

Log-normal galaxy simulation for PFS

Ryu Makiya (Kavli IPMU/MPA)

collaborating with

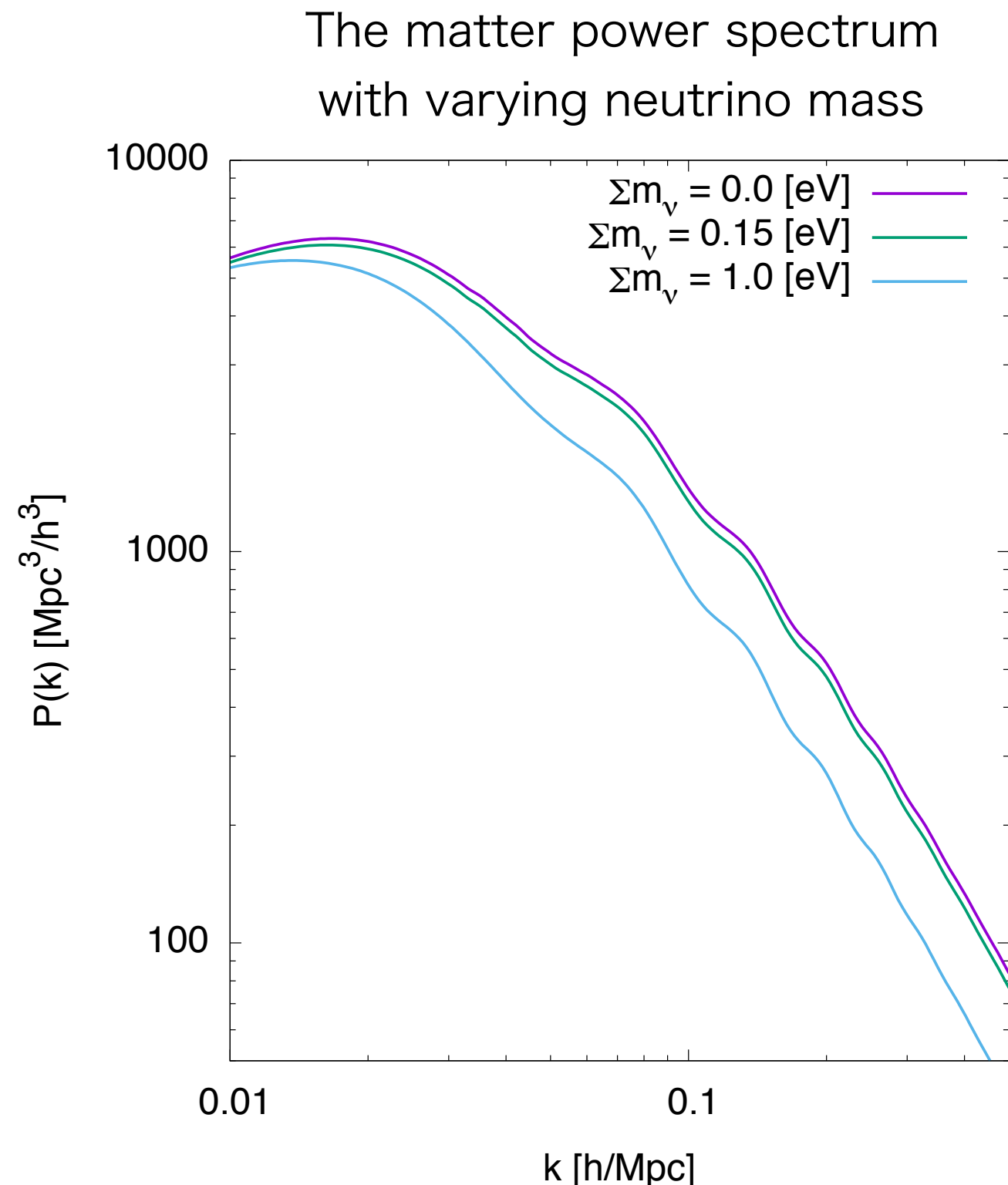
Eiichiro Komatsu, Shun Saito, Issha Kayo, Keitaro
Takahashi, Aniket Agrawal and Aoife Boyle

“Cosmic Acceleration” Symposium, KEK

March 10, 2017

neutrino cosmology

- free-streaming of massive neutrinos suppress the amplitude of matter power spectrum
- If $\Sigma m_\nu < 0.1$ [eV], we can rule out the inverted mass hierarchy
- How accurately can PFS constrain neutrino mass? Need for an end-to-end simulation.
=> **log-normal simulation!**



Log-normal simulation in redshift space

- We generate velocity field using the linearized continuity equation

$$\frac{d\delta_m(\boldsymbol{x})}{d\tau} + \nabla \cdot \boldsymbol{v}(\boldsymbol{x}) = 0$$

$$\nabla \cdot \boldsymbol{v} = -aHf\delta_m, \text{ where } f = \frac{d \ln \delta_m}{d \ln a}$$

first time that this is included in LN simulation!

- matter density field is generated following the same procedures for galaxies

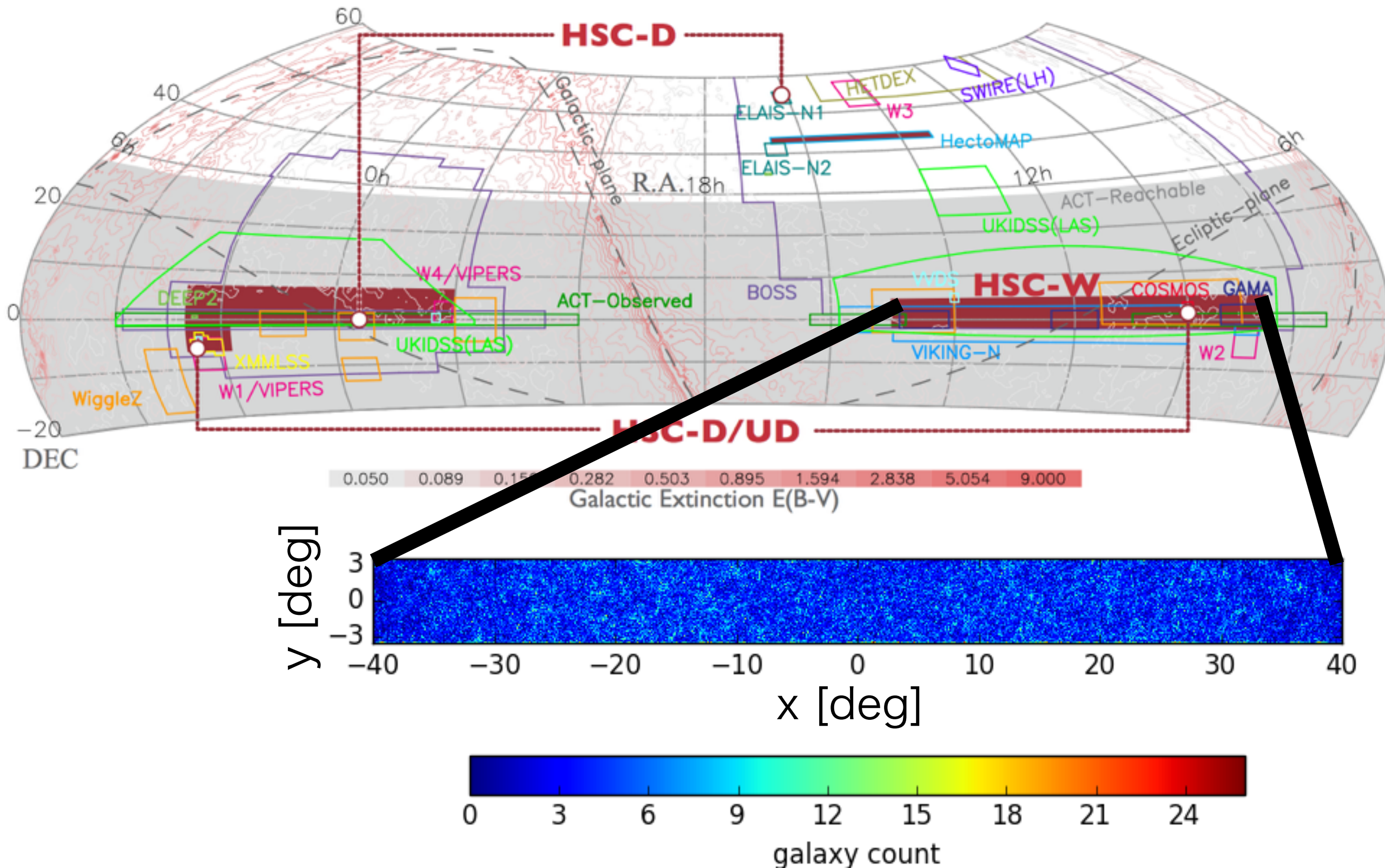
Log-normal simulation in redshift space

- real-to-redshift space mapping

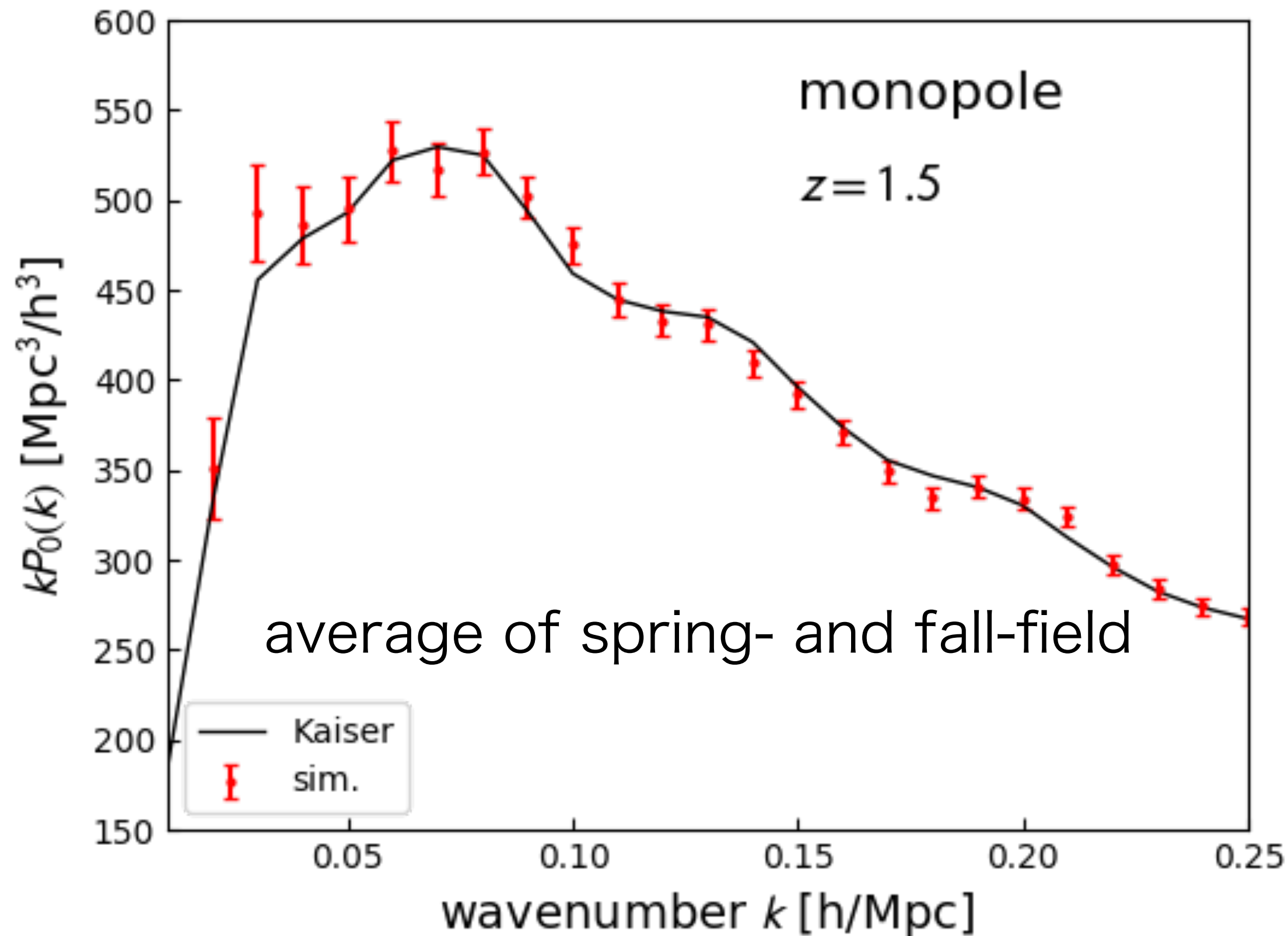
$$\overset{\text{redshift-space}}{1 + \boxed{\delta_g^s(\boldsymbol{s})}} = \frac{\overset{\text{real-space}}{1 + \boxed{\delta_g(\boldsymbol{x})}}}{\left| 1 + \frac{\nabla_z v_z(\boldsymbol{x})}{aH} \right|}$$

simulated galaxy map

$z = 1.5$, spring field



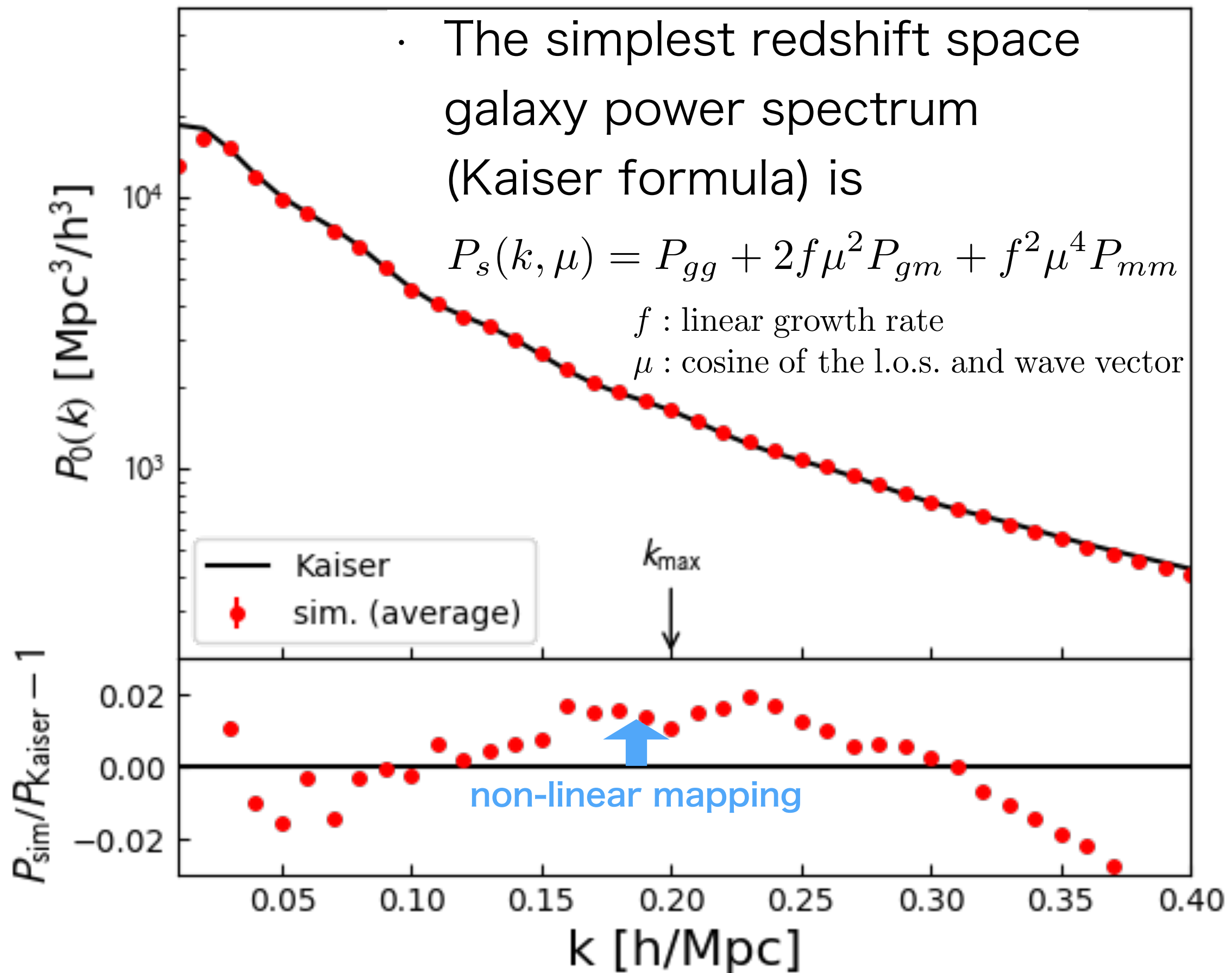
Power spectrum



Effects of Real-to-redshift space Mapping

- By construction, the output power spectrum in “real space” [without peculiar velocities] is the same as the input
- Mapping from real space to redshift space including redshift space distortion is non-linear, and this needs to be included in the theoretical model
- Of course this can be calculated precisely from the first principle. In practice, we find that such a calculation is cumbersome and intractable...

Effects of Real-to-redshift space Mapping



Effects of Real-to-redshift space Mapping

- the simulation doesn't exactly match with the Kaiser formula due to the effect of non-linear mapping, thus we introduce a correction factor F_{corr} :

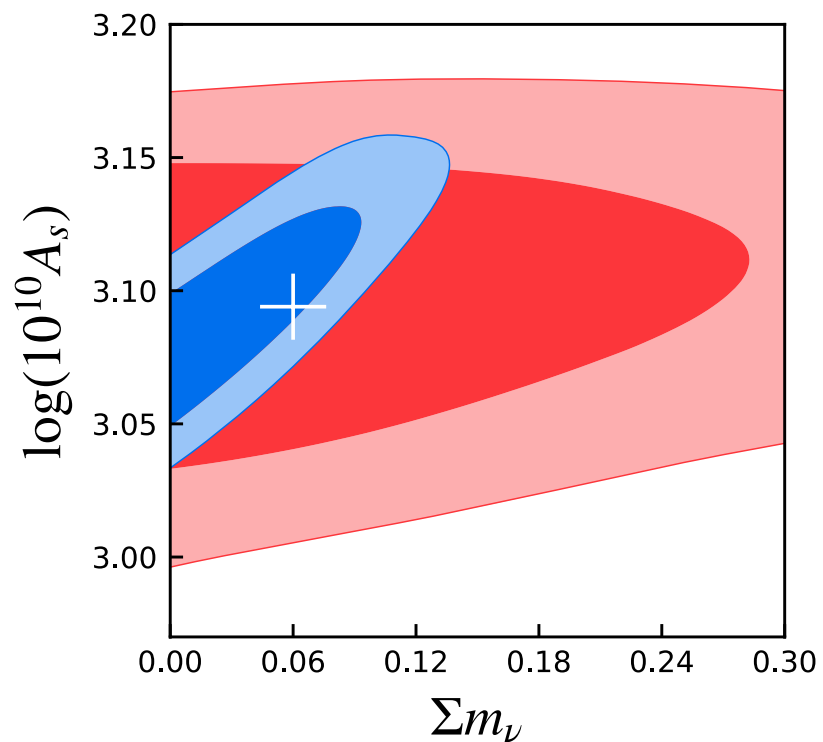
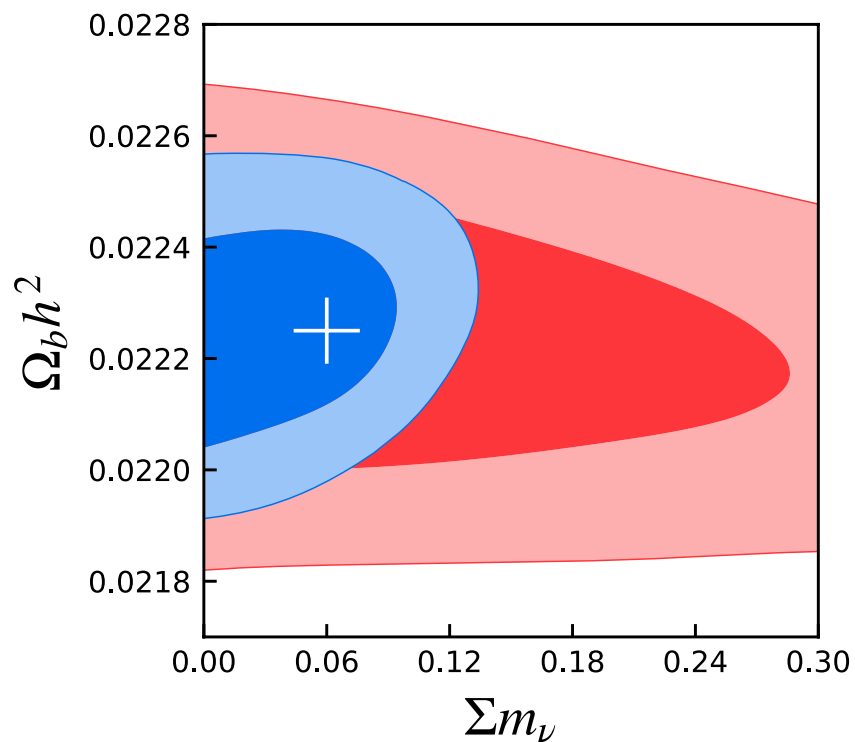
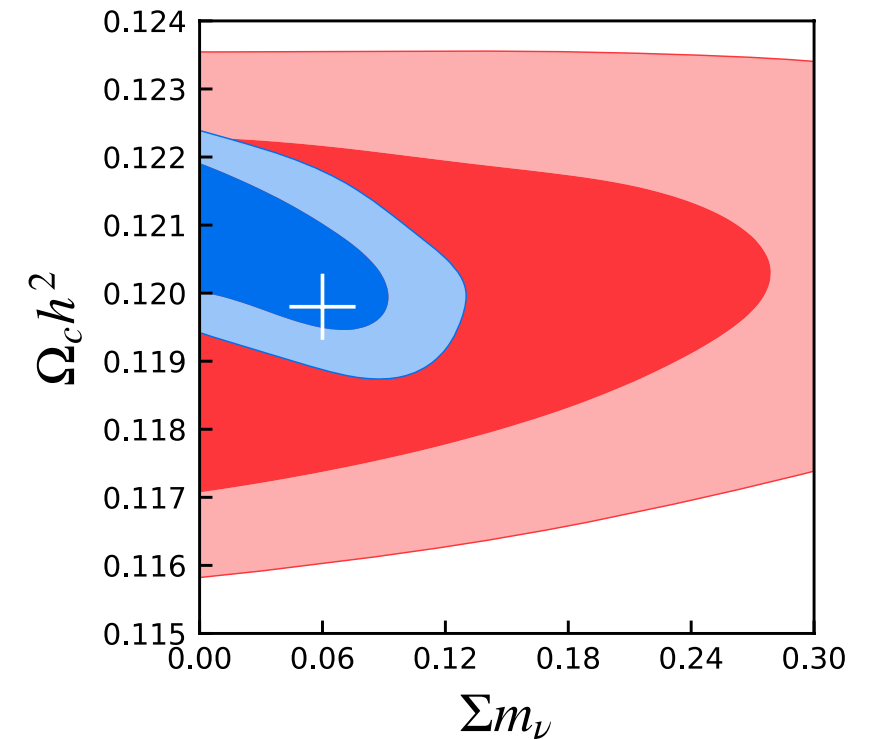
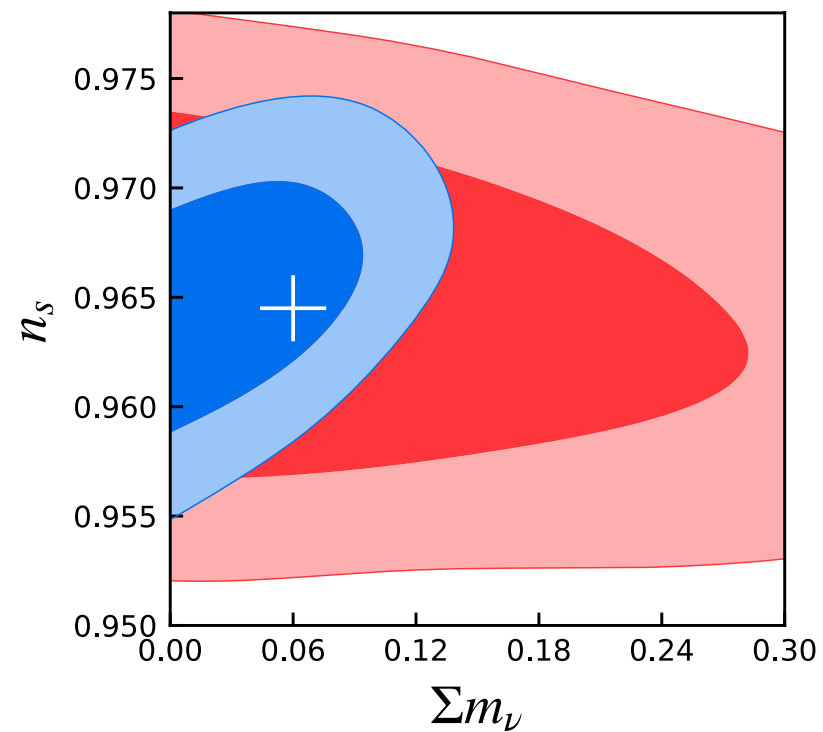
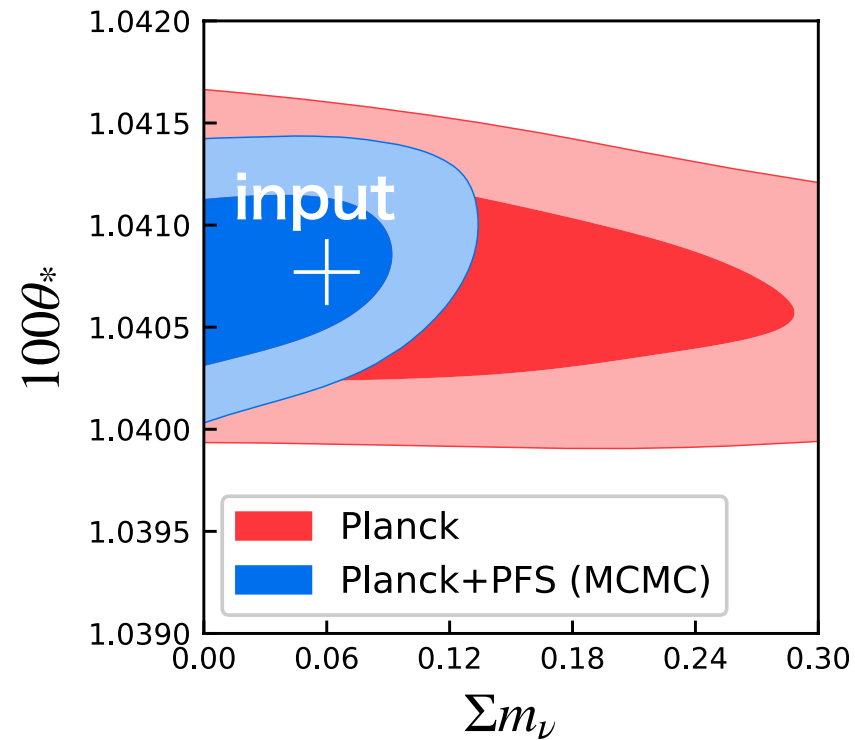
$$P_{\text{Kaiser,mod}} = F_{\text{corr}}(k, z) P_{\text{Kaiser}}$$

- F_{corr} is chosen so that the model power spectra exactly match with the average of simulations
- Assuming that F_{corr} doesn't depend on the cosmology

Parameter fitting

- Fit the model to power spectra of simulated galaxies by using the MCMC method
- Covariance matrix is estimated from 1,000 realizations of the log-normal simulation
- Use both of monopole and quadrupole power spectra
 - $k_{\text{max}} = 0.2 \text{ h/Mpc}$
- Taking into account the Alcock-Paczynski effect
- Use the prior distribution of cosmological parameters obtained by Planck 2015

Constraint on neutrino mass (Λ CDM)

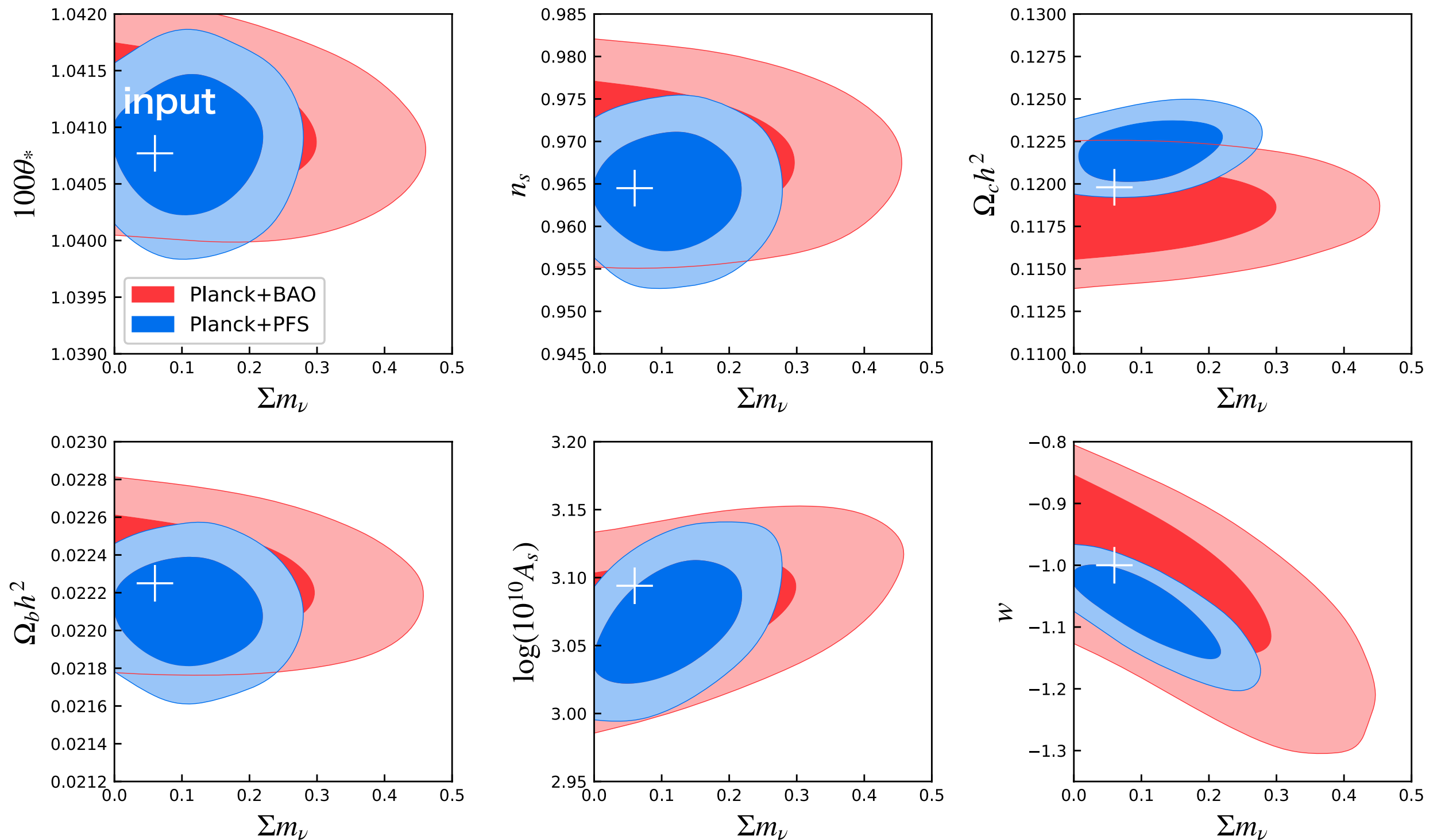


$$\Sigma m_\nu < 0.104 \text{ [eV]} \\ (95\% \text{ C.L.})$$

* Planck only
 $\Sigma m_\nu < 0.487 \text{ [eV]}$

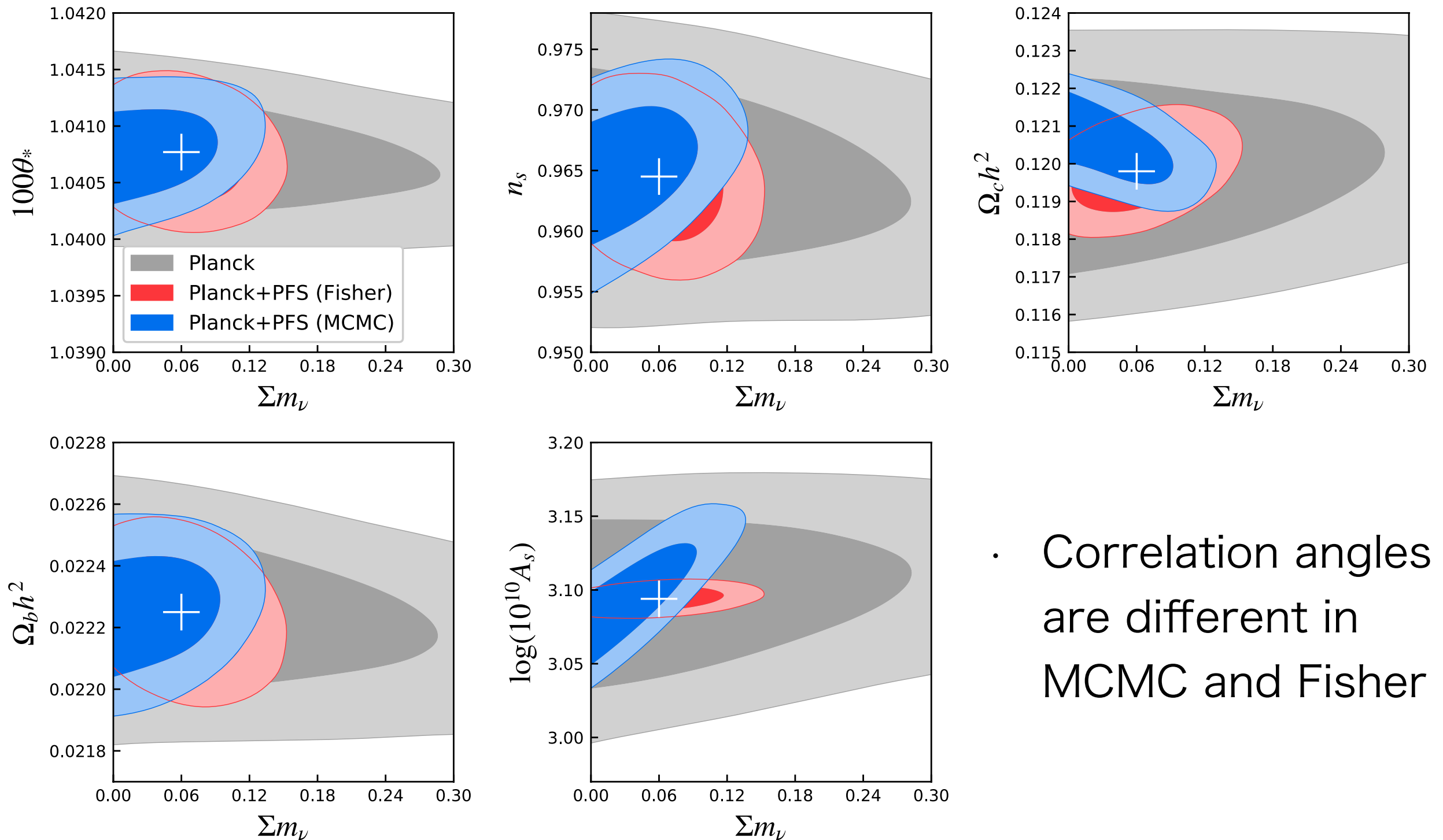
* Planck + BOSS
 $\Sigma m_\nu < 0.17 \text{ [eV]}$

Constraint on neutrino mass (wCDM)



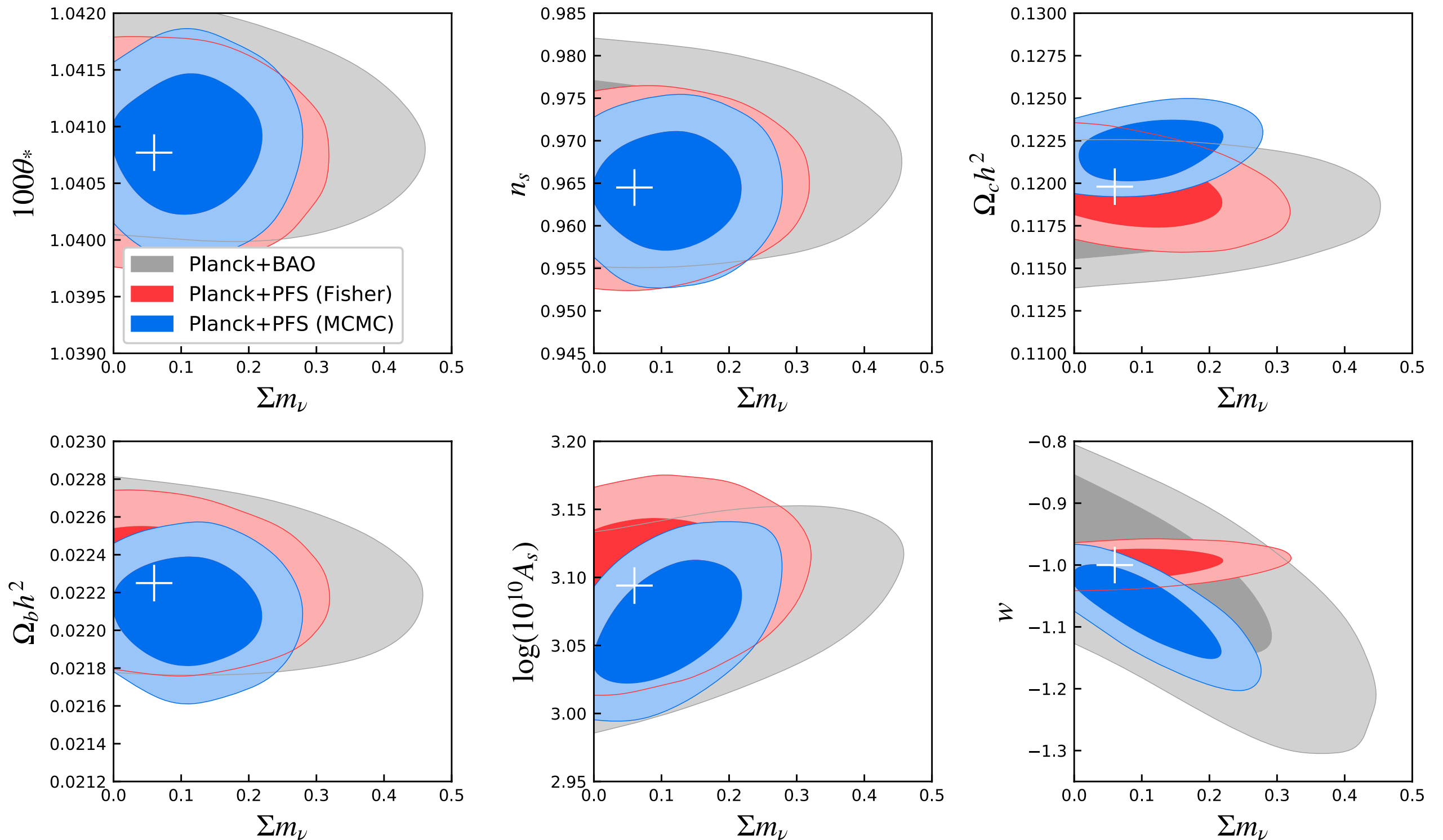
$$\Sigma m_\nu < 0.238 \text{ [eV]}, \quad -1.18 < w < -0.992 \quad (95\% \text{ C.L.})$$

Fisher forecast vs MCMC (Λ CDM)



- Correlation angles are different in MCMC and Fisher

Fisher forecast vs MCMC (wCDM)



Summary

- We have developed the code for large scale structure simulation and made predictions for the constraints on cosmological parameters from PFS
- Constraint on neutrino mass
 - < 0.10 eV for Λ CDM and < 0.24 eV for wCDM
 - HSC lensing may help rule out the inverted mass hierarchy!
- Caveats
 - non-linear property of log-normal simulation is still not fully understood
 - Fisher forecast does not match with MCMC

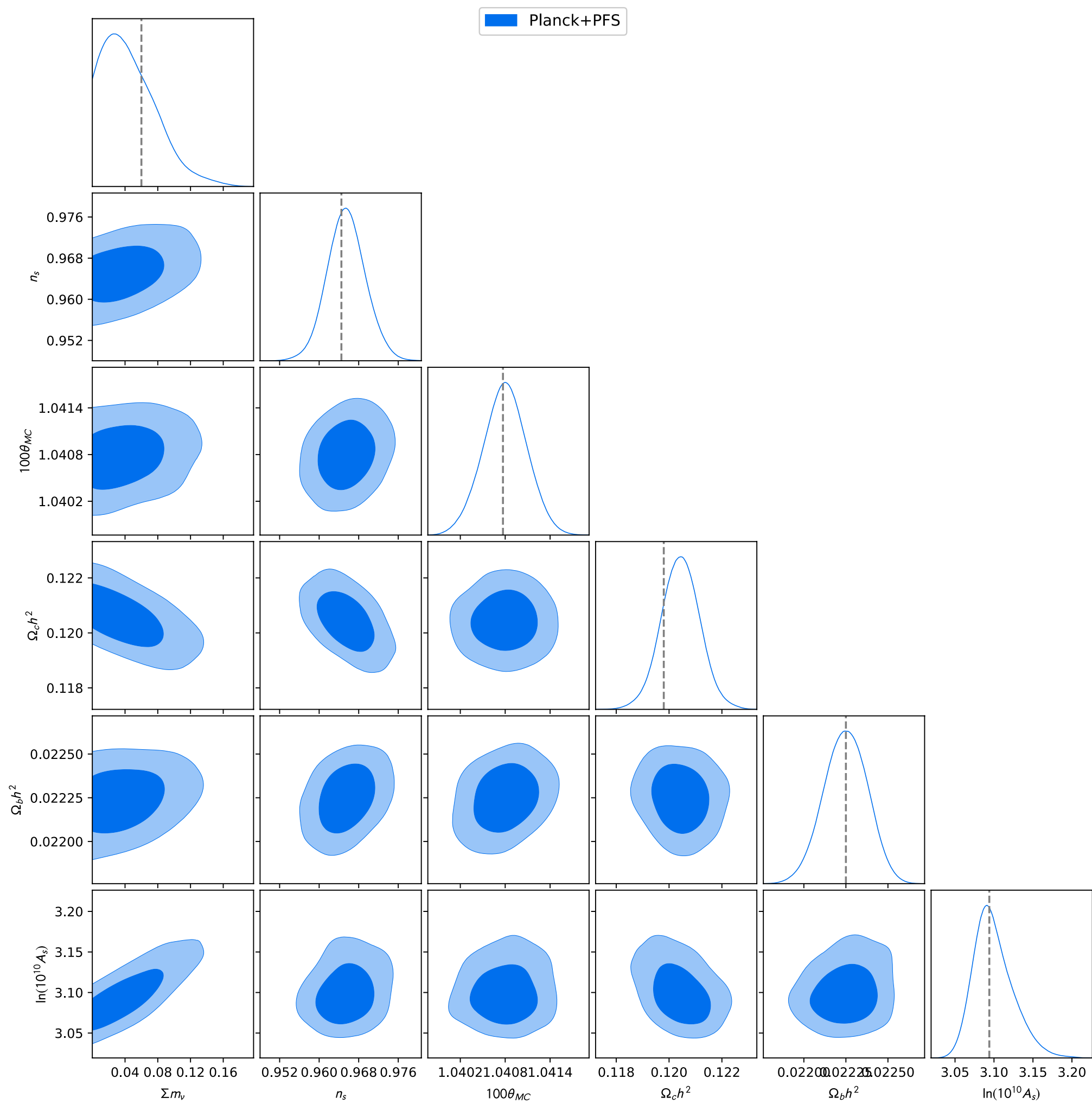
Appendix

log-normal simulation

- Assume that a logarithm of density fluctuation δ , $G=\ln(1+\delta)$, follows Gaussian distribution
- generate galaxy density field from input power spectrum, then Poisson-sample them to create mock galaxy catalog
- N-body simulations show that the non-linear density field is well approximated by log-normal distribution (e.g., Kayo, Suto and Taruya 2001)
- Why we use such a simple model?
 - Because we can precisely know what the outcome of the model should be

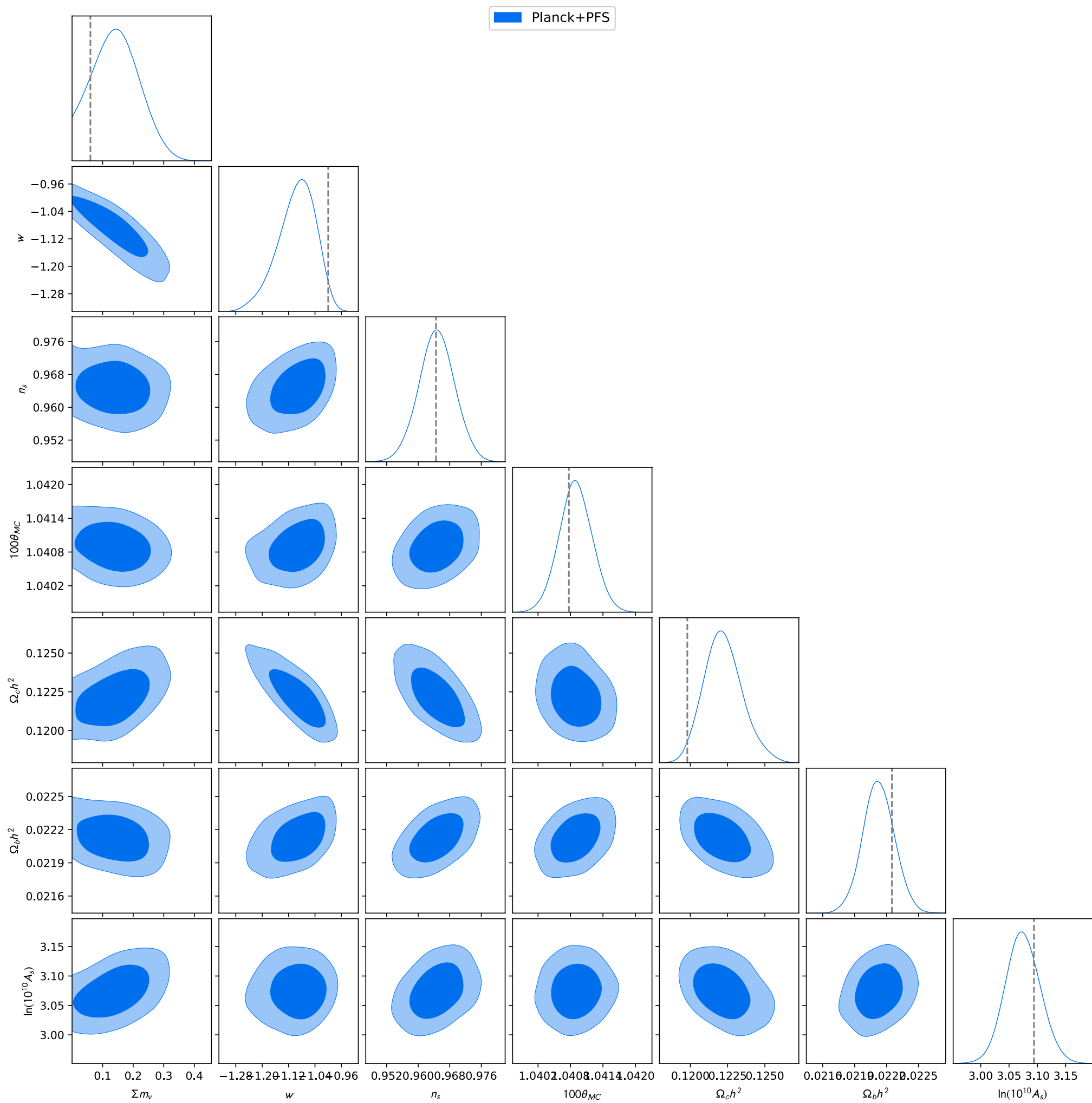
Λ CDM+m_nu (P_Kaiser x F_corr)

	input	best-fit	mean	95%
Σm_ν	6.000e-02	3.609e-02	4.819e-02	[0.000e+00, 1.090e-01]
$\Omega_b h^2$	2.225e-02	2.217e-02	2.225e-02	[2.200e-02, 2.249e-02]
$\Omega_c h^2$	1.198e-01	1.204e-01	1.204e-01	[1.190e-01, 1.219e-01]
$100\theta_*$	1.04077	1.04080	1.04080	[1.04022, 1.04137]
n_s	9.645e-01	9.633e-01	9.655e-01	[9.581e-01, 9.733e-01]
$\ln(10^{10} A_s)$	3.094	3.091	3.099	[3.053, 3.153]
bias (z=0.7)	1.180	1.165	1.166	[1.130, 1.202]
bias (z=0.9)	1.260	1.247	1.245	[1.215, 1.274]
bias (z=1.1)	1.340	1.337	1.334	[1.302, 1.365]
bias (z=1.3)	1.420	1.399	1.403	[1.371, 1.433]
bias (z=1.5)	1.500	1.487	1.482	[1.448, 1.513]
bias (z=1.8)	1.620	1.618	1.617	[1.581, 1.651]
bias (z=2.2)	1.780	1.758	1.754	[1.716, 1.794]

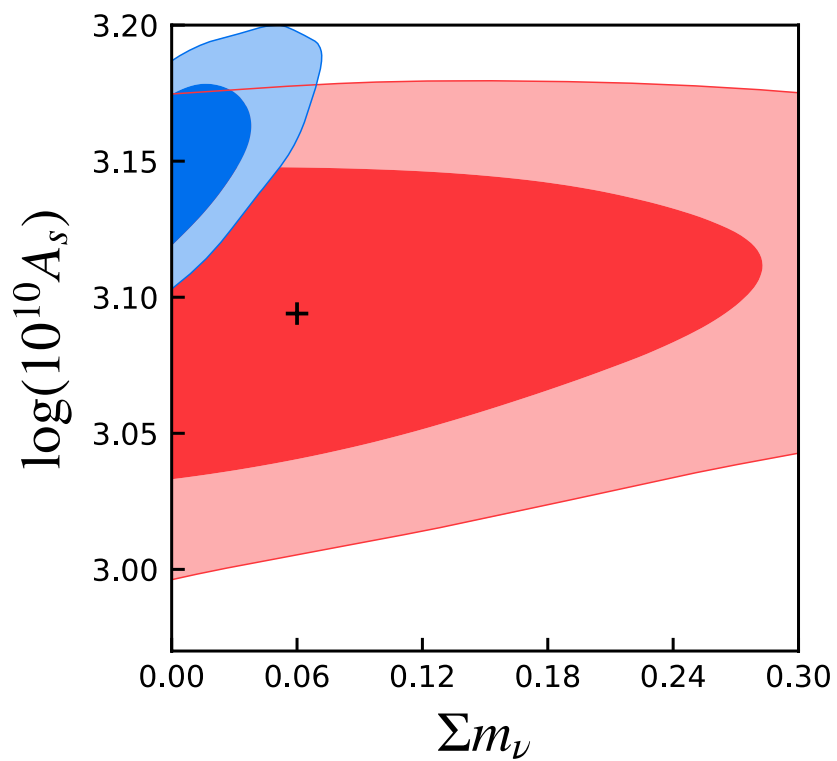
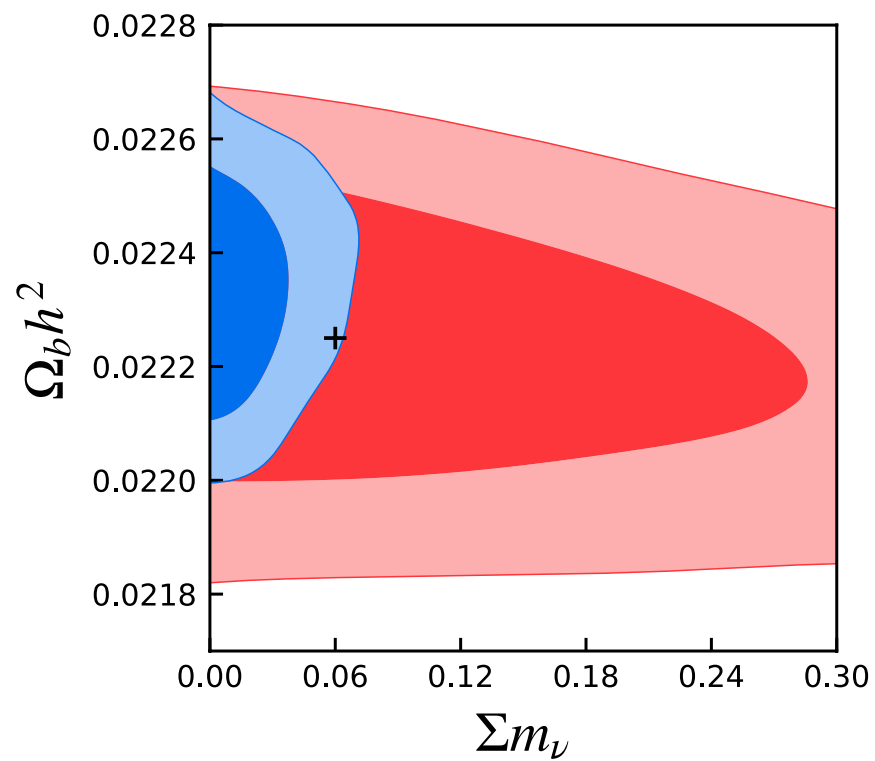
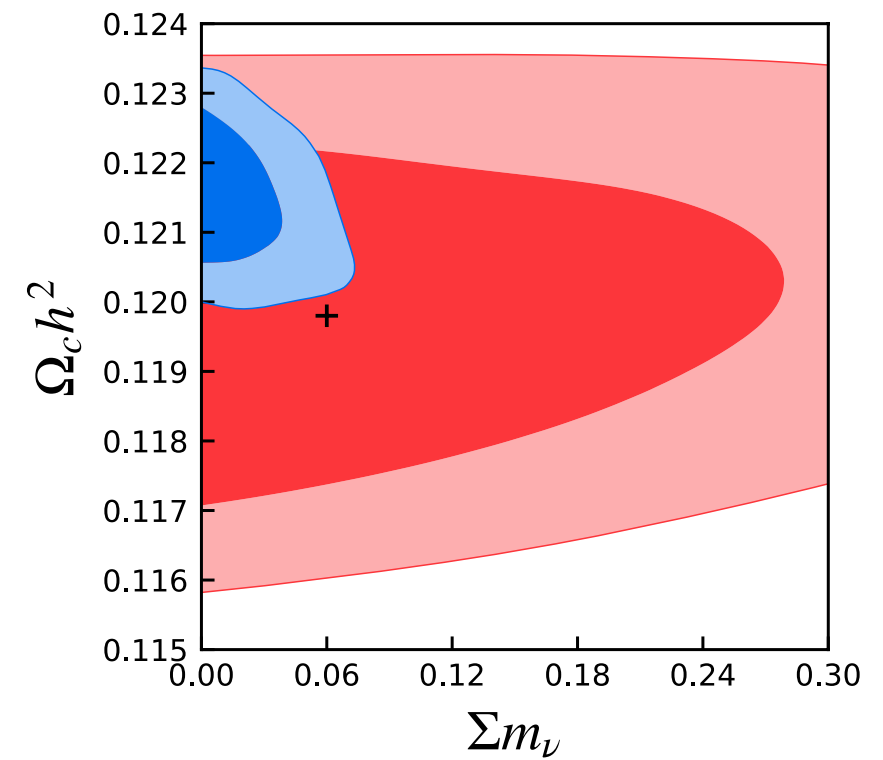
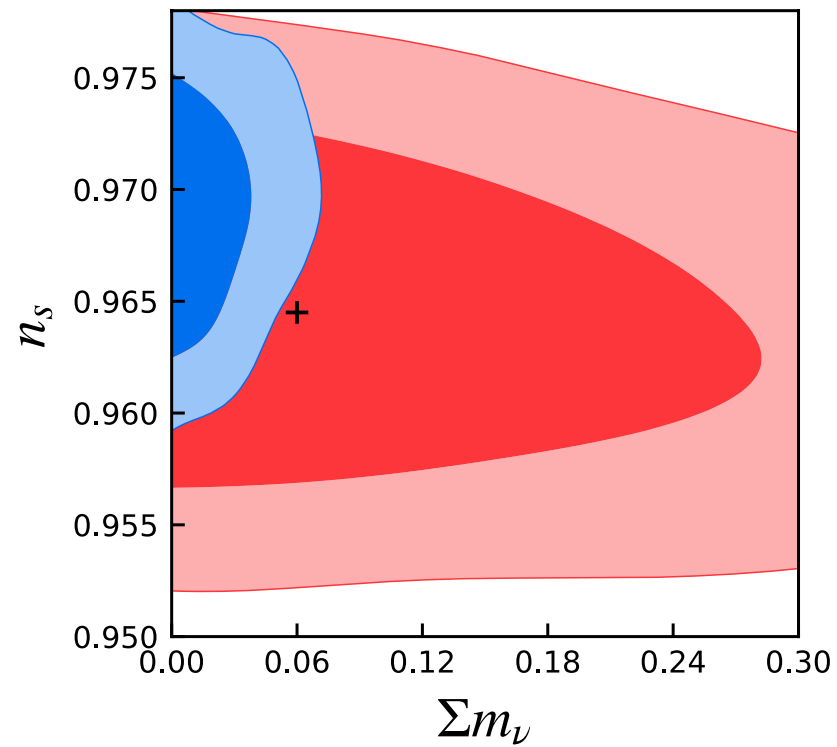
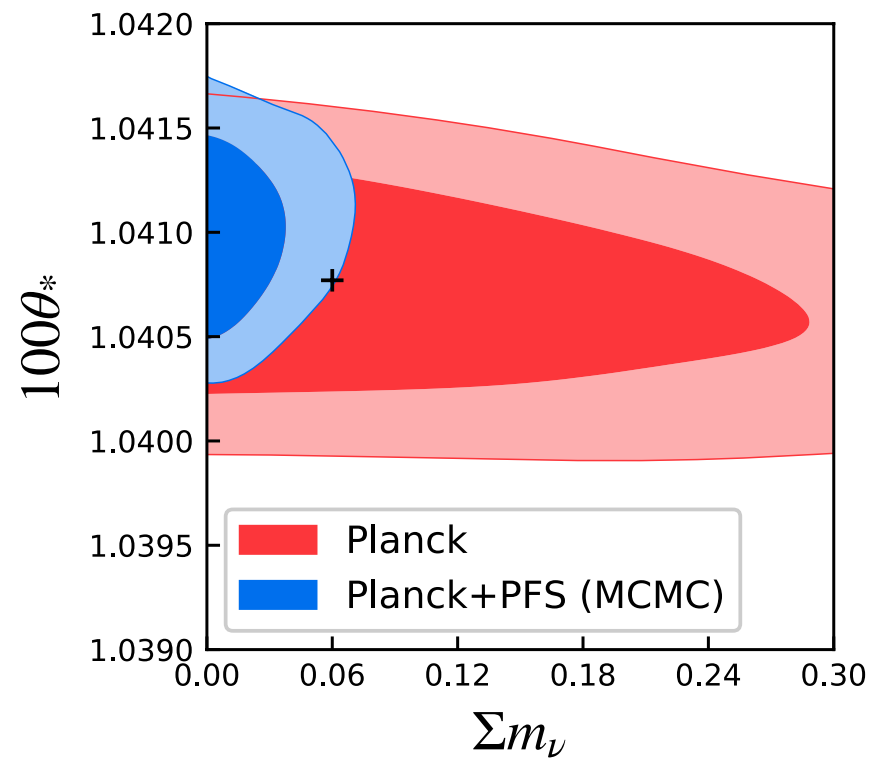


wCDM+m_nu (P_Kaiser x F_corr)

	input	best-fit	mean	95%
Σm_ν	6.000e-02	1.511e-01	1.453e-01	[0.000e+00, 2.729e-01]
w	-1.000e+00	-1.112e+00	-1.095e+00	[-1.211e+00, -9.923e-01]
$\Omega_b h^2$	2.225e-02	2.211e-02	2.213e-02	[2.183e-02, 2.242e-02]
$\Omega_c h^2$	1.198e-01	1.225e-01	1.222e-01	[1.198e-01, 1.248e-01]
$100\theta_*$	1.04077	1.17199	1.04090	[1.04029, 1.04151]
n_s	9.645e-01	9.643e-01	9.647e-01	[9.558e-01, 9.737e-01]
$\ln(10^{10} A_s)$	3.094	3.074	3.075	[3.016, 3.137]
bias (z=0.7)	1.180	1.172	1.173	[1.137, 1.210]
bias (z=0.9)	1.260	1.256	1.257	[1.226, 1.290]
bias (z=1.1)	1.340	1.341	1.347	[1.315, 1.381]
bias (z=1.3)	1.420	1.411	1.420	[1.386, 1.453]
bias (z=1.5)	1.500	1.495	1.500	[1.464, 1.538]
bias (z=1.8)	1.620	1.628	1.638	[1.600, 1.676]
bias (z=2.2)	1.780	1.774	1.778	[1.737, 1.821]



Λ CDM model (Kaiser)

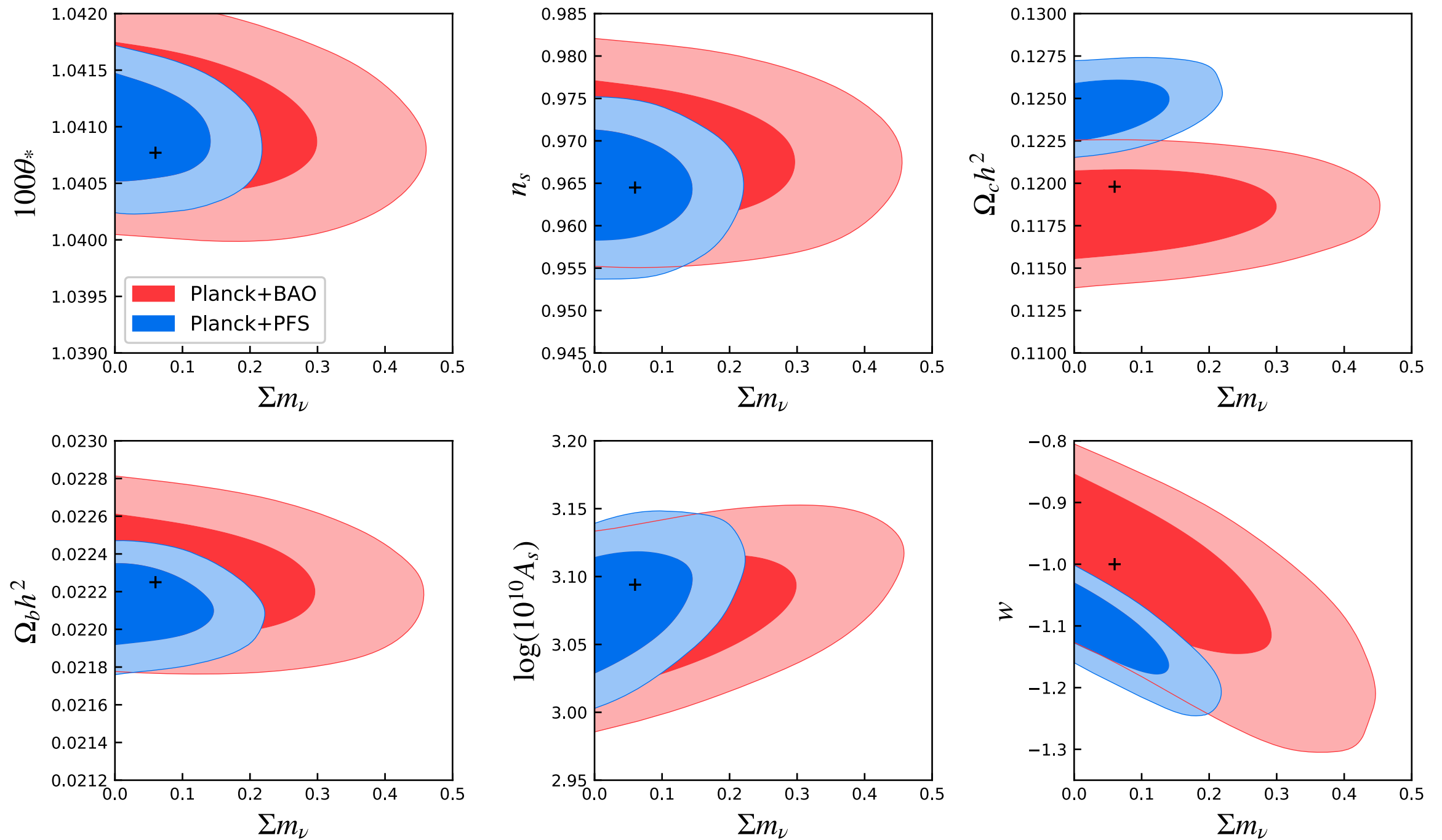


$$\Sigma m_\nu < 0.0551 \text{ [eV]}$$

$$\Sigma m_\nu < 0.487 \text{ [eV]}$$

(Planck only)

wCDM model (Kaiser)



$$\Sigma m_\nu < 0.1787 \text{ [eV]}$$

Λ CDM+m_nu (Kaiser)

	input	best-fit	mean	95%
Σm_ν	6.000e-02	6.643e-03	2.054e-02	[0.000e+00, 5.507e-02]
$\Omega_b h^2$	2.225e-02	2.225e-02	2.234e-02	[2.208e-02, 2.259e-02]
$\Omega_c h^2$	1.198e-01	1.218e-01	1.215e-01	[1.201e-01, 1.228e-01]
$100\theta_*$	1.041e+00	1.041e+00	1.041e+00	[1.040e+00, 1.042e+00]
n_s	0.96450	0.96745	0.96909	[0.96194, 0.97643]
$\ln(10^{10} A_s)$	3.094e+00	3.149e+00	3.157e+00	[3.121e+00, 3.194e+00]
bias (z=0.7)	1.180	1.081	1.089	[1.055, 1.124]
bias (z=0.9)	1.260	1.173	1.176	[1.149, 1.204]
bias (z=1.1)	1.340	1.267	1.265	[1.238, 1.297]
bias (z=1.3)	1.420	1.332	1.334	[1.305, 1.364]
bias (z=1.5)	1.500	1.416	1.412	[1.381, 1.445]
bias (z=1.8)	1.620	1.540	1.535	[1.504, 1.571]
bias (z=2.2)	1.780	1.664	1.660	[1.626, 1.696]

wCDM+m_nu (Kaiser)

	input	best-fit	mean	95%
Σm_ν	6.000e-02	2.080e-02	7.486e-02	[0.000e+00, 1.787e-01]
w	-1.000e+00	-1.108e+00	-1.125e+00	[-1.222e+00, -1.036e+00]
$\Omega_b h^2$	2.225e-02	2.215e-02	2.212e-02	[2.184e-02, 2.240e-02]
$\Omega_c h^2$	1.198e-01	1.244e-01	1.246e-01	[1.224e-01, 1.272e-01]
$100\theta_*$	1.04077	1.09398	1.04093	[1.04034, 1.04152]
n_s	9.645e-01	9.627e-01	9.645e-01	[9.555e-01, 9.731e-01]
$\ln(10^{10} A_s)$	3.094	3.056	3.084	[3.027, 3.142]
bias (z=0.7)	1.180	1.094	1.091	[1.055, 1.126]
bias (z=0.9)	1.260	1.187	1.183	[1.153, 1.212]
bias (z=1.1)	1.340	1.280	1.276	[1.247, 1.307]
bias (z=1.3)	1.420	1.347	1.347	[1.316, 1.379]
bias (z=1.5)	1.500	1.432	1.427	[1.394, 1.461]
bias (z=1.8)	1.620	1.554	1.554	[1.519, 1.590]
bias (z=2.2)	1.780	1.683	1.682	[1.642, 1.721]

