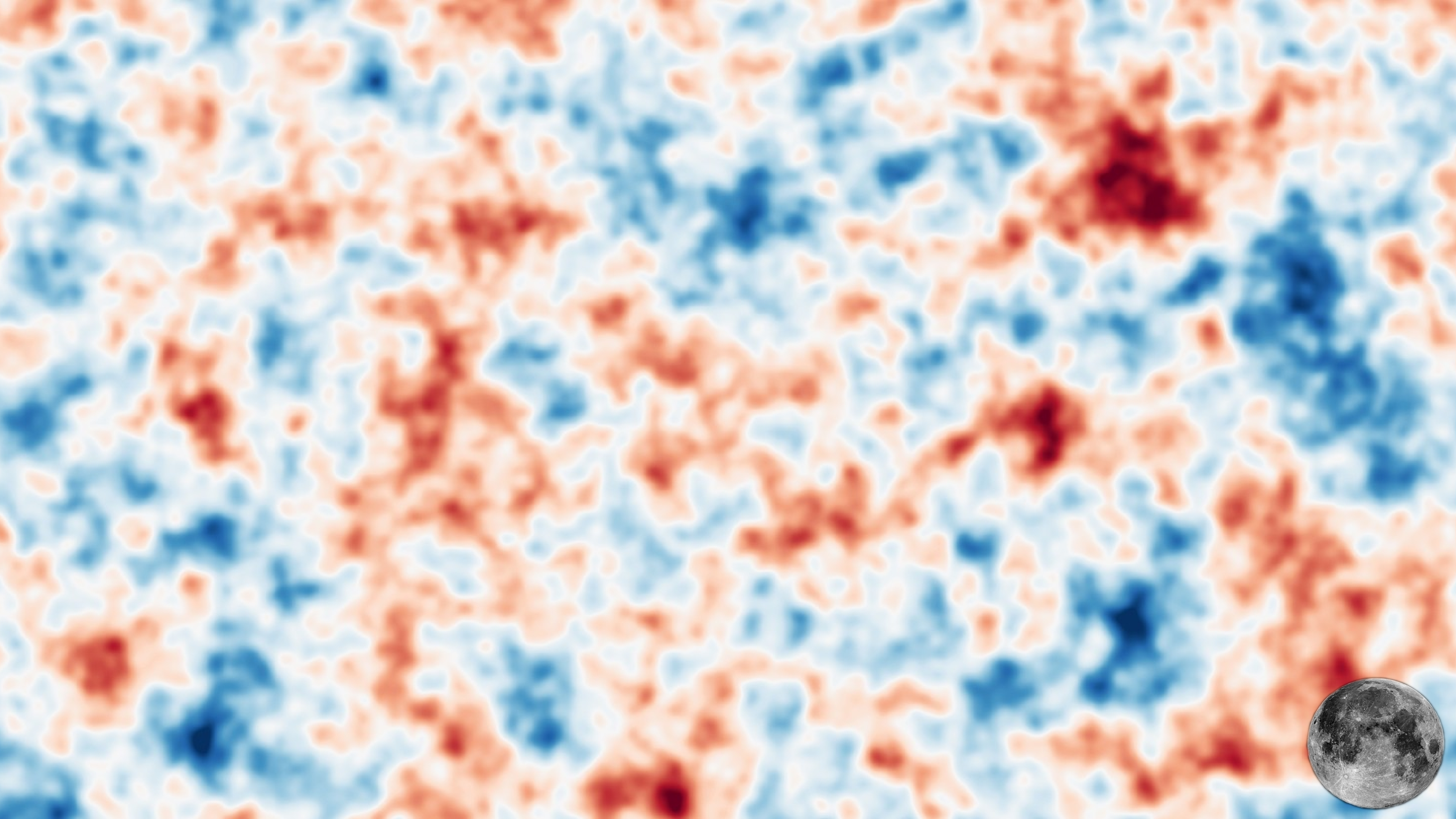
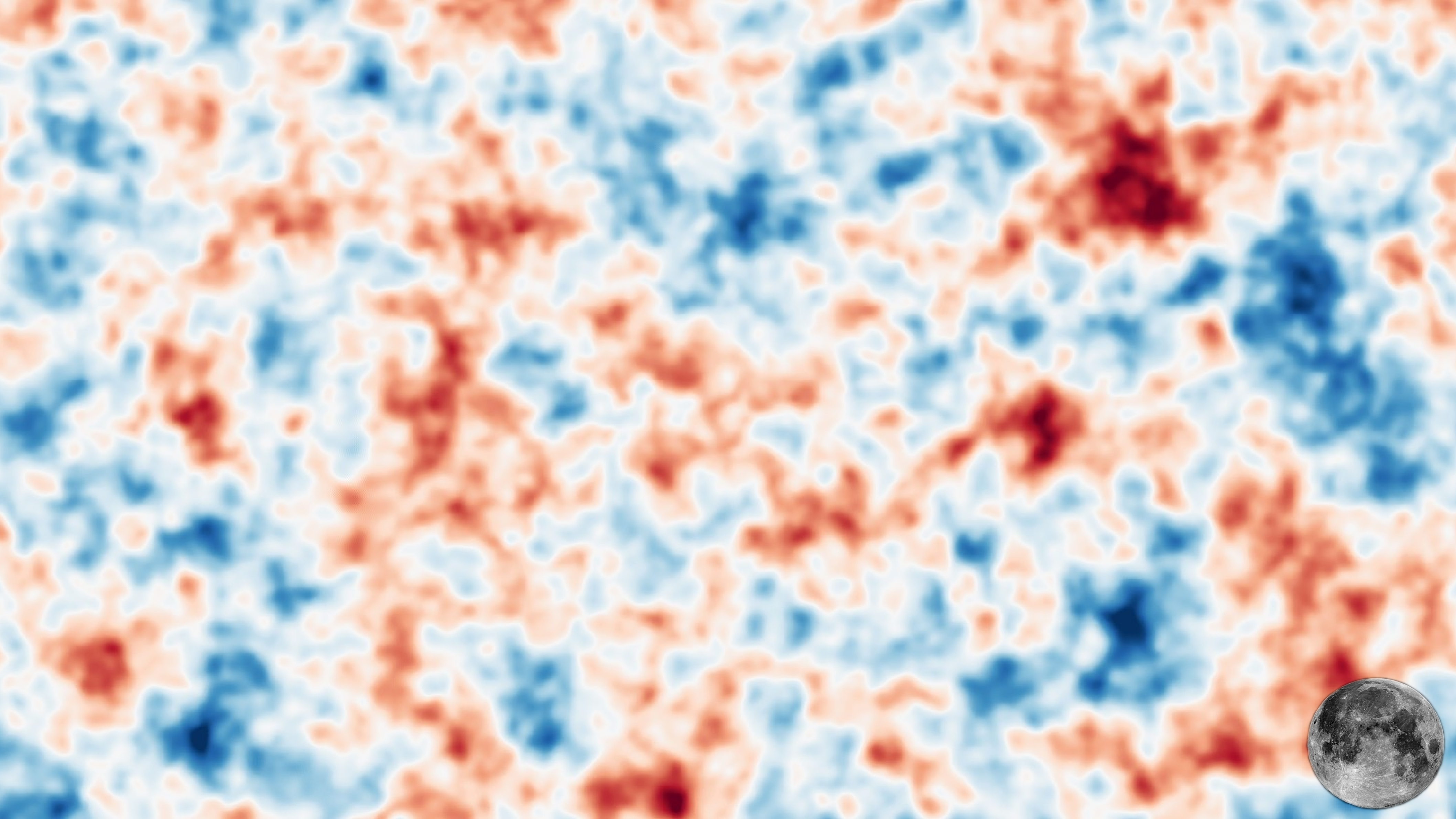
CMB Lensing for Large Scale Structure

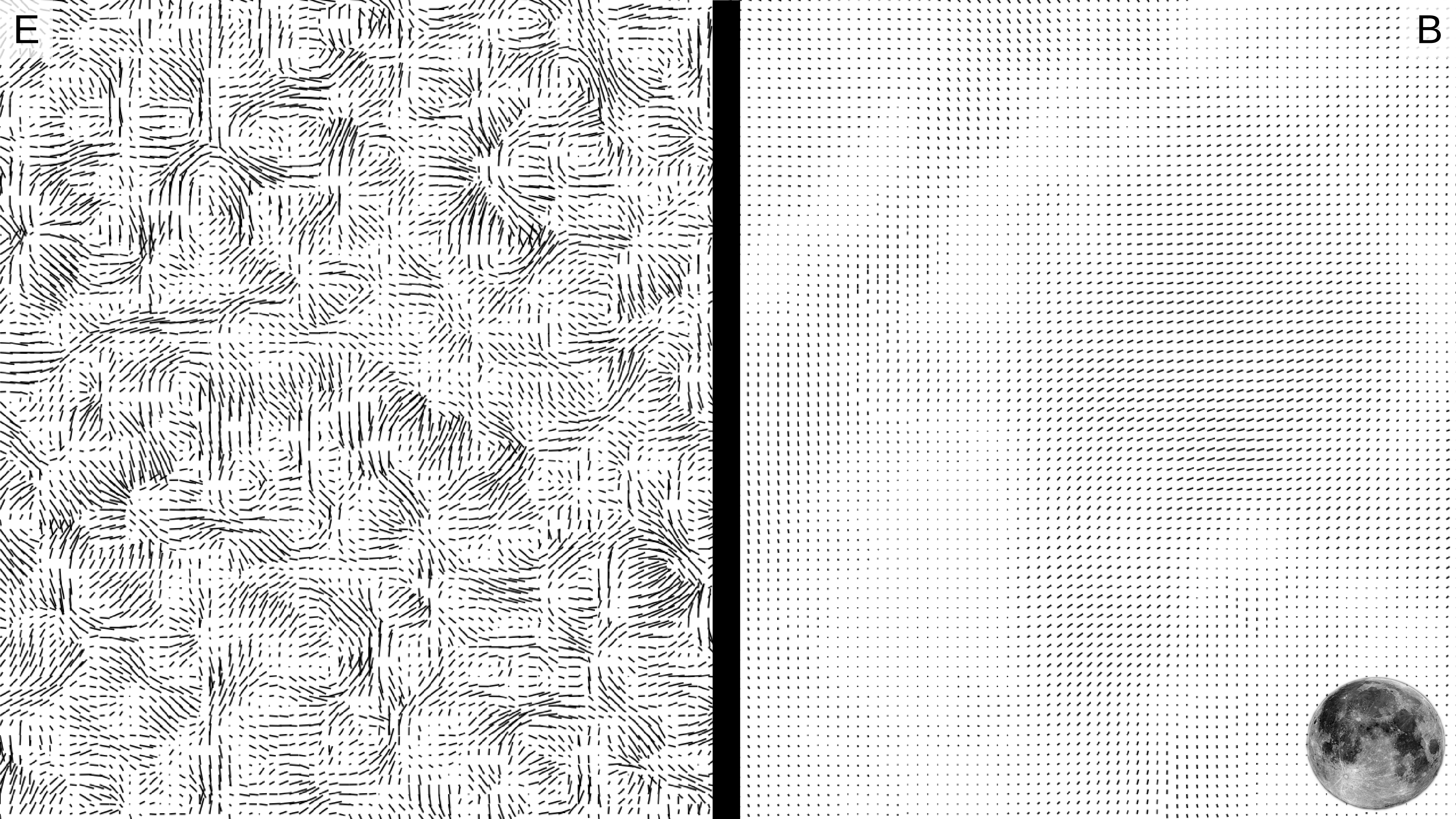
Marius Millea (UC Davis)

CMB-S4 Meeting

July 31, 2023



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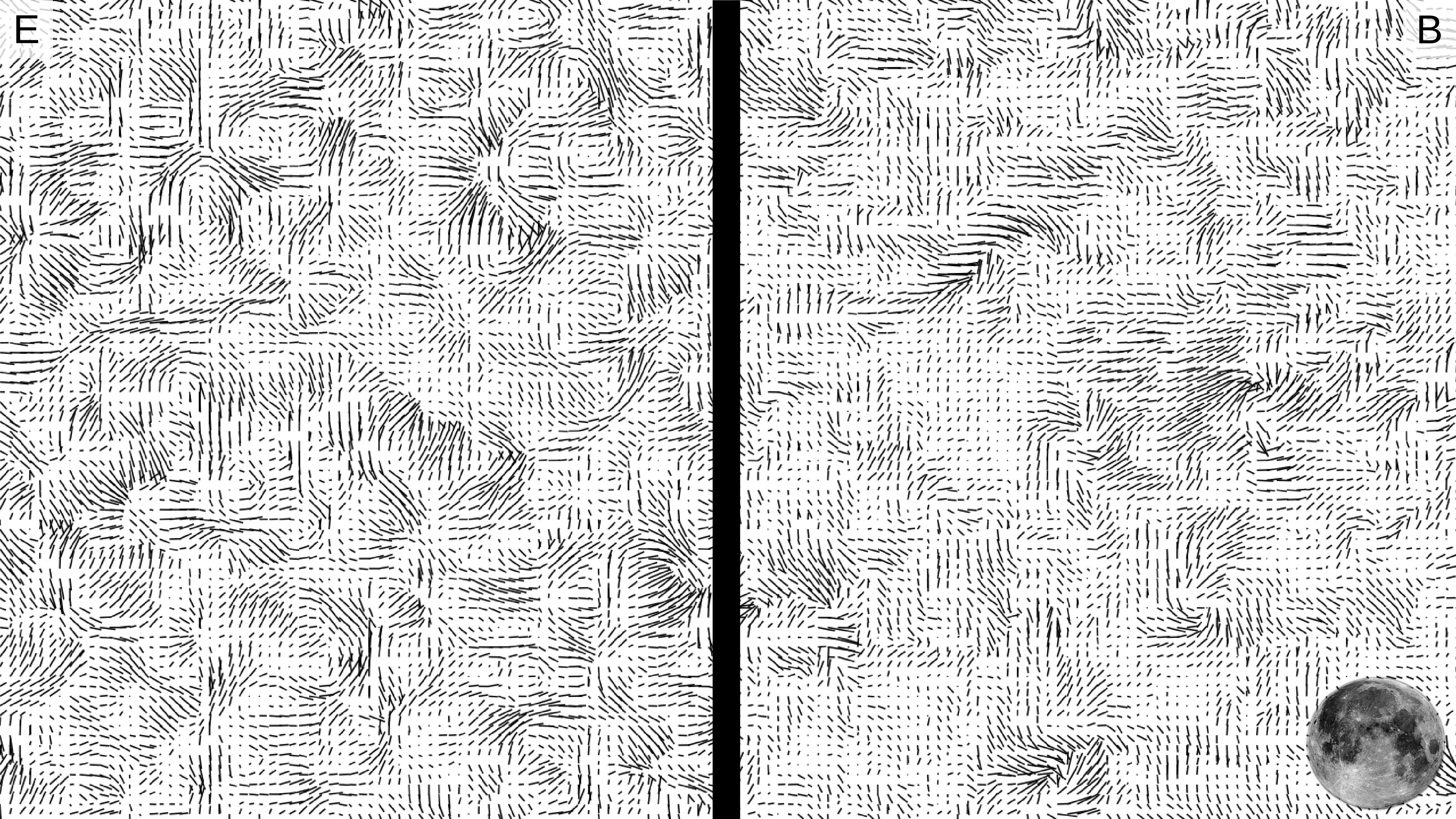
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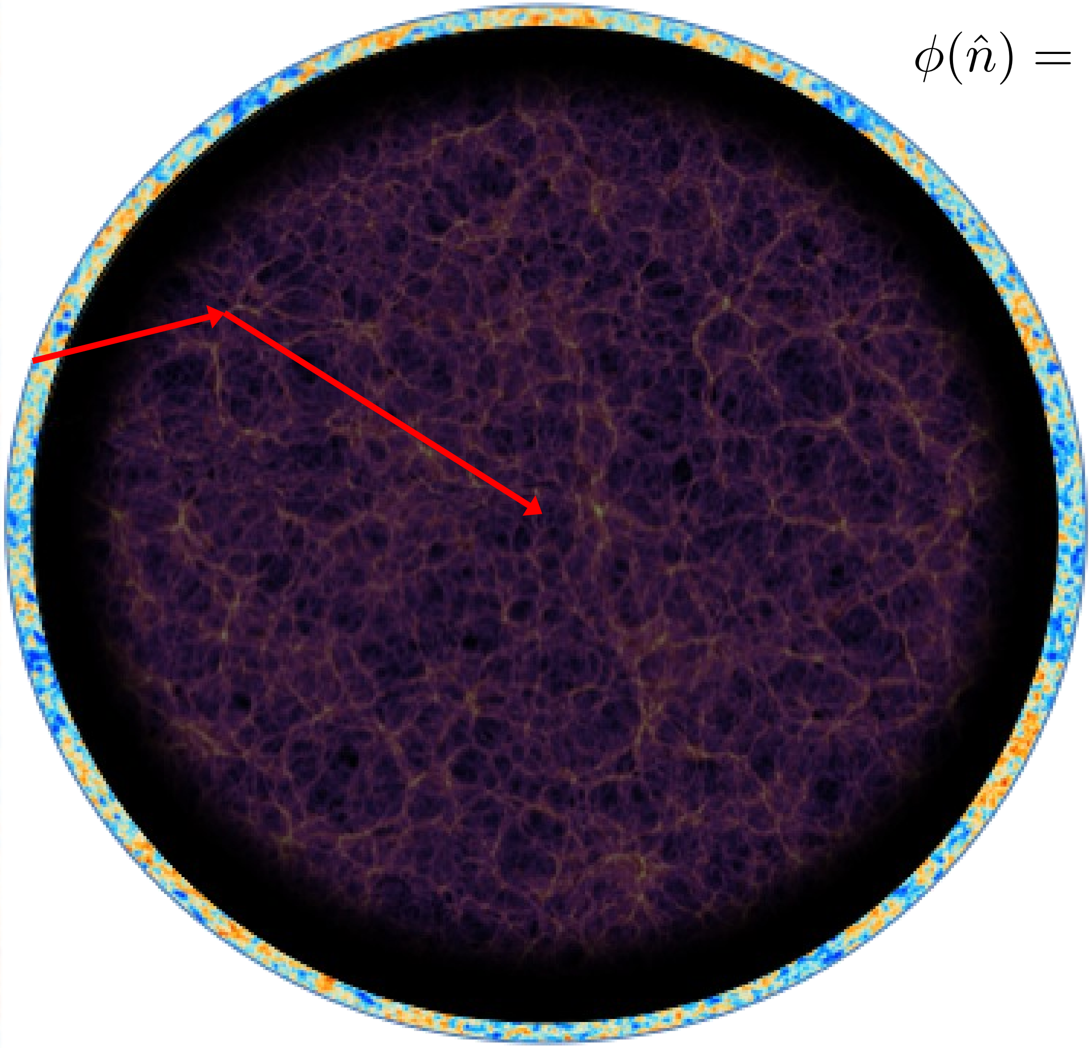
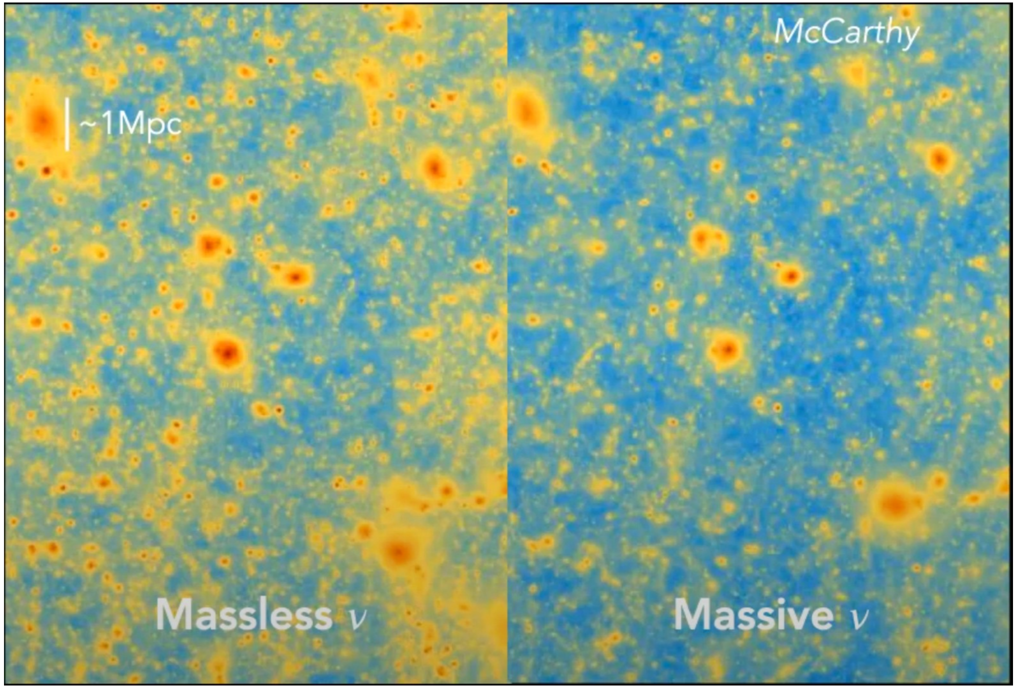


Image: Blake Sherwin

$$\phi(\hat{n}) = -2\int_0^{\chi_*} d\chi \frac{f_K(\chi_* - \chi)}{f_K(\chi_*) f_K(\chi)} \Psi(\chi\hat{n}; \eta_0 - \chi)$$

- Solely gravitational effect
- Linear LSS theory + Born approximation highly accurate
- “Source plane” very well understood
- Some perturbative effects relevant
  - Non-linear LSS
  - Post-Born
  - Baryonic effects

Lensing science: weighing neutrinos



Oscillations

$$\Delta m_{ij}^2 = m_i^2 - m_j^2$$

Beta decay

$$\langle m_\beta \rangle = \sqrt{\sum_{i=1}^{3} |U_{ei}|^2 m_i}$$

Double beta decay

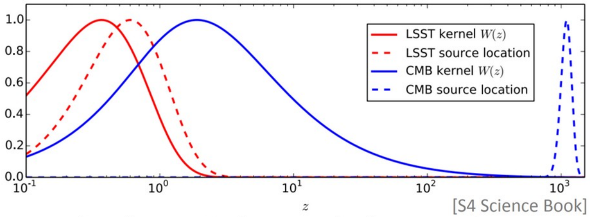
$$\langle m_{\beta\beta} \rangle = \sum_{i=1}^{3} |U_{ei}|^2 m_i \epsilon_i$$

S4: $\Sigma m_\nu = m_1 + m_2 + m_3$

- LSS unique and complementary probe of *sum* of neutrino masses
- S4 (+ LSS) guaranteed 3σ detection

Lensing science: cross correlations

CMB lensing cross-correlates with nearly any other low-z probe of structure.



[S4 Science Book]

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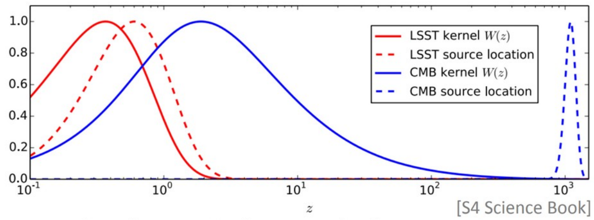

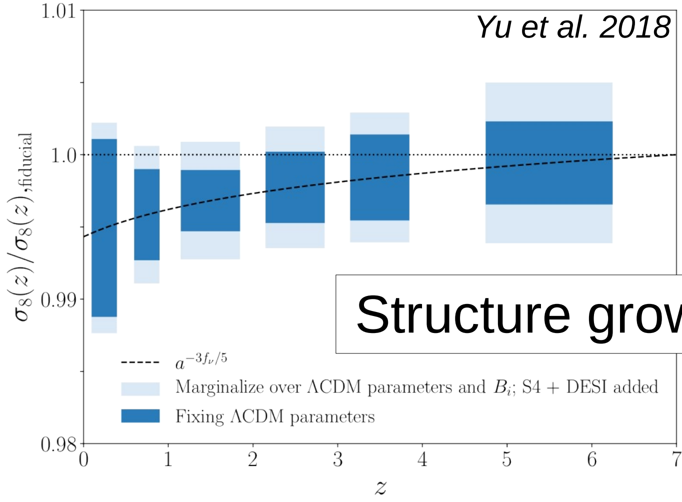

Structure growth

Lensing science: cross correlations

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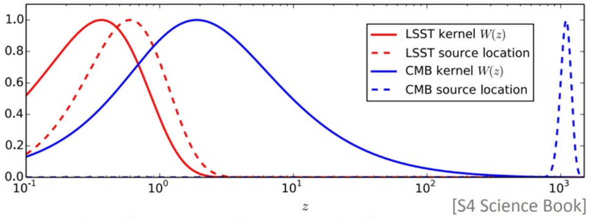

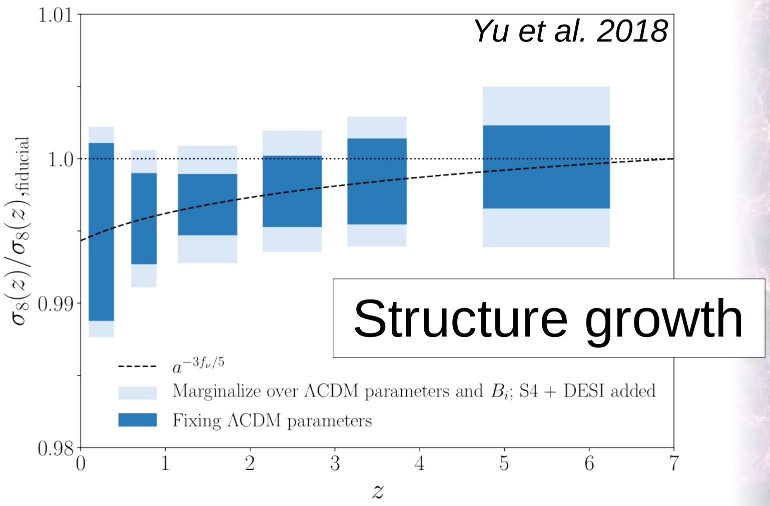

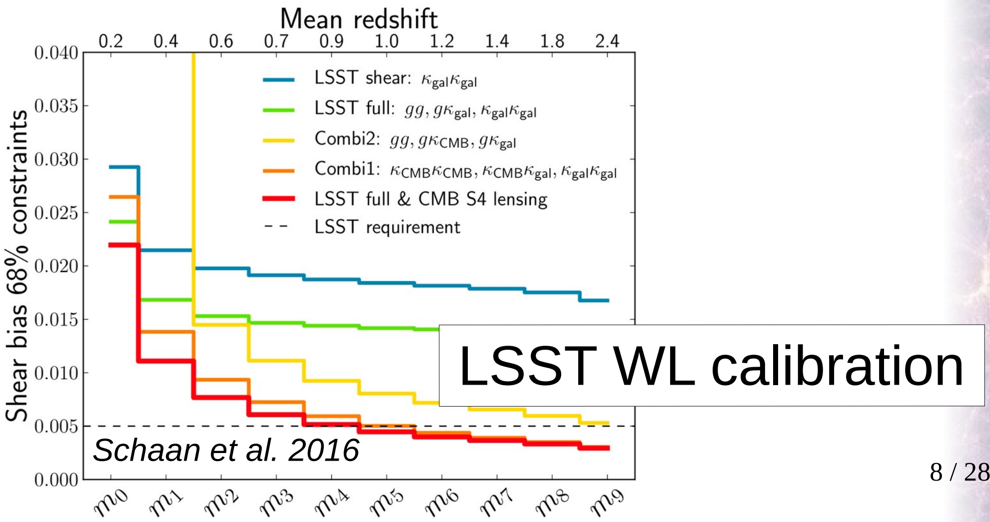

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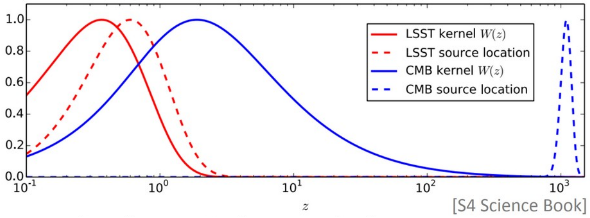
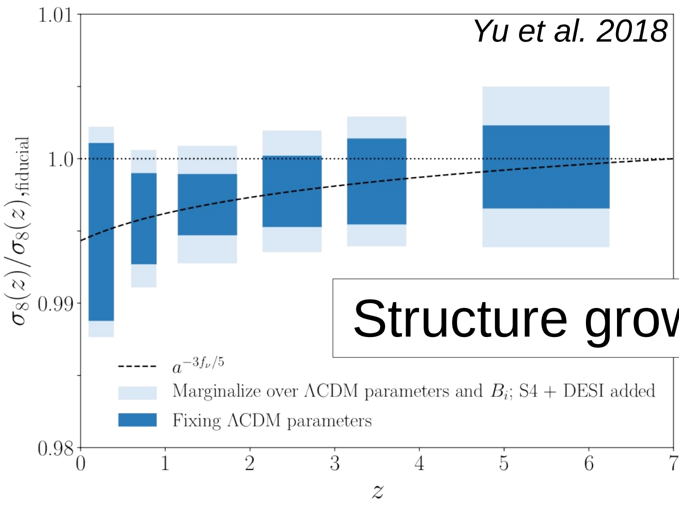
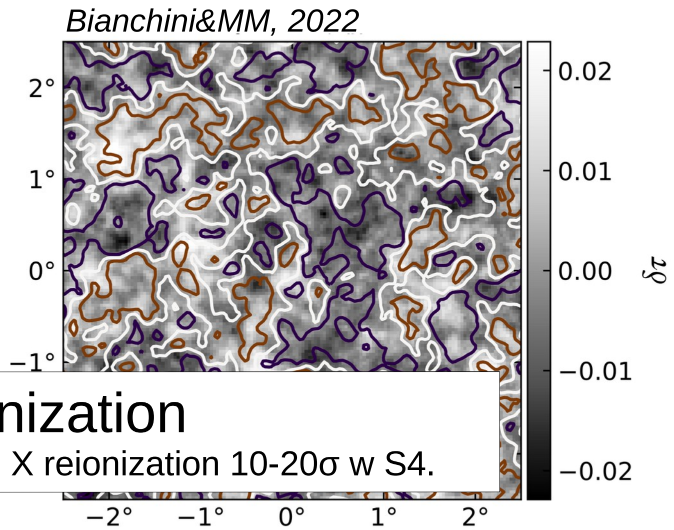


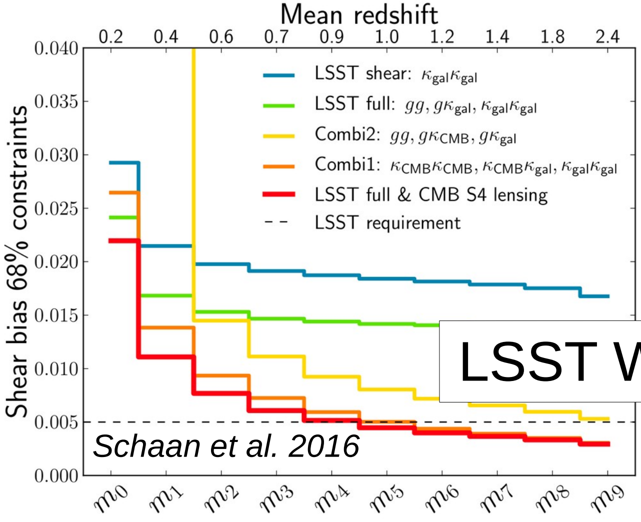


Structure growth



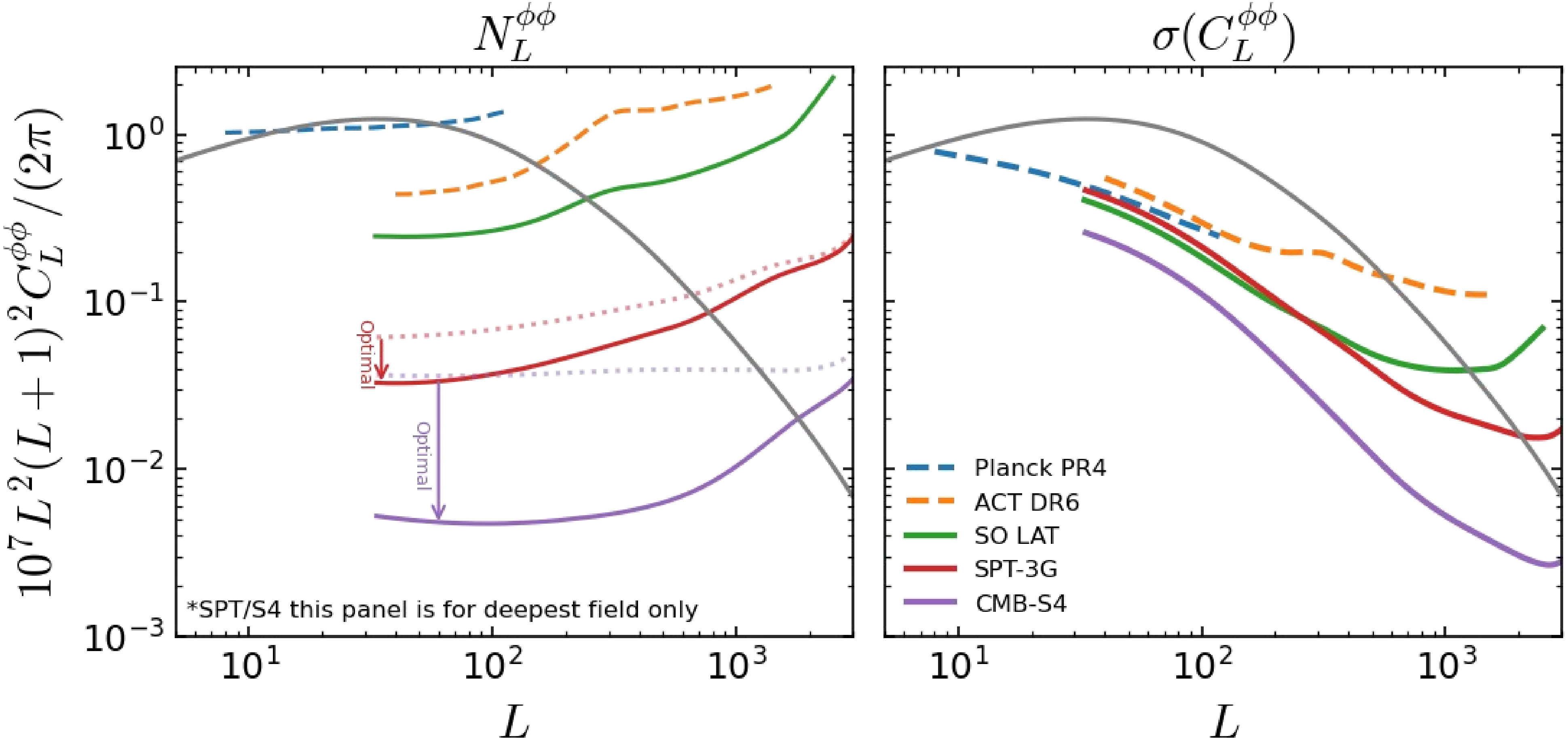
Reionization

Lensing X reionization 10-20σ w S4.



LSST WL calibration

New era of lensing reconstruction noise and methodology



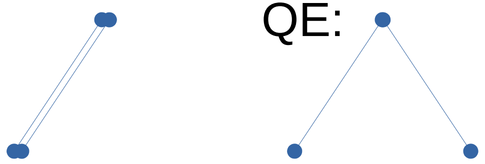
*SPT/S4 are (my) map-level Bayesian forecasts

Estimator-based (QE)

“process my data in some way to get an estimate of what I want”

Estimators:

Cl: QE:



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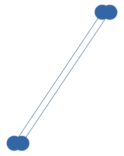
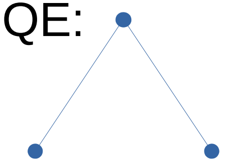
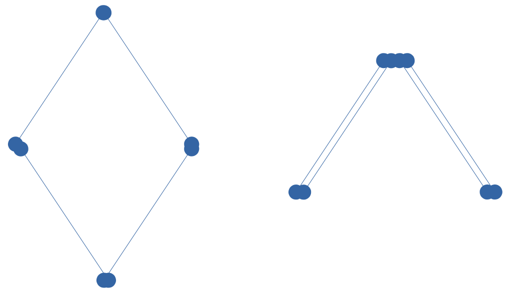
Cl:  QE: 

QE Bias: 

Estimator-based (QE)

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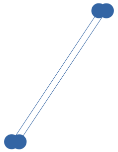
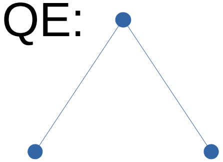
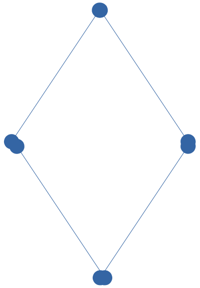
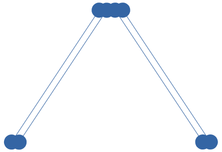


QE:



QE Bias:





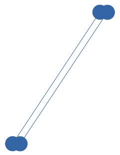
Higher order:

Estimator-based (QE)

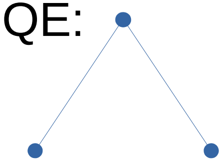
“process my data in some way to get an estimate of what I want”

Estimators:

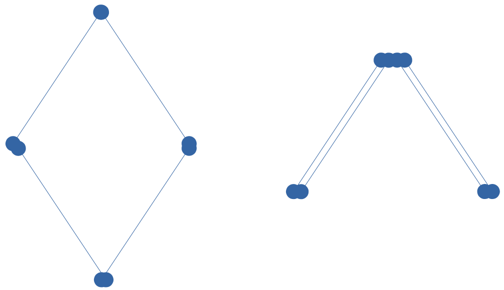
Cl:



QE:



QE Bias:



Higher order:

Forward modeling (Bayesian)

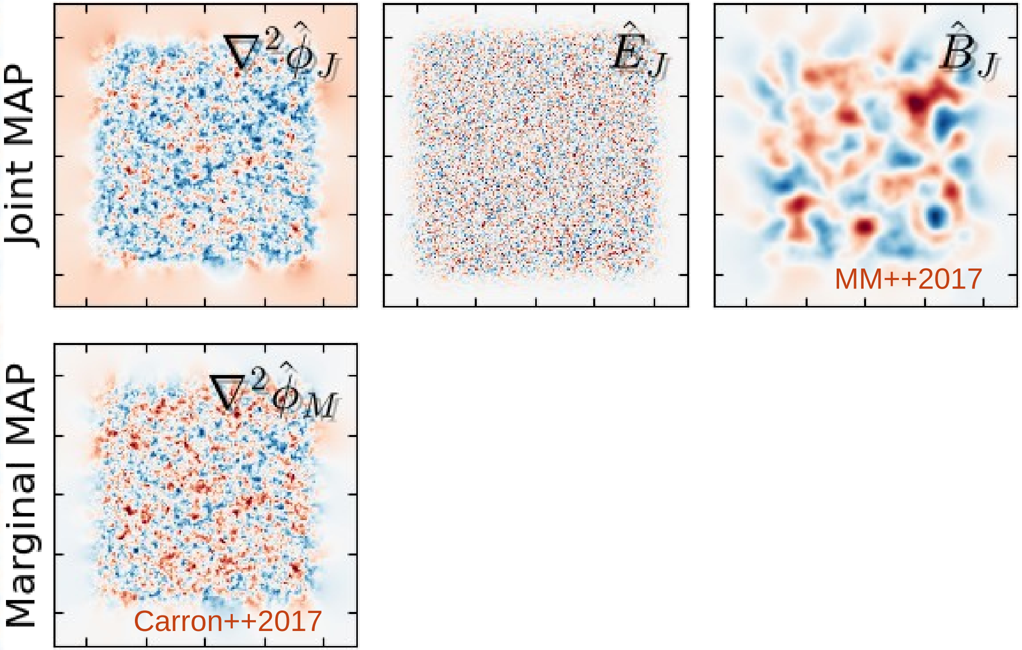
“model my data as a function of the thing I want, then see what fits”

$$d = L(\phi) f + n$$

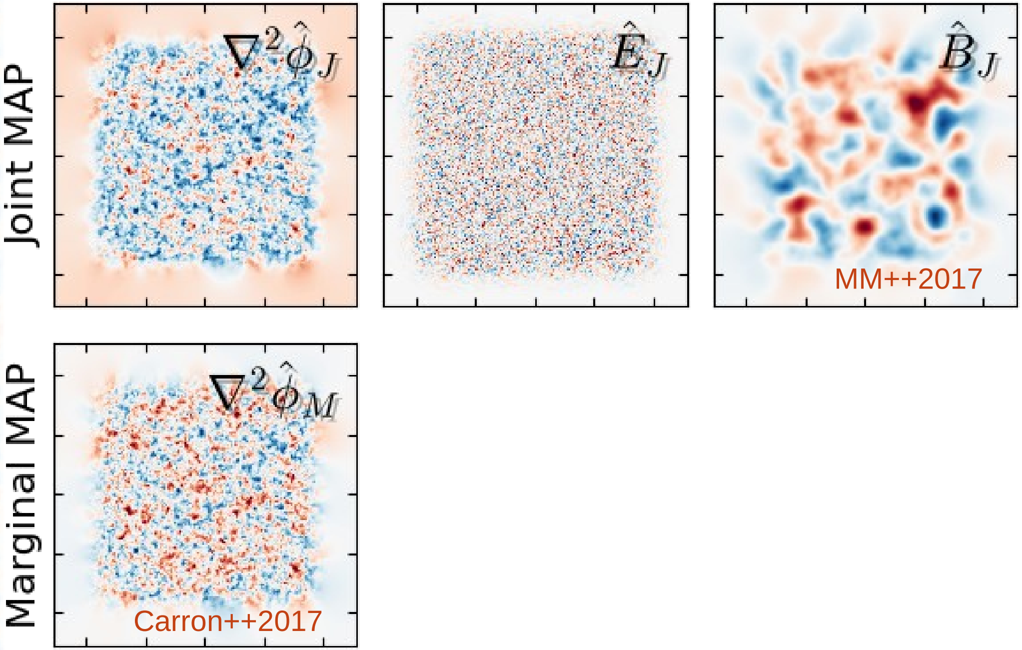
$$\mathcal{P}(C_\ell^{\phi\phi} \,|\, d) = \int \mathrm{d}f \, \mathrm{d}\phi \, \mathcal{P}(f, \phi, C_\ell^{\phi\phi} \,|\, d)$$

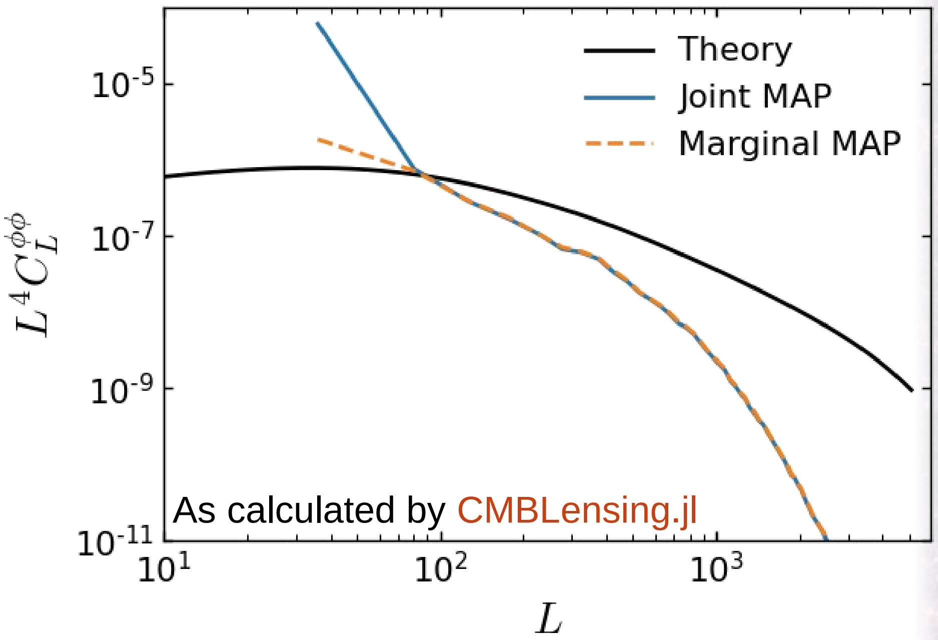
- Implicitly extracts all-orders info
- Good if you have a great model
- Marginalization is hard
- *Doesn’t* impose extra modeling requirements per se

Data-ready Bayesian lensing building blocks

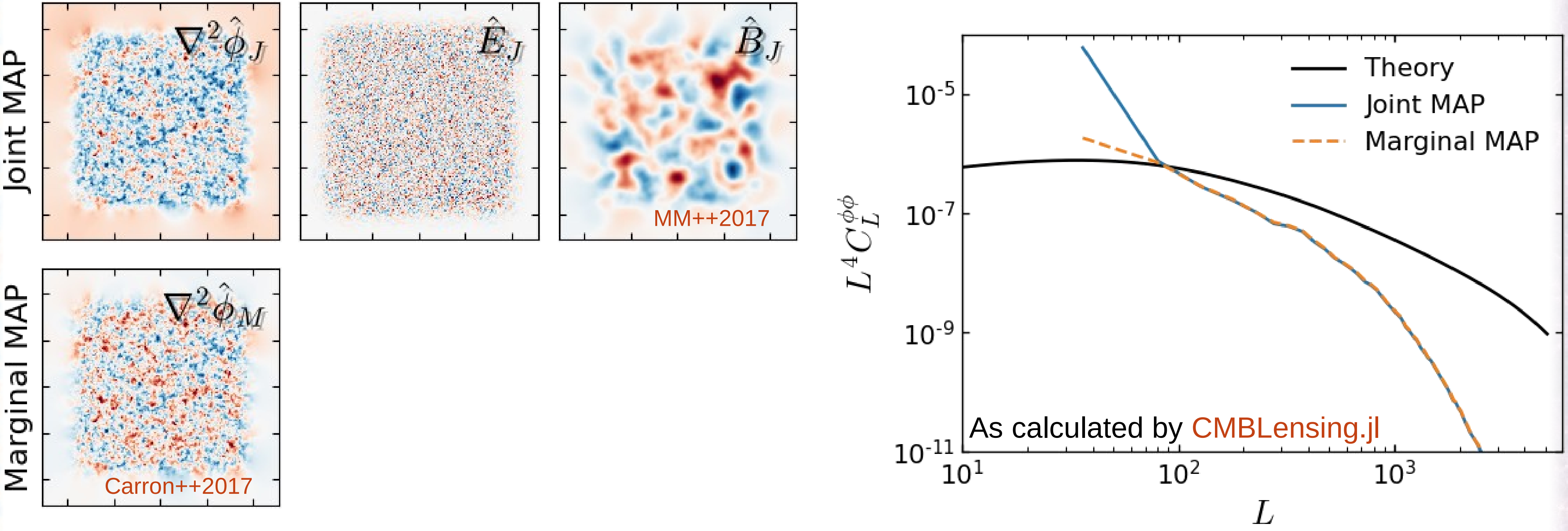


Data-ready Bayesian lensing building blocks



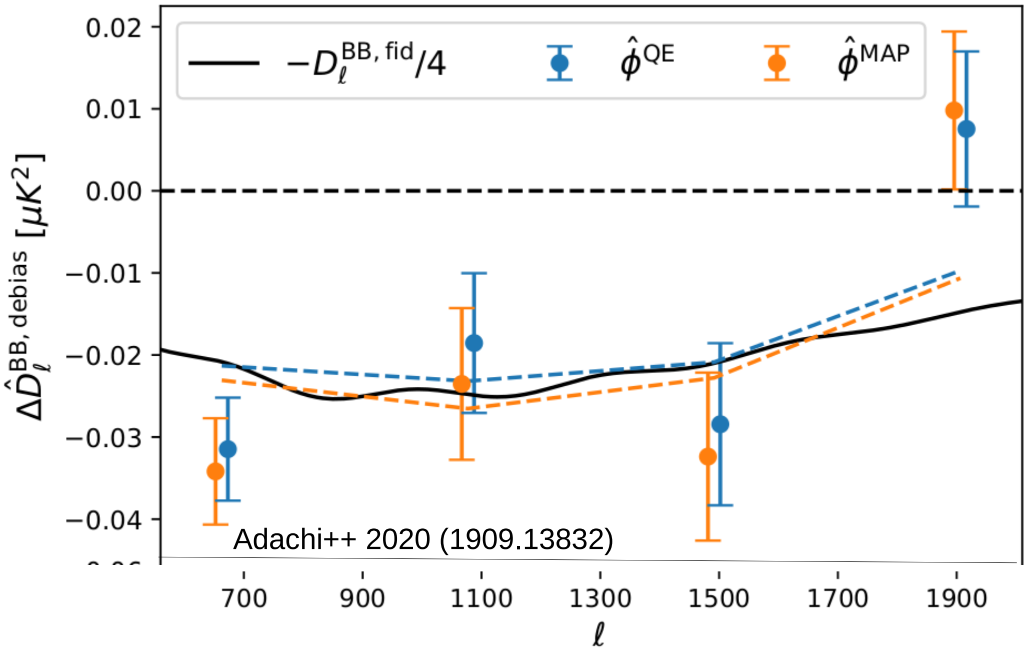


Data-ready Bayesian lensing building blocks



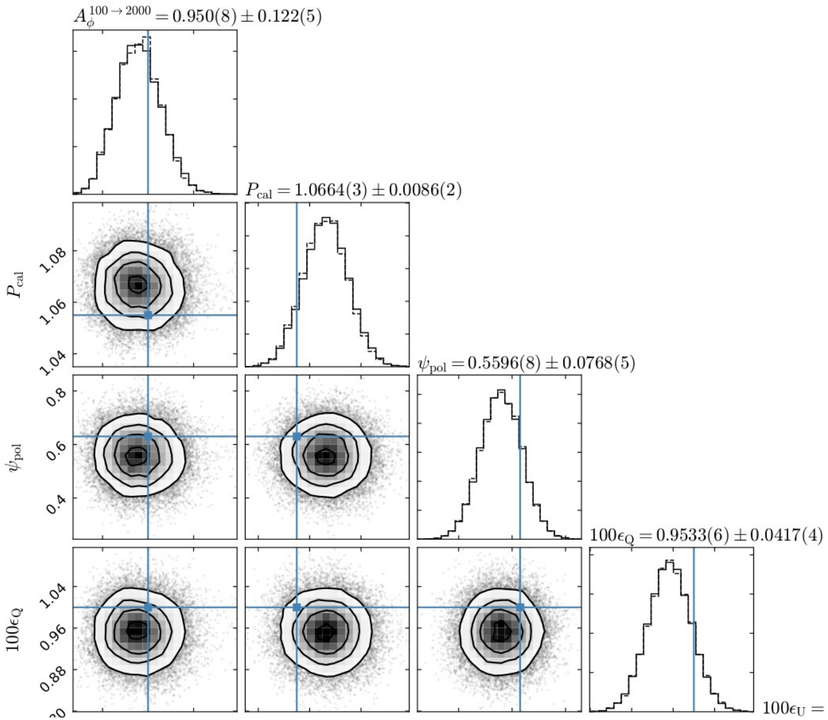
- Both MAPs well tested on realistic sims and data (other e.g. gradient inversion, machine learning, etc.. methods exist)
- Bayesian maximum a posteriori (MAP) estimates of lensing have some a priori unknown transfer function and noise
- “Debiasing” this spectrum is a significant (and somewhat solved) challenge

Bayesian lensing results on data



- First beyond-QE application to data on 25deg^2 of POLARBEAR data
- Using Marginal MAP
- Targeting delensing, not measurements of LSS

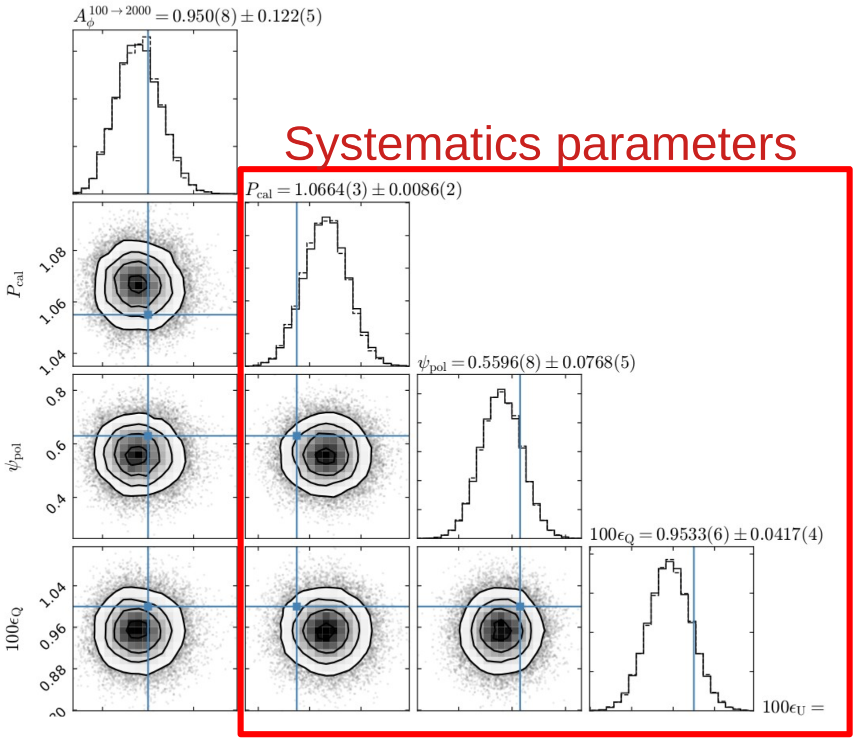
Bayesian lensing results on data



SPTpol, 100deg^2, marginalization with Hamiltonian Monte Carlo

MM&SPT++ 2020 (2012.01709)

Bayesian lensing results on data



SPTpol, 100deg^2,
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MM&SPT++ 2020 (2012.01709)

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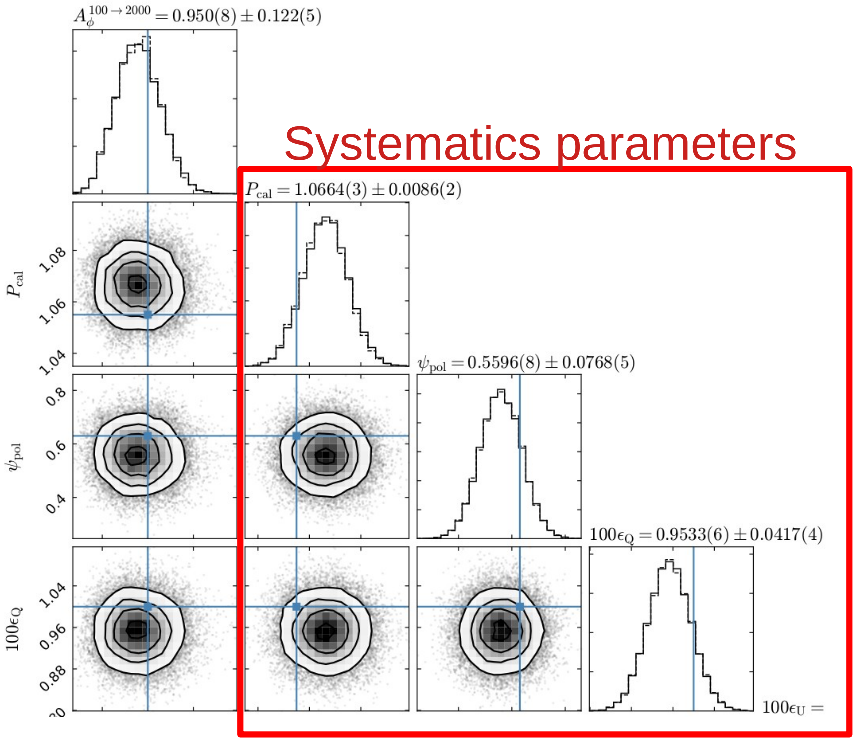
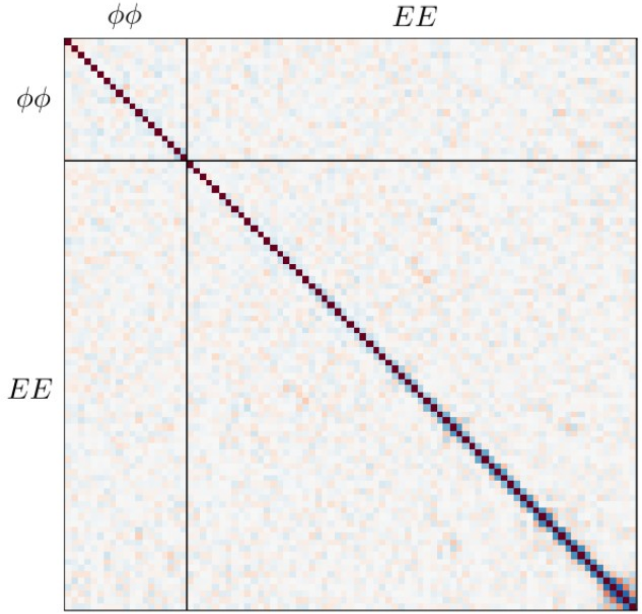


SPTpol, 100deg^2, marginalization with Hamiltonian Monte Carlo

MM&SPT++ 2020 (2012.01709)

Delensed EE bandpowers l=(500,4000)

Lensing bandpowers L=(100,3000)



bandpower covariance

SPT-3G, 1500deg^2, marginalization with MUSE

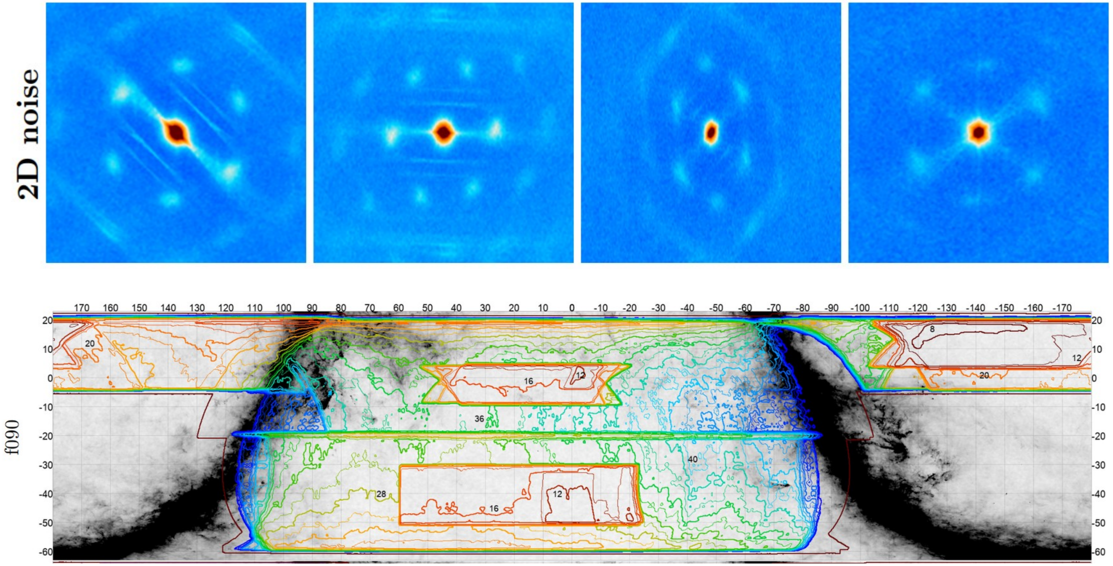
(in prep)

S4 Lensing Probortunities:
→ areas to strengthen our case
→ opportunities for contribution

Optimal probortunity: wide surveys?

Wide (Chile) survey has complicated beam & transfer functions, inhomogenous noise, less opportunity for “sign-flipped noise realizations.”

To extract lensing information from (N>2)-pt functions of data, we must accurately model instrumental effects on these correlation functions.

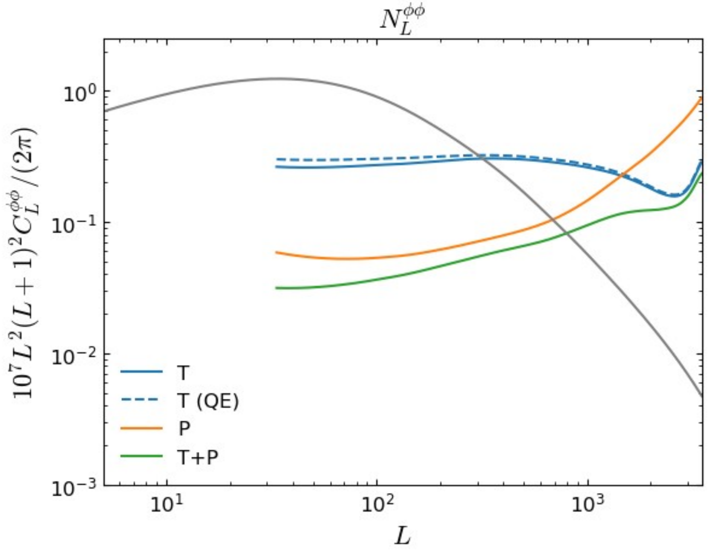


Complex transfer functions: unexplored c.f. optimal lensing afaik

Inhomogenous noise: promising results in Legrand & Carron 2023

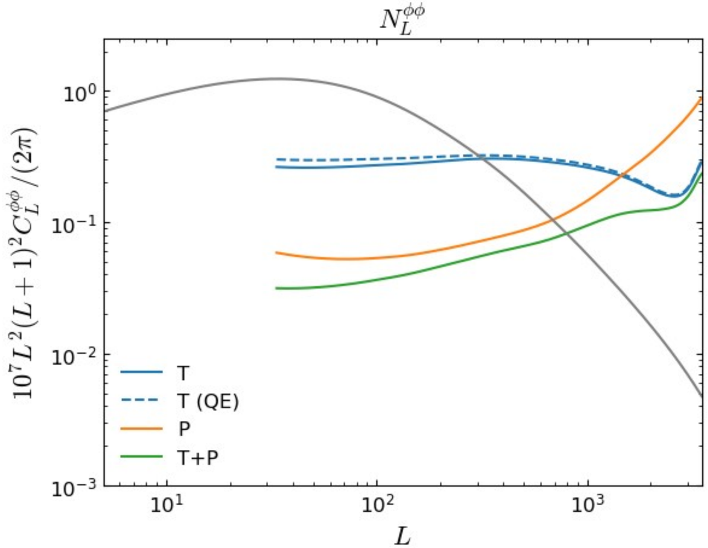
Naess++ 2021 (2007.07290)

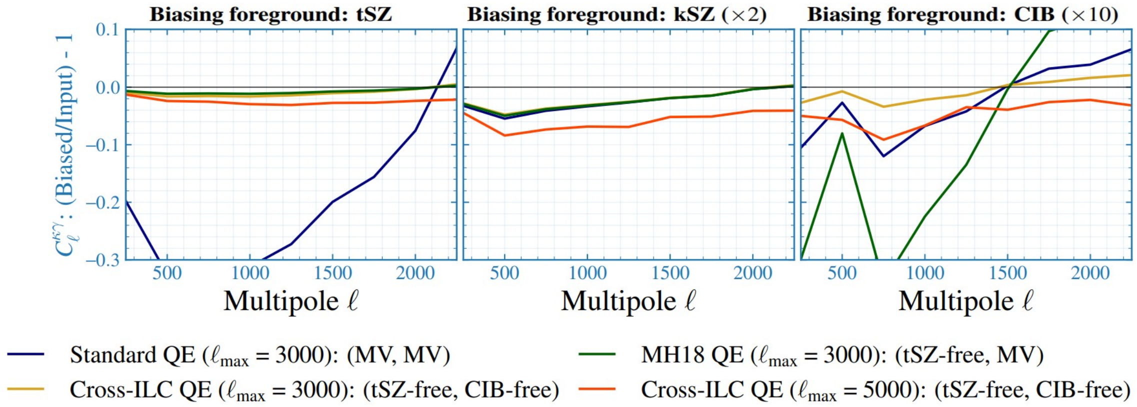
Optimal probortunity: foregrounds?



- For the wide survey, temperature contributes non-negligible lensing information
- The QE is nearly optimal for temperature
- Options:
  - QE-T + Optimal-P *(how to combine?)*
  - Optimal T+P *(how to deal with foregrounds?)*

Optimal probortunity: foregrounds?





Ragunathan & Omori 2023 (2304.09166)
see also Sailer++ 2022, Madhavacheril & Hill 2018, others...

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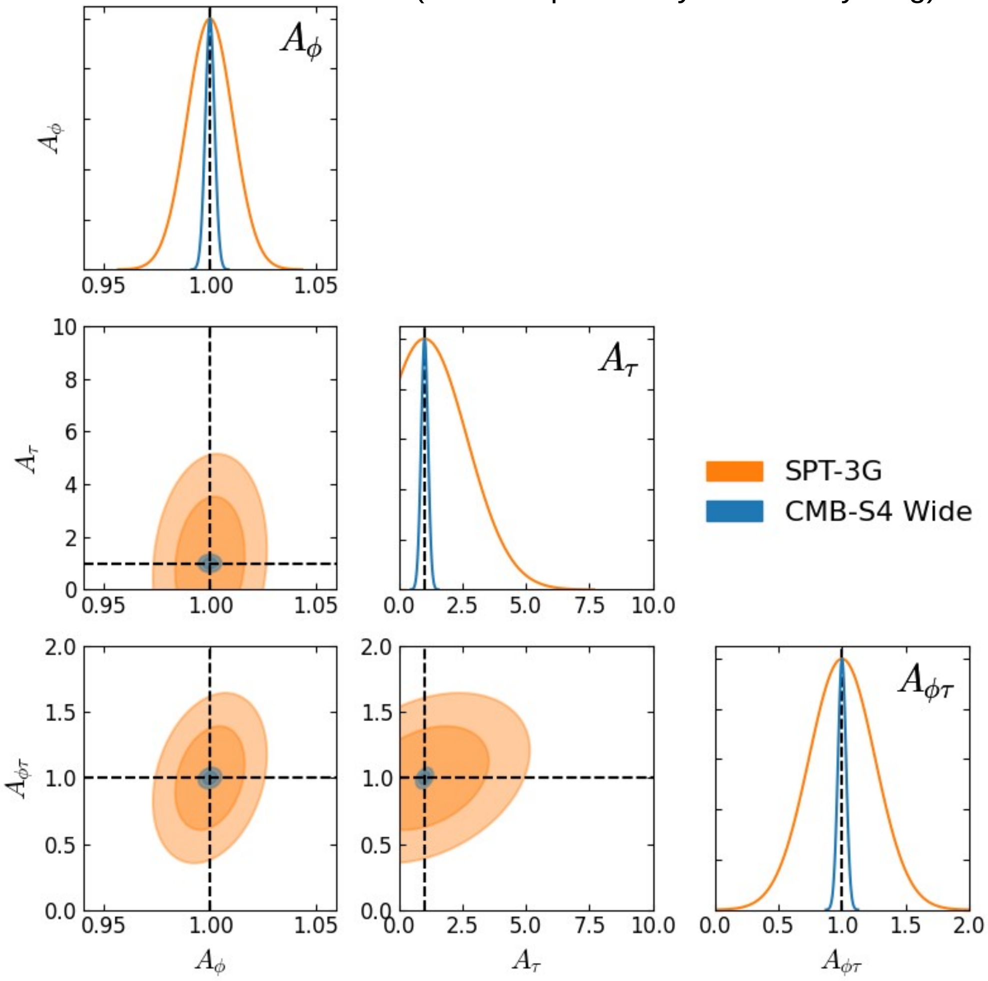
Optimal probortunity: cross-correlations?

- In practice, how do we do optimal lensing X external LSS?
  - Bayesian version of extrenal LSS?
  - MAP-based CMB?
- In which cross-correlations are we even motivated to bother with optimal lensing?

Lensing X Patchy Reionization

(An example of Bayesian everything)



Bianchini&MM 2022 (2210.10893)

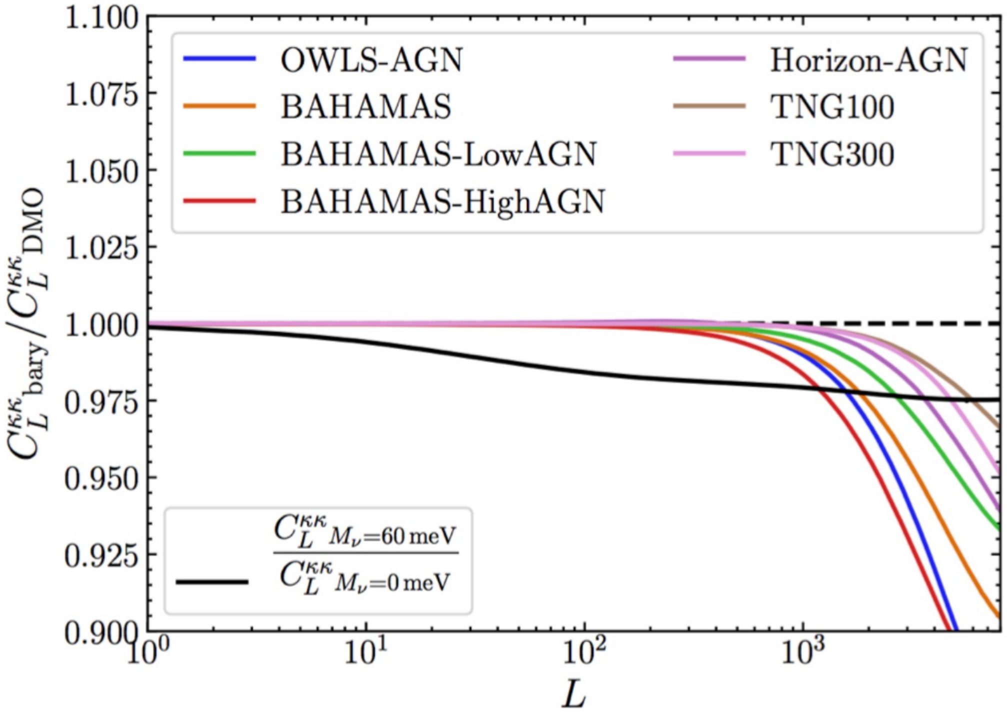
Optimal probortunity: ...

- Delensing for primordial non-Gaussianities
- Modeling non-Gaussianities in the lensing
- Optimal post-Born effects
- …?

Conclusions

- CMB-S4 is a transformative probe of lensing & LSS
- Huge progress is being made, driven by S3 surveys
- Some gaps still exist where we could strengthen our case

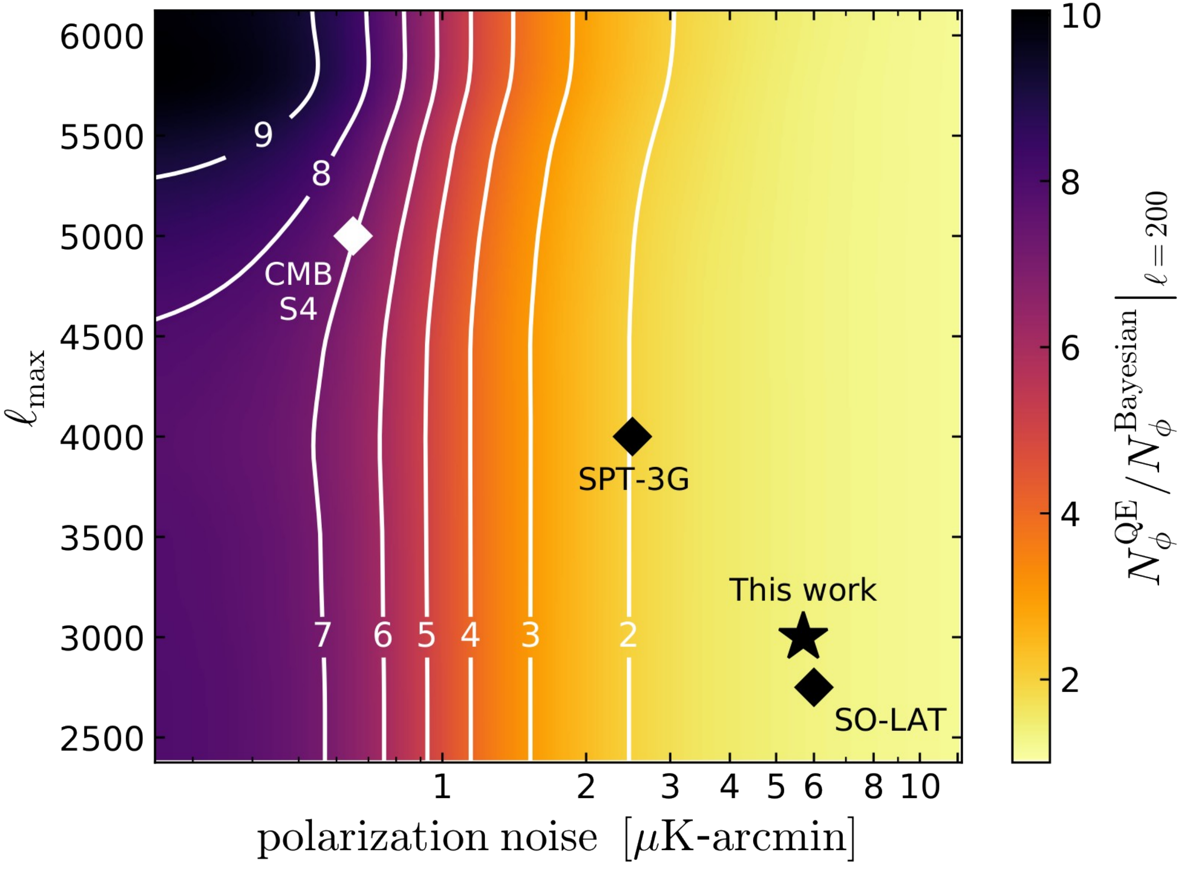
Backup



1.100
1.075
1.050
1.025
1.000
0.975
0.950
0.925
0.900
$C_L^{\kappa\kappa}{}_{\rm bary}/C_L^{\kappa\kappa}{}_{\rm DMO}$
10^0
10^1
10^2
10^3
L
OWLS-AGN
BAHAMAS
BAHAMAS-LowAGN
BAHAMAS-HighAGN
Horizon-AGN
TNG100
TNG300
$\frac{C_L^{\kappa\kappa}{}_{M_\nu=60\,\rm meV}}{C_L^{\kappa\kappa}{}_{M_\nu=0\,\rm meV}}$

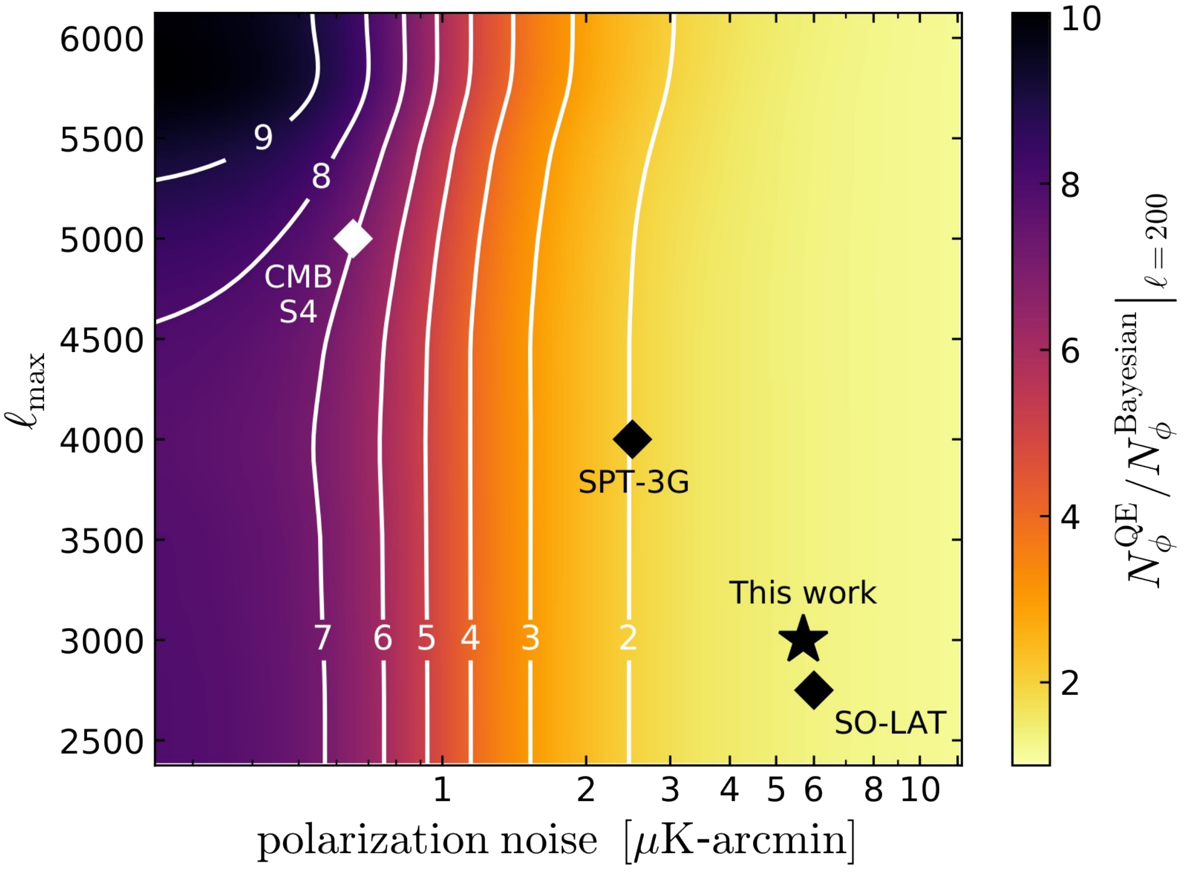
McCarthy++

Why beyond-QE / “optimal” lensing?



- QE is suboptimal because it only uses 2-pt information in the data
- Almost 10X lower noise and 3X better delensing than QE is possible using all-orders, at CMB-S4 depths

Why beyond-QE / "optimal" lensing?



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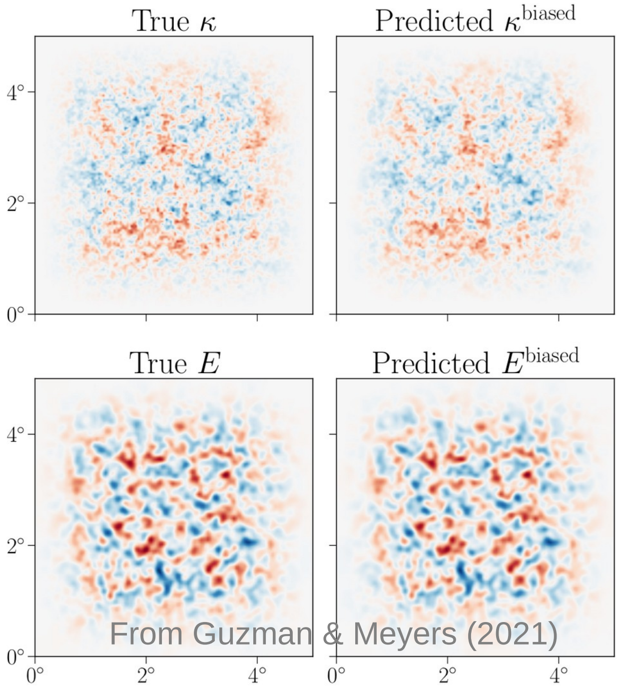
Not a small effect, next-gen CMB depends on this!

Machine-learned and human-learned estimators

Machine learning: Caldeira et al (2020), Guzman & Meyers (2021), Li et al (2022).



From Guzman & Meyers (2021)

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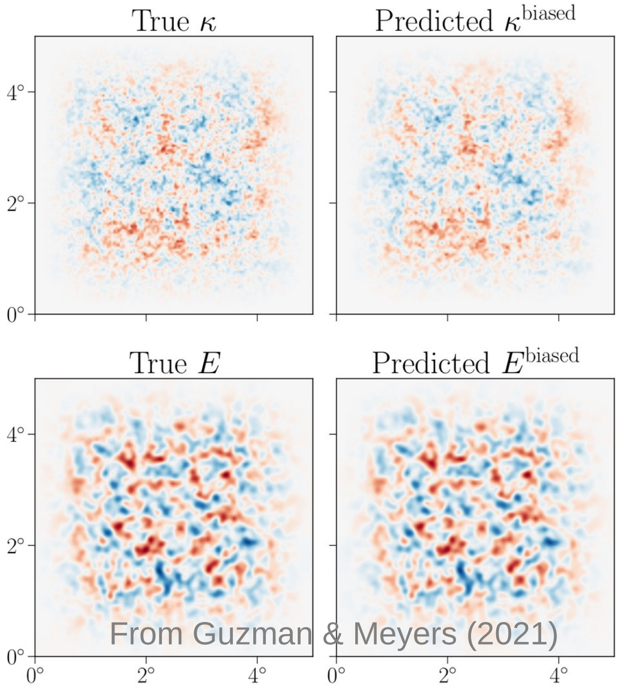
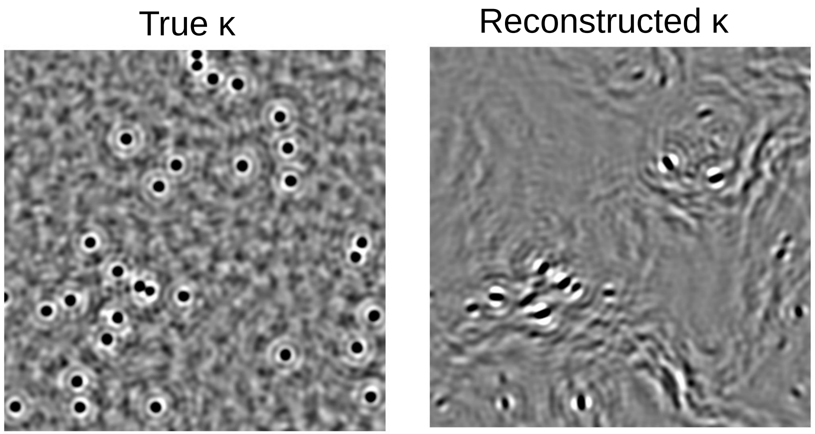


From Guzman & Meyers (2021)

Gradient inversion: Horowitz et al (2017), Hadzhiyska et al (2019)



From Hadzhiyska et al (2019)

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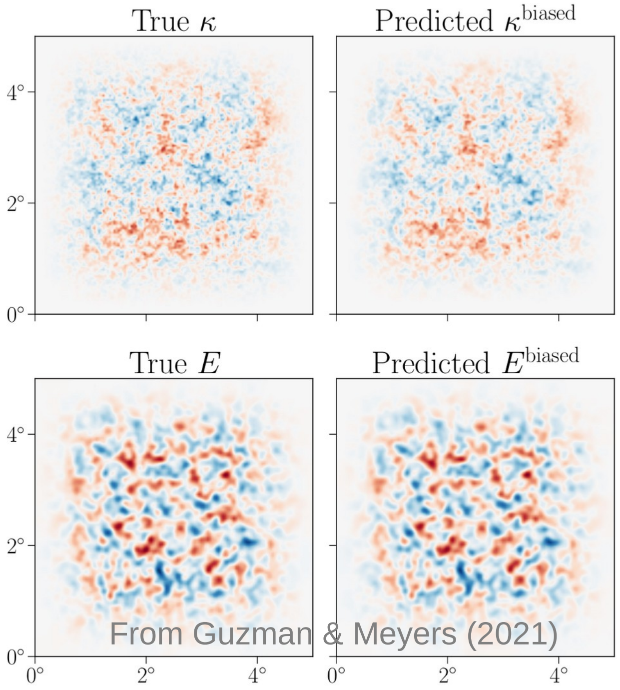

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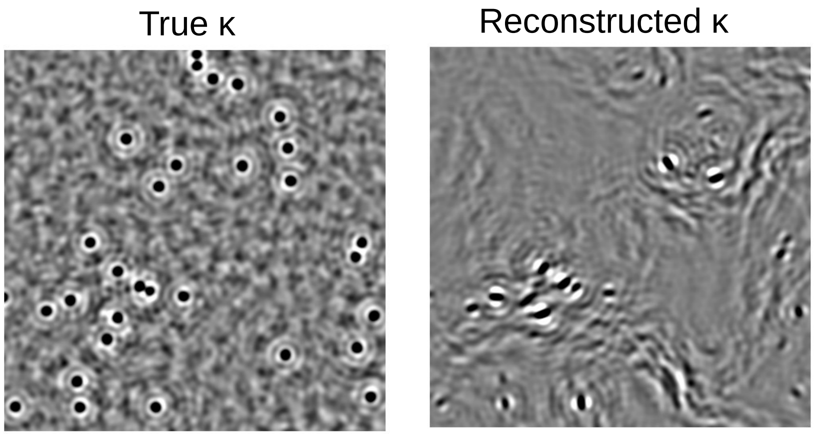


From Hadzhiyska et al (2019)

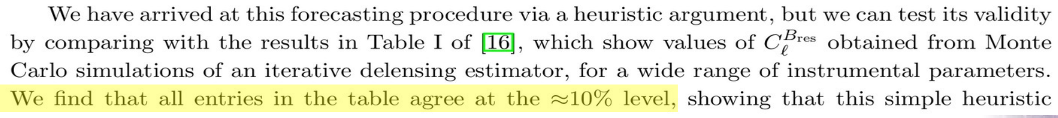
Why are these not a final solution?

- Same biased spectrum issue as MAPs
- Only applicable to ultra-highres data

Powerspectrum-based “iterative” forecasting, ~2016, 2019

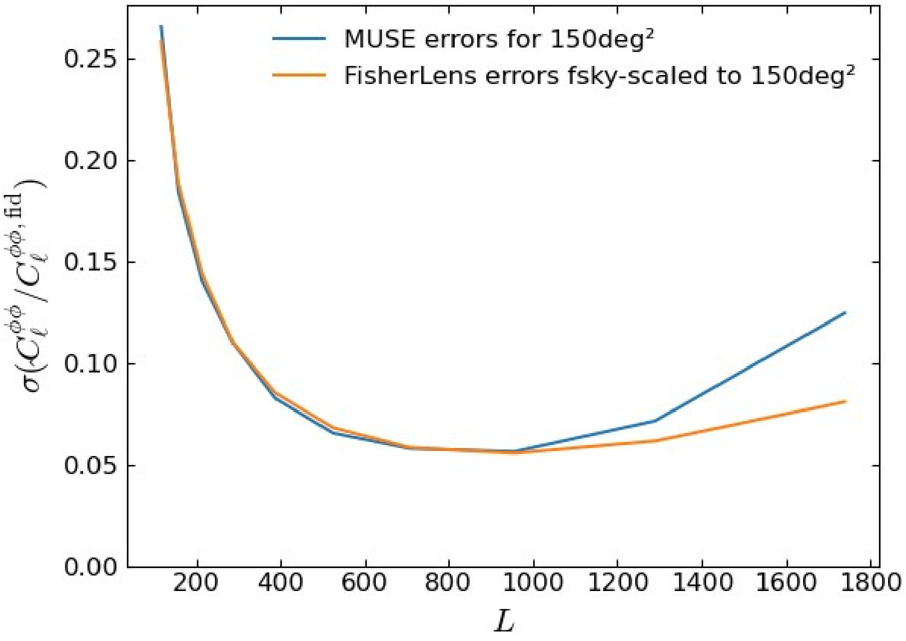
- Smith et al (2015) introduced a procedure to compute the noise power-spectrum for an “optimal” lensing estimate
- Green et al (2016), Hotinli et al (2021) developed this further to include temperature and full covariances
- Great for forecasting, but neither is a map-level procedure which can be done to data

Original validation:



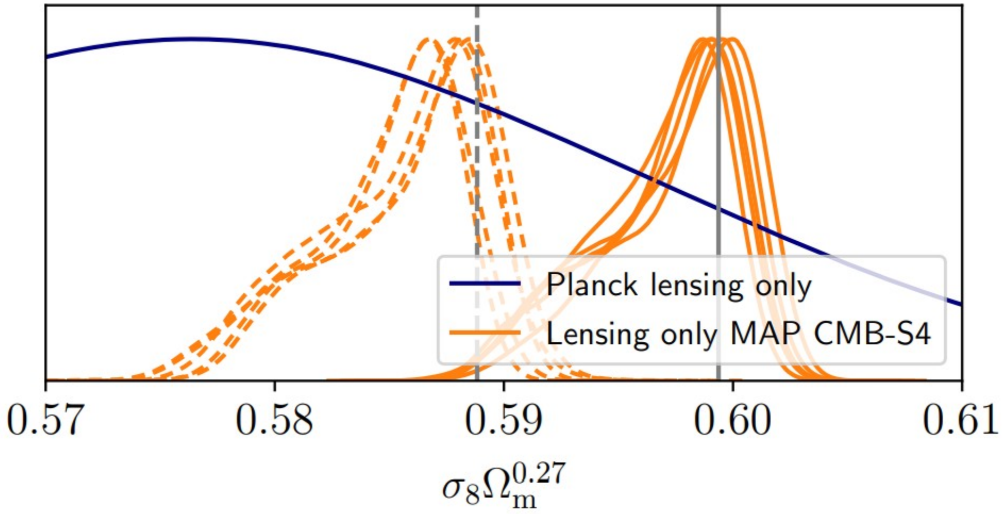
We have arrived at this forecasting procedure via a heuristic argument, but we can test its validity by comparing with the results in Table I of [16], which show values of $C_\ell^{B_{\rm res}}$ obtained from Monte Carlo simulations of an iterative delensing estimator, for a wide range of instrumental parameters. We find that all entries in the table agree at the ≈10% level, showing that this simple heuristic

Better validation:



Unbiased map-level estimators of the power-spectrum, ~2022

For a solution which debiases the marginal MAP lensing spectrum on mask-free data and produces unbiased spectra and parameters, see Legrand & Carron (2022) and Louis Legrand's talk.



Approximate marginalization with MUSE, ~2021 (Marginal Unbiased Score Expansion)

MUSE MM+Seljak (2021) does this integral:

$$\mathcal{P}(C_\ell |\, d) = \int df\, d\phi\, \mathcal{P}(C_\ell, f, \phi \,|\, d)$$

with a **generic** and **fast approximation** (10-100X faster than HMC) which is exact in the Gaussian limit and always unbiased regardless, and **only needs joint MAPs.**

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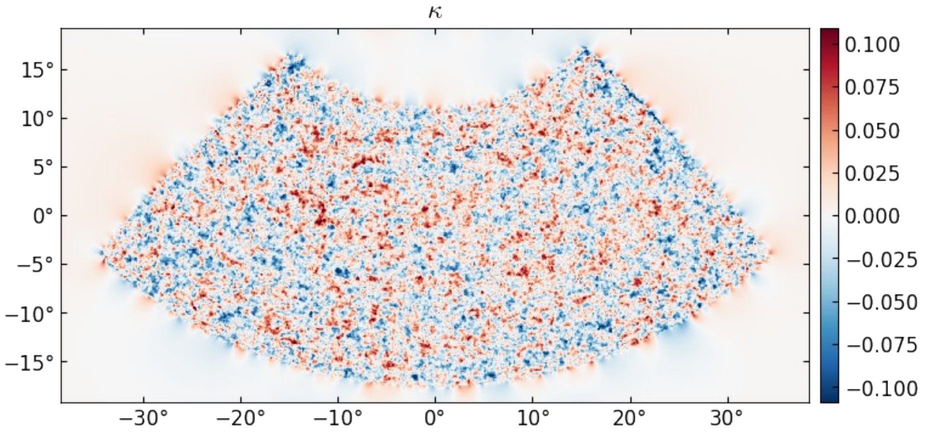

Preliminary typical joint MAP from simulated SPT-3G 2019/2020 (90+150+220) GHz (incl. instrumental effects & GPU sky curvature). *See more at my Friday talk.*

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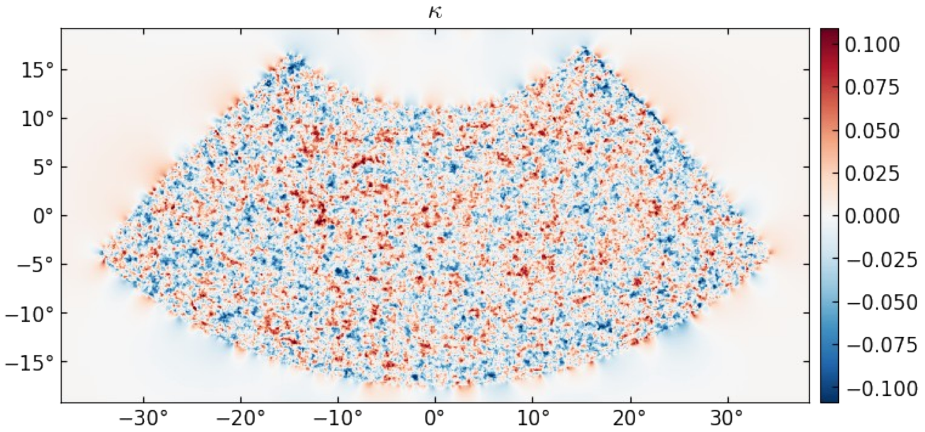

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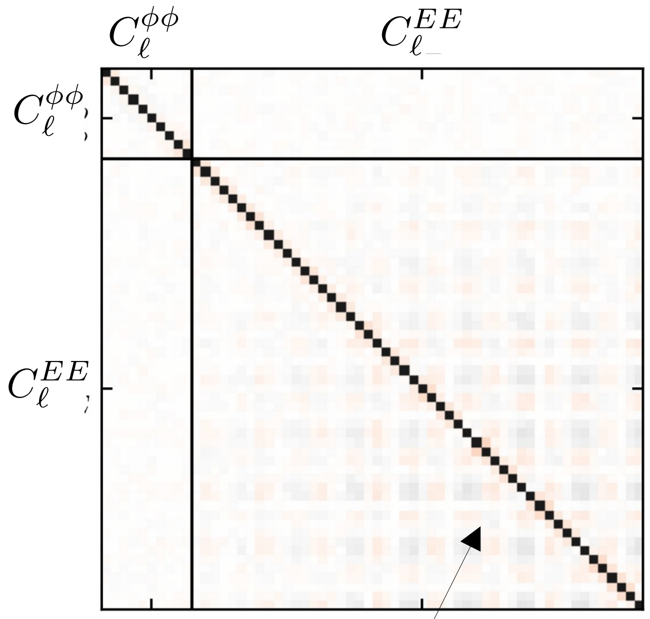
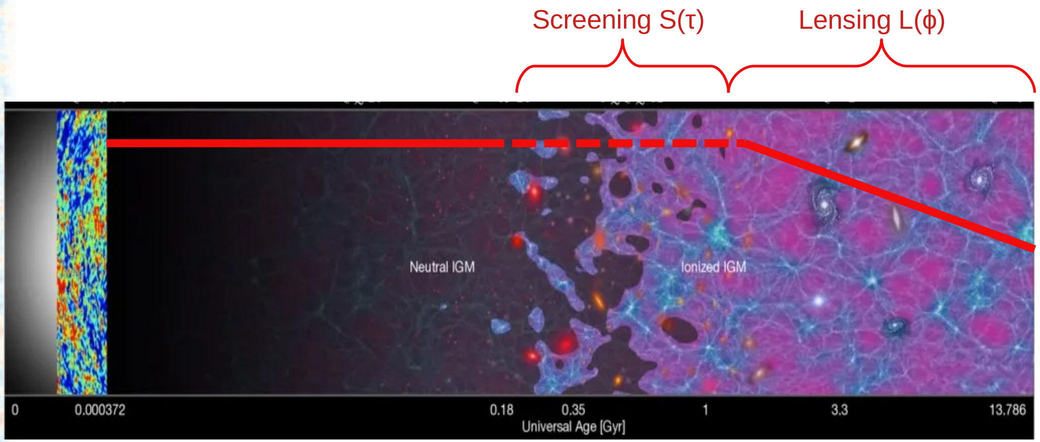
And provides a semi-analytic covariance:

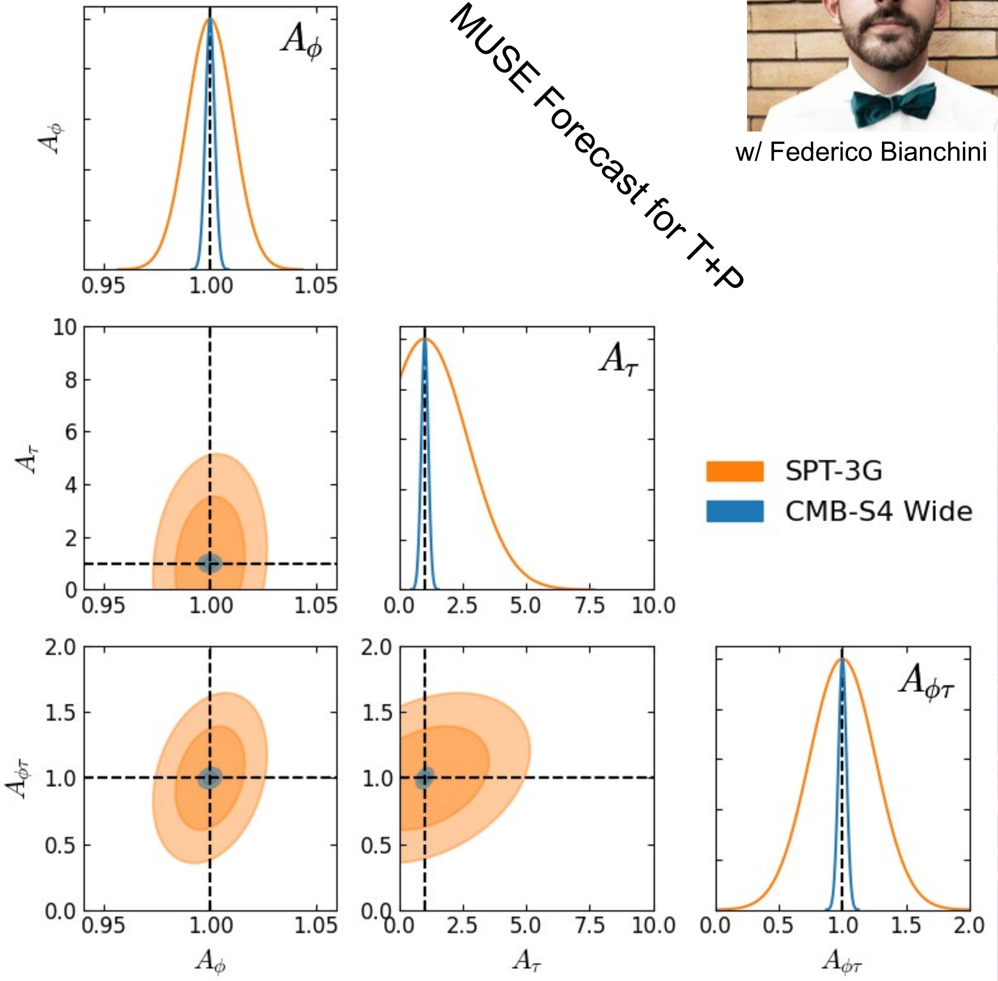


Off-diagonals due to masking/lensing

MUSE: Lensing and patchy reionization inference



MUSE Forecast for T+P



w/ Federico Bianchini

Model:

$$A_\phi, A_\tau, A_{\phi\tau} \sim \mathcal{U}$$

$$f \sim \mathcal{N}\left(0, \begin{bmatrix} C_\ell^{TT} & C_\ell^{TE} & 0 \\ C_\ell^{TE} & C_\ell^{EE} & 0 \\ 0 & 0 & C_\ell^{BB} \end{bmatrix}\right)$$

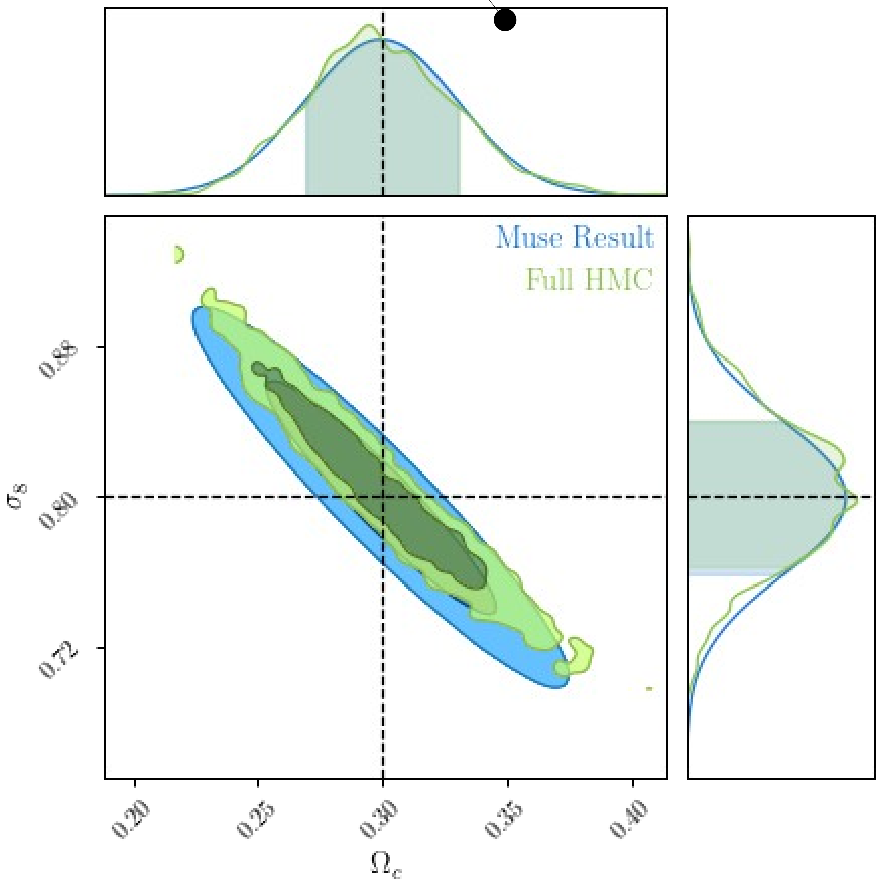
$$\phi, \tau \sim \mathcal{N}\left(0, \begin{bmatrix} A_\phi\, C_\ell^{\phi\phi} & A_{\phi\tau}\, C_\ell^{\phi\tau} \\ A_{\phi\tau}\, C_\ell^{\phi\tau} & A_\tau\, C_\ell^{\tau\tau} \end{bmatrix}\right)$$

$$d \sim \mathcal{N}(\mathcal{L}(\phi) S(\tau) f, N_\ell)$$

MUSE: Cosmic shear

w/ Francois Lanusse

Good agreement for MUSE (10min) vs. HMC (2hrs):



Model:

$$\Omega_c, \sigma_8 \sim \mathcal{N}$$

$$C_\ell^\kappa = C_\ell(\Omega_c, \sigma_8)$$

$$N_\ell^\kappa = C_\ell(\bar{n}_g, \sigma_e)$$

$$\kappa \sim \mathcal{N}(0, C_\ell^\kappa)$$

$$d \sim \mathcal{N}(\kappa, N_\ell^\kappa)$$