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Harnessing AI and Computing to Advance Climate Modeling and Prediction

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There are contrasting views on how to produce the accurate predictions that are needed to guide climate change adaptation. Here, we argue for harnessing AI, building on domain-specific knowledge, and generating ensembles of moderately high-resolution (10–50 km) climate simulations, as anchors for detailed hazard models.

Adaptation planners, local decision makers and industries are demanding detailed assessments of climate risks[1], which necessitate large ensembles of climate simulations[2]. However, climate models struggle to provide the needed granular predictions with quantified uncertainties. A step change in the accuracy and usability of climate predictions is needed.

One proposed approach for a step change in climate modeling is to focus on global models with 1 km horizontal resolution, which can improve simulations, for example, of atmospheric convective storms and the resulting extreme precipitation[3,4]. However, because kilometer-scale models stretch the limits of what is computationally feasible, only a few simulations can be generated with kilometer-scale models, primarily in select centers in the Global North. An alternative approach increases the model resolution to 10–50 km (relative to around 100 km that are standard today) and focuses on calibration with Earth observations and higher-resolution regional simulations using AI tools[5]. This enables the generation of large ensembles to quantify uncertainties and support detailed impact assessments using offline hazard models. We argue that a balanced approach, incorporating higher-resolution modeling, AI, and learning from observational and simulated data, offers the most robust path to accurate climate risk assessments.

Kilometer-scale Models

Climate models with a horizontal resolution around 1 km are appealing because their resolution closely matches the scale at which many climate risk assessments are needed. They promise to reduce errors, for example, in simulations of regional precipitation and its extremes[3,4].

However, while kilometer-scale models have been referred to as "digital twins" of Earth[3], they still have limitations and biases similar to current models. They fail to capture important sub-kilometer scale processes, such as the dynamics of the energetically crucial low-lying clouds[6], which operate at scales of 1–10 m. They are far from resolving atmospheric turbulence, which occupies a continuum of scales from the planetary scale to the dissipation (Kolmogorov) scale of around 1 mm. Therefore, although an atmosphere model with 1 km horizontal resolution and 200 vertical levels would have 10^{11} spatial degrees of freedom, this is a factor 10^{17} less than the turbulence in Earth's atmosphere. Furthermore, below the smallest turbulent scales operate processes that contribute to major uncertainties in climate predictions. Cloud microphysical processes, controlling the formation of of cloud droplets and ice crystals and occurring on nano- and micrometer scales, regulate Earth's energy balance. Uncertainties in their representation contribute substantially to the divergent sensitivities of climate models to increasing greenhouse gas concentrations[7]. Errors in the representation of such small-scale processes percolate upscale and lead to biases in a model's large-scale energy balance and simulated features such as precipitation patterns.

Thus, because kilometer-scale models do not resolve many crucial small-scale processes, they exhibit some of the same large-scale biases—for example, in tropical rainfall patterns—that have plagued coarser-resolution models for decades[8]. Accuracy gains in going from 10 km to 1 km resolution so far have been incremental[9], and the intensity of convective storms has not reached convergence at kilometer resolution[10]. In fact, without calibration, large-scale biases can be larger at higher than at lower resolution.

Overall, kilometer-scale models do not offer the step change in accuracy that would justify accepting the limitations they impose on the size of simulation ensembles, which are needed both to calibrate the unavoidable empirical models of unresolved processes and to quantify uncertainties.

Harnessing AI and Data to Improve Earth Systems Models

Rather than prioritizing kilometer-scale resolution, we propose a balanced approach that capitalizes on advances in computing and AI. By moderately increasing global resolution while extensively harnessing observational and simulated data, this approach is more likely to achieve the objective of climate modeling for risk assessment, which involves minimizing model errors and quantifying uncertainties. Model resolution is no panacea but one of several parameters to be optimized in pursuit of this objective. It serves as a potent lever for optimization because computational cost scales cubically with horizontal resolution when vertical resolution is fixed: 1000 simulations at 10-km resolution cost the same as one simulation at 1-km resolution. Transitioning to global resolutions around 10 km would represent a significant improvement over current standards, while still enabling the generation of large ensembles. These ensembles are essential for quantifying uncertainties and leveraging AI tools to learn from data about crucial small-scale processes, such as cloud dynamics and microphysics, which cannot be directly resolved.

Because climate predictions focus on statistical quantities such as mean temperatures or probabilities of extreme precipitation events, it is natural to learn about unresolvable processes in models from climate statistics accumulated over time[5]; this contrasts with the assimilation of weather states in weather forecasting (see Box 1 for crucial differences between weather forecasting and climate prediction). The relatively smooth spatial and temporal variation of climate statistics also helps mitigate challenges stemming from resolution disparities between simulations and observations.

However, learning from climate statistics using AI tools poses its own challenges:

- The widely adopted machine learning (ML) paradigm of supervised learning, which typically relies on model gradients for training, is too restrictive because it requires direct training data at the level of the processes to be learned. However, climate data (e.g., cloud cover statistics) usually only provide indirect information about the processes to be learned (e.g., cloud microphysics).
- Learning from statistics such as multi-year averages or the seasonal cycle requires accumulating simulated statistics over years to decades, making the training stage computationally expensive.

These challenges can be met. Ensemble Kalman methods, widely employed for state assimilation in weather forecasting, can be adapted to learn about parameters, parametric functions, or even ML components of climate models by solving inverse problems[5,11]. These methods avoid the restrictions of supervised learning and the reliance on model gradients. They allow calibrating models with noisy, heterogeneous, and indirect data, such as the plethora of Earth observations now available (Fig. 1). They can be paired with ML emulators to speed up uncertainty quantification, reducing the number of climate model runs required from a prohibitive $O(10^6)$, with standard Markov chain Monte Carlo methods, to a manageable $O(10^3)$[12,13].

The otherwise overwhelming data demands arising from the vast range of unresolvable scales in the climate system and the need to generalize from available observations to unseen climates can be mitigated by pairing learning from data with domain-specific knowledge (e.g., theories and conservation laws). The area of combining data and new AI tools with domain-specific knowledge is ripe for further advances. Progress will be important not just for the climate sciences but for the computational sciences and engineering broadly, where learning closure models for unresolved processes from limited data is a common problem.

Whichever AI tools will prevail, we need to be able to run climate models $O(10^3)$ times to calibrate unresolvable processes, quantify model uncertainties, and to produce large ensembles of predictions that sample from the learned models and span plausible climate outcomes[2,12,13]. Producing these large ensembles will remain infeasible at kilometer-scale resolution for the next decade. Therefore, while we should push the resolution frontier as computer performance increases, climate modeling in the next decade needs to focus on resolutions in the 10–50 km range. In this range, tropical cyclones and mesoscale ocean turbulence begin to be resolved[14,15], improving the simulation of the most damaging weather hazards and of the rate of ocean heat and carbon uptake relative to the $O(100\text{ km})$ resolution that is standard today.

Large ensembles then remain feasible and, in fact, are beginning to be generated. Simulations at yet higher resolutions, from kilometers down to meters, have a role to play here, in providing training and validation data for coarser-resolution models, including in climates different from today's for which we do not have observations; however, these simulations do not need to span the globe but can be targeted to specific regions or climate conditions where they are particularly informative[5]—an approach that lends itself well to distributed (cloud) computing (Fig. 1).

A Hierarchy of Models in a Distributed Research Program

Climate modeling must support a variety of adaptation decisions, many on local scales. This requires that ensembles of climate predictions are downscaled to impact-relevant scales and anchor a hierarchy of offline hazard models, based on process models or generative AI, for the efficient exploration of scenarios and propagation of uncertainties to specific climate impacts. Hazard models include meter-scale models of inland and coastal flooding[16], of compound storm-heatwave impacts on infrastructure and vulnerable populations[17], and of wildfire risks[18].

Importantly, climate models must be developed so that they can be used and improved upon through rapid iteration, in a globally inclusive and distributed research program that does not rely on the few monolithic centers that would be needed if the focus is on kilometer-scale global modeling. An approach focused on generating large ensembles of simulations at moderately high resolution (10–50 km) provides a better assessment of climate risks and enables wider adoption. After computationally costly calibration and uncertainty quantification, such models can be run by diverse groups, tapping into the talent pool of those most vulnerable to climate change and knowledgeable about risks to their communities.

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Competing Interests

T.S. has an additional affiliation as Visiting Researcher at Google LLC.

Box 1: Weather Forecasting vs. Climate Prediction

Improved data assimilation has driven recent progress in weather forecasting. Similar progress may be at hand in climate prediction. However, weather forecasts and climate predictions differ fundamentally. Weather forecasts are predictions of the first kind, aiming to predict future system states given initial conditions[19]. Predictability of the first kind is limited by chaos: the state of the atmosphere is forgotten in about two weeks. Daily assimilation of weather observations provides initial conditions for weather forecasting. It also compensates for errors in the representation of unresolved processes by repeatedly pulling, for example, simulated temperatures back toward observations, offsetting biases in a model's energy balance.

By contrast, climate predictions are predictions of the second kind[19], aiming to predict future climate statistics given evolving boundary conditions, such as greenhouse gas emissions. Predictability of the second kind is limited because the signal of changing climate statistics emerges only slowly against the chaotic background variability. To predict these slowly changing climate statistics, a climate model must run freely for decades into the future, without a chance to compensate for errors through assimilation of observed climate states. Therefore, our ability to predict how climate statistics change on multidecadal timescales is principally limited by uncertainties and errors in the representation of unresolved processes. Uncertainties about emission scenarios additionally begin to contribute substantially on timescales around 30 years and dominate on centennial scales[20].

Thus, improved weather forecasts, whether with traditional numerical or ML models, do not directly translate into improved climate predictions. But some of the tools that led to progress in weather forecasting, such as data assimilation, can be adapted for climate models to learn from data, albeit with data consisting of climate statistics rather than weather states.

Figure 1: To improve climate models, model components encoding domain-specific knowledge should learn from diverse climate statistics obtained from Earth observations or regional high-resolution simulations. Ideally, the model components learn jointly, and have their joint uncertainties quantified, to reduce and reveal compensating errors among components, through a shared layer of data assimilation and ML tools wrapping all model components[10]. Large ensembles of climate simulations are necessary for this model calibration and UQ, and large ensembles are also necessary to sample the space of plausible climate outcomes[9]. These simulation ensembles can be generated at moderately high resolution (10–50 km) but currently not at kilometer scales.