Co-Evolving Climate Models under Uncertainty to Improve Predictive Skill

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Focal Area: Predictive modeling through the use of AI techniques and AI-derived model components; the use of AI and other tools to design a prediction system comprising of a hierarchy of models

Science Challenge: Advances in modeling of climate and improved observational capabilities have led to great improvements in understanding large-scale historical climate effects. It however remains a challenge to reliably *predict* the risk of fine-scale regional climate events on human systems even as such risks are on the rise because warmer and wetter climates are more prone to hydrometeorological extremes,

Rationale: The climate attractor plays a fundamental role in determining predictability of climate. Unfortunately, however, the collective experience of modeling of climate over the past half a century highlights the difficulty of eliminating bias when using a first principles based model to estimate the actual climate attractor. Such bias between the actual and modelled climate attractors fundamentally undermines both, better establishing sources of predictability and predictive modeling of climate. Given recent developments in data and information science and technology, we think that alternative ML/AI-based strategies have the potential to address the issue of bias in a fashion so as to enable meaningful progress with regard to both prediction and predictability.

Narrative. Lack of a theoretical basis: In weather prediction where one is interested in being able to shadow a particular trajectory, the nature of the cascade of error in scale space is the underlying dynamical mechanism that determines predictability ([5] and others, e.g., see [8, 2]). For example, depending on the distribution of energy in a system at the different scales, the cascade of error may be such that the system has a finite predictability horizon, or that horizon may be arbitrarily extended by continually reducing errors in the initial conditions: When the spectral slope of (the kinetic energy spectrum is shallower than k^{-3} where k is the one-dimensional wave-number, the system has finite predictability and the timescale for the predictability horizon at a particular spatial scale is determined by the fastest growing instability at that spatial scale. In the climate context, however, in the absence of such theoretical bases currently, predictability of climate is based on an intuitive understanding that a physical explanation of observed slow variations in the climate system should have predictive value. Such an approach to estimating predictability of climate may be overly simplistic in the sense that it may not take into account various uncertainties.

Near-term and Long-term: We split future climate into near-term and long-term and define near-term to mean the period over which initial conditions (IC) matter. Thus while long-term predictability is solely determined by boundary conditions (BC) and/or forcing, near-term predictability is affected by both BC/forcing and IC. We focus on the near-term.

Importance of the Climate Attractor and Bias in the Modelled Estimate: Given the statistical nature of the predictability of climate, the system attractor plays an important role, somewhat like the role played by the KE spectrum in the predictability of weather. And as

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indicated in the rationale, it is unfortunately the case that it is difficult to eliminate bias when using a first principles based model to model the actual climate attractor. This is because climate is characterized by feedback among diverse yet interconnected layers, and include interactions that drive dynamic evolution over an enormous range of spatial and temporal scales. And deficiencies in any model such as insufficient resolution and inaccurate parameterizations of unresolved processes almost always prevent the model from being able to accurately simulate the exact and particular, delicate dynamical balance of processes that give rise to both the mean state and the modes of variability of the climate system.

Perfect Model Predictability: Because of such bias, model predictions invariably decorrelate rapidly from observations [6] and for this reason predictability studies have had to largely focus on so-called “perfect model” experiments wherein *a* model trajectory is assumed to be the trajectory of interest (“true” trajectory) and the analysis of an ensemble of model integrations forms the basis for characterizing predictability. Even as ensemble-based predictability studies with comprehensive climate models have been performed at great expense, the model-specific nature of such studies makes it difficult to relate the results of such studies to the actual climate system. To wit, while studies of the Atlantic Meridional Overturning Circulation (AMOC) in many models have found decadal to multidecadal predictability [3, 7, 1, 4, 9], these findings have tended to be disparate and model-specific, and establishing the relevance of such findings to the real system has been difficult.

Way Forward: A prediction-centric framework that co-evolves different models under uncertainty: In predictive modeling of climate, it is common to consider two types of prediction experiments: uninitialized projections (UP) that account for changes in climate due to changes in external-forcing and initialized predictions (IP) which aim to augment the external-forcing related predictability realized in UP with natural-variability related predictability by appropriate observation-based initialization. Since we concern ourselves with the near-term presently, we focus on IPs.

The top panel in the figure is a schematic of the current state of the field of IP. The inset shows the actual model behavior of a particular climate model and most other models behave similarly. Because predictability is state-dependent, and because anomaly-based methods do not fully account for such state-dependence, we only consider full-field based models/methods. The schematic shows ensemble integrations of two models (red: Model 1 and blue: Model 2) that are initialized using data assimilation in early 1972 and 1978. Because of data assimilation, initial condition errors are small. (The heavy black line is a simplified representation of observations and constitutes the trajectory of interest.) However, because of different model errors, the two models have attractors that are each different from the actual attractor, which contains the trajectory of interest. Also, because the two models themselves are chaotic, the model ensembles spread, illustrating the model attractor for each of the two models.

We propose that a prediction-centric strategy be developed that, e.g., takes the two model ensembles in the top panel and then uses recent developments in ML/AI to co-evolve the two model ensembles in an optimization setting that seeks to satisfy certain desirable global objectives. Such an approach would use active and physics-informed machine learning and uncertainty quantification to transform the usual paradigm of ensemble integrations (e.g., as they are used to address initial condition and parametric uncertainties) into a mutually-interacting and learning ensemble that displays self-organization towards satisfying certain desirable global objectives. The success of the approach, on having developed it, is shown in the bottom panel

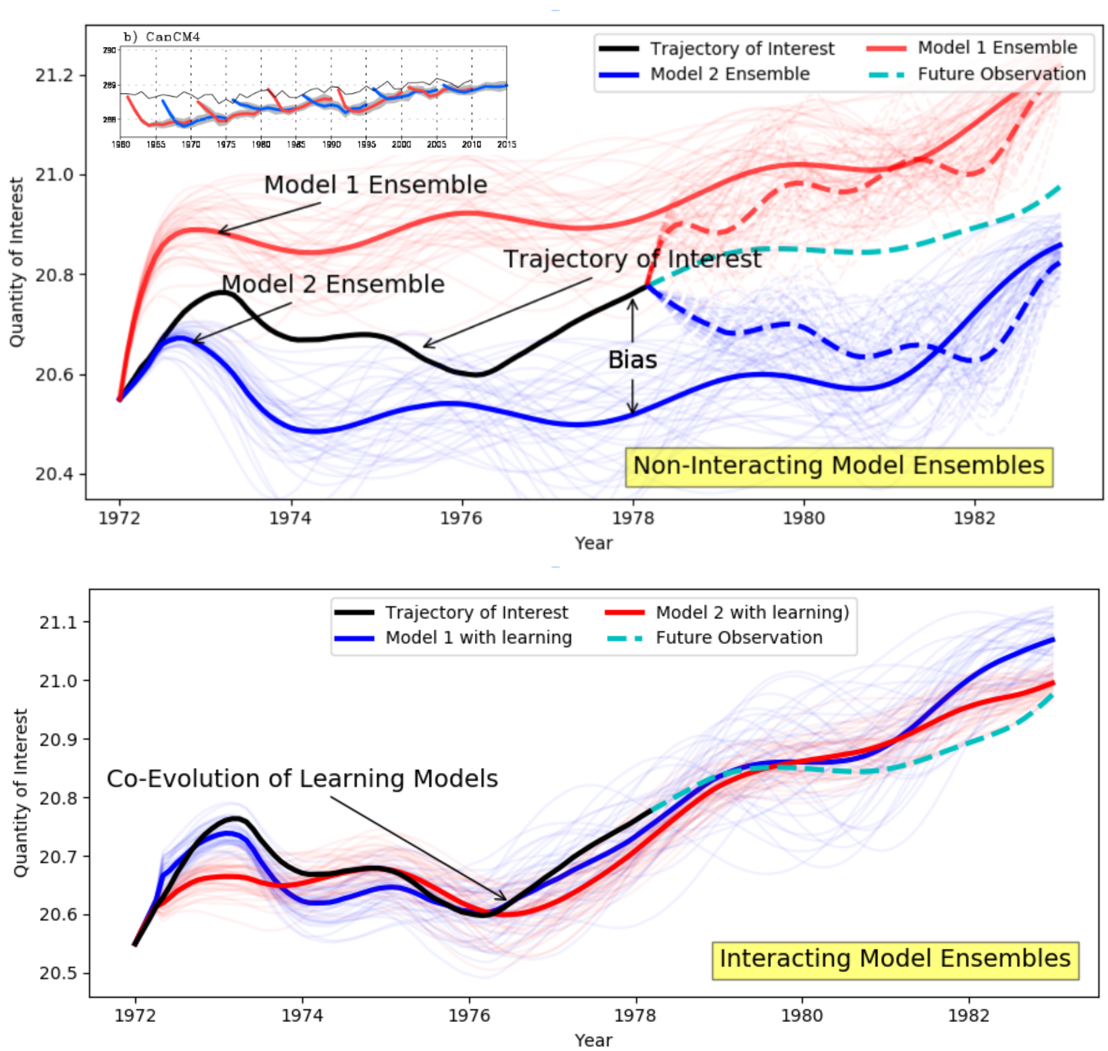

Figure 1: Top: Current state of the field. The inset shows actual model behavior of a particular model(cf. CMIP; most other models behave similarly). The schematic shows ensemble integrations of two models (red: Model 1 and blue: Model 2) that are initialized using data assimilation in early 1972 and 1978. Because of data assimilation, initial condition errors are small. However, because of different model errors, the two models have attractors that are each different from the actual attractor, which contains the trajectory of interest. Also, because the two models themselves are chaotic, the model ensembles spread, illustrating the model attractor for each of the two models. The problems illustrated here are excacerbated in regional fine-scale climate models since these problems are controlled by the smaller of the resolved scales.
Bottom: Our proposed new paradigm solves these serious shortcomings by using recent developments in data and information sciences to allow models 1 & 2 to interact as they evolve and learn to obey certain constraints. The anticipated success of the approach is shown (a) in model 1 and model 2 ensembles containing the observations upto 1978 and (b) in continued tracking of the actual climate attractor beyond 1978.

(a) in model 1 and model 2 ensembles containing the observations upto 1978 and (b) in continued tracking of the actual climate attractor beyond 1978.

For simplicity, we have illustrated the method in terms of Models 1 and 2, but we envision the method to be able to automatically formulate a model hierarchy given a root model such as E3SM, and capable of numerous other tasks including data-assimlation and producing bounds and estimates of quantities of interest related to hydrometeorological extremes.

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