Improving convection parameterizations with a library of large-eddy simulations

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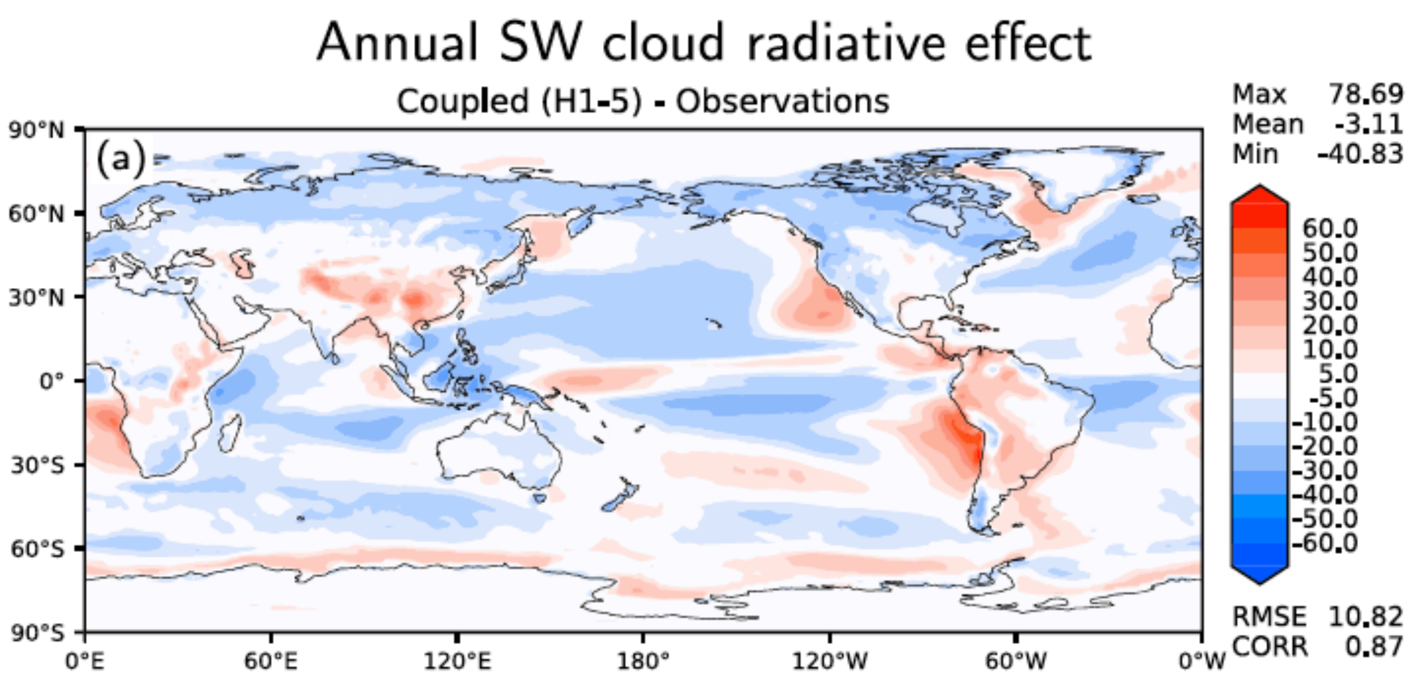
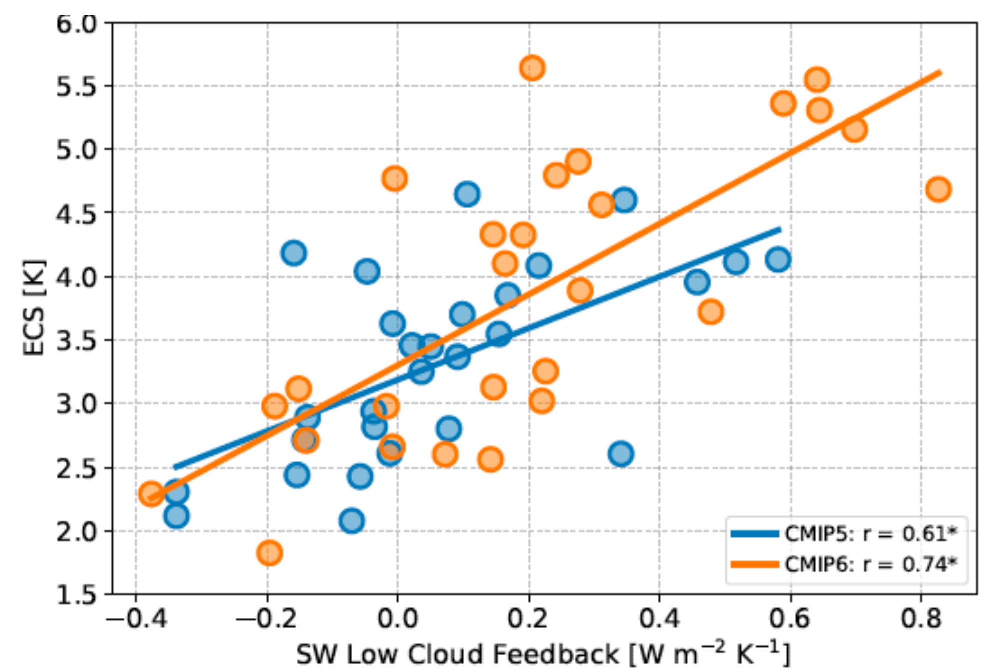
CLIMATE MODELING ALLIANCE

Low clouds dominate uncertainties in climate predictions

- Strong biases remain in GCM simulated cloud radiative effects.
- Low cloud feedback is strongly correlated with climate sensitivity.



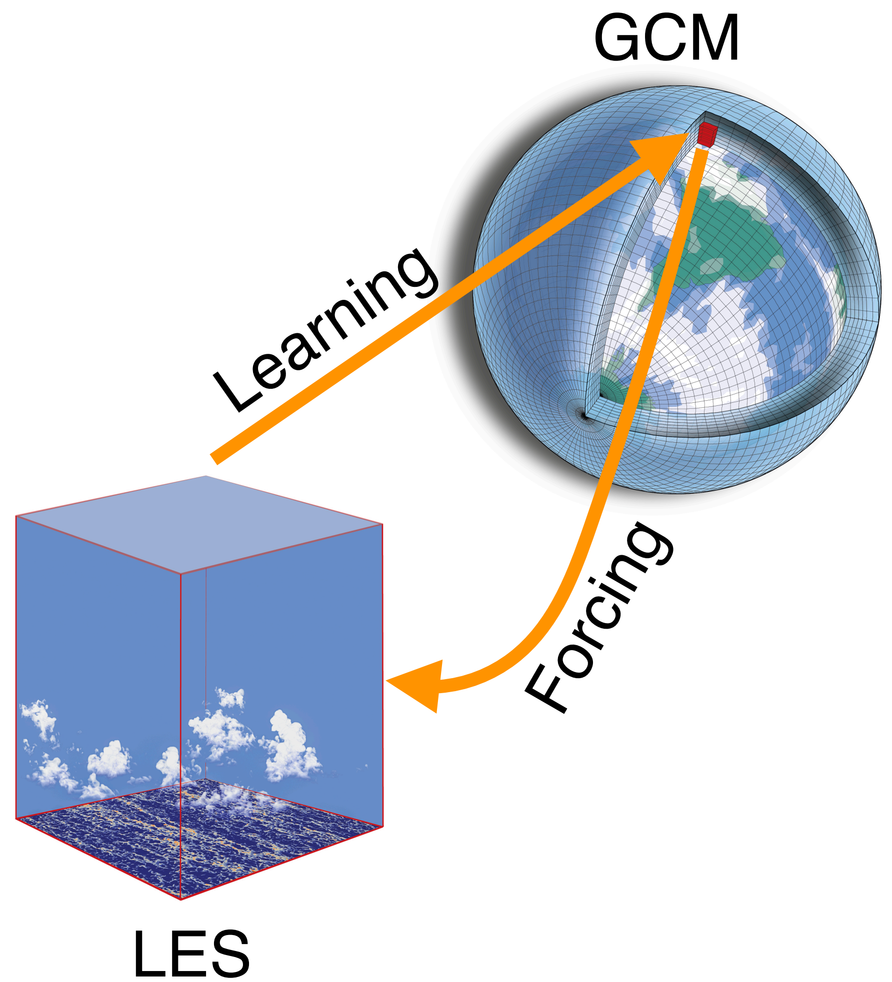
[Golaz et al. 2019]



[Zelinka et al. 2020]

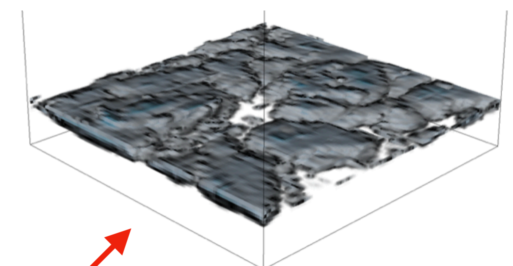
LES can be used to train GCM parameterizations

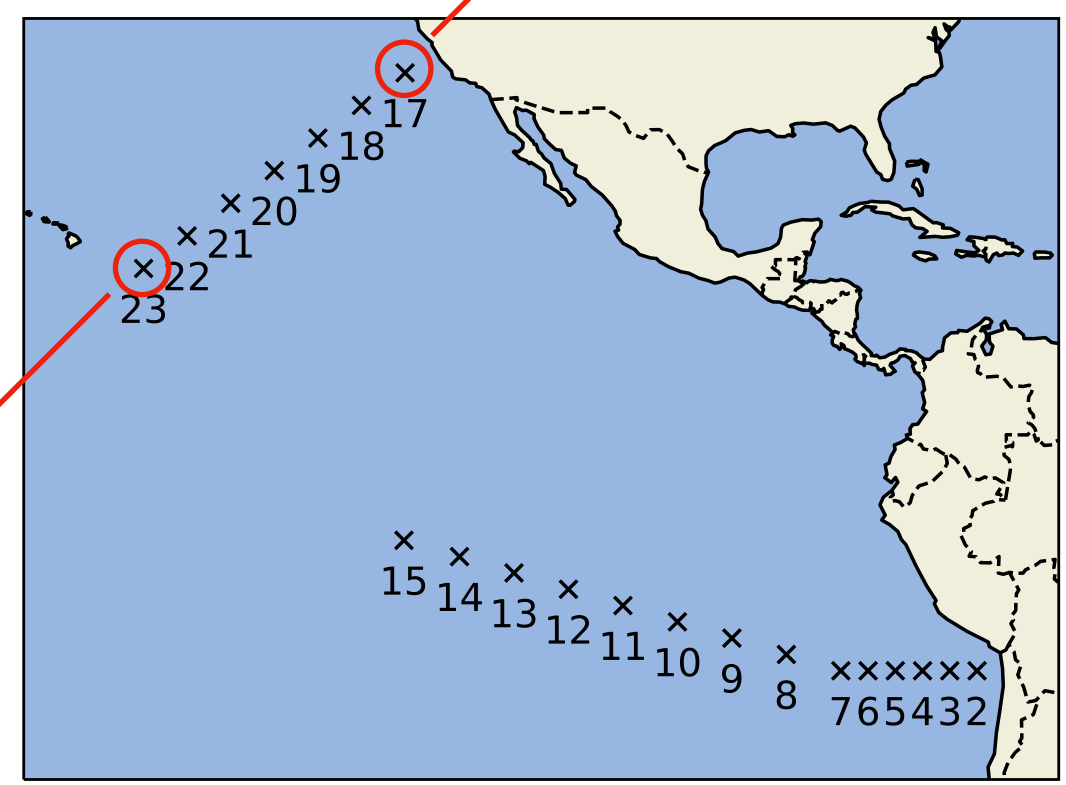
- While GCMs cannot simulate them, LES can provide high fidelity simulations of clouds in limited area, which can be used to improve GCM parameterizations.
- We can run many LES driven by large-scale forcing in a GCM at different locations to generate data that span a wide range of cloud regimes. [Shen et al. 2020]

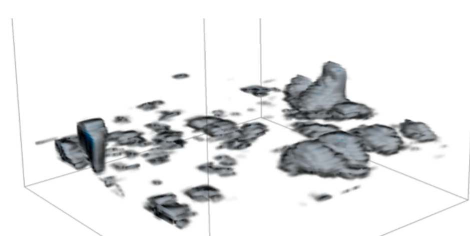


Sampling the East Pacific with LES simulations

- PyCLES [Pressel et al. 2015]
- 5-year averaged monthly mean forcing from HadGEM2-A amip experiments
- Prescribed SST, RRTM, one-moment microphysics based on Kessler
- Domain size: 6km x 6km x 4km, resolution: 75m x 75m x 20m
- Simulation time: 6 days







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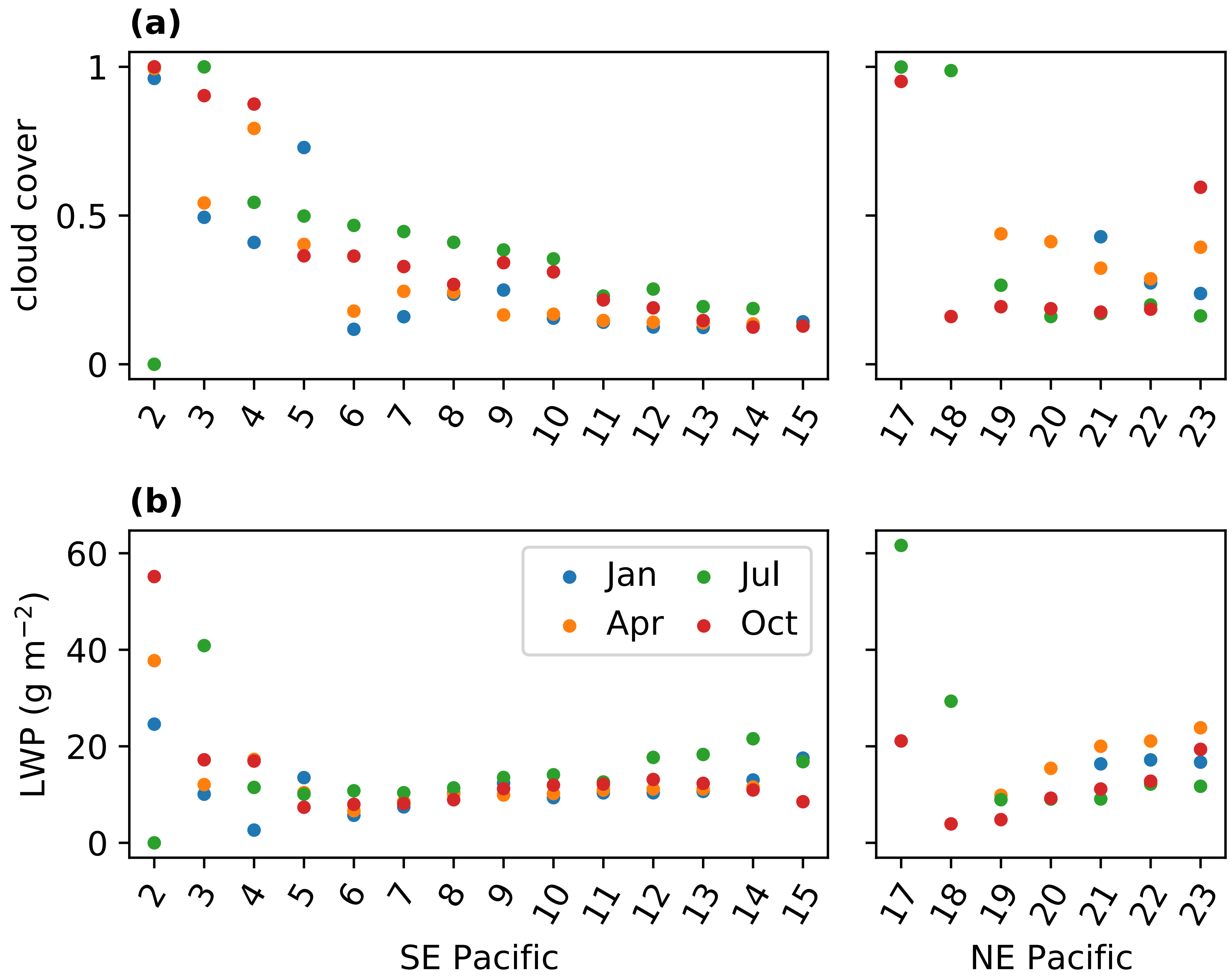
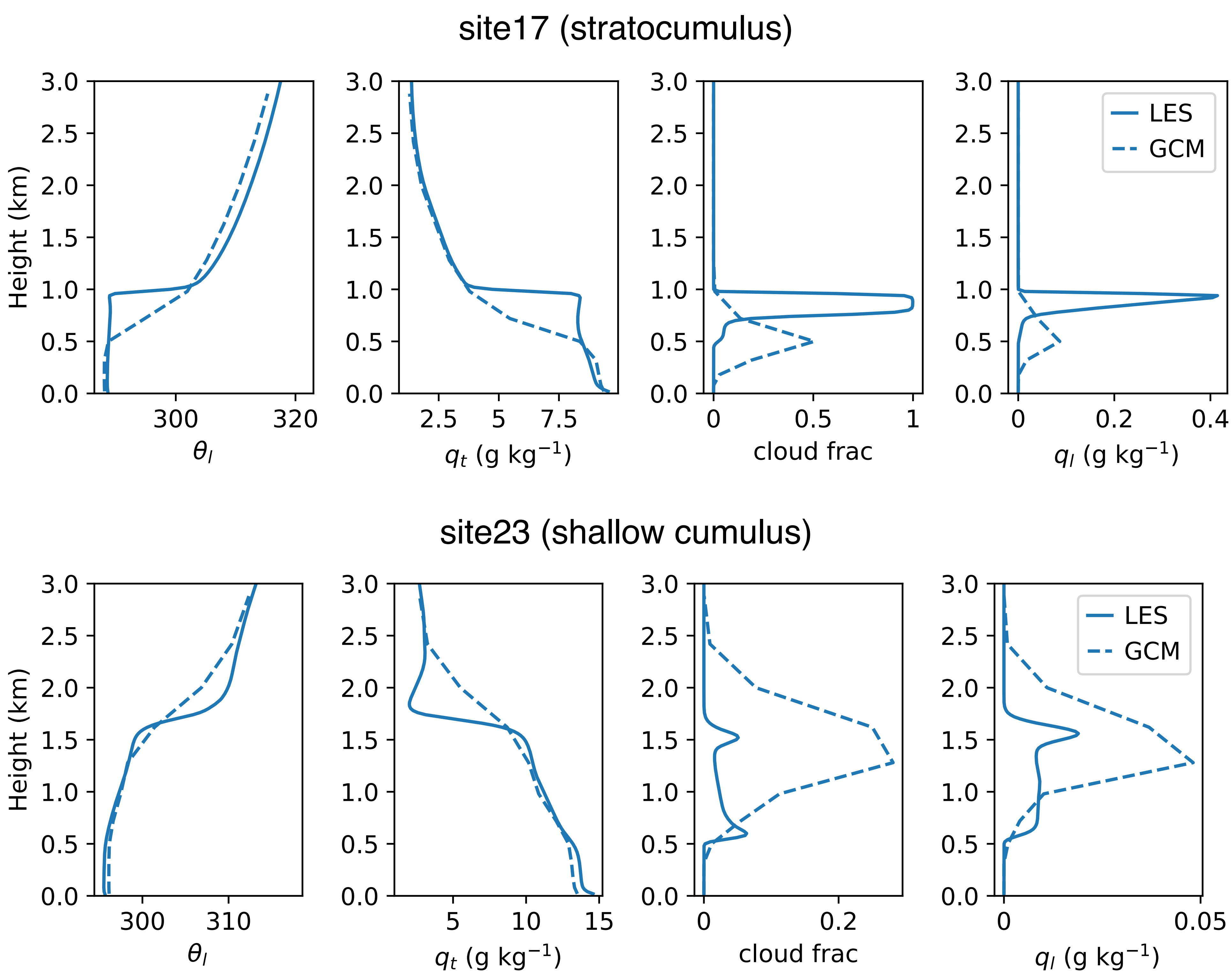
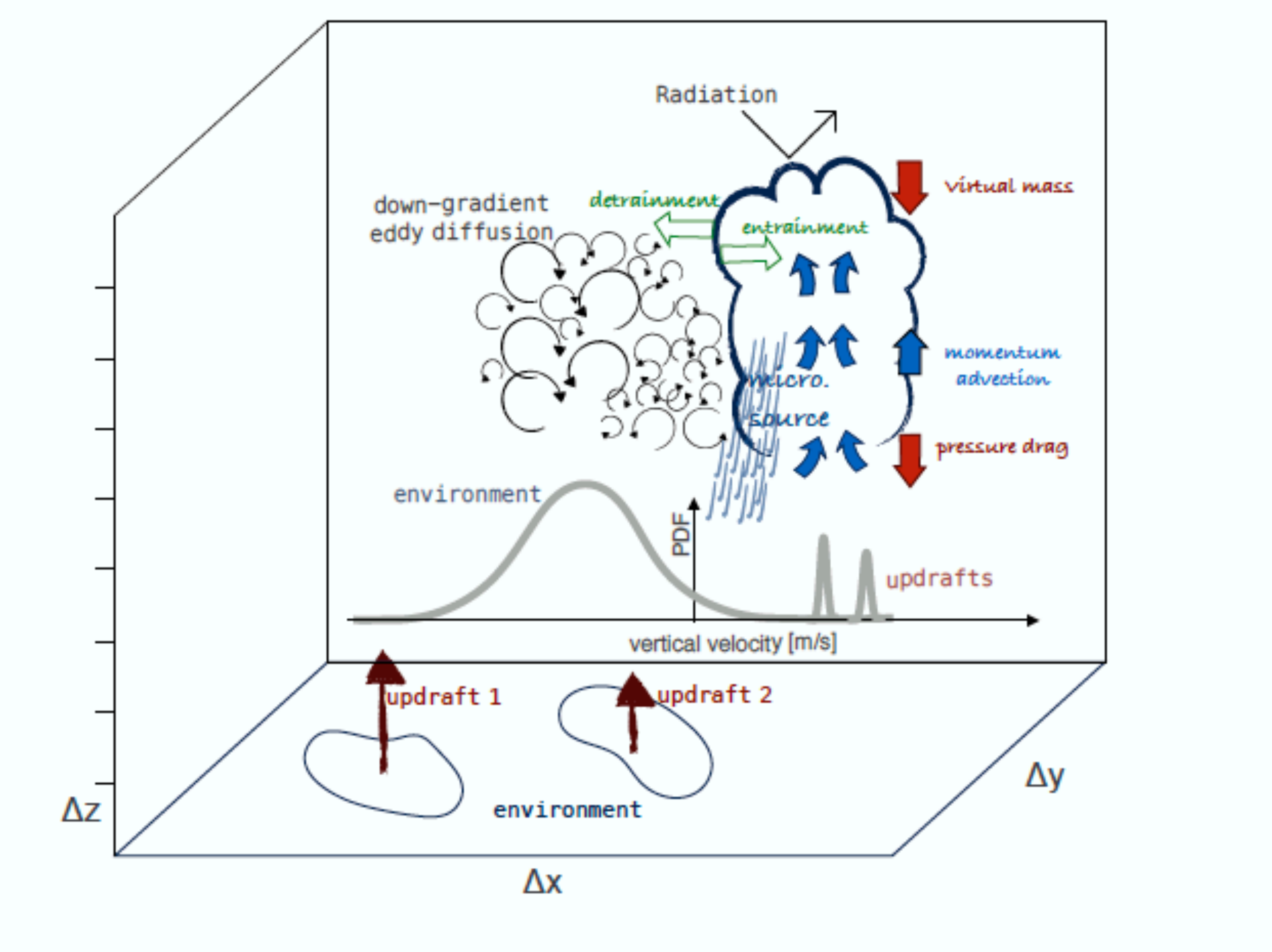


GCM-LES differences suggest biases in parameterizations



Eddy diffusivity mass flux (EDMF) scheme

- A unified parameterization of turbulence and convection
- Decompose the domain into convective plumes and chaotic environment
- Closures are needed for mass and momentum exchange between the plumes and the environment, and turbulent mixing in the environment
- [Cohen et al. 2020, Lopez-Gomez et al., 2020, He et al. submitted]



Calibrate EDMF parameters (example)

$$y \quad = \quad G(\theta) \quad + \quad \eta$$

LES mean — EDMF mean — LES covariance

$y \in \mathbb{R}^d,\ d = 632$ Time averaged vertical profiles in the LES

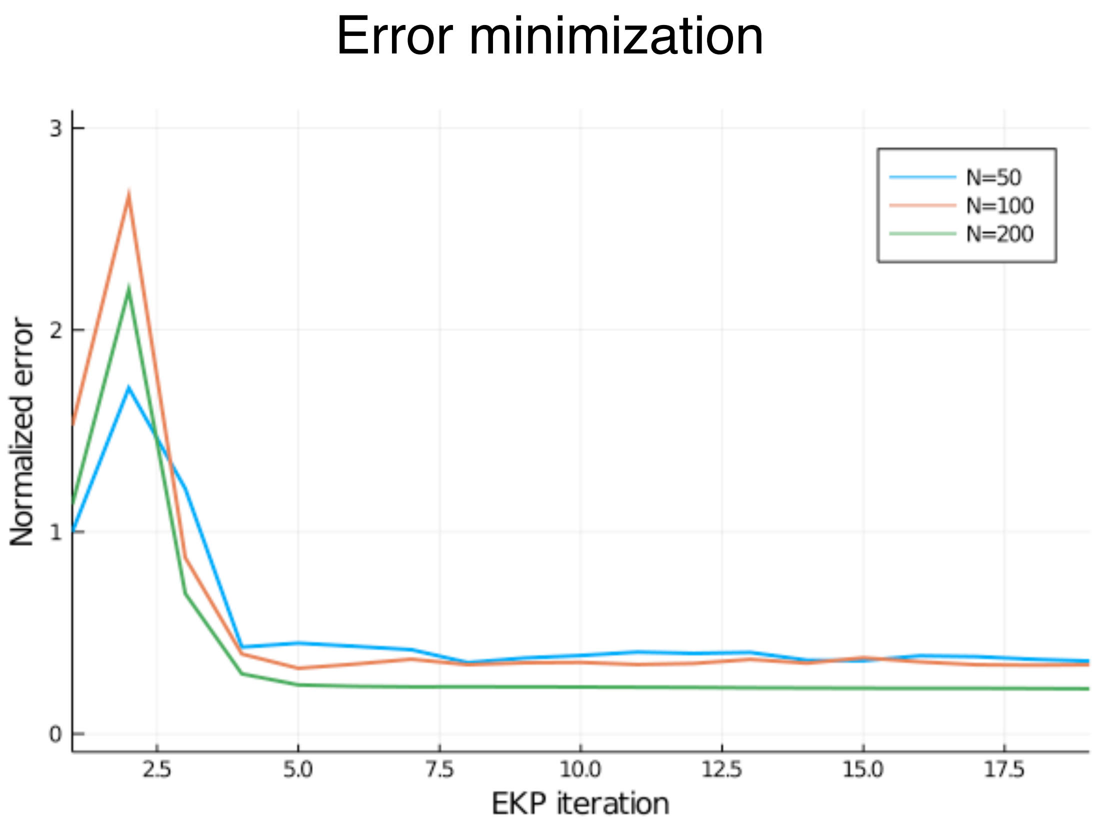
$\eta \in \mathbb{R}^d,\ \eta \sim N(0, \Gamma)$ Temporal covariance in the LES

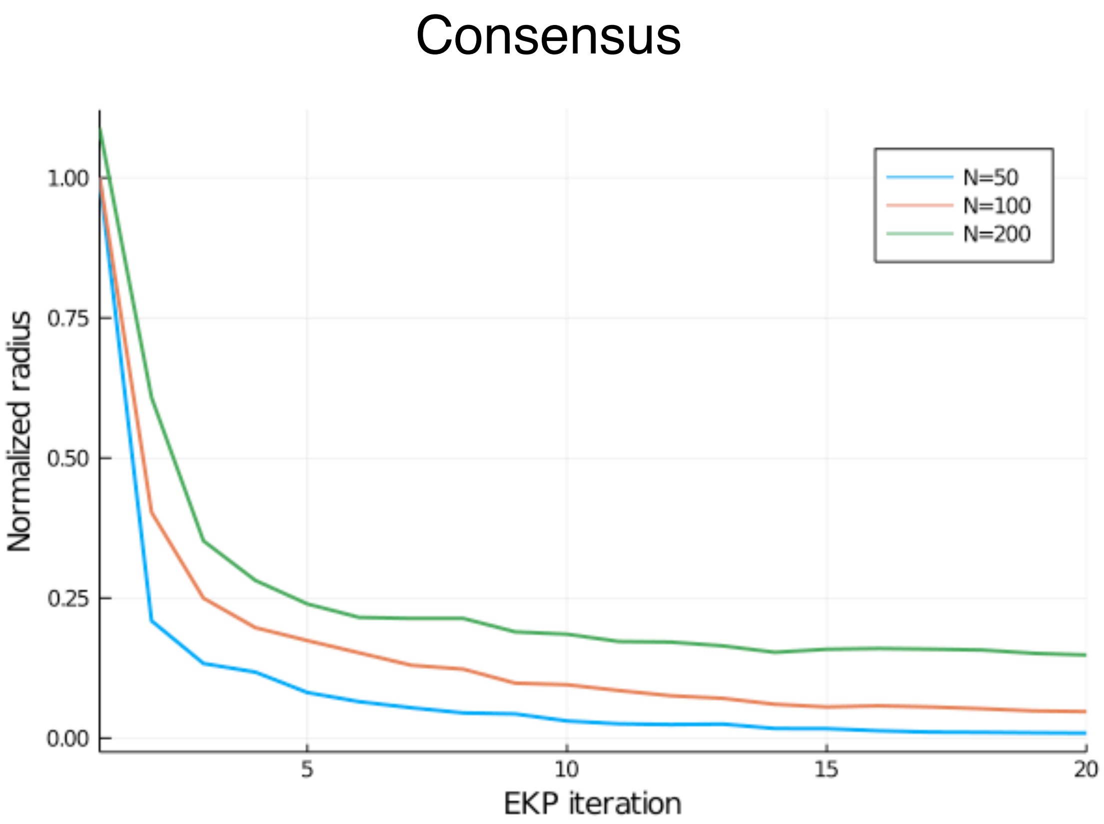
$\theta \in \mathbb{R}^d,\ p = 9$ EDMF free parameters

$\theta_0 \sim LN(\mu_0, C)$ Lognormal prior to enforce positivity of parameters

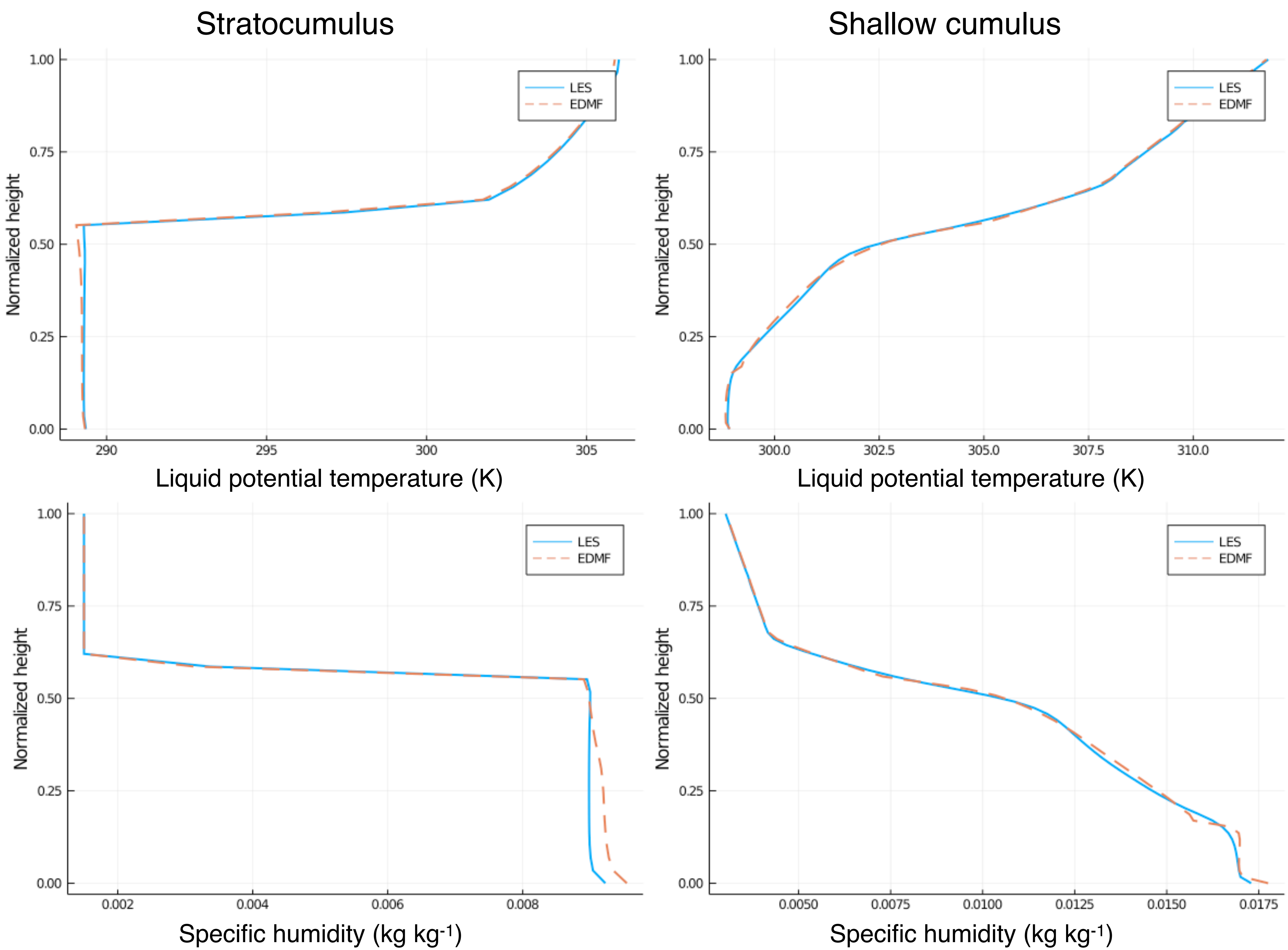
Minimize $L(\theta) = \|y - G(\theta)\|_\Gamma^2 + \|\theta - \theta_0\|_C^2$

Calibrate: Ensemble Kalman Inversion





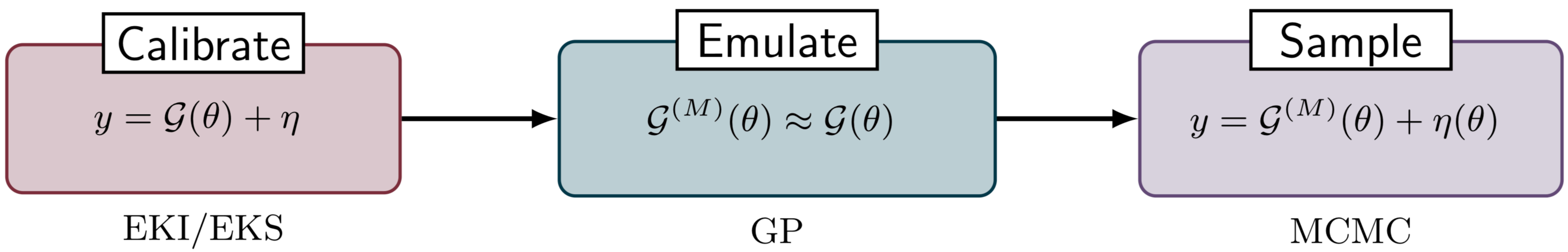
Calibration results



Uncertainty quantification: Calibrate, Emulate, Sample

- Ensemble Kalman Inversion does not provide good uncertainty quantification of parameters.

- A framework to recover the uncertainty information:



Find parameters and generate (expensive) samples

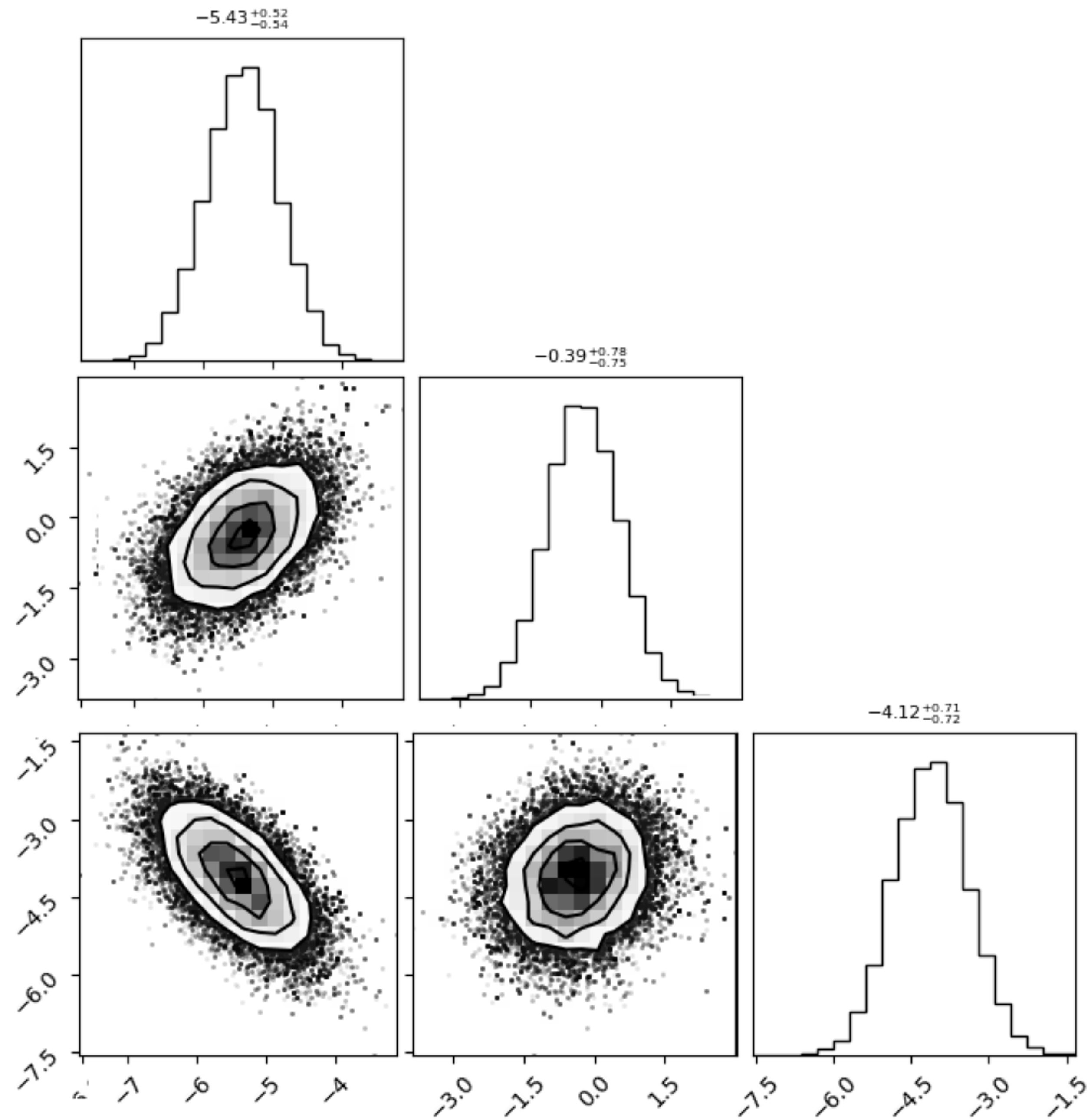
Train an emulator on calibration data

Produce (cheap) samples from the emulator and recover the posterior

[Cleary et al. 2021]

Sample the posterior using the emulator and MCMC

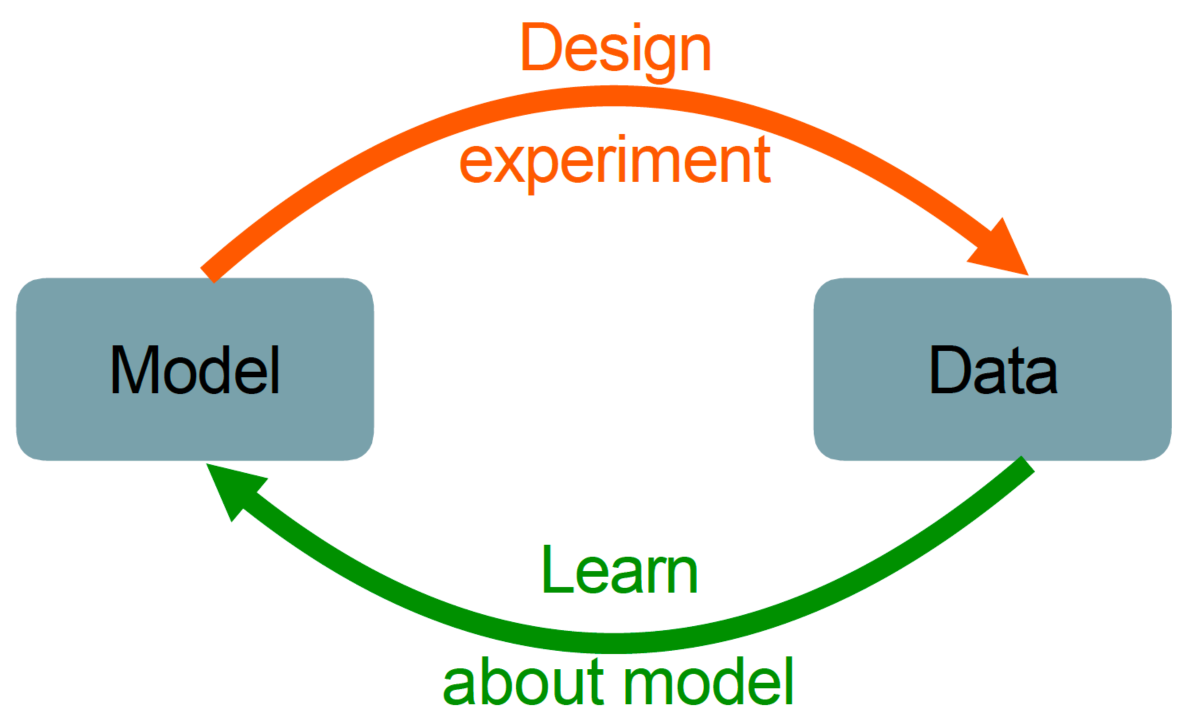
- Use Gaussian Process to train the emulator and sample with MCMC
- ~10^6 evaluations in minutes
- Recover information about correlations in the parameters
- Smoother posterior in general



Posterior distribution in log-transformed space

Summary and future work

- We design and prototype a framework that generates a library of LES that spans a wide range of cloud regimes.
- We show that parameters in convection parameterizations can be learned from the LES data.
- We aim to run O(1000) LES to expand the training dataset and demonstrate online learning of GCM parameterizations.



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