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Harnessing AI and computing to advance climate modelling 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 artificial intelligence, 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 modelling is to focus on global models with 1-km horizontal resolution. These can improve simulations, such as those of atmospheric convective storms and the resulting extreme precipitation[3,4]. However, because kilometre-scale models stretch the limits of what is computationally feasible, they can only generate a few simulations – primarily in select centres in the Global North. An alternative approach increases the model resolution to 10–50 km (from around 100 km, which is standard today) and focuses on calibration with Earth observations and higher-resolution regional simulations using artificial intelligence (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 such a balanced approach – incorporating higher-resolution modelling, AI and learning from observational and simulated data – offers the most robust path to accurate climate risk assessments.

Kilometre-scale models

Climate models with a horizontal resolution of 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[4].

However, although kilometre-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-kilometre-scale processes, such as the dynamics of the energetically crucial low-lying clouds[6] that 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. Consequently, although an atmosphere model with 1-km horizontal resolution and 200 vertical levels would have

BOX 1

Weather forecasting versus 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[18]. 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[18], 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. The ability to predict how climate statistics change on multidecadal timescales is therefore principally limited by uncertainties and errors in the representation of unresolved processes. Uncertainties about emission scenarios also begin to contribute substantially on timescales around 30 years and dominate on centennial scales[19].

Thus, improved weather forecasts, whether obtained by traditional numerical or machine learning 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.

10^{11} spatial degrees of freedom, this is less than the turbulence in Earth's atmosphere by a factor of 10^{17}.

Furthermore, below the smallest turbulent scales, processes operate that contribute to major uncertainties in climate predictions. Cloud microphysical processes, which control the formation of cloud droplets and ice crystals and occur on nano- and micrometre scales, regulate Earth's energy balance. Uncertainties in their representation contribute substantially to the divergent sensitivities of climate models to increasing greenhouse gas concentrations. Errors in the representation of such small-scale processes percolate upscale and lead to biases in a model's large-scale energy balance and in simulated features such as precipitation patterns.

Thus, because kilometre-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[7]. Accuracy gains in going from 10-km to 1-km resolution so far have been incremental[8], and the intensity of convective storms has not reached convergence at kilometre resolution[9]. In fact, without calibration, large-scale biases can be larger at higher than at lower resolution[8].

Overall, kilometre-scale models do not offer the step change in accuracy that would justify accepting the limitations that 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 kilometre-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 modelling 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: 1,000 simulations at 10-km resolution cost the same as 1 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 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 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 (for example, cloud cover statistics) usually only provide indirect information about the processes to be learned (for example, cloud microphysics). Learning from statistics such as multi-year averages or the seasonal cycle also requires accumulating simulated statistics over years to decades, making the training stage computationally expensive.

These challenges can be met. Ensemble Kalman methods, which are widely employed for state assimilation in weather forecasting, can be adapted to learn about parameters, parametric functions or even machine learning components of climate models by solving inverse problems[10]. These methods avoid the restrictions of supervised learning and the reliance on model gradients. They allow calibration of models using noisy, heterogeneous and indirect data, such as the plethora of Earth observations now available (Fig. 1). They can be paired with machine learning emulators to speed up uncertainty quantification, reducing the number of climate model runs required from a

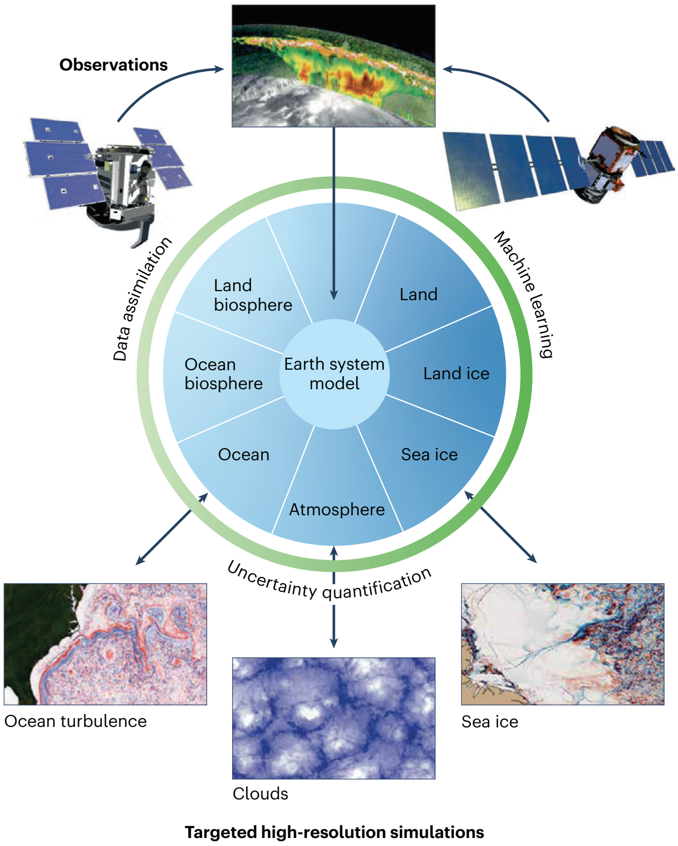

Fig. 1 | Improving climate models and predictions by learning from observational and simulated data. To improve climate models, model components encoding domain-specific knowledge should learn from diverse climate statistics that are obtained from Earth observations or regional high-resolution simulations. Ideally, the model components learn jointly, and have their joint uncertainties quantified, to reveal and reduce compensating errors among components through a shared layer of data assimilation and machine learning tools wrapping all model components[5]. Large ensembles of climate simulations are necessary for this model calibration and uncertainty quantification, and large ensembles are also necessary to sample the space of plausible climate outcomes[2]. These simulation ensembles can be generated at moderately high resolution (10–50 km), but not yet at kilometre scales.

prohibitive $O(10^6)$, with standard Markov chain Monte Carlo methods, to a manageable $O(10^3)$ (refs. 11,12).

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 (for example, 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 also for the computational sciences and engineering, 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 produce large ensembles of predictions that sample from the learned models and span plausible climate outcomes[2]. Producing these large ensembles will remain infeasible at kilometre-scale resolution for the next decade. Therefore, although we should push the resolution frontier as computer performance increases, climate modelling in the next decade needs to focus on resolutions in the 10–50 km range. In this range, tropical cyclones[13] and mesoscale ocean turbulence[14] begin to be resolved, improving the simulation of the most damaging weather hazards and the rate of ocean heat and carbon uptake relative to today's standard of O(100 km) resolution.

Large ensembles then remain feasible, and are even beginning to be generated. Simulations at yet higher resolutions, from kilometres down to metres, have a role to play here in providing training and validation data for coarser-resolution models, including in climates that are different from that of today 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 programme

Climate modelling 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 metre-scale models of inland and coastal flooding[15], compound storm–heatwave impacts on infrastructure and vulnerable populations[16], and wildfire risks[17].

Importantly, climate models must be developed so that they can be used and improved on through rapid iteration, in a globally inclusive and distributed research programme that does not concentrate resources in the few monolithic centres that would be needed if the focus is on kilometre-scale global modelling. 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 global 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 a visiting researcher at Google LLC. All other authors declare no competing interests.