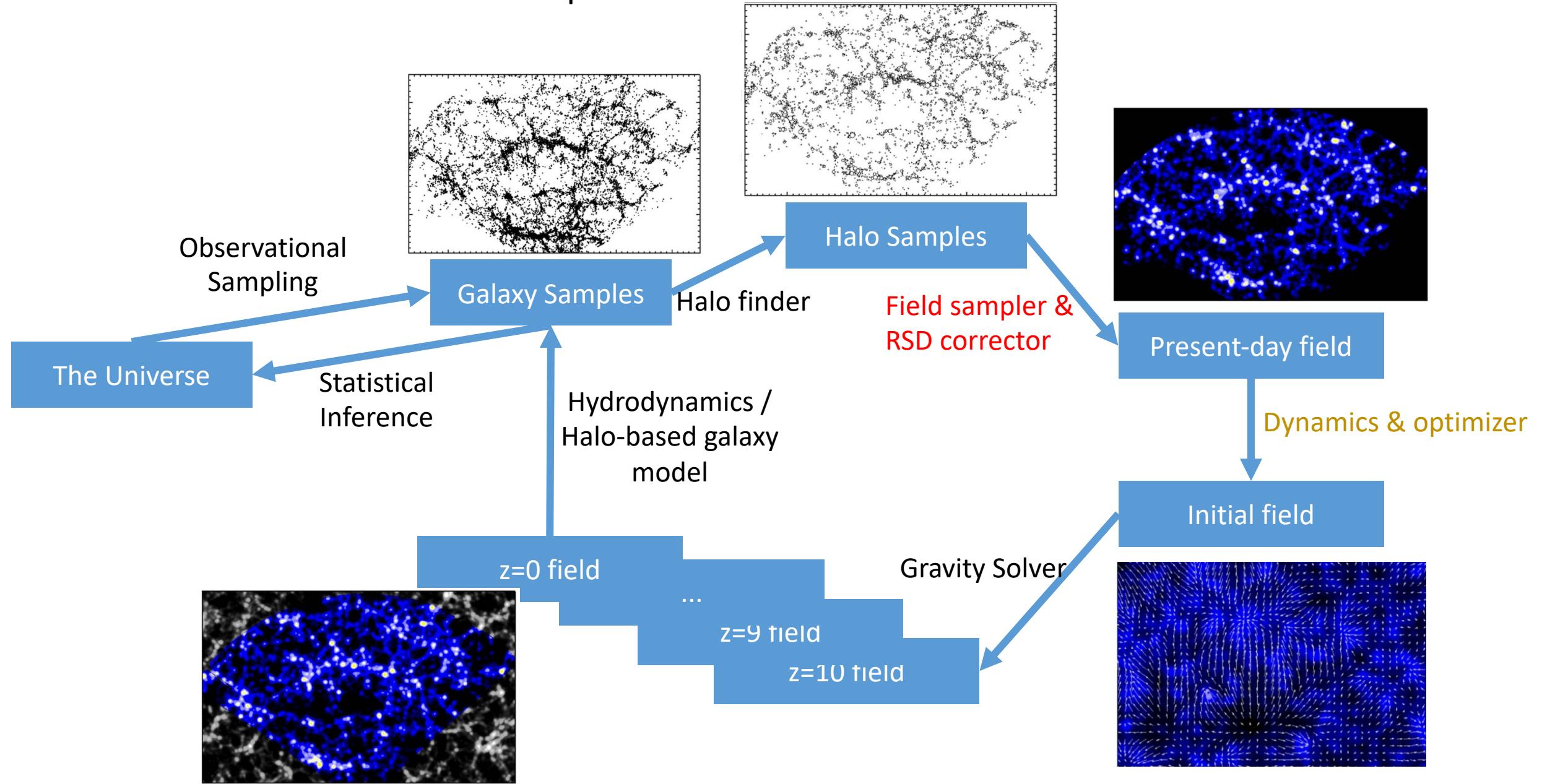


Cosmological Field Reconstruction

The Methods

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The Field Reconstruction Pipeline of ELUCID



2-D maps, e.g., lensing kappa, as constraints for the removal of void-overestimate.

The Choice of Field Tracers

- Samples from galaxy redshift surveys, e.g., 2MASS (all-sky at $z < 0.08$), SDSS ($\sim 7000 \text{ deg}^2$, $z < 0.2$), DESI (on-going, $z < \sim 1.5$).
 - Direct observable, large number, wide sky coverage and deep redshift range.
 - Suffering from redshift-space distortion.
 - Being biased and model-dependent tracers of the density field.
- Halos from galaxy group finders, e.g., Yang's group catalogs, improvements and extensions made by Lim, Wang, etc.
 - Halo-scale redshift-space distortion (Finger of God effect) removed.
 - Large-scale distortion (Kaiser effect) still present.
 - Small/isolated galaxies and poor-groups missed.
 - Issues in **mass estimation**, membership assignment, and group center positioning.
- Samples from peculiar velocity surveys.
 - Partially independent constraints to the field.
 - Sample size, typically $< 10k$.
 - Systematics and noises in the distance measurement (very precise for SNIa, $\sim 5\%$ for SBF, 10% to 20% for Tully-Fisher).
 - Shallow redshift range, $z < 0.05$.
- A combinations of above
 - More information extracted as constraints.
 - Biases and degeneracies/covariances among samples.

Avaible Peculiar Velocity Datasets

Fundamental-Plane catalog.

- 6dF; $z < 0.05$ & south sky

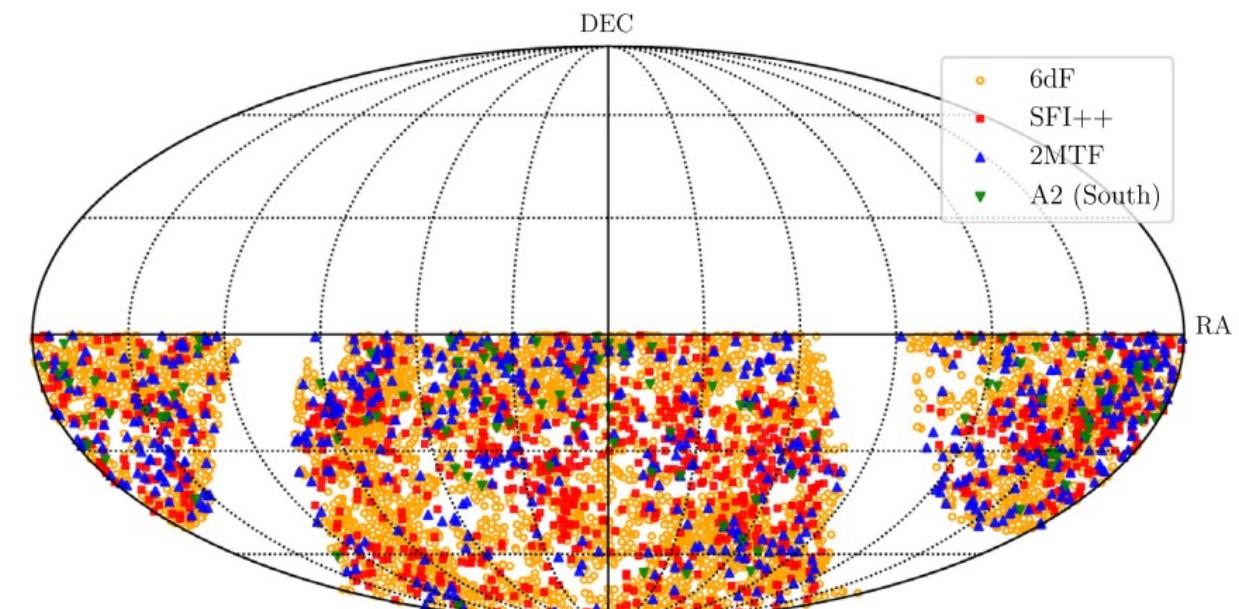
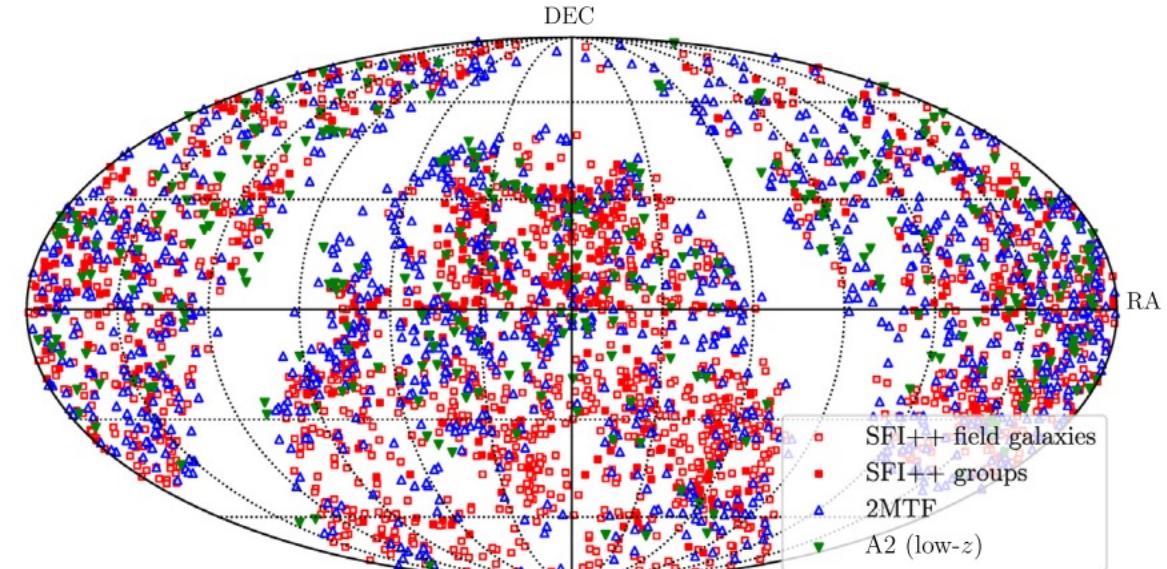
Tully-Fisher (website)

- SFI++, 2MTF, SuperTF; $z < 0.03$
- error = 10% - 20%

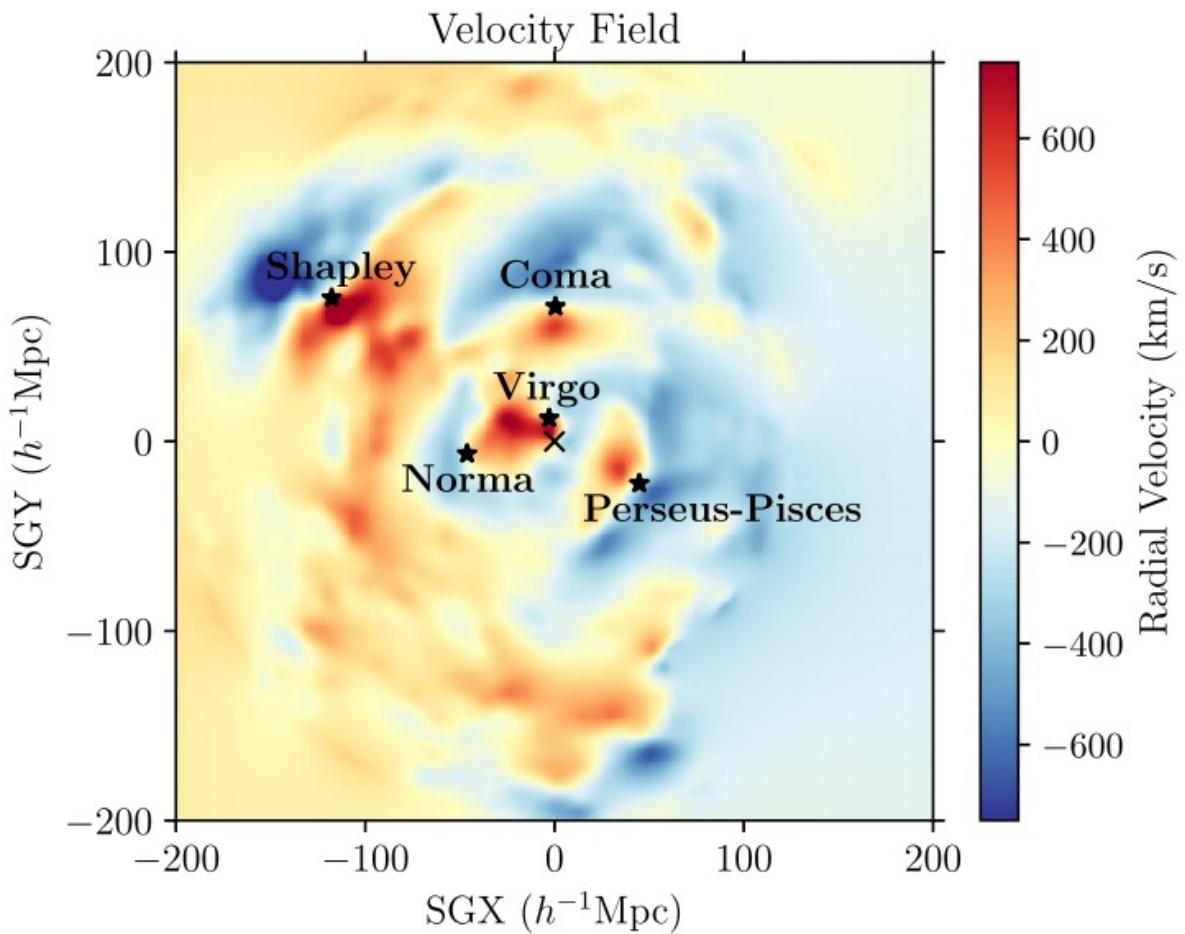
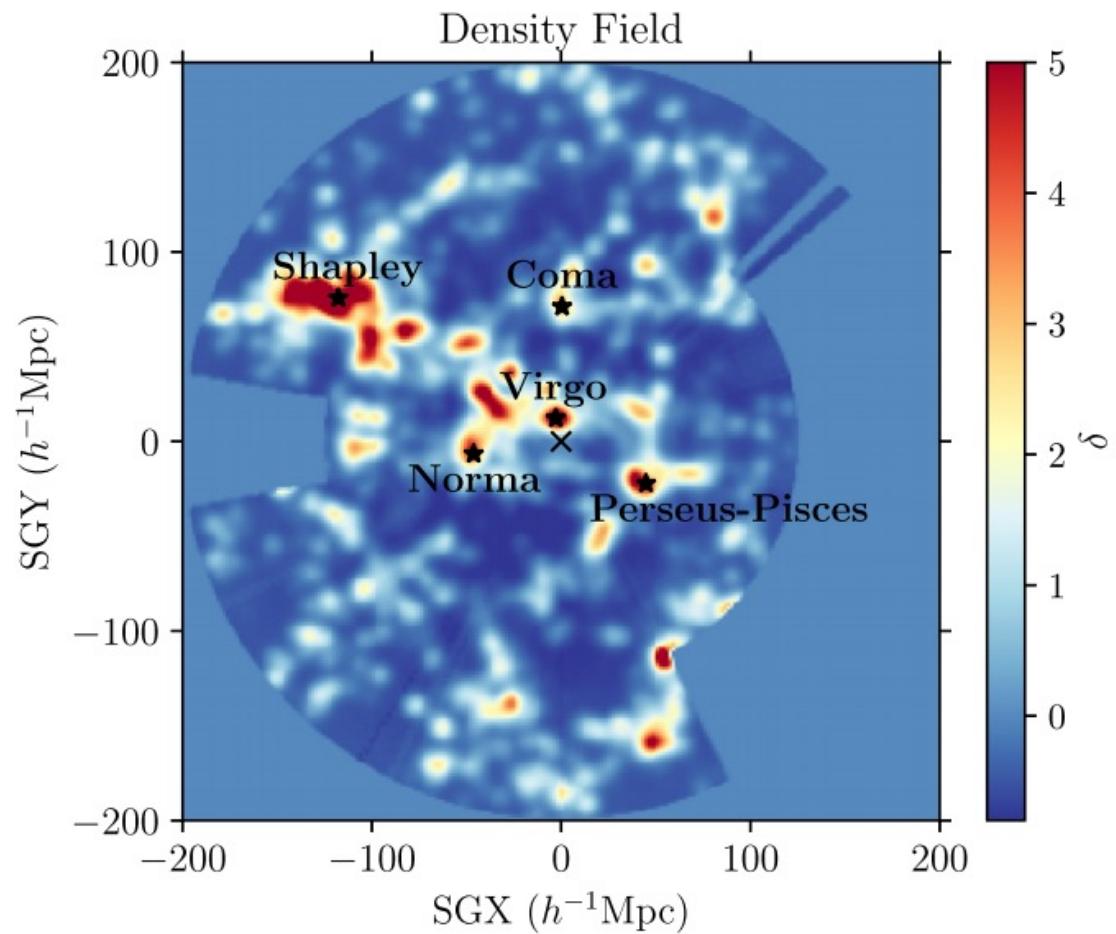
Type IA SNe

- A2; low- z , only ~ 500 samples

SBF (proposed to CSST)

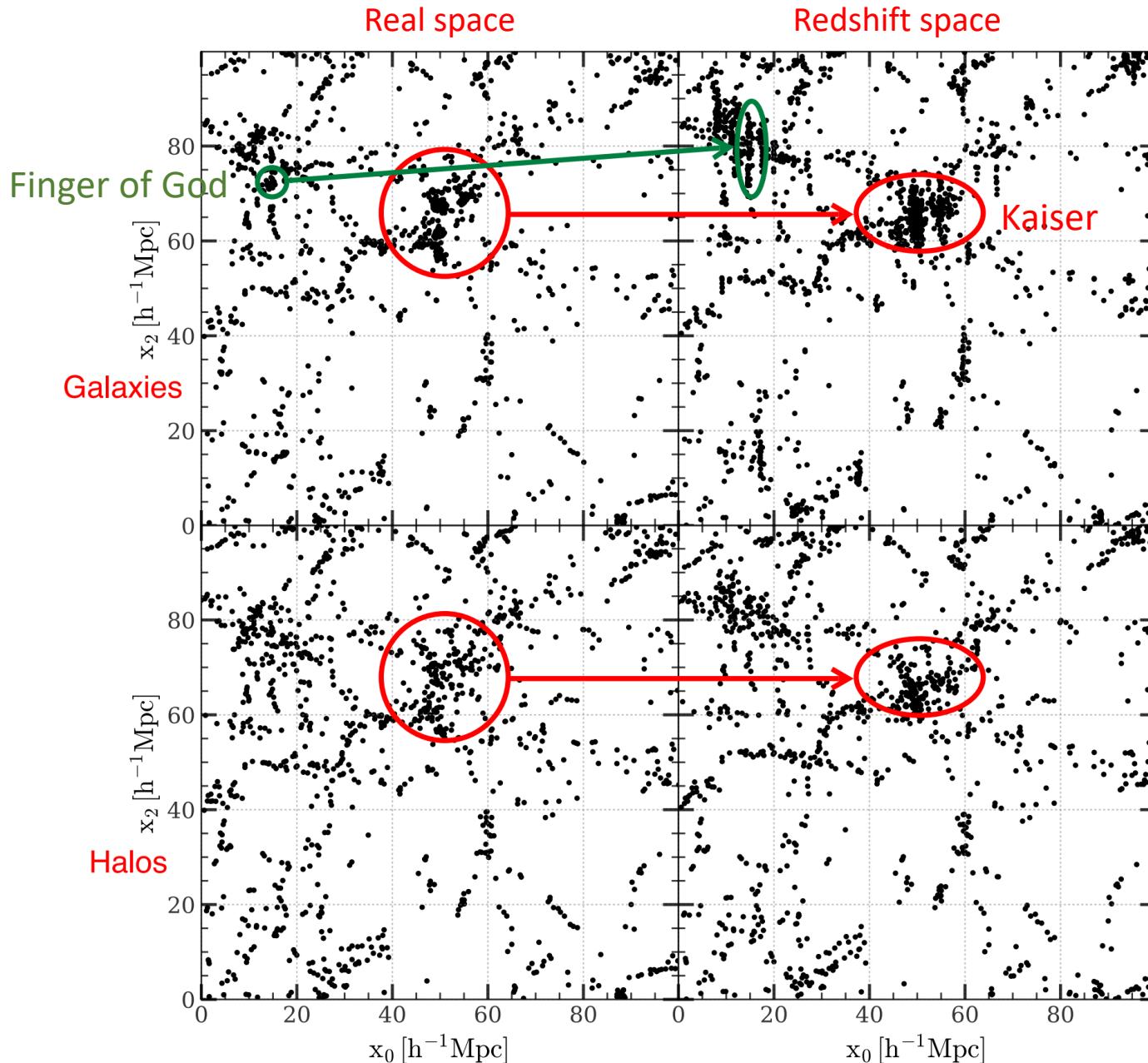


Example: peculiar velocity field as density field constraints



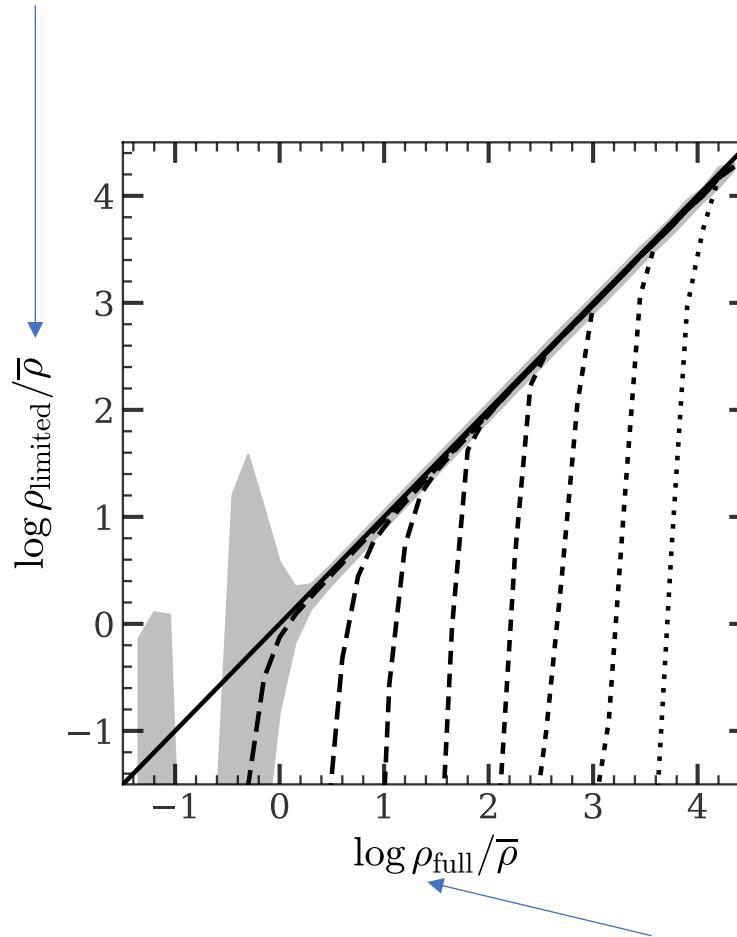
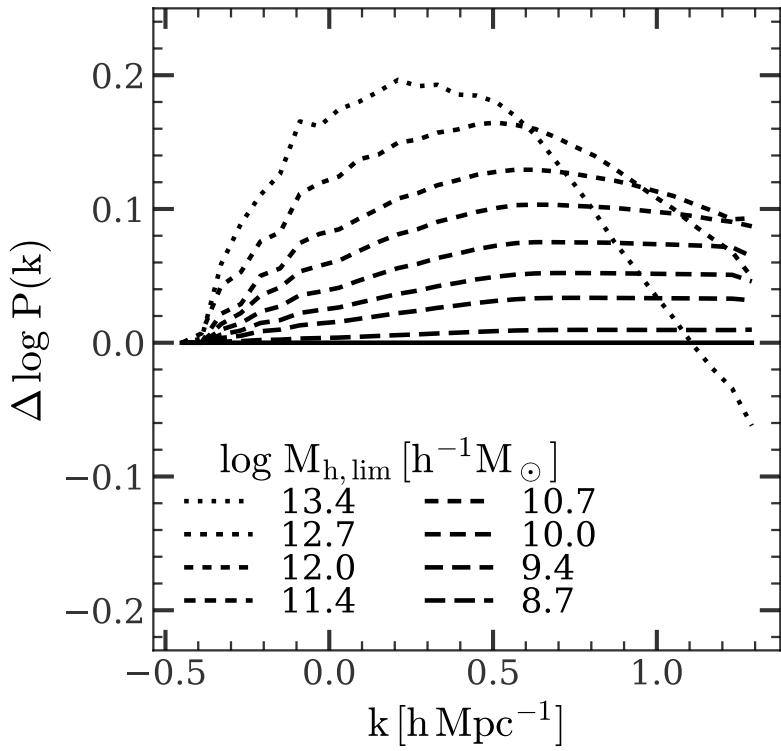
Borush+ 2020, 2M++ catalog (2MASS + 6dF + SDSS)

Example: field tracers – galaxies vs halos

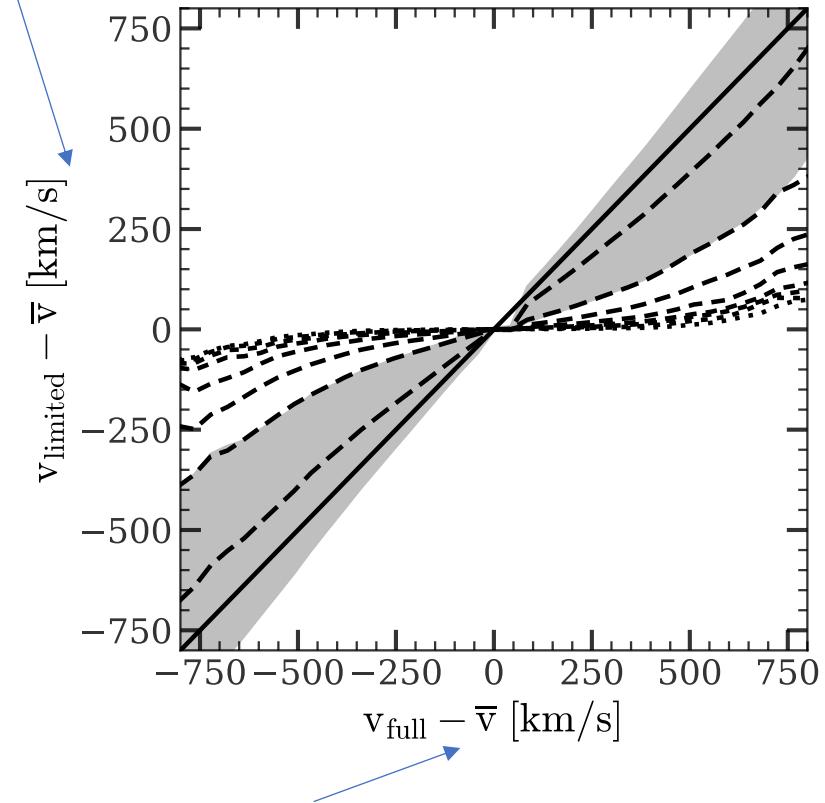


Example: the representativeness of halos vs the mass limit

Only halo-hosted particles are included (i.e., diffuse matter are ignored)



When all matter are included



The Samplers of Present-Day Field

Galaxy-field bias models and halo-field bias models.

- Simplest to implement and fastest to run.
- Model-dependent (galaxy-field bias).
- Requiring large smoothing scale, not feasible to resolve inner peaks of halo profiles.

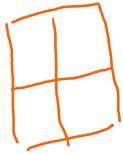
Halo-domain methods.

- Slowest to run (no convex constraints in spatial query).
- More precise, as long as halo profiles are universal.
- Limited by the lower bound mass of representative halos.
- Unlikely to resolve fine structures (e.g., small halos, filaments).

Deep learning based mappings.

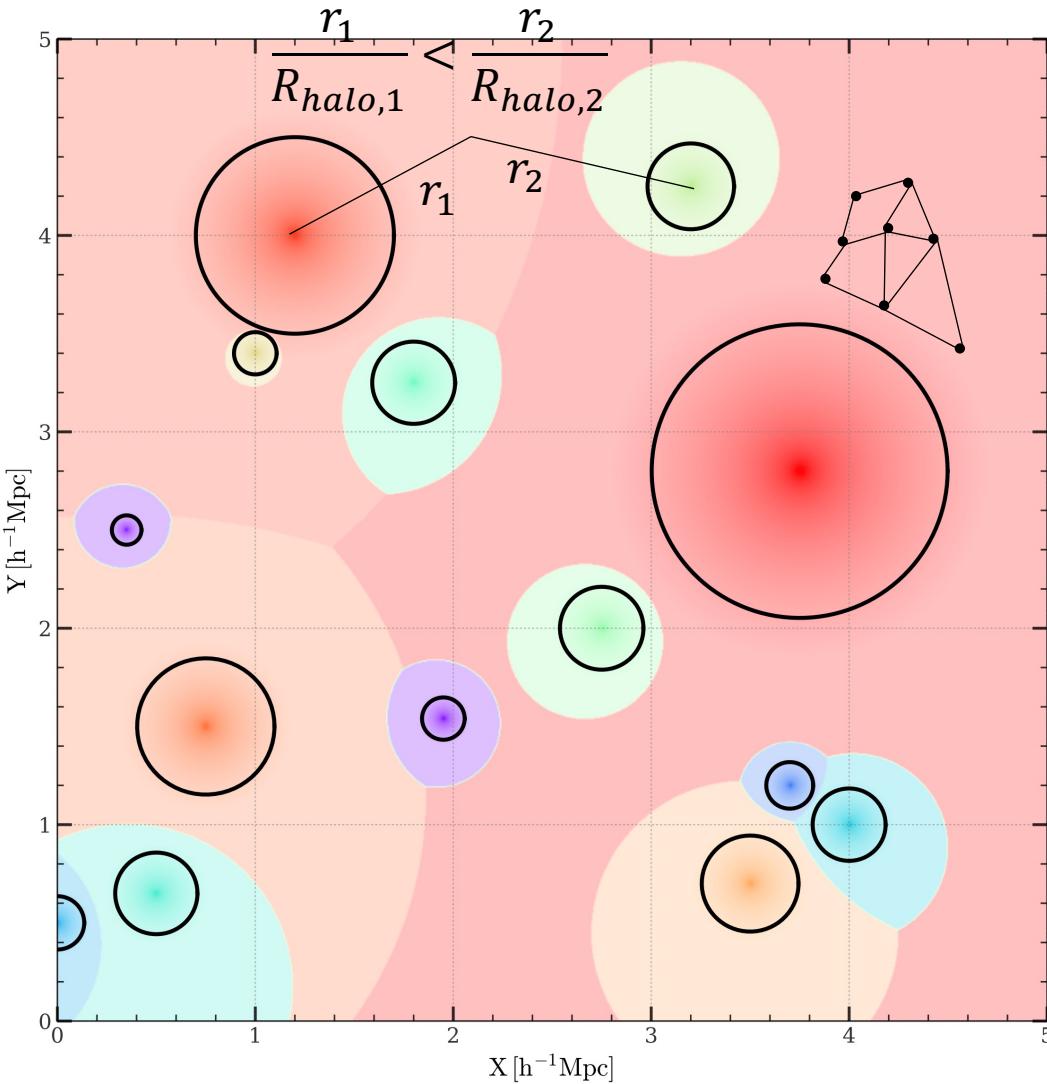
- Easy and fast, given good machines and training dataset.
- No theoretical guarantee on halo profile, power spectrum, etc.

The combination of above (planned to test).



Example: Halo-Domain Methods

halo – to – field, application;
profile overlapping;



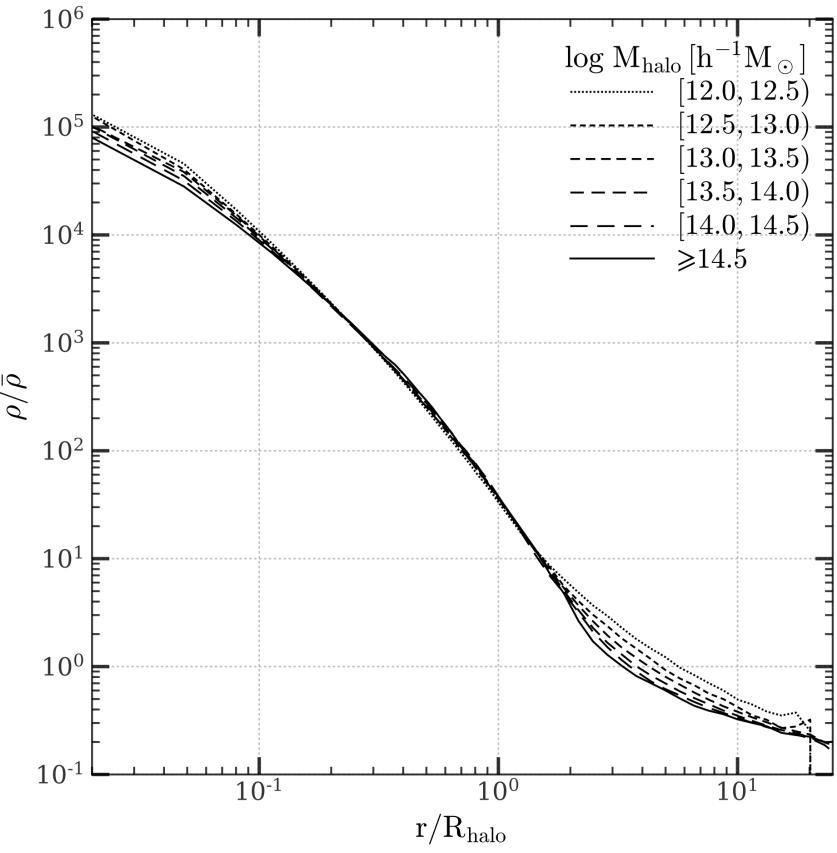
Learn the profiles of halos from dark matter only simulations.

- Divide the simulated volume into domains of halos, based on the scaled distance.
- Assign dark matter particles into domains.
- Perform Delaunay triangulation, divide the whole space into tetrahedrons, estimate the volume occupation and local density of every particle, accumulate the densities into radial bins to find halo profiles.

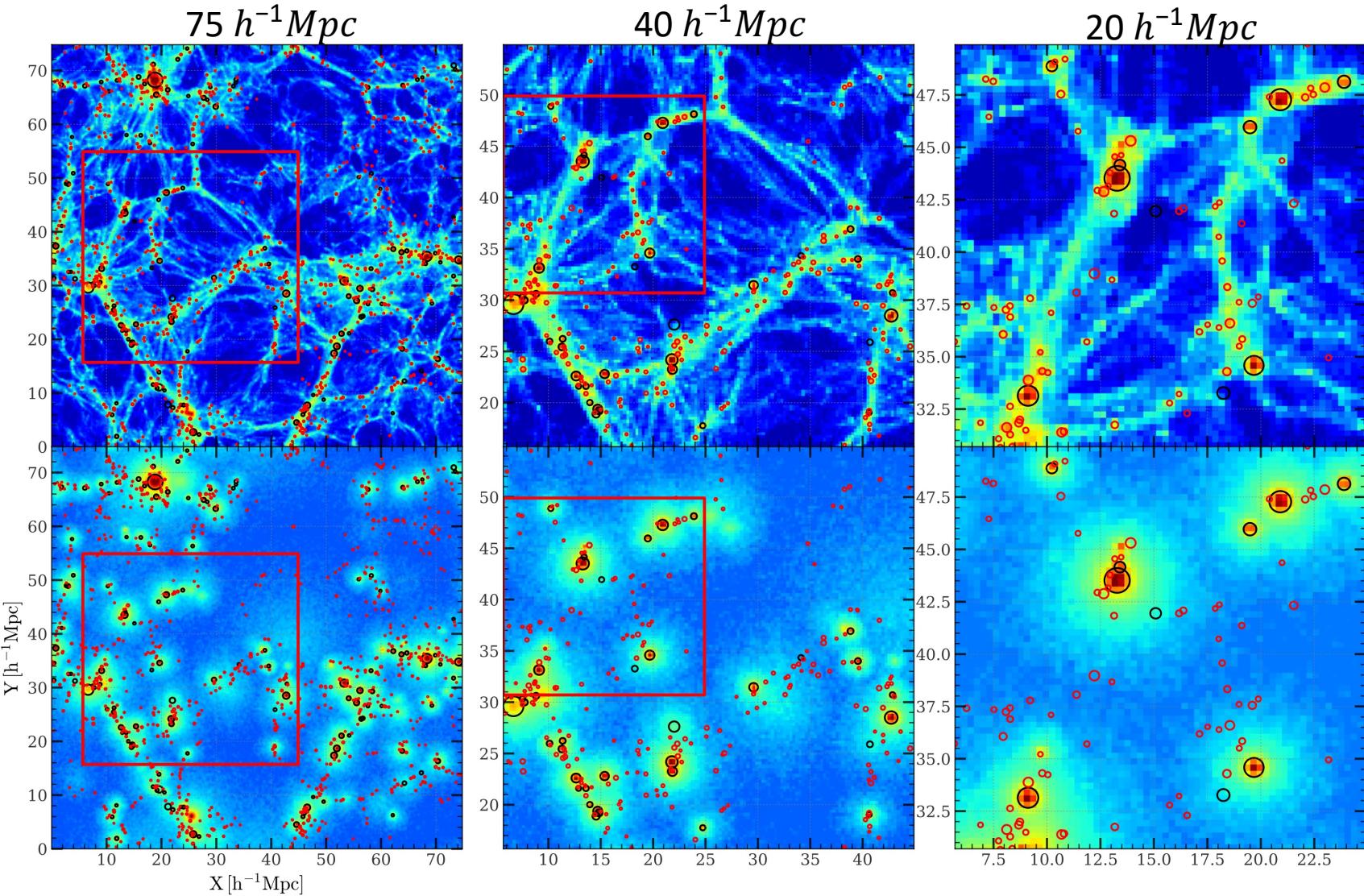
Sample the field based on the learned profiles and observational halos.

- Choose a galaxy group catalog as input, embed it into a box.
- Divide the box into domains based on groups and their properties (location and mass).
- Put sampled particles into domains, using the learned profiles and a rejection sampling method.

Spherically Averaged Density Profiles

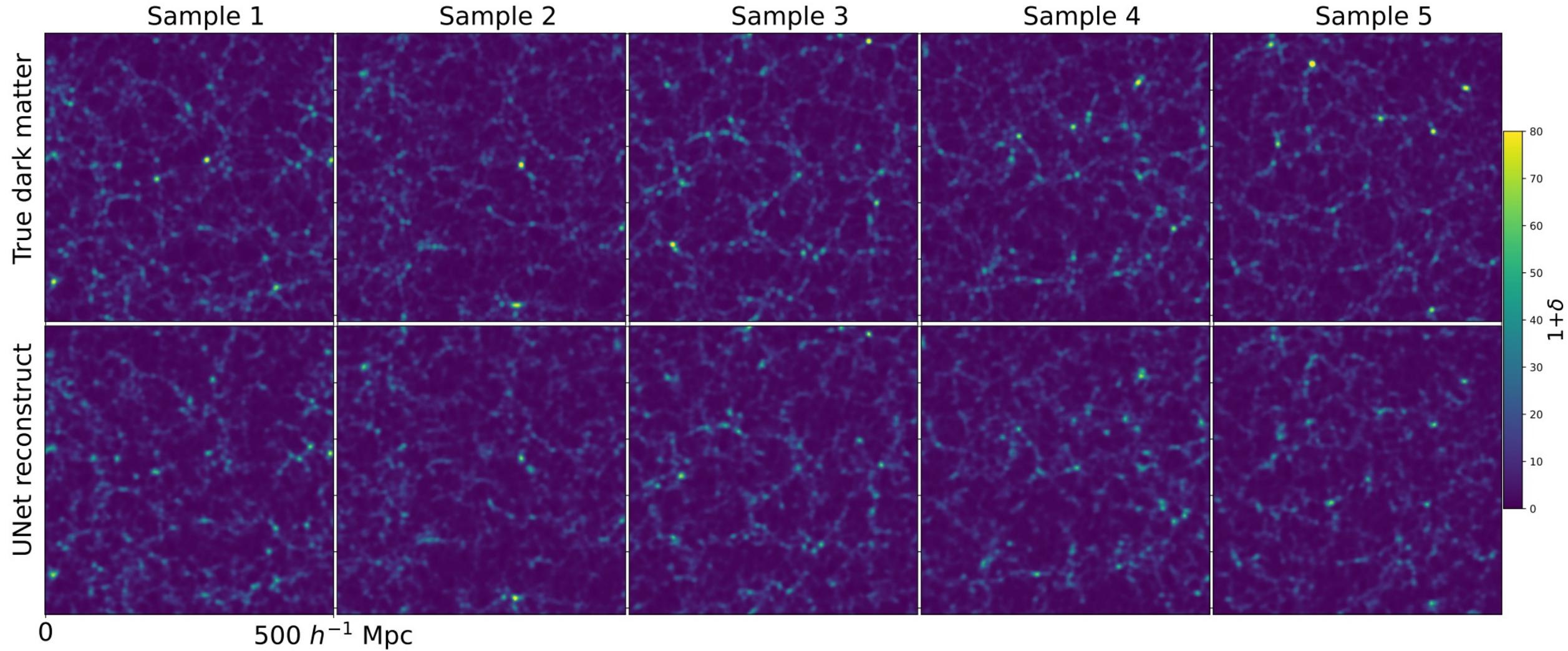


Simulated fields



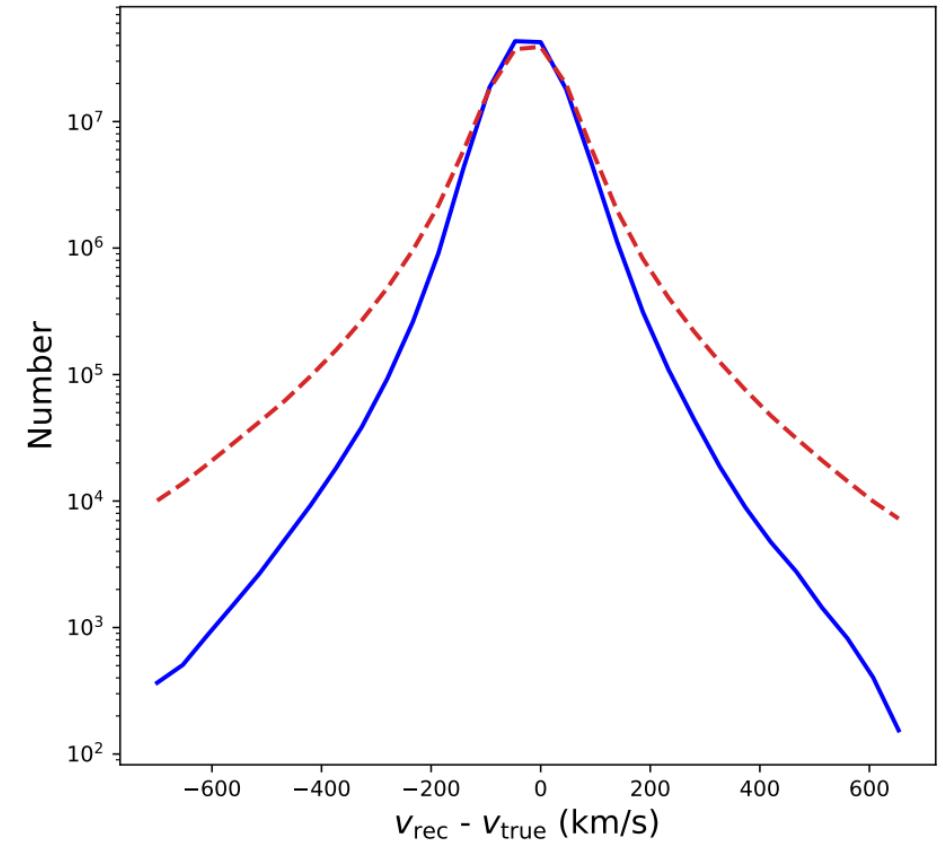
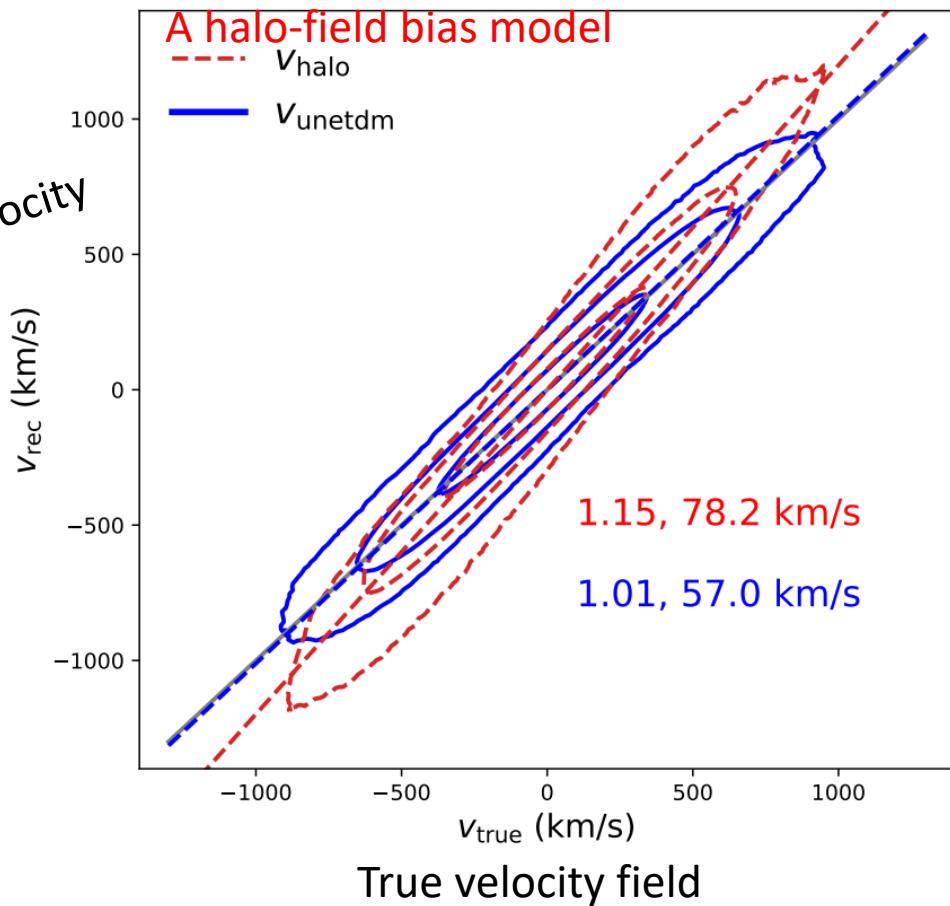
Halo-domain sampled fields with halos above $M_{\text{limit}} = 10^{12}h^{-1}M_{\odot}$ (black circles)

Example: AI-based Field-to-Field Mappings



Zitong Wang, Feng Shi+ 2023

Reconstructed density field
+ linear theory predicted velocity



Field Smoothing

- Fixed kernel smoothing
 - Nearest-Grid-Point (NGP), Could-in-Cell (CIC), Triangular-Shaped-Cloud (TSC), etc.
 - Grid-based smoothing, using kernels such as Tophat and Gaussian.
 - The combination of above two: assign points into grids and add higher-order smoothing with FFT.
- Adaptive kernel smooth.
 - SPH smooth with given kernel function.
 - Grid-based smoothing, by using locally defined aperture that encloses given amount of mass.

Example: fields smoothed with locally adaptive kernel with $M = 10^{13} h^{-1} M_{\odot}$

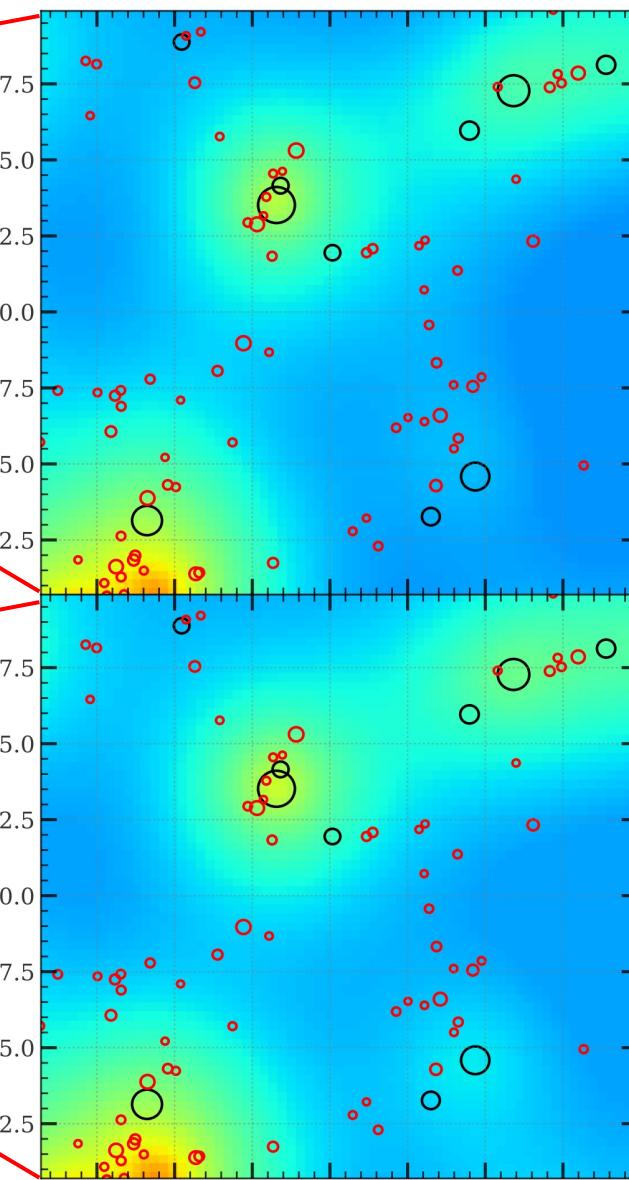
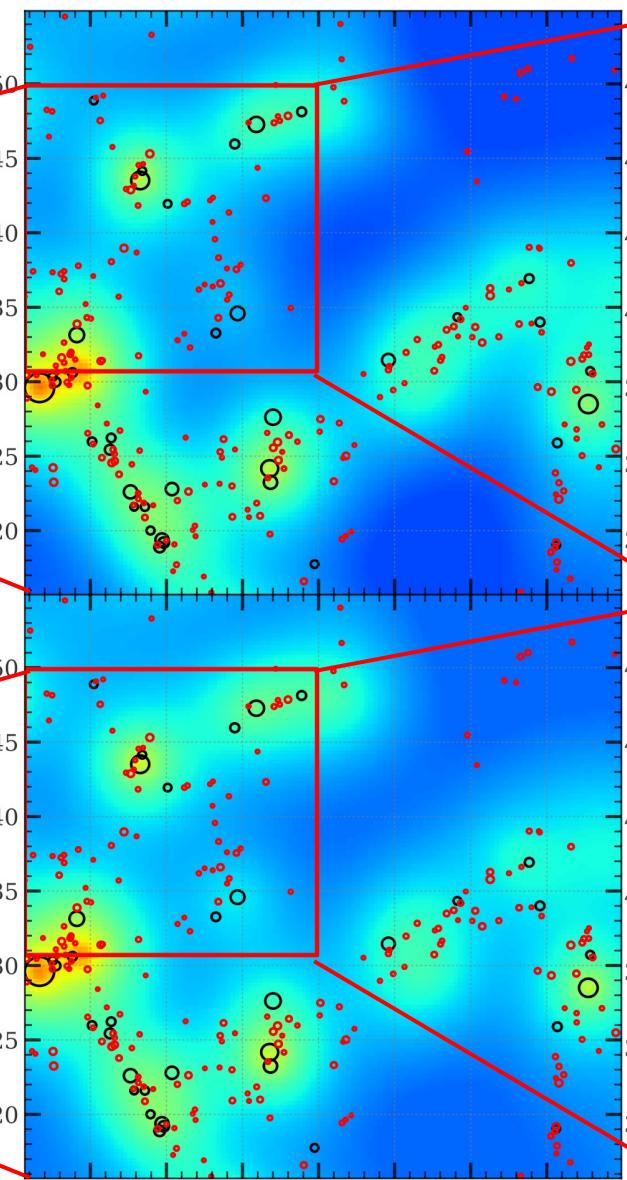
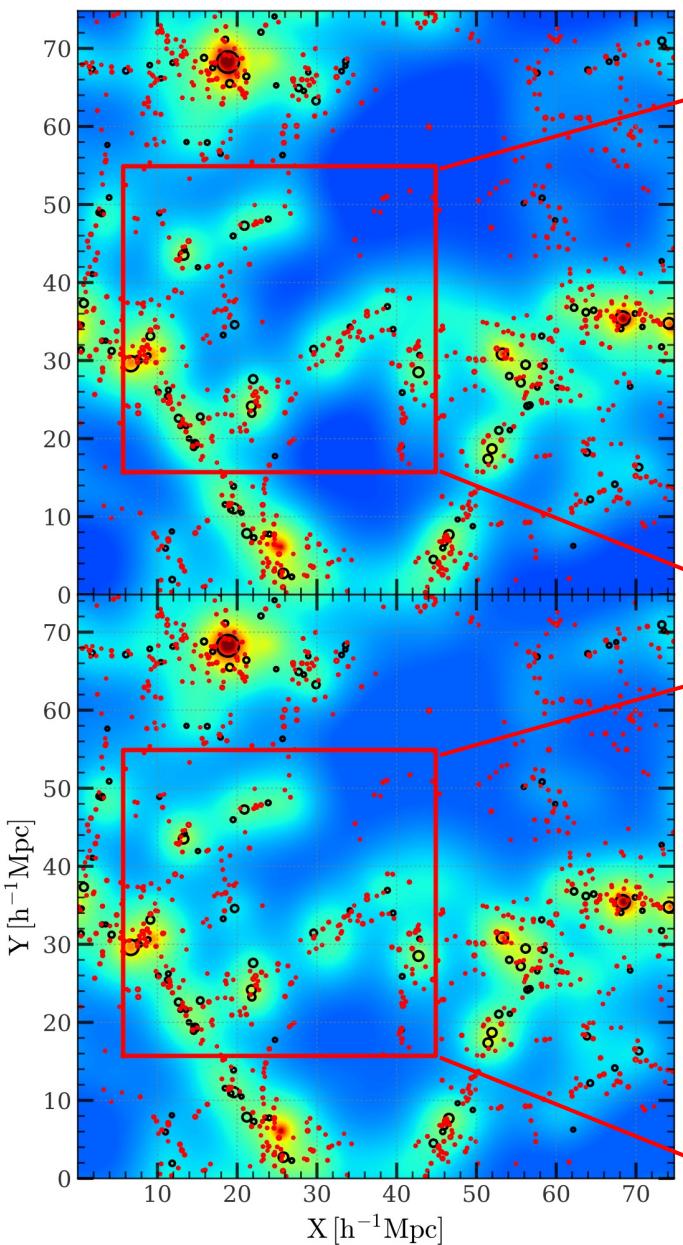
$75 h^{-1} Mpc$

$40 h^{-1} Mpc$

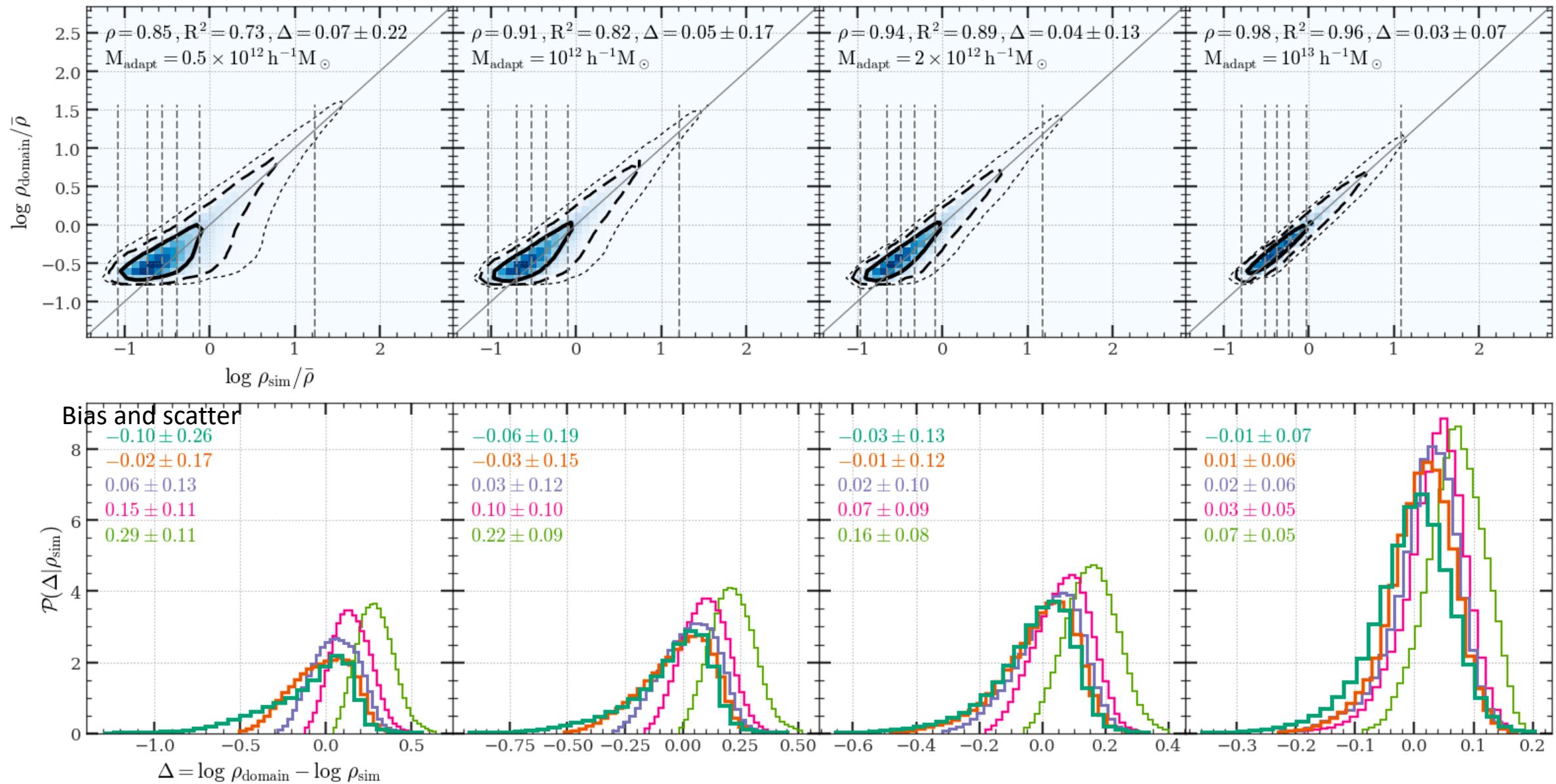
$20 h^{-1} Mpc$

Simulated

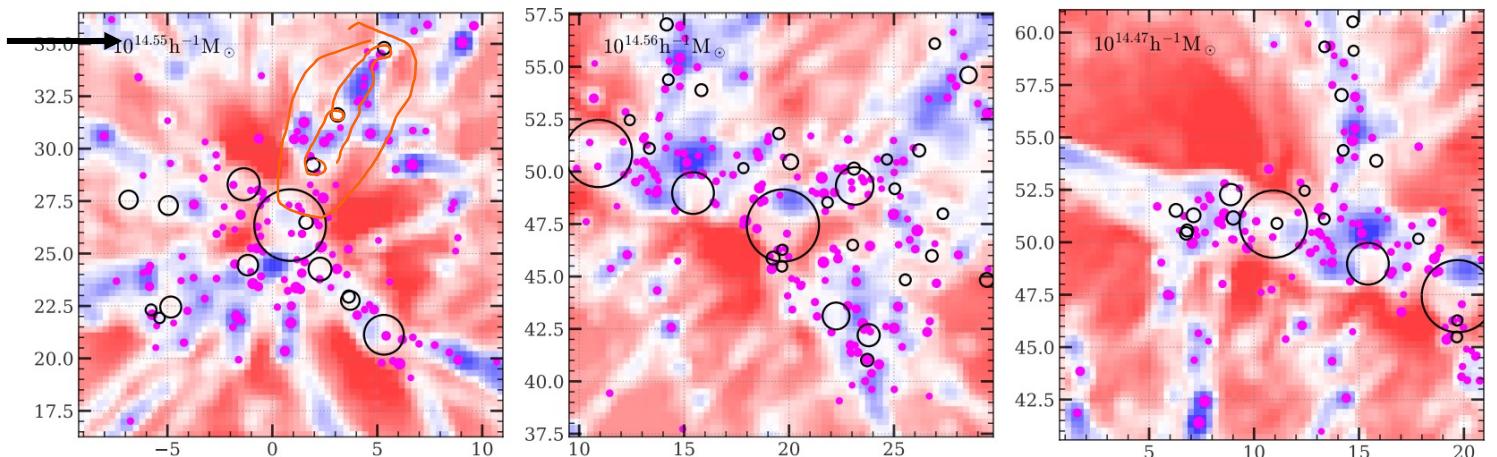
Halo-domain sampled



Smoothed field in comparison with simulated field using adaptive smoothing scales

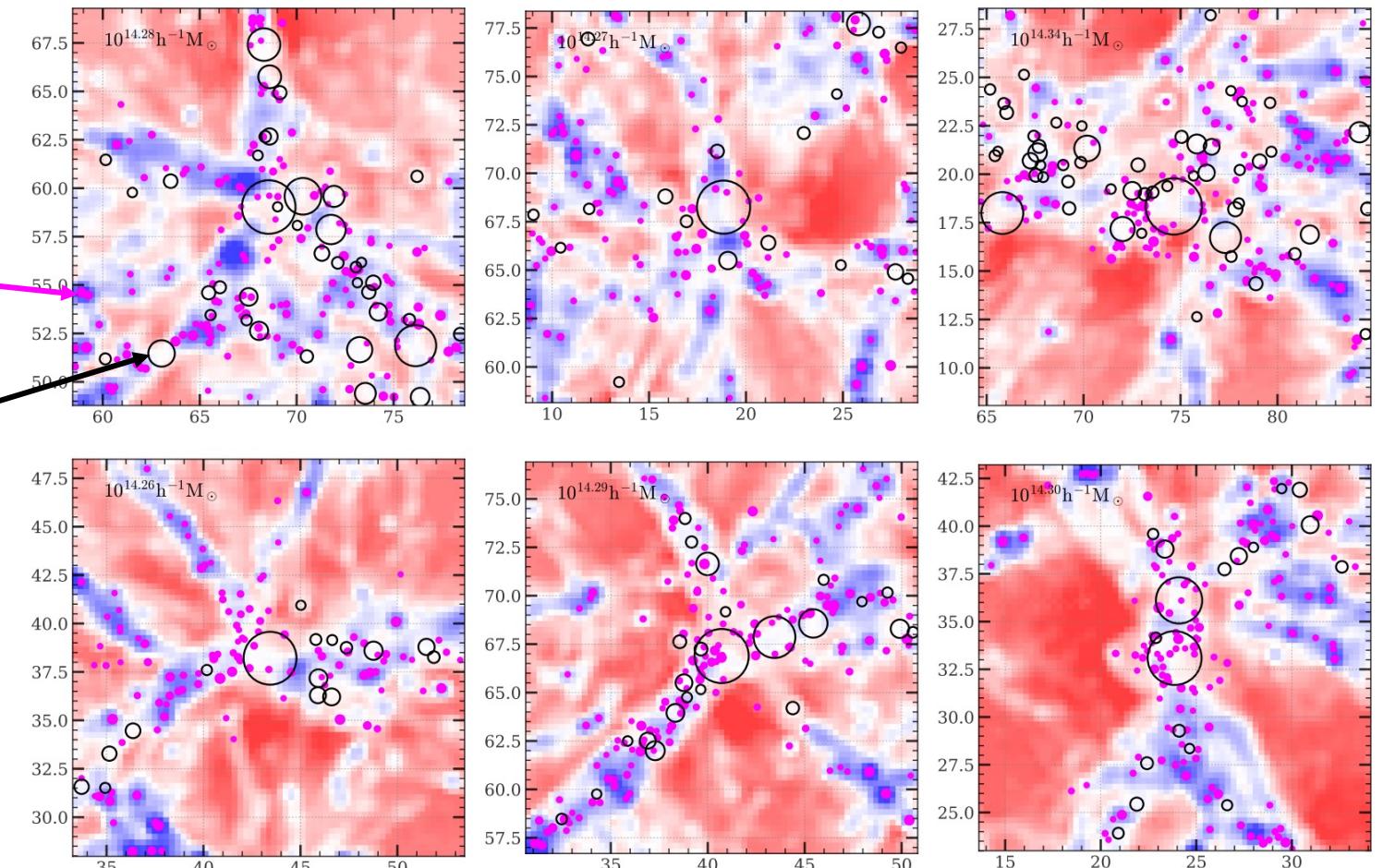


Mass of the halo at panel center



Halos not used in the field sampling

Halos used in the field sampling



Correction for the Redshift-Space Distortion

Methods based on perturbation theories (linear and higher-order theories).

- Fast and easy to implement.
- Theory-guaranteed error bounds and convergence.
- Work well only in linear/mild-non-linear regime.

AI-based field-to-field mappings (CNN layers + residual/U-Net architectures).

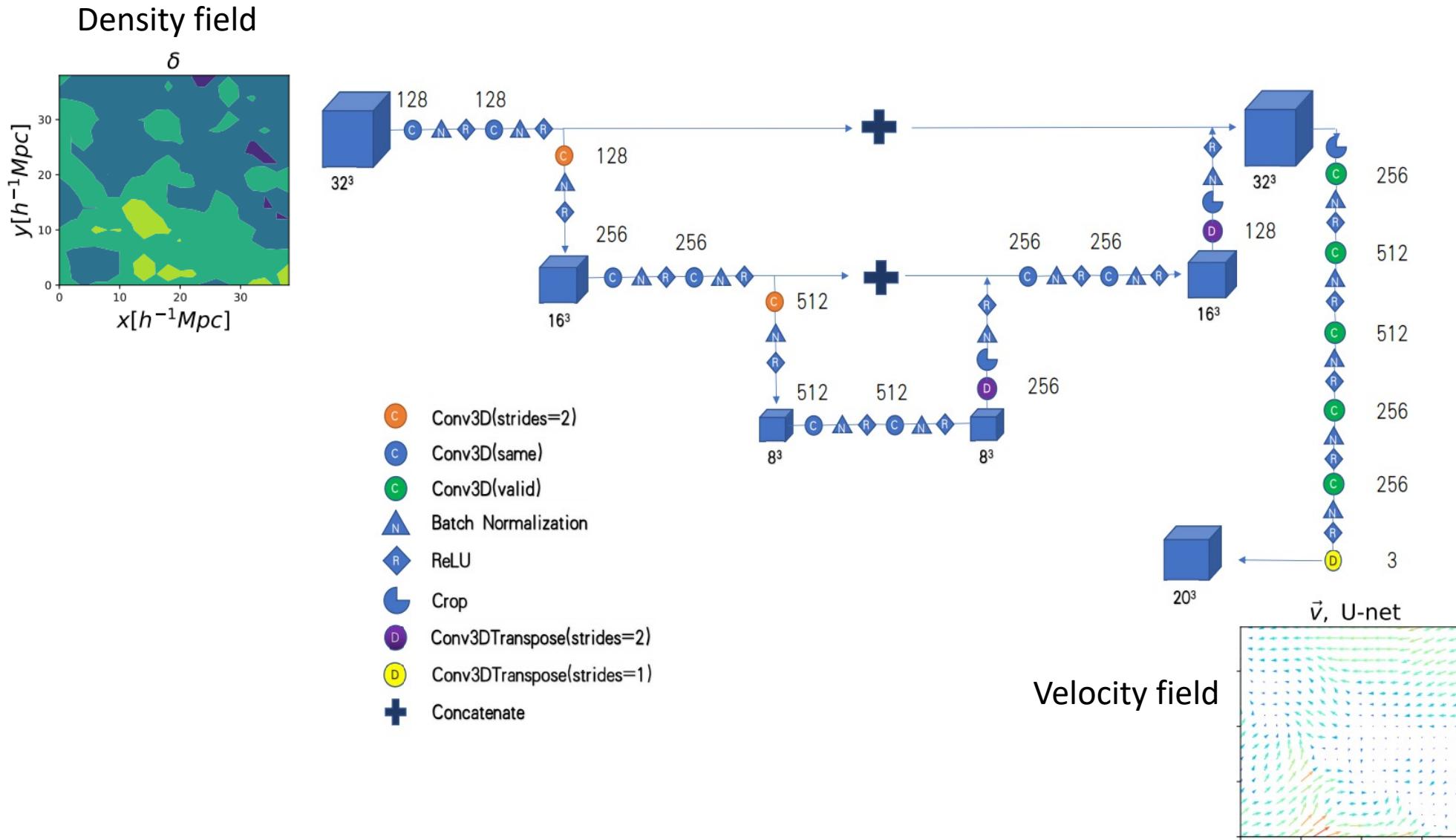
- Fast and easy to implement (limited by only hardware resources and size/quality of training sets).
- More precise than perturbation theories, especially in
- Black box, little physical insight; overfitting; no guarantee in the presence of distribution shift of input.

Methods based on initial condition sampling and forward simulation (planned to test with HMCMC).

The combination of above.

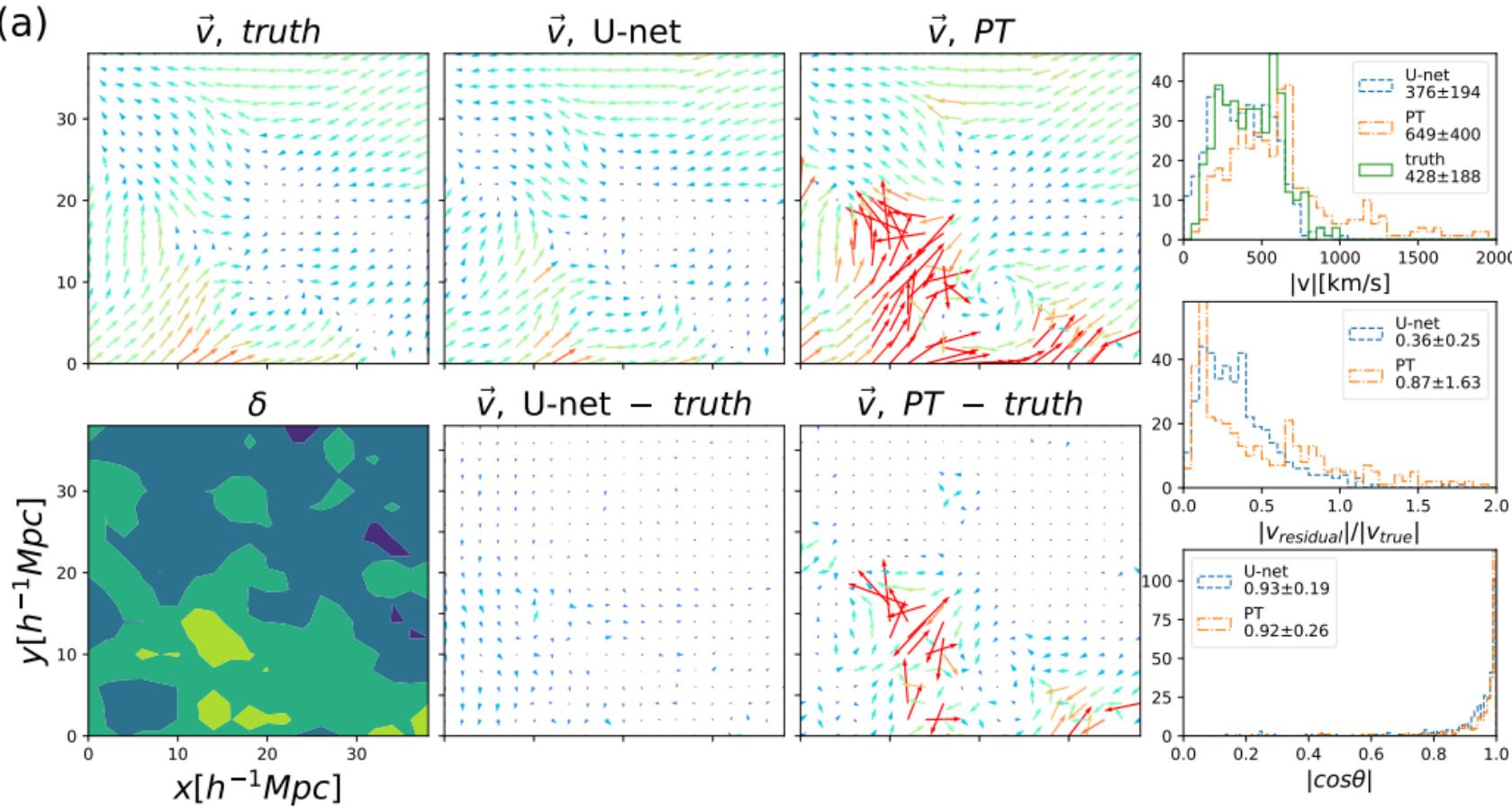
- Fit only residual field where perturbation theories behave less precise.

AI-based field-to-field mappings – network architecture



AI-based field-to-field mappings – predicted field

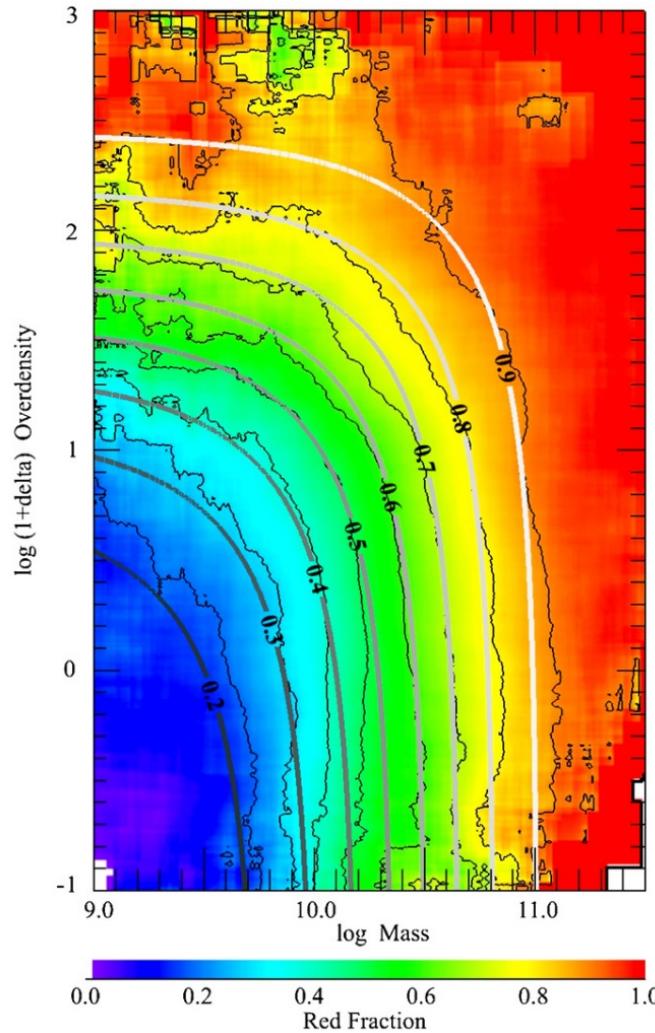
(a)



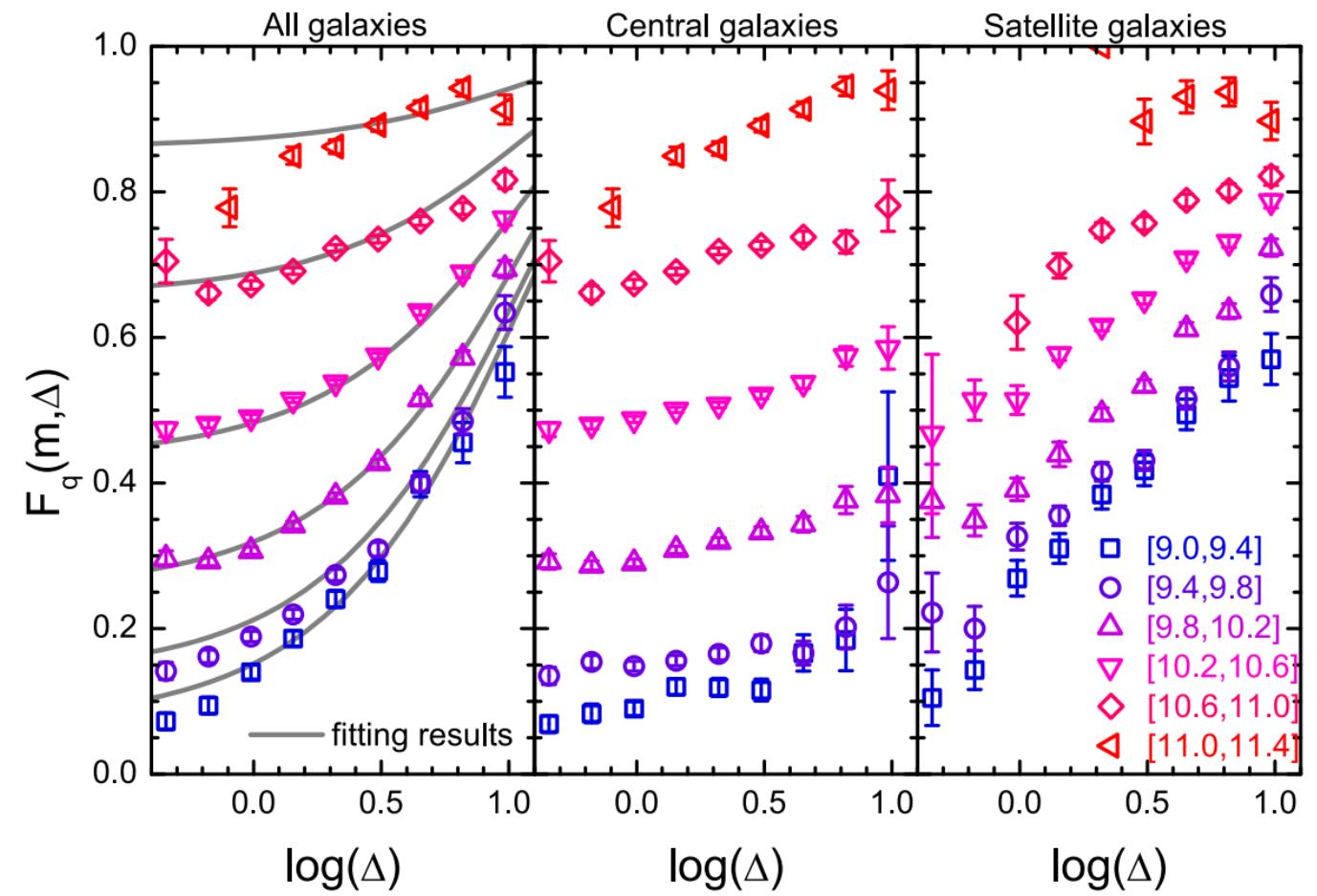
Applications of the Reconstructed Present-day Fields

Environmental Quenching

Yingjie Peng+ 2010, using kNN
density estimator on galaxy sample.



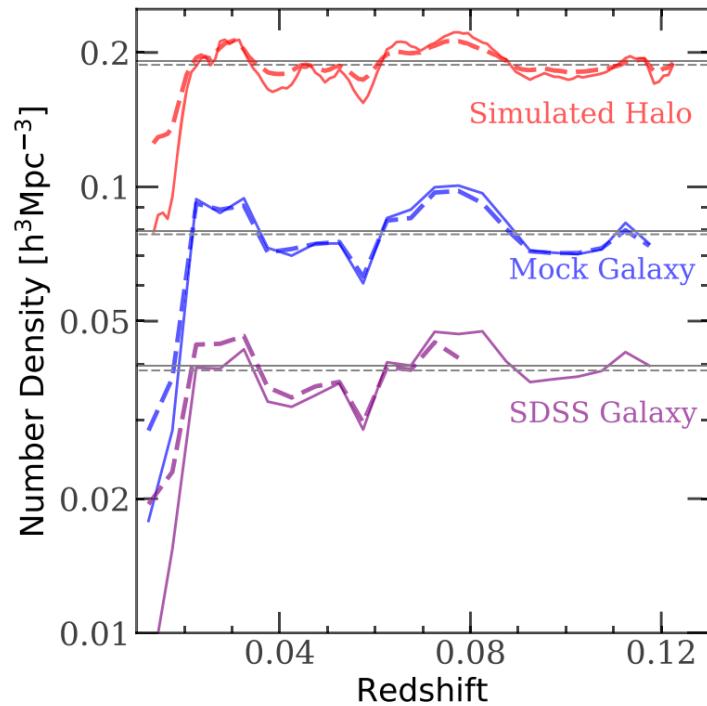
Huiyuan Wang+ 2018, using reconstructed density field.



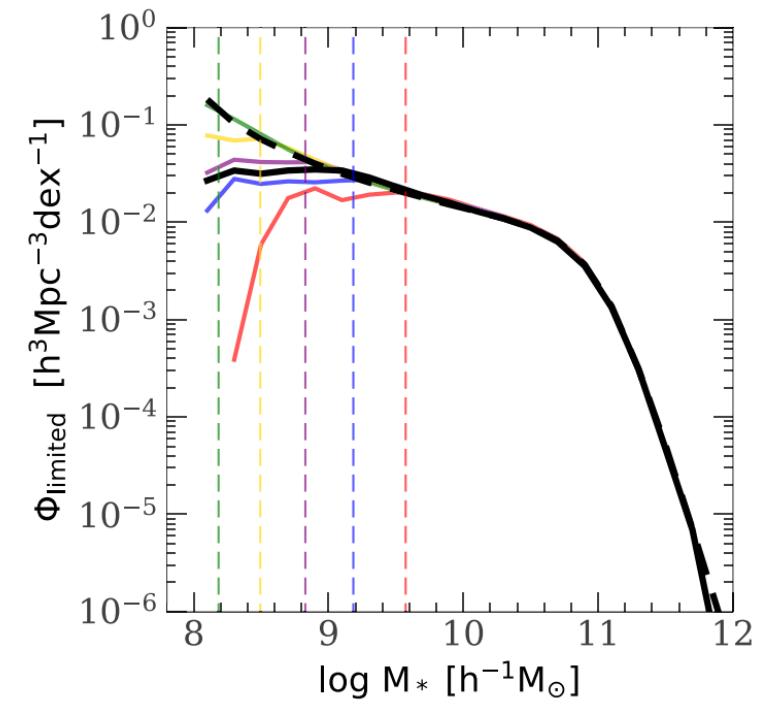
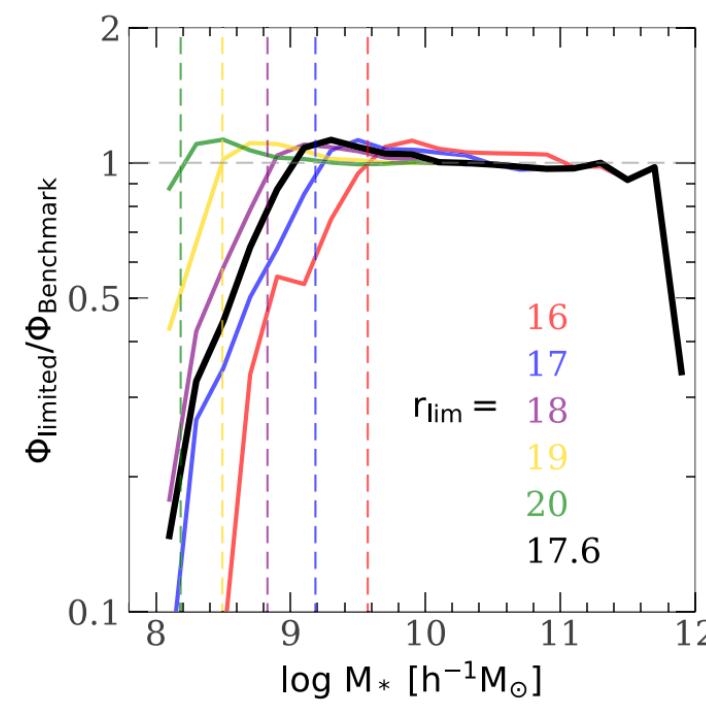
Applications of the Reconstructed Present-day Fields

Yangyao Chen+ 2019, Cosmic Variance on Galaxy Statistics

Object density vs redshift
in the local SDSS volume



Galaxy stellar mass functions inferred from
magnitude-limited samples



The Field Reconstruction Pipeline of ELUCID

