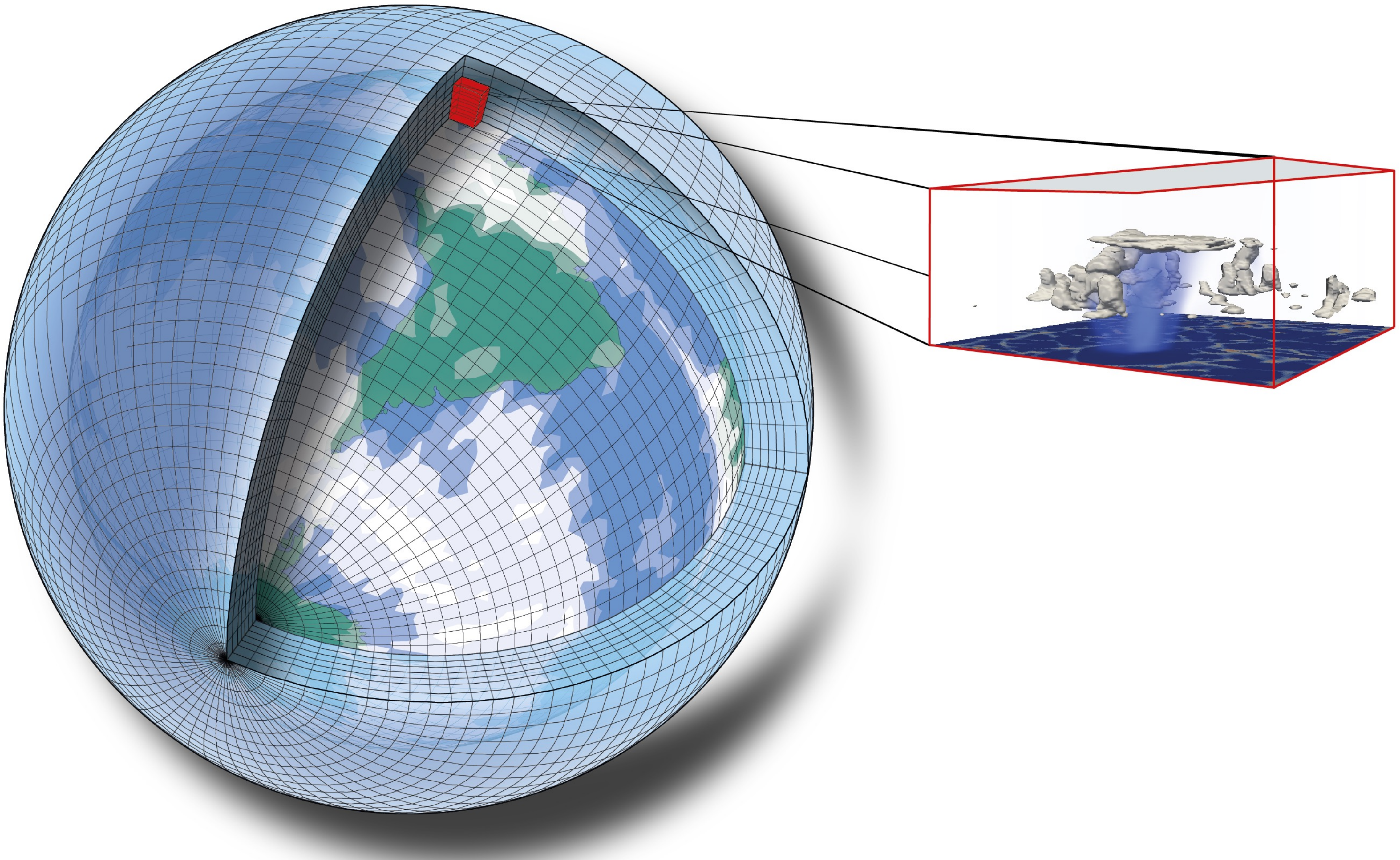
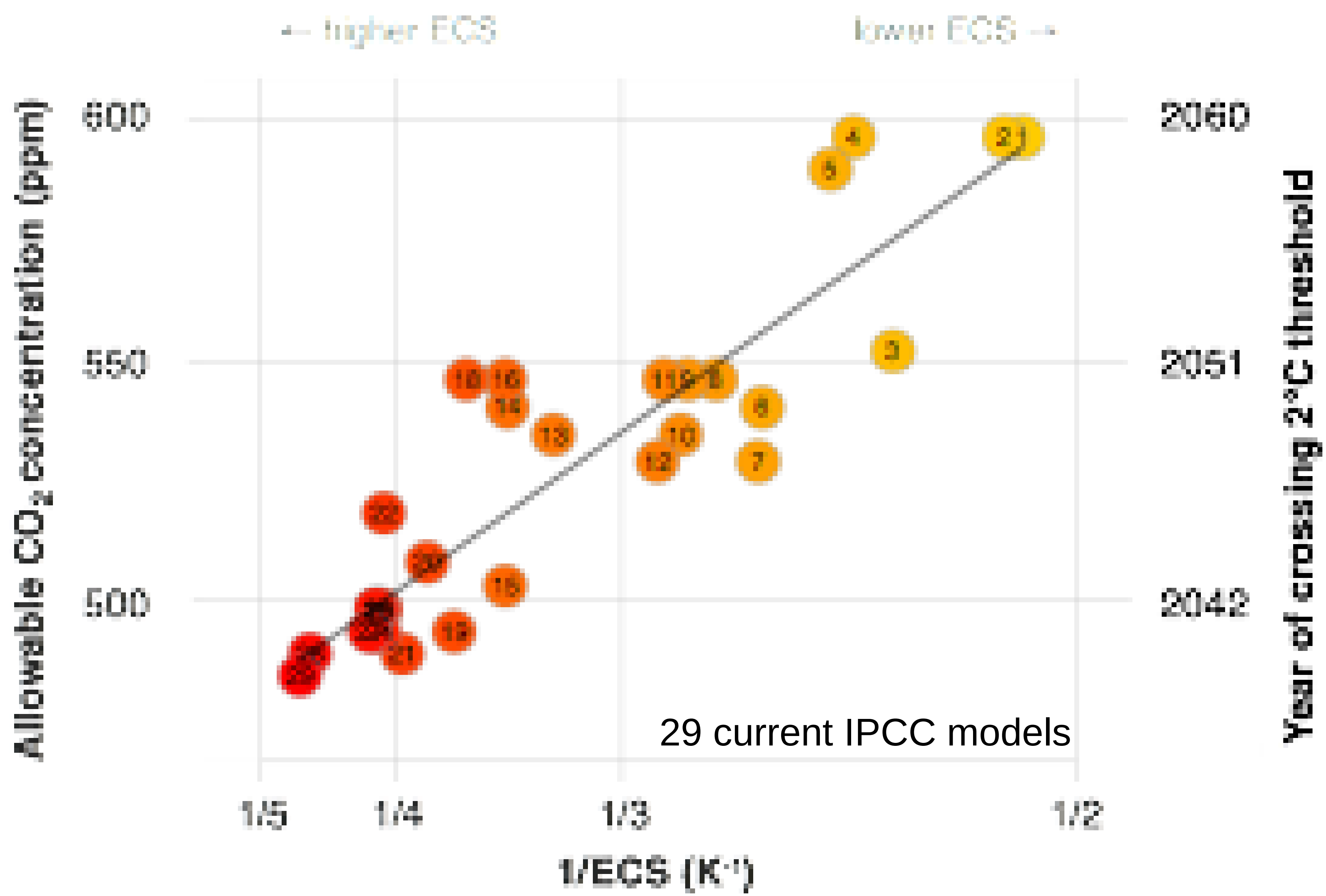


Assessing Geoengineering Proposals and Climate Risks Through Data-Informed Modeling

Tapio Schneider
Andrew Stuart

Climate predictions remain highly uncertain: E.g., allowable CO_2 concentration before crossing 2°C warming threshold



Schneider et al., *Nature Climate Change* 2017

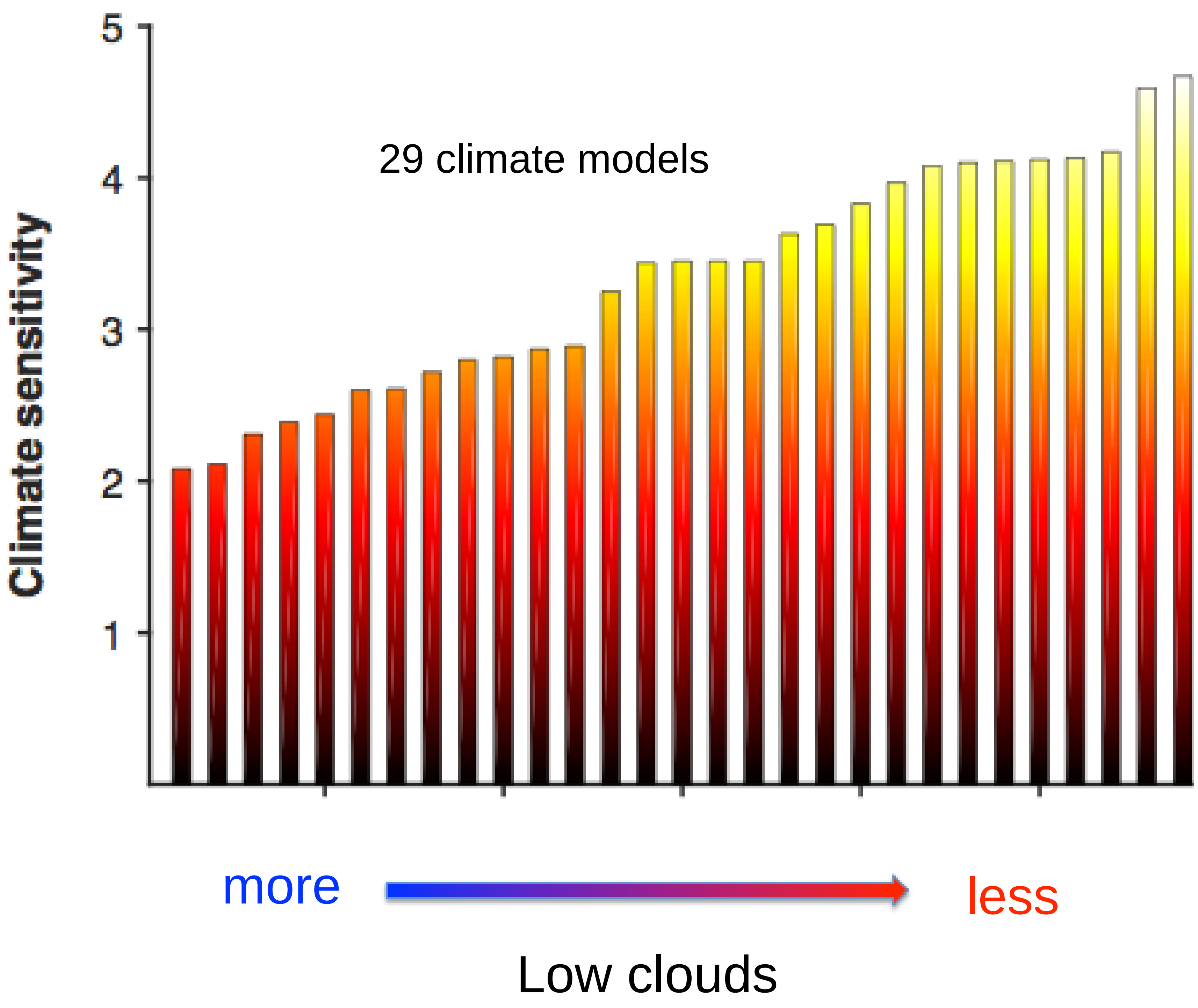
Climate response is uncertain mostly because of low clouds

Stratocumulus: colder

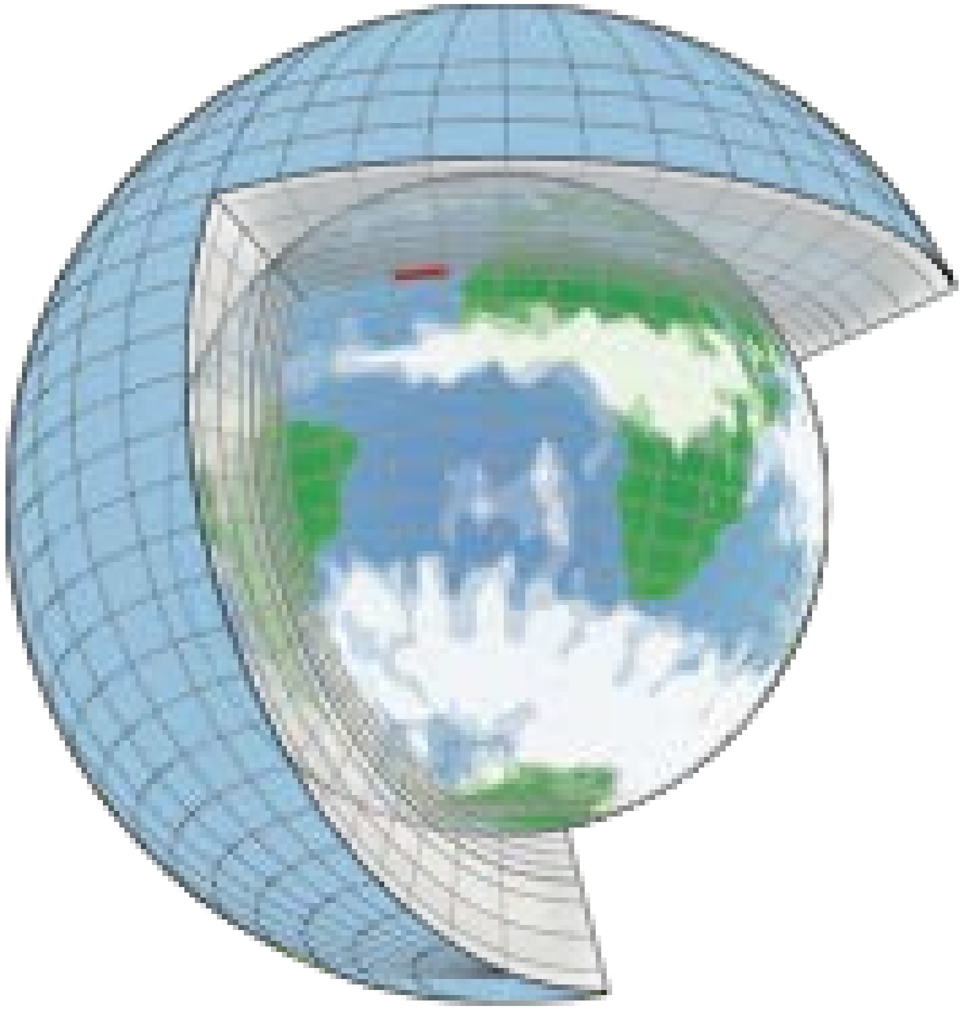
http://eoimages.gsfc.nasa.gov

Cumulus: warmer

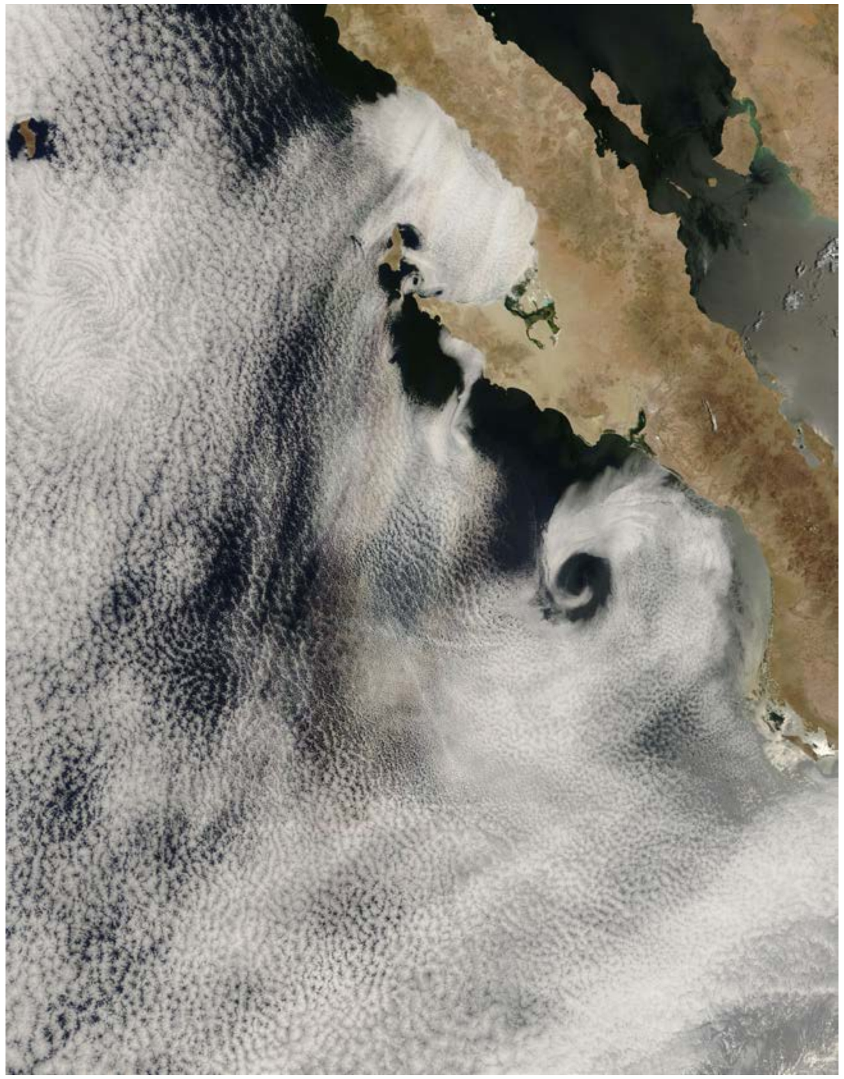
In some models, low clouds dampen warming; in some, they amplify warming



Climate models are too coarse to resolve clouds



Global model:
~10-50 km resolution

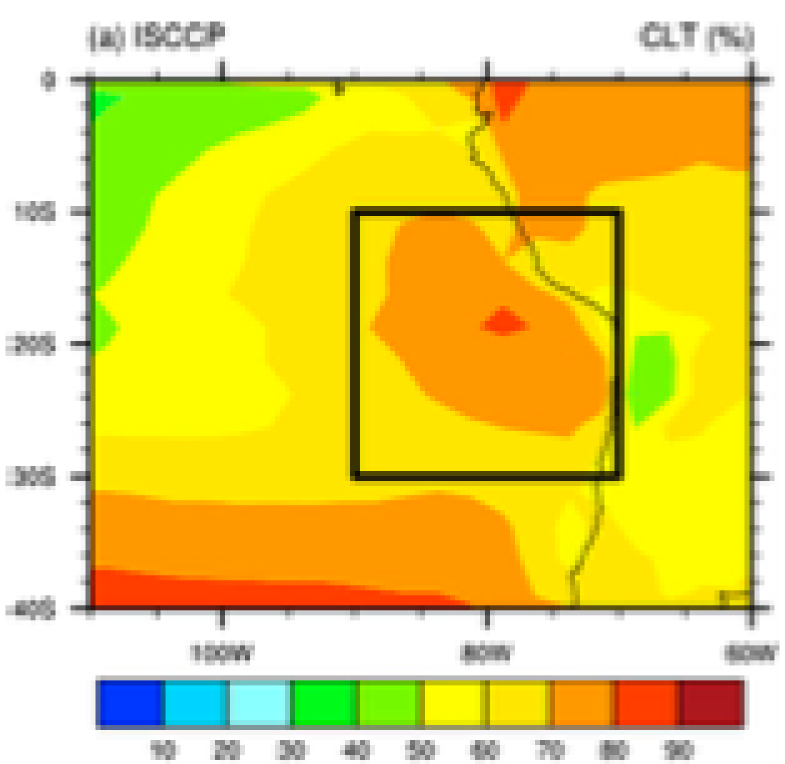


NASA MODIS

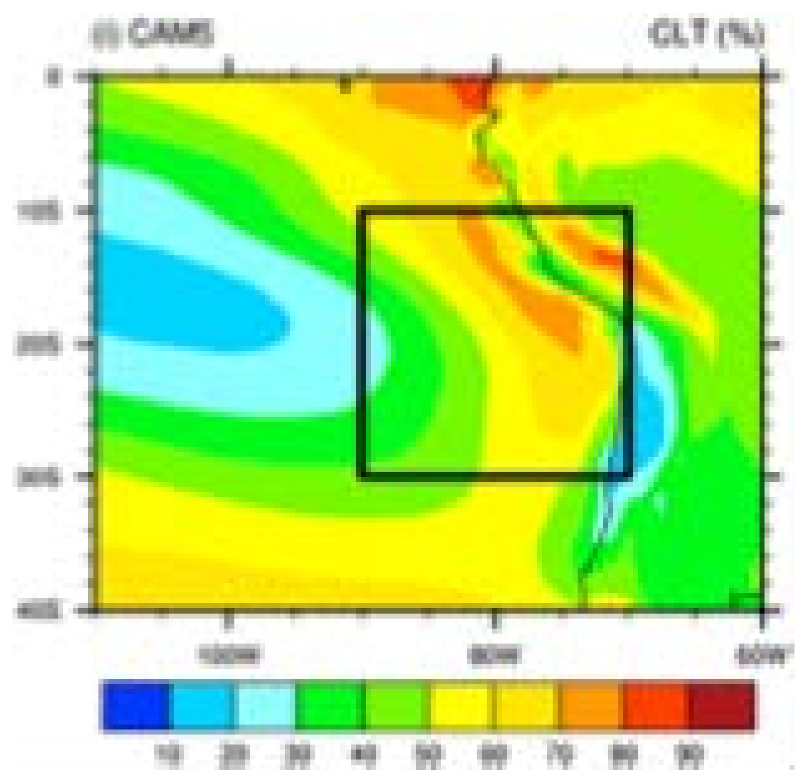
Cloud scales: ~10-100 m

No model simulates stratocumulus well

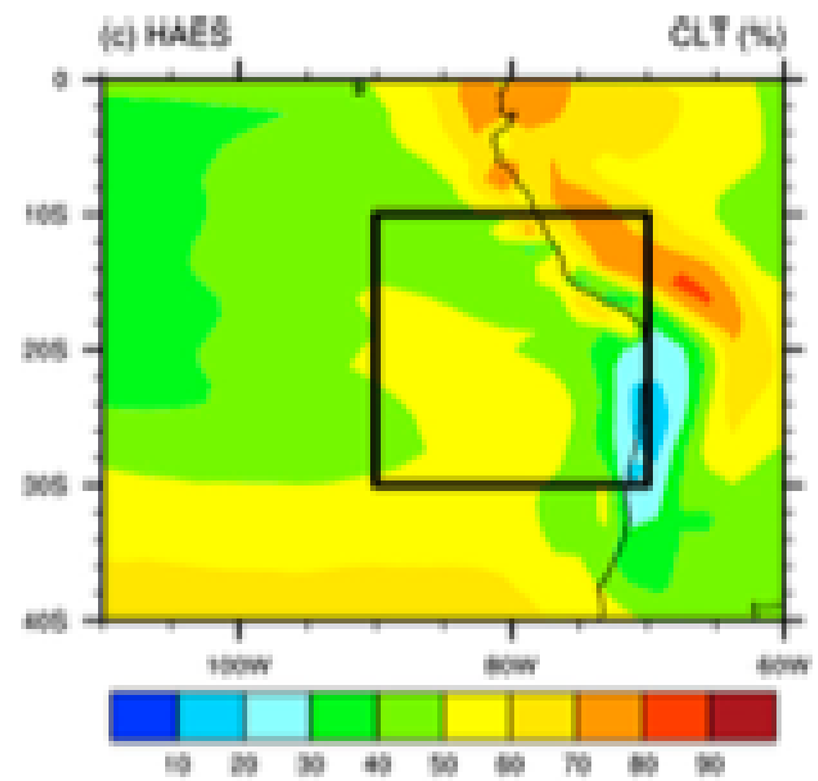
Obs



NCAR



Hadley



Cloud cover (%)

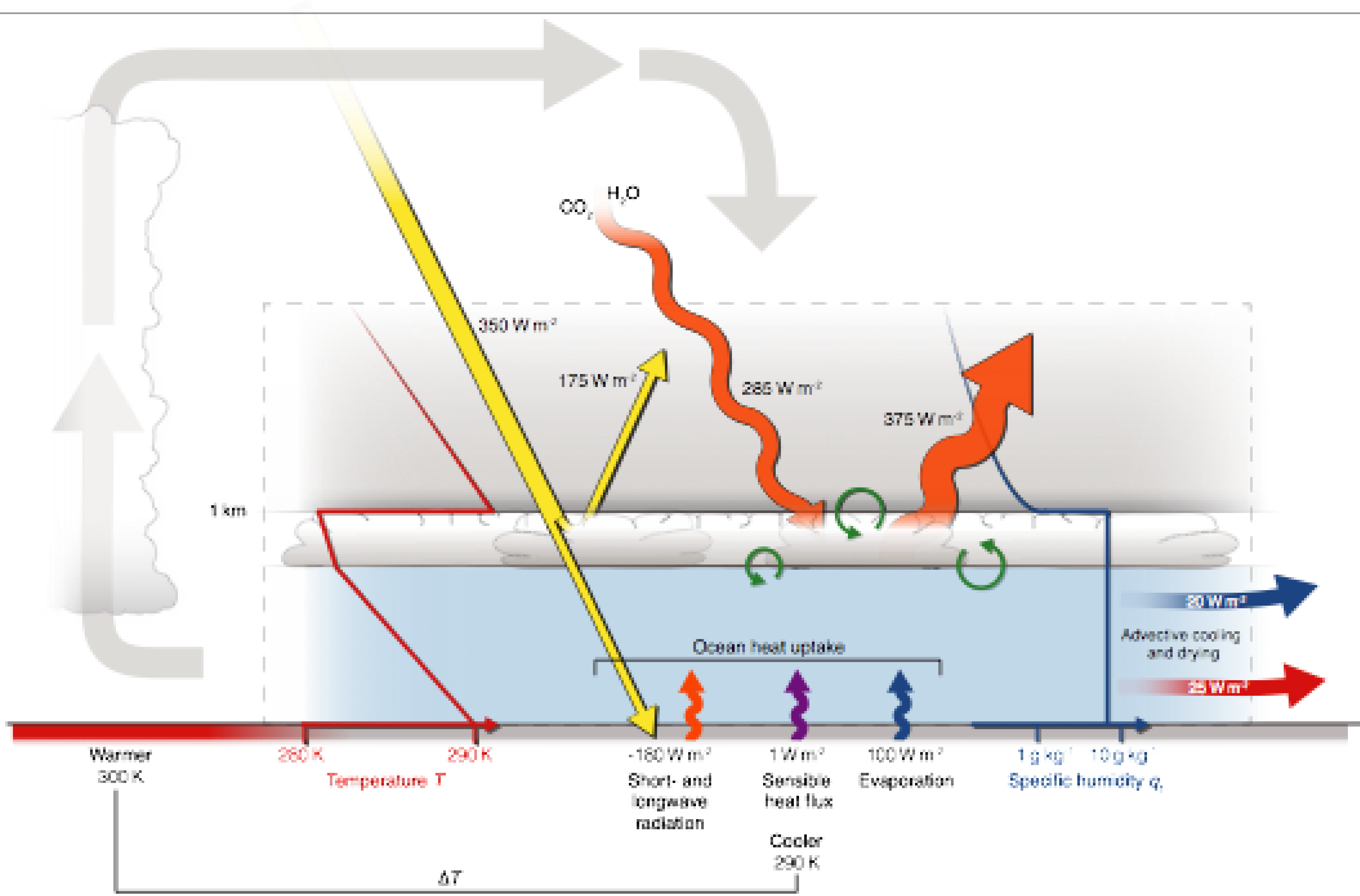
"Too few, too bright bias"

Lin et al. 2014

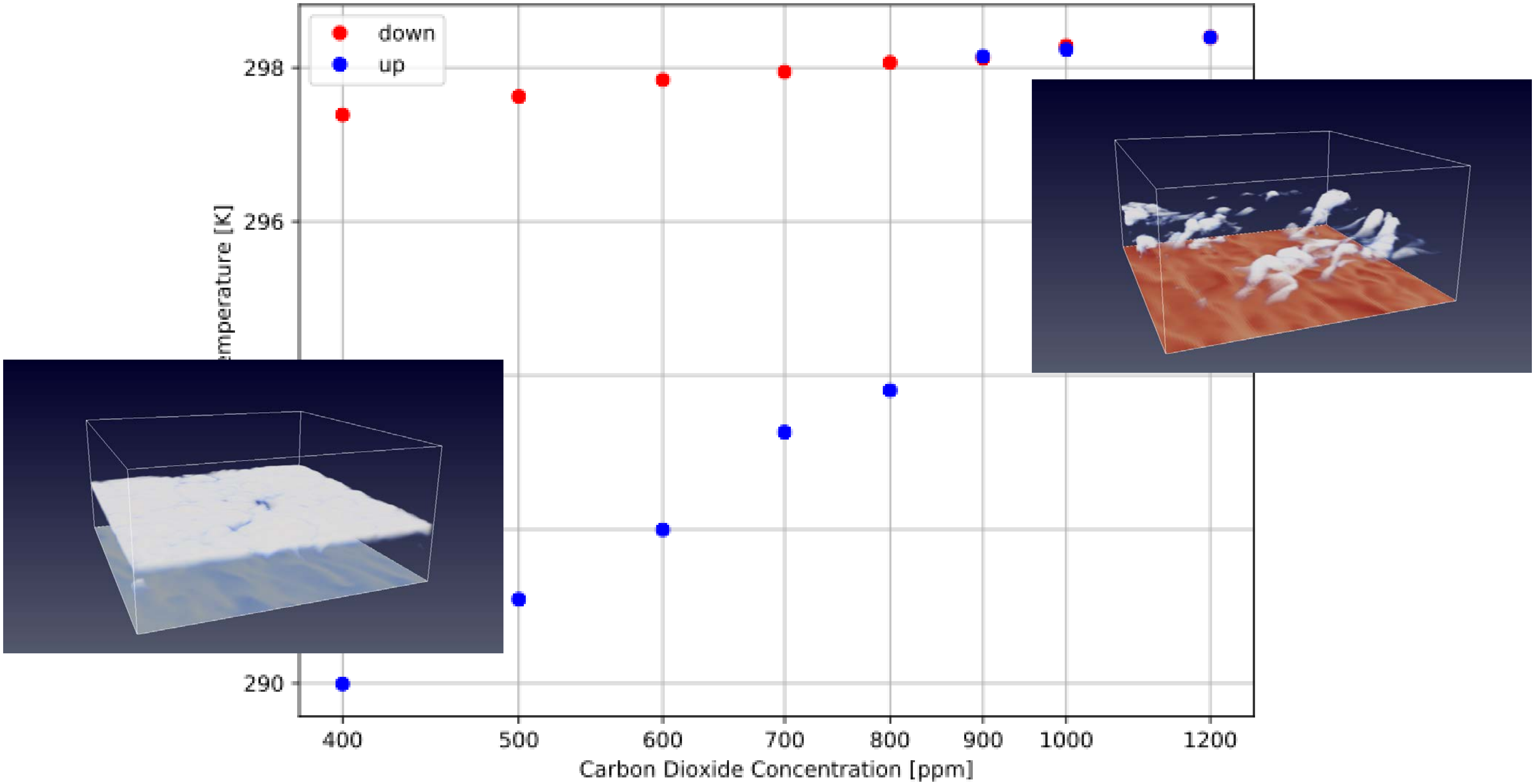
But we can simulate stratocumulus in limited areas

Simulation with PyCLES (Pressel et al. 2015)

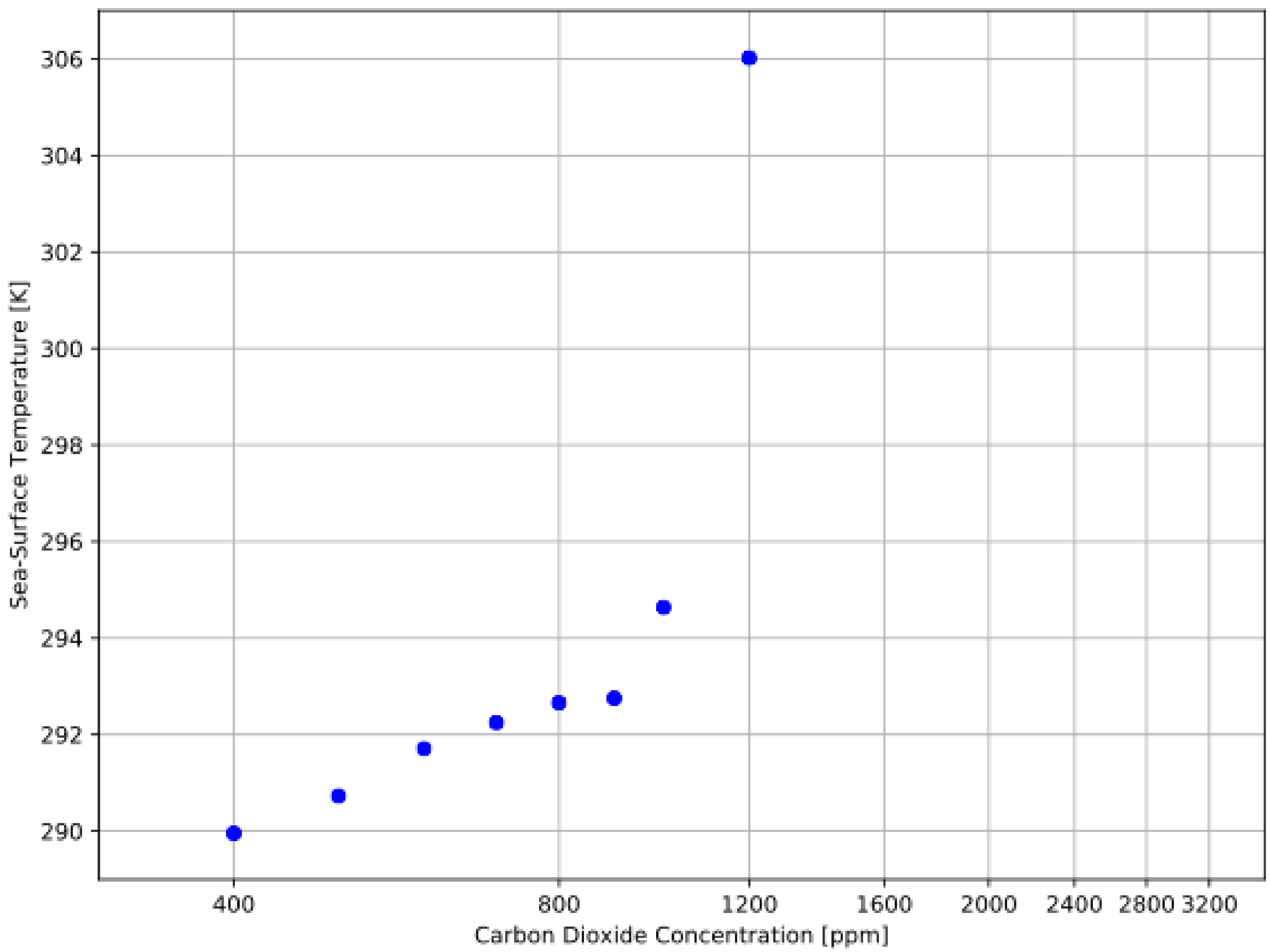
Interactions among many physical processes need to be modeled in stratocumulus clouds



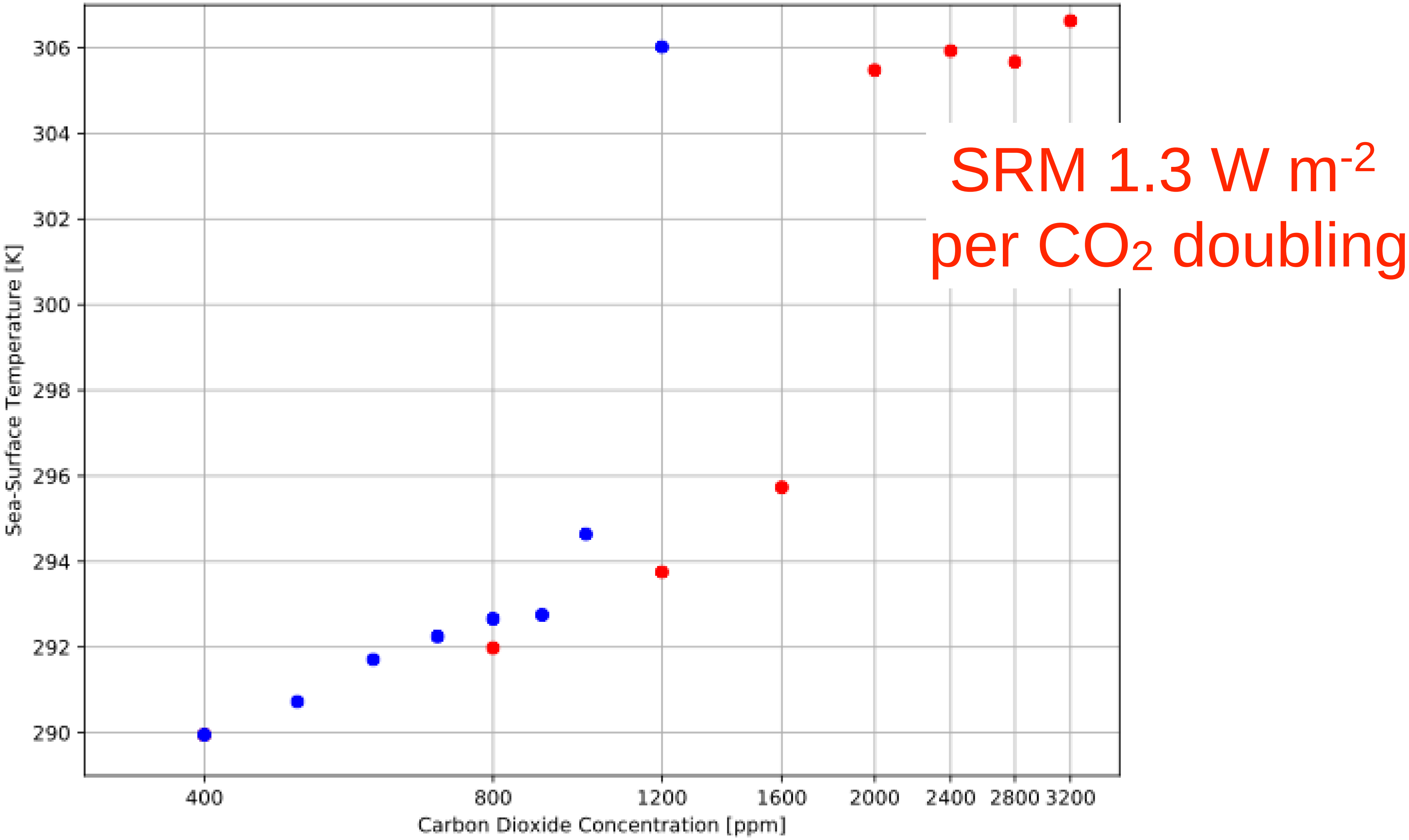
Explicitly simulating stratocumulus yields surprises that all climate models have missed



With less efficient lateral energy transport, warming is even more dramatic

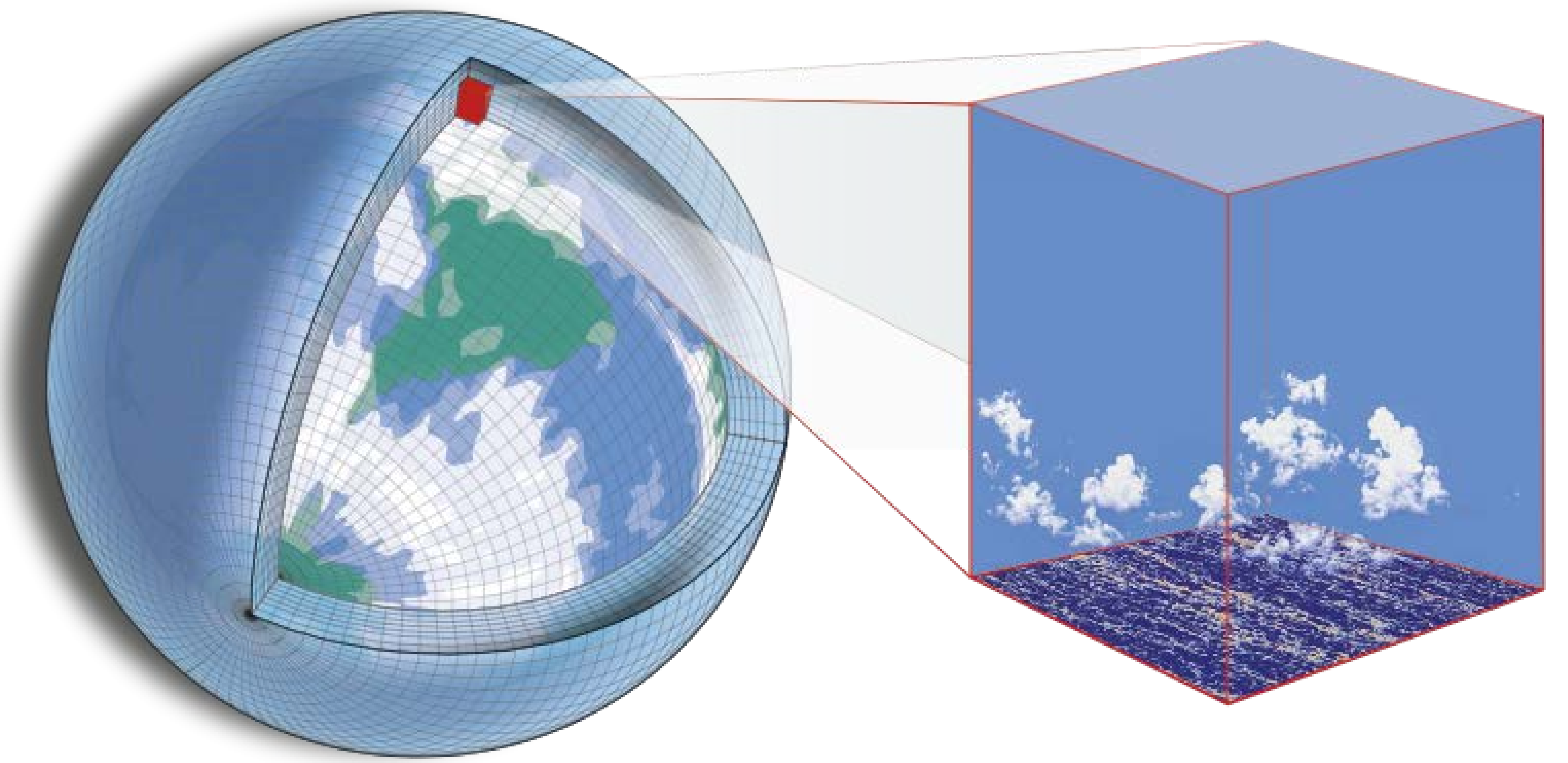


SRM geoengineering only delays the stratocumulus instability, but it remains



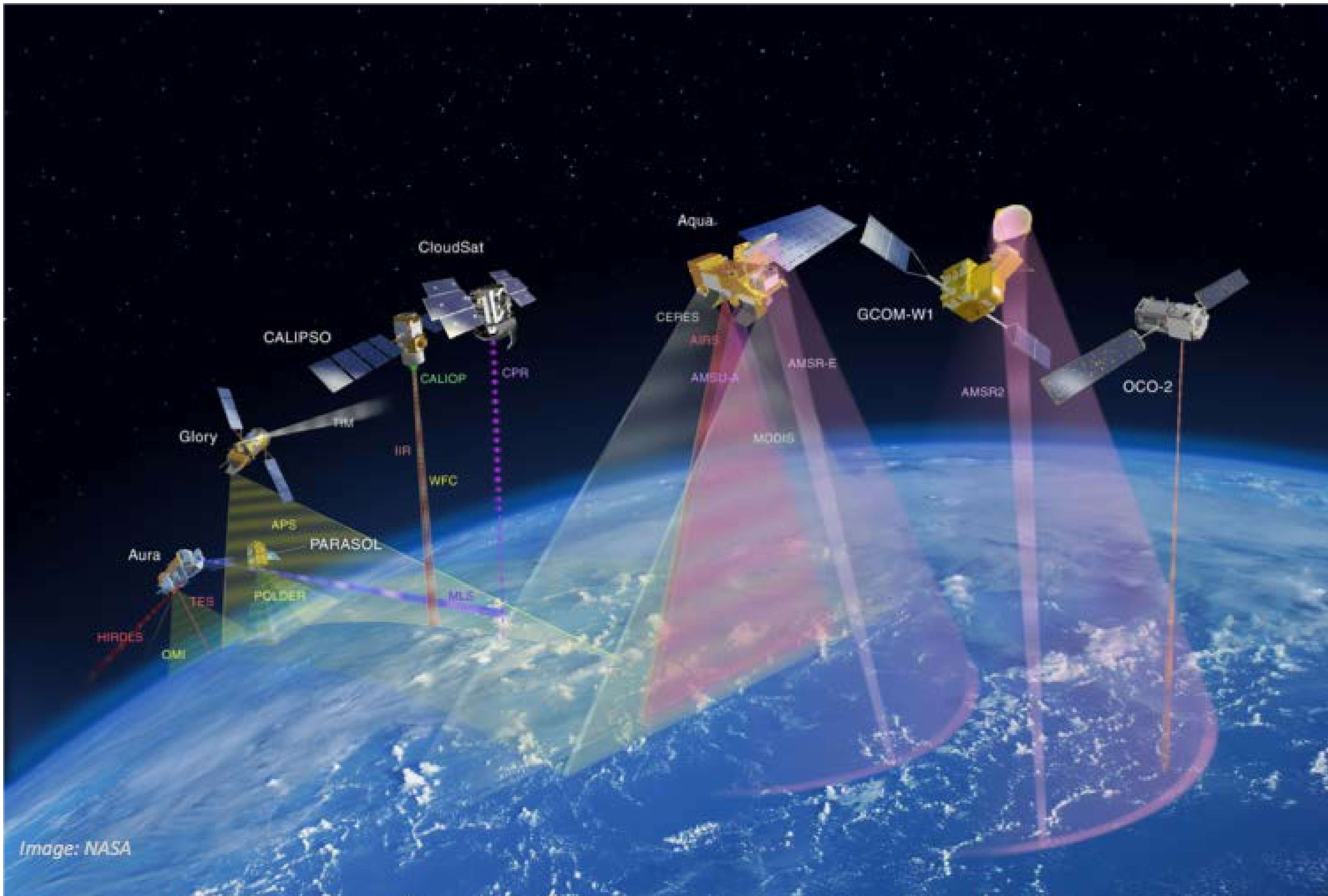
Progress on modeling low clouds is urgent

What we can do now

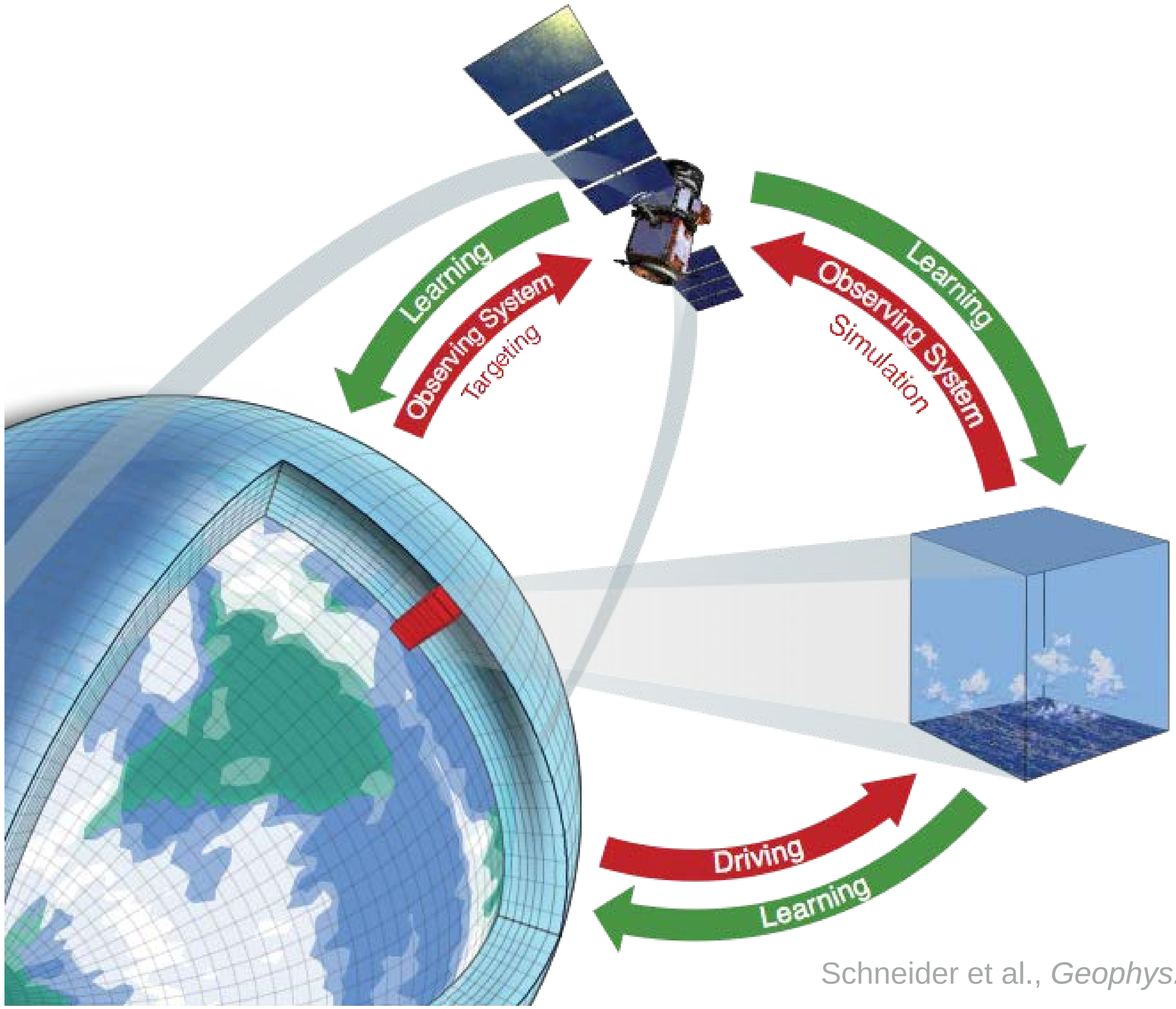


Use global and limited-area models in hierarchical framework (e.g., to develop parameterizations)

Additionally, a wealth of observations is available, whose potential to improve models is untapped



We want to integrate high-resolution simulations, global models, and observations in machine-learning system



Schneider et al., *Geophys. Res. Lett.*, in press

Objective of learning about parameters is bias reduction and exploitation of "emergent constraints"

- Need to accumulate statistics over timescales >10 days:

$$\langle \phi \rangle_T = \frac{1}{T}\int_{t_0}^{t_0+T} \phi(t)\, dt.$$

- Objective function should penalize mean deviations (bias) and covariance mismatch ("emergent constraints"). E.g.:

$$J_o(\theta) = \frac{1}{2}\left\| \langle f(y)\rangle_T - \langle f(\tilde{y})\rangle_T \right\|^2_{\Sigma_y}$$

with moment function

$$f(y) = \begin{pmatrix} y \\ y_i' y_j' \end{pmatrix}$$

- Creates computational challenges because objective function evaluation is expensive

- But also creates an opportunity to radically improve ESM in similar way in which data assimilation has improved NWP

Schneider et al., in press

Earth System Modeling 2.0: Toward models that learn from observations and targeted high-resolution simulations

- Use machine learning techniques to learn about uncertain model components from observations. E.g.,
  - Learn parameters in physics-based cloud and ice models
  - Learn biogeochemical models empirically
- Additionally, learn about physical models from high-resolution models nested within targeted ESM columns

We want to develop ESM with quantified uncertainties that are at least factor 2 smaller than current models

Climate goals and computing the future of clouds

Tapio Schneider, João Teixeira, Christopher S. Bretherton, Florent Brient, Kyle G. Pressel, Christoph Schär and A. Pier Siebesma

How clouds respond to warming remains the greatest source of uncertainty in climate projections. Improved computational and observational tools can reduce this uncertainty. Here we discuss the need for research focusing on high-resolution atmosphere models and the representation of clouds and turbulence within them.

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Earth System Modeling 2.0: A Blueprint for Models That Learn From Observations and Targeted High-Resolution Simulations†

Tapio Schneider, Shiwei Lan, Andrew Stuart, João Teixeira

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