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Combining process-level constraints with global climatology using Bayesian statistics and machine learning to improve the warm rain process representation in E3SM

Increasingly, Earth system models are being improved by systematic parameter inference ("tuning"), informed largely by global satellite products. This is an improvement on more ad hoc tuning methods where parameters are adjusted one-at-a-time or via limited tunings known to improve specific metrics of interest. In either case, such methodologies are considered "top-down" in that they consider the emergent state produced by many interacting atmospheric processes as the primary way to correct model behavior. By contrast, at process-level scales, cloud radars, lidar, and in situ probes provide new insights into the details of microphysical processes that evolve clouds, and these insights can result in "bottom-up" improvement of parameterization schemes. Meaningful and lasting improvement in climate model fidelity should leverage both of these advances, but there is no obvious methodology for accomplishing this, and consistently applying both “bottom-up” and “top-down” constraints faces substantial challenges. A probabilistic perspective, as afforded by Bayesian statistics, allows for the combination of uncertain information from different sources and spatiotemporal scales. However, the uncertainty in parameterization schemes is only partly quantifiable via parameters; much of the current uncertainty in microphysics exists in the form of discrete choices between competing schemes --- a manifestation of *structural* uncertainty. We develop a system for smoothly and comprehensively evaluating both structural and parametric microphysical choices, thus paving the way to an integrated top-down and bottom-up climate model improvement. We focus on the warm rain process representation first, but our final tuning methodology will incorporate other physics parameterizations in Earth system models, with Bayesian Markov Chain Monte Carlo parameter estimation accelerated by machine learning surrogate models. This allows for integrated top-down and bottom-up improvement of model fidelity together with estimates of uncertainty and multiple "equally plausible" model configurations.