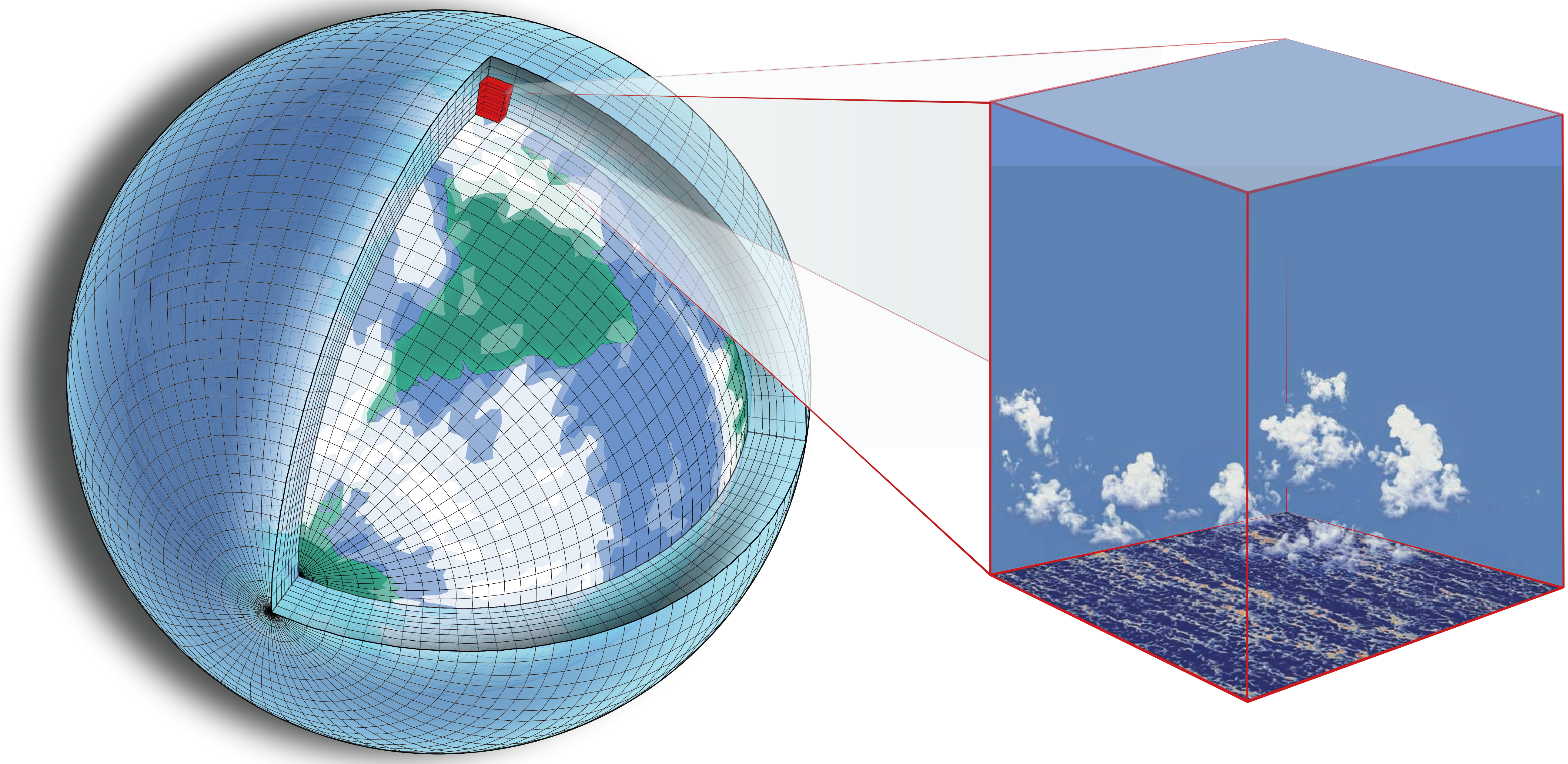
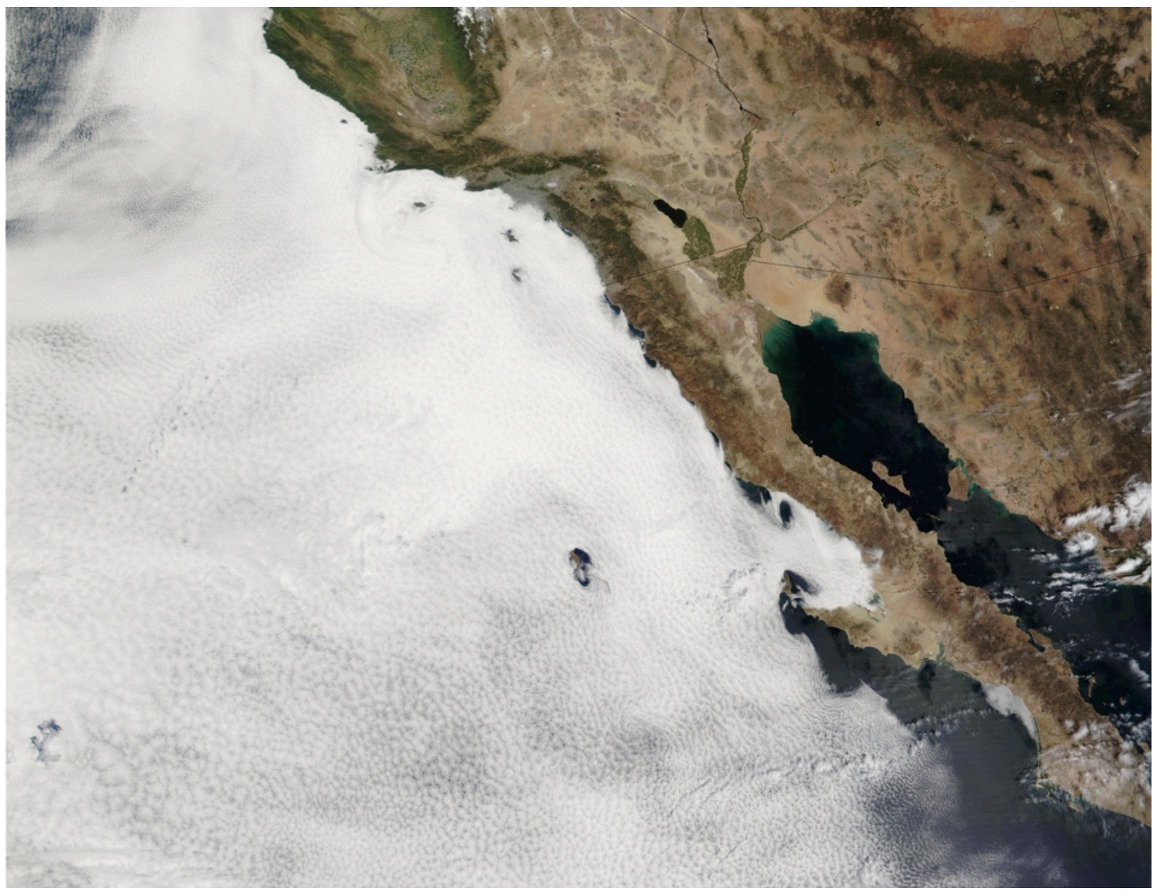
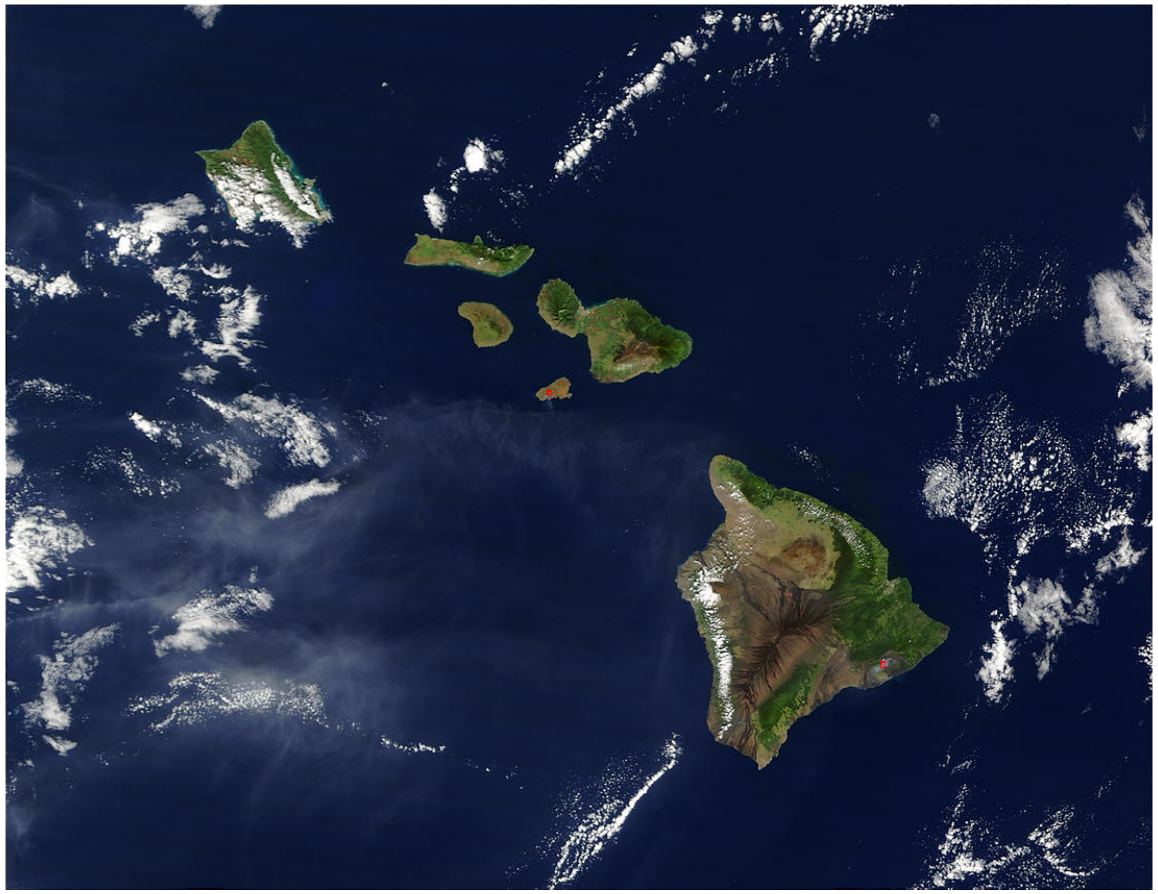


AI-Aided Hybrid Parameterizations

Tapio Schneider and the CliMA Team (clima.caltech.edu)

Clouds and low clouds especially have been the primary source of uncertainty in climate predictions for decades





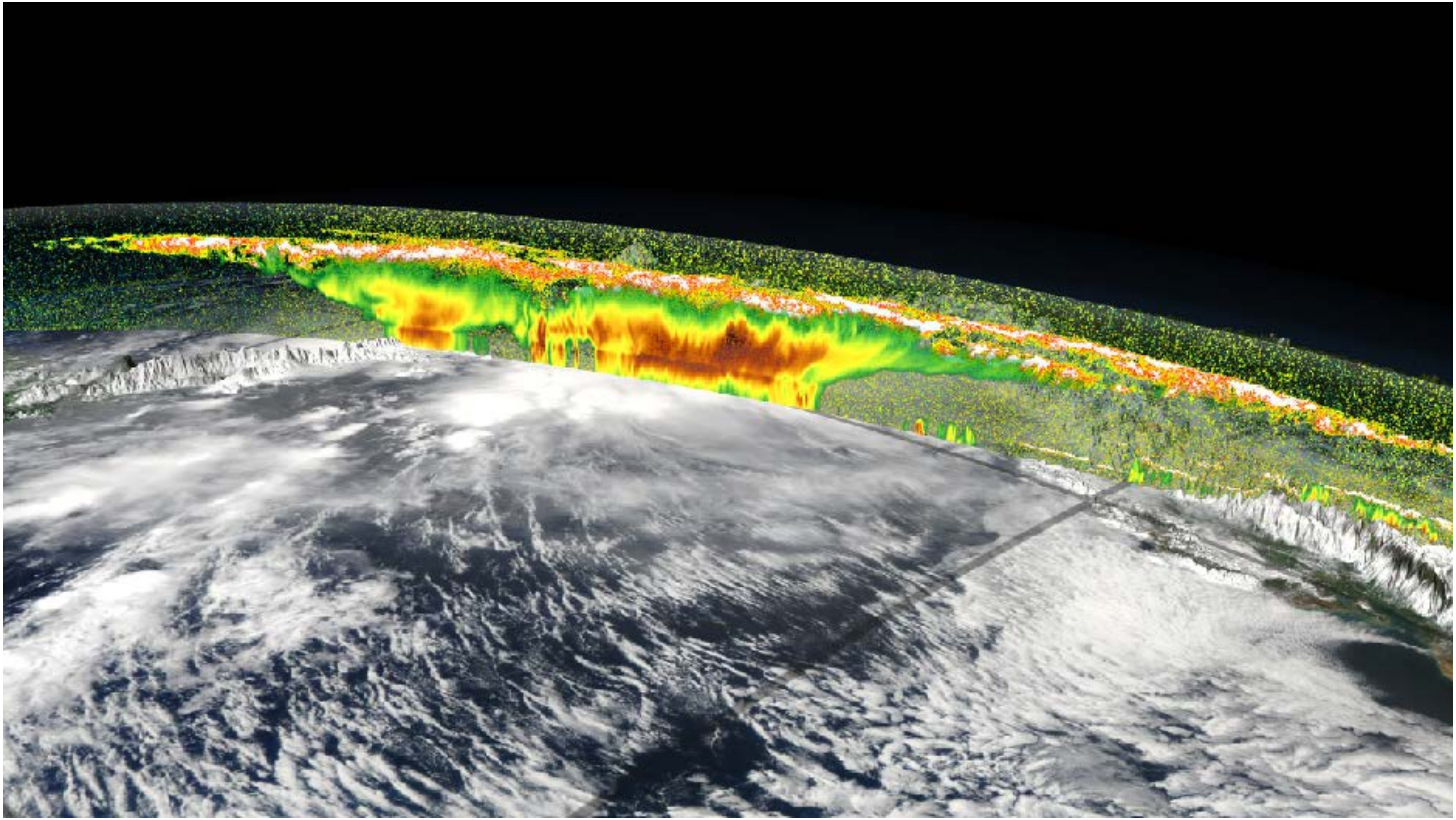
http://eoimages.gsfc.nasa.gov

Stratocumulus: colder

Cumulus: warmer

They will remain globally unresolvable for decades to come

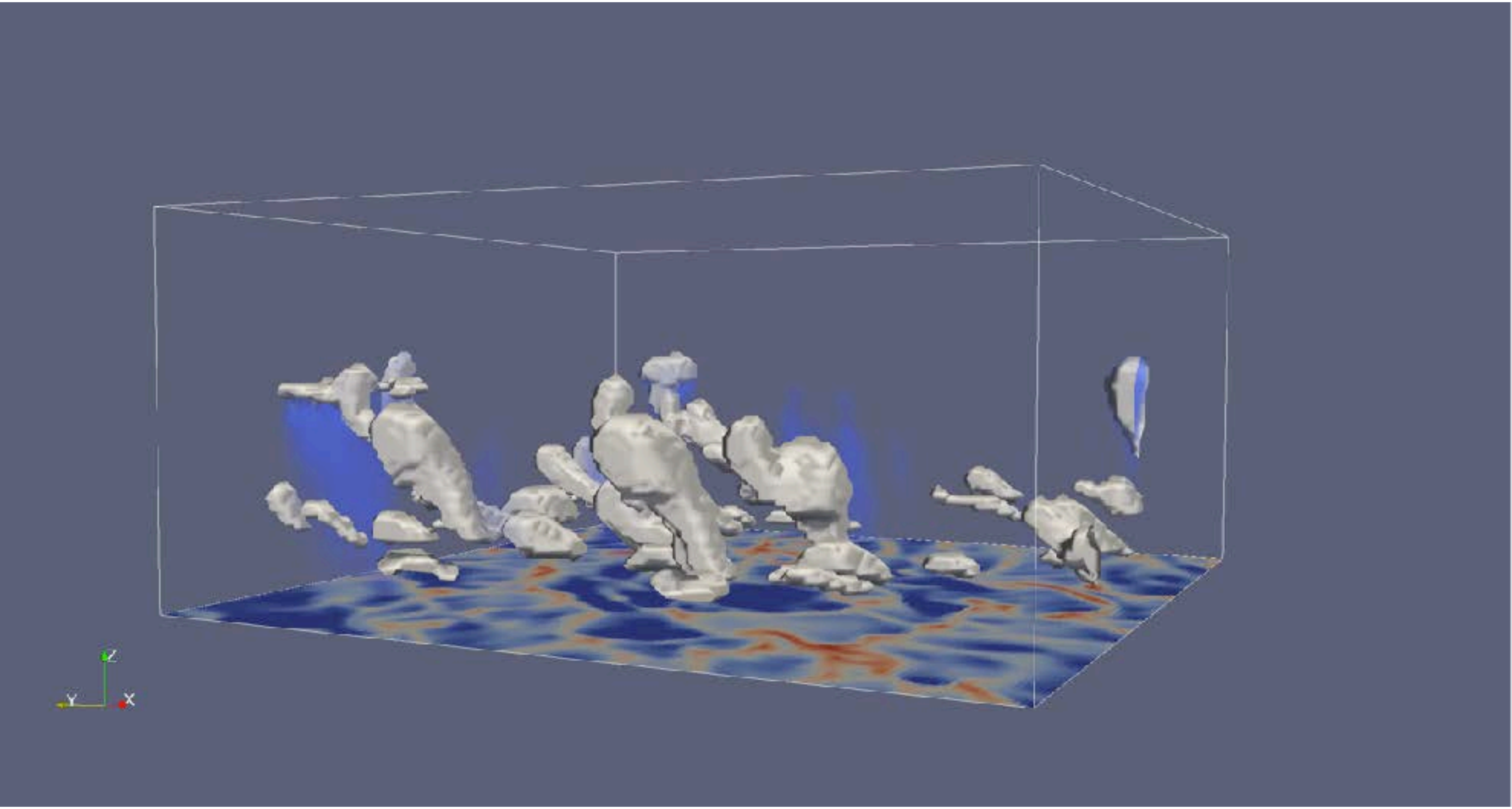
Yet we have detailed data about clouds and other small-scale features, albeit with low temporal resolution



CloudSat, CALIPSO, and MODIS

NASA/Goddard Space Flight Center Scientific Visualization Studio

And we can generate data computationally in limited-area high-resolution simulations



Simulation of tropical cumulus with *O*(10 m) resolution (blue: rain)

Simulation with PyCLES (Kyle Pressel et al. 2015)

Exploiting both observational and computationally generated data with AI tools is the solution to the parameterization problem.

But climate prediction comes with special challenges

Data-informed Earth system models must meet three critical requirements

1. **Generalizability out of sample:** To predict a climate without an observed analogue

2. **Interpretability:** To trust models that cannot immediately be verified with climate-change data

3. **Uncertainty quantification (UQ):** To estimate risks for climate change adaptation

Schneider, Jeevanjee, Socolow, *Accelerating Progress in Climate Science*, Physics Today 6/2021

The requirements can be met by *combining* the best of reductionist science with data science approaches

- **Deep learning**'s success rests on *overparameterization*:
  - Leads to expressive models and data-hungry methods
  - Makes generalizability, interpretability, and UQ challenging
- **Reductionist science**'s success rests on *parametric sparsity:*
  - Generalizable and interpretable (e.g., Newton's Law of Universal Gravitation)
  - Reaches limits in complex systems such as the Earth system

Combine both, traditional reductionist science with AI where reductionism reaches its limits

We are exploiting a three-pronged hybrid approach

- **Advance Theory:** Use known equations as far as possible, with systematic coarse-graining approaches, to promote parametric sparsity.

- **Harness Data:** Exploit detailed Earth observations now available, together with data generated computationally.

- **Leverage Computing Power:** Transition to hardware with accelerators (GPUs, TPUs, …) is an opportunity, e.g., in enabling distributed local simulations of small-scale processes

(Schneider, Jeevanjee, Socolow, *Physics Today 06/2021*)

Advance theory: We use a unified, physics-based model, derived by conditional averaging of equations of motion

For example, to model clouds, we coarse-grain fluids equations by conditionally averaging over coherent plumes (*i*=1, …, *N*) and isotropic environment (*I*=0), leading to exact conservation laws:

- Continuity:

$$\frac{\partial(\rho a_i)}{\partial t} + \frac{\partial(\rho a_i \overline{w}_i)}{\partial z} + \nabla_h \cdot (\rho a_i \langle \mathbf{u}_h \rangle) = \boxed{\underbrace{\rho a_i \overline{w}_i \left(\sum_j \epsilon_{ij} - \delta_i \right)}_{\text{Mass entrainment/detrainment}}}$$

Closure functions

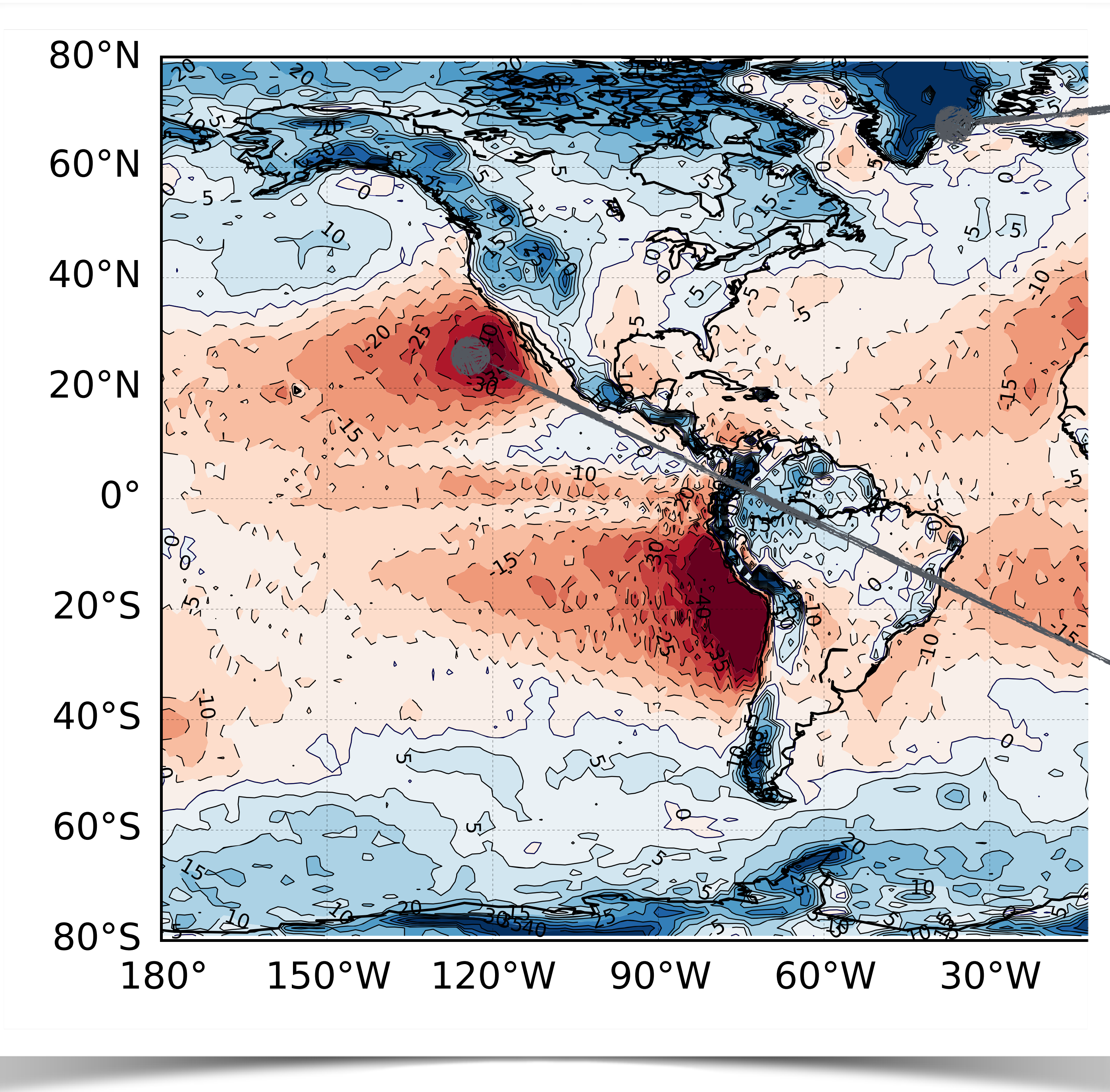
- Scalar mean:

$$\frac{\partial(\rho a_i \overline{\phi}_i)}{\partial t} + \frac{\partial(\rho a_i \overline{w}_i \overline{\phi}_i)}{\partial z} + \nabla_h \cdot (\rho a_i \langle \mathbf{u}_h \rangle \overline{\phi}_i) = \boxed{\underbrace{-\frac{\partial(\rho a_i \overline{w_i' \phi_i'})}{\partial z}}_{\text{Turbulent transport}}} + \underbrace{\boxed{\rho a_i \overline{w}_i \left(\sum_j \epsilon_{ij} \overline{\phi}_j - \delta_i \overline{\phi}_i \right)}}_{\text{Entrainment/detrainment}} + \underbrace{\rho a_i \overline{S}_{\phi,i}}_{\text{Sources/sinks}}$$

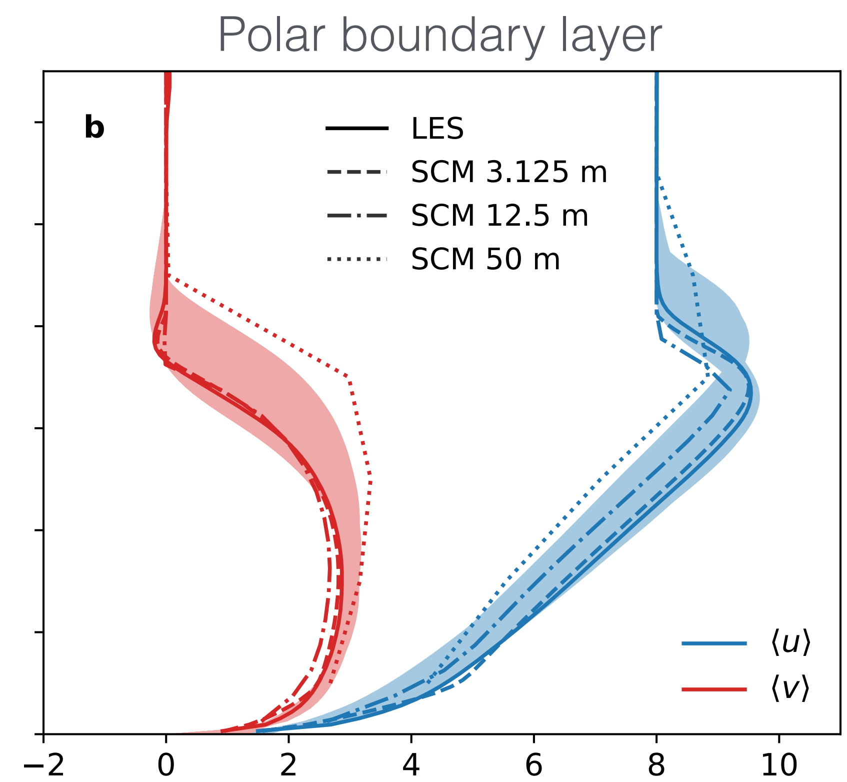
Closure functions are excellent targets for ML approaches; they can be stochastic and should include structural error models

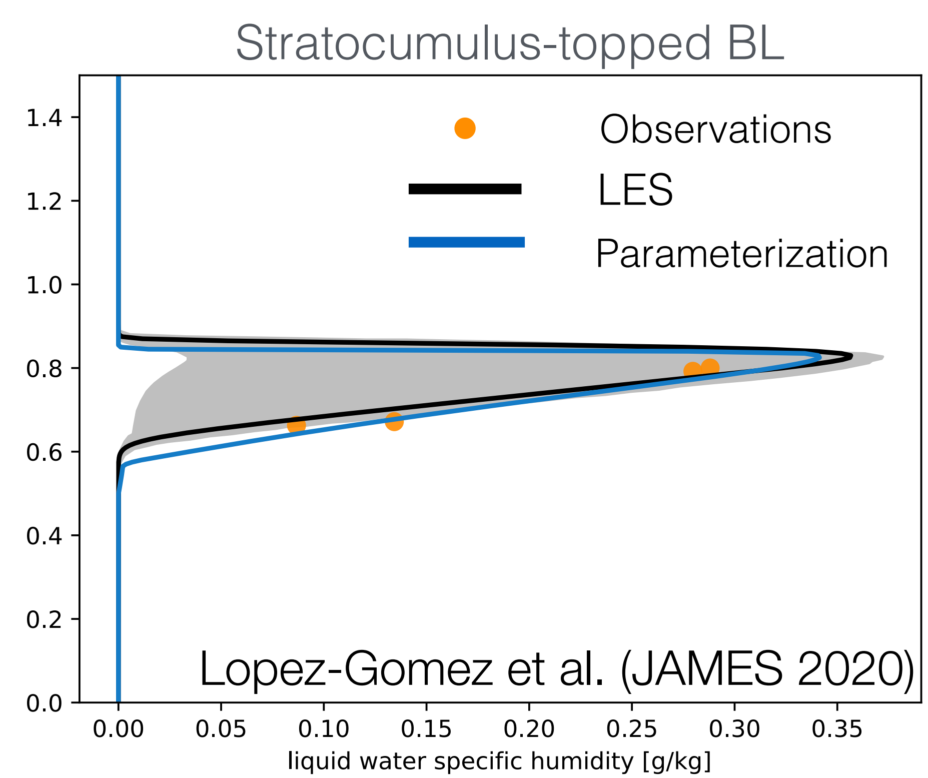
Tan et al., *JAMES* 2018, Cohen et al. *JAMES* 2020, Lopez-Gomez et al. *JAMES* 2020

Parameterization with empirical closure functions and 9 hand-tuned parameters captures polar and subtropical boundary layer and clouds

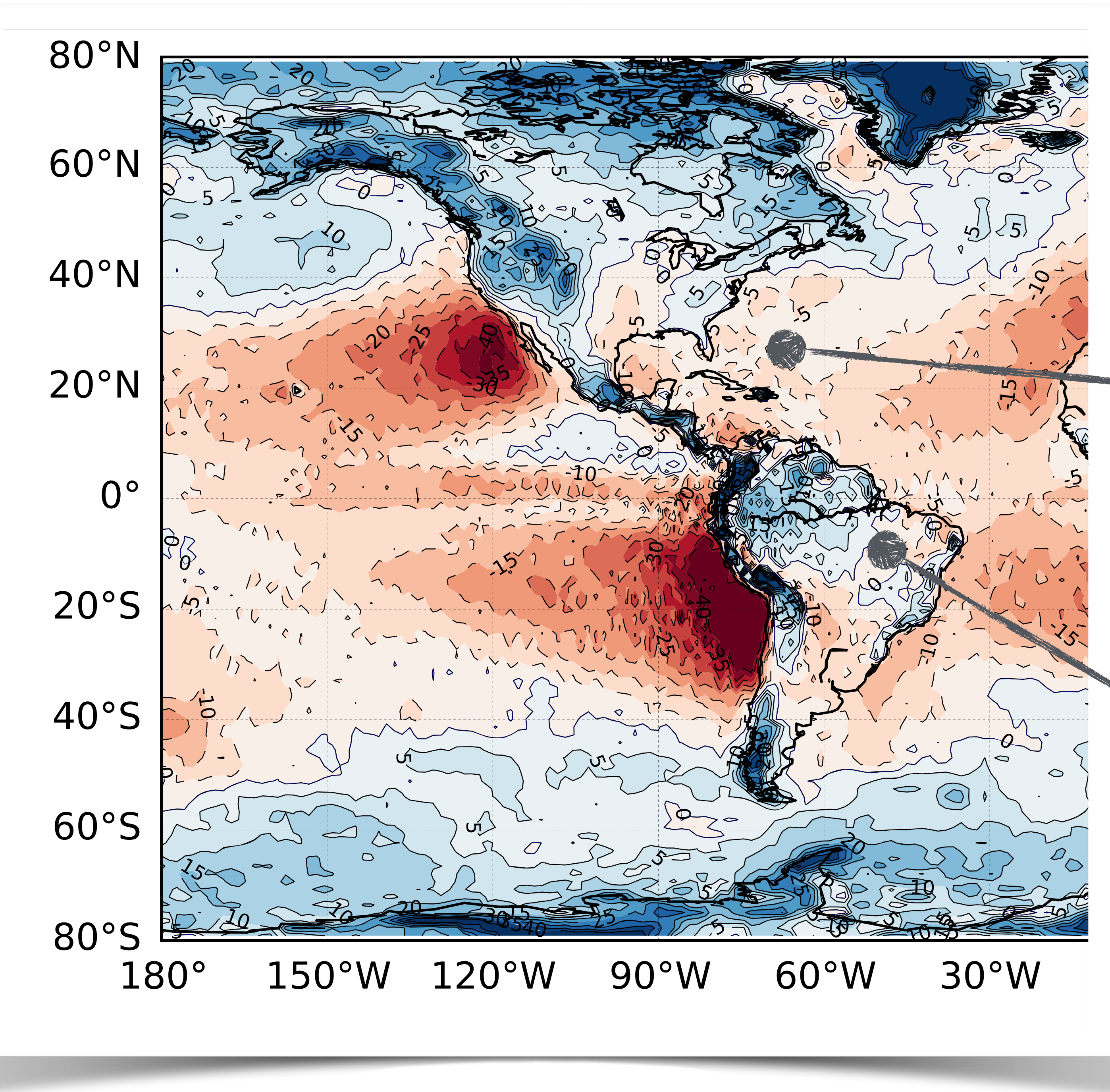


Low-cloud bias in typical model

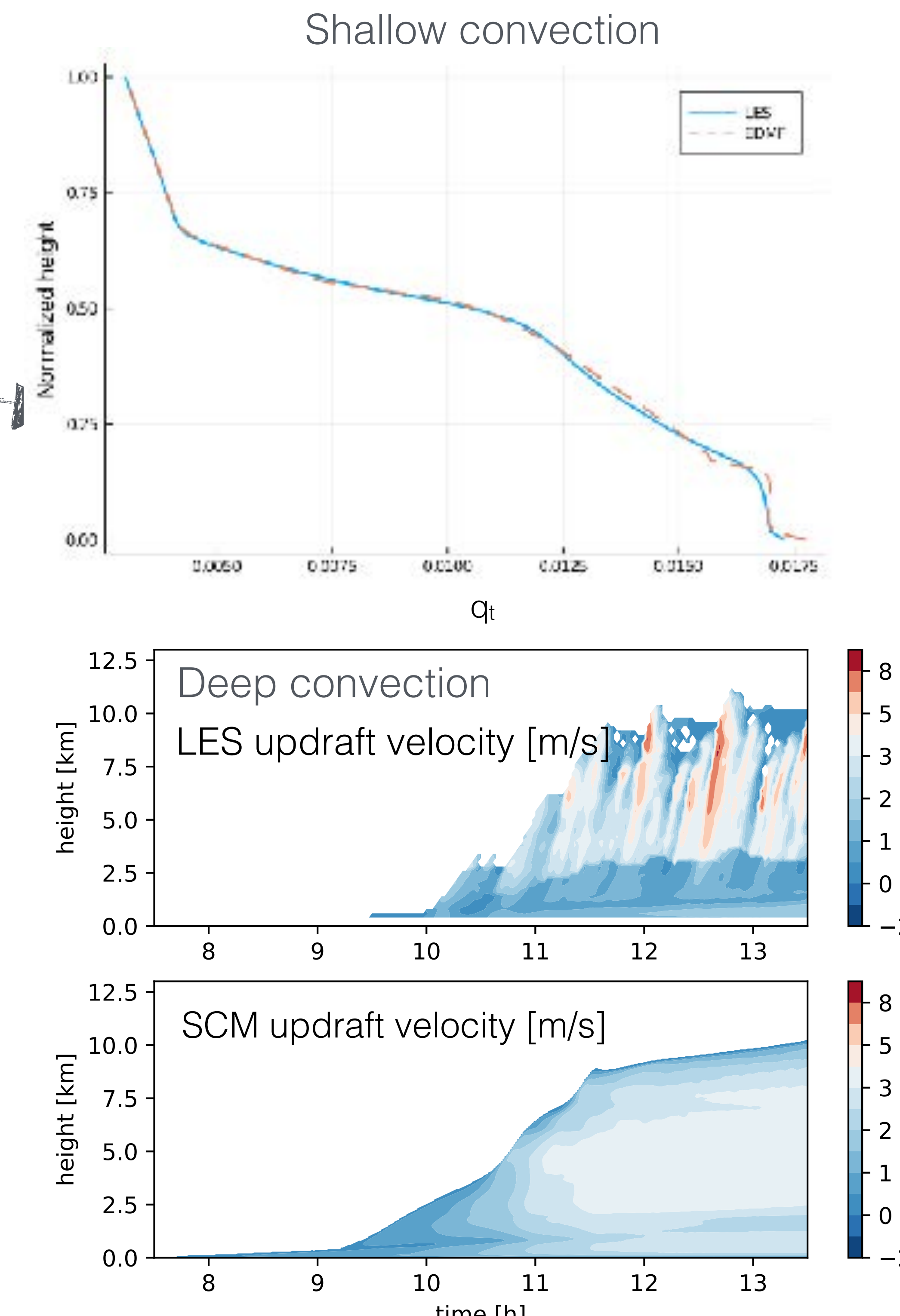




It also captures shallow and deep cumulus convection, *within the same physical and parametric framework*

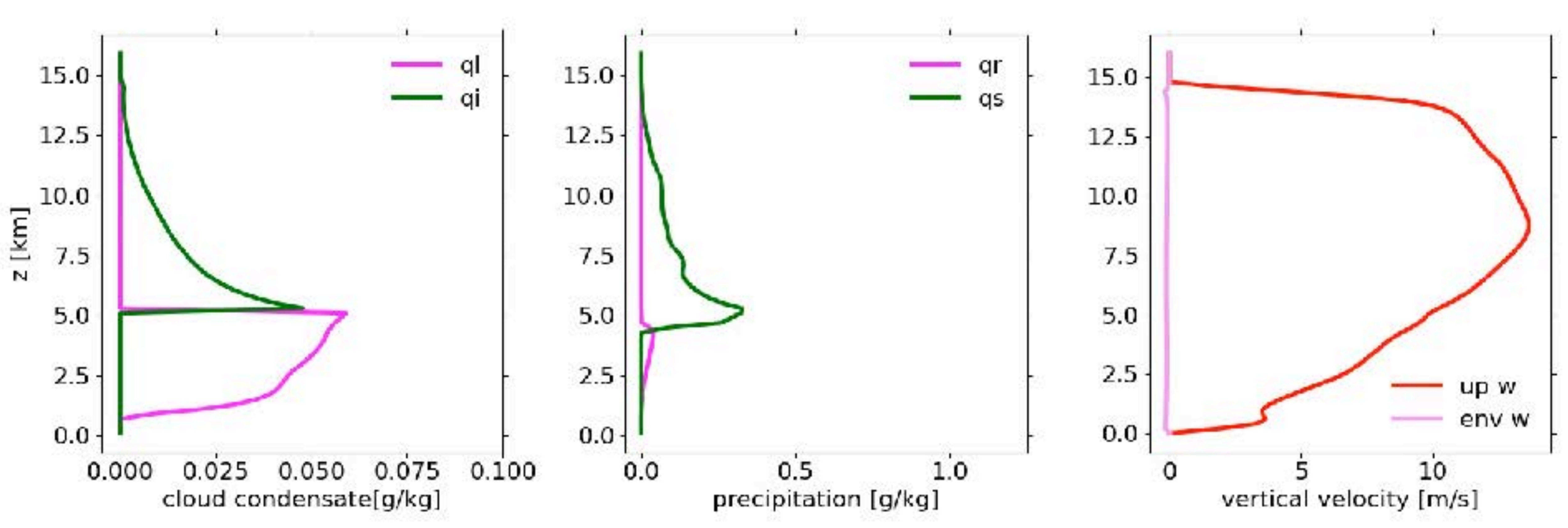


Low-cloud bias in typical model



(Cohen et al. JAMES 2020)

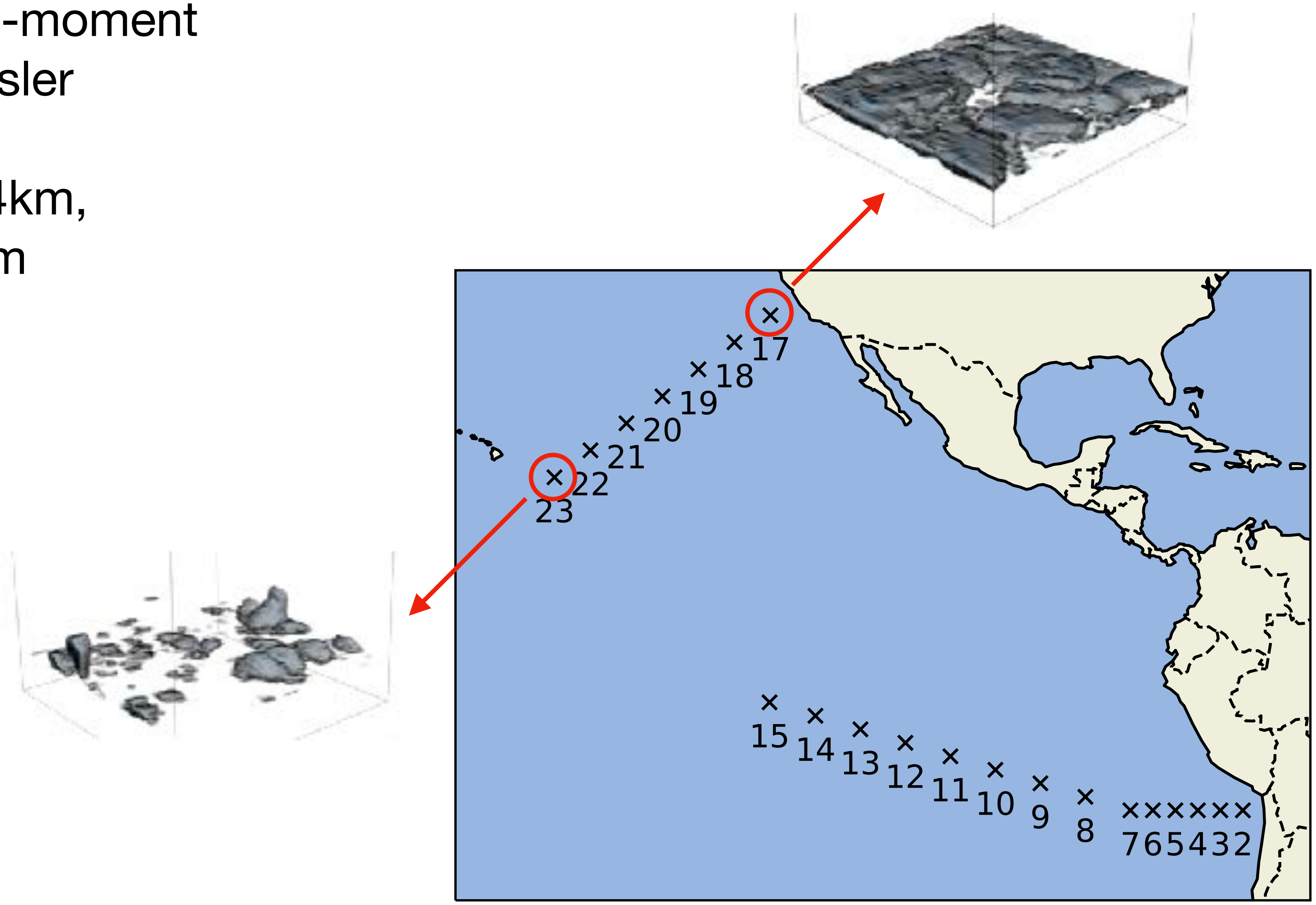
We can also represent the continuous transition from shallow to deep convection in time



(Anna Jaruga, in prep.)

Leverage computing power: We have generated a large (500 members so far) library of LES to calibrate parameterization

- 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

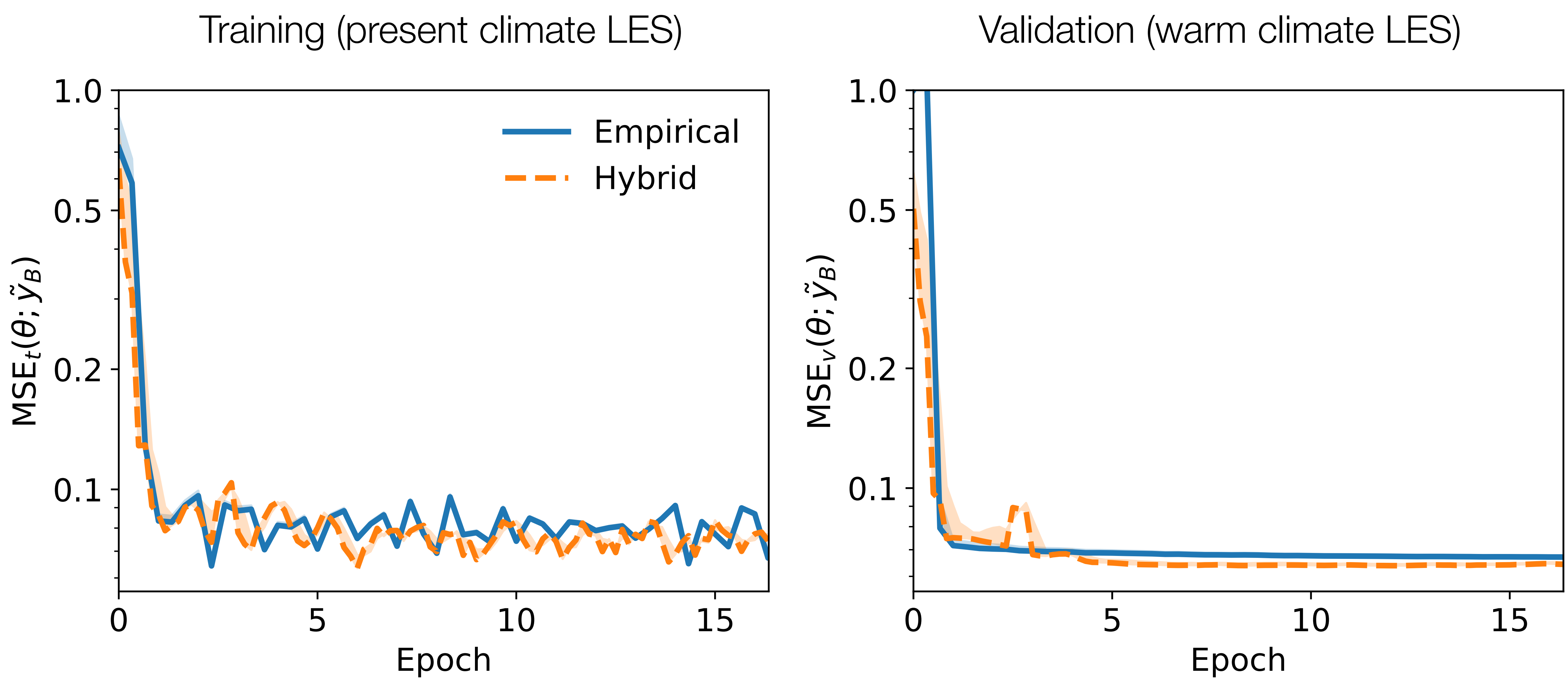


Shen et al., *JAMES* 2022

Harness data: Learn from ***time-averaged climate statistics****,* which are what's relevant for climate prediction and are observationally available

- Spatial smoothness of statistics **overcomes observation/simulation resolution mismatch**
- **Climate-relevant statistics** can include, e.g., emergent constraints and precipitation extremes
- Treats learning as **inverse problem**, rather than supervised learning; can be solved with ensemble Kalman inversion and variants

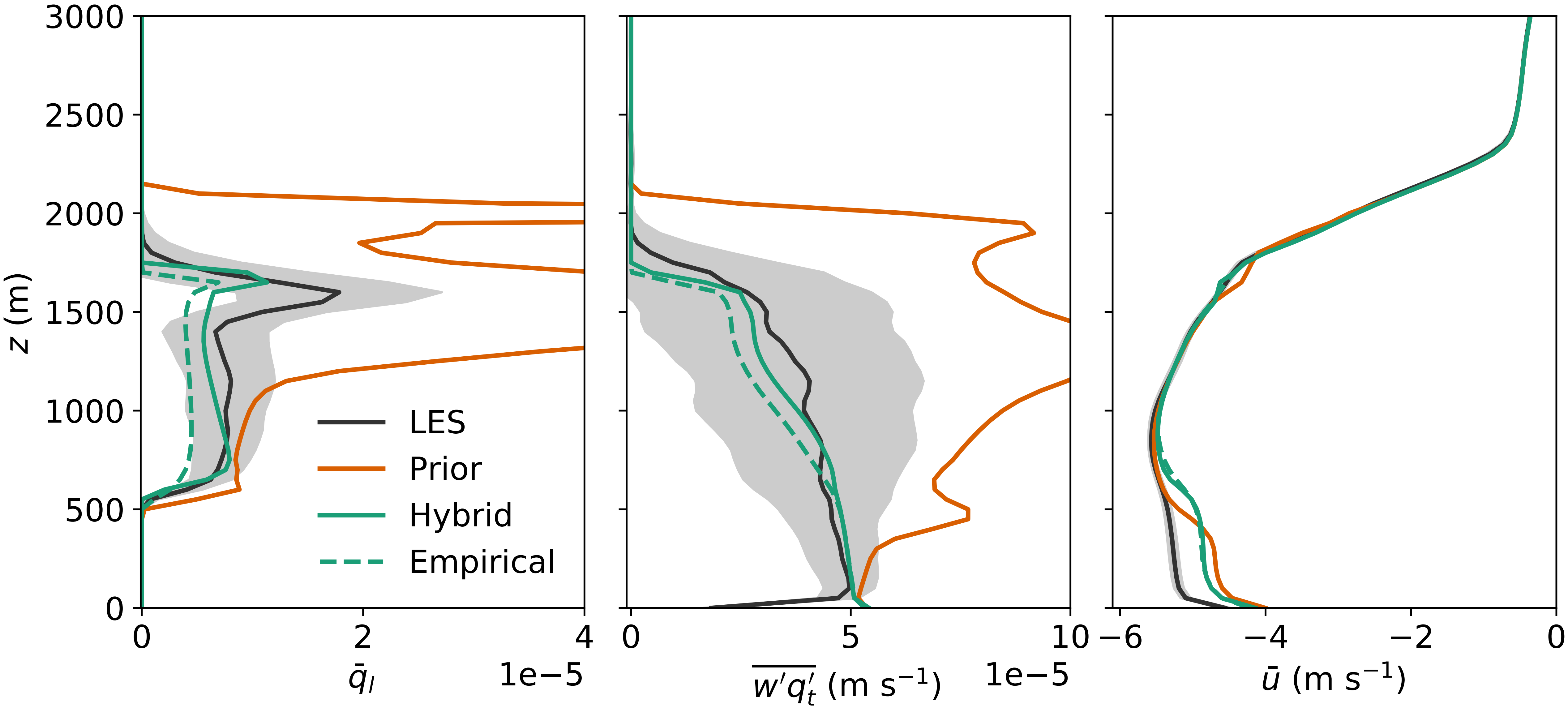
Replacing empirical entrainment/detrainment rates by shallow NN and calibrating with LES library improves parameterization and generalizes well



Training epoch (Kalman iteration with mini-batching)

(Ignacio Lopez Gomez, in prep.)

When training the model only with present-day LES, validation tests with global-warming LES (AMIP+4K) performs very well



Same inverse-problem approach to closure functions can be used with other ML tools: NN, neural operators, random feature models etc.

Conclusions

- To reduce and quantify uncertainties, **combine *process-informed* models with *data-driven* approaches harnessing *climate statistics***
- **Sparsely parameterized, physics-based subgrid-scale models** can capture turbulence and cloud regimes that have vexed climate models for decades
- Our subgrid-scale models can **learn both from observations (coming soon) and from high-resolution simulations**
- We have developed algorithms (**calibrate-emulate-sample**) for fast observation-based calibration of the parameterizations and are in the process of integrating them in GCM

Much interesting work (coarse-graining theory, scaling on HPC architectures, optimal targeting of high-res simulations…) remains to be done!

The turbulence, convection, and cloud parameterization team

Yair Cohen

Haakon Ervik

Jia He

Ignacio Lopez-Gomez

Anna Jaruga

Charles Kawczynski

Zhaoyi Shen

With thanks to CliMA's funders

ERIC AND WENDY SCHMIDT / SCHMIDT FUTURES

HEISING-SIMONS FOUNDATION

NSF

DARPA

CHARLES TRIMBLE