Title: Funny Thing Happened on the Way to Convergence.

Date: Aug 10, 2015 04:30 PM

URL: http://pirsa.org/15080006

Abstract: Modeling the cosmic velocity field, and especially estimating its lowest order moment, the bulk flow, has been a popular pursuit among aficionados in the cosmological community for three decades now. Other than estimating the magnitude and direction of the flow, one of the main difficulties has been defining the scale of flow detected. There is a nearly universal agreement as to the direction of the flow, however, there is some disagreements regarding the magnitude and scale of the flow. We developed and applied the Minimal Variance (MV) formalism to optimize and clearly define the scale of a particular analysis, using the width of the survey window function as a proxy for scale. Comparing the MV ideal window function to any analysis window function gives an unbiased estimate to the survey width (or scale) and thus provides a method to directly compare various results. Further, I will introduce a new estimator of the peculiar velocity from redshift and distance estimates. This estimator results in peculiar velocity estimates that are statistically unbiased and have
Gaussian distributed errors. The adoption of the new estimator significantly improves the accuracy and validity of studies of the large-scale peculiar velocity field and eliminates potential systematic biases, thus helping to bring peculiar velocity analysis into the era of precision cosmology. I will discuss the method, compare various recent analyses and show that the disagreements are not as significant as they appear.
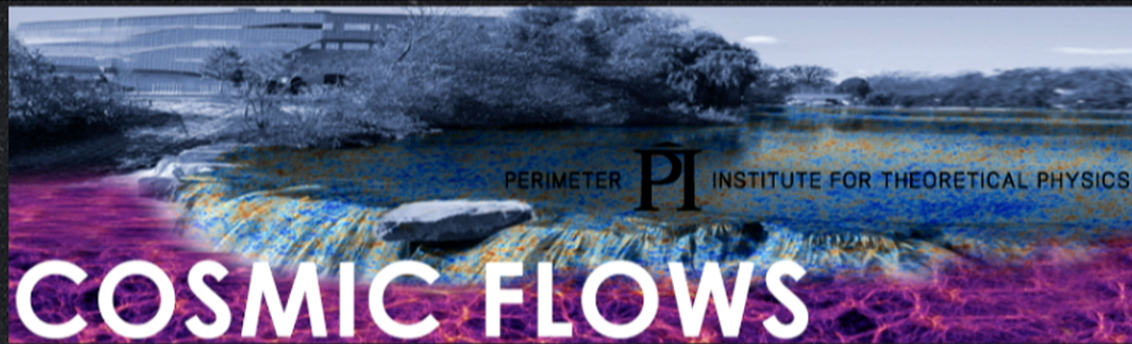
COSMIC FLOWS

COSMIC FLOWS

PERIMETER PI INSTITUTE FOR THEORETICAL PHYSICS

Funny thing happened on the way to convergence: Large-scale Cosmic Flows

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Funny thing happened on the way to convergence: Large-scale Cosmic Flows

Hume A. Feldman

PERIMETER PI INSTITUTE FOR THEORETICAL PHYSICS
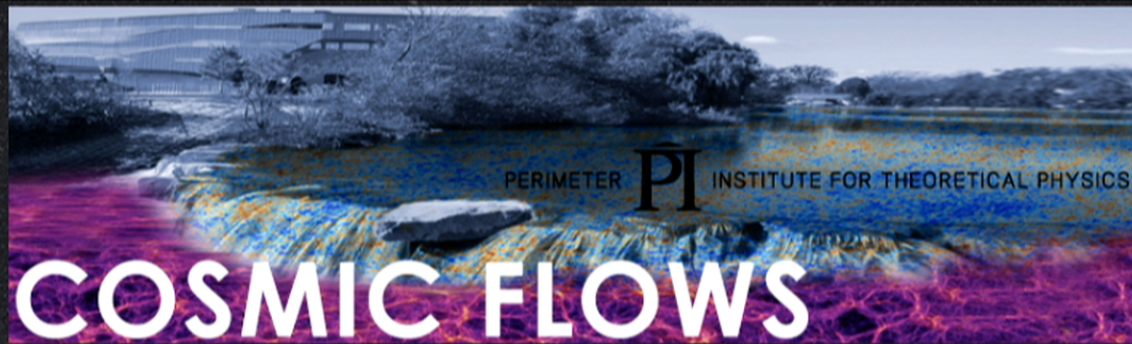
COSMIC FLOWS

Funny thing happened on the way to convergence: Large-scale Cosmic Flows

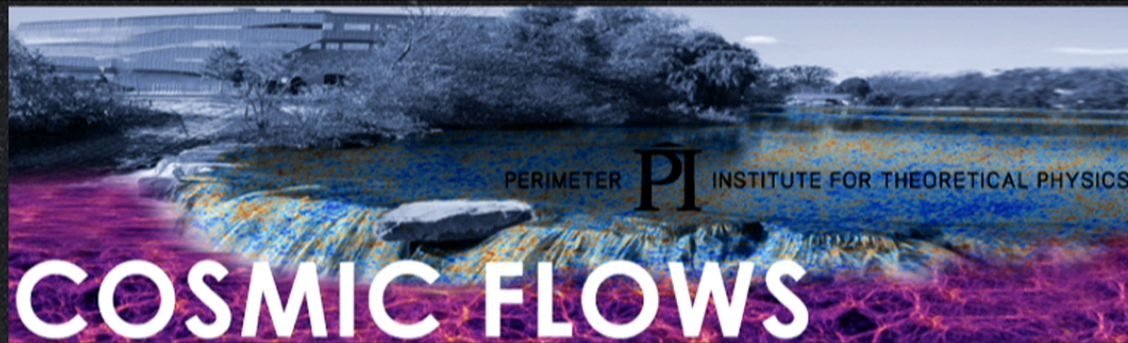**Hume A. Feldman**

Physics & Astronomy

University of Kansas

Watkins & HAF, MNRAS 450, 1868-1873 (2015)
Watkins & HAF, MNRAS 447, 132-139 (2015)
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Macaulay, HAF, Ferreira, Jaffe, Agarwal, Hudson & Watkins, MNRAS 425, 1709-1717 (2012)
Agarwal, HAF & Watkins, MNRAS 424, 2667-2675, (2012)
Abate & HAF MNRAS, 419, 3482-3490, (2012)
Turnbull, Hudson, HAF, Hicken, Kirshner & Watkins MNRAS, 420, 447-454, (2012)
Macaulay, HAF, Ferreira, Hudson & Watkins, MNRAS, 414, 621-626 (2011)
HAF, Watkins & Hudson, MNRAS, 407, 2328-2338 (2010)
Watkins, HAF & Hudson, MNRAS, 392, 743-756 (2009)

Likelihood Methods for Peculiar Velocities

A catalog of peculiar velocities galaxies, labeled by an index n

Positions r_n

Estimates of the line-of-sight peculiar velocities S_n

Uncertainties σ_n

Assume that observational errors are Gaussian distributed.

Likelihood Methods for Peculiar Velocities

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Estimates of the line-of-sight peculiar velocities S_n

Uncertainties σ_n

> Assume that observational errors are Gaussian distributed.

Model the velocity field as a uniform streaming motion, or bulk flow (BF), denoted by U_i, about which are random motions drawn from a Gaussian distribution with a 1-D velocity dispersion σ_*

Likelihood Methods for Peculiar Velocities

Statistics of S_n are biased by the existence of nonlinear flows on small scales.

Likelihood Methods for Peculiar Velocities

The measured line-of-sight peculiar velocity of galaxy n

$$S_n = \hat{r}_{n,i} v_i(\mathbf{r}_n) + \epsilon_n$$

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Likelihood Methods for Peculiar Velocities

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$$S_n = \hat{r}_{n,i} v_i(\mathbf{r}_n) + \epsilon_n$$

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The covariance matrix for the set u_a formed from S_n

$$R_{ab} = \langle u_a u_b \rangle = \sum_{m,n} w_{a,m} w_{b,n} \langle S_m S_n \rangle$$

Likelihood Methods for Peculiar Velocities

The covariance matrix for the set u_a can be written as:

$$R_{ab} = R_{ab}^{(v)} + R_{ab}^{(\epsilon)}$$

Likelihood Methods for Peculiar Velocities

the angle-averaged weighted tensor
window function

$$\mathcal{W}_{ab}^2(k) = \sum_{n,m} w_{a,n} w_{b,m} \int \frac{d^2\hat{k}}{4\pi} \left(\hat{\mathbf{r}}_n \cdot \hat{\mathbf{k}} \ \ \hat{\mathbf{r}}_m \cdot \hat{\mathbf{k}} \right)$$

$$\times \exp\left(i\mathbf{k} \cdot (\mathbf{r}_n - \mathbf{r}_m) \right)$$

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The WF's

- depend on the weights and the distribution of
  points in the survey

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The WF's

- depend on the weights and the distribution of points in the survey

- tell us which scales contribute to the value of the moments

Window Function Design

Example 1

Estimate the BF as accurately as possible

The BF Maximum Likelihood Estimates of the weights (MLE)

Kaiser (1988)

$$w_{i,n} = A_{ij}^{-1} \sum_n \frac{\mathbf{x}_j \cdot \mathbf{r}_n}{\sigma_n^2 + \sigma_*^2}$$

Window Function Design

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Weights depend on the spatial distribution and the errors.

Since the distribution and errors are survey dependent, the WF's are survey dependent and so is the BF.

$\Rightarrow$ We found a BF for a particular survey

Window Function Design

Example 2

Estimate the BF as a function of scale

Consider an ideal survey

- Very large number of points N_o

- Isotropic distribution

- Gaussian falloff

$$n(r) \propto \exp\left(-\frac{r^2}{2R_G^2}\right)$$

R_G Depth of the survey

Example 2 *Window Function Design*

Estimate the BF as a function of scale

Consider an ideal survey

- Very large number of points N_o

- Isotropic distribution

- Gaussian falloff
$$n(r) \propto \exp\left(-\frac{r^2}{2R_G^2}\right)$$

R_G Depth of the survey

The BF moments of this ideal survey are

$$U_i = \frac{1}{N_o} \sum_{n=1}^{N_o} \hat{r}_{i,n} s_n$$

Window Function Design

Find the Minimum Variance (MV) weights for u_i

$$u_i = \sum_n w_{i,n} S_n$$

that minimize the variance

$$\langle (u_i - U_i)^2 \rangle$$

Window Function Design

Find the Minimum Variance (MV) weights for u_i

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Provide survey independent Gaussian BF that can be compared across surveys

Likelihood Methods for Peculiar Velocities

It all comes down to the weights.
The weights assigned to galaxies determine the information we get from the survey.

Likelihood Methods for Peculiar Velocities

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The weights assigned to galaxies determine the information we get from the survey.

- Design window functions to address a specific measurement.

- Estimate a quantity that

  - is survey independent (can be compared across surveys)

window functions
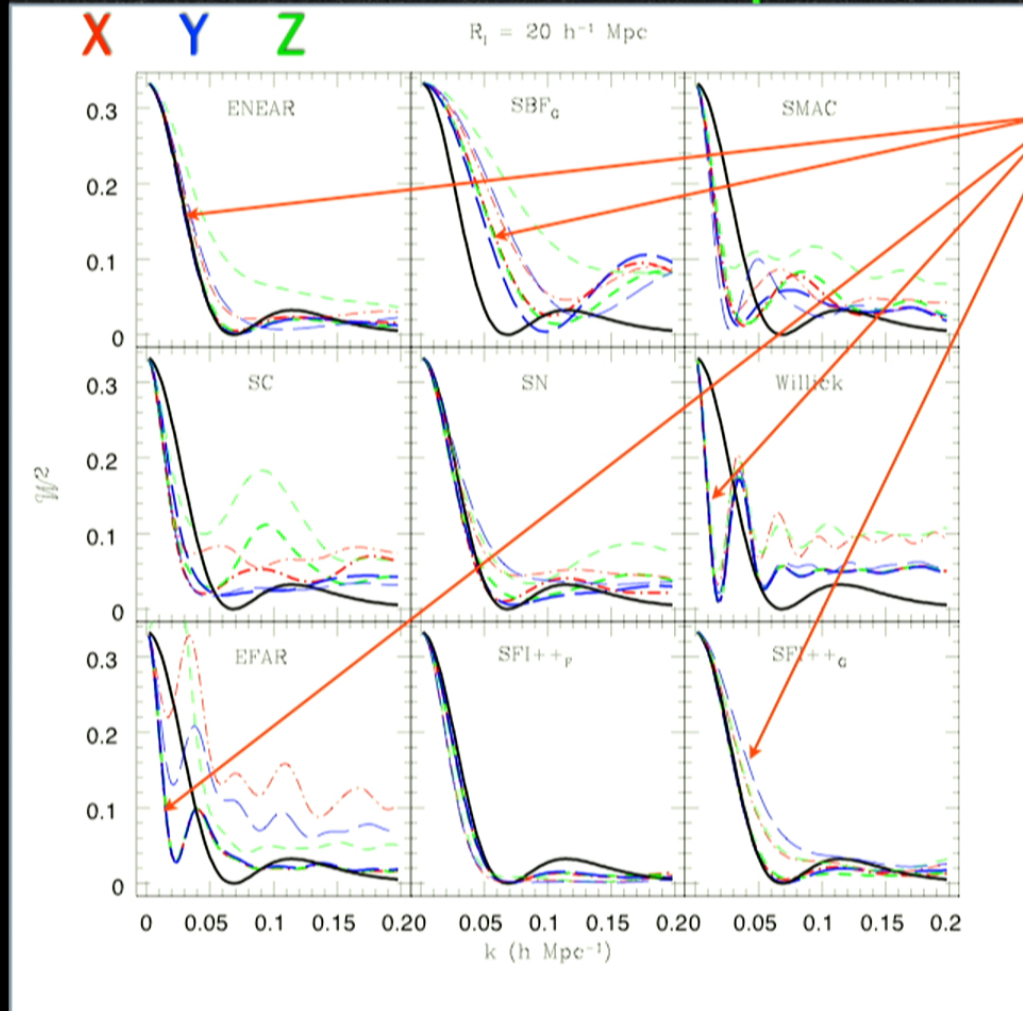
Scales:

Surveys probe
different scales

Peculiar Velocity Surveys

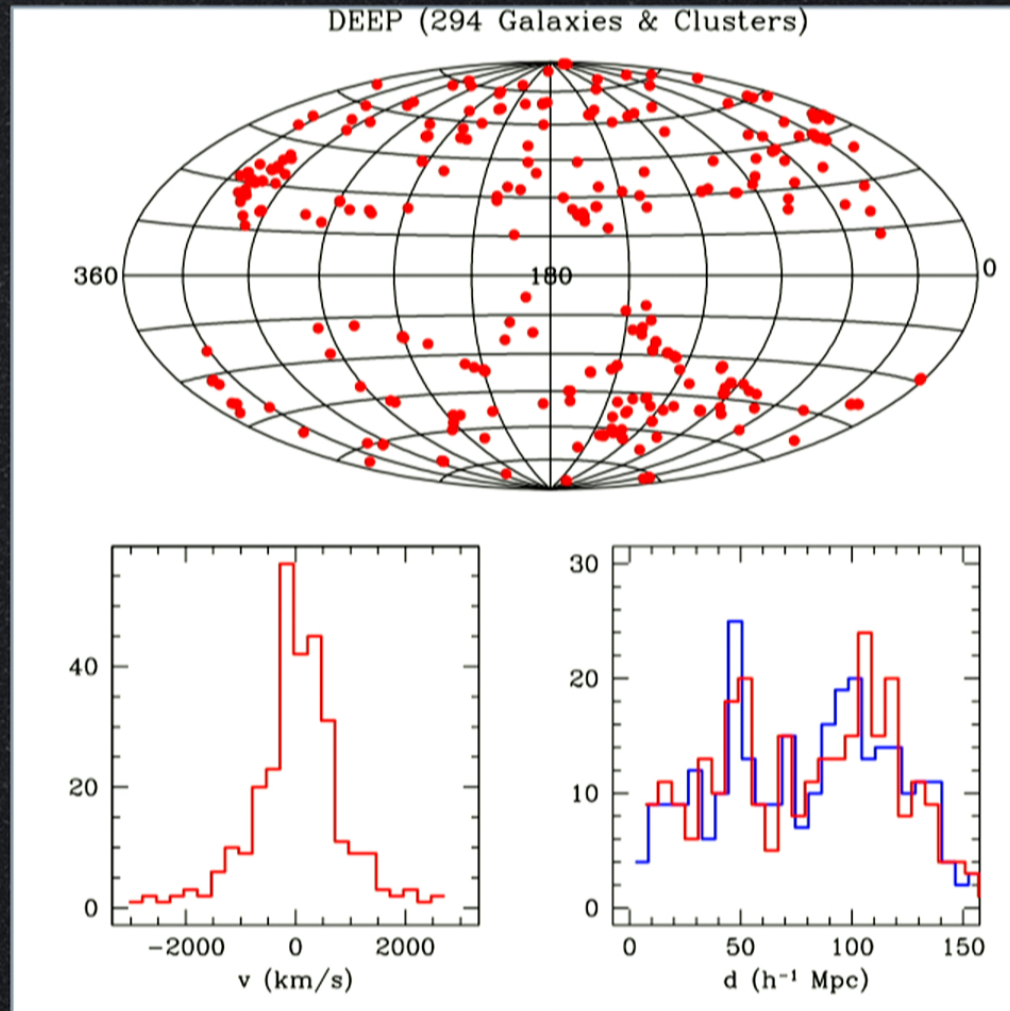SC (70 TF Clusters)

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Peculiar Velocity Surveys

SFI++$_F$ (2675 TF Galaxies)

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Peculiar Velocity Surveys

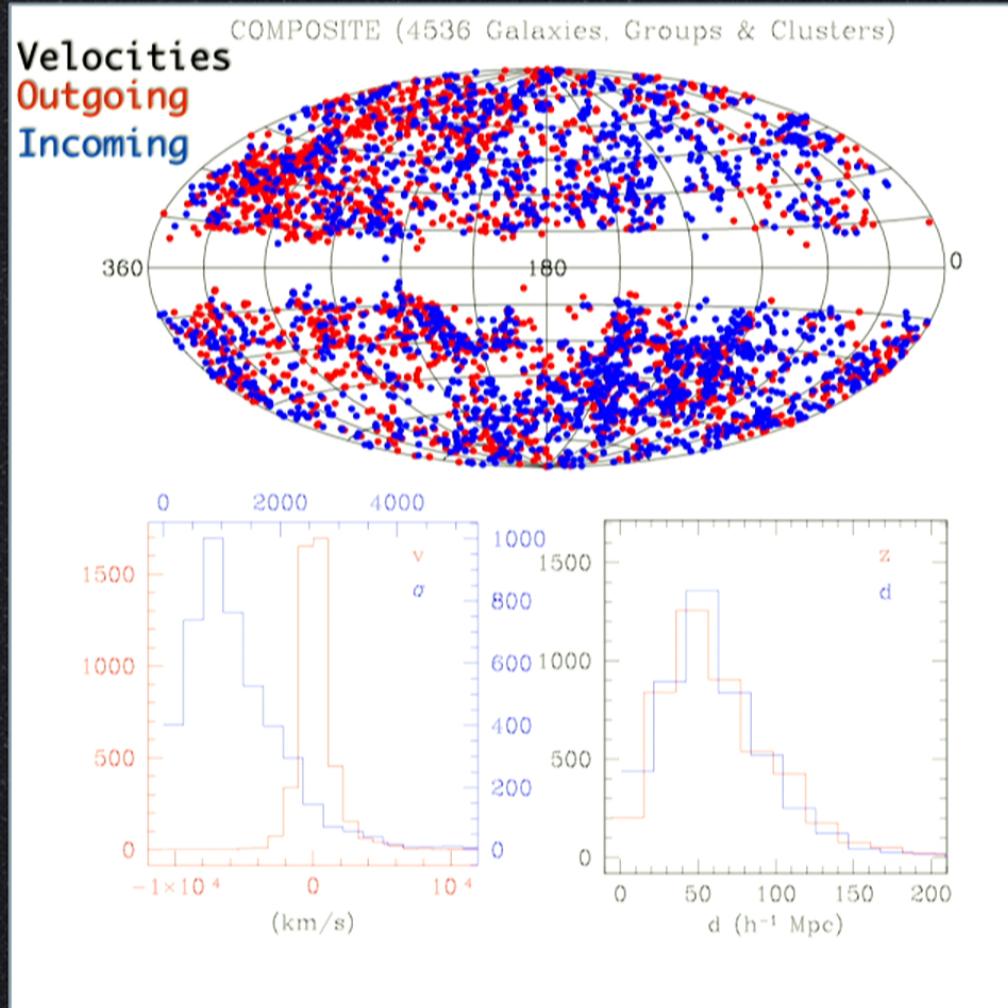DEEP (294 Galaxies & Clusters)
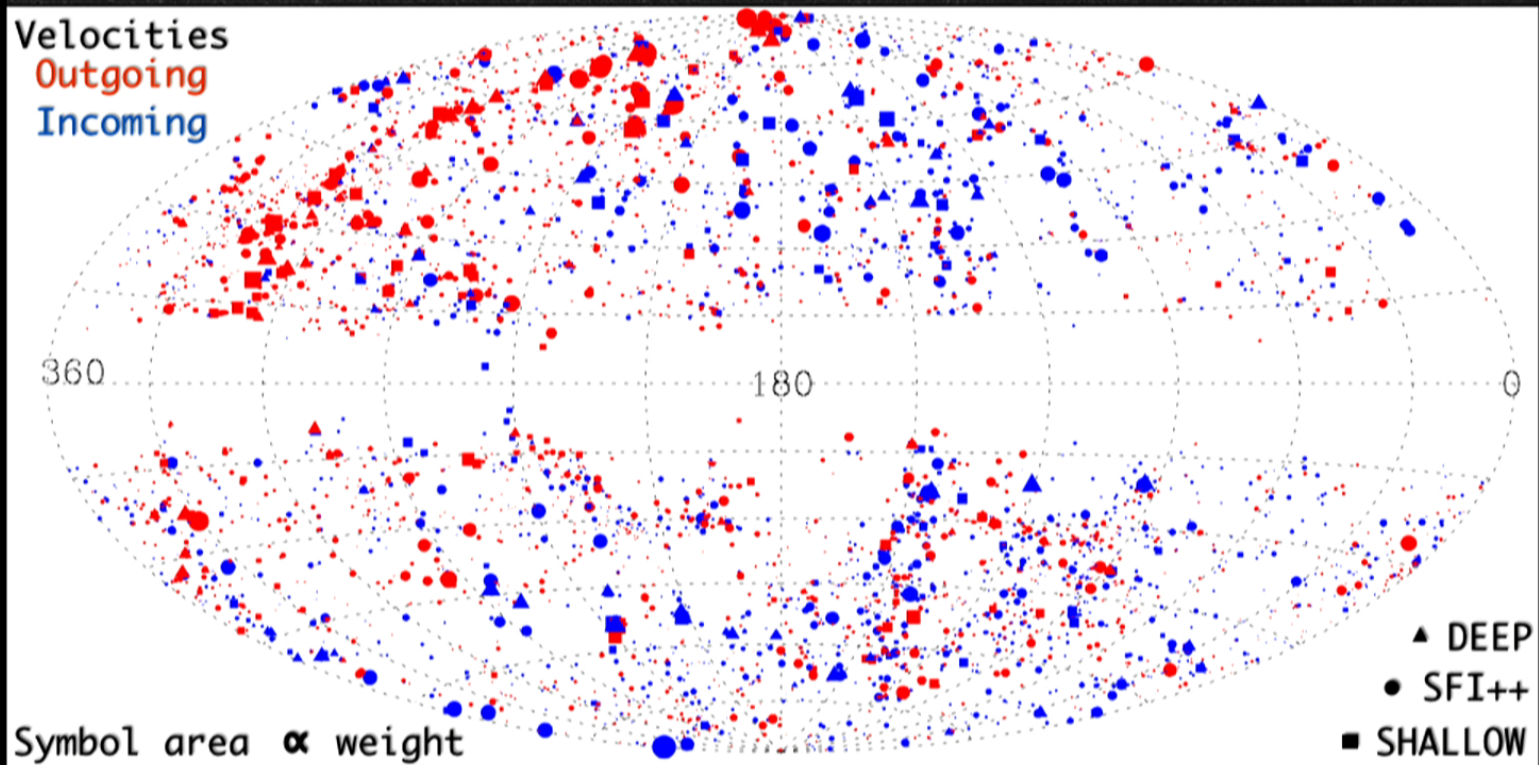
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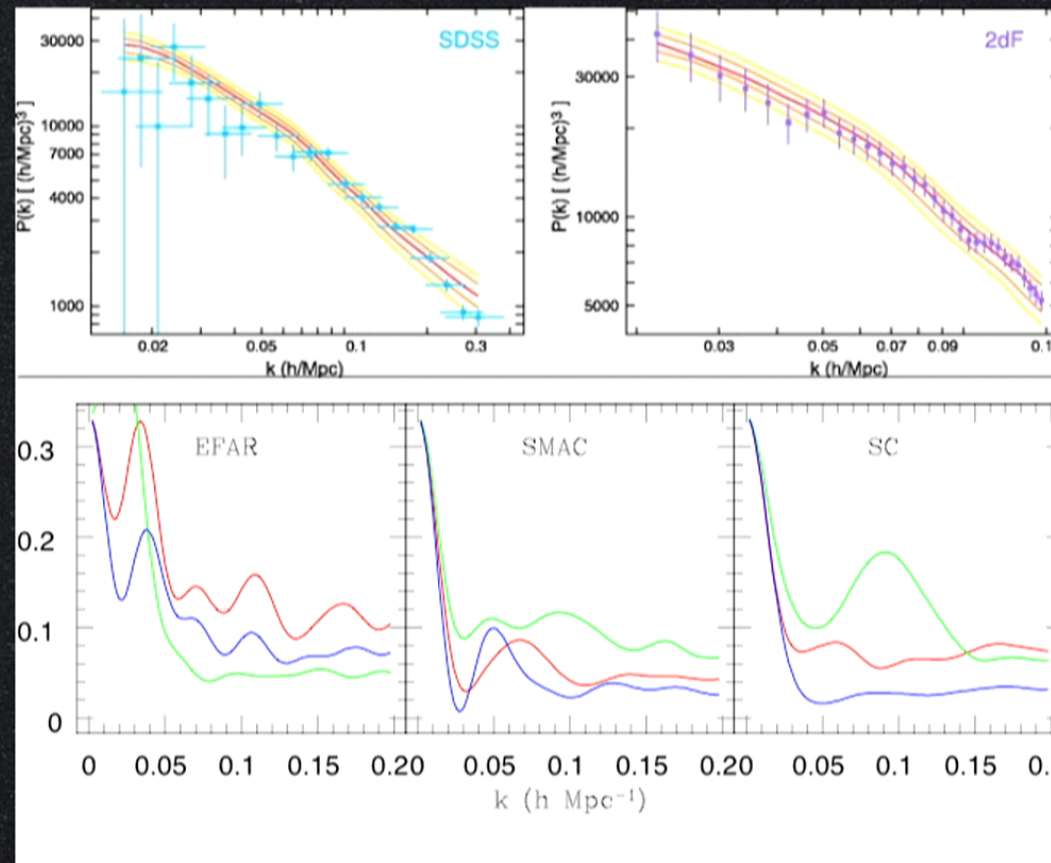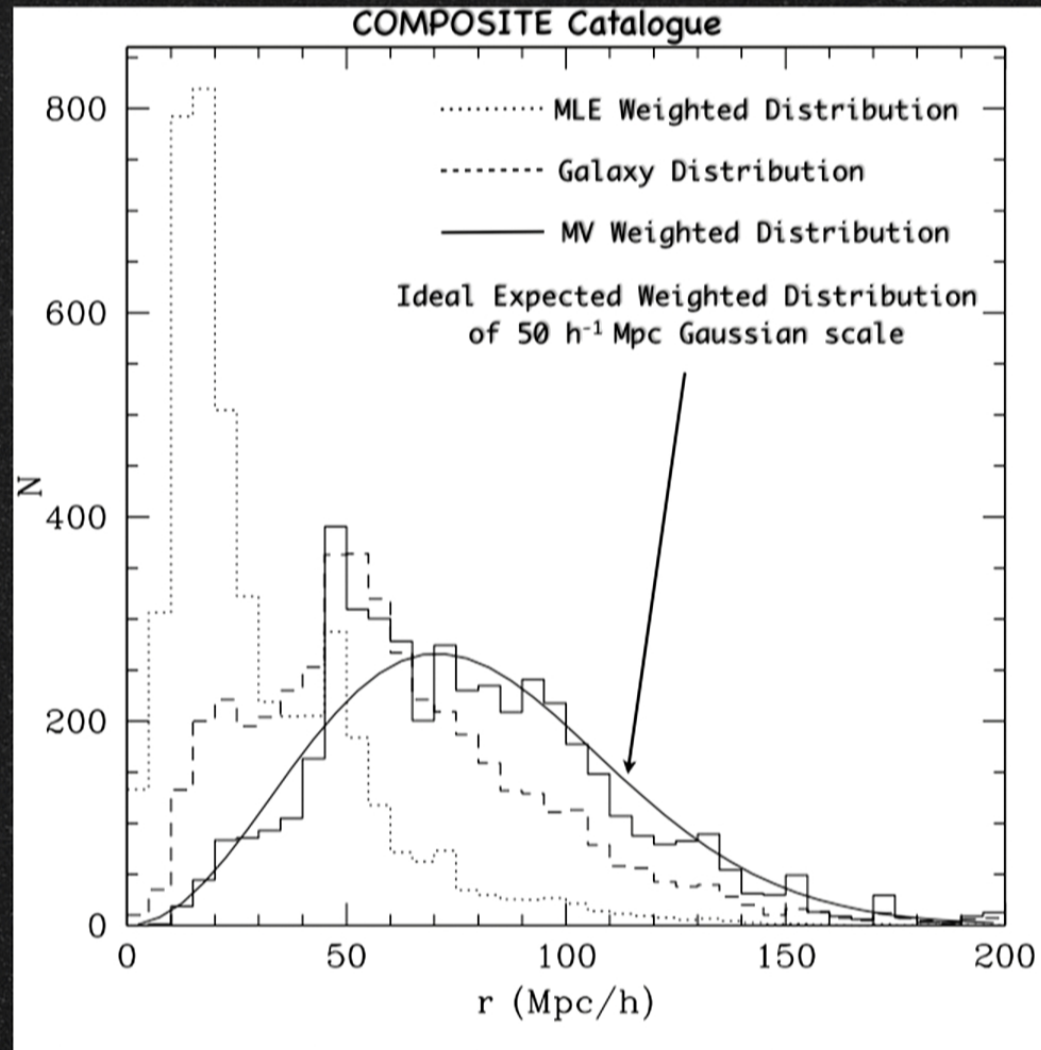
Peculiar Velocity Surveys

Maximum Likelihood Estimates (MLE)

$$R_{ab}^{(v)} = \frac{\Omega_m^{1.1}}{2\pi^2} \int_0^\infty dk \; \mathcal{W}_{ab}^2(k) P(k)$$
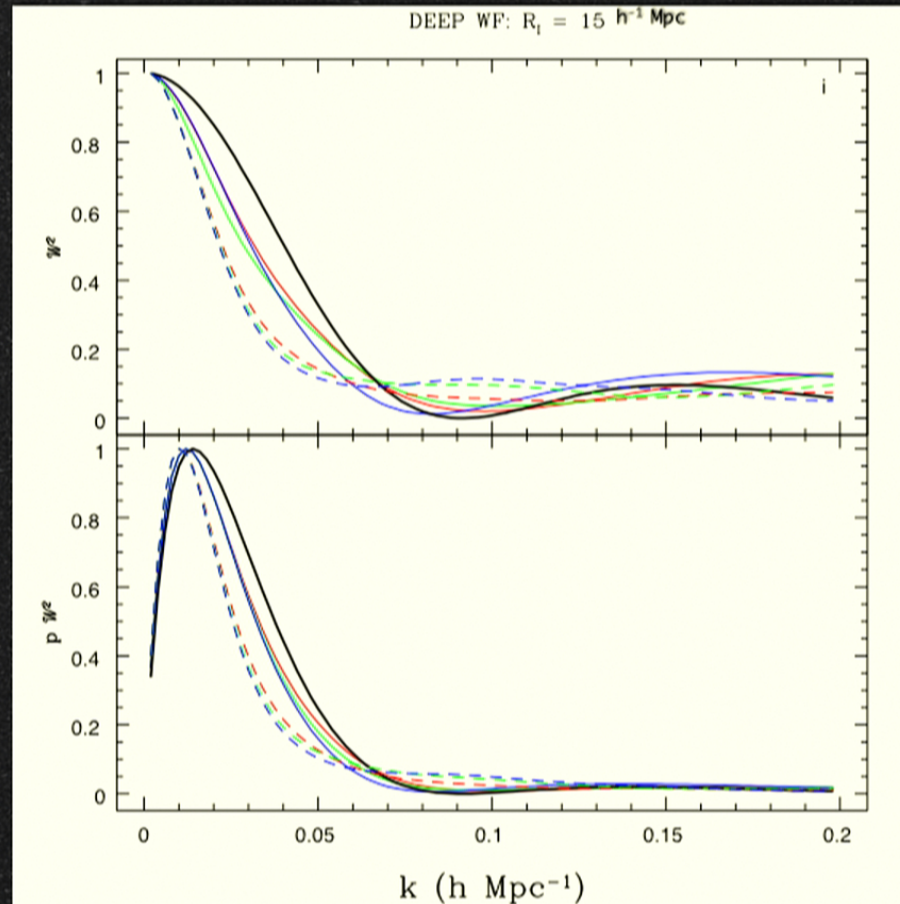
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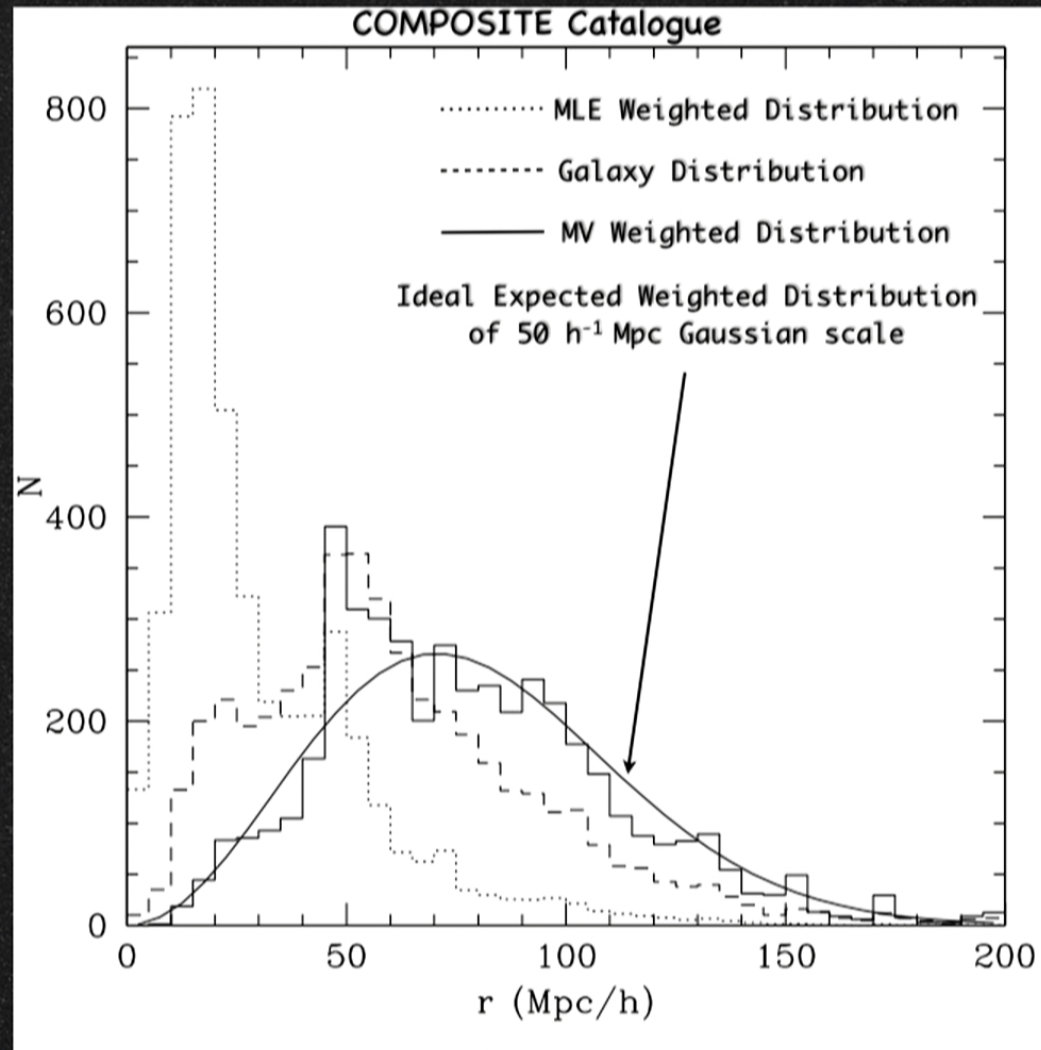
COMPOSITE Catalogue

········· MLE Weighted Distribution

-------- Galaxy Distribution

——— MV Weighted Distribution

Ideal Expected Weighted Distribution of 50 h^{-1} Mpc Gaussian scale

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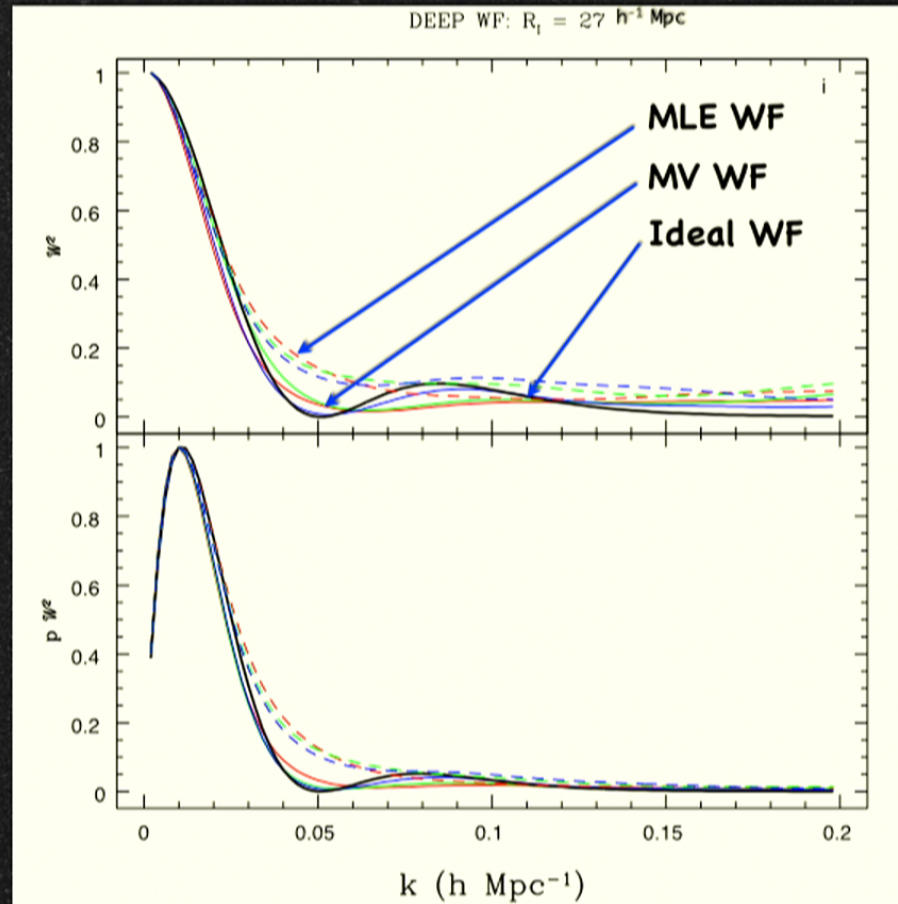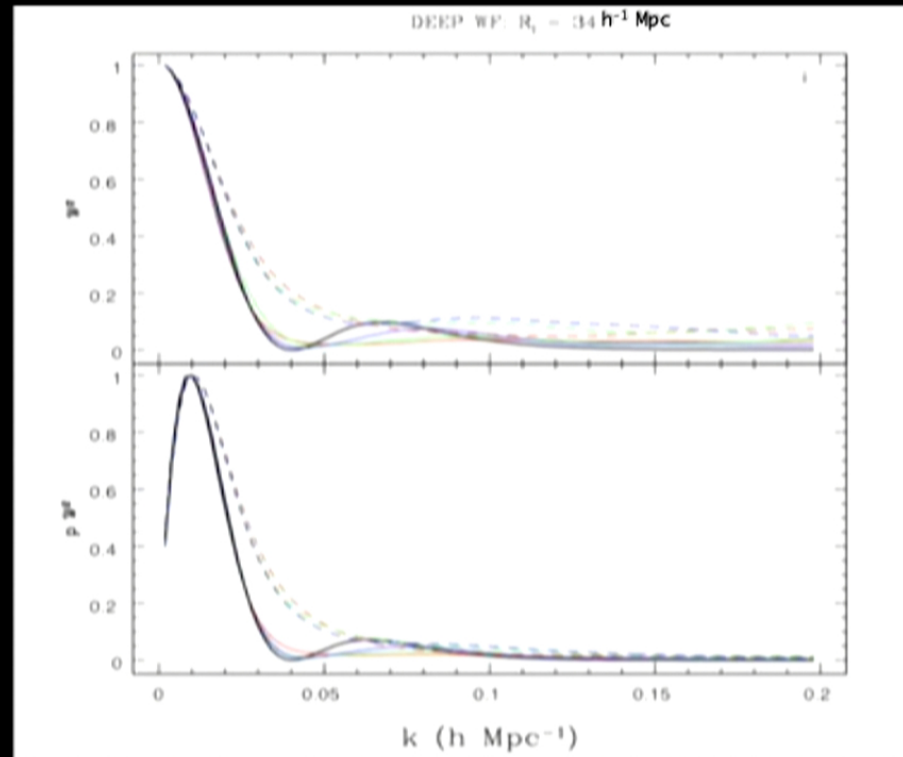
COMPOSITE Catalogue

.... MLE Weighted Distribution

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window function design

Window functions for DEEP mock survey

window function design

DEEP WF: $R_I = 27$ h^{-1} Mpc

MLE WF
MV WF
Ideal WF

k (h Mpc^{-1})

Window functions for DEEP mock survey

window function design

Window functions for DEEP mock survey

window function design

In the MV formalism we chose a Gaussian distribution.

It is possible to use any distribution.

A popular one is a tophat, a sphere in real space.

Estimators

Determination of the line-of-site peculiar (local) motion
requires the measurement of the galaxy's distance

$$v = cz - H_o r$$

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At large distances, we can include the effects of cosmic acceleration

$$z_{\mathrm{mod}} = z[1 + 0.5(1 - q_o)z - (1/6)(1 - q_o - 3q_o^2 + 1)z^2]$$

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$$z_{\mathrm{mod}} = z[1 + 0.5(1 - q_o)z - (1/6)(1 - q_o - 3q_o^2 + 1)z^2]$$

Since redshift is not an additive quantity

See also Davis & Scrimgeour 2014; Springob et al. 2014

$$(1 + z_{\mathrm{mod}}) = (1 + H_o r/c)(1 + v/c)$$

The peculiar velocity is

$$v = \frac{cz_{\mathrm{mod}} - H_o r}{1 + H_o r/c} \approx \frac{cz_{\mathrm{mod}} - H_o r}{1 + z_{\mathrm{mod}}}$$

Estimators

Determination of the line-of-site peculiar (local) motion requires the measurement of the galaxy's distance

Distance estimators give the distance moduli (μ), that is, log distances with Gaussian distributed errors.

Distance errors are skewed, not Gaussian and with non-zero average.

Estimators

Determination of the line-of-site peculiar (local) motion requires the measurement of the galaxy's distance

Distance estimators give the distance moduli (μ), that is, log distances with Gaussian distributed errors.

Distance errors are skewed, not Gaussian and with non-zero average.

$$\langle r_e \rangle \neq r \quad \Rightarrow \quad \langle v_e \rangle \neq v$$

These undesirable features can lead to biases and invalidate our statistical assumptions about the errors in peculiar velocities.

Estimators

Proposal: estimate peculiar velocities using

$$v_e = cz \log(cz/H_o r_e)$$

log distance $\Rightarrow$ Gaussian distributed errors.

The uncertainty in the peculiar velocity

$$\delta v_e = cz \delta l_e$$

Estimators

A more accurate estimator at large redshift

$$v_e = \frac{cz_{mod}}{(1 + z_{mod})} \log(cz_{mod}/H_o r_e)$$

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A more accurate estimator at large redshift

$$v_e = \frac{cz_{mod}}{(1 + z_{mod})} \log(cz_{mod}/H_o r_e)$$

with uncertainty

$$\delta v_e = cz_{mod}\delta l_e/(1 + z_{mod})$$

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Estimators

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We assume that actual velocity (v) is small compared to the redshift, not the estimated velocity (v_e).

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$$v_e = \text{few} \times 10^3 \, \text{km/s} \qquad \text{whereas} \qquad v = \text{few} \times 10^2 \, \text{km/s}$$

Estimators

A more accurate estimator at large redshift

$$v_e = \frac{cz_{mod}}{(1 + z_{mod})} \log(cz_{mod}/H_o r_e)$$

with uncertainty

$$\delta v_e = cz_{mod} \delta l_e / (1 + z_{mod})$$

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$v_e = \text{few} \times 10^3 \, \text{km/s}$ whereas $v = \text{few} \times 10^2 \, \text{km/s}$

Should hold quite well for galaxies at distances $\gtrsim 20 \, \text{Mpc}$

Malmquist Bias Correction

Probability of a galaxy being at some distance

$$p(r_i) = k_1 p_{\mathrm{TF}}(r_i) p_{\mathrm{mag}}(r_i) p_{\mathrm{lss}}(r_i)$$

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Normalization constant

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Probability distribution for the galaxy being at a position as given by the TF measurement

Probability of finding a galaxy with an apparent magnitude at a distance

Malmquist Bias Correction

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Normalization
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Probability distribution for the
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Probability of
finding a galaxy
with an apparent
magnitude at a
distance

Density
distribution
along the line
of sight

Instead calculate the corrected probability

$$p(\mu_i) = k_1 p_{\mathrm{TF}}(\mu_i) p_{\mathrm{mag}}(\mu_i) p_{\mathrm{lss}}(\mu_i)$$

Malmquist Bias Correction

Example: A uniform density of galaxies with log distances $l_i = \log(r_i)$

Homogeneous Malmquist bias: galaxies are more likely to scatter from larger than smaller radius due the increasing volume.

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Homogeneous Malmquist bias: galaxies are more likely to scatter from larger than smaller radius due the increasing volume.

$$p_{\text{lss}}(r_i)dr_i \propto r^2 dr_i \qquad \Rightarrow \qquad p_{\text{lss}}(l_i)dl_i \propto e^{3l_i} dl_i$$

Assuming that $p_{\text{mag}}(l_i)$ is constant and that $p_{\text{TF}}(l_i)$ is a Gaussian distribution centered on the value l_o with uncertainty Δ, we have

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$$p(l_i) \propto \exp(-(l_i - l_o)^2/2\Delta^2)e^{3l_i}$$

$$\propto \exp(-(l_i - (l_o + 3\Delta^2))^2/2\Delta^2)$$

$\Rightarrow$ as long as the product $p_{\mathrm{mag}}(r_i) p_{\mathrm{lss}}(r_i) \propto r_i^n$

in the region around the galaxy's location, the effect will be

to shift the peak of $p(\mu_i)$ relative to $p_{\mathrm{TF}}(\mu_i)$ while maintaining a

Gaussian distribution.

$\Rightarrow$ as long as the product $p_{\mathrm{mag}}(r_i)p_{\mathrm{lss}}(r_i) \propto r_i^n$

in the region around the galaxy's location, the effect will be to shift the peak of $p(\mu_i)$ relative to $p_{TF}(\mu_i)$ while maintaining a Gaussian distribution.

Since p_{mag} and p_{lss} are typically slowly varying compared to p_{TF}, we expect that Malmquist-corrected μ_i will still have Gaussian errors.

Error Distribution Estimators
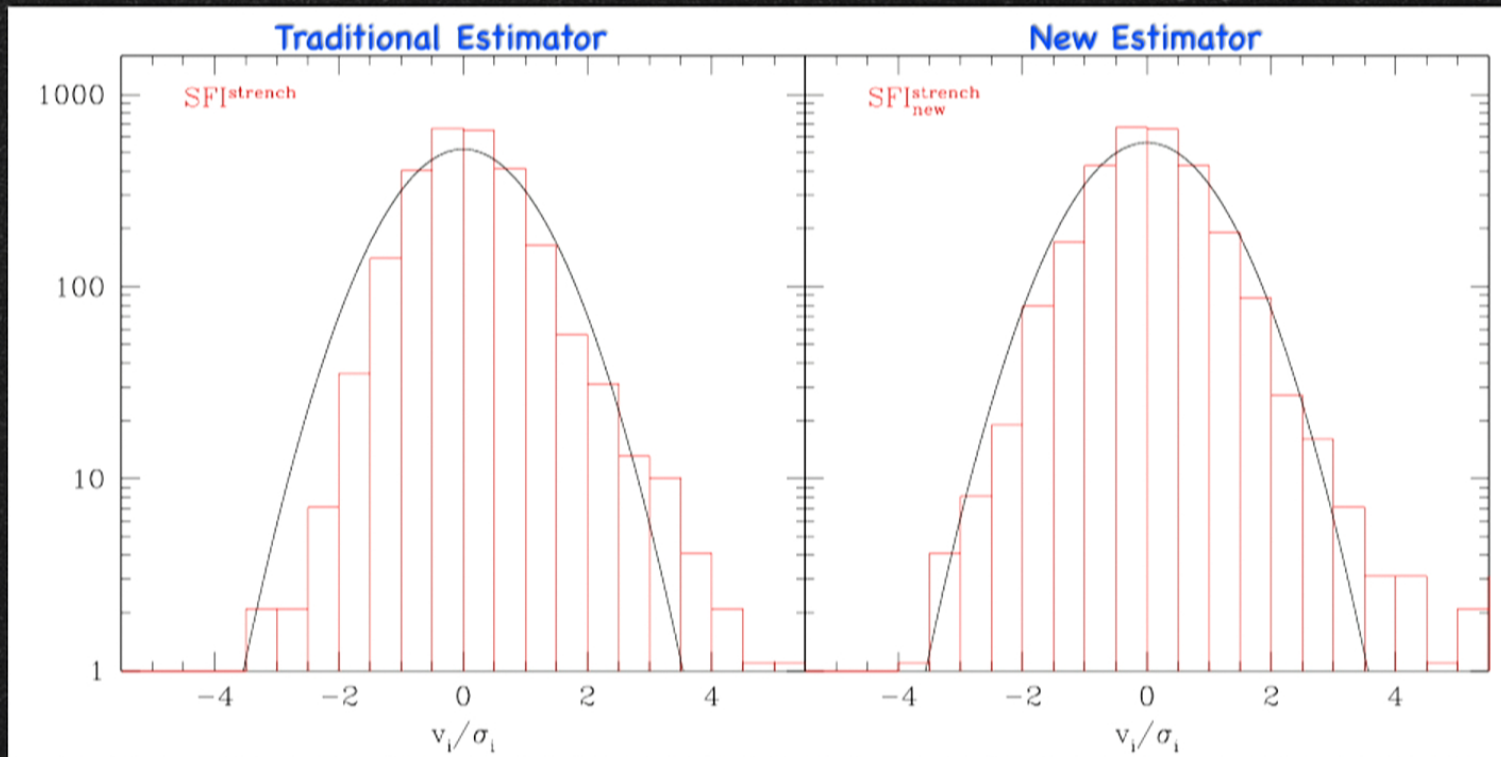
Bulk Flow as a function of Scale
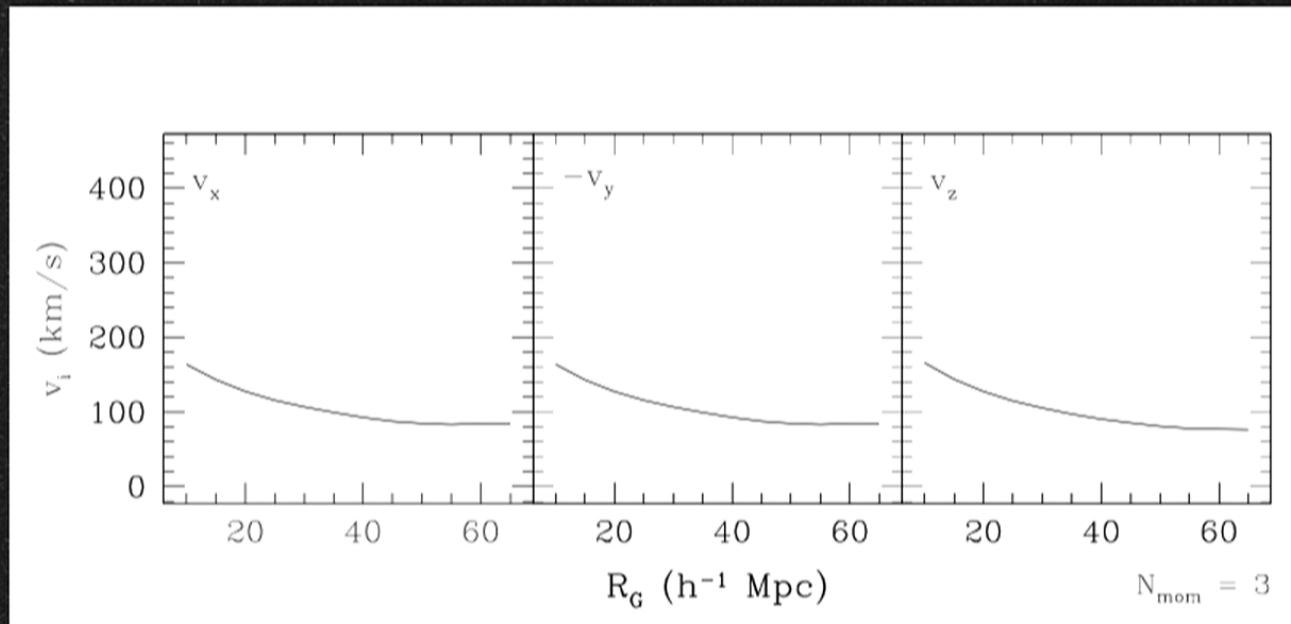
Bulk Flow as a function of Scale
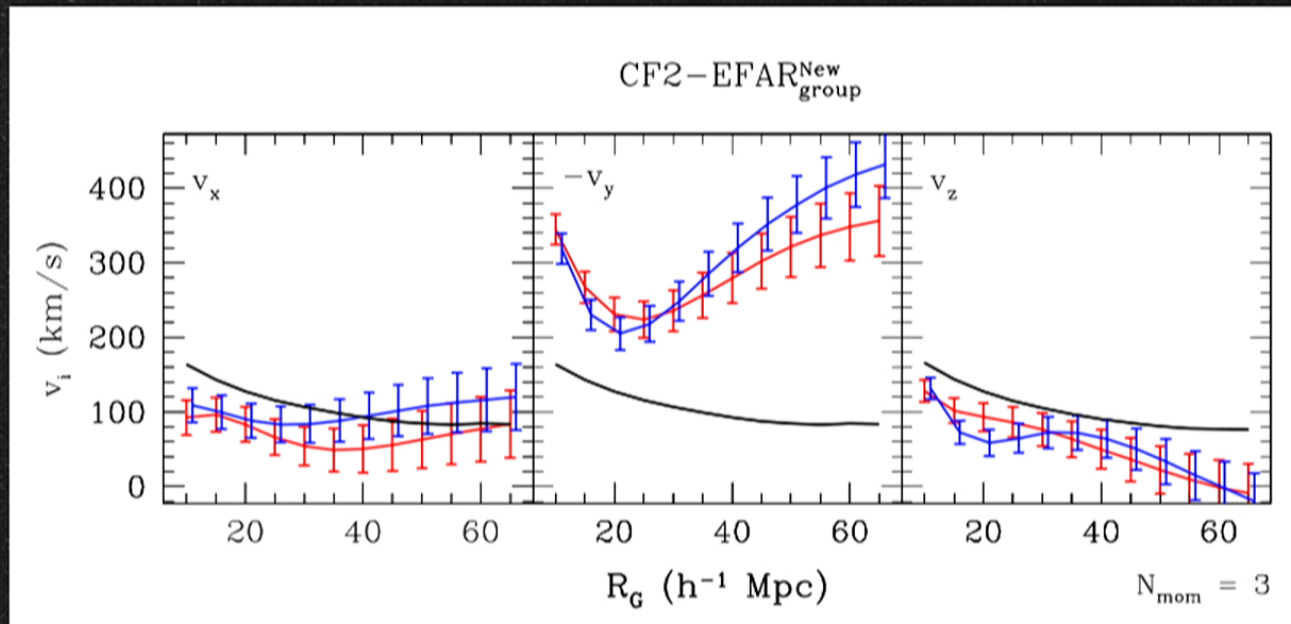
Bulk Flow as a function of Scale
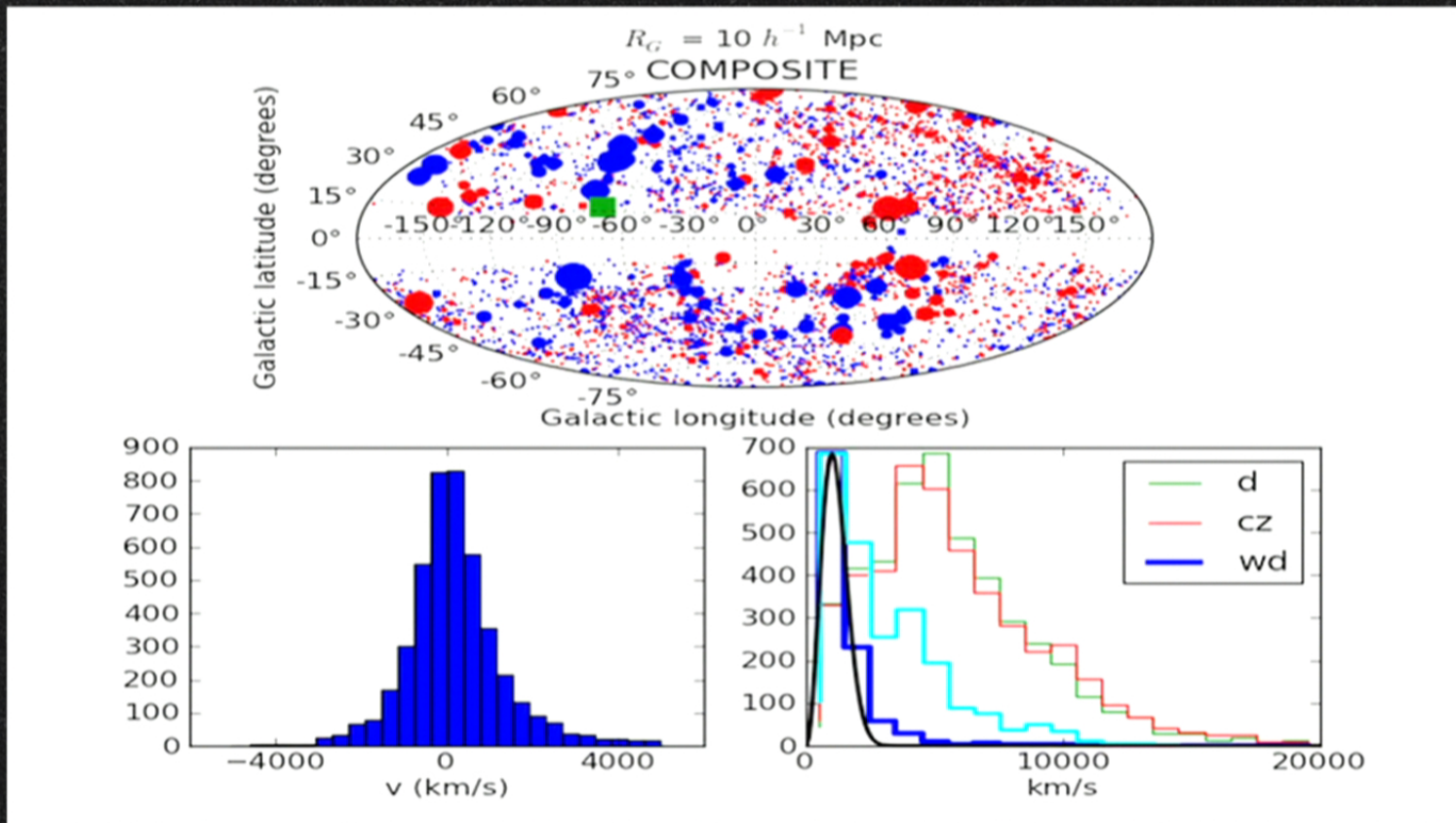
Direction of flow

Velocities Outgoing
            Incoming

Symbol area ∝ weight

Sources of the Flow

COMPOSITE

$$\frac{u_y}{u_{yy}}$$

$$<\frac{u_x}{u_{xx}}>_{WMAP5}$$

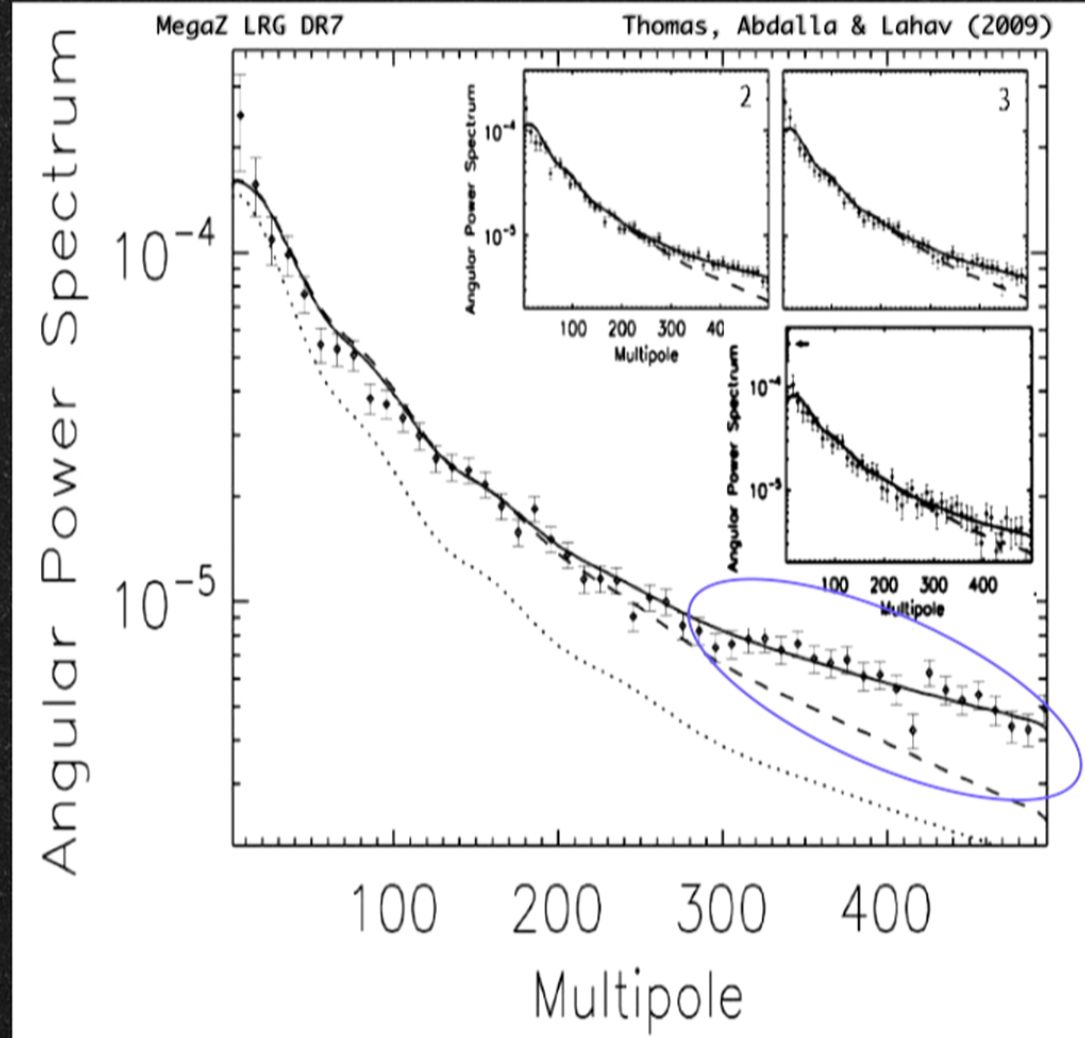D_y (h^{-1}Mpc)

R_l (h^{-1} Mpc)
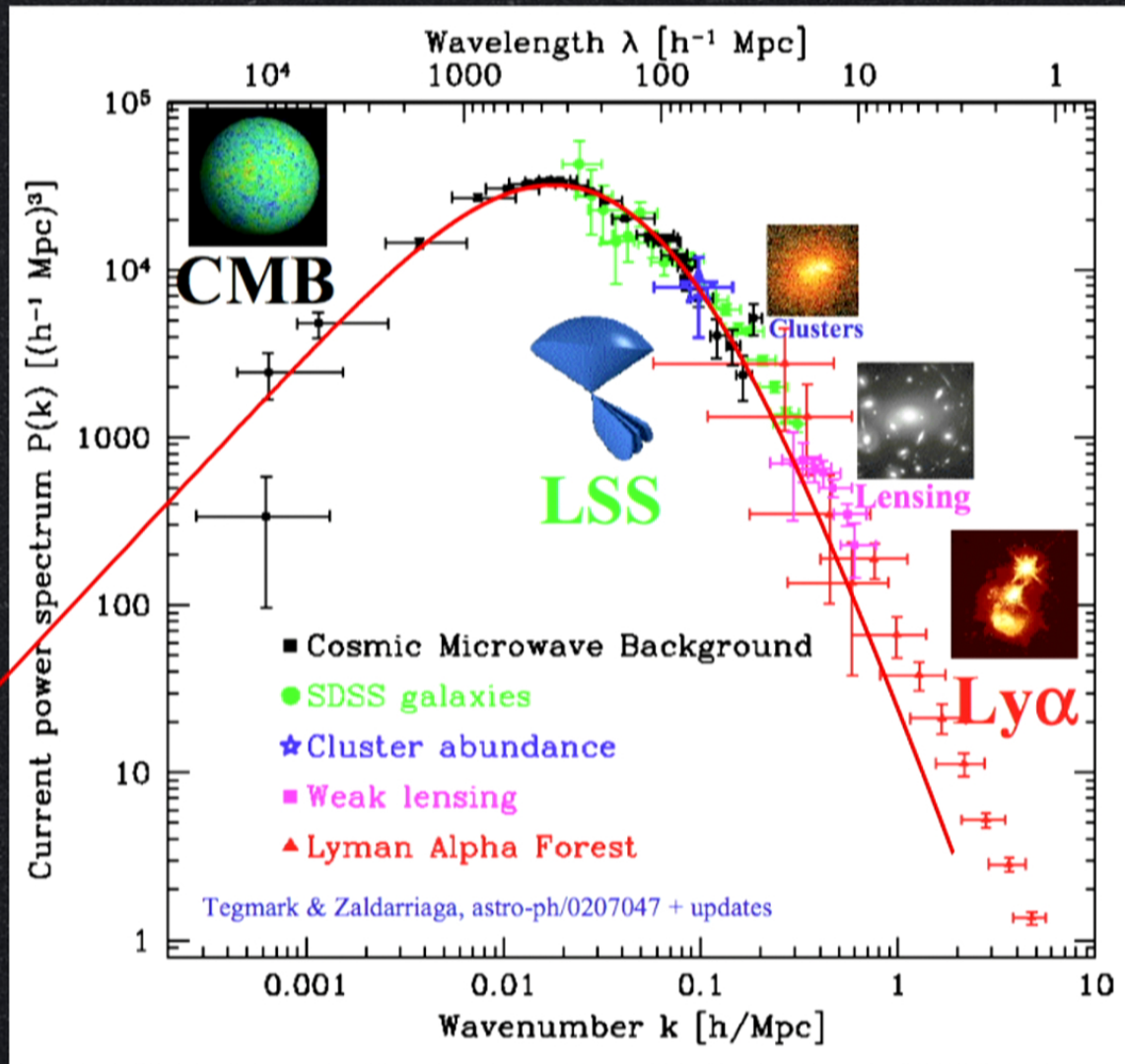
$N_{mom} = 19$

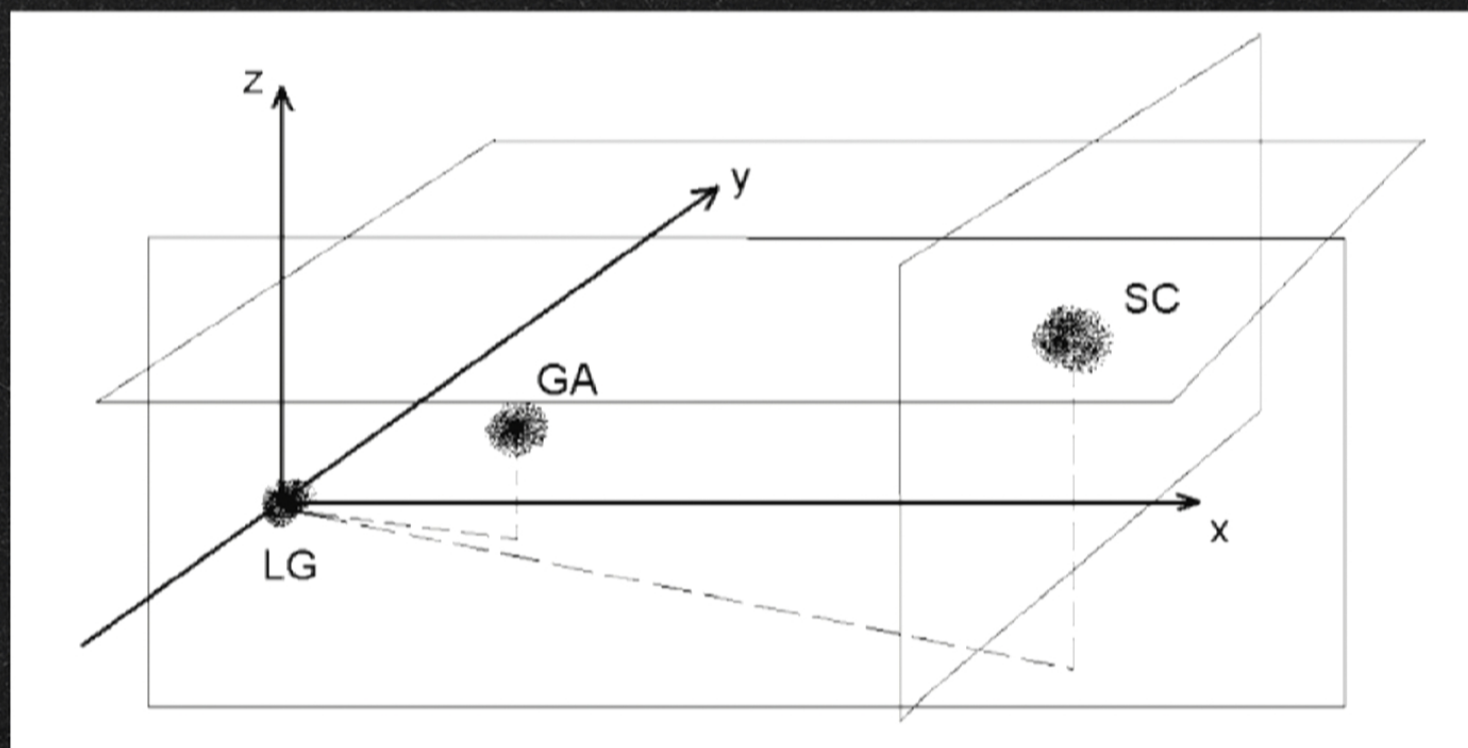KU Hume A. Feldman   **Scale Dependent Cosmic Flows**   Cosmic Flows (and Other Novelties on Large Scales – Perimeter Institute   10 August, 2015   61

MegaZ LRG DR7 — Thomas, Abdalla & Lahav (2009)

Macaulay, HAF, Ferreira, Hudson, Watkins, 2010

Current power spectrum P(k) vs Wavenumber k — showing CMB, LSS, Clusters, Lensing, and Lyα data. Tegmark & Zaldarriaga, astro-ph/0207047 + updates

Is there an attractor?

Is there an attractor?

Is there an attractor?

$l \approx 295°$
$b \approx 10°$
$d \approx 296 \pm 62 h^{-1} Mpc$

Conclusions

☑️ MV method re-designs the survey window function in a way that minimizes the aliasing of small-scale power onto large scales

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☑ MV method re-designs the survey window function in a way that minimizes the aliasing of small-scale power onto large scales

☑ The MV formalism correctly predicts the bulk flow of the volume of a particular scale

☑ Linear theory correctly predicts the flow

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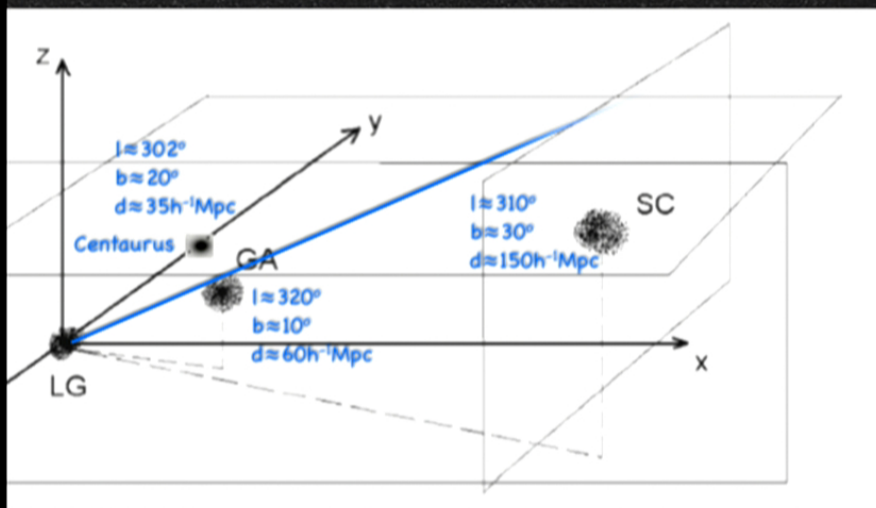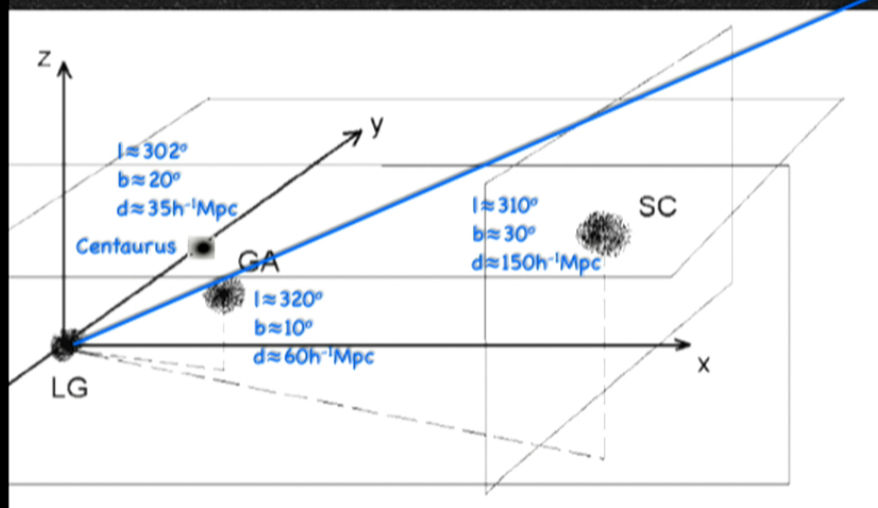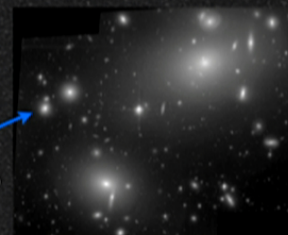
Conclusions

- ☑ MV method re-designs the survey window function in a way that minimizes the aliasing of small-scale power onto large scales

- ☑ The MV formalism correctly predicts the bulk flow of the volume of a particular scale

- ☑ Linear theory correctly predicts the flow

- ☑ Nonlinear, small-scale motions do not significantly affect the MV estimators.

Conclusions

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Agrees with the standard ΛCDM parameters on smallish scales

$< 35 \ h^{-1}$ Mpc Gaussian distribution

or

$< 75 \ h^{-1}$ Mpc Tophat distribution

Conclusions
Weights Rule

- No matter which formalism is used, galaxies in the survey are weighted

- These weights determine
  - the results
  - the effective scale
  - how parochial the measurement is

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