Impact of Weak Lensing Mass Mapping Algorithms on Cosmology Inference

June 11th, 2025

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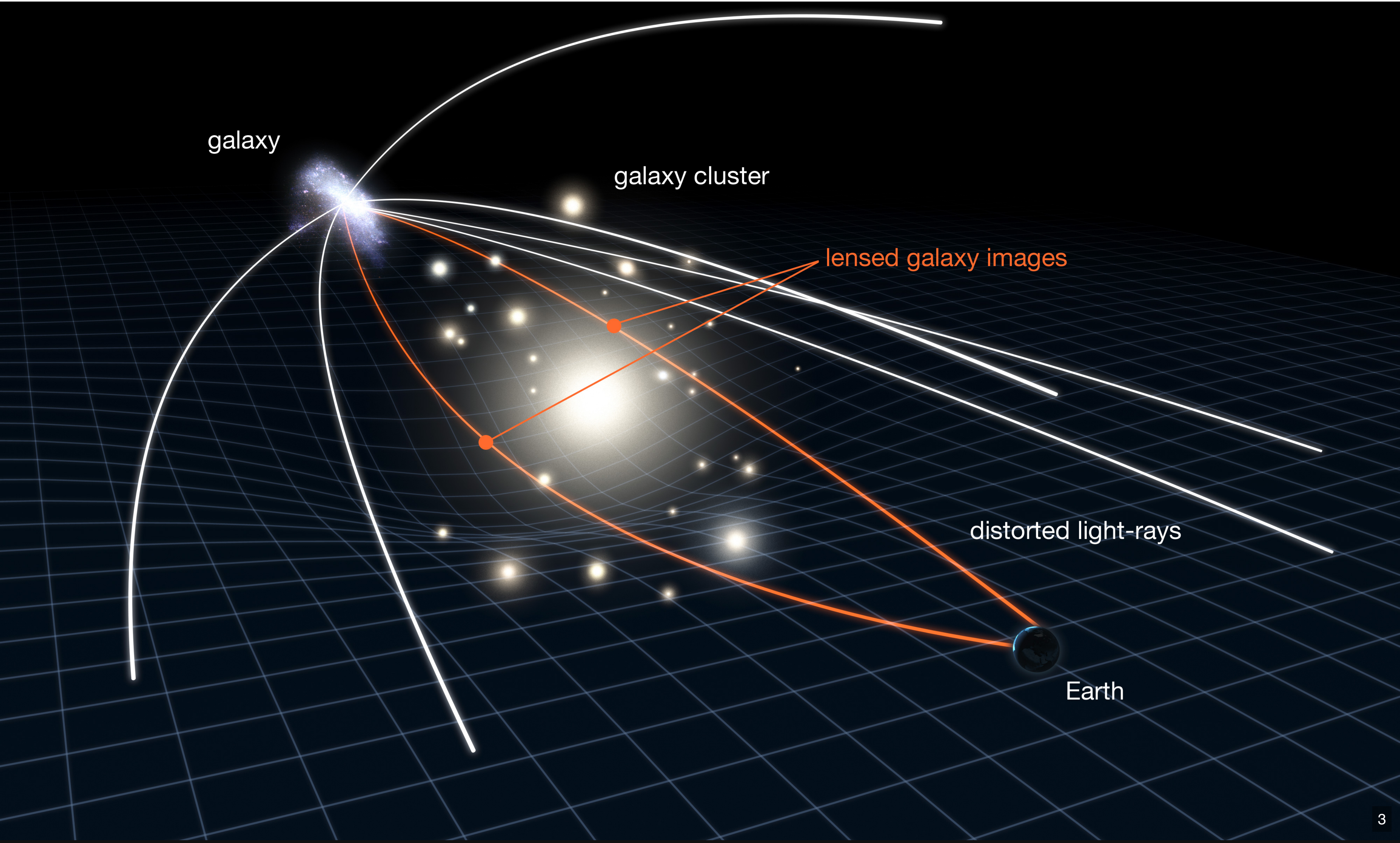
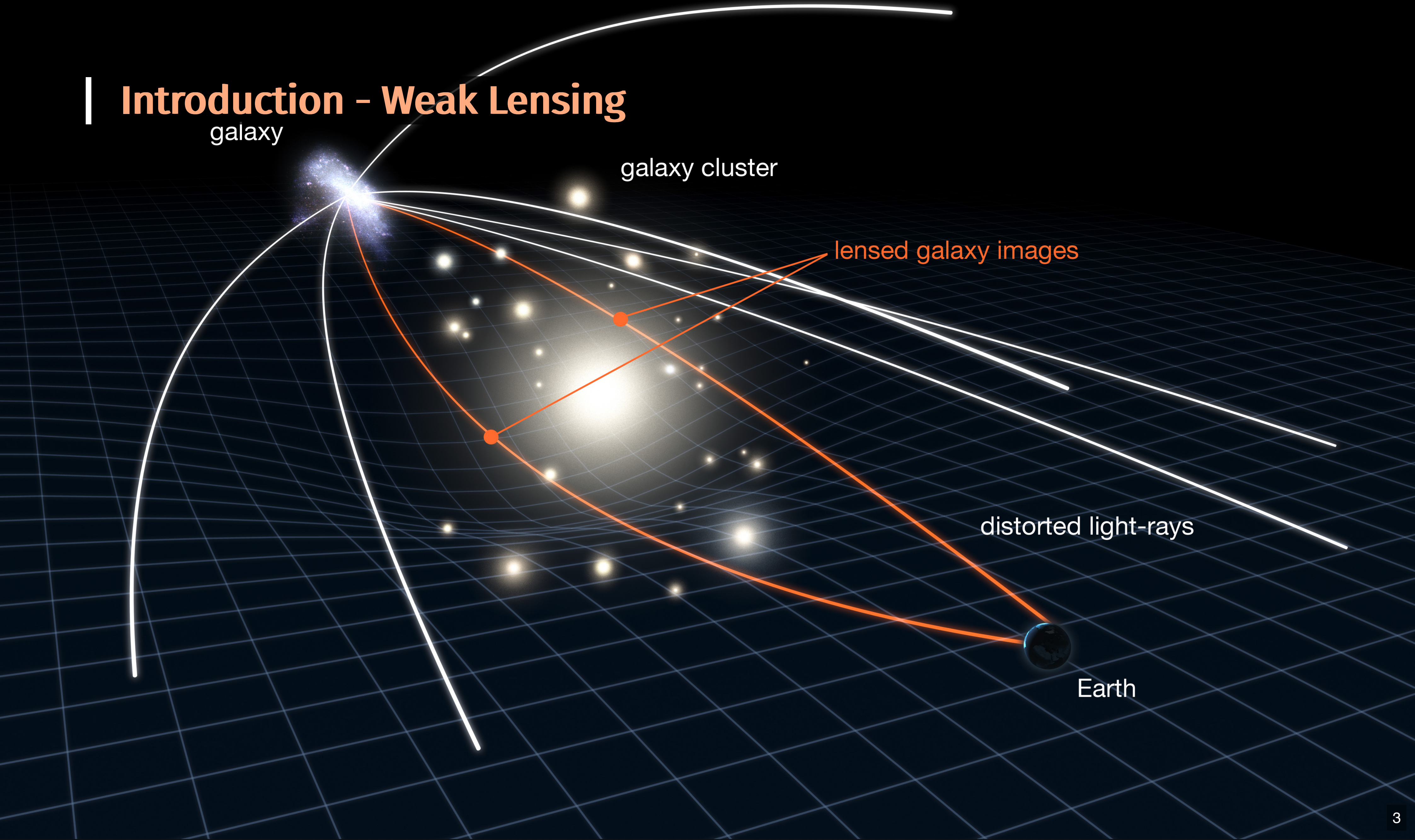
COLOURS workshop, Saclay

if you are seeing this in pdf, a nicer version of the slides is available at
andreastersenov.github.io/talks/COLOURS_Saclay_2025/

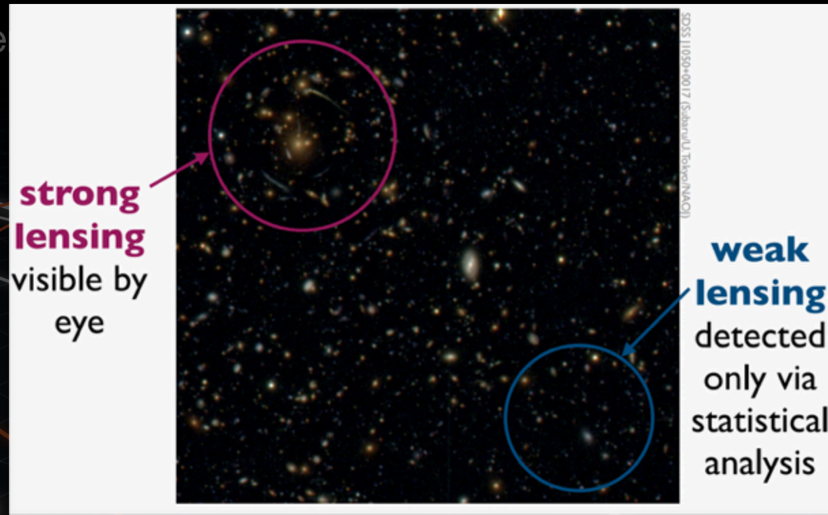

galaxy
galaxy cluster
lensed galaxy images
distorted light-rays
Earth

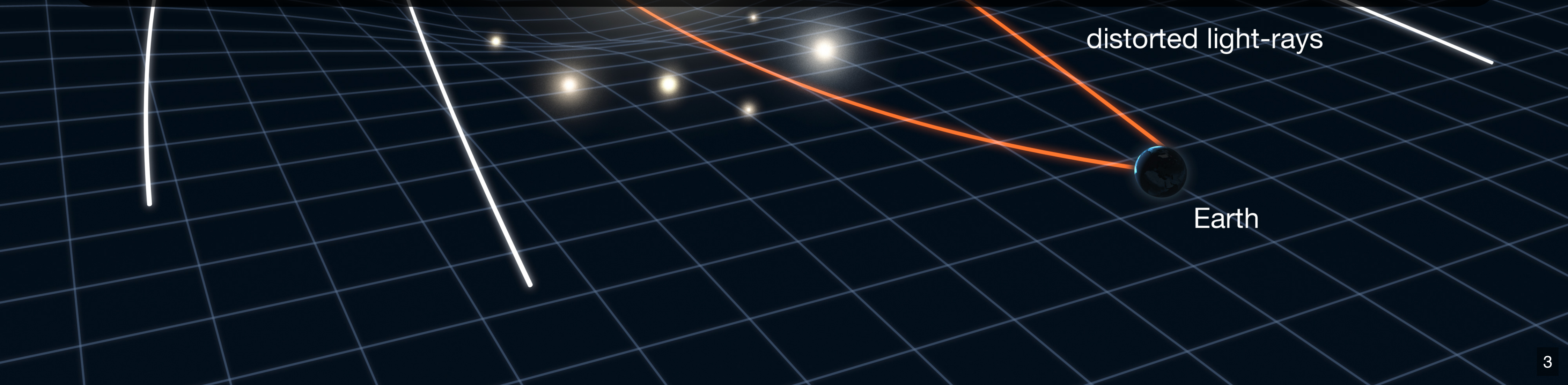
Introduction - Weak Lensing



Introduction – Weak Lensing

- **WL** = Observational technique in cosmology for studying the matter distribution in the universe
- **Principle:** deflection of light from distant galaxies by gravitational fields → causes image distortion
- **Weak** → subtle & coherent distortions of background galaxy shapes





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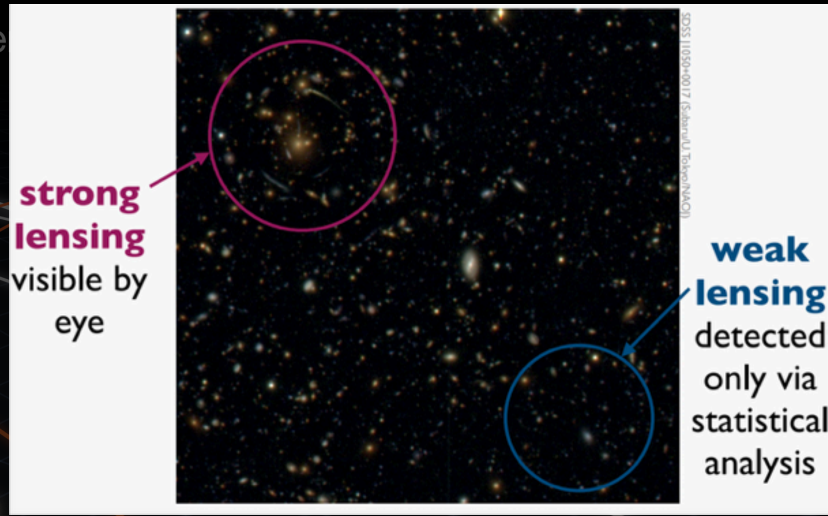
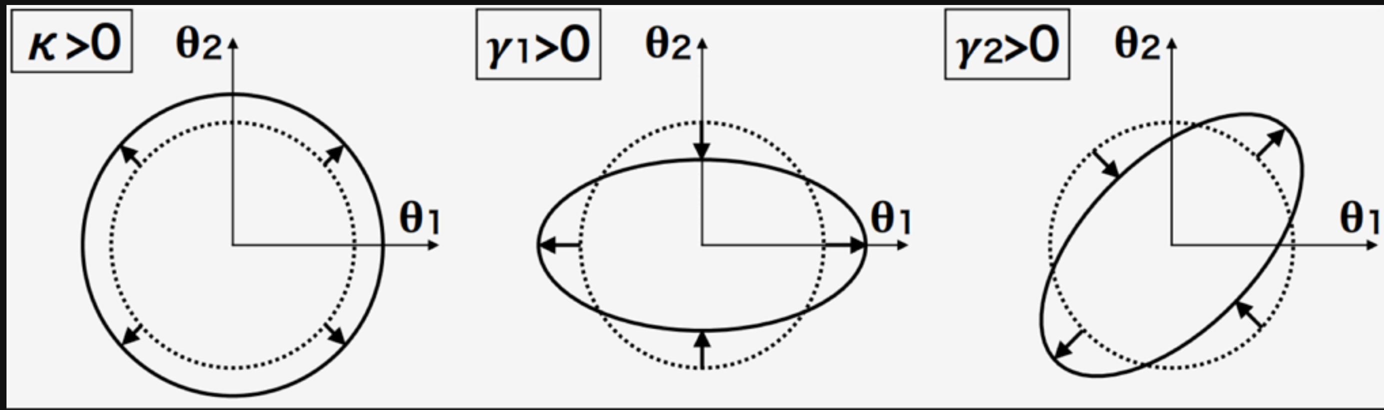


- WL provides a direct measurement of the gravitational distortion.
- WL enables us to probe the cosmic structure, investigate the nature of dark matter, and constrain cosmological parameters.

Shear & Convergence



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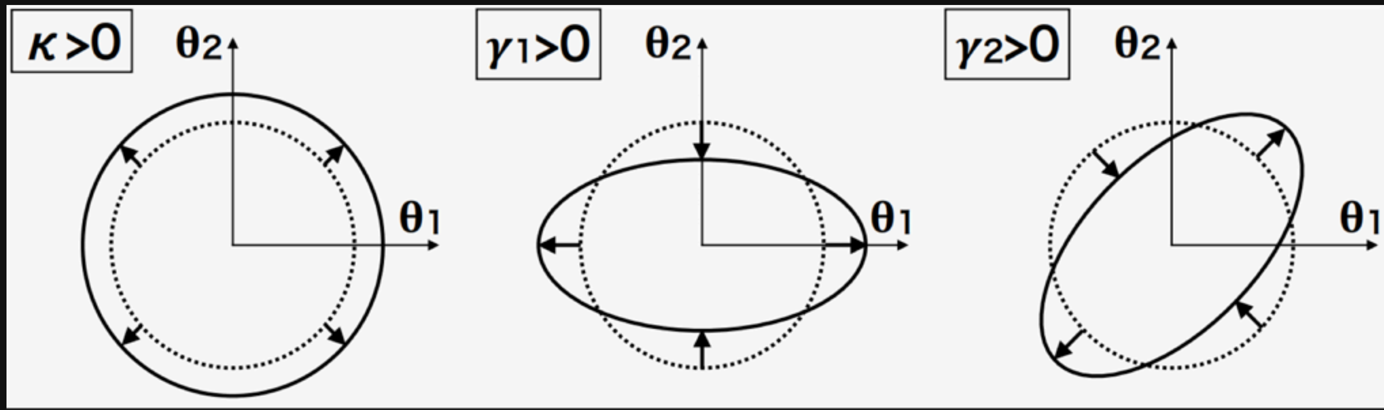

Convergence κ

$$\kappa = \frac{1}{2}(\partial_1\partial_1 + \partial_2\partial_2)\psi = \frac{1}{2}\nabla^2\psi$$

$\longrightarrow$ difficult to measure

Shear γ

$$\gamma_1 = \frac{1}{2}(\partial_1\partial_1 - \partial_2\partial_2)\psi, \;\; \gamma_2 = \partial_1\partial_2\psi$$

$\longrightarrow$ can be measured by statistical analysis of galaxy shapes

Relation between κ and γ

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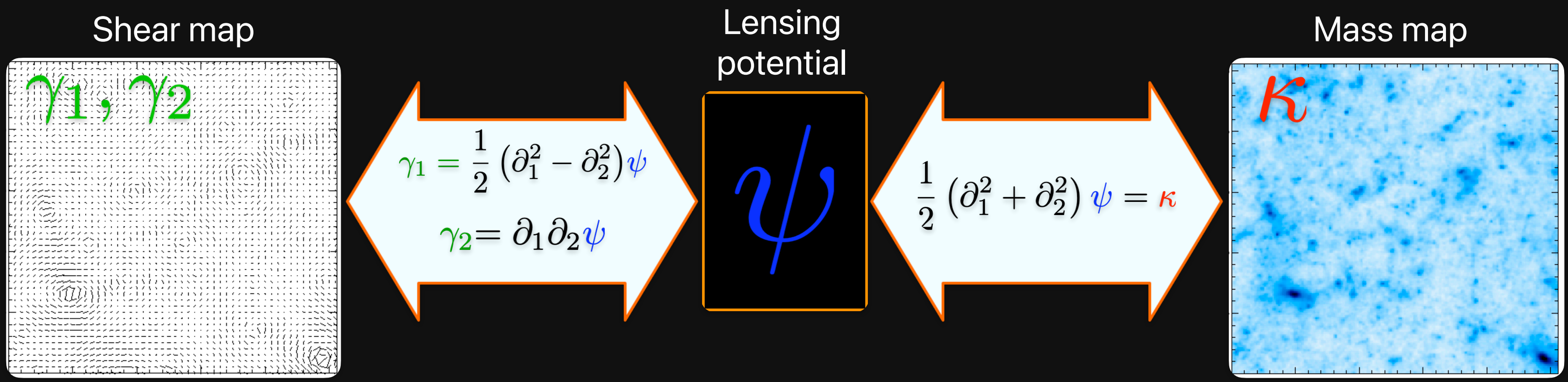

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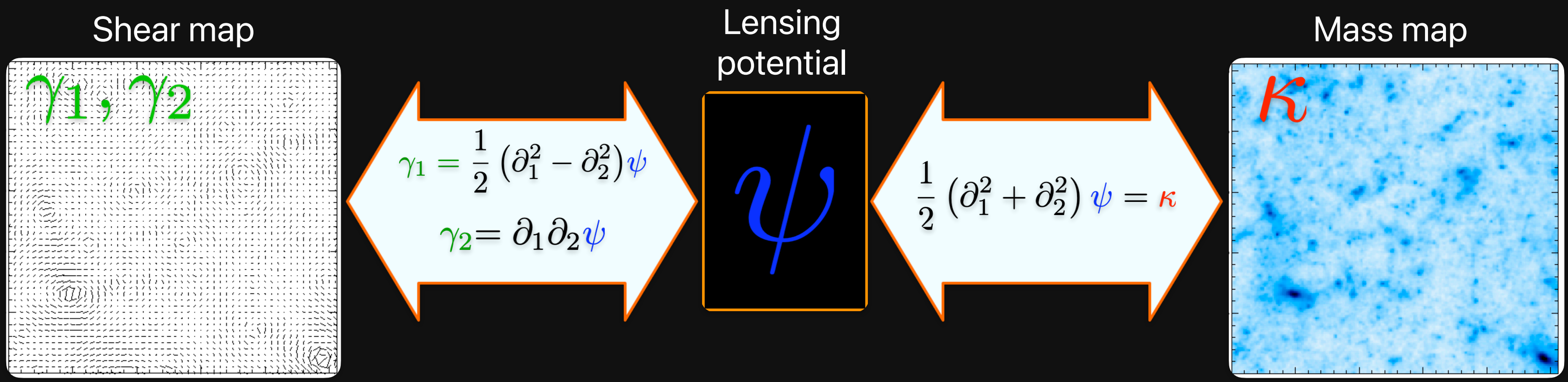

- From **convergence** to **shear**: $\gamma_i = \hat{P}_i\kappa$
- From **shear** to **convergence**: $\kappa = \hat{P}_1\gamma_1 + \hat{P}_2\gamma_2$

$$\hat{P}_1(k) = \frac{k_1^2 - k_2^2}{k^2}, \quad \hat{P}_2(k) = \frac{2k_1k_2}{k^2}$$

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Advantages:

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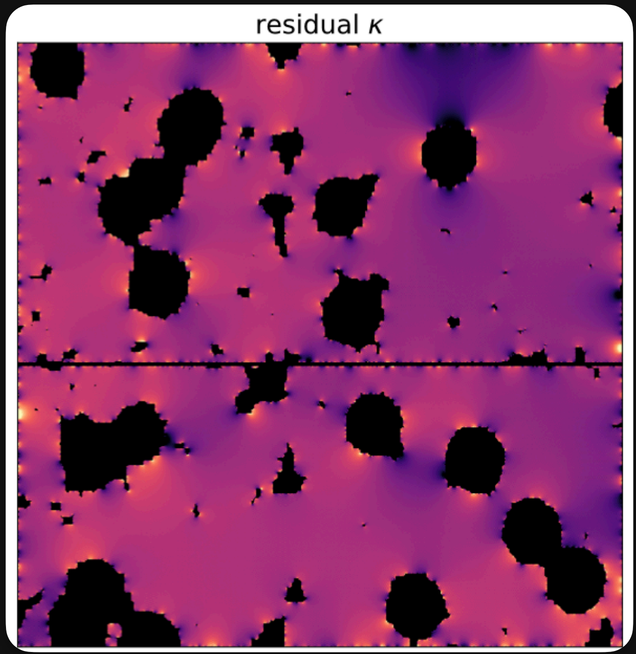
Practical difficulties:

- Shear measurements are discrete, **noisy**, and **irregularly sampled**
- We actually measure the **reduced shear**: $g = \gamma/(1-\kappa)$
- Masks and integration over a subset of $\mathbb{R}^2$ lead to border errors ⇒ **missing data problem**
- Convergence is recoverable up to a constant ⇒ **mass-sheet degeneracy problem**



Bayesian reconstruction

Bayesian reconstruction

- Mass mapping problem → statistical inference problem
- **Goal**: infer most probable value of κ-field given observed shear data

$$\underbrace{p(\boldsymbol{\kappa} \mid \boldsymbol{\gamma}, \mathrm{M})}_{\text{Posterior}} \propto \underbrace{p(\gamma \mid \boldsymbol{\kappa}, \mathrm{M})}_{\text{likelihood}} \underbrace{p(\boldsymbol{\kappa} \mid \mathrm{M})}_{\text{prior}}$$

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Proximal operator

- Acts as a "smart denoiser" by finding the closest solution that satisfies the prior.
- *Example*: sparsity prior → proximal operator performs thresholding to enforce sparsity in the solution.

MCALens

- Models κ-field as a sum of a **Gaussian** and **non-Gaussian** component

$$\kappa = \underbrace{\kappa_{\mathrm{NG}}}_{\text{Standard Wiener filter approach}} + \underbrace{\kappa_{\mathrm{G}}}_{\text{Modified wavelet approach}}$$

$$\min_{\kappa_G, \kappa_{NG}} \|\gamma - \mathbf{A}\left(\kappa_G + \kappa_{NG}\right)\|^2_{\Sigma_n} + C_{\mathrm{G}}\left(\kappa_G\right) + C_{\mathrm{NG}}\left(\kappa_{NG}\right)$$

- **MCA** (morphological Component Analysis) performs an alternating minimization scheme:
  - Estimate κ_{G} assuming κ_{NG} is known:

$$\min_{\kappa_G} \|(\gamma - \mathbf{A}\kappa_{NG}) - \mathbf{A}\kappa_G\|^2_{\Sigma_n} + C_{\mathrm{G}}\left(\kappa_G\right)$$

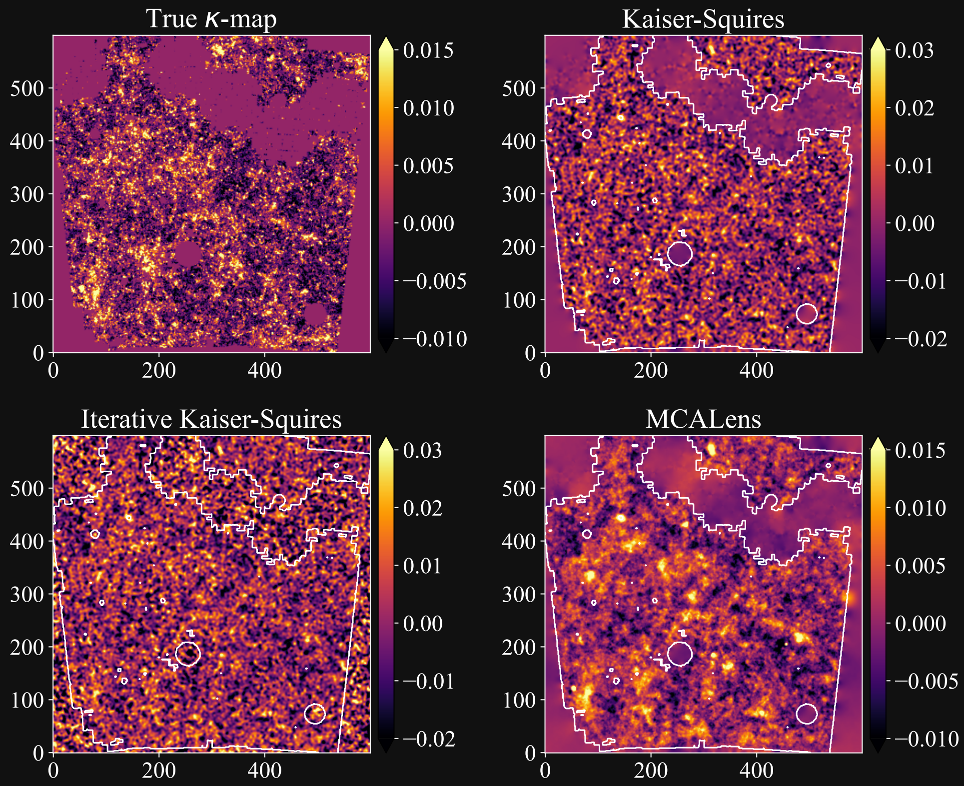
  - Estimate κ_{NG} assuming κ_{G} is known:

$$\min_{\kappa_{NG}} \|(\gamma - \mathbf{A}\kappa_G) - \mathbf{A}\kappa_{NG}\|^2_{\Sigma_n} + C_{\mathrm{NG}}\left(\kappa_{NG}\right)$$

Does the choice of mass-mapping method matter for cosmology?

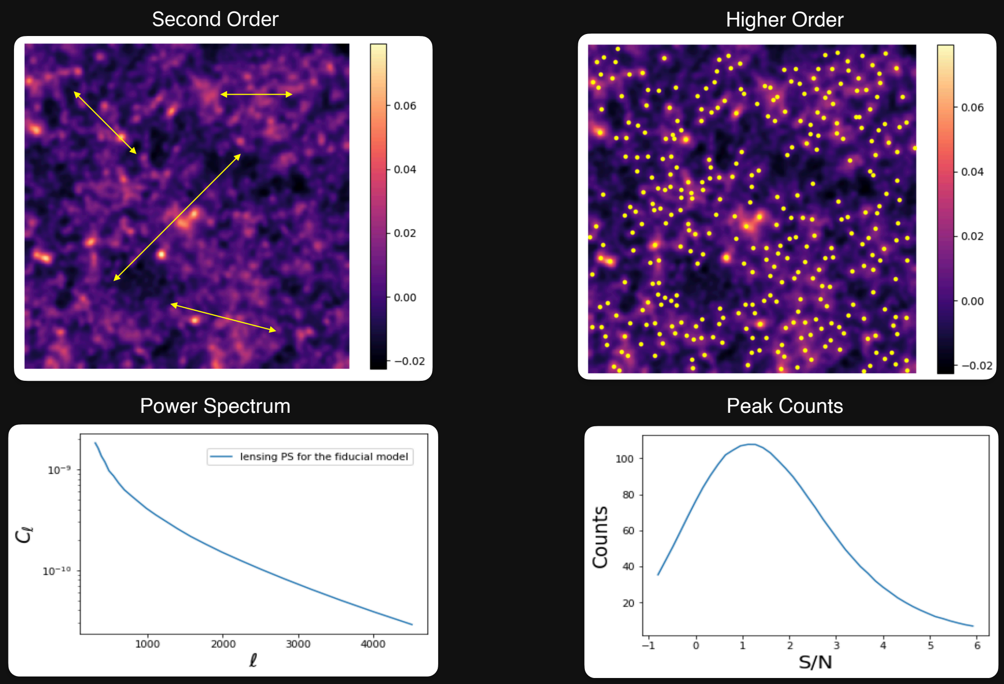
A. Tersenov, L. Baumont, J.L. Starck, M. Kilbinger, doi.org/10.1051/0004-6361/202553707

Mass mapping methods:



Method	RMSE↓
KS	1.1×10^{-2}
iKS	1.1×10^{-2}
MCALens	9.8×10^{-3}

Higher Order Statistics: Peak Counts



- **Peaks**: local maxima of the SNR field $\nu = \dfrac{(\mathcal{W} * \kappa)(\theta_{\text{ker}})}{\sigma_n^{\text{filt}}}$
- Peaks trace regions where the value of κ **is high** → they are associated to **massive structures**

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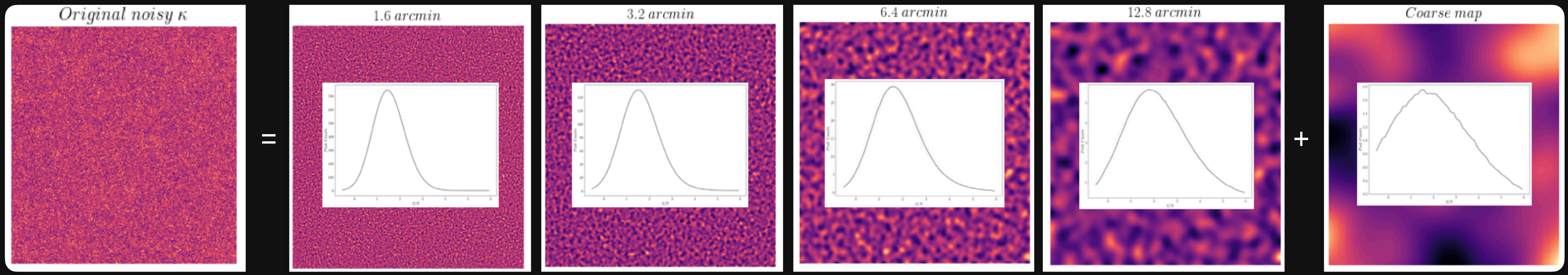

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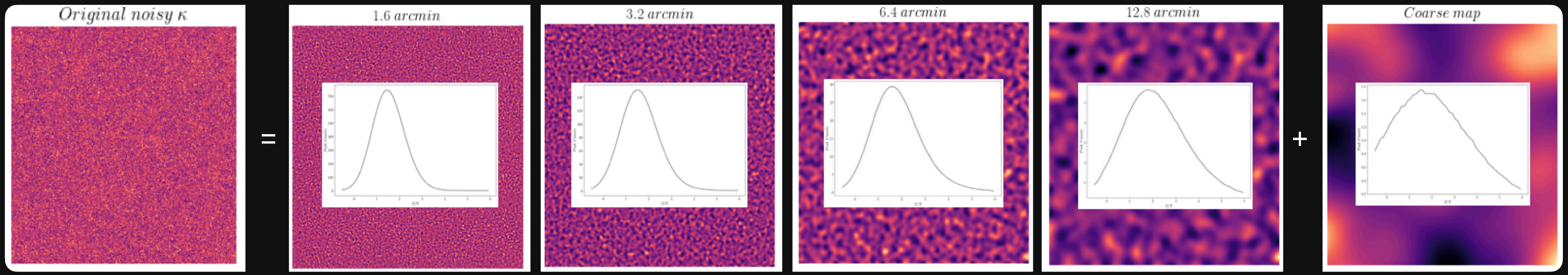

- Allows for the **simultaneous** processing of data at different scales → **efficiency**
- Each wavelet band covers a different frequency range, which leads to an almost **diagonal peak count covariance matrix**

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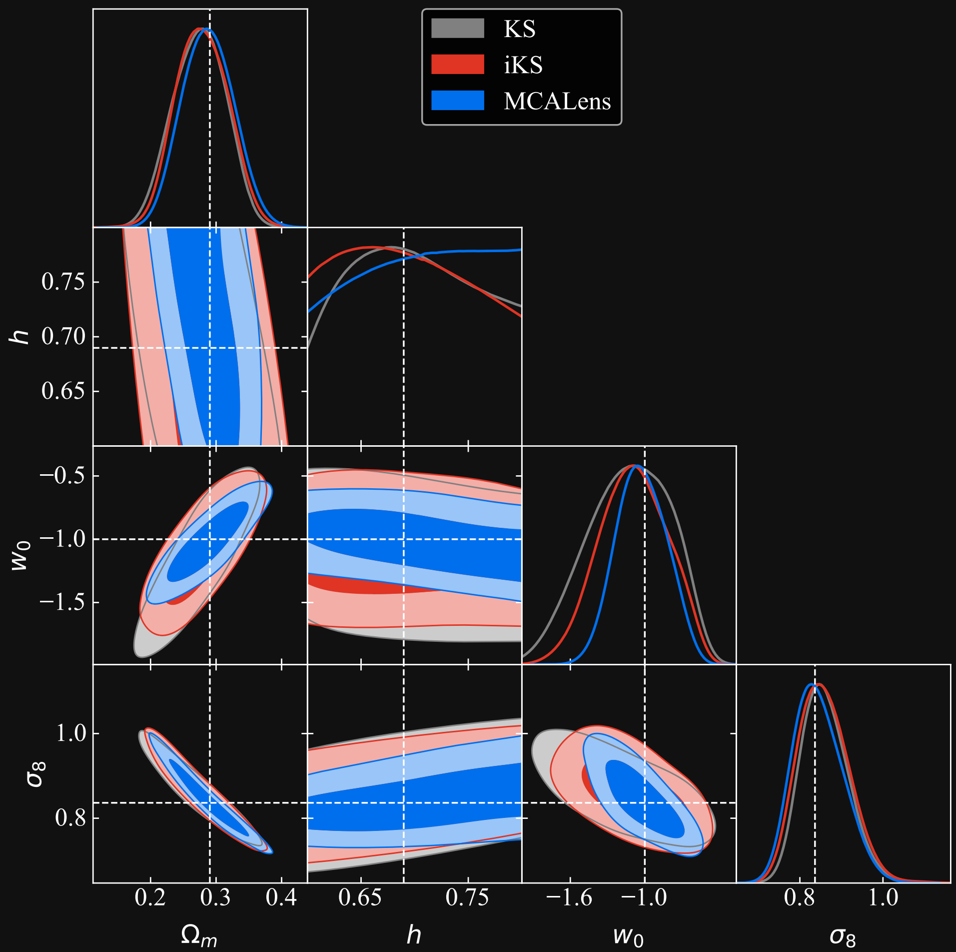
- To have a prediction of each HOS **given a new set of parameters**→ employ an interpolation with **Gaussian Process Regressor** (GPR)

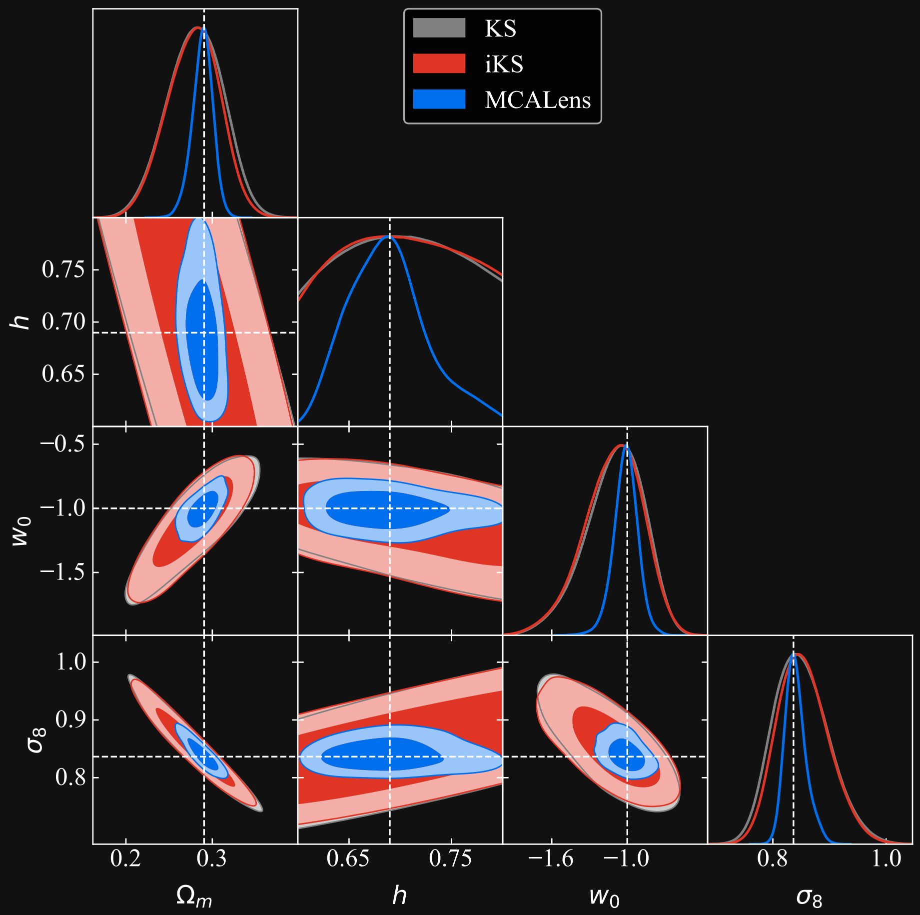
So does the choice of the mass mapping algorithm matter for the final constraints?

The (standard) mono-scale peak counts



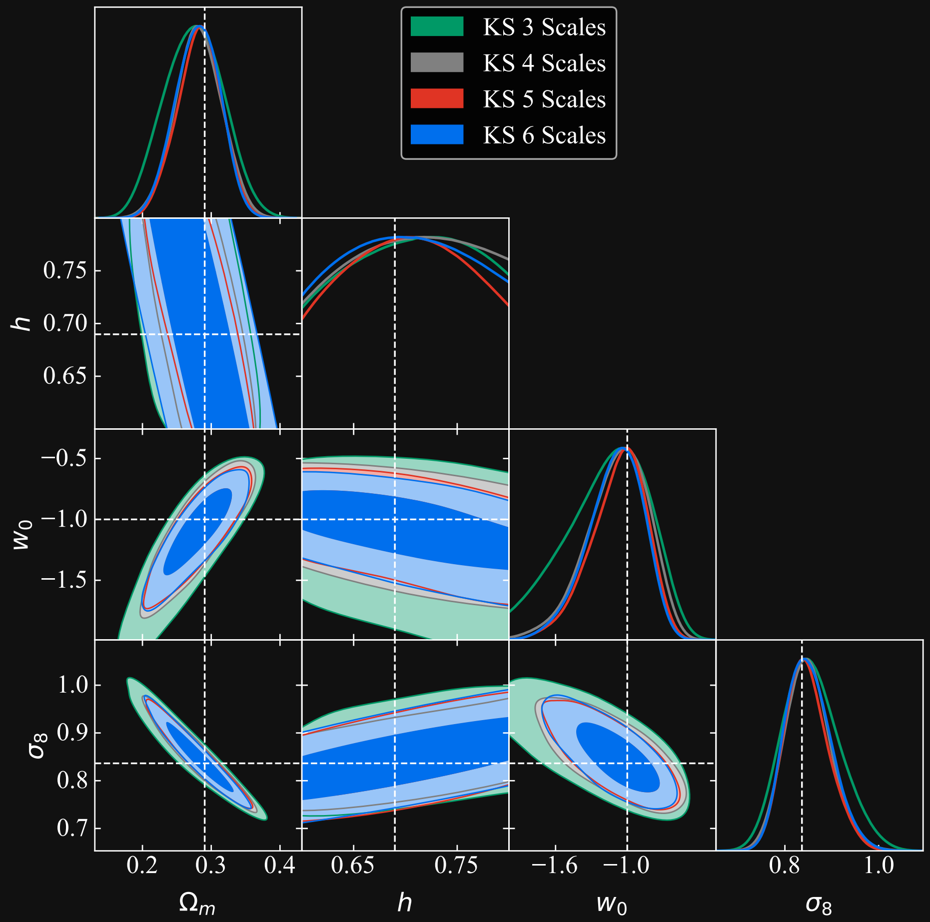
FoM	KS	iKS	MCALens
(Ω_m, h)	476	453	450
(Ω_m, w_0)	152	141	233
(Ω_m, σ_8)	1323	1285	1740
(h, w_0)	55	63	87
(h, σ_8)	336	292	293
(w_0, σ_8)	75	72	124
$(\Omega_m, h, w_0, \sigma_8)$	492	444	578

Wavelet multi-scale peak counts



FoM	KS	iKS	MCALens
(Ω_m, h)	670	702	2159
(Ω_m, w_0)	247	244	1051
(Ω_m, σ_8)	2414	2517	9039
(h, w_0)	82	80	259
(h, σ_8)	411	433	1335
(w_0, σ_8)	131	129	577
$(\Omega_m, h, w_0, \sigma_8)$	758	755	1947

Where does this improvement come from?



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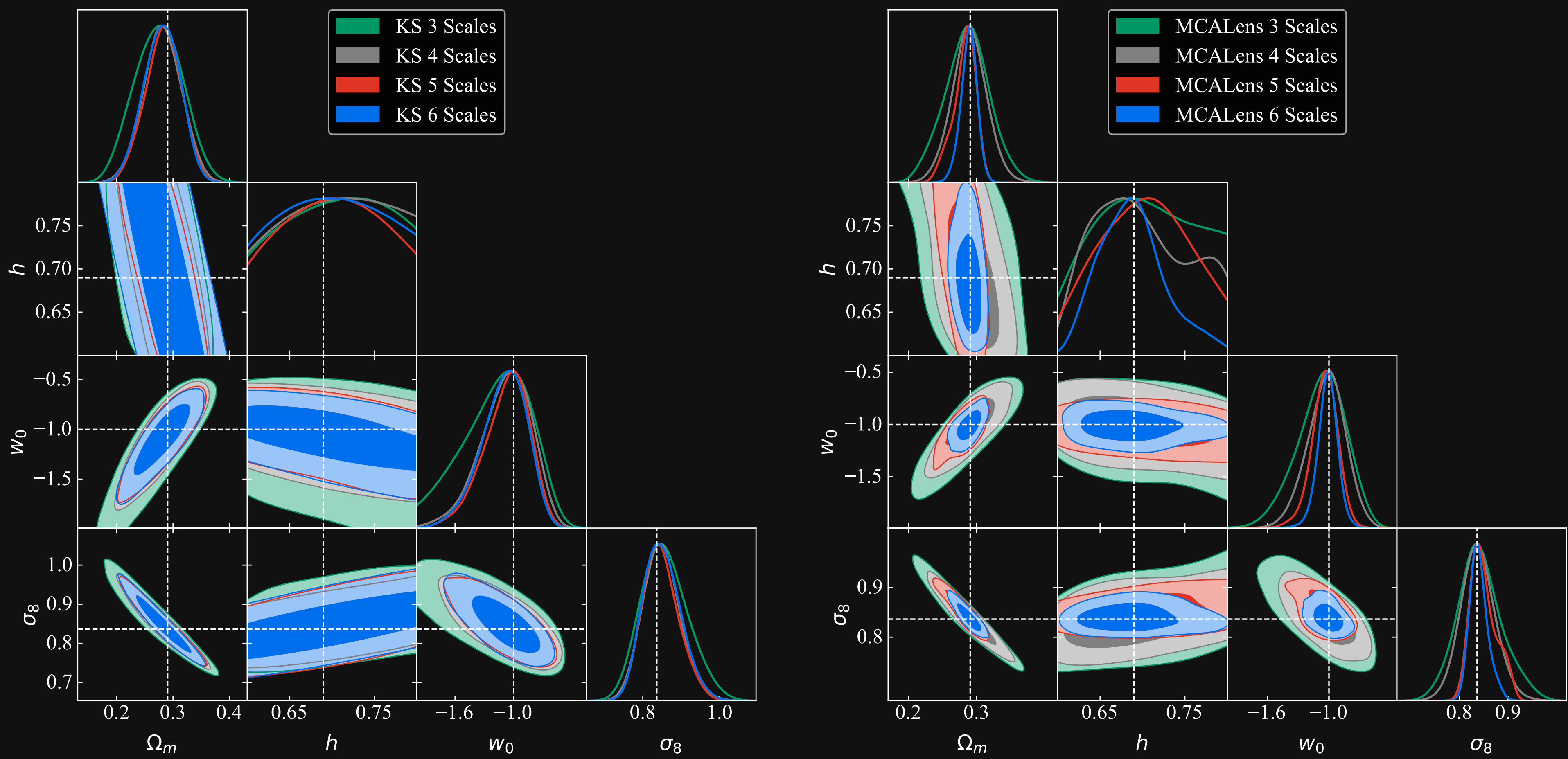

Part 2

A plug-and-play approach with fast uncertainty quantification for weak lensing mass mapping

H. Leterme, A. Tersenov, J. Fadili, and J.-L. Starck (in prep.)

Wait... what about Deep Learning for Mass Mapping?

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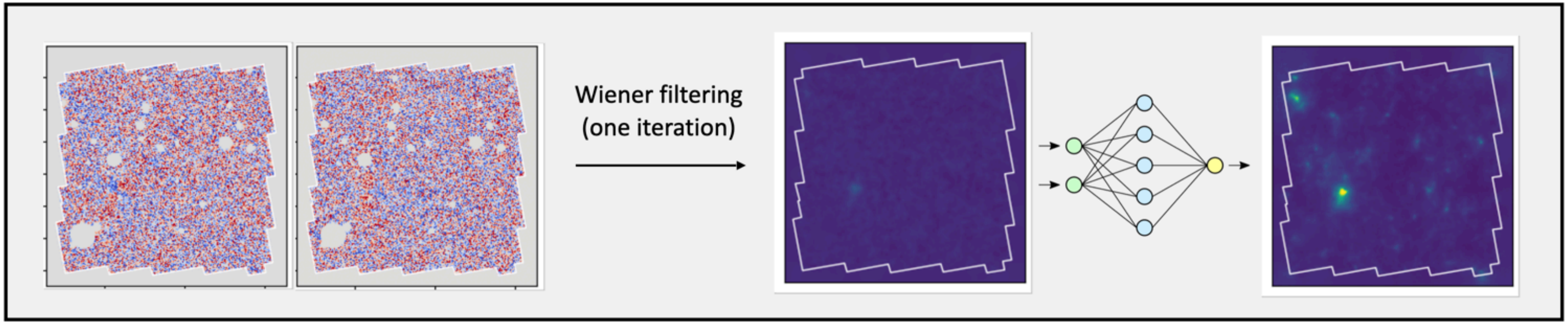

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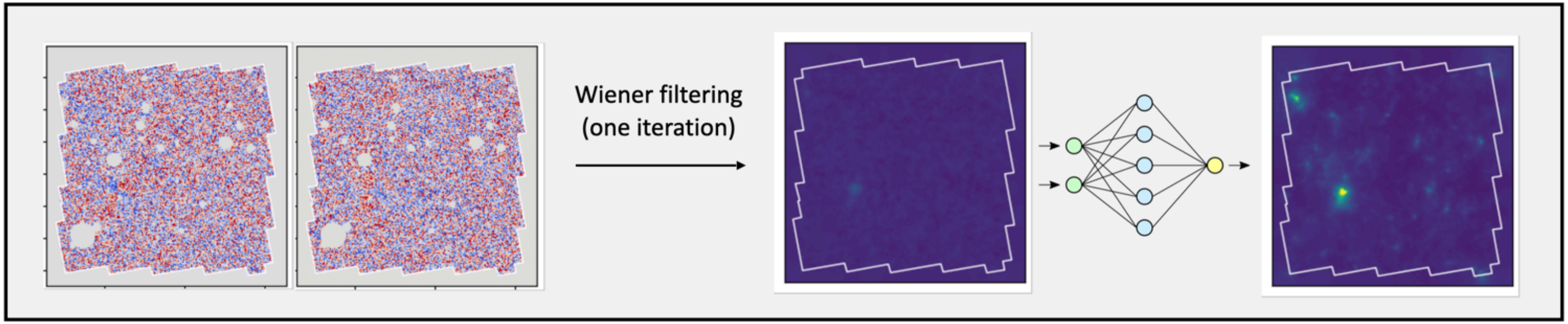

So what's the problem?

Deep Learning for Mass Mapping?

Mass mapping method	Type	Accurate	Flexible	Fast rec.	Fast UQ
Iterative Wiener	Model-driven (Gaus. prior)	✗	✓	✓	✗
MCALens	Model-driven (Gaus. + sparse)	≈	✓	✗	✗
DeepMass	Data-driven (UNet)	✓	✗*	✓	✓
DeepPosterior	Data-driven (UNet + MCMC)	✓	✓	✗	✗
MMGAN	Data-driven (GAN)	✓	✗*	≈	≈

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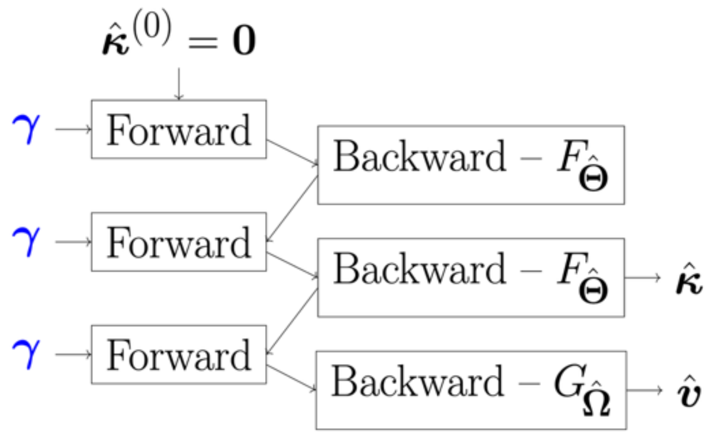
MMGAN	Data-driven (GAN)	✓	✗*	≈	≈
What we'd like	**Data-driven**	✓	✓	✓	✓

Plug-and-Play Mass Mapping

Plug-and-Play Mass Mapping

Main idea:

- *Use PnP framework:* replace **prox** by an on-the-shelf **deep denoiser** trained on simulations $\kappa^{n+1} = \mathrm{prox}_{\tau g} \left(\kappa^n - \tau \nabla f(\kappa^n) \right) \kappa^{n+1} = F_{\Theta} \left(\kappa^n - \tau \mathbf{B} \left(\mathbf{A} \kappa^n - \gamma \right) \right) \kappa^{n+1} = \mathrm{Denoiser} \left(\kappa^n + \mathrm{Data \, residual} \right)$
- Series **converges** towards a **fixed point** $\hat{\kappa}$
- If we choose $\mathbf{B} = \mathbf{A}^T \Sigma^{-1}$ → training phase independent of the noise covariance matrix



Instead of explicitly writing down a prior, we learn what a "likely" \kappa looks like from simulations and enforce it through denoising.

Implementation

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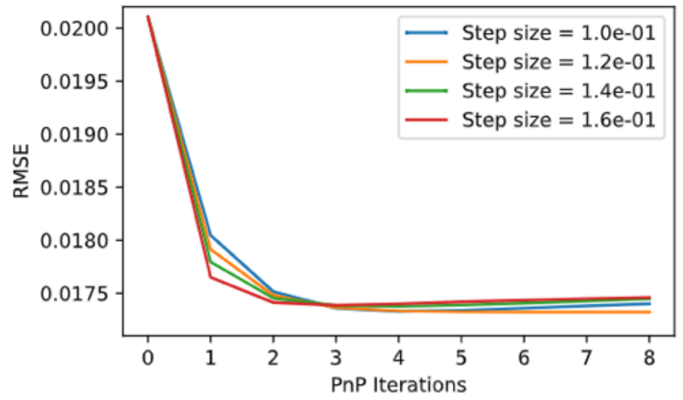
Training

- Denoiser models implemented: **DRUNet** & **SUNet**
- Trained on **κTNG** and **cosmoSLICS** simulations, using pairs of (\kappa_{\rm true}, \gamma_{\rm obs}) as training data



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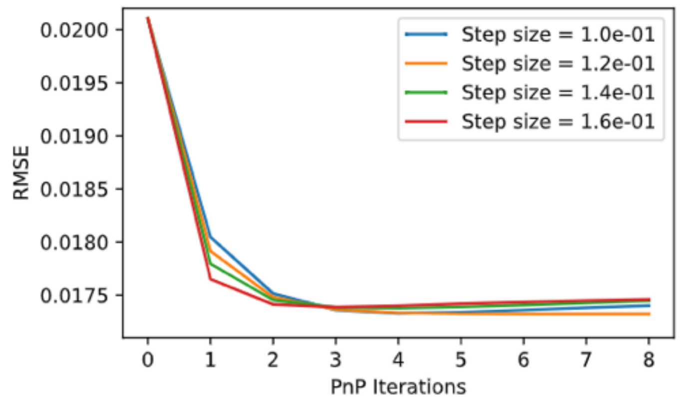

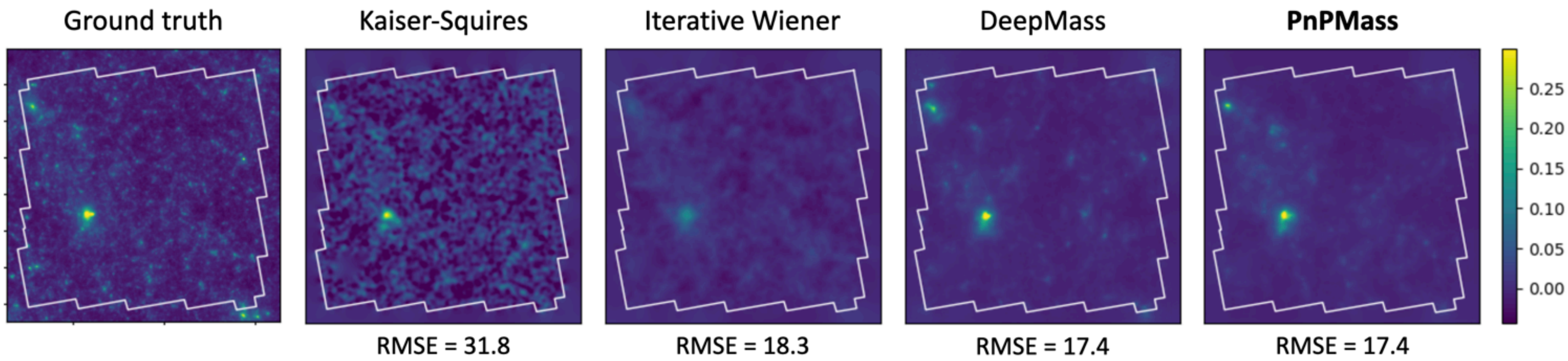

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Step 1

- We train a second neural network to estimate the **posterior variance** of \kappa: \arg\min_{\Omega} \mathbb{E} \left[\left\| G_{\Omega}(\gamma) - \big(\kappa - F_{\Theta}(\gamma) \big)^2 \right\|^2_2 \right]
- Trained on simulated pairs (\kappa, \gamma), just like the denoiser — but now focused on uncertainty.
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Step 2

- Neural networks tend to produce miscalibrated uncertainties.
- We apply conformal quantile regression (CQR) to adjust uncertainty intervals so they have guaranteed statistical coverage.
- CQR uses a held-out calibration set to compute a correction factor for each pixel.
- Result: Reliable, data-driven uncertainty maps — with built-in coverage guarantees.

Uncertainty bounds

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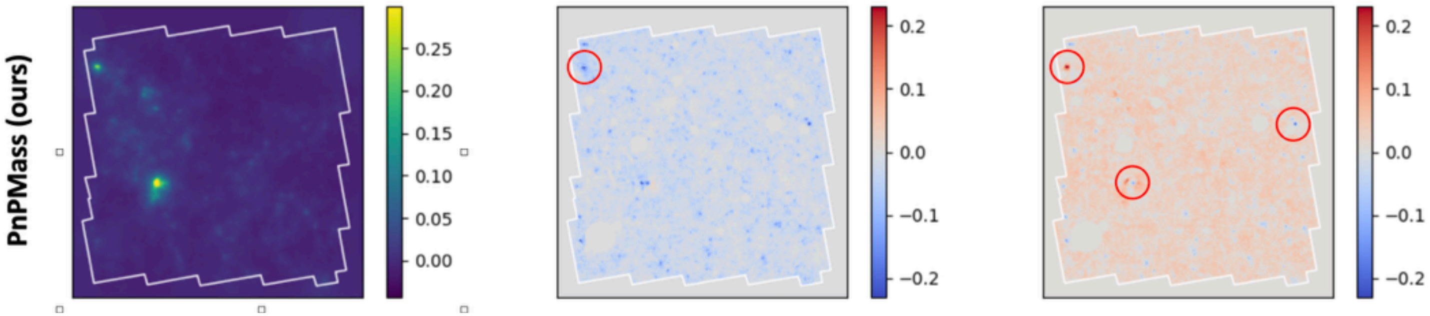

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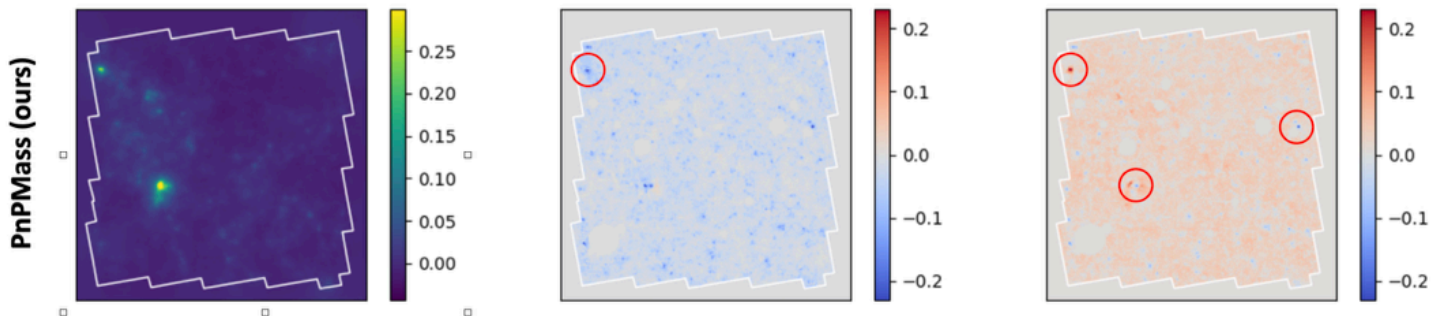

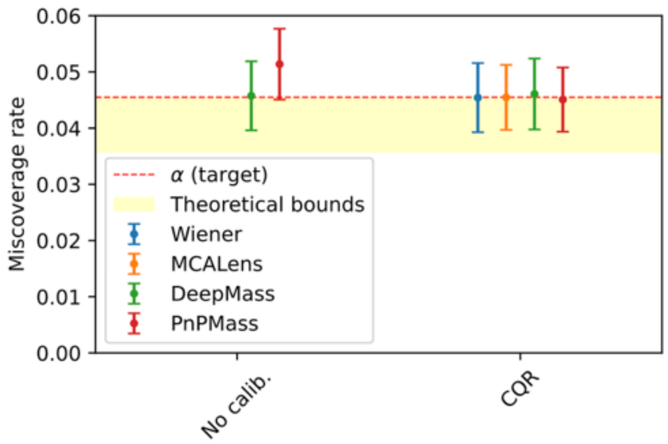

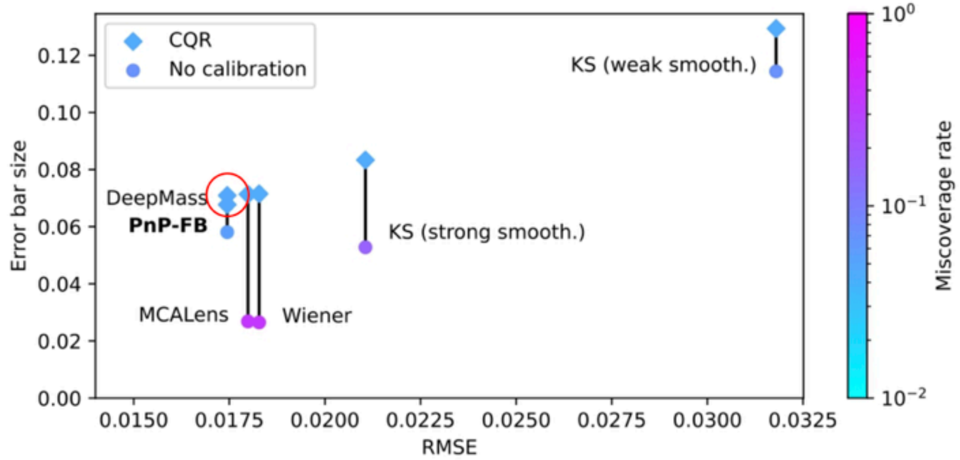

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- Increase in constraining power comes from the more accurate recovery of the **smaller scales**.
- **Wavelet Peak Counts**: Provide tighter constraints than single-scale peak counts.
- **PnP Mass Mapping**:
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  - Provides **fast** and **reliable** uncertainties using **moment networks** and **conformal quantile regression**.

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Takeaway

- **Mass-mapping Matters**: Choosing an advanced mass mapping method significantly enhances constraints on cosmological parameters from HOS.