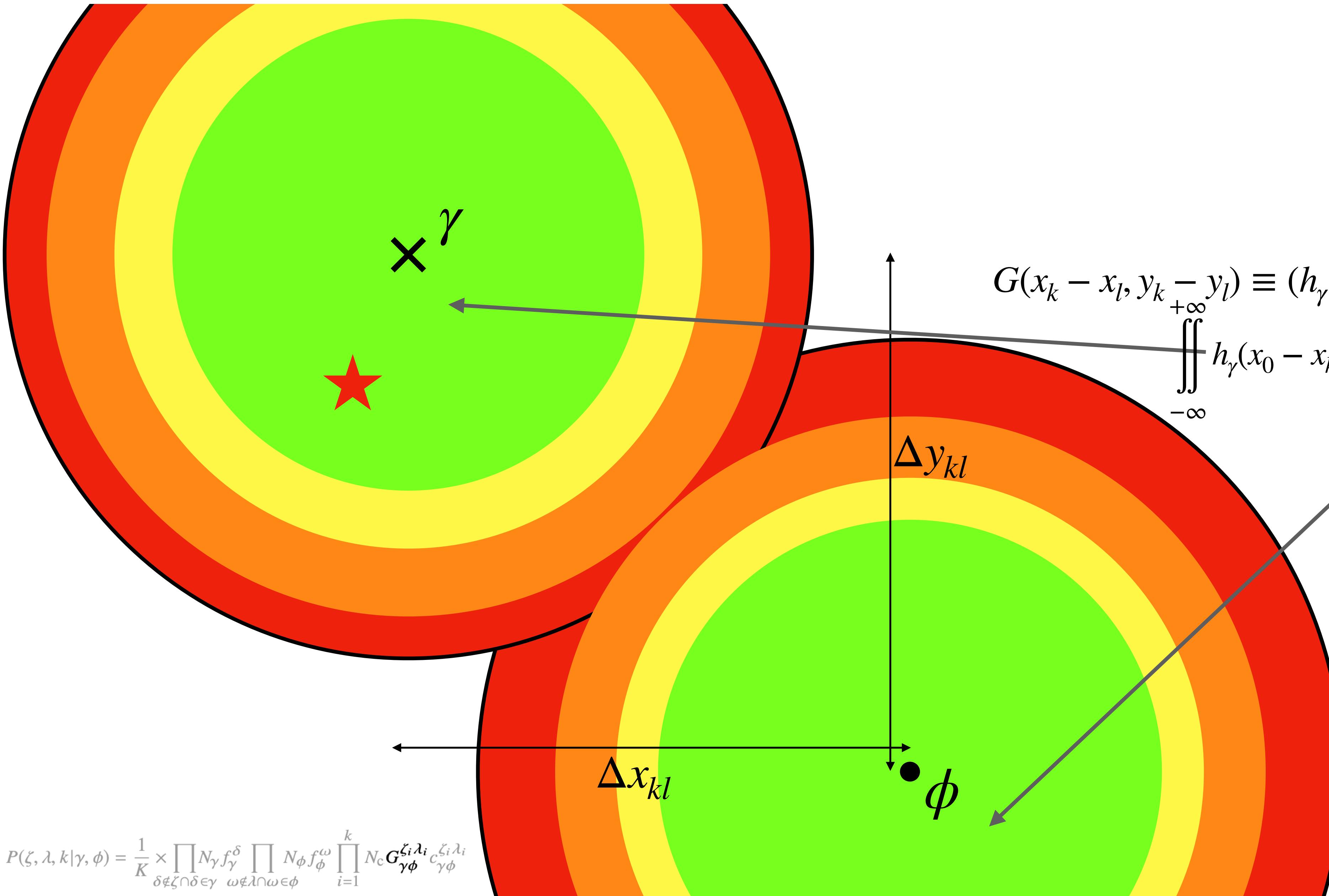
Including Magnitude Information

$$P(\zeta, \lambda, k | \gamma, \phi) = \frac{1}{K} \times \prod_{\delta \notin \zeta \cap \delta \in \gamma} N_\gamma f_\gamma^\delta \prod_{\omega \notin \lambda \cap \omega \in \phi} N_\phi f_\phi^\omega \prod_{i=1}^k N_c G_{\gamma\phi}^{\zeta_i \lambda_i} c_{\gamma\phi}^{\zeta_i \lambda_i}$$



The photometry-based likelihoods (c and f) allow us to reject some matches in crowded fields, but now we need the position-based likelihood G

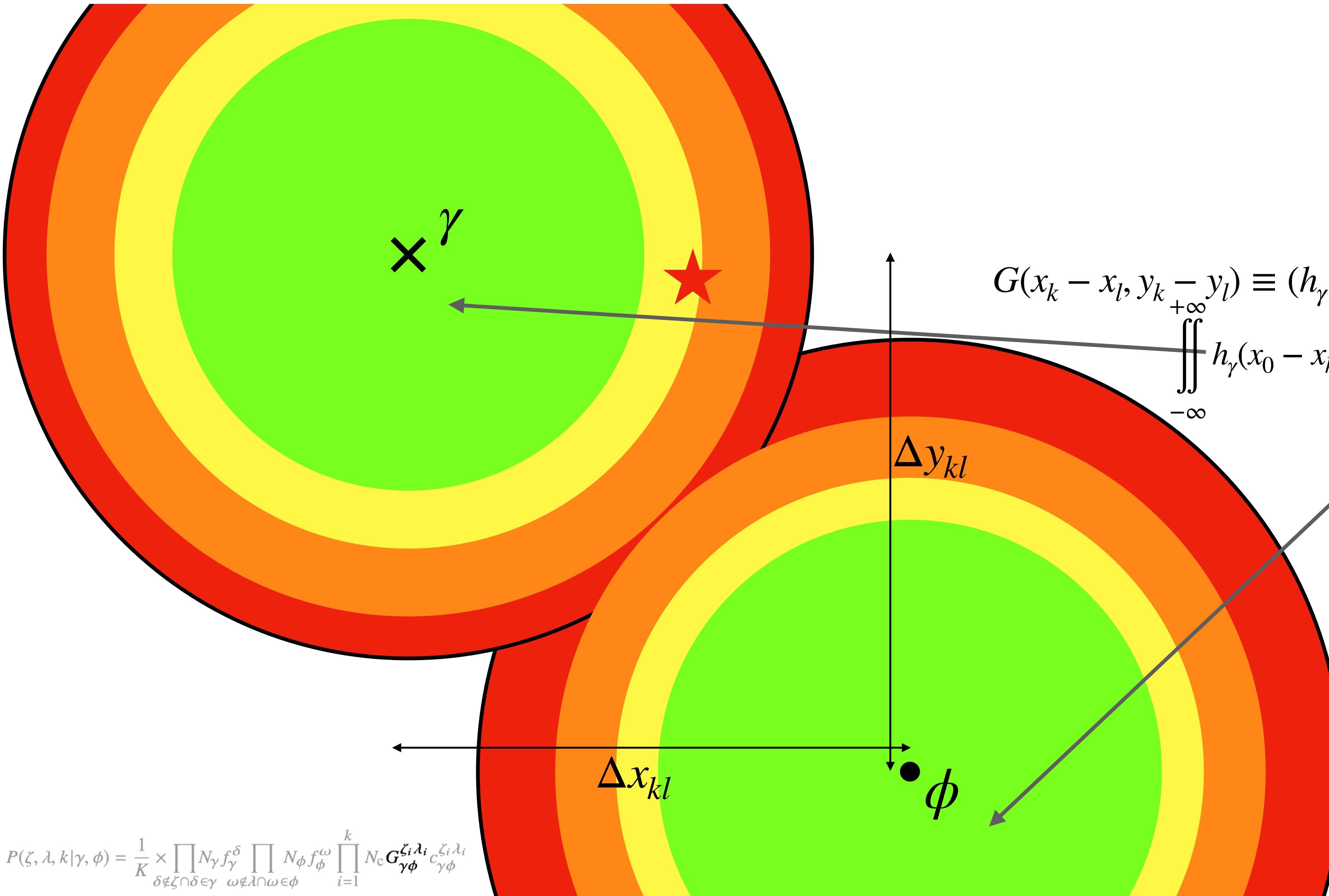
Match Separation Probability



$$G(x_k - x_l, y_k - y_l) \equiv (h_\gamma * h_\phi)(\Delta x_{kl}, \Delta y_{kl}) =$$
$$\iint_{-\infty}^{+\infty} h_\gamma(x_0 - x_k, y_0 - y_k) h_\phi(x_l - x_0, y_l - y_0) dx_0 dy_0$$

Wilson & Naylor (2018a)

Match Separation Probability



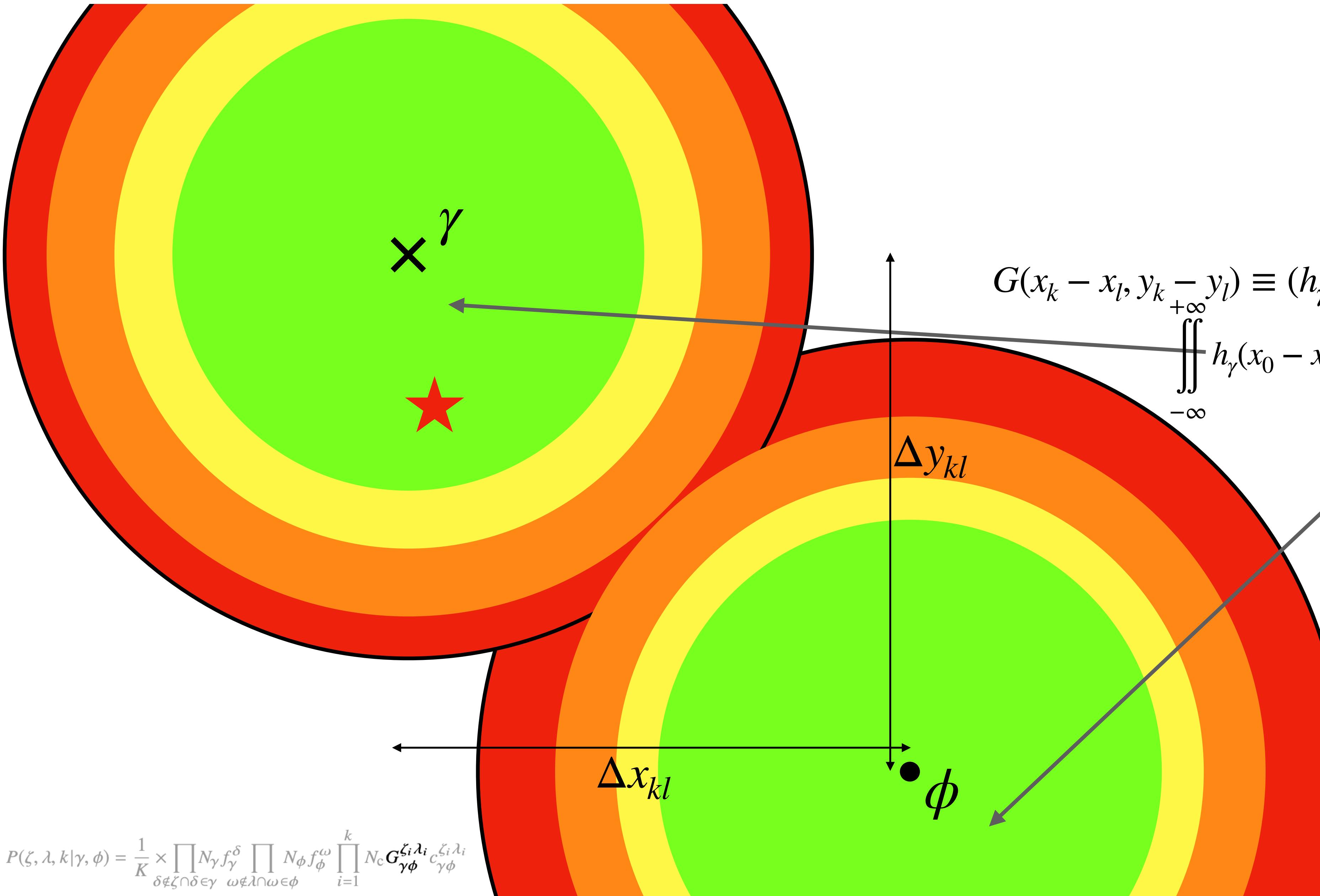
$$G(x_k - x_l, y_k - y_l) \equiv (h_\gamma * h_\phi)(\Delta x_{kl}, \Delta y_{kl}) = \iint_{-\infty}^{+\infty} h_\gamma(x_0 - x_k, y_0 - y_k) h_\phi(x_l - x_0, y_l - y_0) dx_0 dy_0$$

Wilson & Naylor (2018a)

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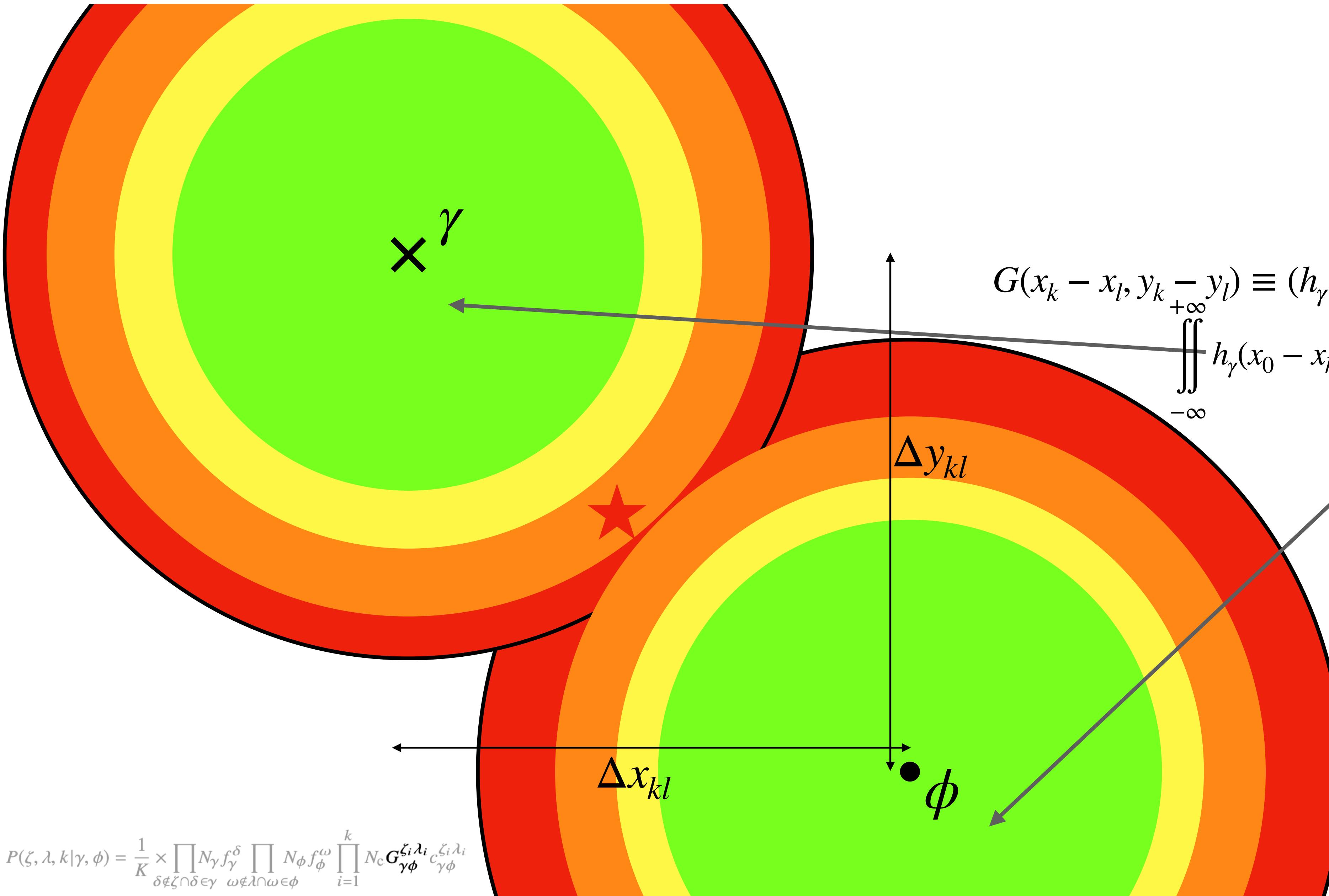
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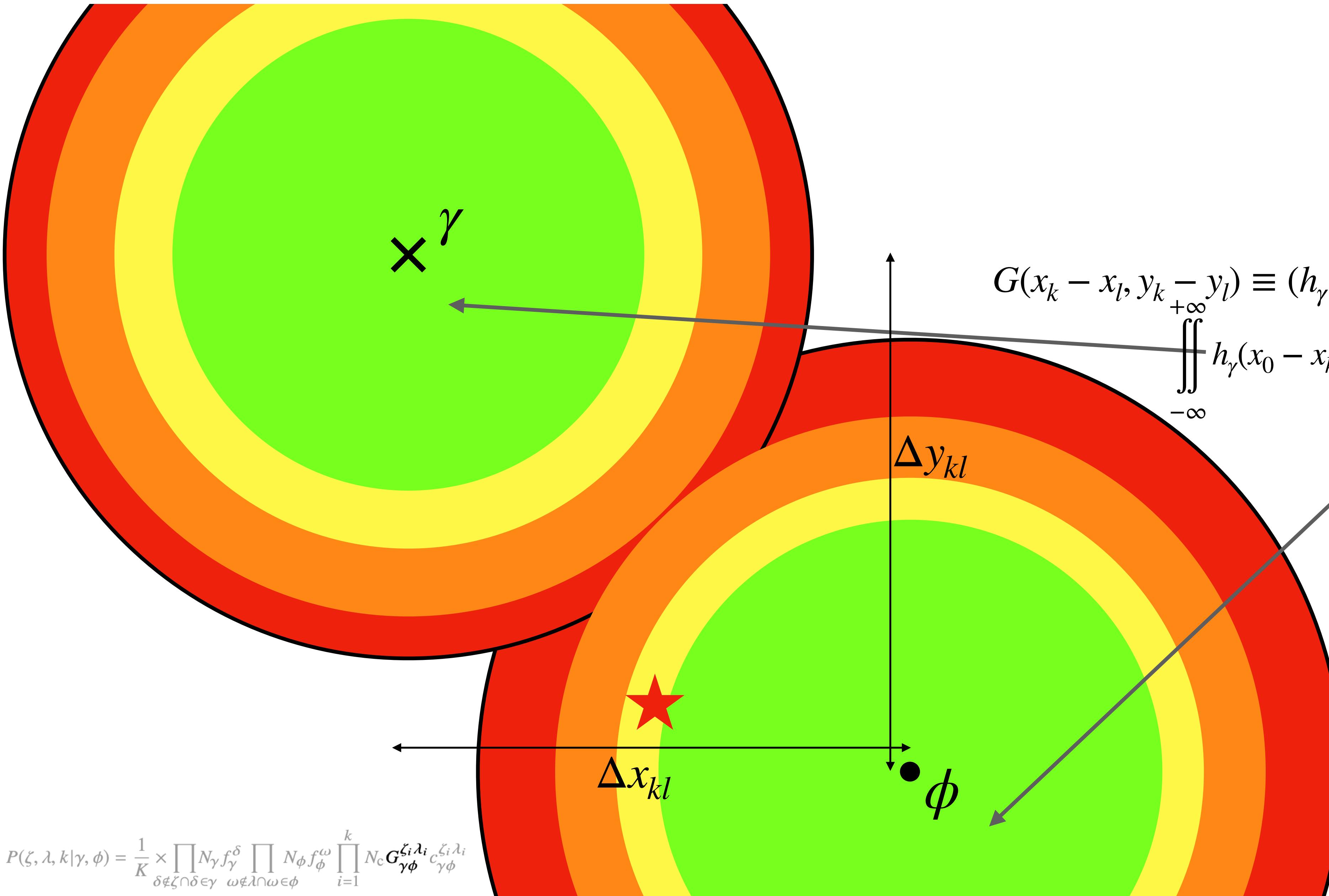
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Match Separation Probability

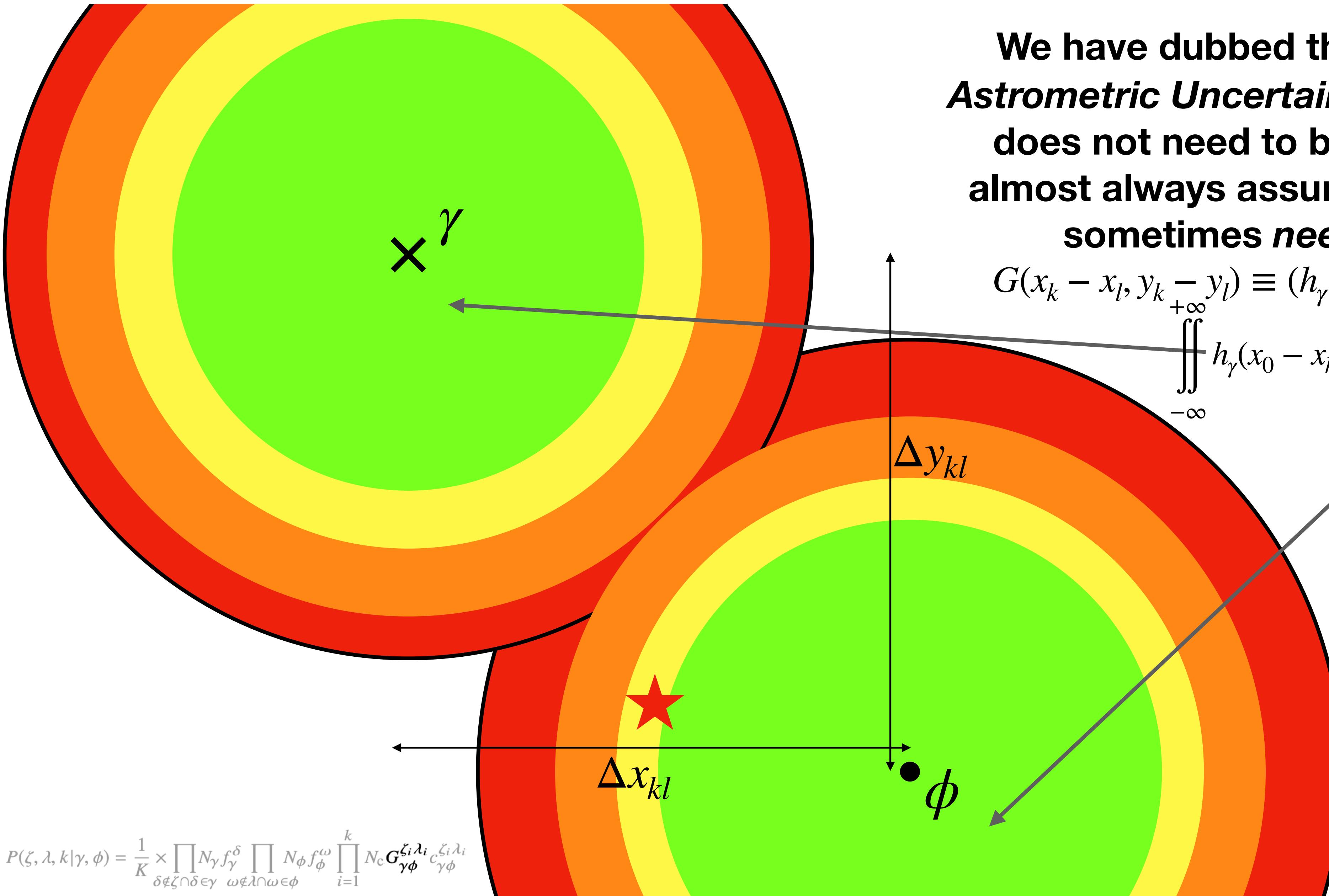


$$G(x_k - x_l, y_k - y_l) \equiv (h_\gamma * h_\phi)(\Delta x_{kl}, \Delta y_{kl}) = \iint_{-\infty}^{+\infty} h_\gamma(x_0 - x_k, y_0 - y_k) h_\phi(x_l - x_0, y_l - y_0) dx_0 dy_0$$

Wilson & Naylor (2018a)

$$P(\zeta, \lambda, k | \gamma, \phi) = \frac{1}{K} \times \prod_{\delta \notin \zeta \cap \delta \in \gamma} N_\gamma f_\gamma^\delta \prod_{\omega \notin \lambda \cap \omega \in \phi} N_\phi f_\phi^\omega \prod_{i=1}^k N_c G_{\gamma\phi}^{\zeta_i \lambda_i} c_{\gamma\phi}^{\zeta_i \lambda_i}$$

Match Separation Probability



We have dubbed this function h the **Astrometric Uncertainty Function**, which does not need to be Gaussian, as is almost always assumed – and indeed sometimes *needs* not to be!

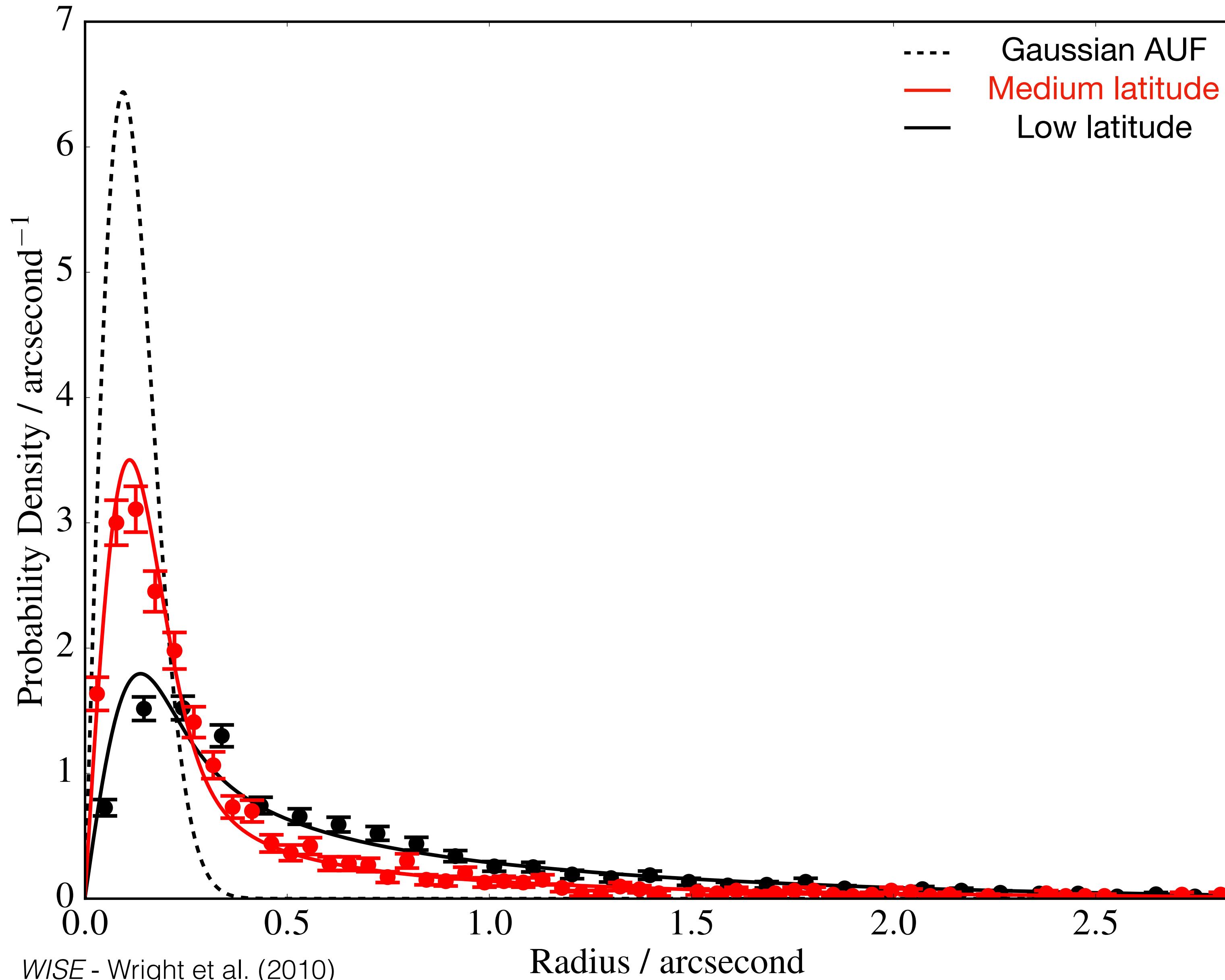
$$G(x_k - x_l, y_k - y_l) \equiv (h_\gamma * h_\phi)(\Delta x_{kl}, \Delta y_{kl}) = \iint_{-\infty}^{+\infty} h_\gamma(x_0 - x_k, y_0 - y_k) h_\phi(x_l - x_0, y_l - y_0) dx_0 dy_0$$

Wilson & Naylor (2018a)

$$P(\zeta, \lambda, k | \gamma, \phi) = \frac{1}{K} \times \prod_{\delta \notin \zeta \cap \delta \in \gamma} N_\gamma f_\gamma^\delta \prod_{\omega \notin \lambda \cap \omega \in \phi} N_\phi f_\phi^\omega \prod_{i=1}^k N_c G_{\gamma\phi}^{\zeta_i \lambda_i} c_{\gamma\phi}^{\zeta_i \lambda_i}$$

Additional Components of the AUF

$$P(\zeta, \lambda, k | \gamma, \phi) = \frac{1}{K} \times \prod_{\delta \notin \zeta \cap \delta \in \gamma} N_\gamma f_\gamma^\delta \prod_{\omega \notin \lambda \cap \omega \in \phi} N_\phi f_\phi^\omega \prod_{i=1}^k N_c G_{\gamma\phi}^{\zeta_i \lambda_i} c_{\gamma\phi}^{\zeta_i \lambda_i}$$



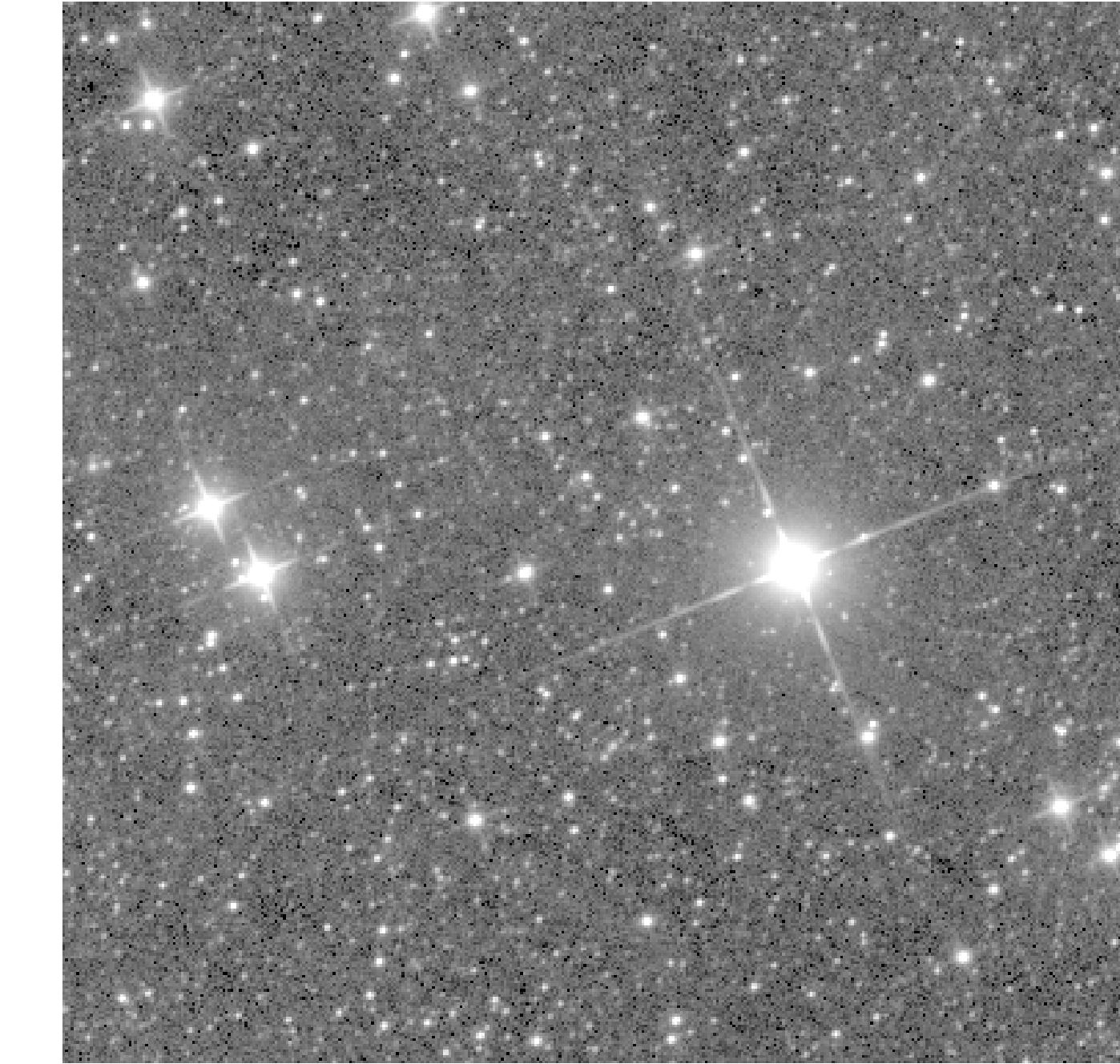
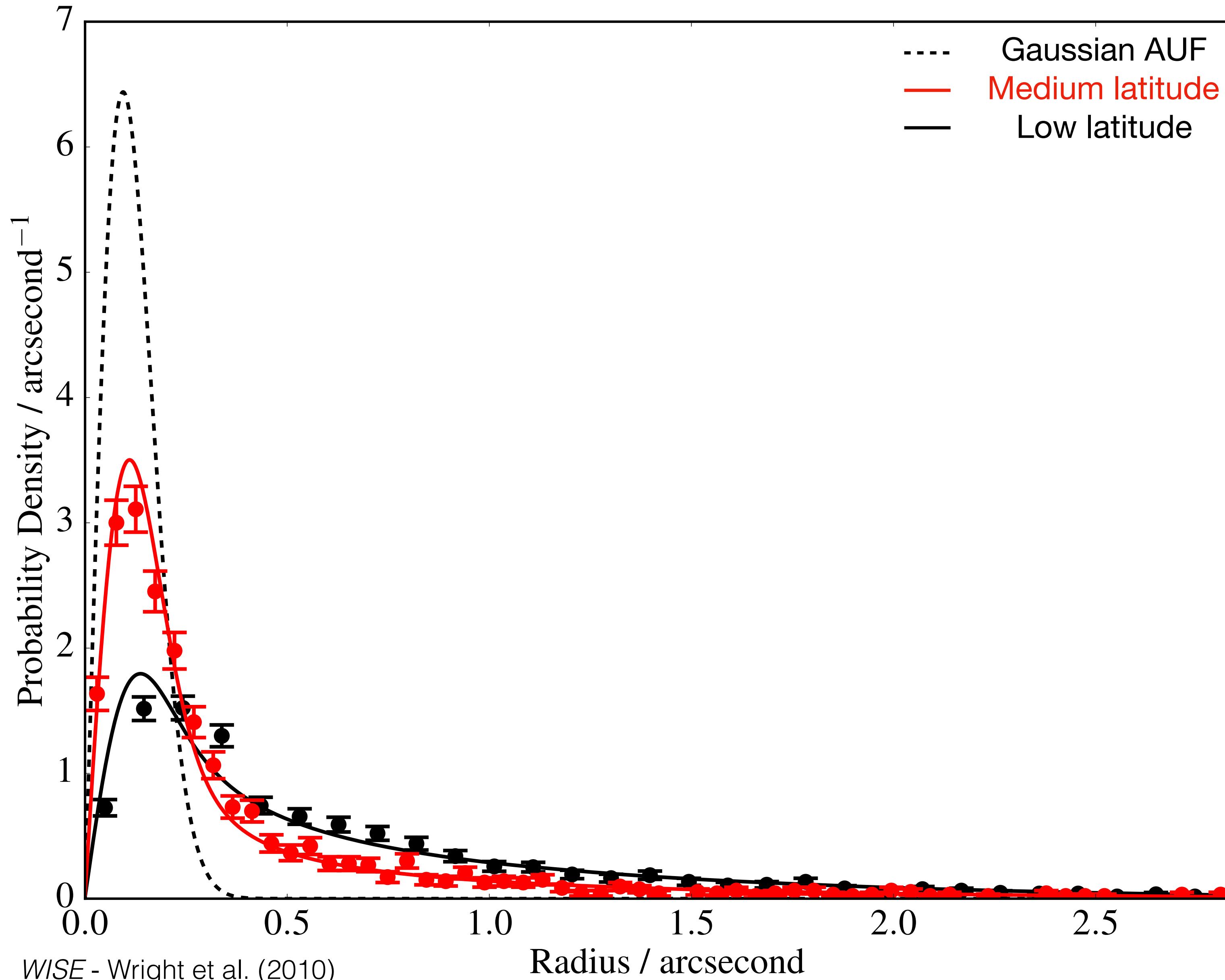
WISE - Wright et al. (2010)

Gaia DR2 - Gaia Collaboration, Brown A. G. A., et al. (2018)

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Additional Components of the AUF

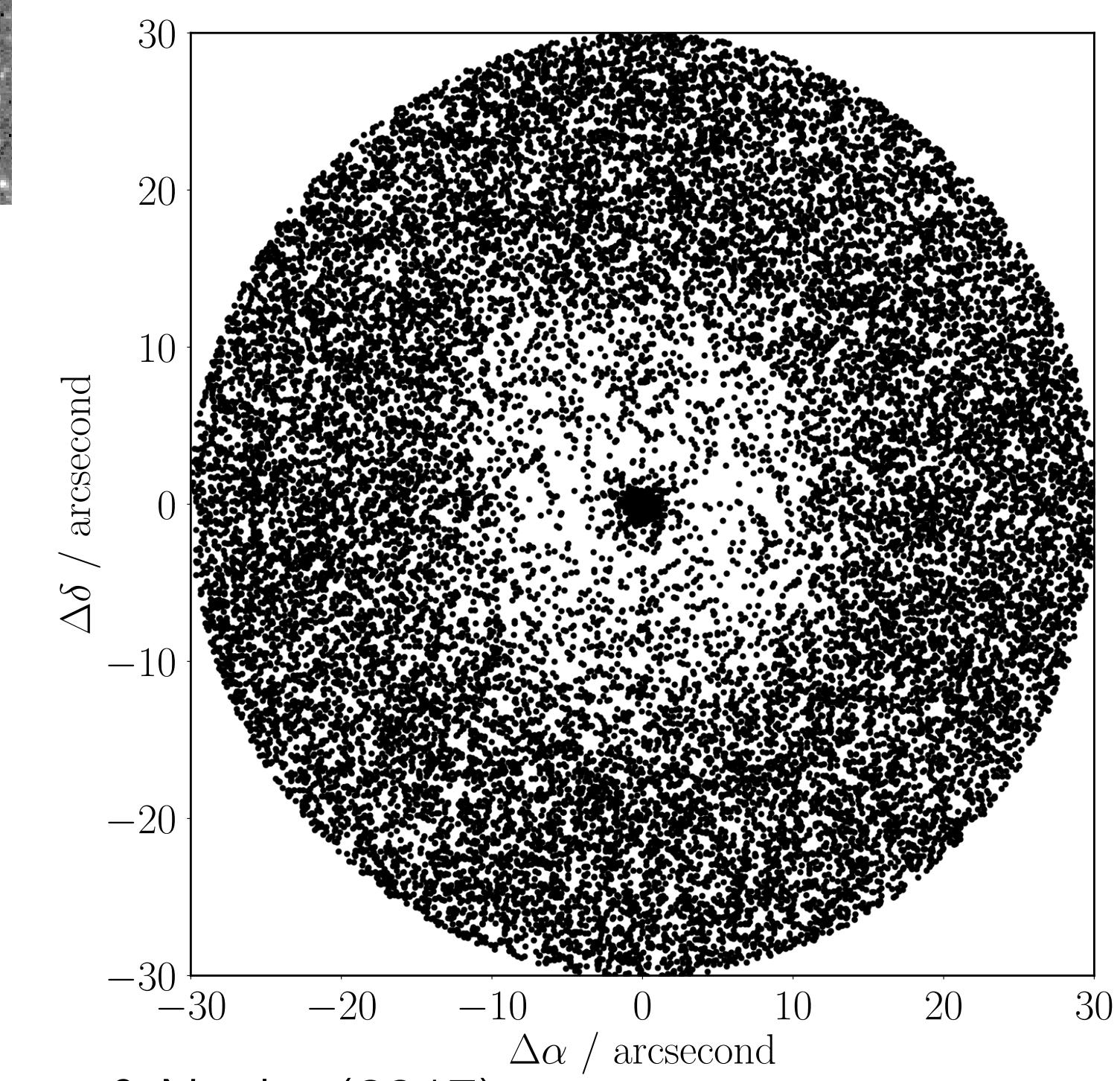
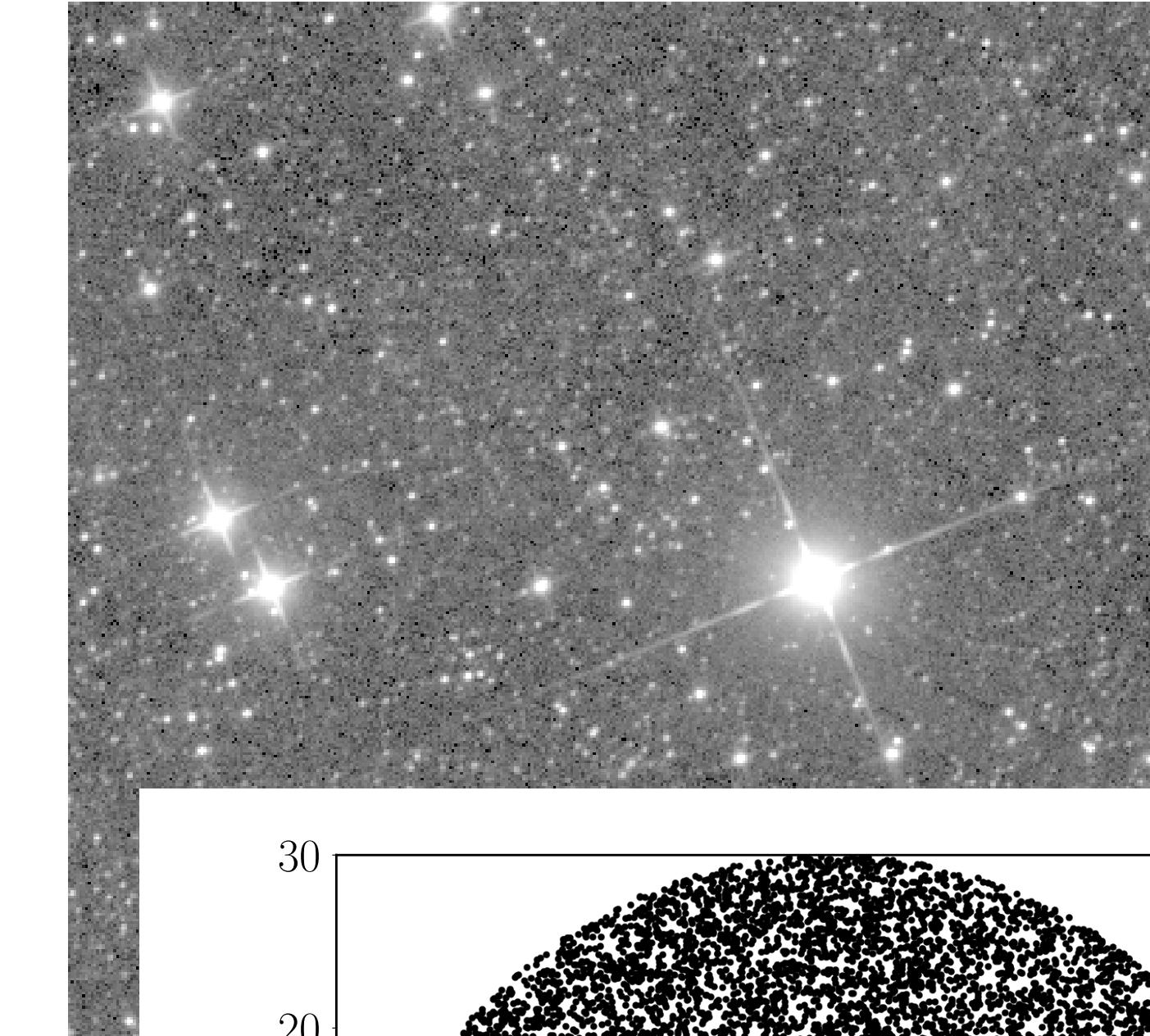
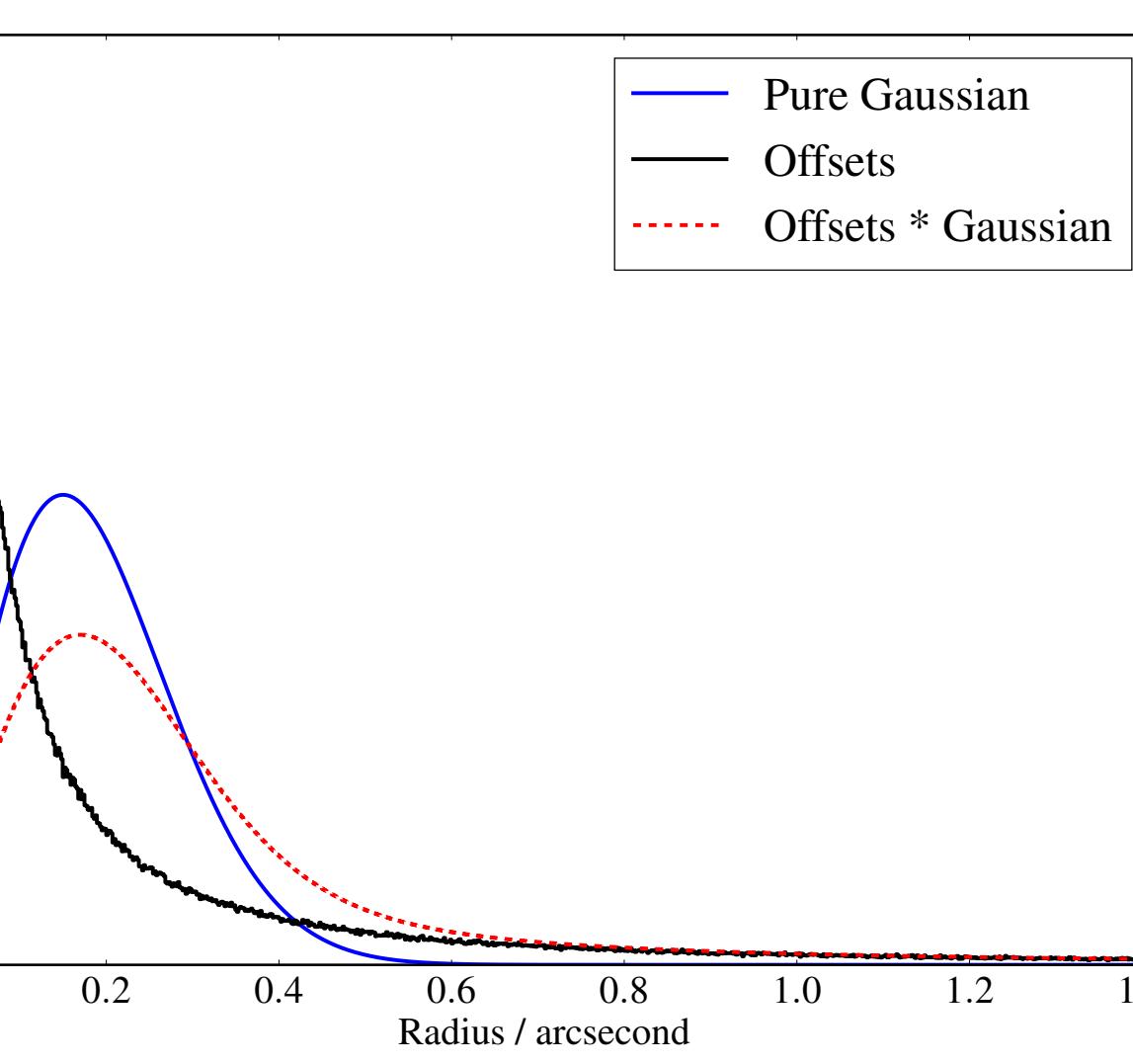
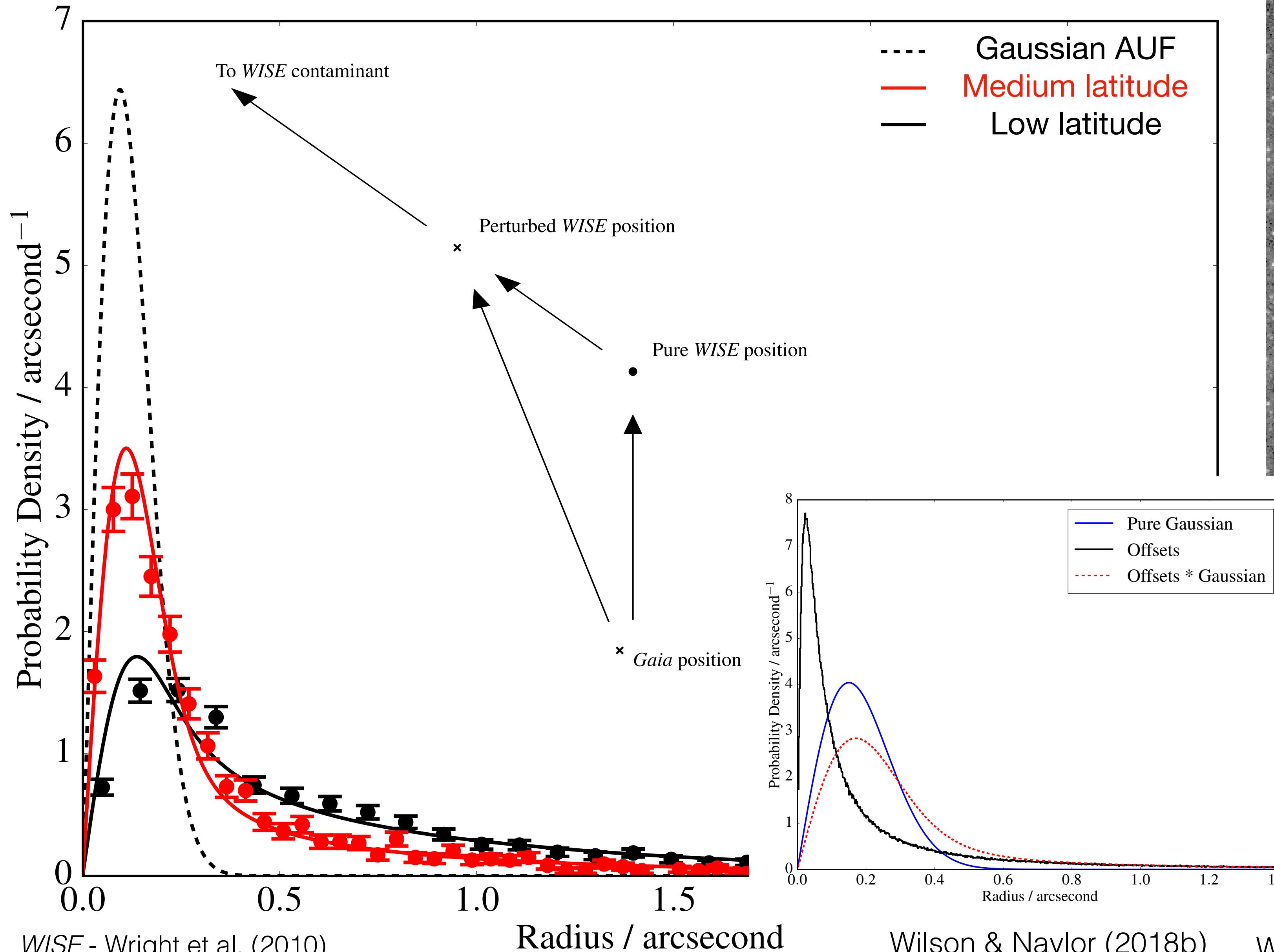
$$P(\zeta, \lambda, k | \gamma, \phi) = \frac{1}{K} \times \prod_{\delta \notin \zeta \cap \delta \in \gamma} N_\gamma f_\gamma^\delta \prod_{\omega \notin \lambda \cap \omega \in \phi} N_\phi f_\phi^\omega \prod_{i=1}^k N_c G_{\gamma\phi}^{\zeta_i \lambda_i} c_{\gamma\phi}^{\zeta_i \lambda_i}$$



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Additional Components of the AUF

$$P(\zeta, \lambda, k | \gamma, \phi) = \frac{1}{K} \times \prod_{\delta \notin \zeta \cap \delta \in \gamma} N_\gamma f_\gamma^\delta \prod_{\omega \notin \lambda \cap \omega \in \phi} N_\phi f_\phi^\omega \prod_{i=1}^k N_c G_{\gamma\phi}^{\zeta_i \lambda_i} c_{\gamma\phi}^{\zeta_i \lambda_i}$$



Wilson & Naylor (2018b)

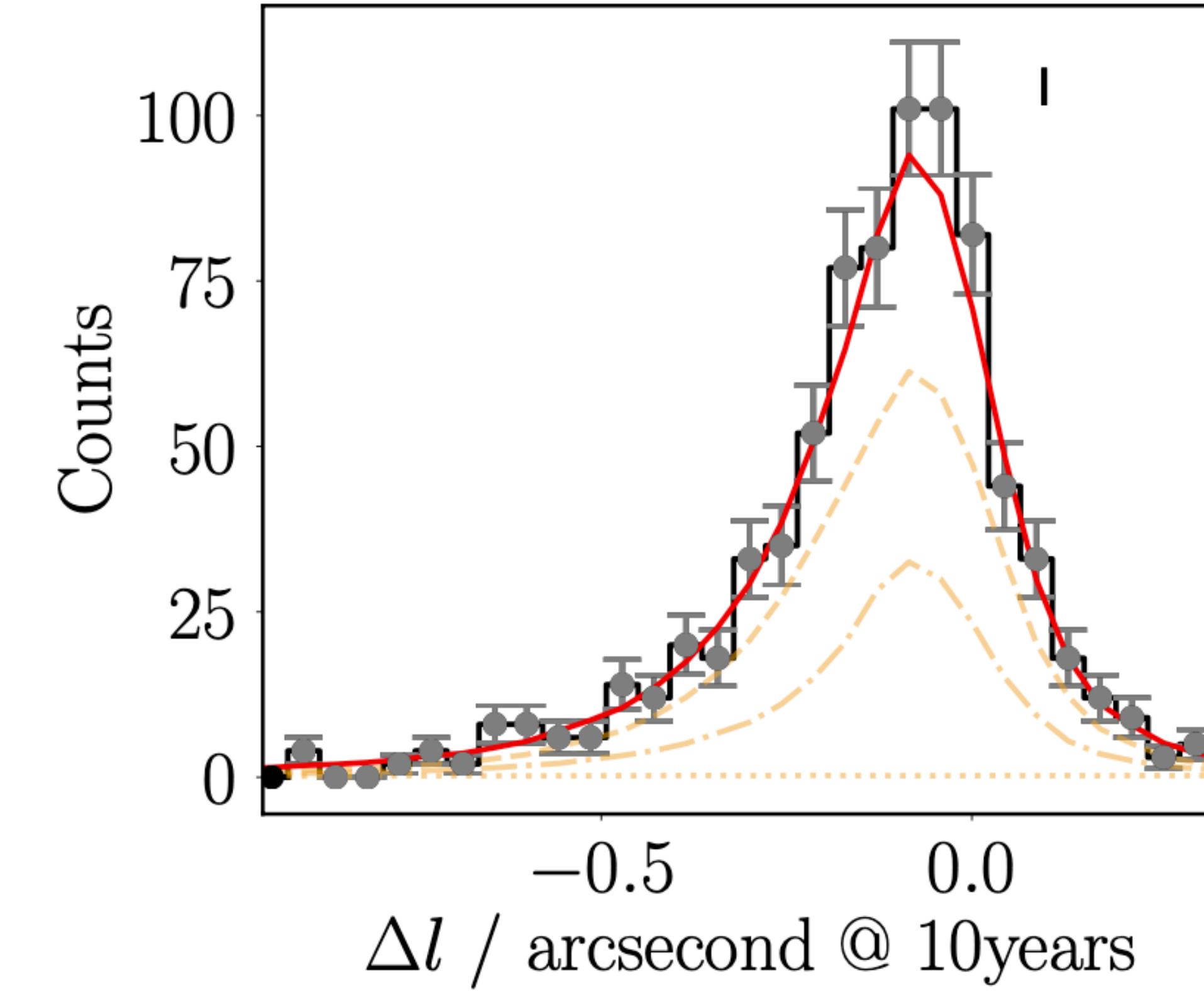
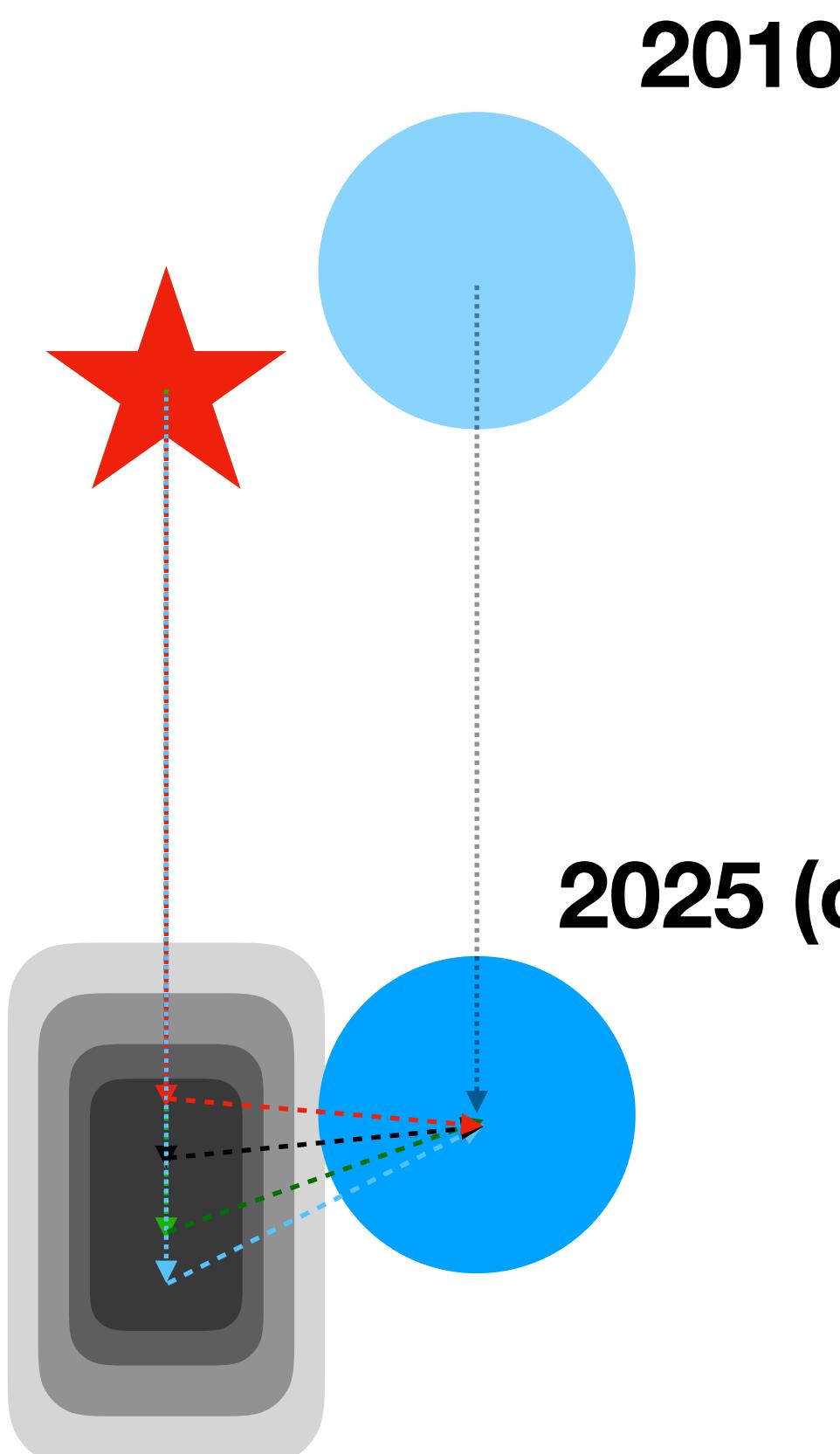
Wilson & Naylor (2017)

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Including Unknown Proper Motions

Using a model for the distribution of potential proper motions, and hence astrometric drifts, of a source of a given sky position and brightness

we can include “fast forwarding” of sources through time across different catalogues when individual proper motions are not known



Because this function works in *separation*, rather than pure *position*, space, we apply the distribution after calculating G .

$$G' = G * h'_{\text{pm}} \quad G = h_\gamma * h_\phi$$

$$h_\gamma = h_{\gamma, \text{centroding}} * h_{\gamma, \text{perturbation}}$$

How To Use Our Cross-Matches

(Or, how this impacts you on a day-to-day basis)

Three tables per cross-match: merged catalogue dataset, and 2x non-match dataset (one per catalogue)

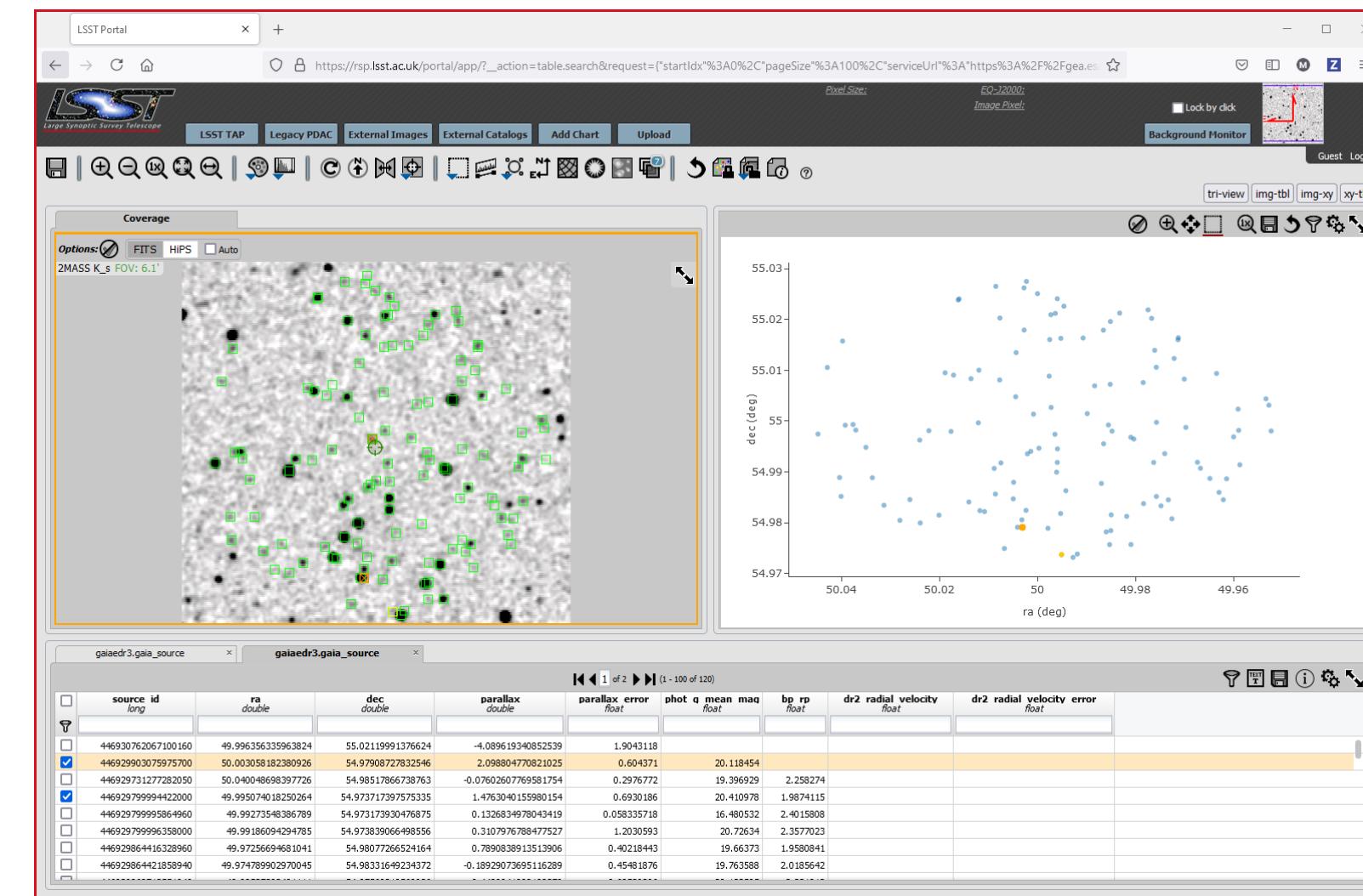
Counterpart columns:

- Designations of the two sources (e.g., WISE J... and Gaia EDR3...)
- RA and Dec (or Galactic l/b) of the two sources
- Magnitudes (corrected for necessary effects, such as e.g. Gaia) in all bandpasses for both objects
- Match probability — probability of the most likely permutation (see equation 26 of Wilson & Naylor 2018a)
- Eta - Photometric likelihood ratio (counterpart vs non-match probability, just for brightnesses; see eq37 of WN18a)
- Xi - Astrometric likelihood ratio (just position match/non-match comparison; see eq38 of WN18a)
- Average contamination - simulated mean (percentile) brightening of the two sources, based on number density of catalogue
- Probability of sources having blended contaminant above e.g. 1% relative flux

Non-match columns:

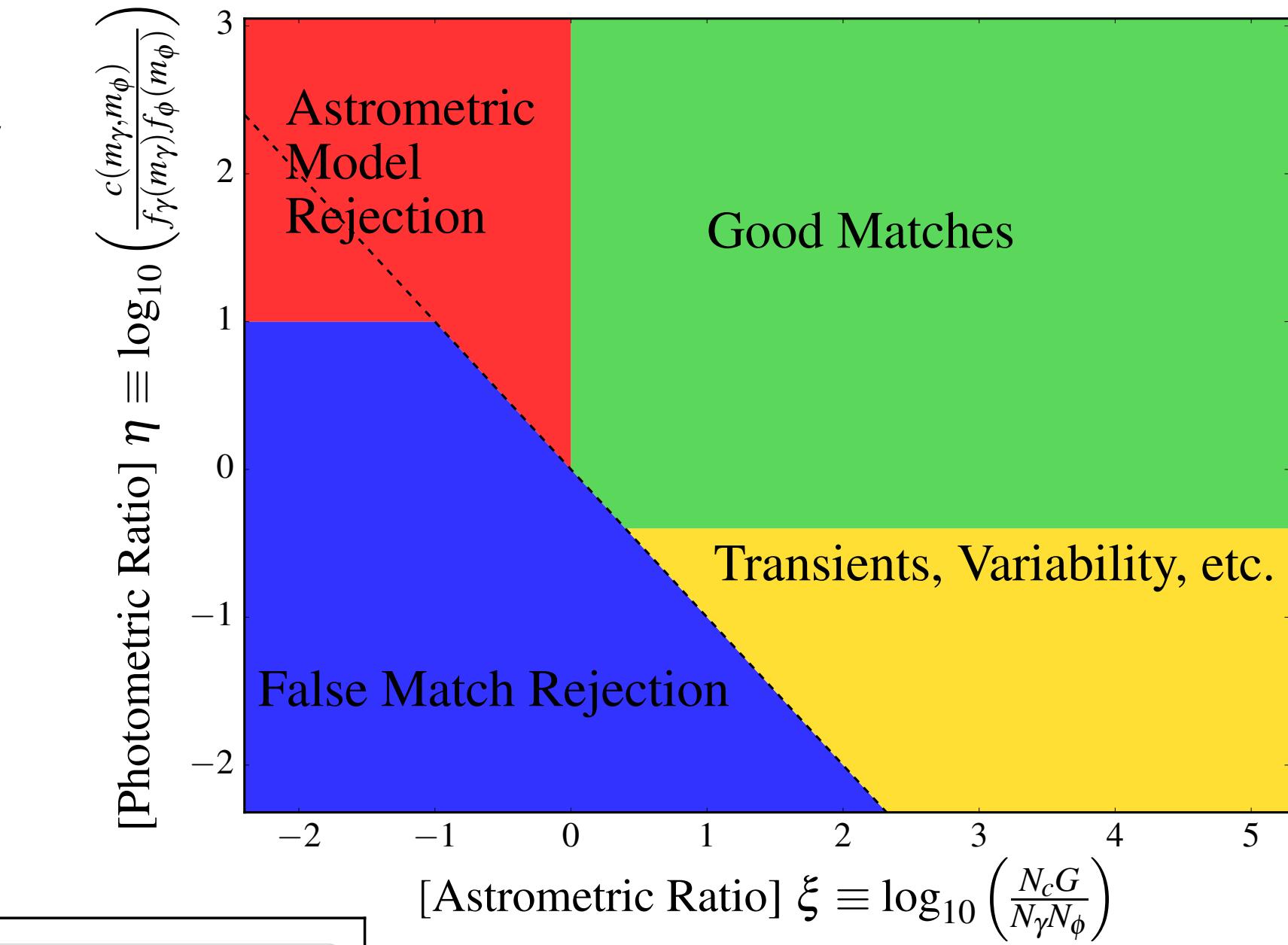
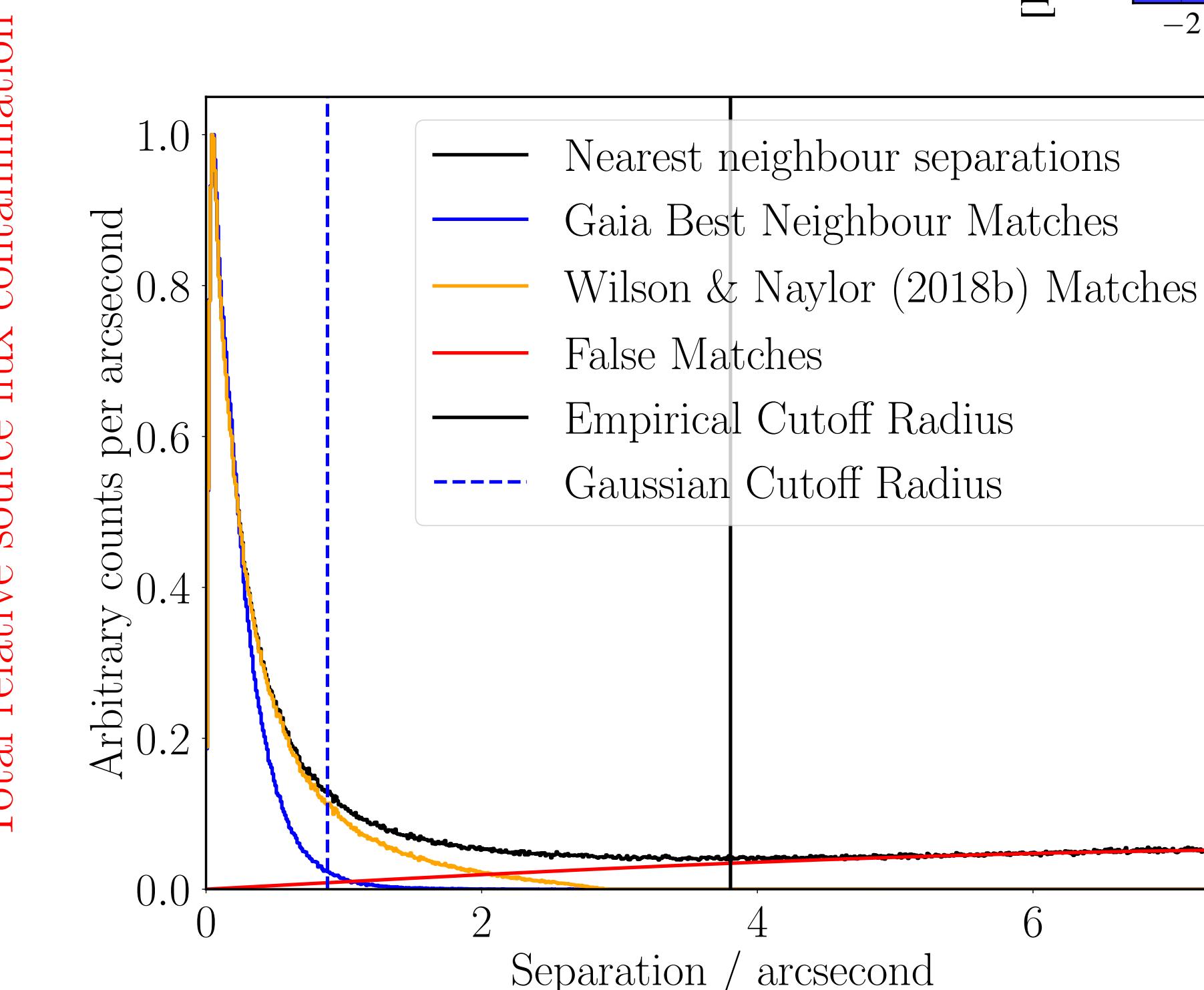
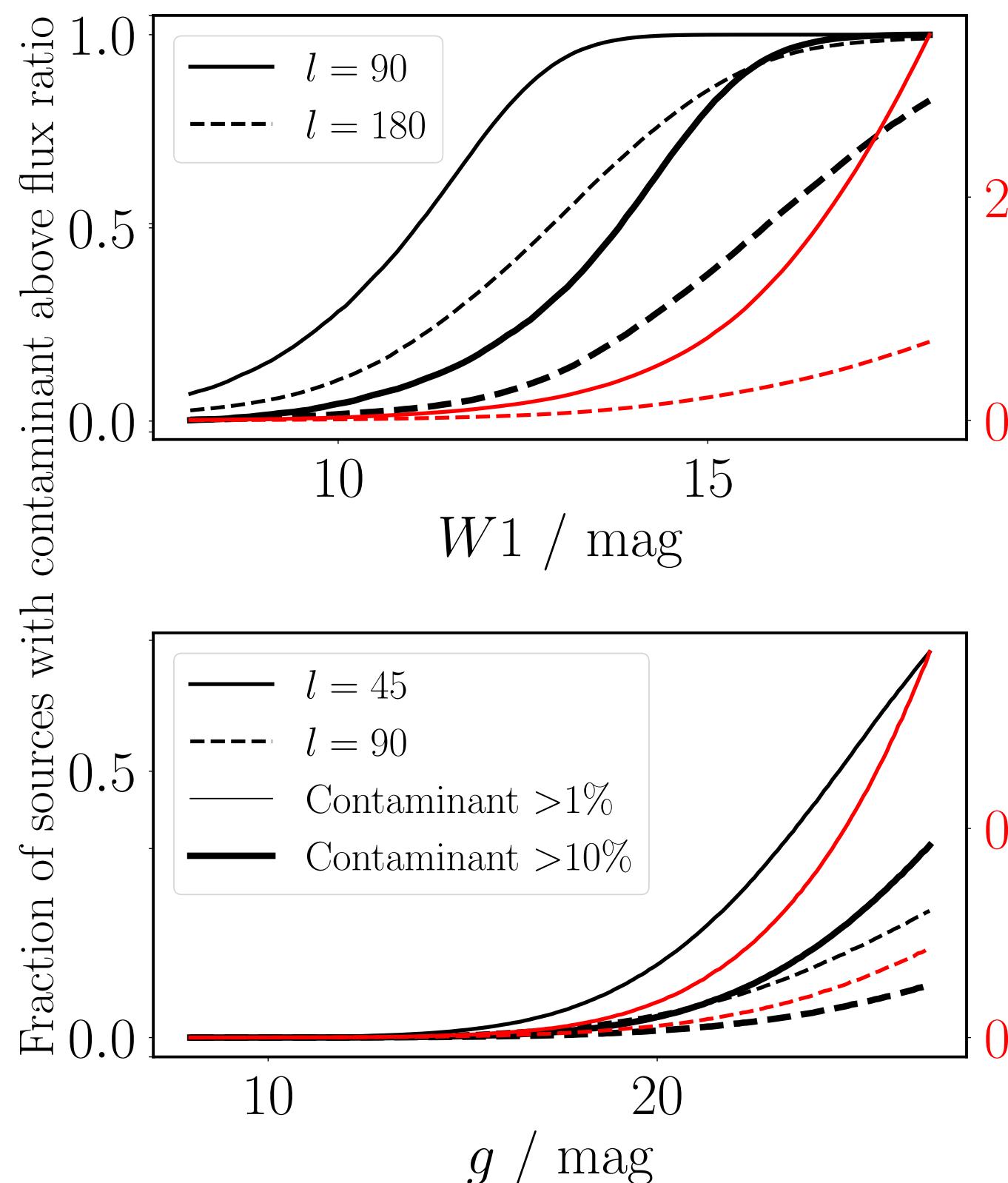
- Designations of the source (e.g., WISE J... or Gaia EDR3...)
- RA and Dec (or Galactic l/b) of the source
- Magnitudes (corrected for necessary effects, such as e.g. Gaia) in all bandpasses
- Match probability — probability of the most likely permutation (see equation 26 of WN18a)
- Average contamination - simulated mean (percentile) brightening of the source, based on number density of catalogue

We will provide a two match runs per catalogue pair match: one with, and one without, the photometry considered, to allow for the recovery of sources with “weird” colours but otherwise agreeable astrometry



Why Use Our Cross-Matches?

- Getting cross-matches, even for “well behaved” fields
- Finding “odd” objects, either using the inclusion vs non-inclusion of the photometry in the two match runs, or via the likelihood ratio space – planned “real time” matching service for transient objects
- Removing e.g. IR excess or correcting for extinction-like crowding brightening, through Average Contamination; crucial for removing completely unknown crowding of catalogues using aperture photometry
- Recovering additional sources missed by other match services – either in crowded fields (we recover 20-50% more *Gaia-WISE* matches than the *Gaia* best neighbour matches), or with our in-progress extension to unknown proper motion modelling



Conclusions

- Upcoming LSST:UK cross-match service **macauff** — let me know your thoughts/needs/hopes/dreams
 - Provide tables of cross-matches between LSST and <your favourite catalogue here!>
- Our cross-matches include two key elements for avoiding issues with the crowded LSST sky
 - A generalised approach to the Astrometric Uncertainty Function allows for the inclusion of the effects of perturbation due to blended sources — and will be extended to unknown proper motions
 - Use of the photometry of sources allows for the rejection of false matches (with >1 “extra” source per 2 arc second circle in most of the LSST Galactic plane)
- Will include additional information on the crowding of sources, allowing for selection of uncontaminated objects, or modelling of excess flux — crucial for removal of red excess in SEDs
 - LSST will suffer of order 10% flux contamination, which could be confused with extinction



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github.io www

Wilson & Naylor, 2017, MNRAS, 468, 2517
Wilson & Naylor, 2018a, MNRAS, 473, 5570
Wilson & Naylor, 2018b, MNRAS, 481, 2148
<https://github.com/Onoddil/macaff>



