

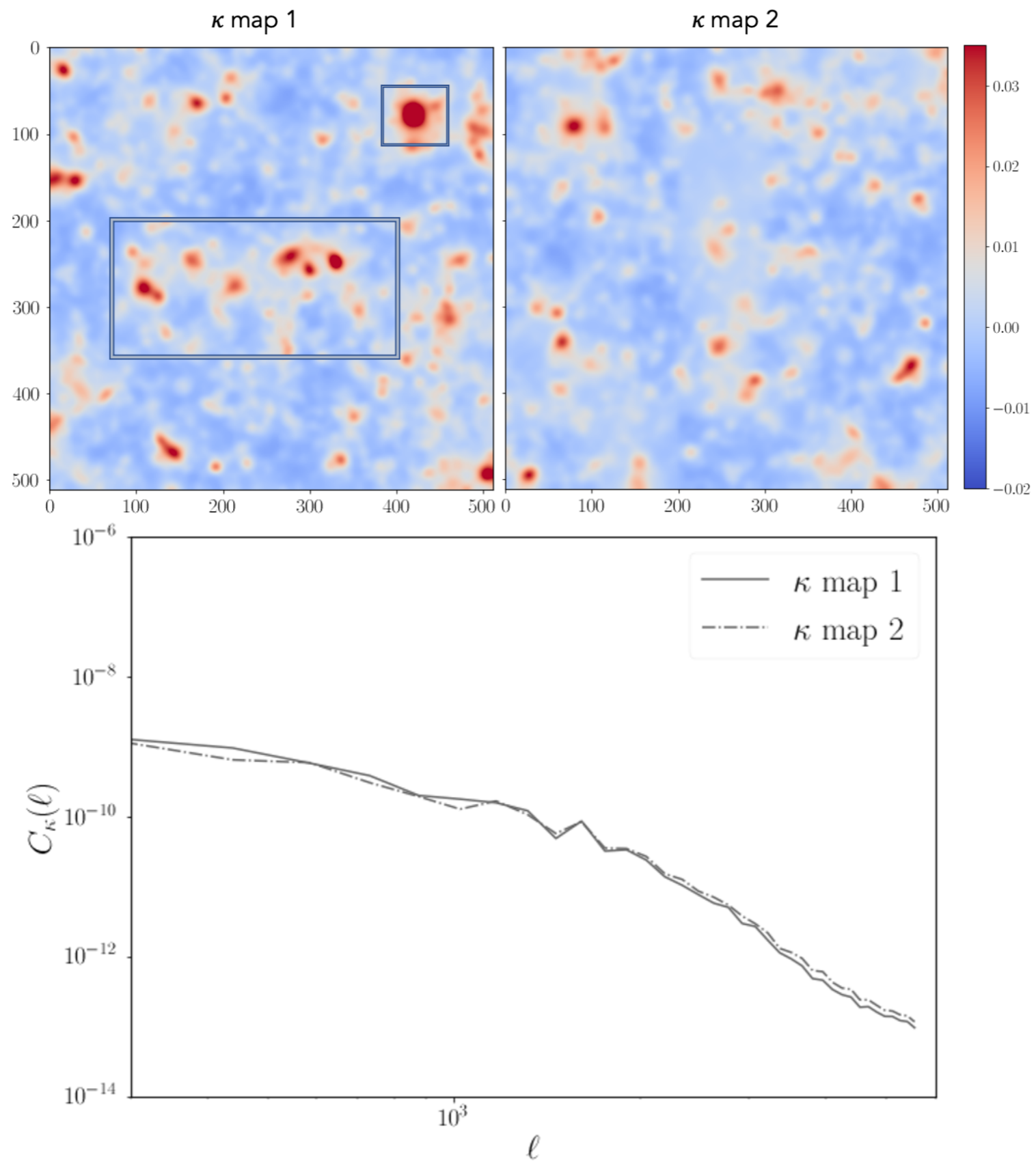
# Forecasting the power of Higher Order Weak Lensing Statistics with automatically differentiable simulations

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Some simulation-based inference approaches proposed to access the non-Gaussian information:

- [Lifting weak lensing degeneracies with a field-based likelihood](#), (*Natalia Porqueres, Alan Heavens, et al. (2021)*)
- [Mining gold from implicit models to improve likelihood-free inference](#) (*Johann Brehmer, Gilles Louppe et al. (2018)*)

### MAIN LIMITATIONS:

- Gradient-based
- Costly as they require a large number of simulations
- Intractable for more than 3 or 4 cosmological parameters.

$$\left. \frac{df(x)}{dx} \right|_{x_1} \approx \frac{f(x_1 + h) - f(x_1)}{h}$$

**DLL (Differentiable lensing light cone)**

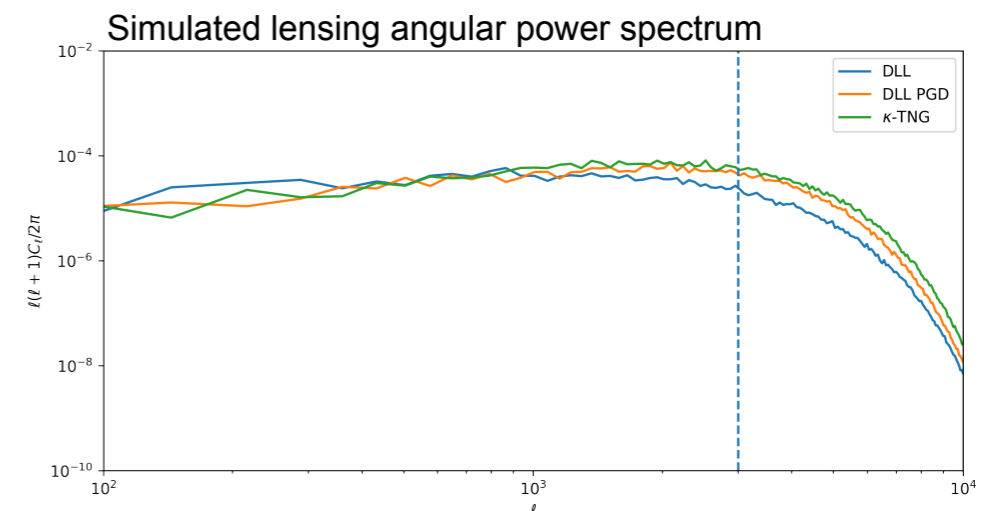
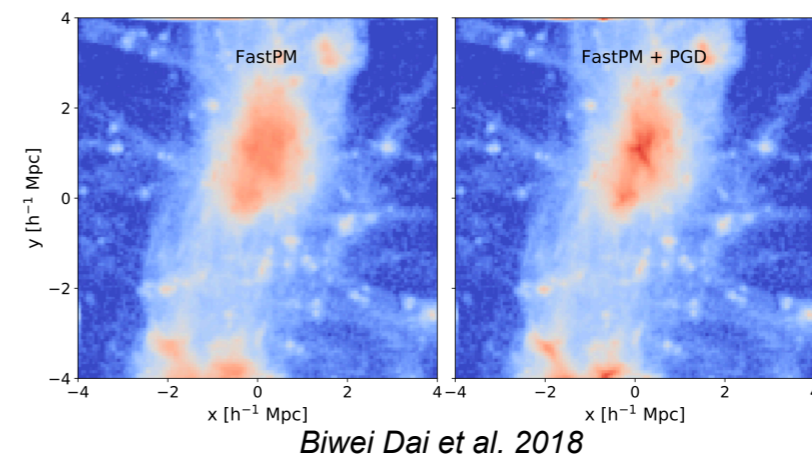
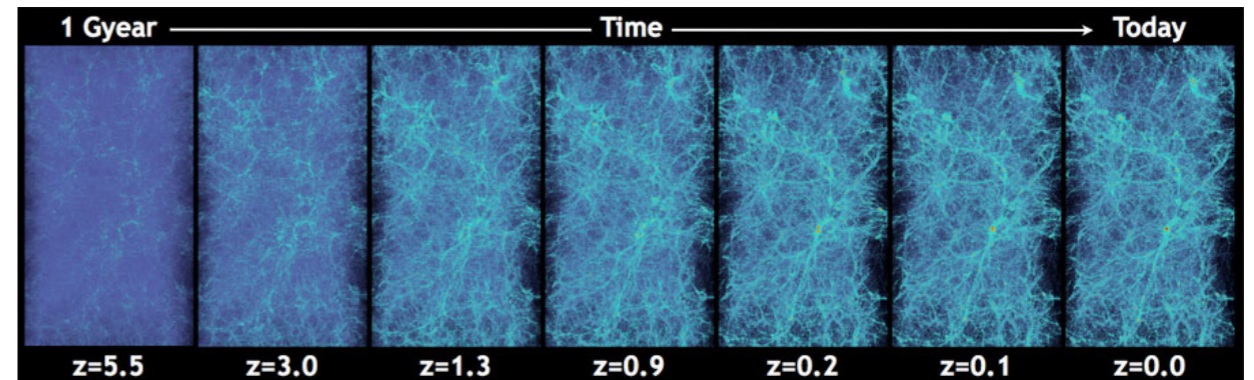
→ **TensorFlow**-based weak gravitational lensing package

- **N-body** simulation (particle-mesh solver)
- Fills the gap in the accuracy-speed space through the PGD scheme
- Provides derivatives with respect to cosmological and nuisance parameters through automatic differentiation

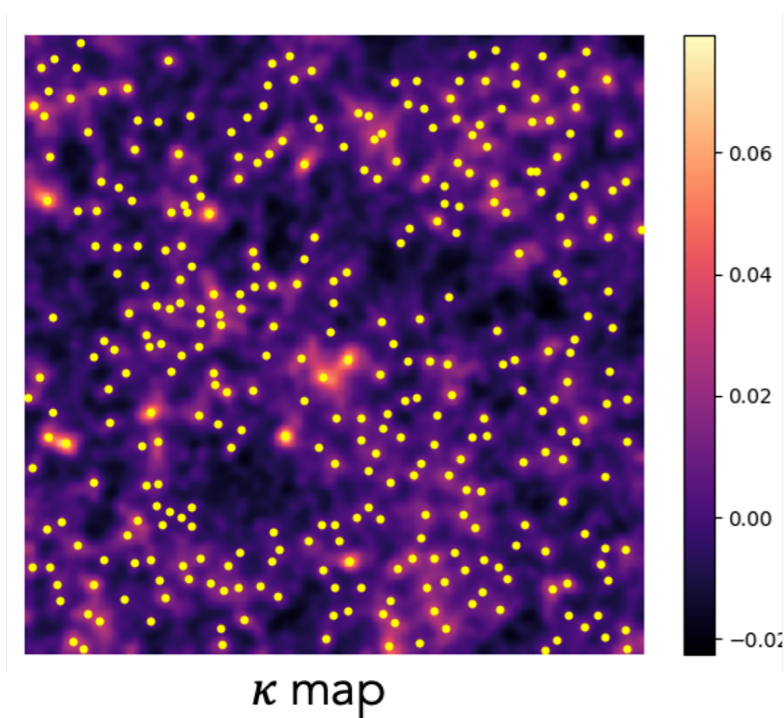


<https://github.com/DifferentiableUniverseInitiative/flowpm>

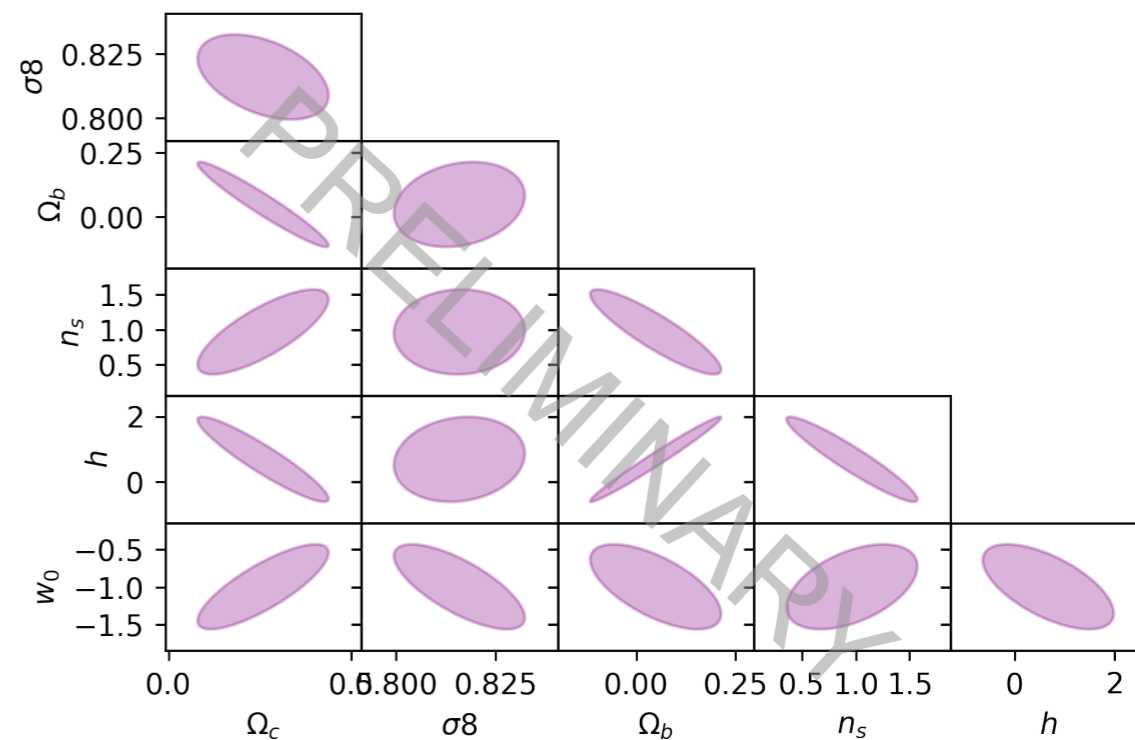
<https://github.com/LSSTDESC/DifferentiableHOS>



Peak counts (local maxima)



$$F_{\alpha,\beta} = \sum_{i,j} \frac{d\mu_i}{d\theta_\alpha} C_{i,j}^{-1} \frac{d\mu_j}{d\theta_\beta}$$



- Forecast for any map-based statistics (Scattering transform, l1norm, neural compression, etc)

## Next step

- Simulation based inference, made efficient by very fast lensing lightcone and having access to gradient

Everyone is most welcome to join! How to get in touch:

- GitHub repo: <https://github.com/LSSTDESC/DifferentiableHOS>  
<https://github.com/DifferentiableUniverseInitiative/flowpm>

Thank you!



