Small scales with approximate methods

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The need for approximate methods

PROBLEM

Provide **mock catalogues** to test pipelines and understand better the measurements

REQUIREMENTS

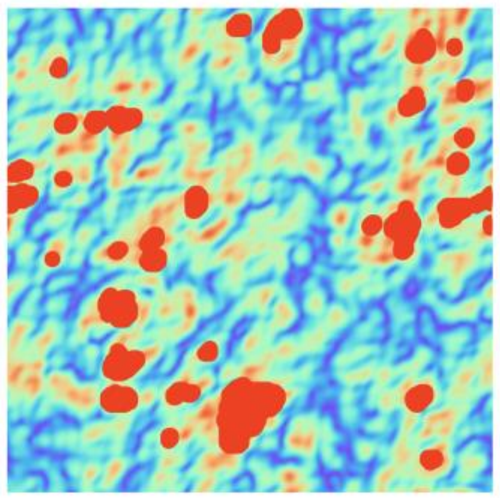
Sample large volumes.
Produce **many realizations.**.
Explore different theoretical models

SOLUTION

Develop **fast methods** that provide the optimal balance between accuracy and speed-up

Approximate methods

- Avoid solving the most expensive part of a numerical simulation



I. Run a cheap evolution of the density field

II.
- Use a biasing prescription to populate the density field (log-normal, Quick Particle Mesh, PATCHY, EZmocks, HALOGEN)
- Identify collapsed regions as halos (**COLA**, PINNOCHIO, PTHalos)

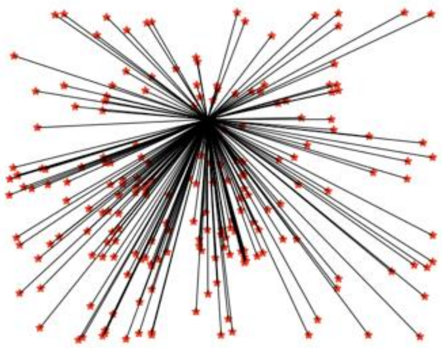
COLA is a cheap N-body

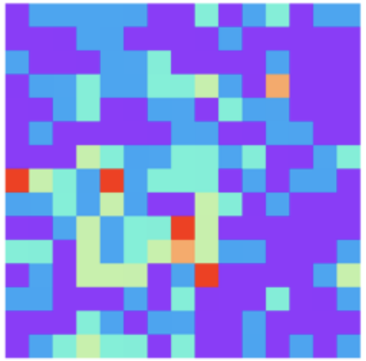
- Sample discretely the phase space by point-like particles

N-body

COLA

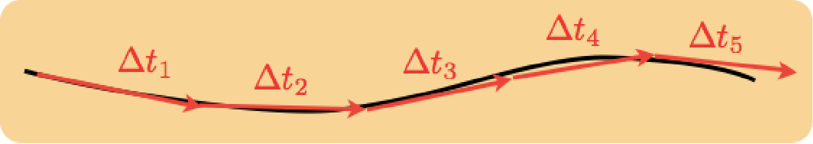
- Estimate forces

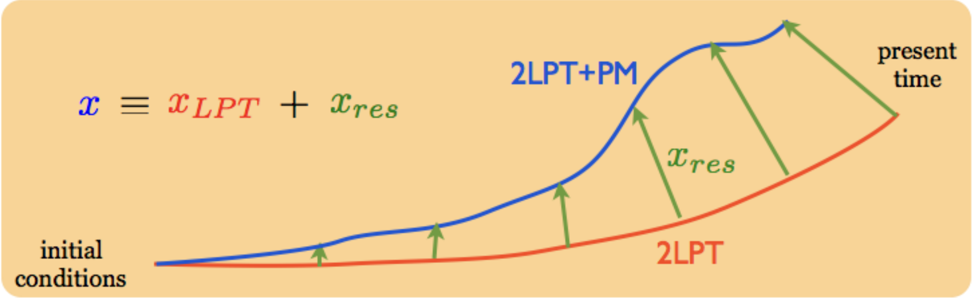




Particle-Mesh
+
FFT

- Integrate equation of motion





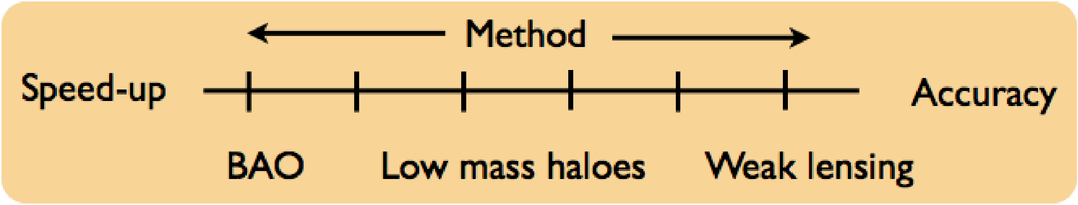
Comparison with other approximate methods

PROS

- ✓ Large scale dynamics is exact
- ✓ Accuracy at small scales is adjustable
- ✓ 2-3 orders of magnitude faster than conventional N-body simulations
- ✓ The dark matter field is available

CONS

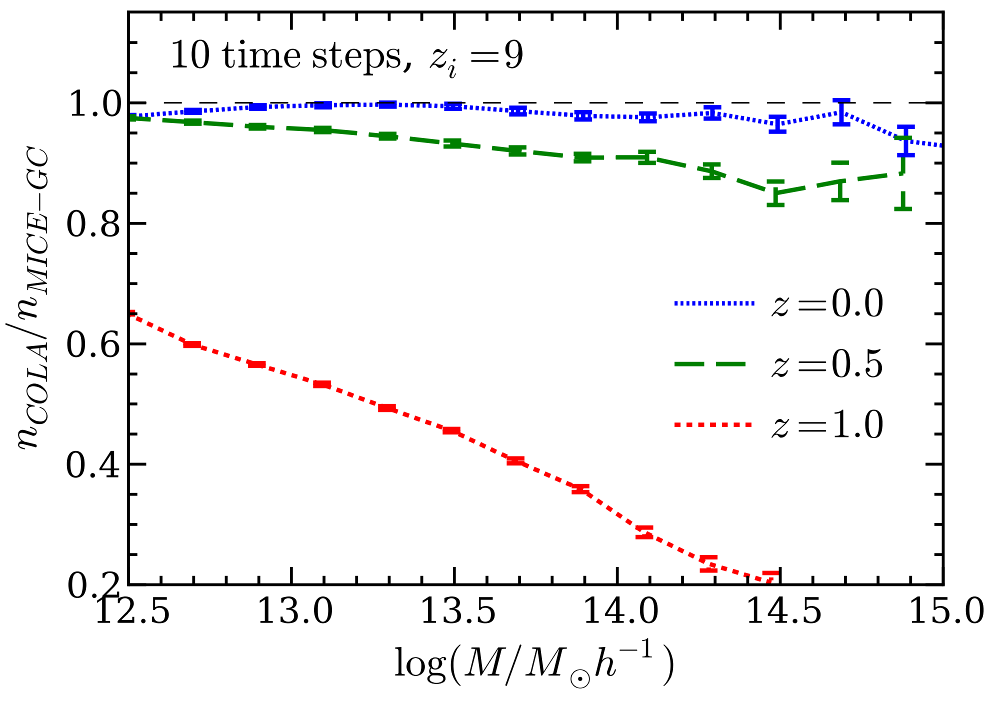
- ❖ Large memory consumption
- ❖ Not as fast as fast methods using biasing prescriptions



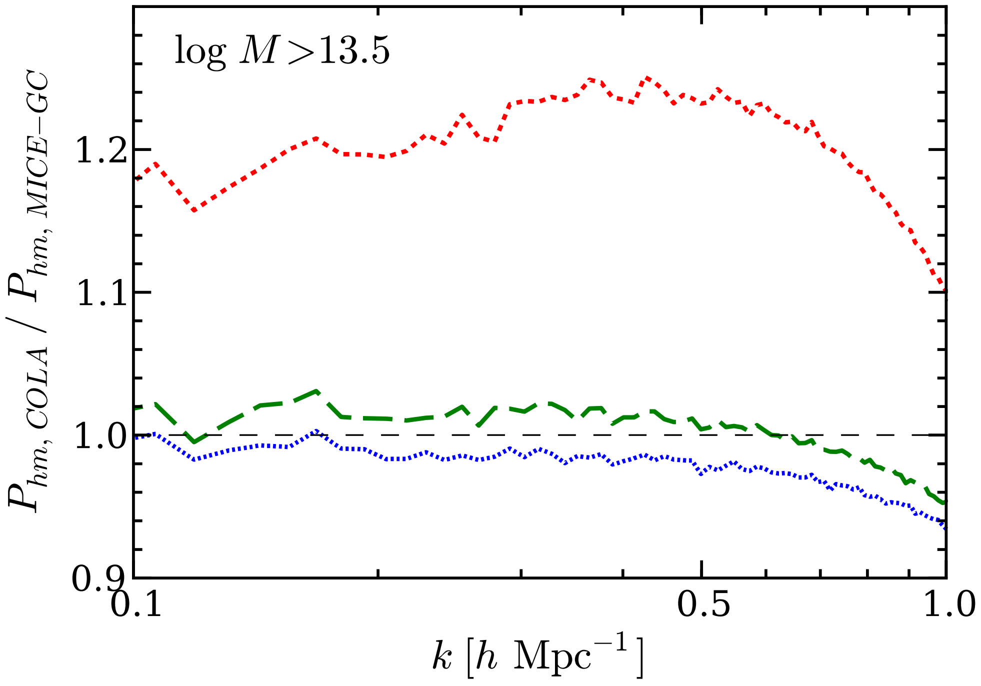
Limitations of 10 time steps

- Halo formation is not accurately captured before 10 time steps

Halo abundance

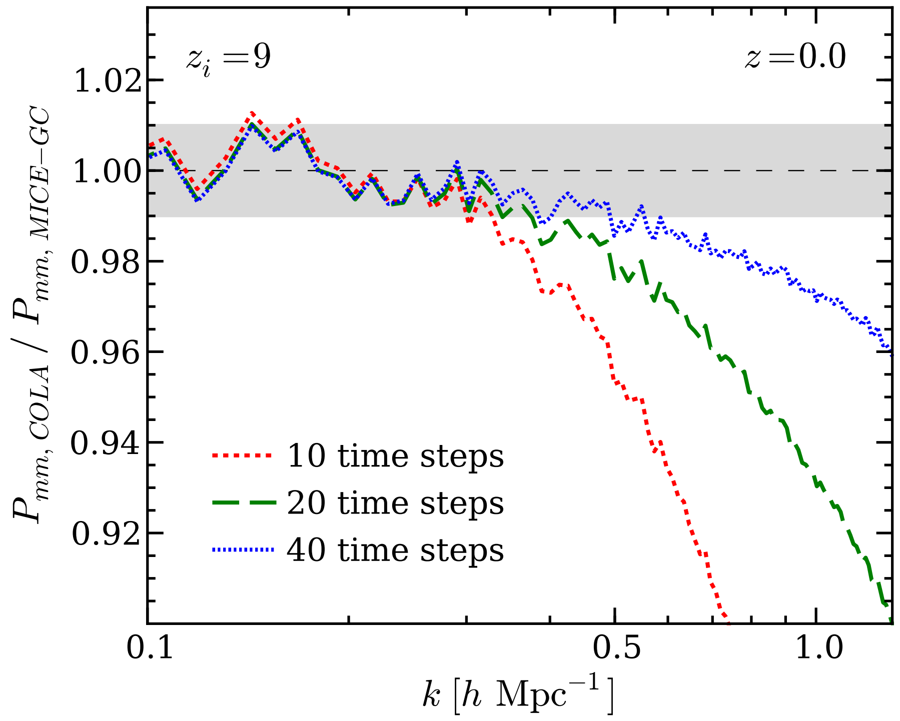


Halo-matter cross-correlation

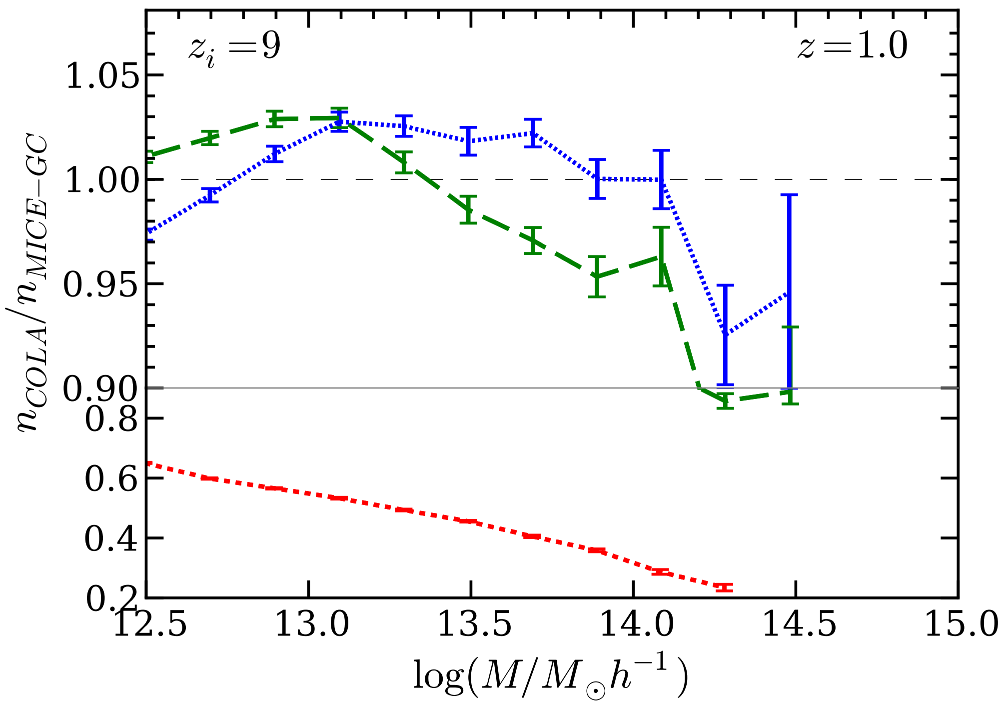


Number of time steps

Matter power spectrum



Halo abundance



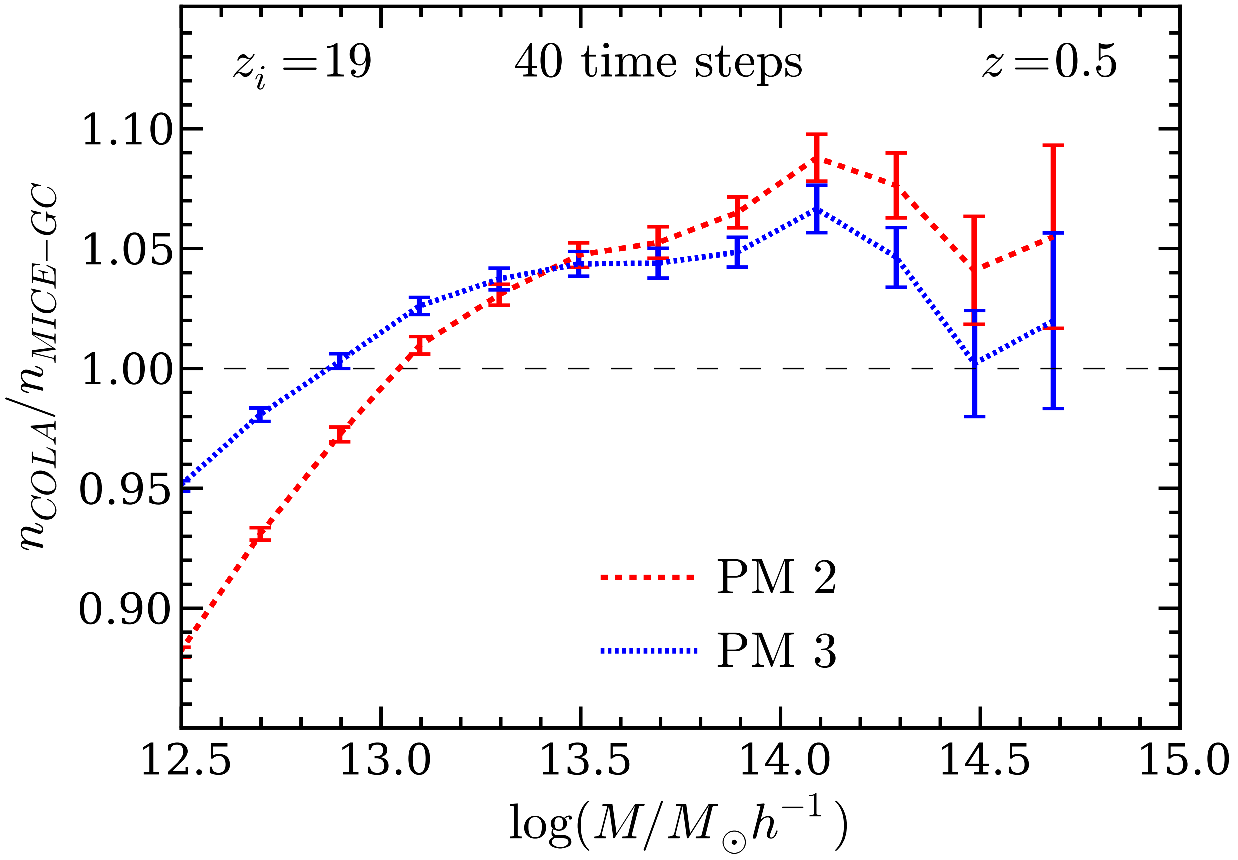
Trade-off

accuracy at small scales
vs
simulation time

> 10 time steps before the redshift of interest

Size of the force mesh

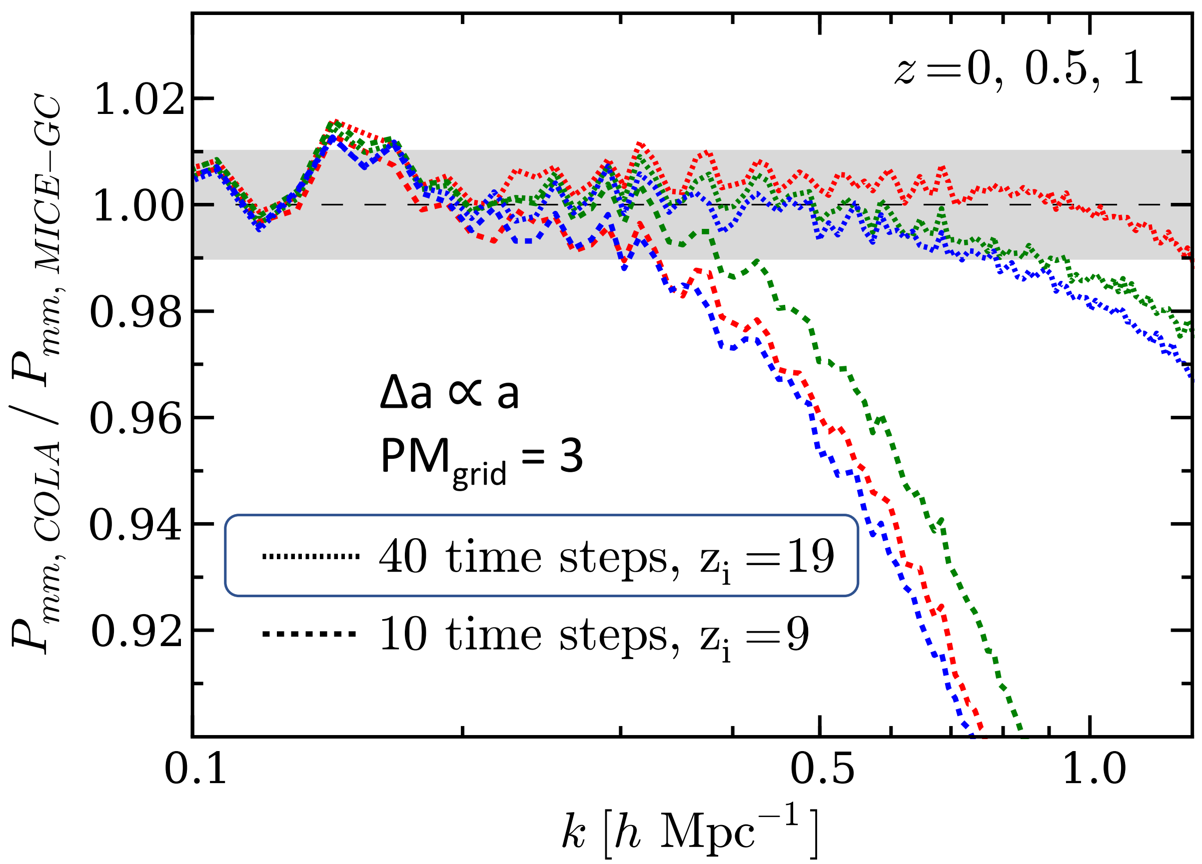
Halo abundance



- PM grid 3 times finer than particle separation is necessary to resolve ~100 particle halos

Optimal set-up for weak lensing covariances

Matter power spectrum

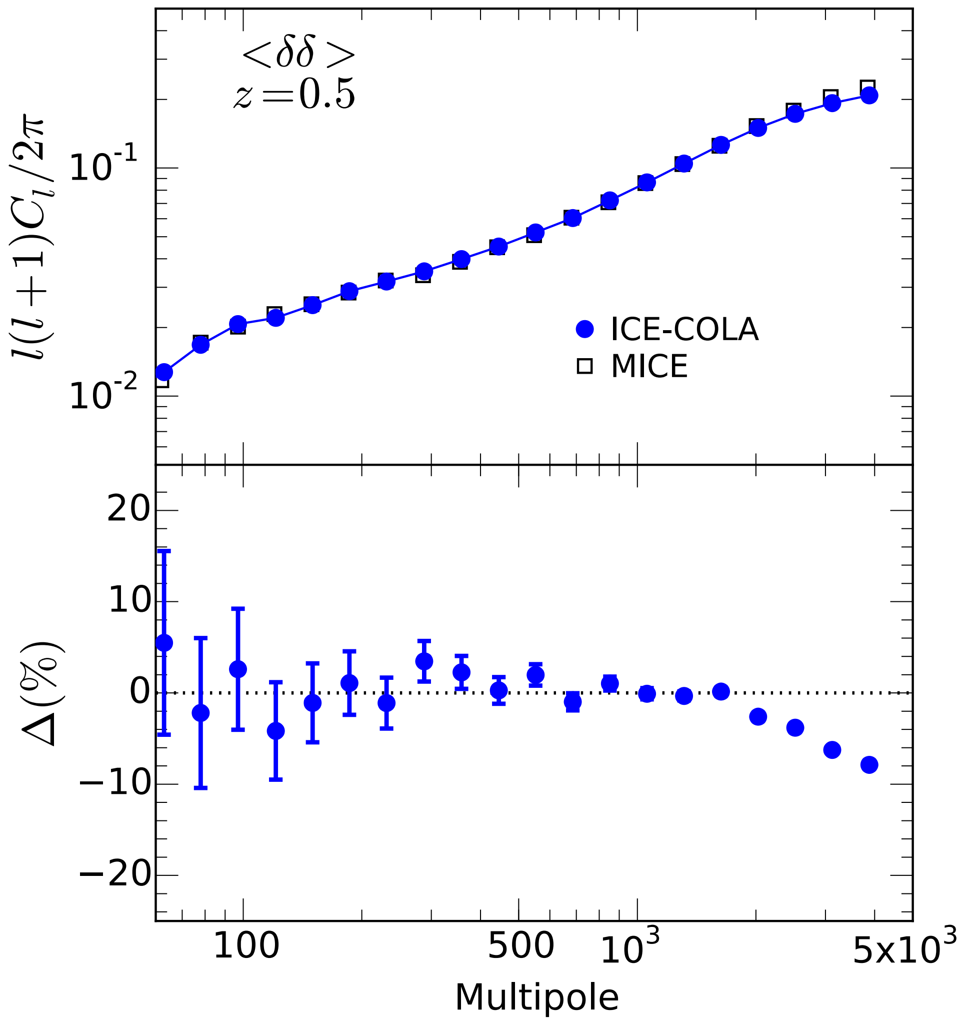


- 2048^3 particles run on 1024 cores in 40 minutes (2.7 Tb memory)
- 1% agreement up to k ~ 1 h/Mpc
- 5% accuracy in the mass function

The challenge of simulating weak lensing

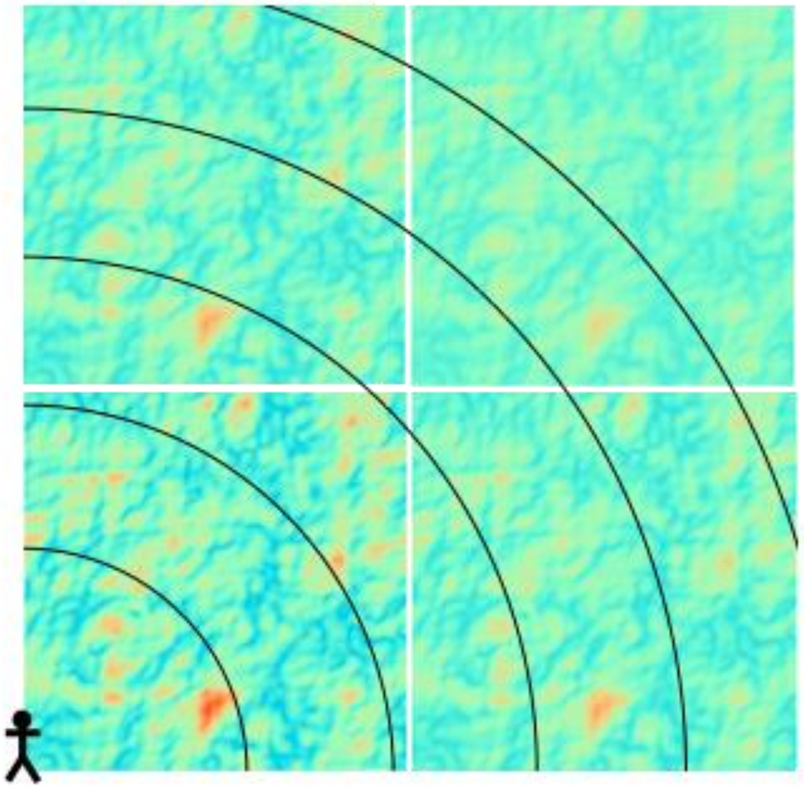
- Weak lensing samples:
  - Large volumes
  - The matter distribution at small scales

Matter angular power spectrum



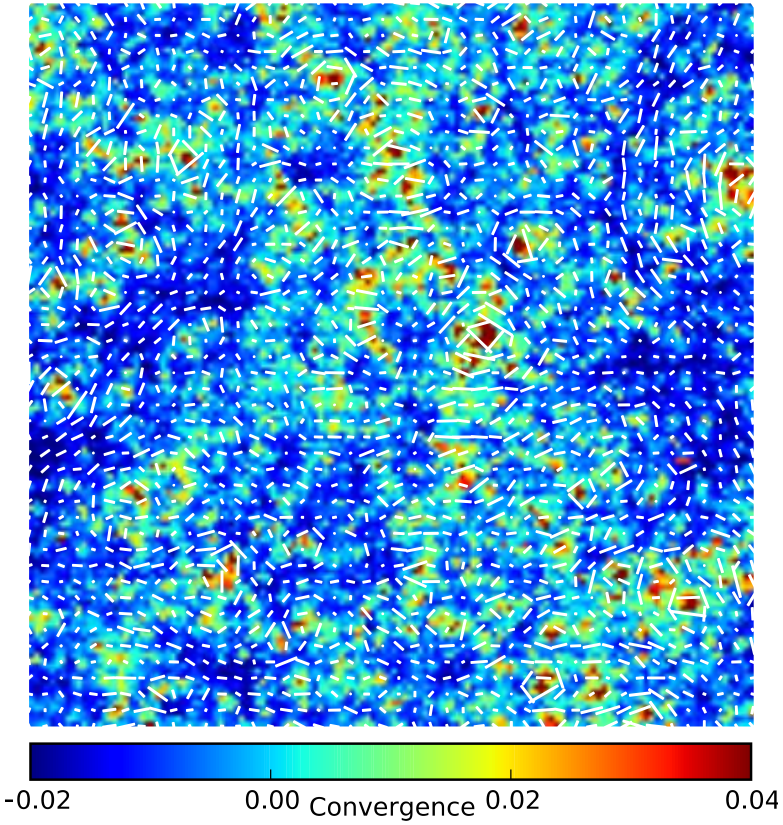
Light cone geometry

Dark matter field in the light cone



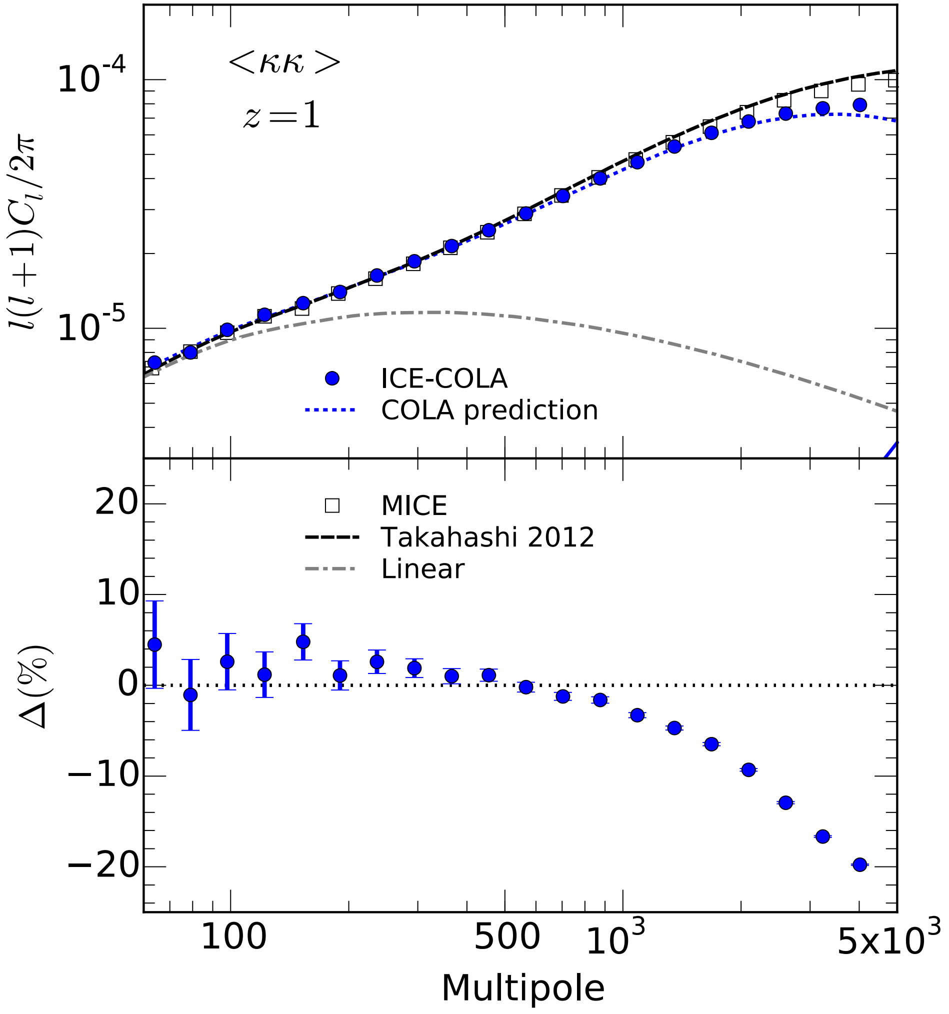
- Full sky 2D DM maps
- Born approximation
- Harmonic space

Maps for the convergence (colors) and shear (white ticks) fields



Convergence

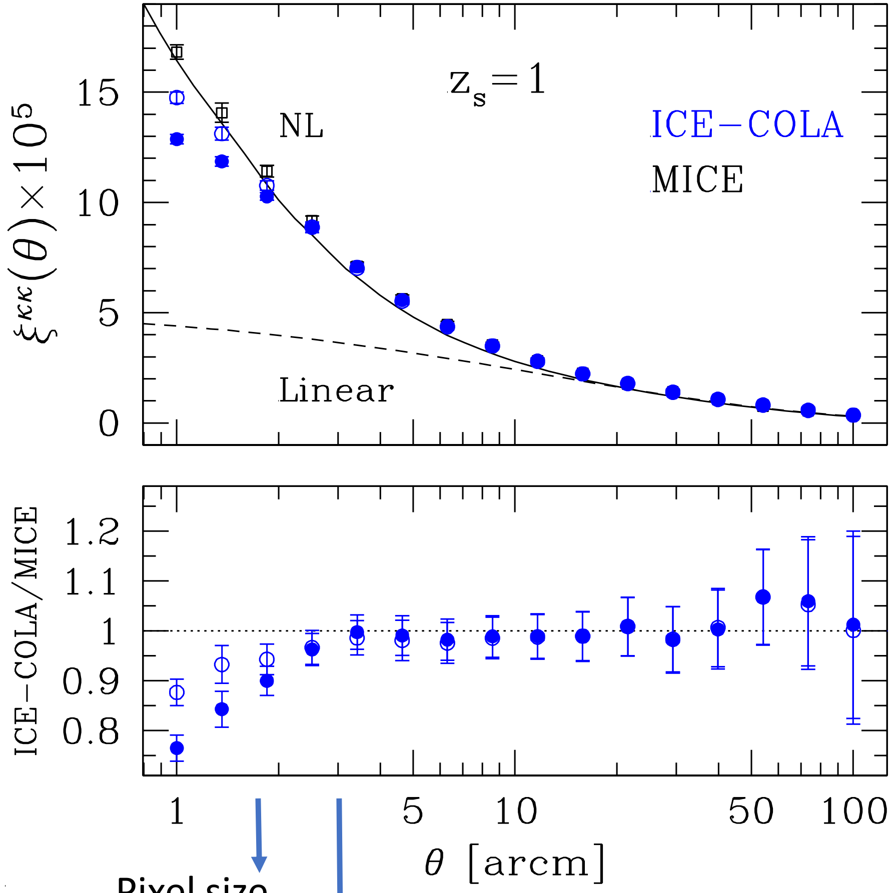
Convergence power spectrum



From the WL maps

From the halo catalogs

Halo convergence correlation function



Pixel size

~1 Mpc/h (z=0.5)

Summary

- The dark matter density field can be modeled down to non-linear scales with COLA.
- Trade-off between computational cost (# time steps) and accuracy at small scales.
- Weak lensing applications are possible, in particular for covariance matrices.

Extra slides…

residual displacement $\boldsymbol{x}_{\rm res}(t) \equiv \boldsymbol{x}(t) - \boldsymbol{x}_{\rm LPT}(t).$

residual acceleration $\partial_t^2 \boldsymbol{x}_{\rm res}(t) = -\nabla\Phi(t) - \partial_t^2 \boldsymbol{x}_{\rm LPT}(t)$

Particle-Mesh $\boldsymbol{k}^2 \tilde{\phi}(\boldsymbol{k}) = 4\pi G \tilde{\rho}(\boldsymbol{k})$

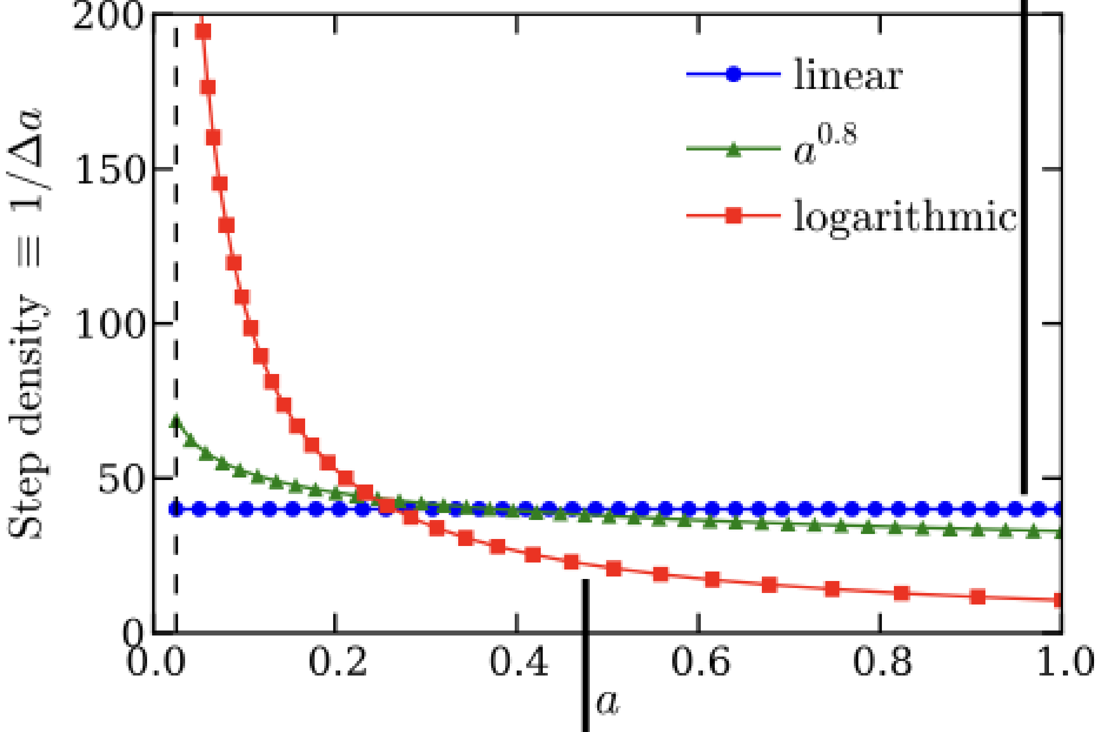
Temporal operators

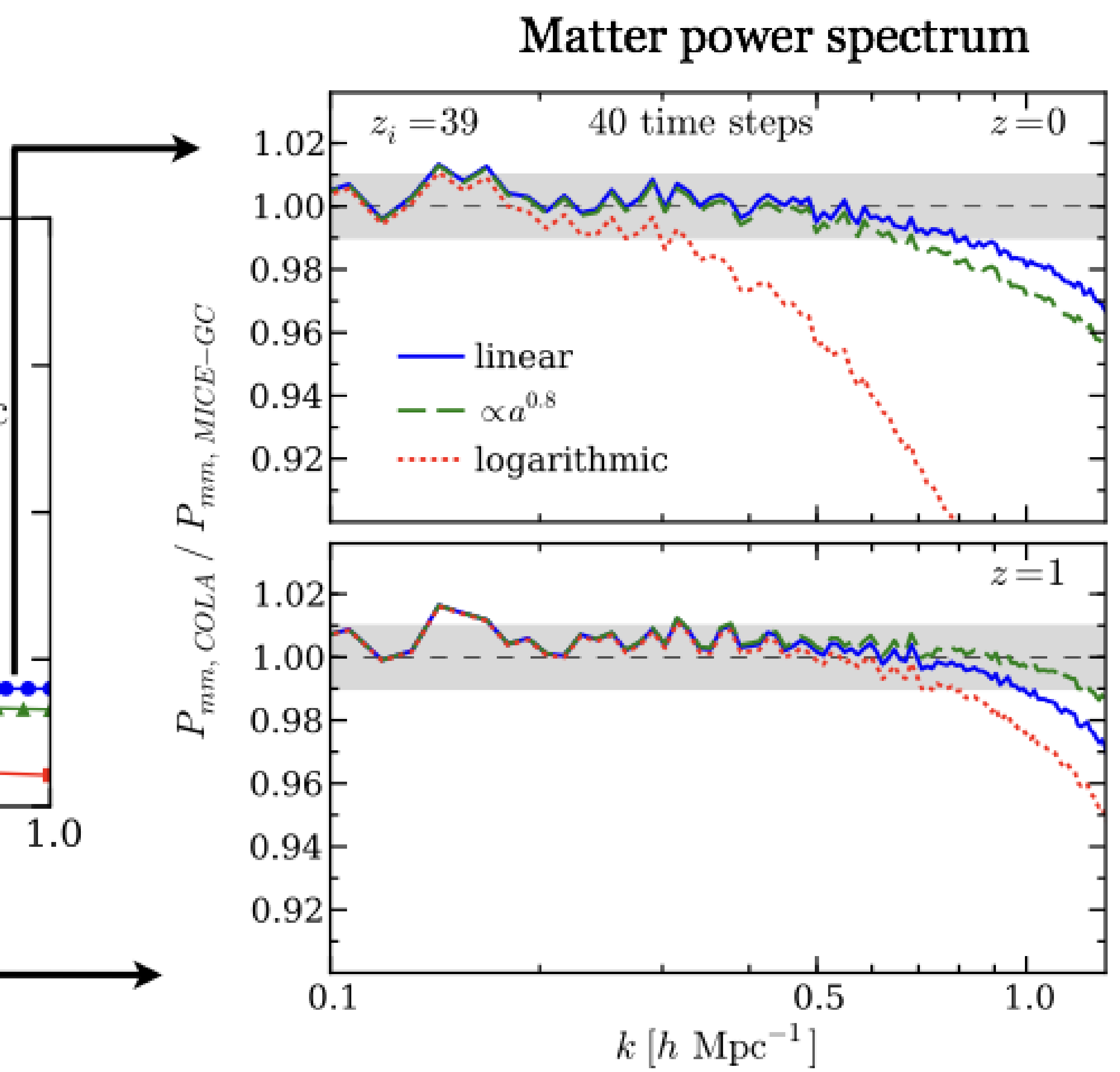
$$\begin{aligned} D(a_i, a_{i+1}): \quad & \boldsymbol{s}(a_i) \mapsto \boldsymbol{s}(a_{i+1}) = \boldsymbol{s}(a_i) + \boldsymbol{v}(a_{i+1/2})\Delta t \\ & \qquad + [D_1(a_{i+1}) - D_1(a_i)]\boldsymbol{s}_1 + [D_2(a_{i+1}) - D_2(a_i)]\boldsymbol{s}_2 \\ K(a_{i+1/2}, a_{i+3/2}): \quad & \boldsymbol{v}(a_{i+1/2}) \mapsto \boldsymbol{v}(a_{i+3/2}) = \boldsymbol{v}(a_{i+1/2}) + \Delta t \times \\ & \qquad \left(-\frac{1}{2}\nabla\phi(a_{i+1}) - \partial_t^2 \boldsymbol{s}_1(t) - \partial_t^2 \boldsymbol{s}_2(t)\right). \end{aligned}$$

Complete evolution $L_+(a)\left(\prod_{i=0}^{n} K(a_{i+\frac{1}{2}}, a_{i+\frac{3}{2}}) D(a_i, a_{i+1})\right) K(a_i, a_{i+\frac{1}{2}}) L_-(a)$

Transform to 2LPT observer $L_\pm(a): \quad \boldsymbol{v}(a) \mapsto \boldsymbol{v}(a) = \boldsymbol{v}(a) \pm (\partial_t \boldsymbol{s}_1(t) + \partial_t \boldsymbol{s}_2(t))$

How to optimally distribute 40 time steps between the initial conditions and z=0?

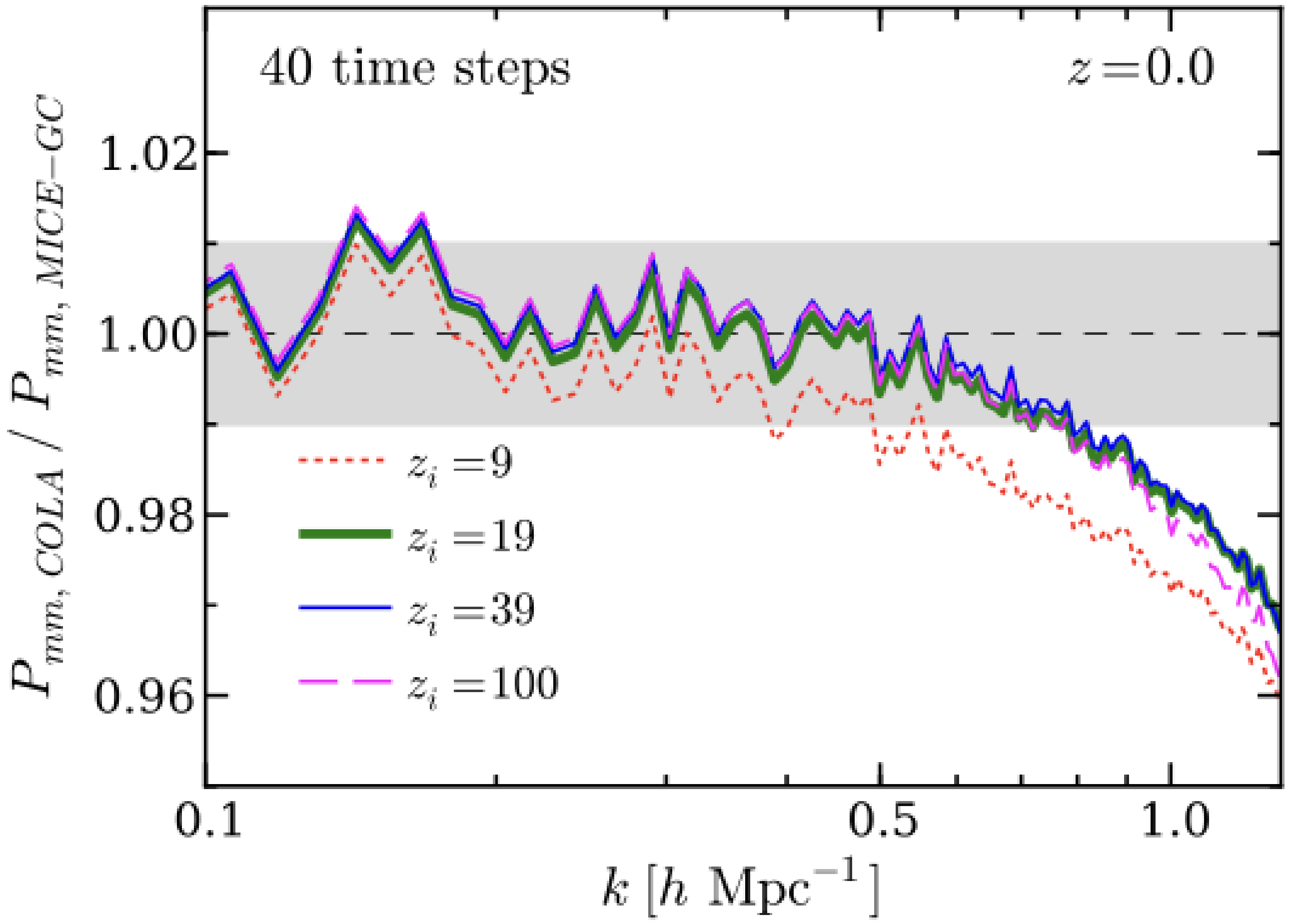




Distributions with varying step density are unbalanced

First guess: initial scale factor equal to the step width

Matter power spectrum



For 40 time steps, z_i=19 gives the best performance (Pk and MF)

Halo clustering

Halo bias is recovered within ~2% without applying any correction

Halo-matter cross-power spectrum