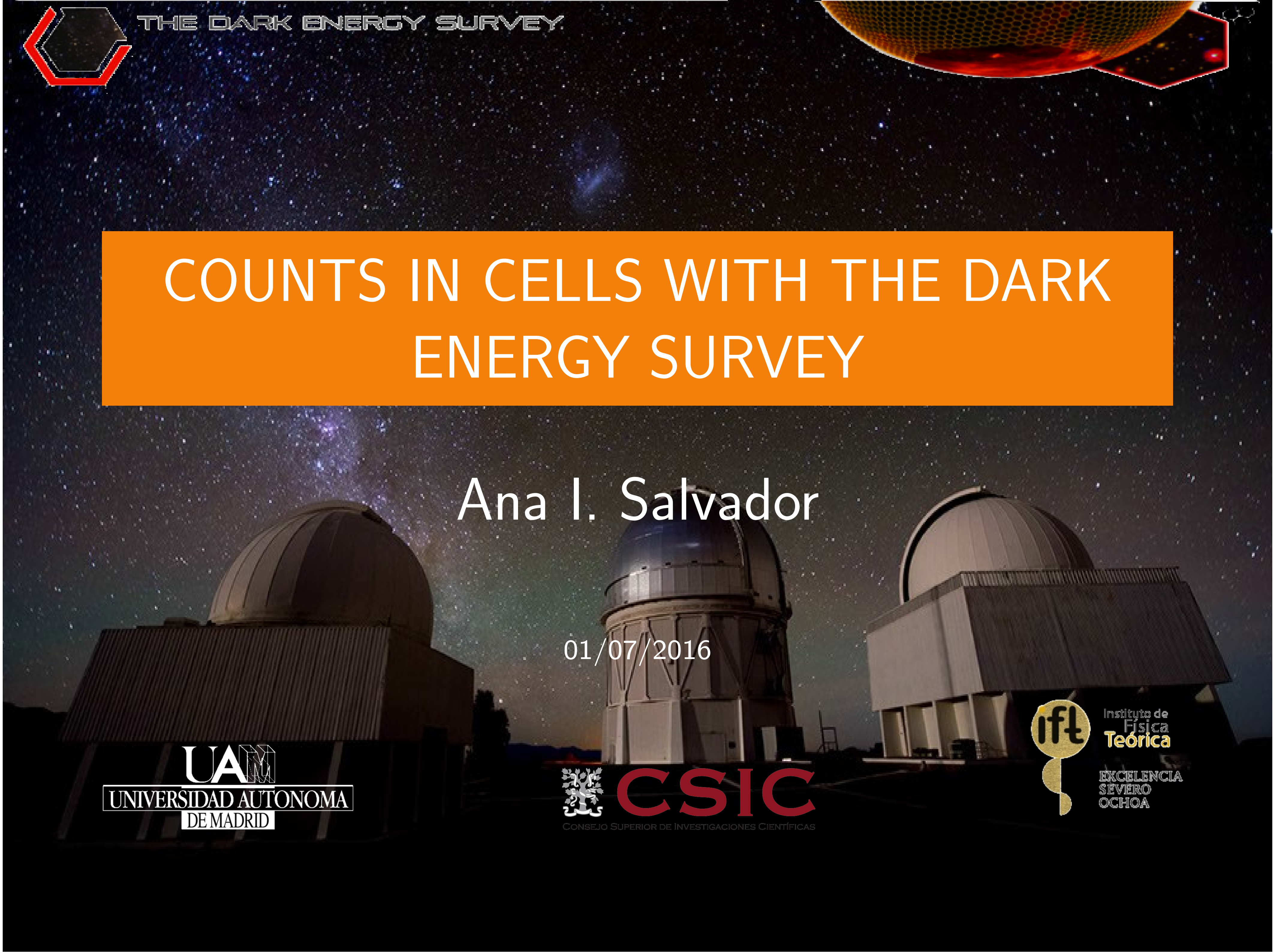

THE DARK ENERGY SURVEY

COUNTS IN CELLS WITH THE DARK ENERGY SURVEY

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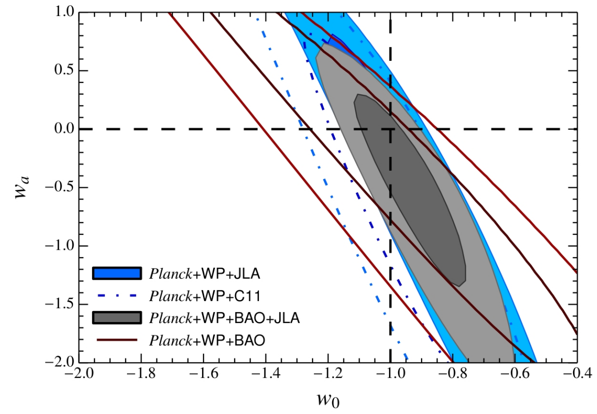
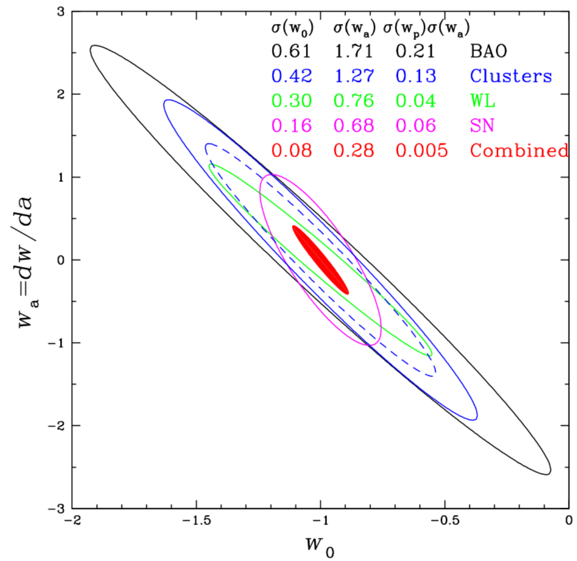
DES Science Summary

4 probes of Dark Energy:

- **Supernovae (SN)** (distance)
  3500 well-sampled SNe Ia to $z \sim 1$
- **Baryon Acoustic Oscillations (BAO)**
  (distance) 300 million galaxies to
  $z \sim 1.4$ and $i < 24$
- **Galaxy clusters (GC)**
  (distance & structure growth) Tens of thousands of clusters to $z \sim 1$ Synergy with SPT, VHS
- **Weak Gravitational Lensing (WL)**
  (distance and structure growth)
  Shape and magnification measurements of 200 million galaxies



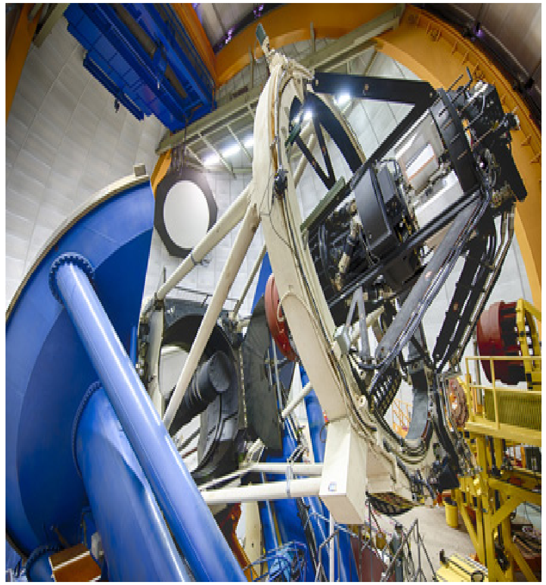
[Betoule et al. 2014]



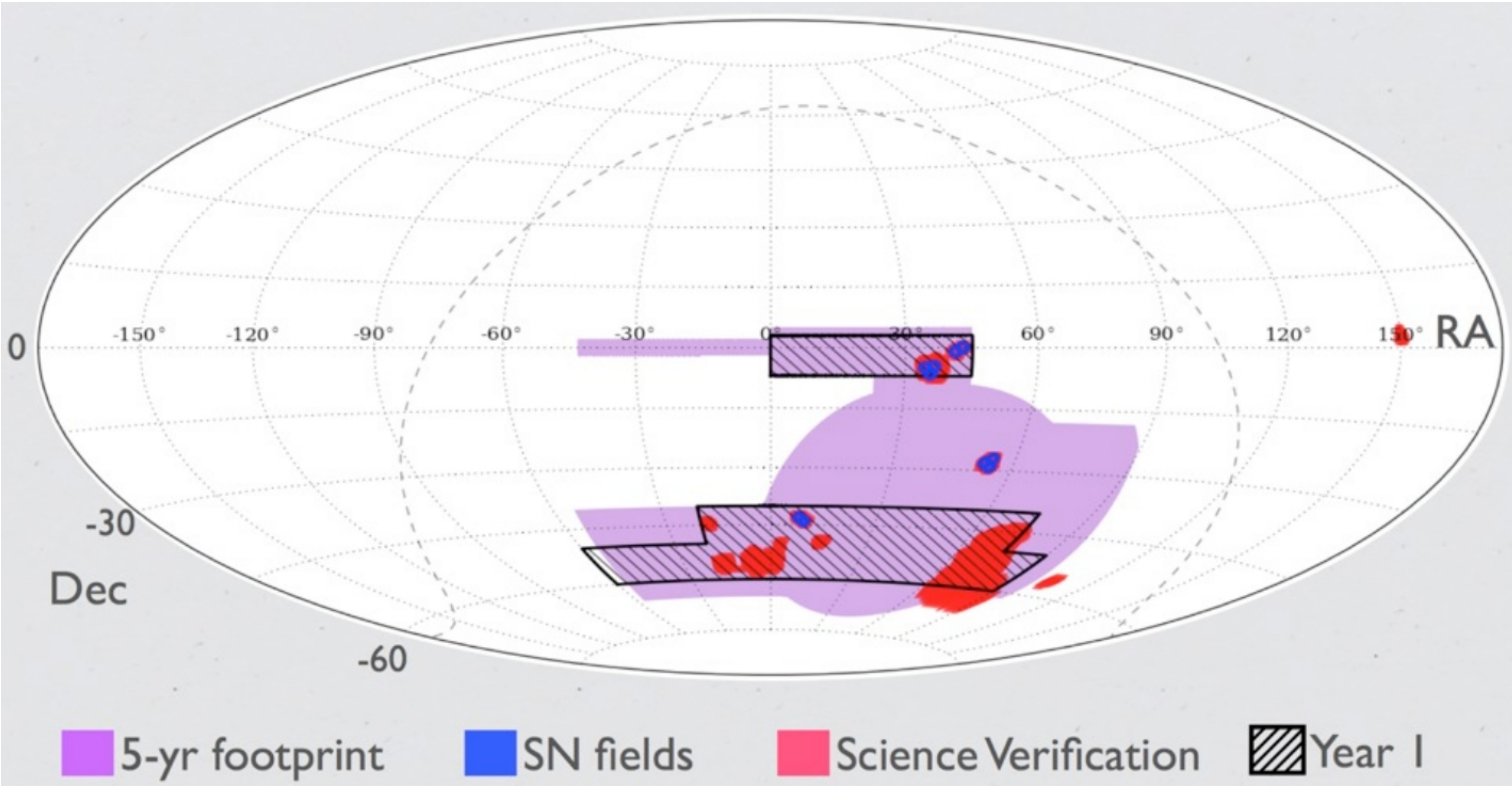
[Weller et al. 2006]

The Dark Energy Survey

- Cerro Tololo Inter-American Observatory Blanco 4-meter telescope
- First light Sept. 12, 2012
- Survey 2013-2018, 525 nights
- DECam: 570 Mpix, 3 deg 2 FOV, griZY filters
- 5000 deg^2 survey footprint, to mag 24 (redshift $\sim$1.5) + 30 deg^2 deep SN fields



DES Survey Footprint

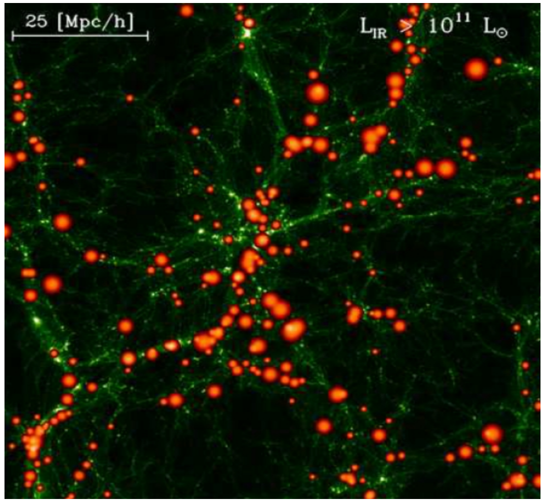


Science Verification ~250 sq.deg. to ~full depth; 45 M objects

Year 1: ~1500 sq. deg. overlap SPT, SDSS: 4/10 tilings; 140 M objects

Counts-in-cells - Why?

- Galaxies are just tracers of Dark Matter.
- The bias relates the matter and galaxy fluctuations (assuming a linear bias)



$$\delta_G = b(z)\delta_M$$

- You can obtain the bias from the 2-point correlation function or the power spectrum:

$$P_G(k,z) = b^2(z)P_M(k,z)$$

- Counts-in-Cells alternative way of estimating the bias from the moments of the density contrast distribution

Counts-in-cells

- We pixelize the sphere and calculate the density contrast in each pixel:

$$\delta = \frac{\rho}{\langle\rho\rangle} - 1 \quad \text{where} \quad \rho = \frac{\mathrm{Ngal}}{\mathrm{Vpix}}$$

- From the density contrast distribution we calculate the moments of the distribution

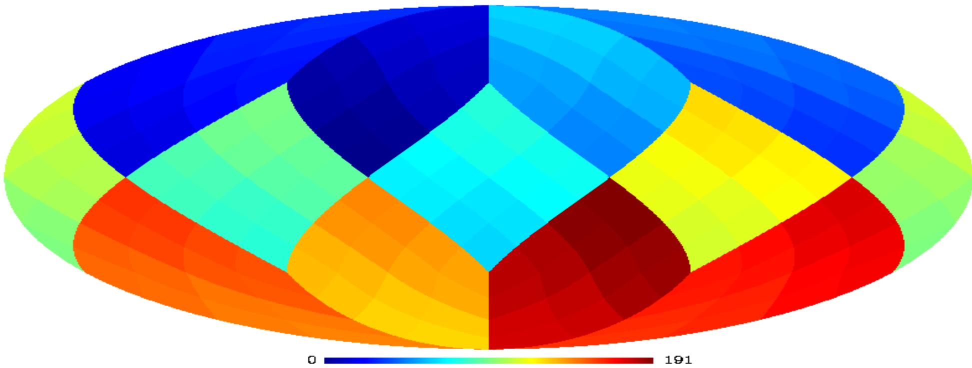
$$S_2 = \langle\delta^2\rangle$$

$$S_3 = \frac{\langle\delta^3\rangle}{\langle\delta^2\rangle^2}$$

$$S_4 = \frac{\langle\delta^4\rangle - 3\langle\delta^2\rangle^2}{\langle\delta^2\rangle^3}$$

CiC Pixels

- In a photometric survey we don't have a high precision radial information $\Longrightarrow$ angular CiC.
- In real data we have masks and systematic effects.
- To deal with these effects we compute the CIC using Healpix



- We do it for different pixel sizes (nside = 64, 128, 256, 512, 1024, 2048, 4096)

CiC theory

We can check our values calculating the moments integrating the p-correlation function

$$\langle \delta^p \rangle = \frac{1}{A^p} \int_A w_p(\theta_1, \theta_2) d\Omega_1 d\Omega_2$$

For second order:

$$\langle \delta^2 \rangle = \frac{1}{A^2} \int_A w_2(\theta_1, \theta_2) d\Omega_1 d\Omega_2$$

CiC theory

For third and fourth order calculating the correlation functions is computationally very expensive.

$$\langle \delta^3 \rangle \propto \int d^3 k_1 \int d^3 k_2 P(k_1) P(k_2) F_2(k_1, k_2)$$

First Peebles and then Hamana et al 2002 have calculated the theoretical values for a power spectrum $P(k) \propto k^n$ and spherical cells:

$$S_3 = \frac{34}{7} - (n+3)$$

$$S_4 = \frac{60712}{1323} - \frac{64}{3}(n+3) + \frac{7}{3}(n+3)^2$$

Obtaining the bias

If we assume a linear bias: $\langle\delta_g\rangle = b(z)\langle\delta_m\rangle$

- From the second order moment:

$$S_2^{(g)} = \langle\delta_g^2\rangle = b^2\langle\delta_m^2\rangle$$

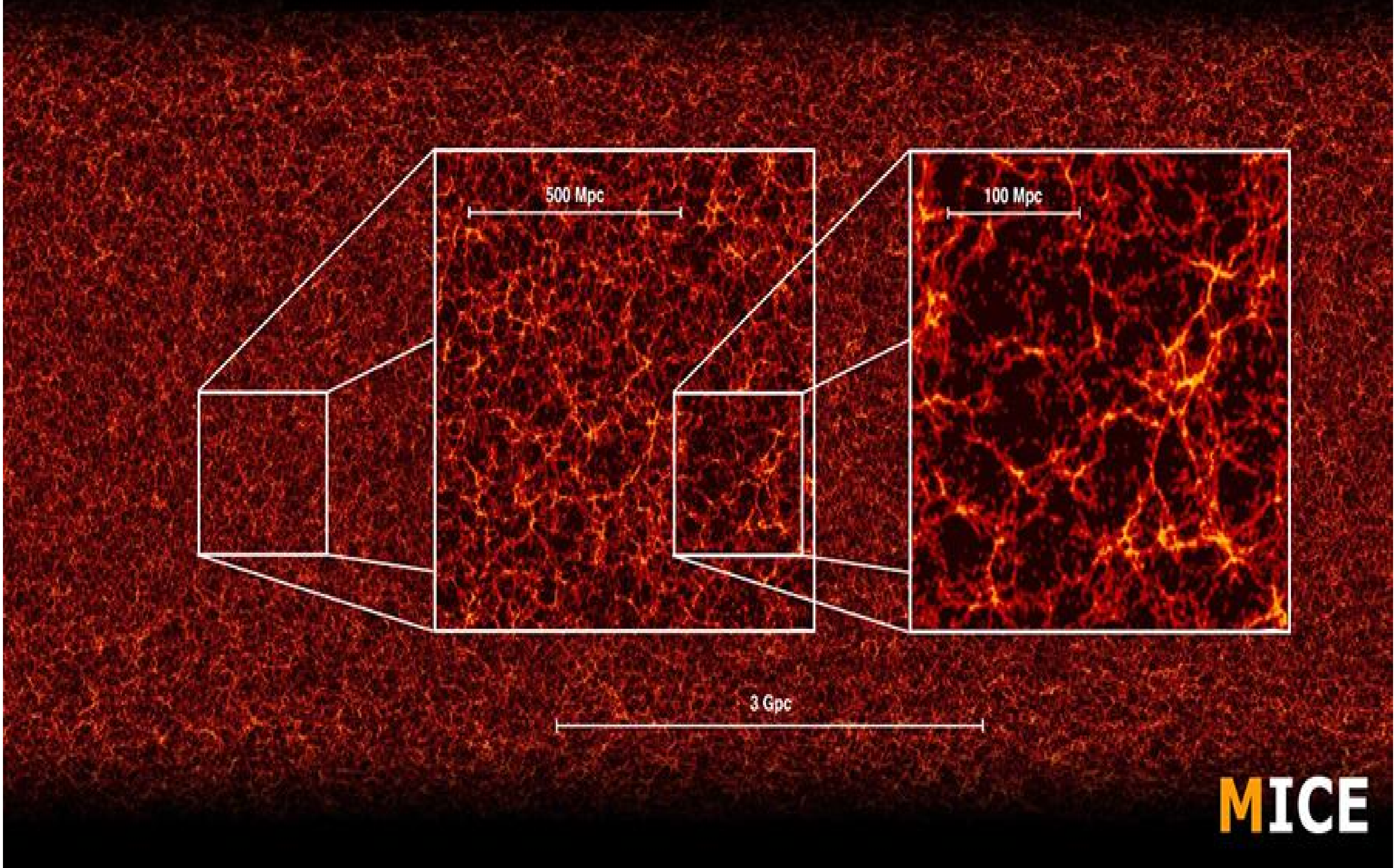
- From the third order moment:

$$S_3^{(g)} = \frac{\langle\delta_g^3\rangle}{\langle\delta_g^2\rangle^2} = \frac{b^3\langle\delta_m^3\rangle}{b^4\langle\delta_m^2\rangle^2} = \frac{1}{b}S_3^{(m)}$$

- From the fourth order moment:

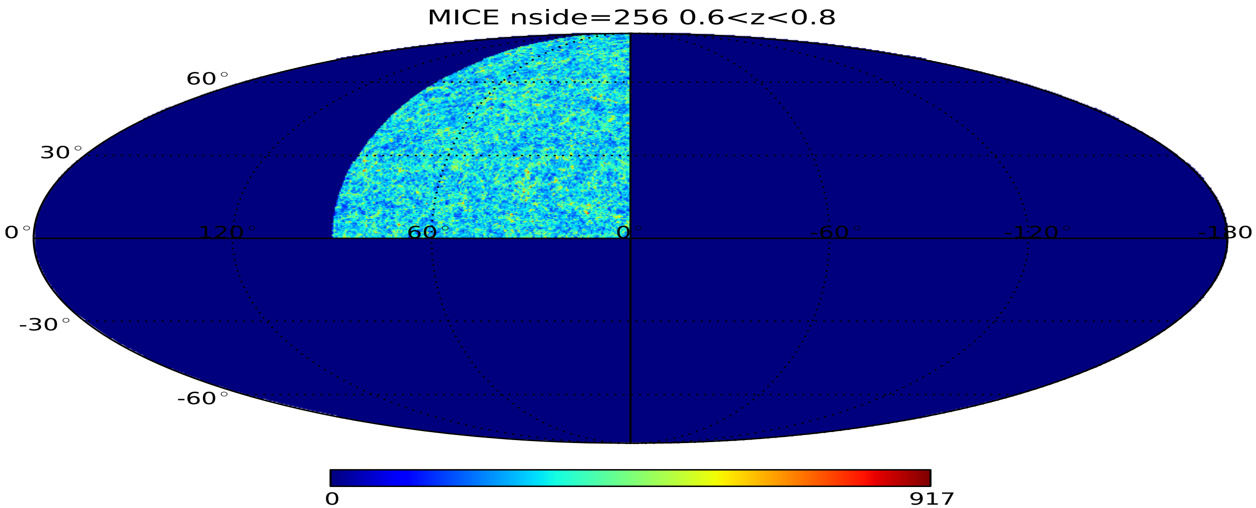
$$S_4^{(g)} = \frac{\langle\delta_g^4\rangle - 3\langle\delta_g^2\rangle^2}{\langle\delta_g^2\rangle^3} = \frac{b^4\langle\delta_m^4\rangle - 3b^4\langle\delta_m^2\rangle^2}{b^6\langle\delta_m^2\rangle^3} = \frac{1}{b^2}S_4^{(m)}$$

MICE Simulation

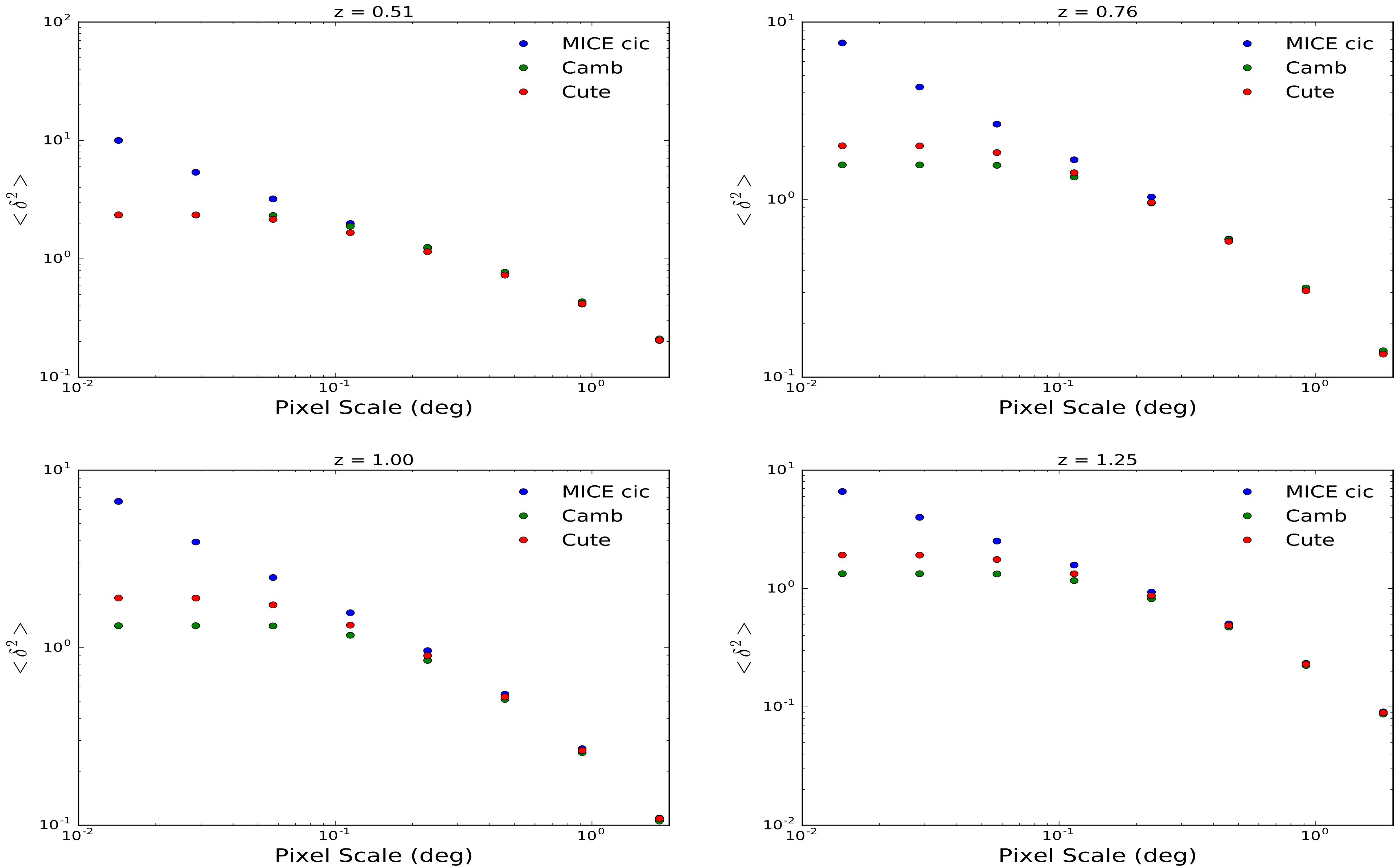


CiC in MICE

- First we take thin redshift bins ($\Delta z = 0.01$) to check the method.
- To simulate real data conditions we take wider redshift bins $\Delta z = 0.2$

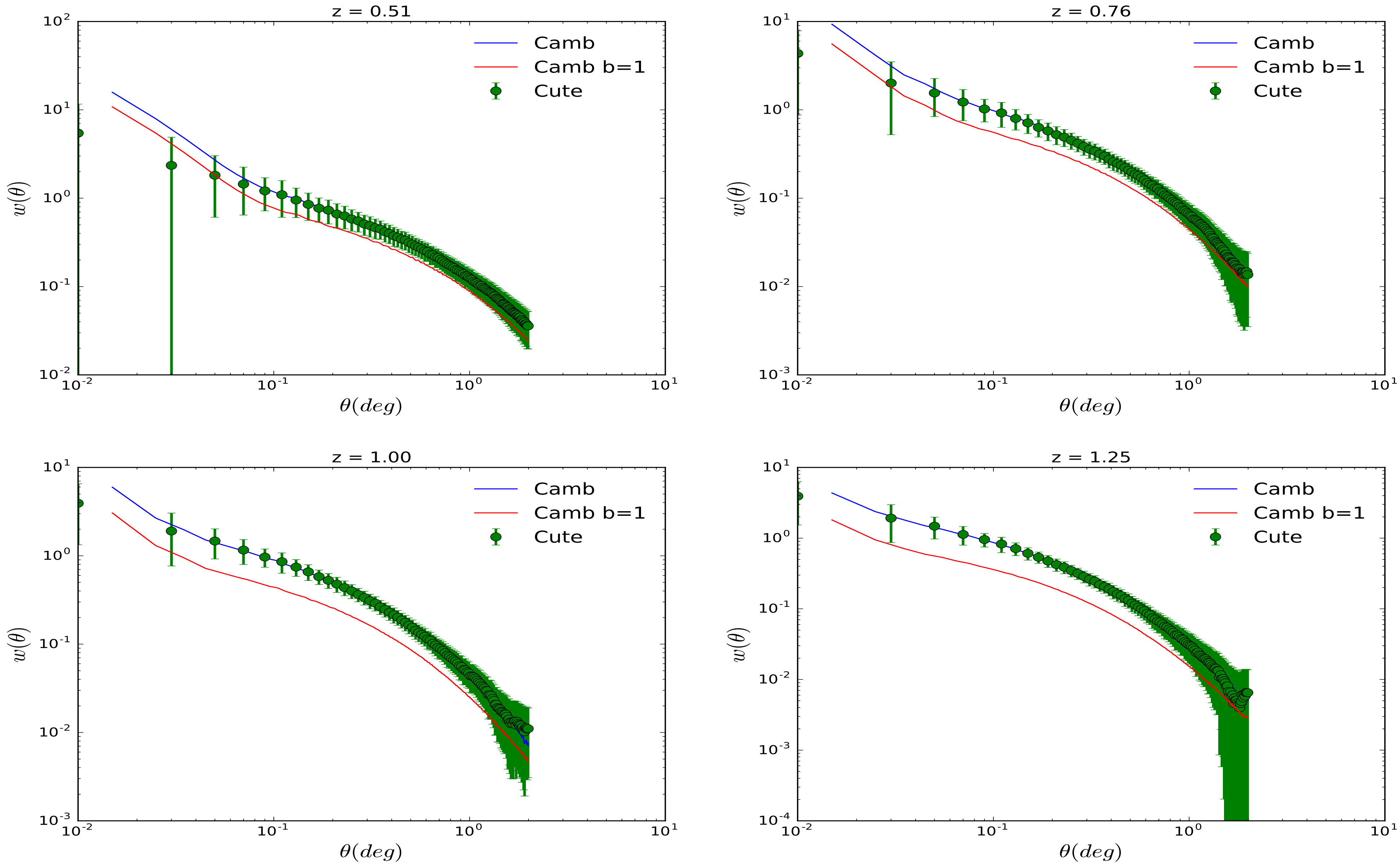


CiC in MICE

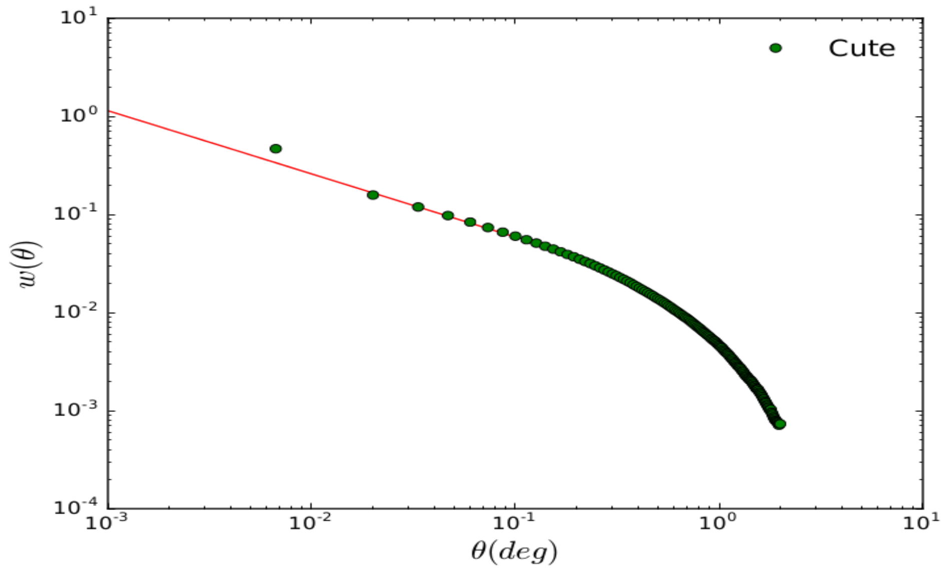


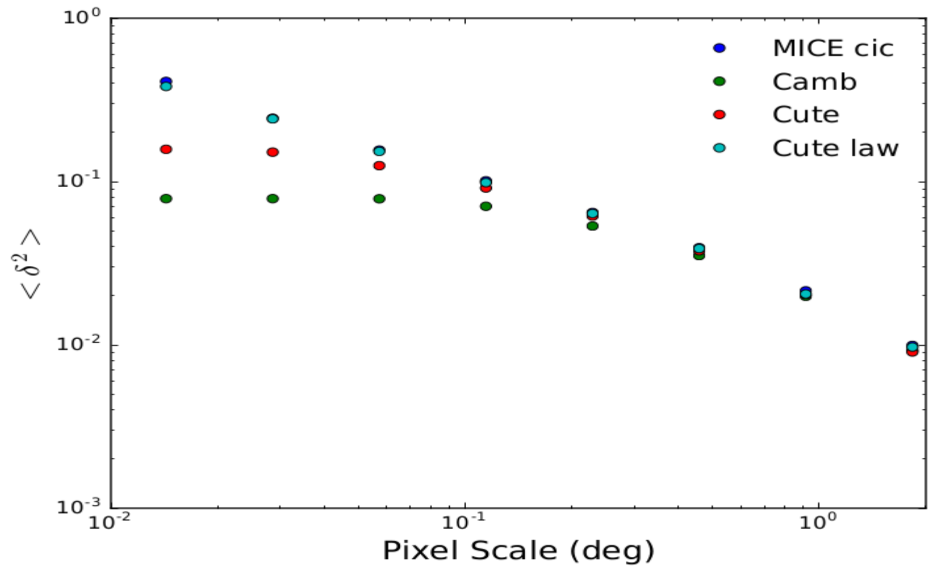
CUTE: cpu code to calculate Correlation functions from D. Alonso (arXiv:1210.1833.)

CiC in MICE

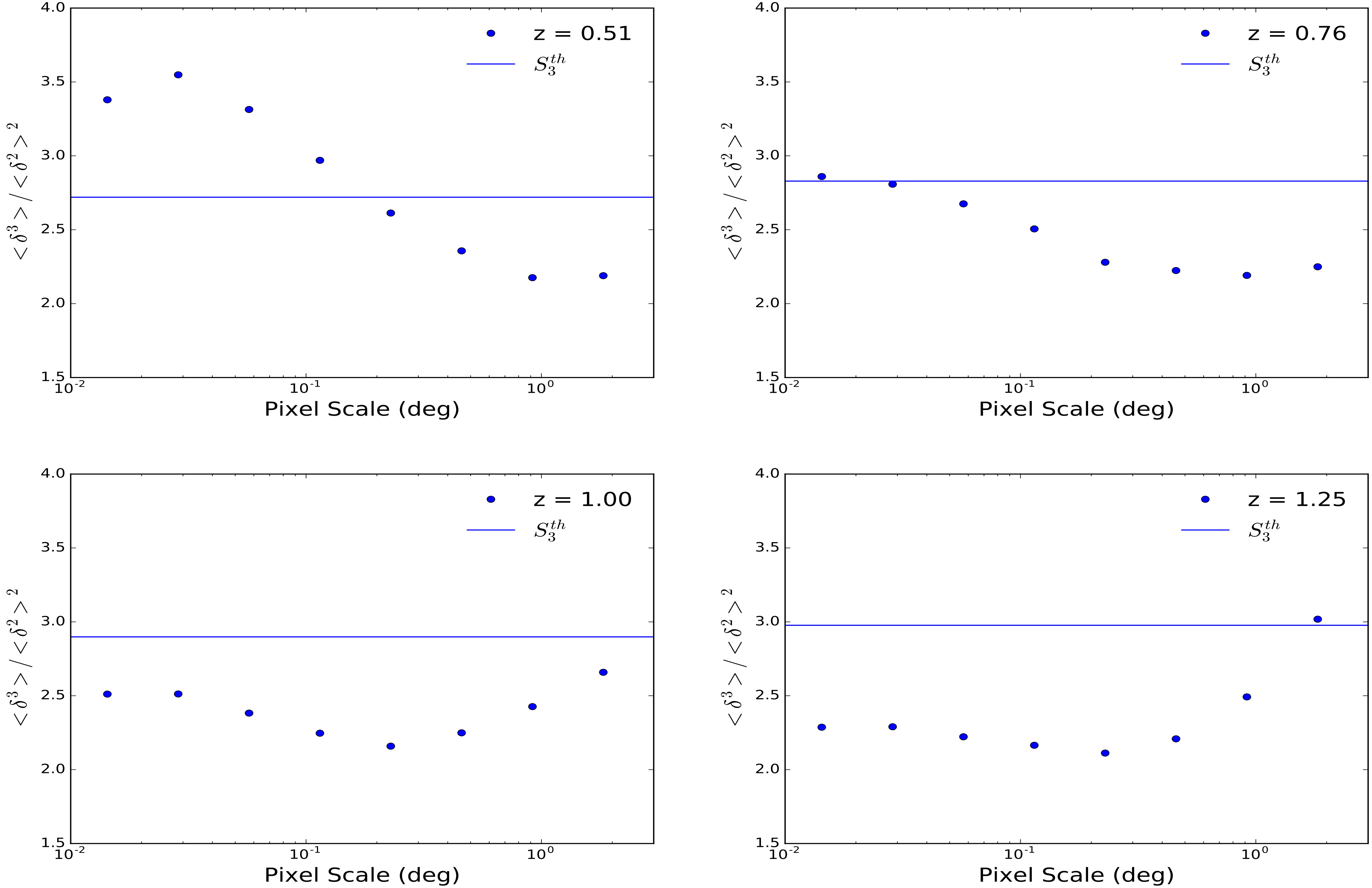


CiC in MICE

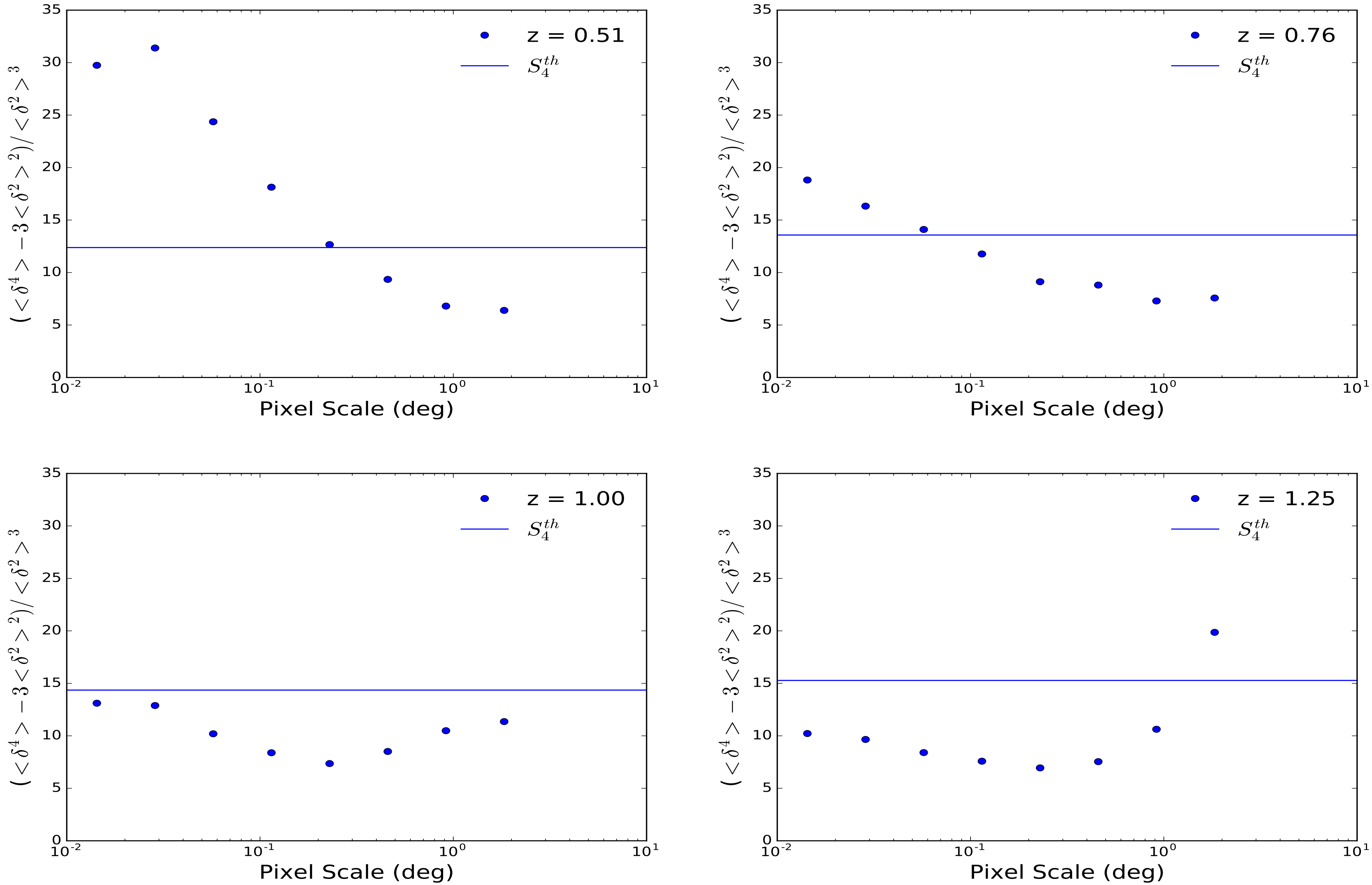

Cute
10^{1}
10^{0}
10^{-1}
10^{-2}
10^{-3}
10^{-4}
$w(\theta)$
10^{-3}
10^{-2}
10^{-1}
10^{0}
10^{1}
$\theta(deg)$


MICE cic
Camb
Cute
Cute law
10^{0}
10^{-1}
10^{-2}
10^{-3}
$<\delta^2>$
10^{-2}
10^{-1}
10^{0}
Pixel Scale (deg)

CiC in MICE

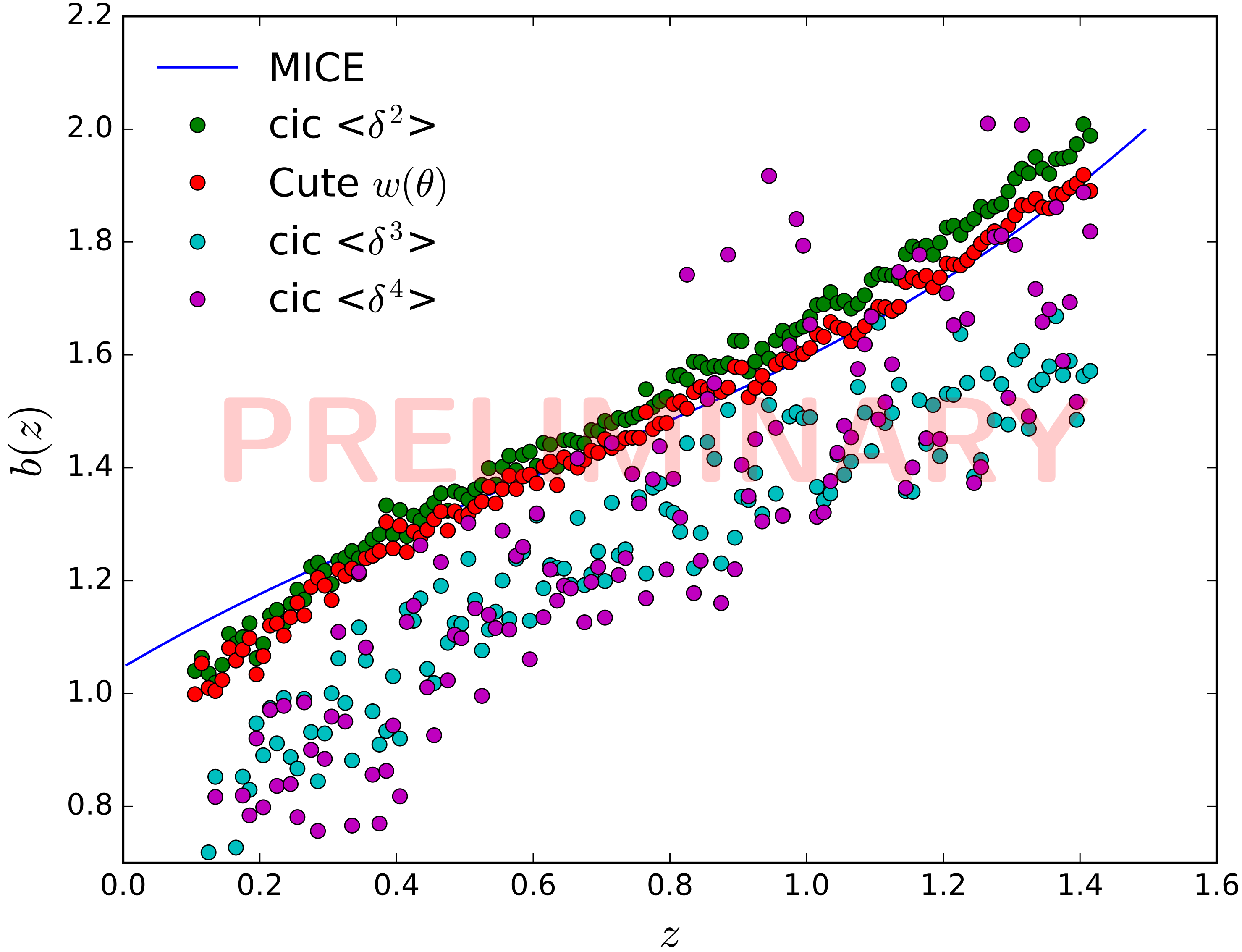

z = 0.51
S_3^{th}
z = 0.76
S_3^{th}
z = 1.00
S_3^{th}
z = 1.25
S_3^{th}
$<\delta^3> / <\delta^2>^2$
Pixel Scale (deg)
4.0
3.5
3.0
2.5
2.0
1.5
10^{-2}
10^{-1}
10^{0}

CiC in MICE

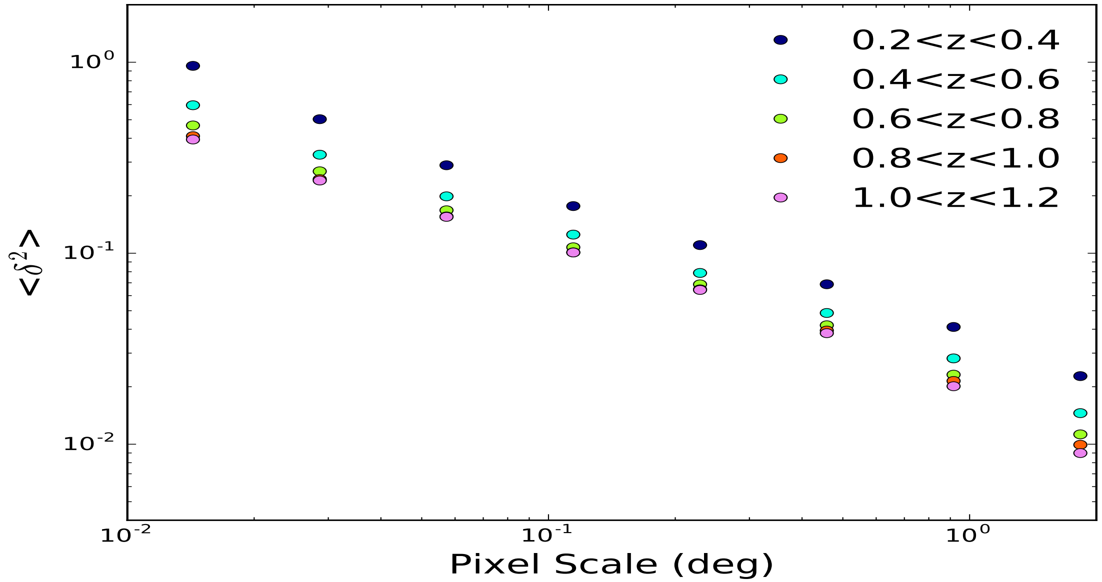


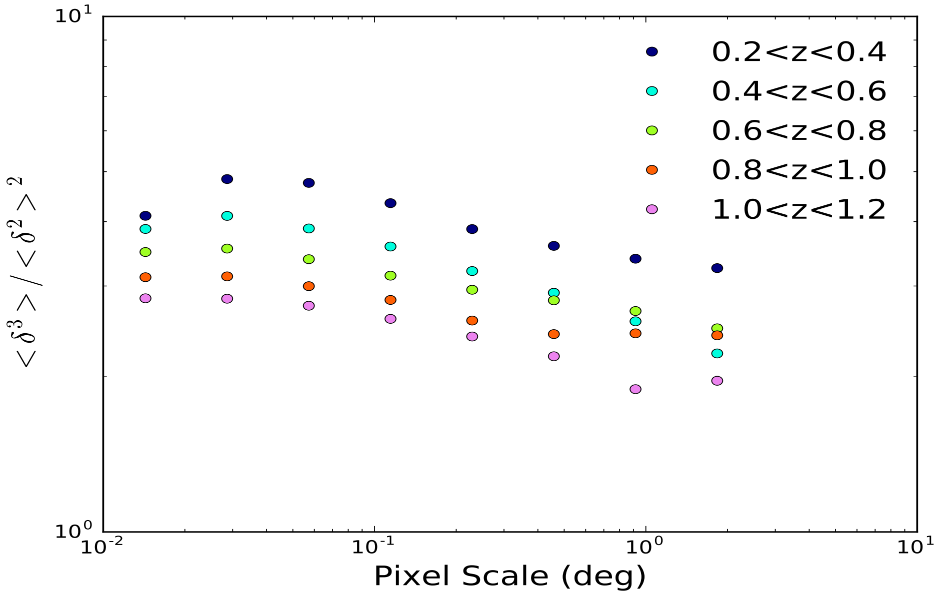
z = 0.51
z = 0.76
z = 1.00
z = 1.25
S_4^{th}
$(<\delta^4> - 3<\delta^2>^2)/<\delta^2>^3$
Pixel Scale (deg)

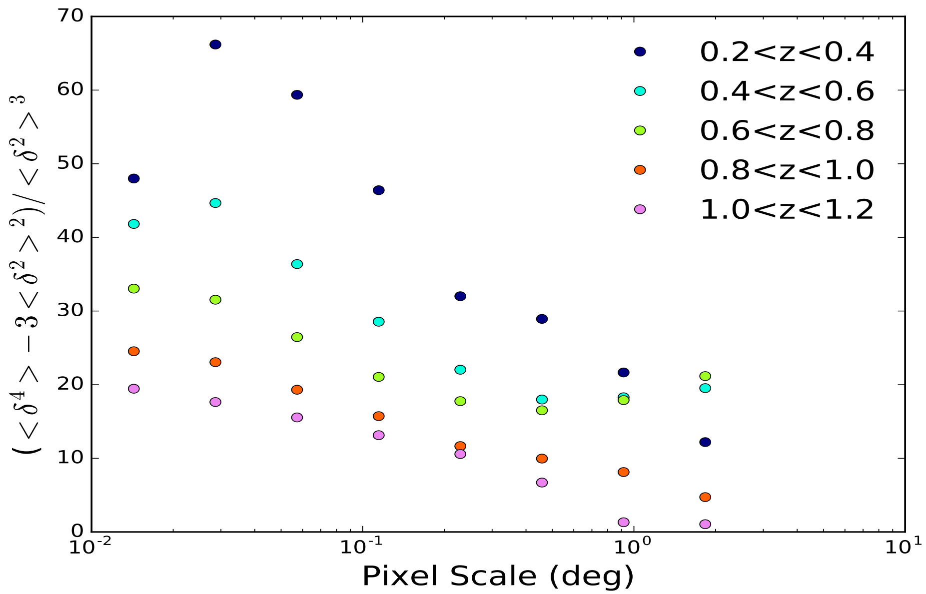
Bias from CiC in MICE



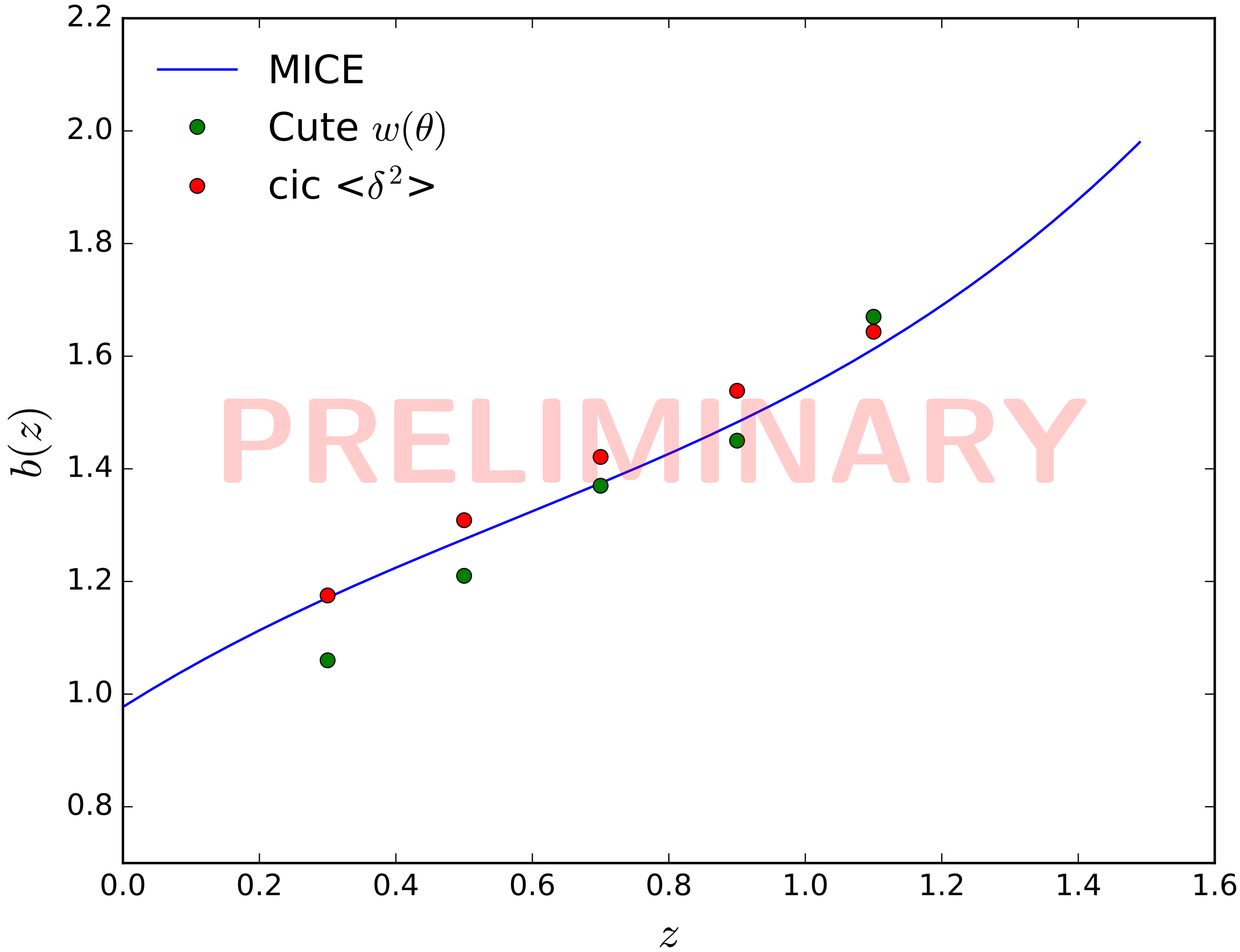
CiC in MICE


10^0
10^{-1}
10^{-2}
$<\delta^2>$
10^{-2}
10^{-1}
10^0
Pixel Scale (deg)
0.2<z<0.4
0.4<z<0.6
0.6<z<0.8
0.8<z<1.0
1.0<z<1.2


10^1
10^0
$<\delta^3>/<\delta^2>^2$
10^{-2}
10^{-1}
10^0
10^1
Pixel Scale (deg)
0.2<z<0.4
0.4<z<0.6
0.6<z<0.8
0.8<z<1.0
1.0<z<1.2


70
60
50
40
30
20
10
0
$(<\delta^4> - 3<\delta^2>^2)/<\delta^2>^3$
10^{-2}
10^{-1}
10^0
10^1
Pixel Scale (deg)
0.2<z<0.4
0.4<z<0.6
0.6<z<0.8
0.8<z<1.0
1.0<z<1.2

Bias from CiC in MICE



Conclusion

- We have an alternative way of estimating the bias beyond second order

- Future work:
  * Apply a photometric redshift to the simulation
  * Apply this method to real data

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