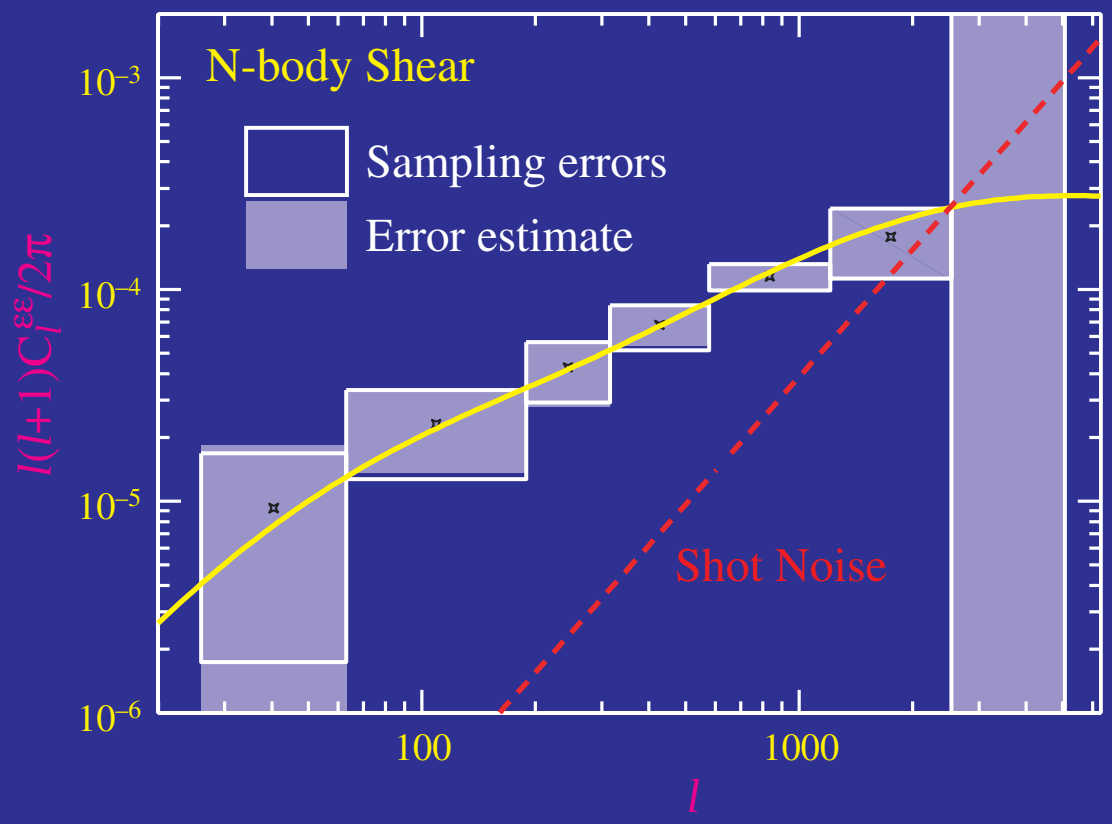
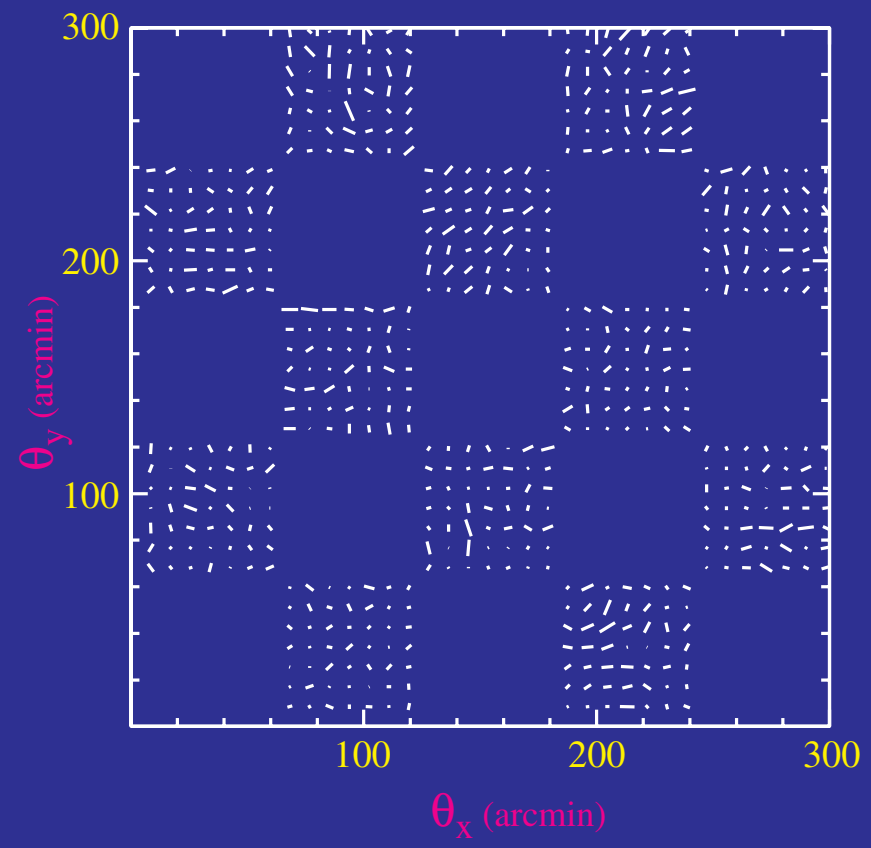
Shear Power of Weak Lensing





Wayne Hu

U. Chicago

Collaborators

- Asantha Cooray
- Dragan Huterer
- Mike Joffre
- Jordi Miralda-Escude
- Max Tegmark
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Why Power Spectrum?

Pros:

- Direct observable: shear-based
- Statistical properties simple on large-scales (cf. variance, higher order)
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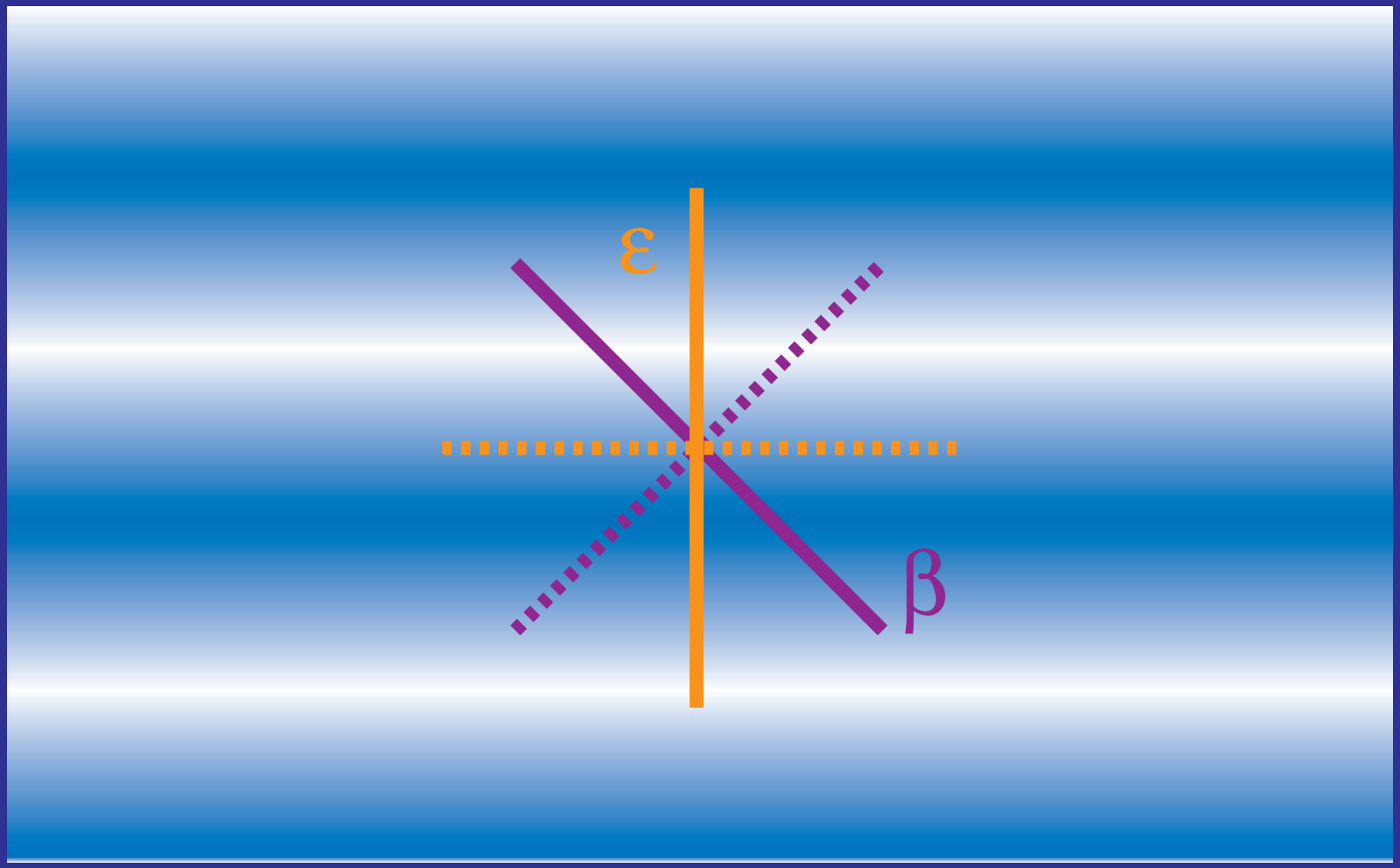
Cons:

- Relatively featureless
- Non-linear below degree scale
- Degeneracies: initial spectrum, transfer function shape, density growth, and angular diameter distance + source redshift distribution
- Computationally expensive: extraction by likelihood analysis N_{pix}^3

Statistics and Modelling

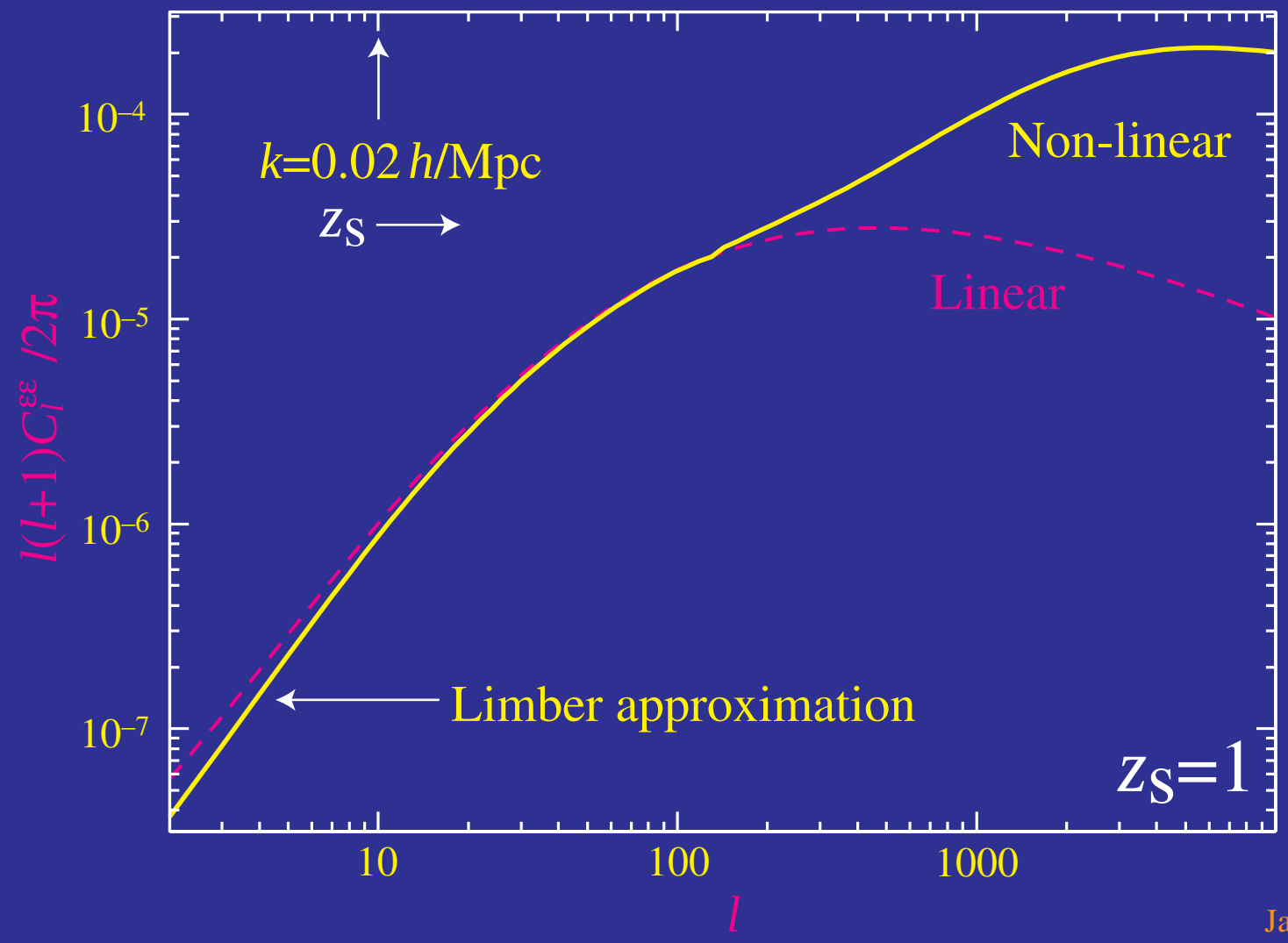
Shear Power Modes

- Alignment of shear and wavevector defines modes



Power Spectrum Roadmap

- Lensing weighted Limber projection of density power spectrum
- ε-shear power = κ-power



Kaiser (1992)
Jain & Seljak (1997)
Hu (2000)

Statistics & Simulations

- Measurement of power in each multipole is independent if the field is Gaussian
- Non-linearities make the power spectrum non-Gaussian
- Need many simulations to test statistical properties of the field in particular: sample variance

White & Hu (1999)

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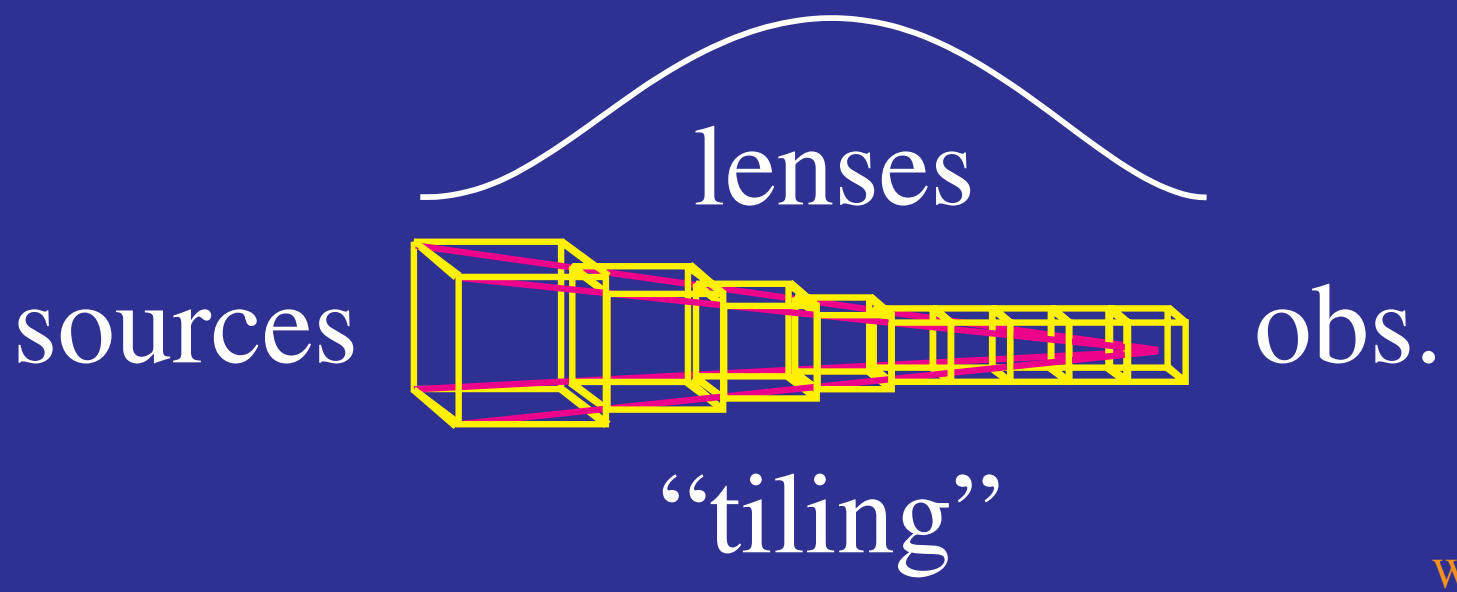
- PM simulations ideal if sufficient angular resolution can be achieved

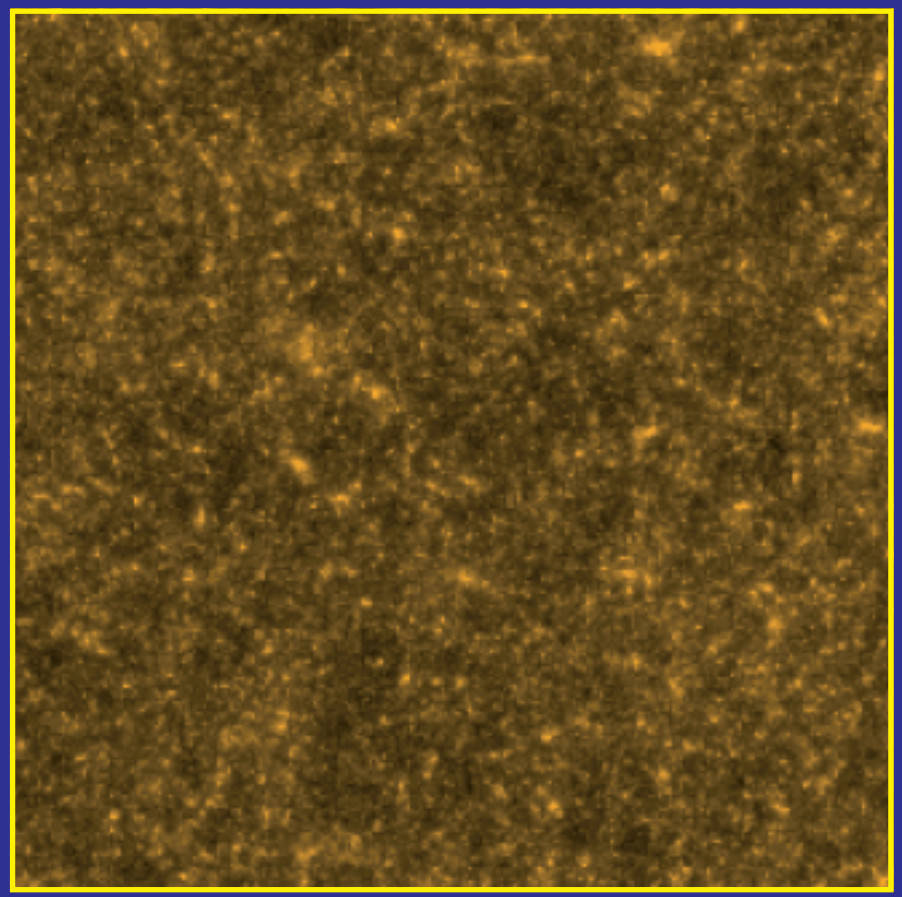


White & Hu (1999)

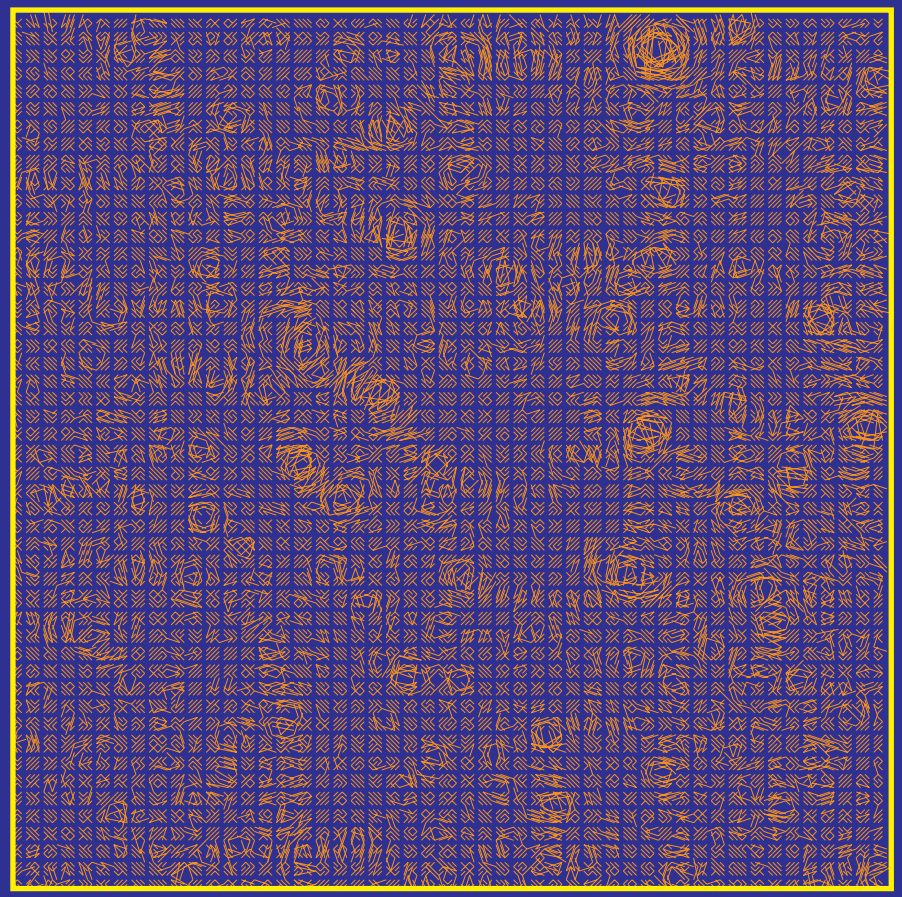
PM Simulations

- Hundreds of independent simulations

Convergence



Shear

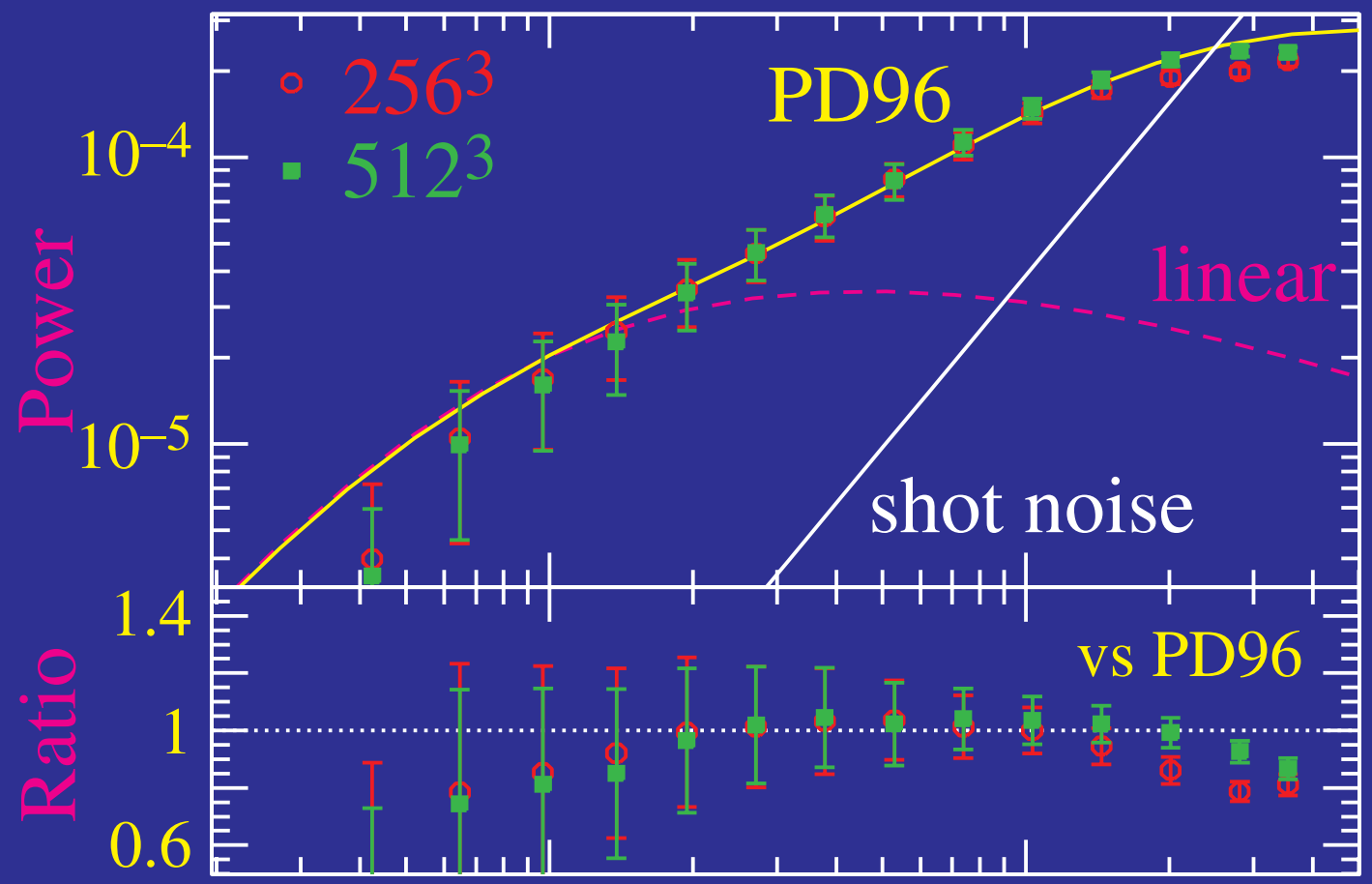


$6° \times 6°$ FOV; 2' Res.; 245–75 h^{-1}Mpc box; 480–145 h^{-1}kpc mesh; 2–70 10^9 $M_\odot$

White & Hu (1999)

Mean & Sampling Errors

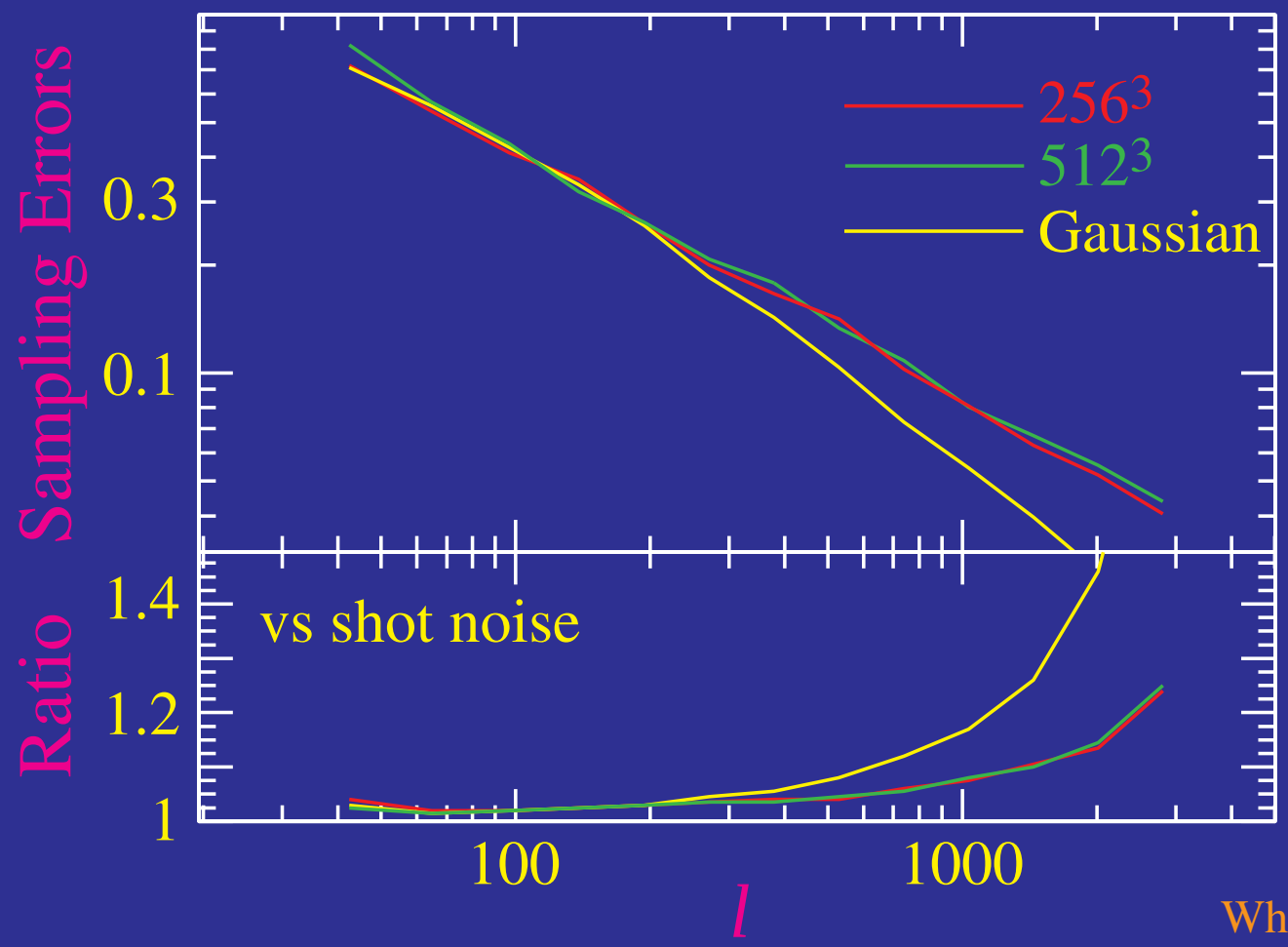
- Mean agrees well with PD96 + Limber (Jain, Seljak & White 1999)
- Sampling errors per 6° x 6° field:



White & Hu (1999)

Mean & Sampling Errors

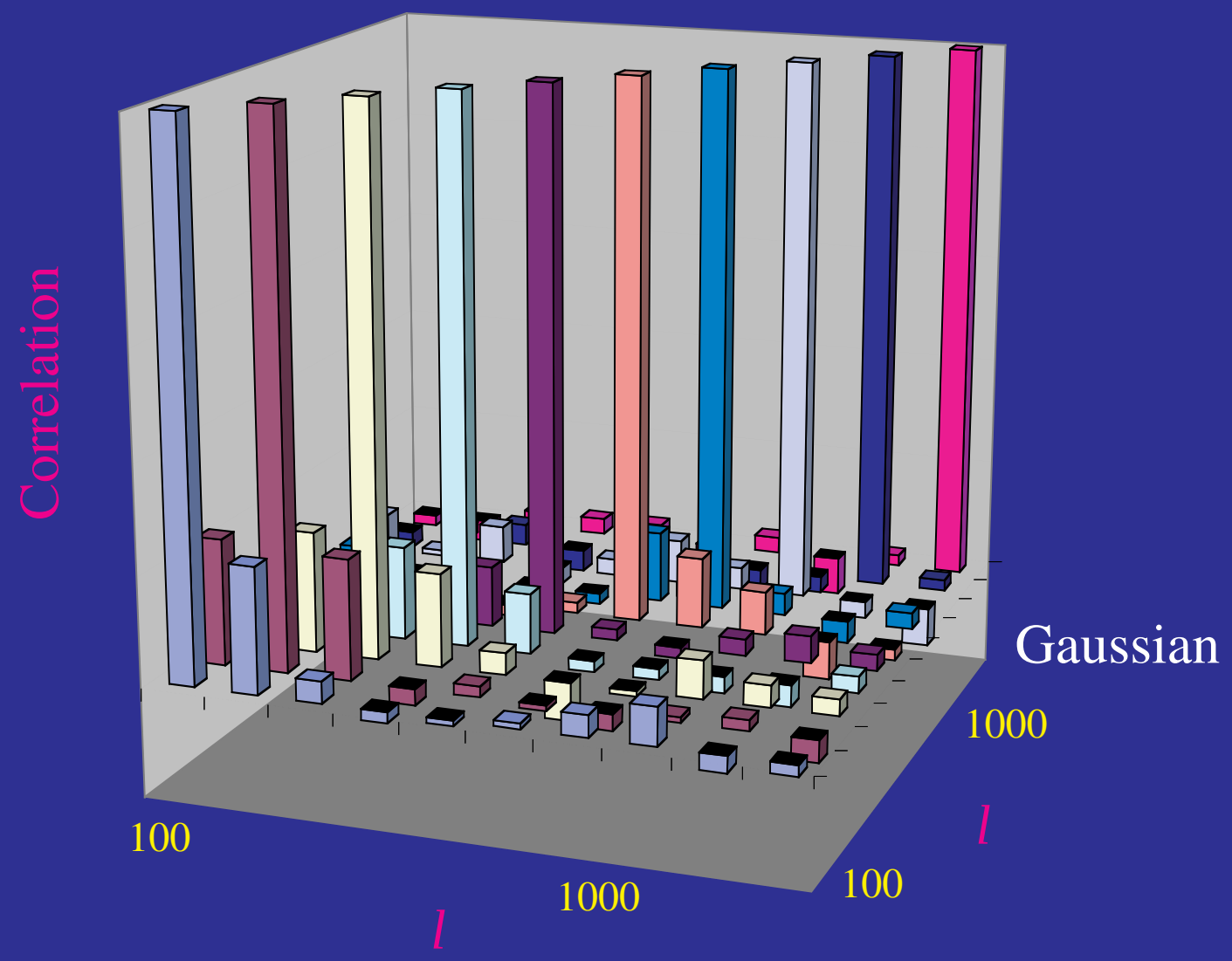
- Sampling errors ~Gaussian at l<1000
- Non-Gaussianity increases sampling errors on binned power spectrum
- At current survey depths, shot noise dominates in non-Gaussian regime



White & Hu (1999)

Mean & Sampling Errors

- Correlation in Band Powers:



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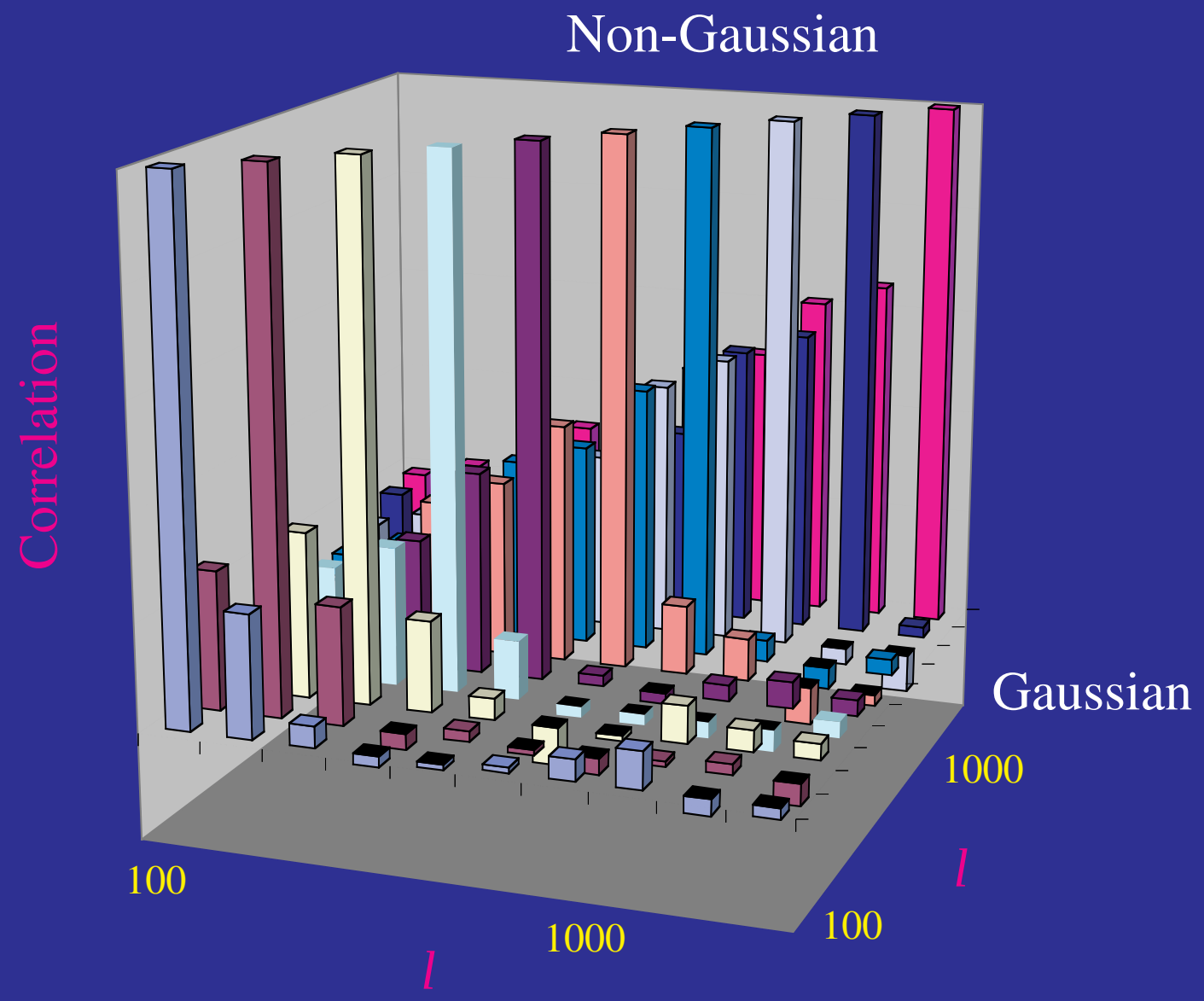
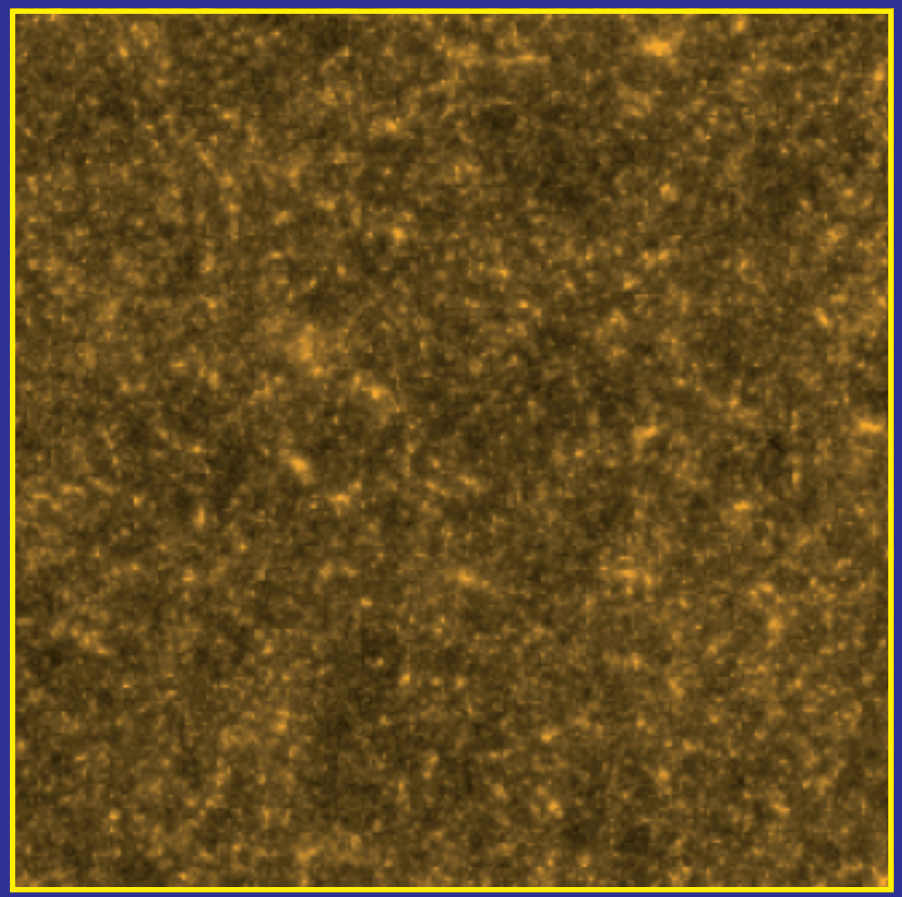


White & Hu (1999)

Halo Model

- Model density field as (linearly) clustered NFW halos of PS abundance:

Simulation



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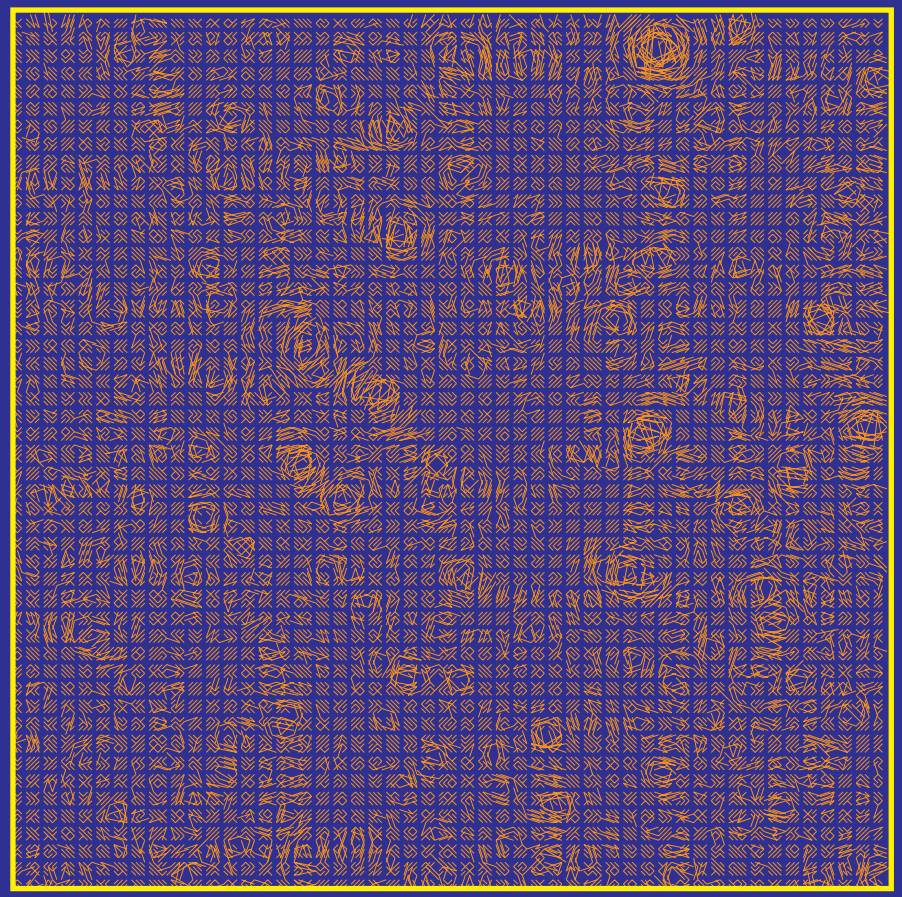

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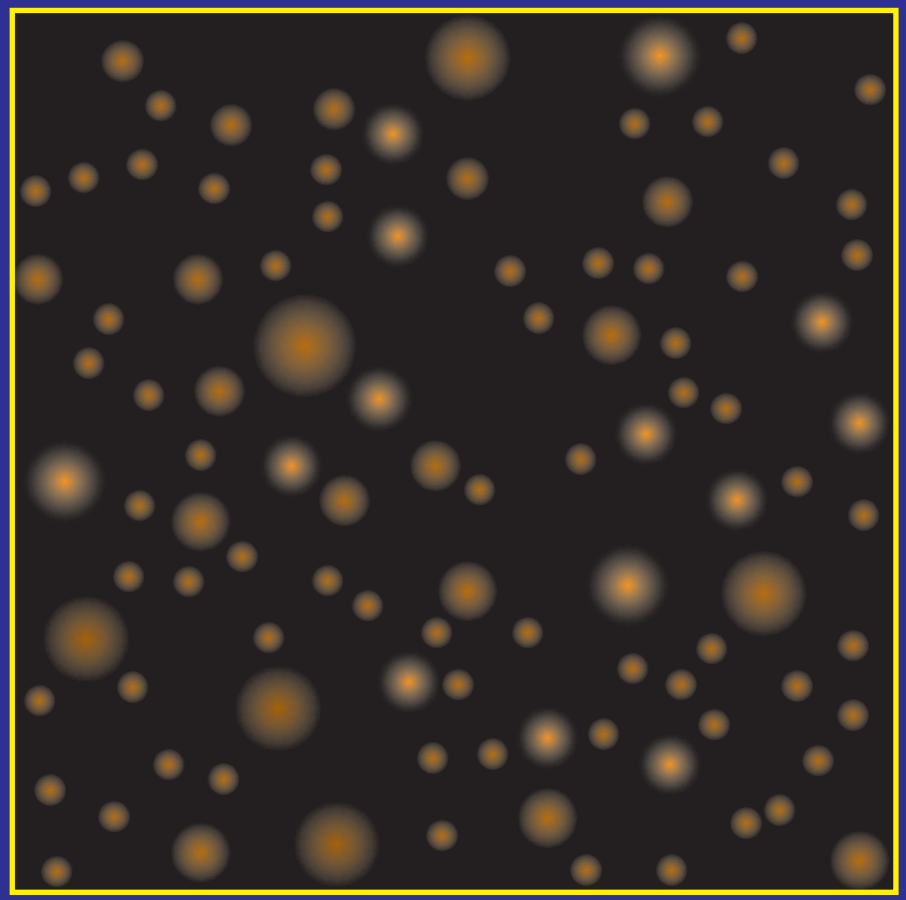

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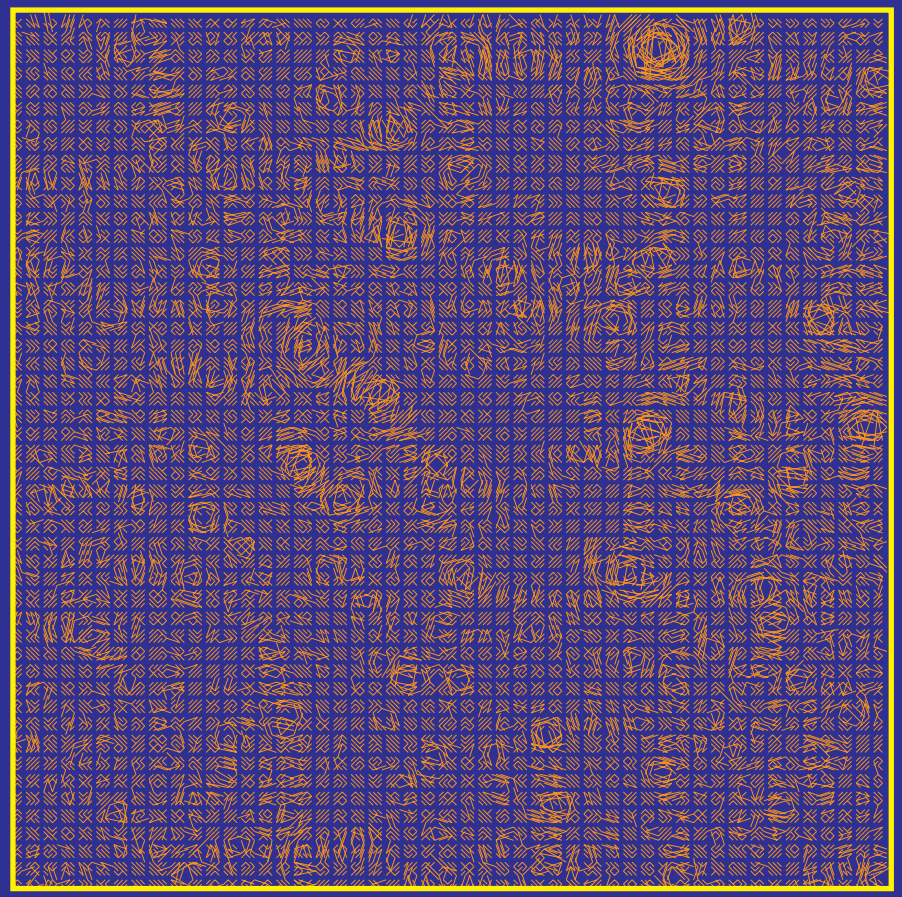
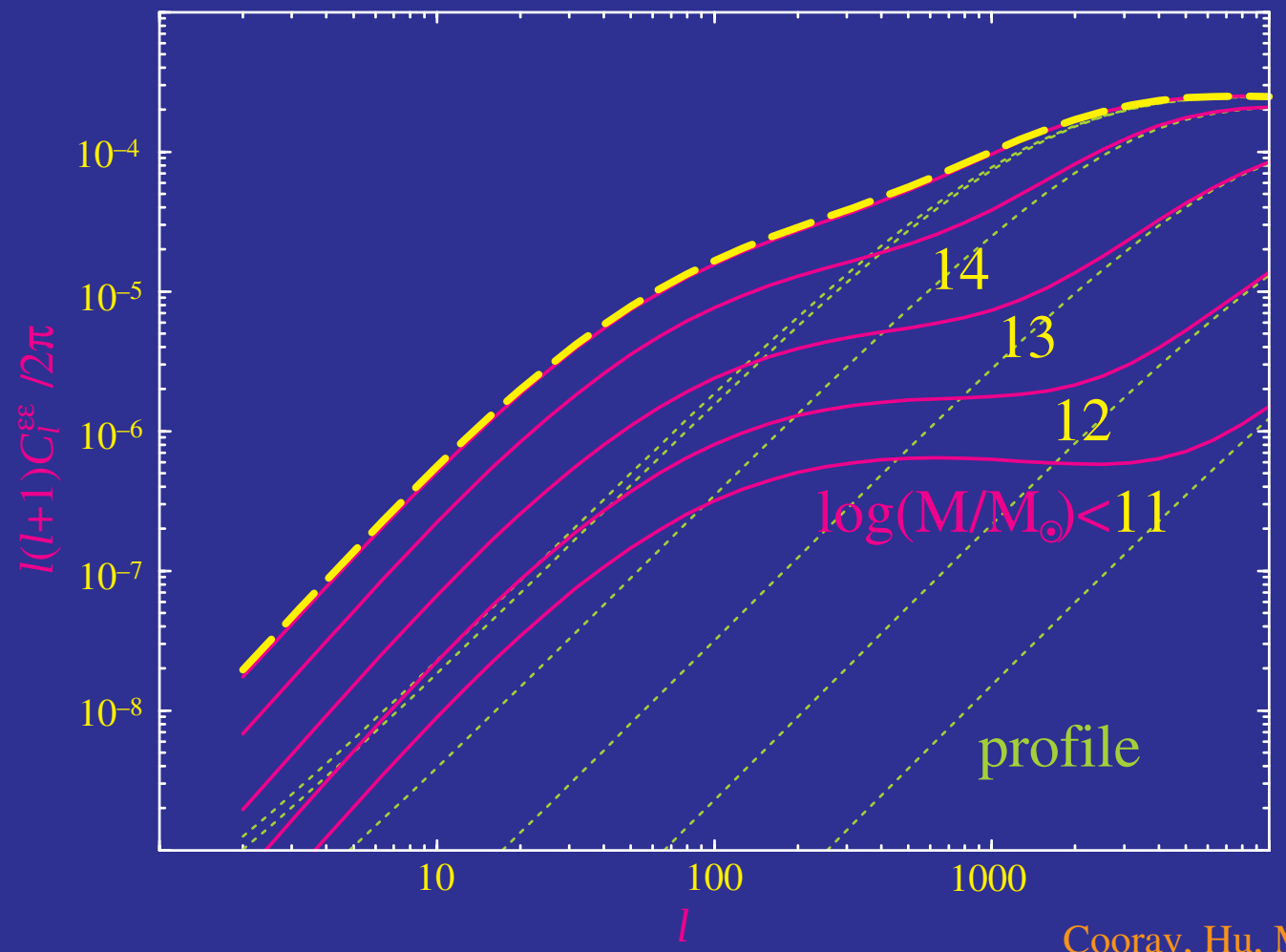


Peebles (1974); Scherrer & Bertschinger (1991)

Komatsu & Kitiyama (1999); Seljak (2001)

Power Spectrum Statistics in Halo Model

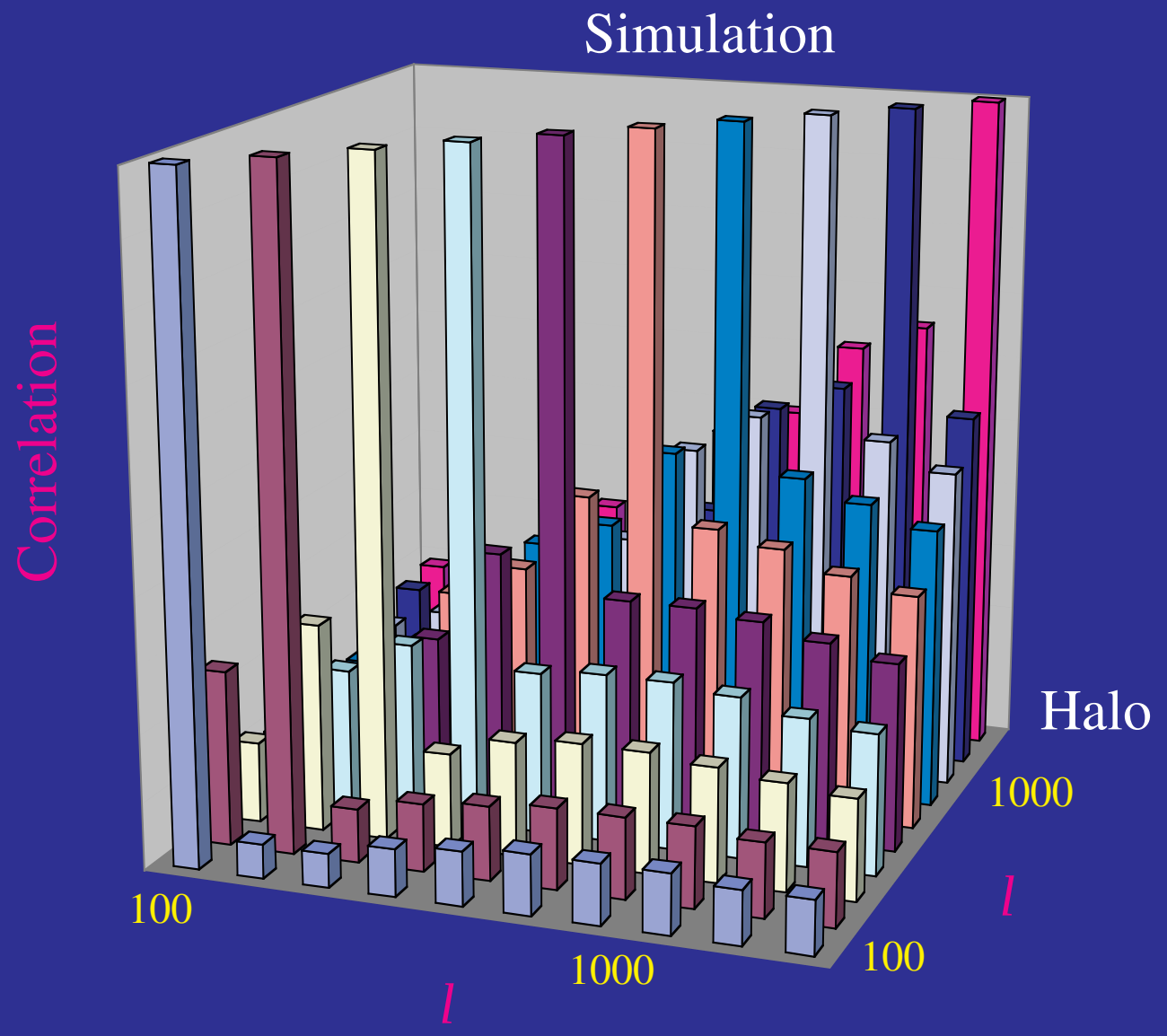
- Power spectrum as a function of largest halo mass included
- Non-linear regime dominated by halo profile / individual halos increased power spectrum variance and covariance



Cooray, Hu, Miralda-Escude (2000)

Halo Model vs. Simulations

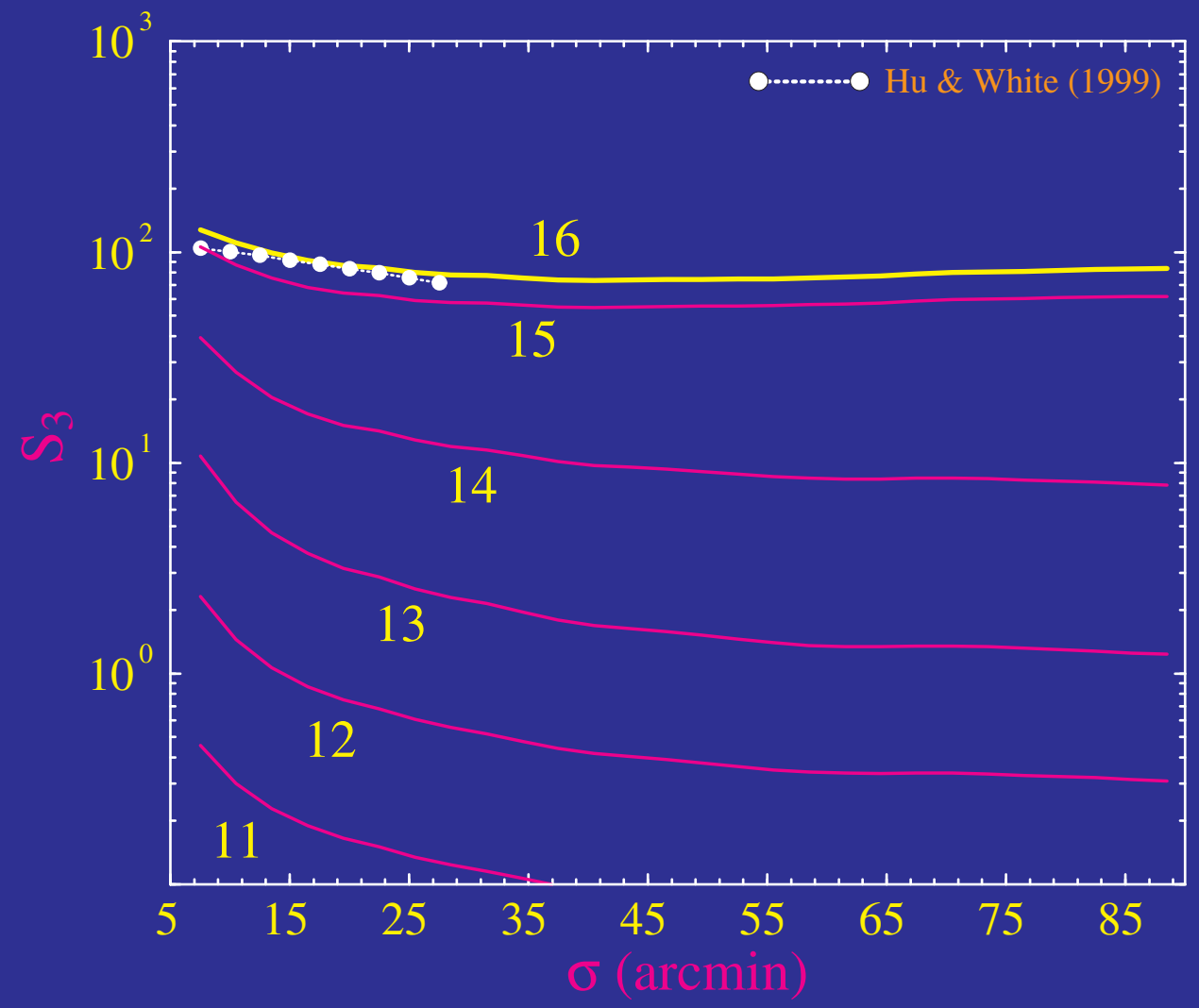
- Halo model for the trispectrum: power spectrum correlation



Cooray & Hu (2001)

Halo Model vs. Simulations

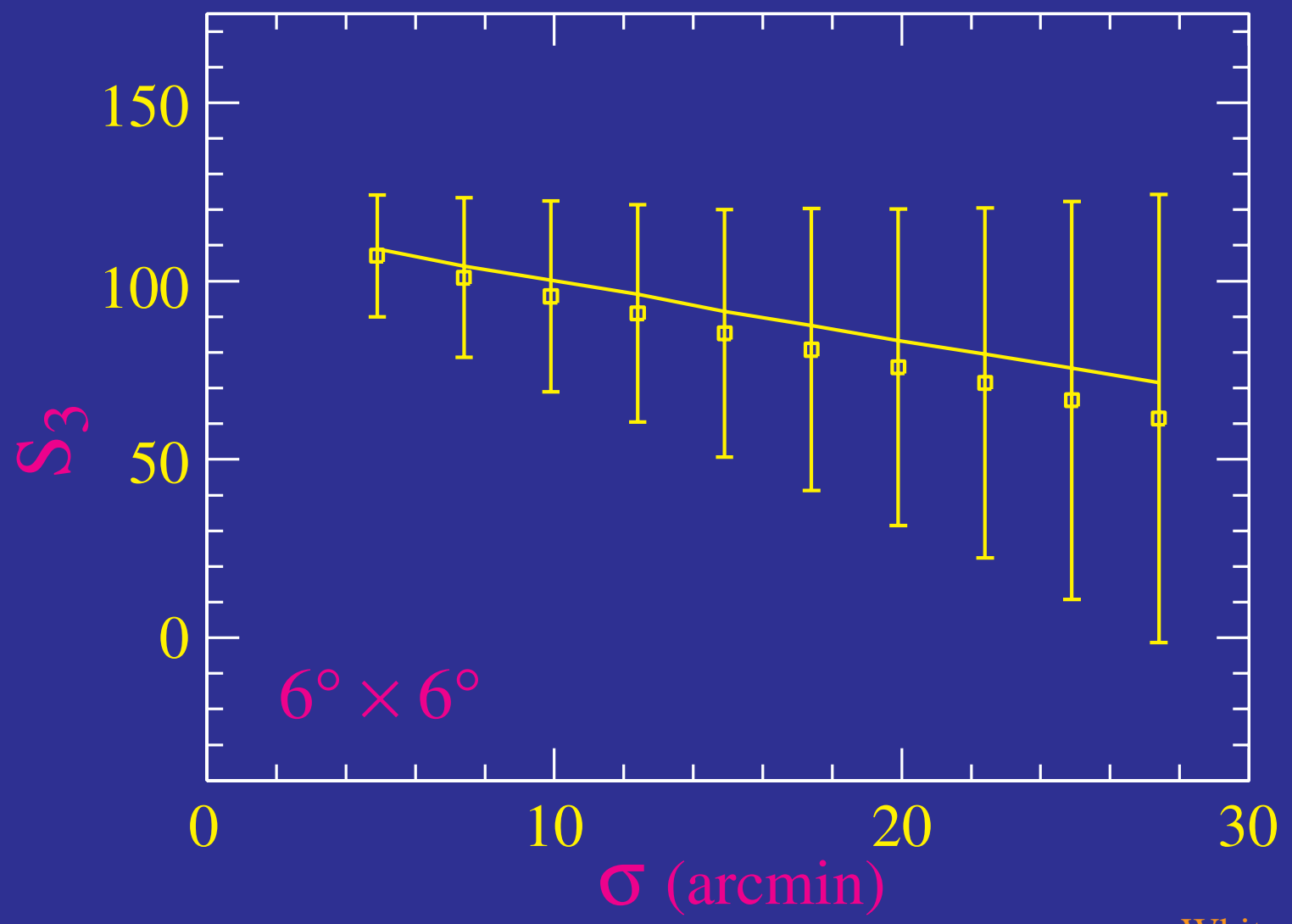
- Halo model for the bispectrum: S_3 dominated by massive halos



Cooray & Hu (2001)

Halo Model vs. Simulations

- Explains large sampling errors:



White & Hu (1999)

Power Spectrum Estimation

Likelihood Analysis

Pros:

- Optimal power spectrum estimator for Gaussian field
- Automatically accounts for irregular (sparse sampled) geometries & varying sampling densities
- Arbitrary noise correlations
- Marginalize over systematic error templates
- (ε, β, cross) checks for non-gravitational effects
- Rigorous error analysis in linear regime

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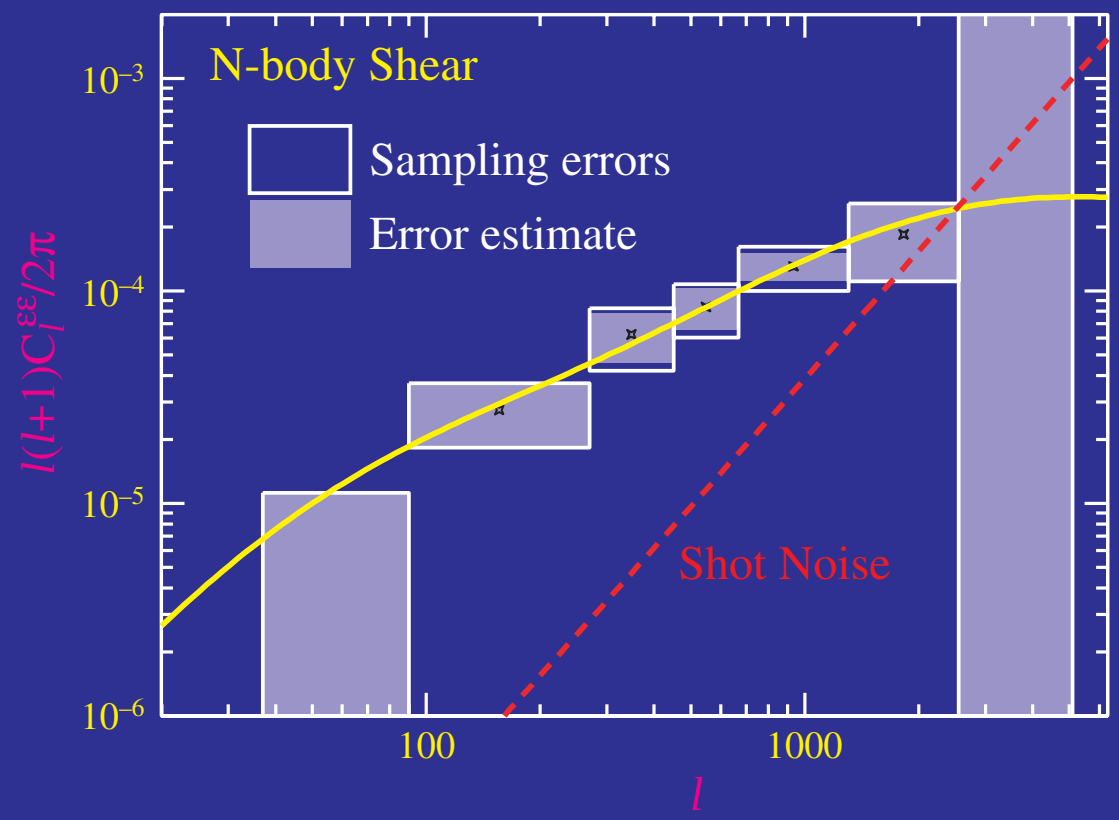
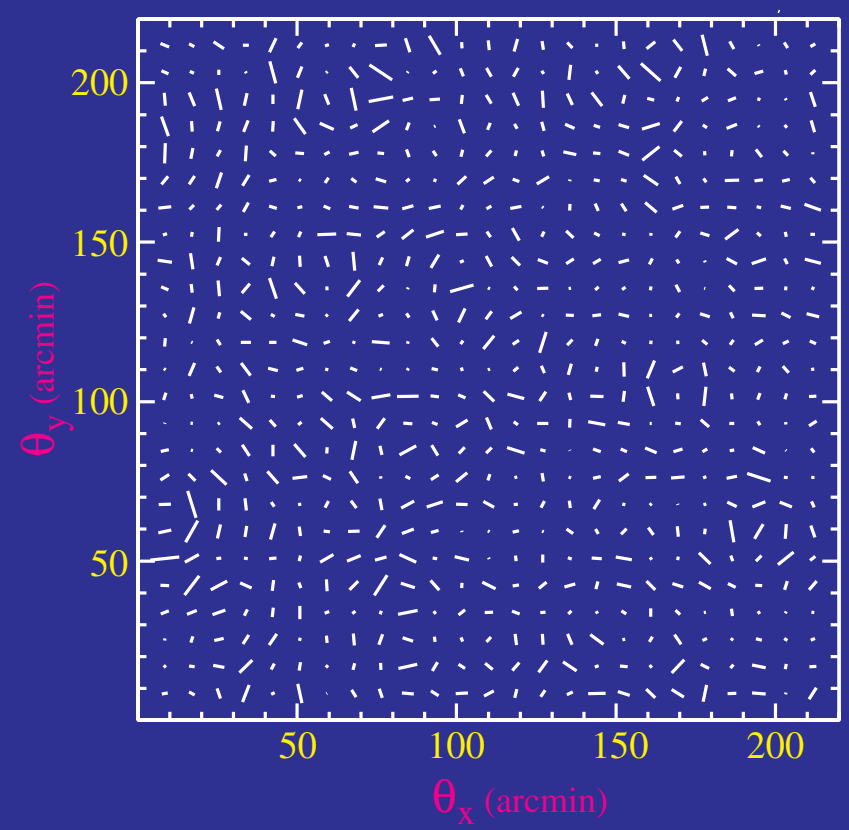
Test iterated quadratic estimator of maximum likelihood solution and error matrix

Testing the Likelihood Method

- Input: pixelized shear data $\gamma_1(\mathbf{n}_i)$, $\gamma_2(\mathbf{n}_i)$; pixel-pixel noise correlation
- Iterate in band power parameter space to maximum likelihood...
- Output: maximum likelihood band powers and local curvature for error estimate including covariance

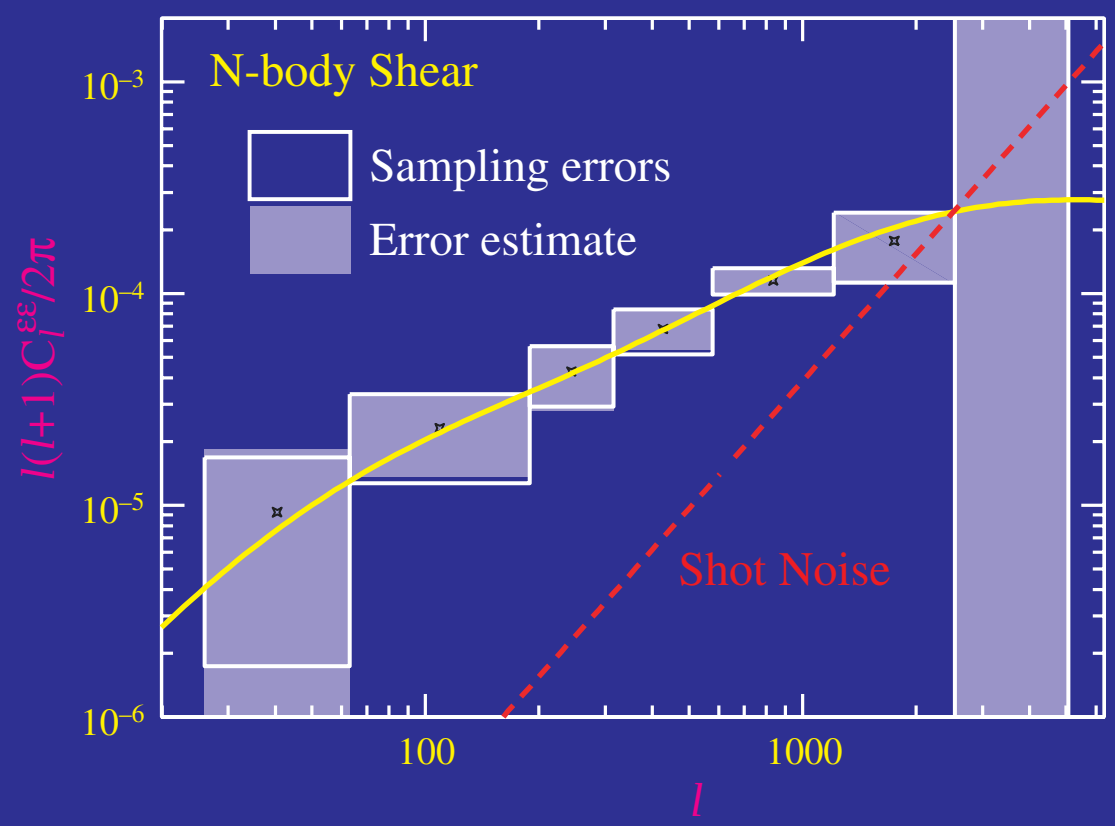


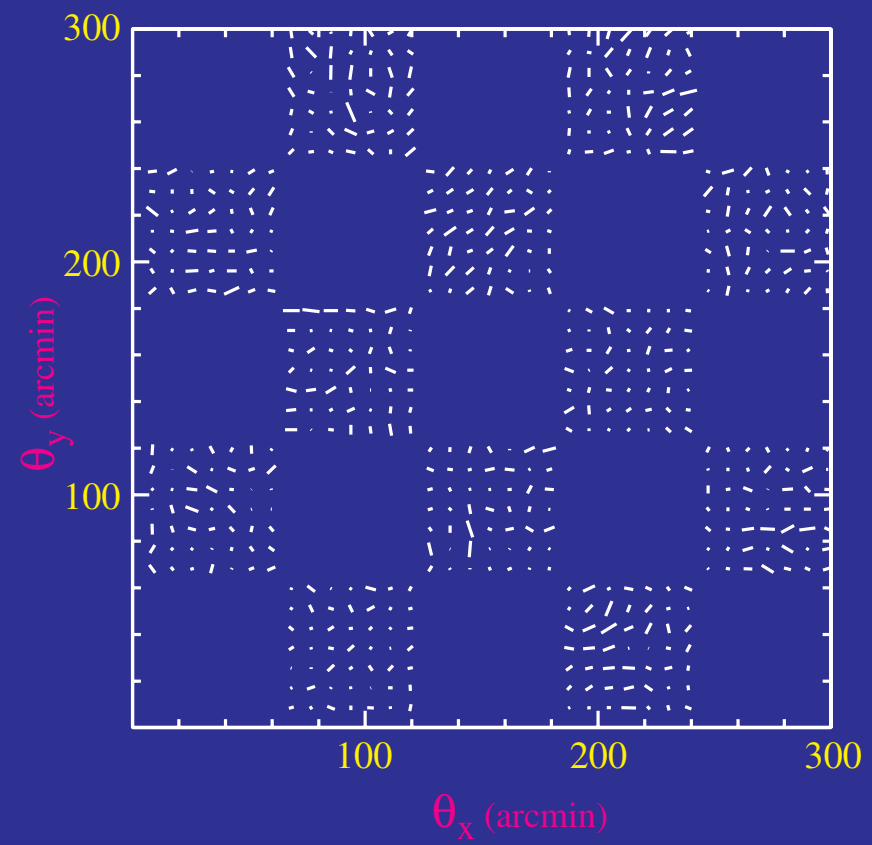


Hu & White (2001)

Testing the Likelihood Method

- Sparse sampling test
- Mean and errors correctly recovered

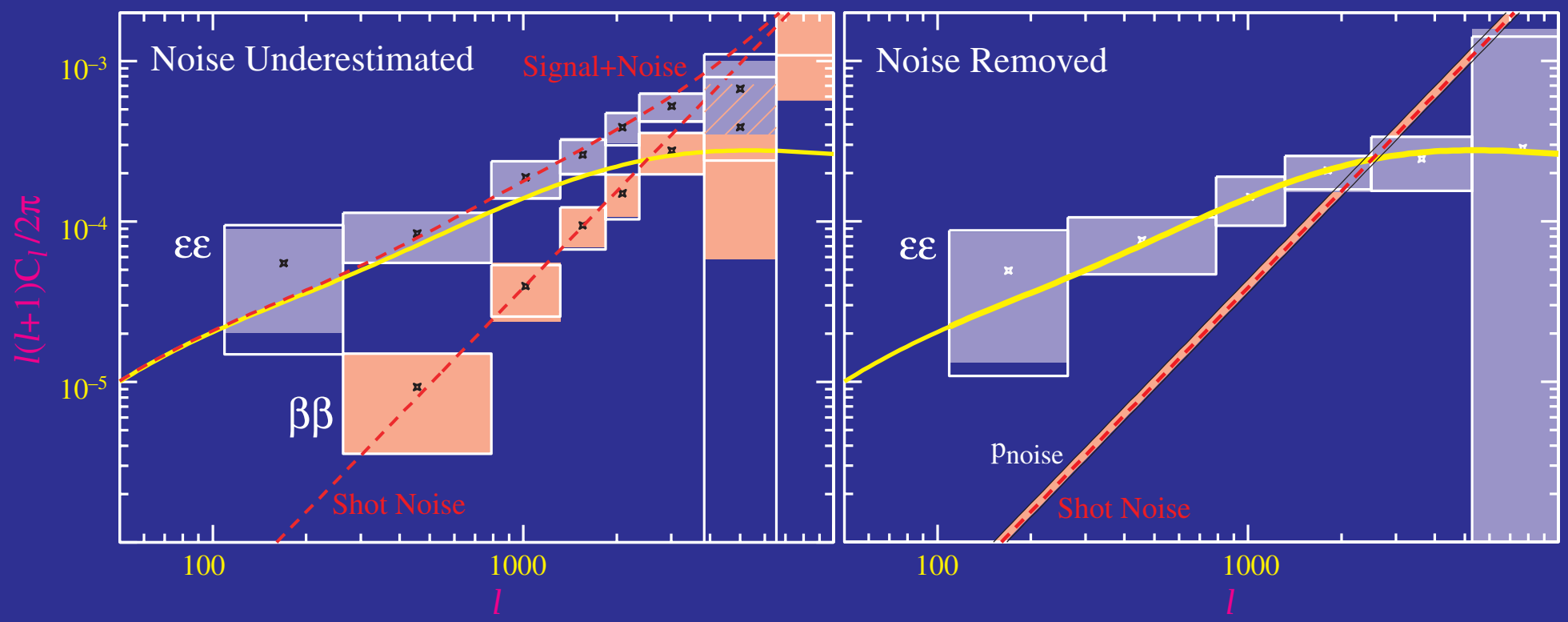




Hu & White (2001)

Testing the Likelihood Method

- Systematic error monitoring: example underestimated shot noise
- β-channel appearance in power
- Systematic error template: jointly estimate or marginalize

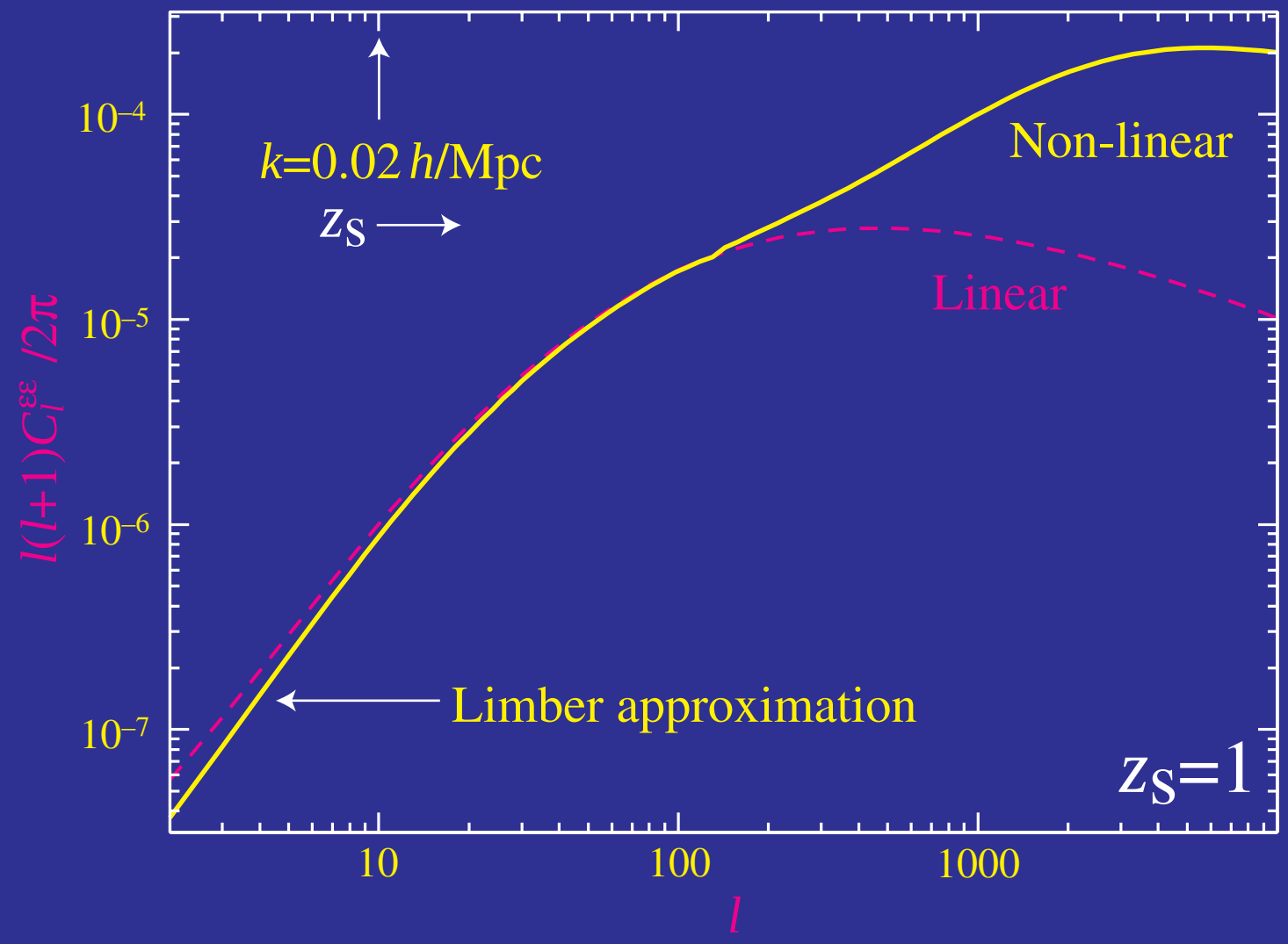


Hu & White (2001)

Cosmological Parameter Forecasts

Degeneracies

- All parameters of ICs, transfer function, growth, angular diam. distance
- Power spectrum lacks strong features: degeneracies



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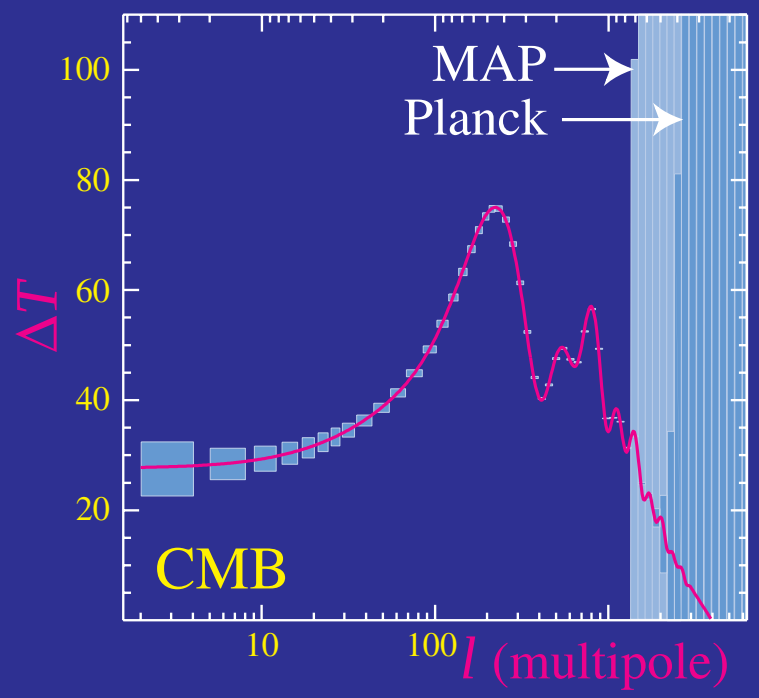


- CMB: provides high redshift side
  IC's, transfer fn., ang. diameter to z=1000
  Lensing: dark energy, dark matter

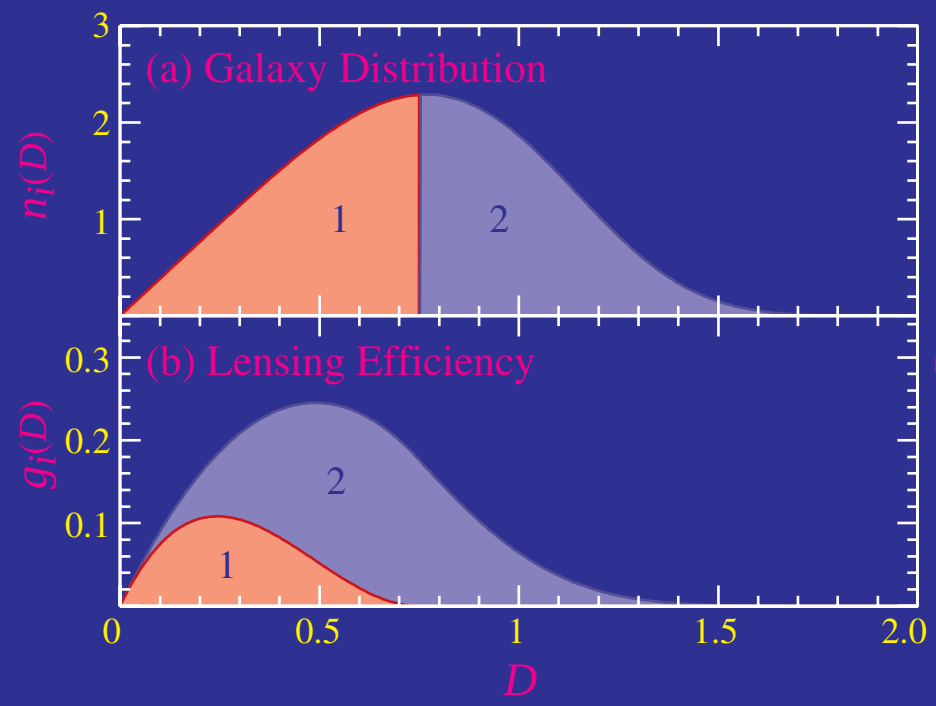
  Hu & Tegmark (1999)

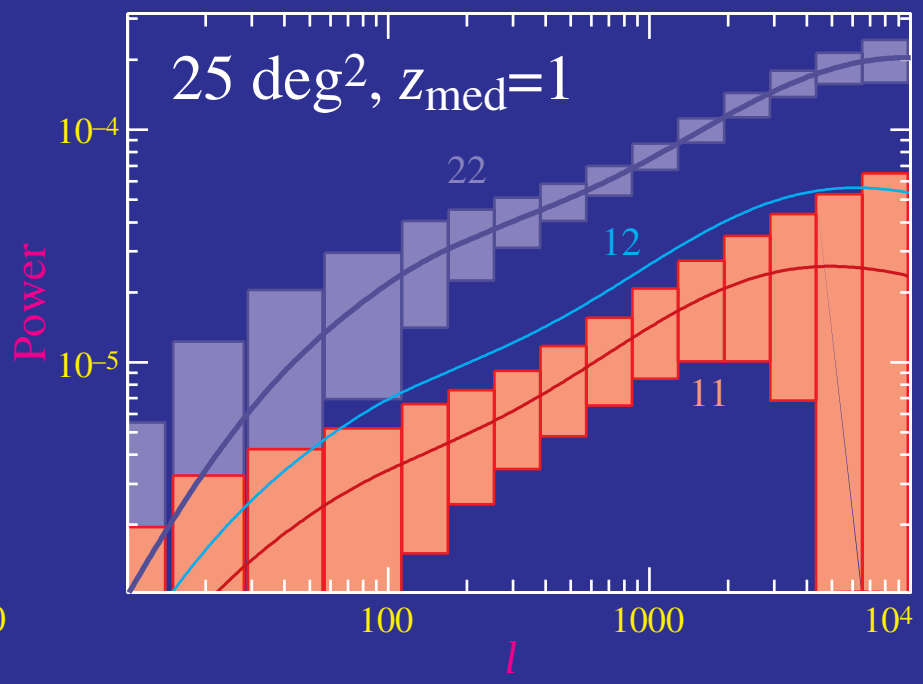
- Redshifts: source (and lens)
  Breaks degeneracies by tomography

  Hu (1999)

Tomography

- Divide sample by photometric redshifts
- Cross correlate samples

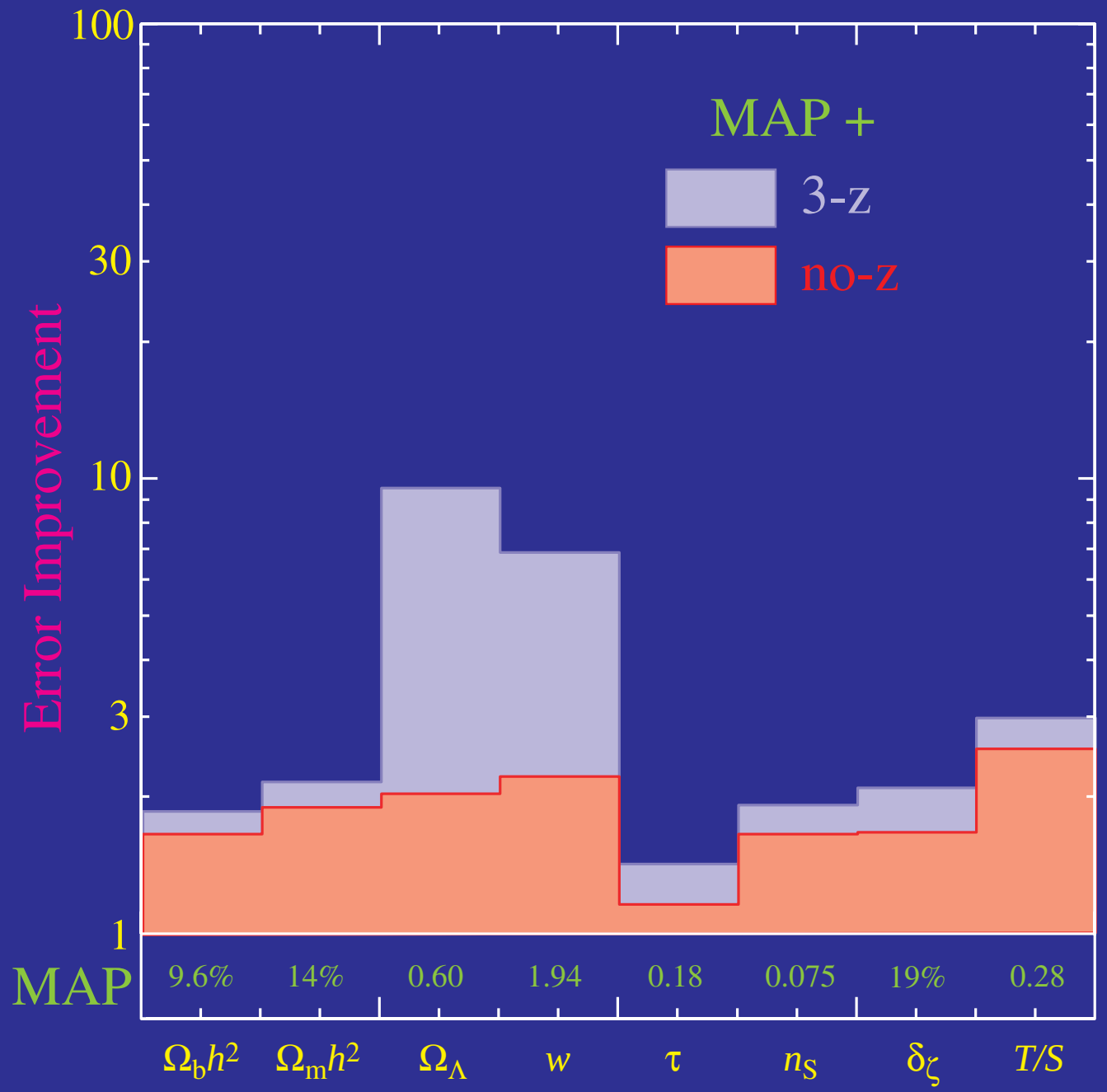




- Order of magnitude increase in precision even after CMB breaks degeneracies

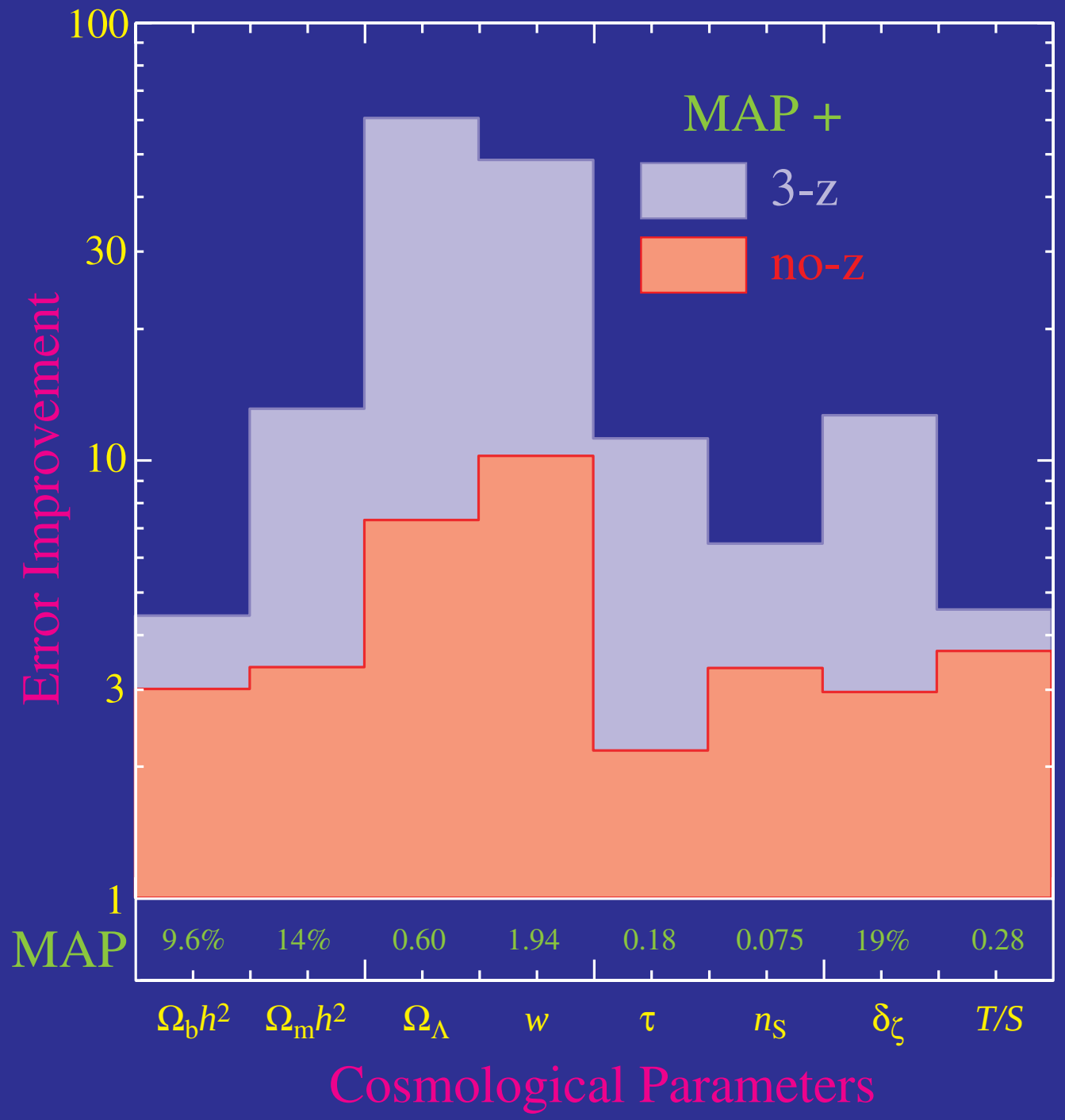
Hu (1999)

Error Improvement: 25deg^2



Hu (1999; 2001)

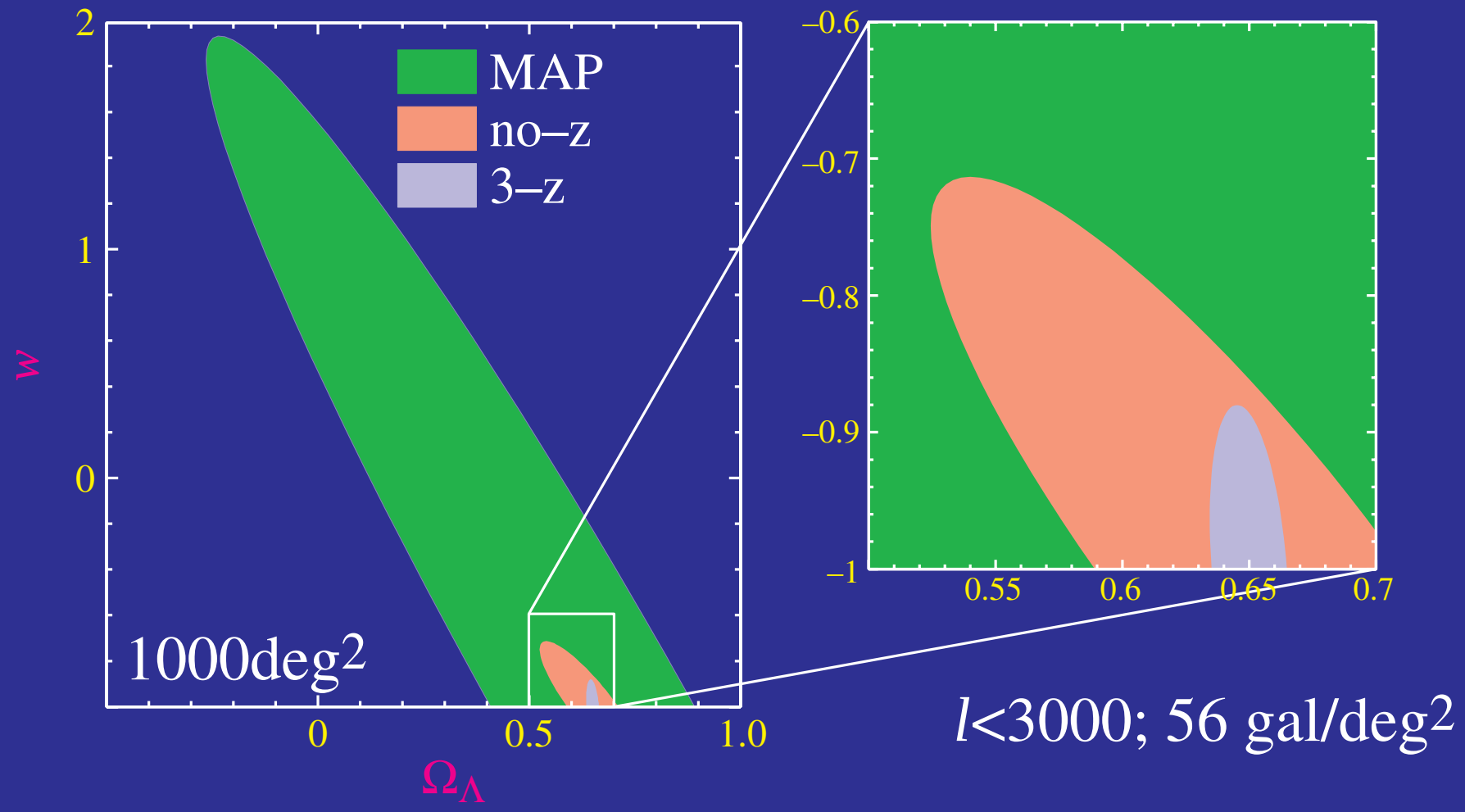
Error Improvement: 1000deg^2



Hu (1999; 2001)

Dark Energy & Tomography

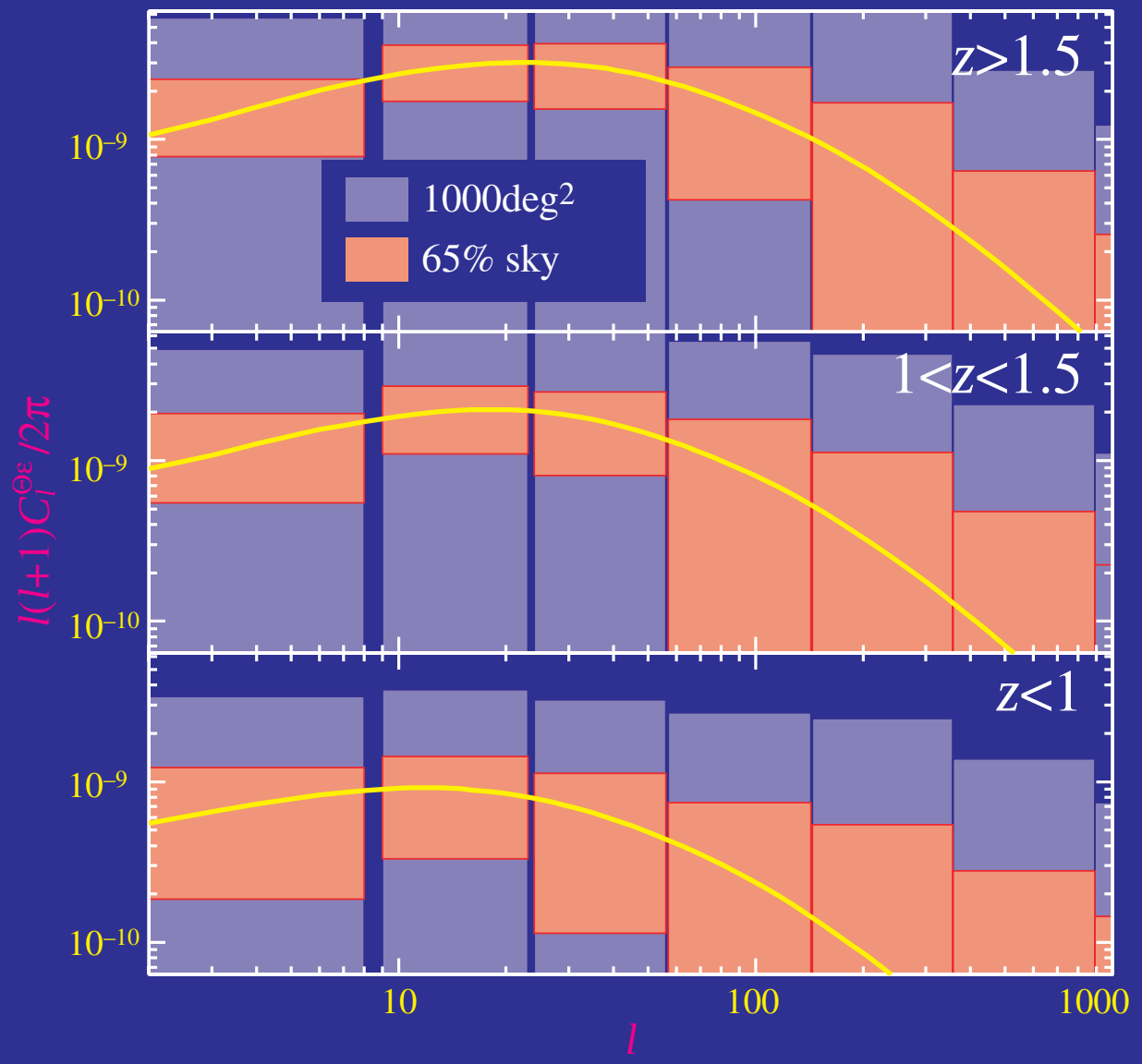
- Both CMB and tomography help lensing provide interesting constraints on dark energy



Hu (2001)

Direct Detection of Dark Energy?

- In the presence of dark energy, shear is correlated with CMB temperature via ISW effect



Hu (2001)

CMB Lensing: Tomography Anchor

- CMB acoustic waves are the ultimate high redshift source!

Hu (2001)

Mass Reconstruction

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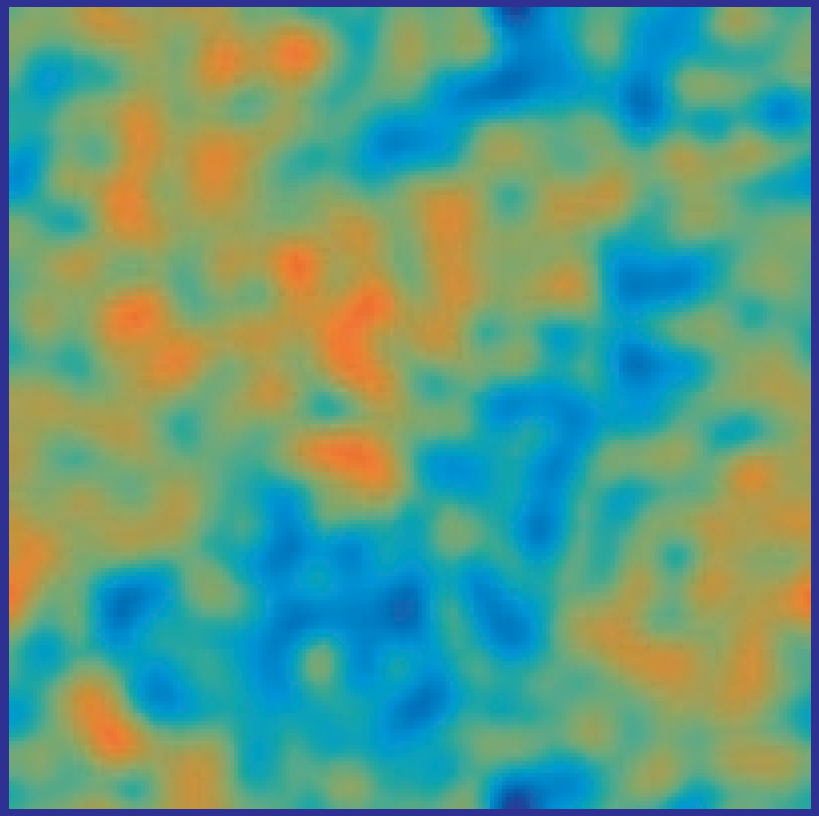
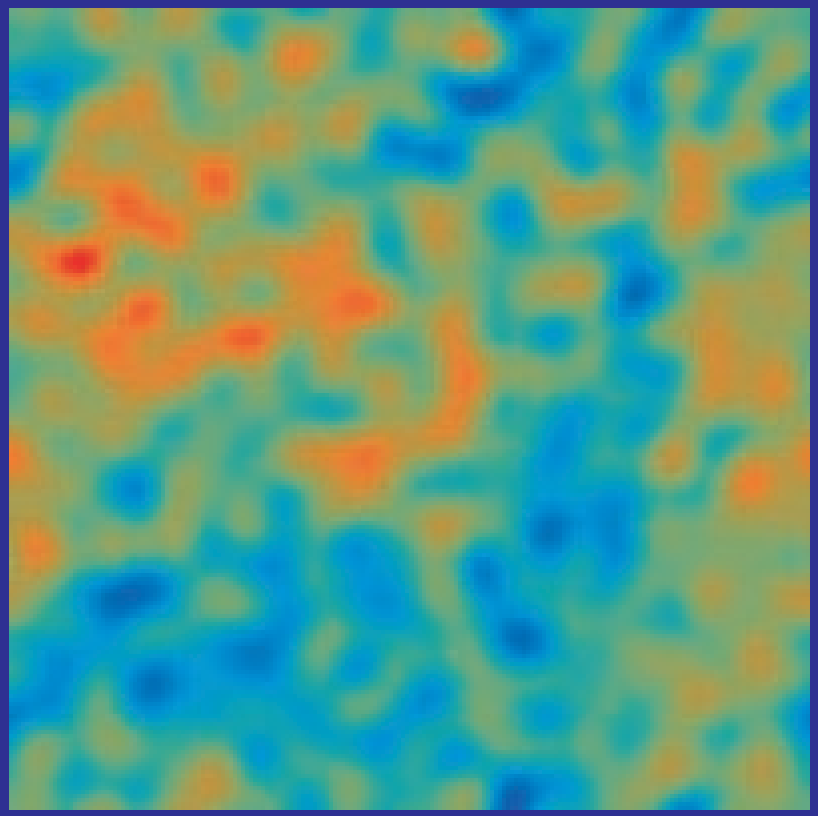


original

mass (deflection) map



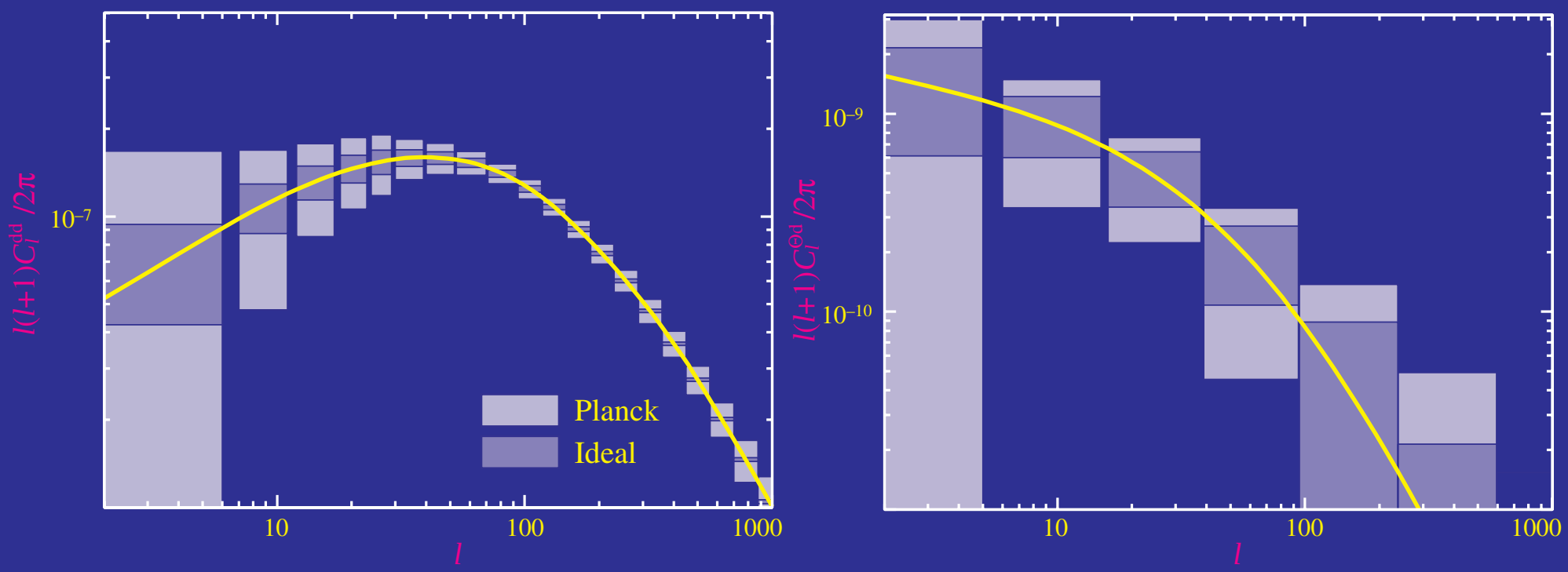
reconstructed

1.5' beam; 27μK-arcmin noise

Hu (2001)

Power Spectra

- Power spectrum of deflection and cross correlation with CMB ISW



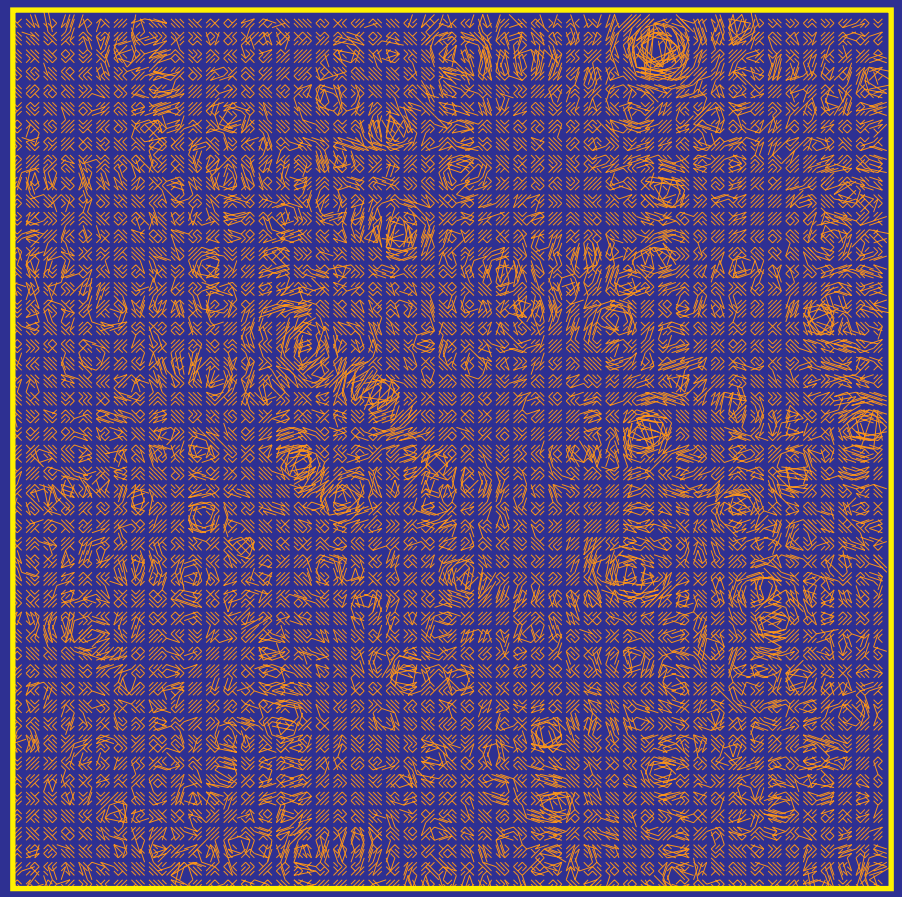
- Extend tomography to larger scales and higher redshift
- Constrain clustering properties of dark energy through ISW correlation

Hu (2001)

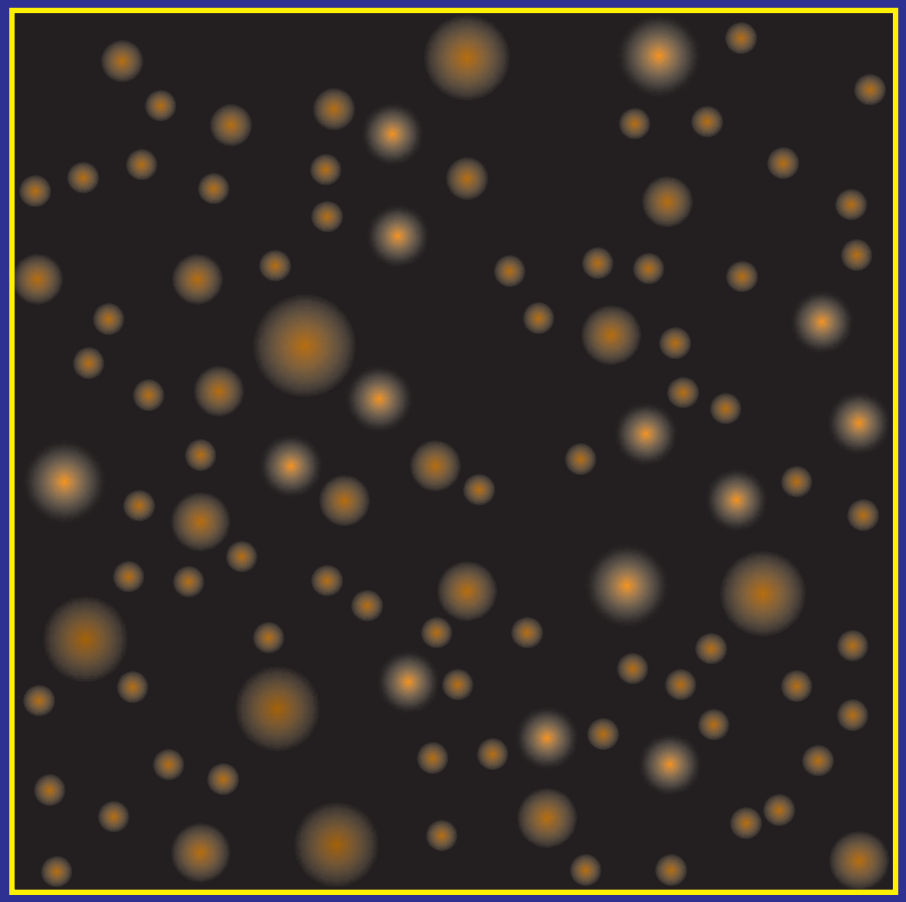
Lens Redshifts

- Shear selected halos: clustered according to well-understood halo bias

Shear



Halo Identification

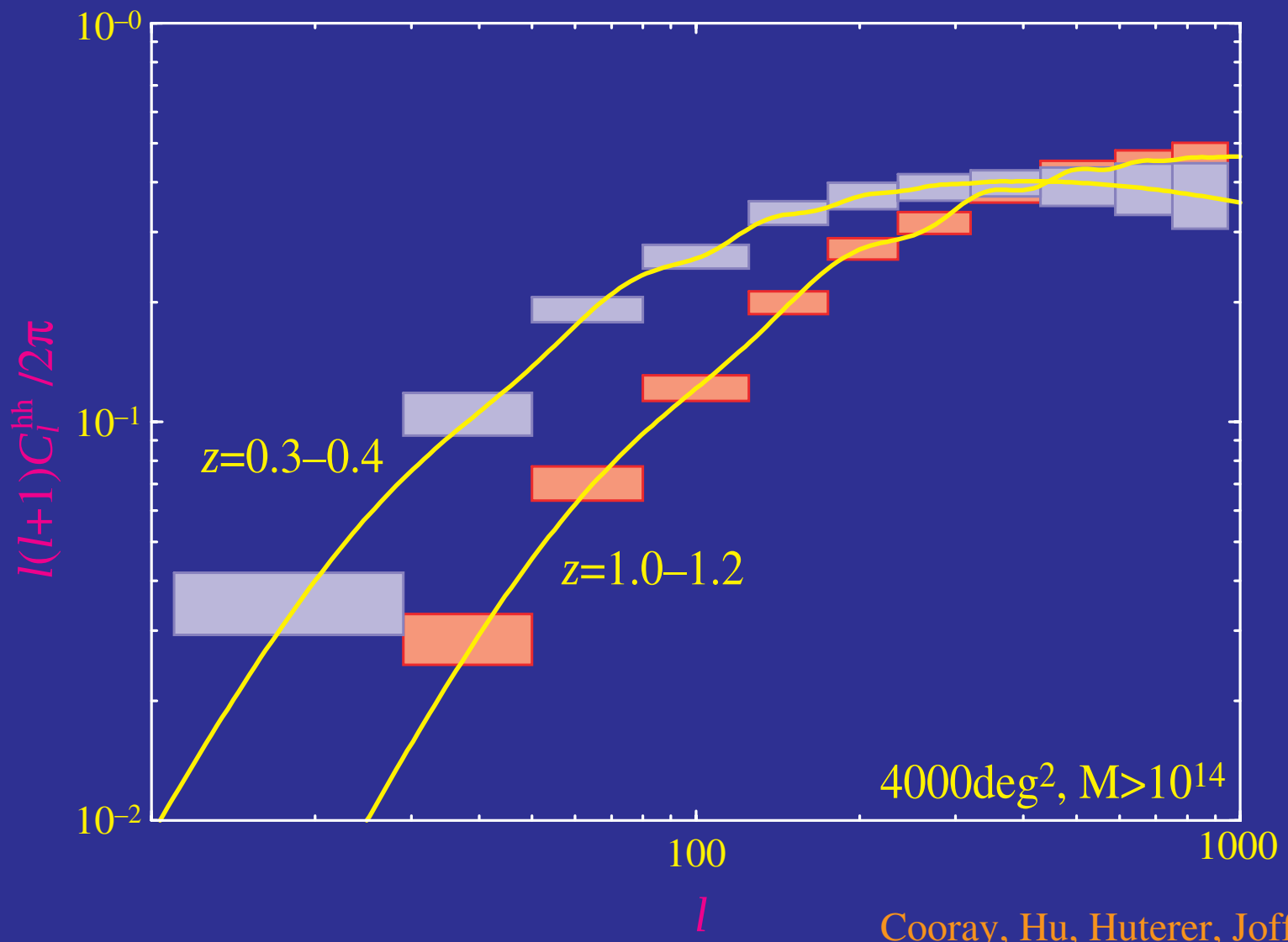


Mo & White (1996)

e.g. aperture mass: Schneider (1996)

Lens Redshifts

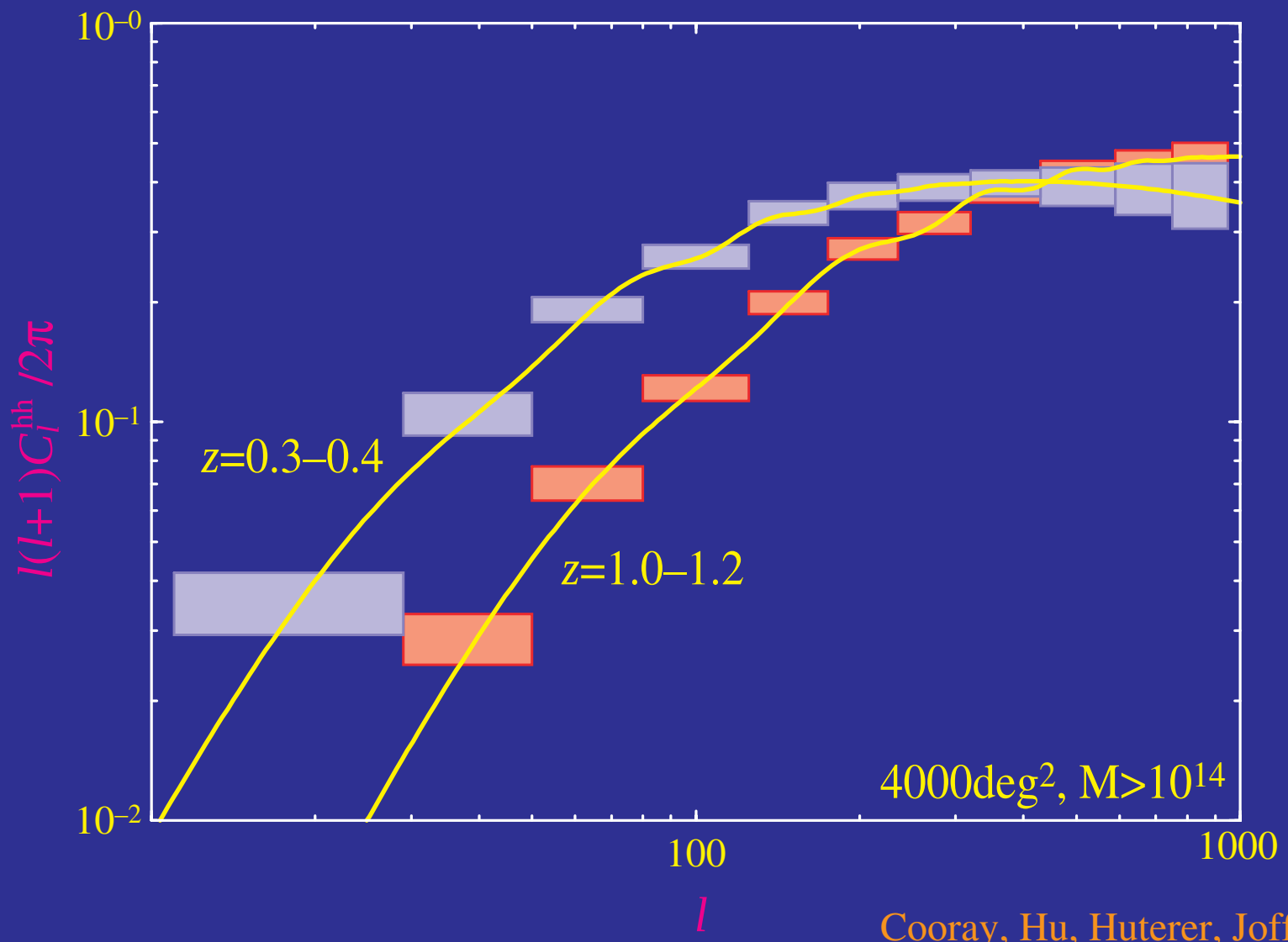
- Shifting of feature(s) in the angular power spectrum: $d_A(z)$



Cooray, Hu, Huterer, Joffre (2001)

Lens Redshifts

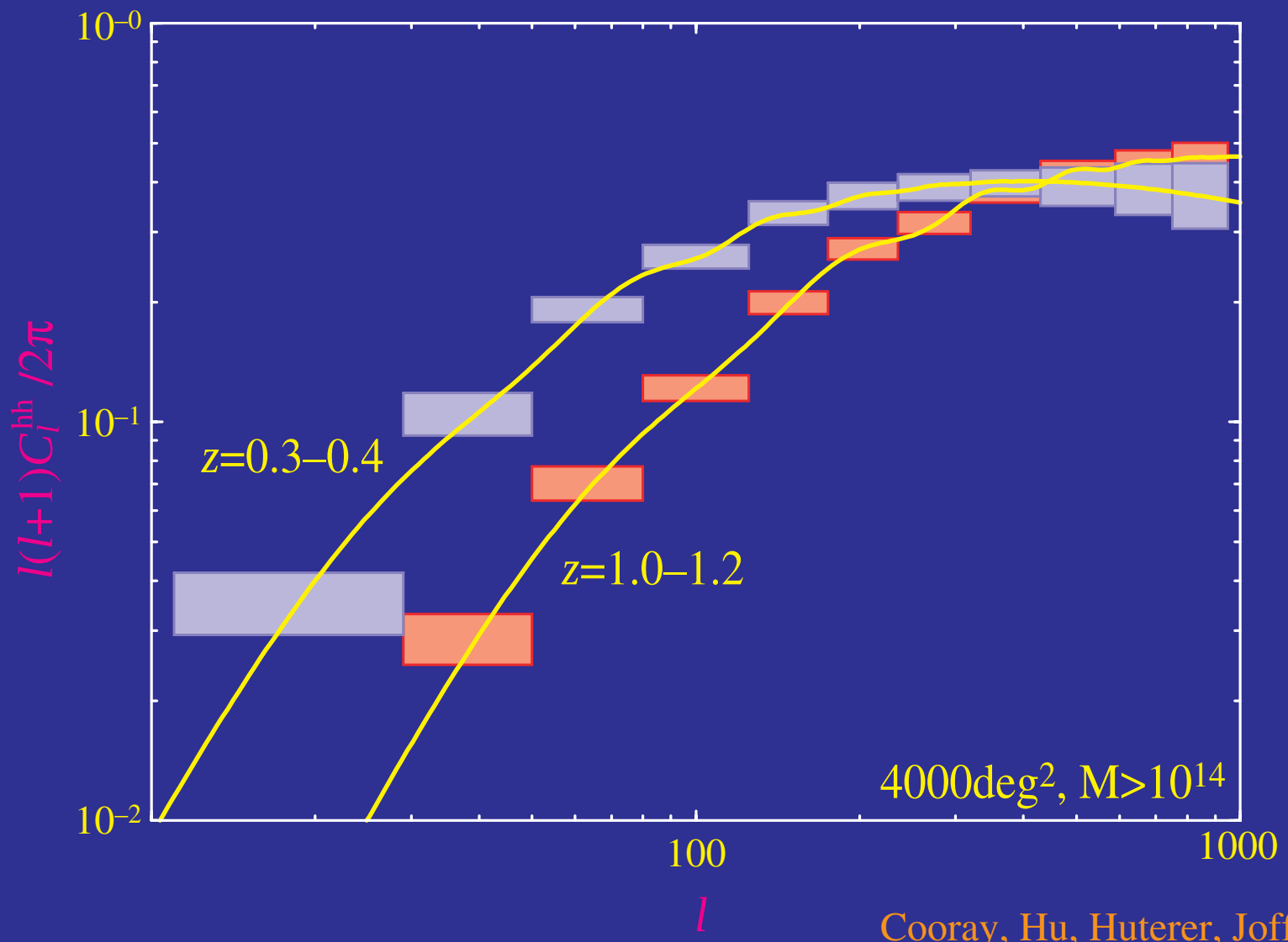
- If baryon features not detected, 10% distances to z~0.7 possible



Cooray, Hu, Huterer, Joffre (2001)

Lens Redshifts

- If baryon features are detected, ultimate standard ruler!



Cooray, Hu, Huterer, Joffre (2001)

Summary

- N-body sims and halo model for understanding power spectrum stats. and higher order correlations
- Likelihood analysis is feasible and near optimal for current generation of surveys

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  properly accounts for sparse or uneven sampling and correlated noise

  built in monitors for systematic errors

  techniques for marginalizing known systematics w. templates

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- Likelihood analysis is feasible and near optimal for current generation of surveys

  properly accounts for sparse or uneven sampling and correlated noise

  built in monitors for systematic errors

  techniques for marginalizing known systematics w. templates

- Power spectrum complements CMB information – order of magnitude increase in precision
- Tomography (including CMB lensing) assists in identifying dark energy (including possible clustering)
- Lens redshifts yield halo number counts and halo power spectra