

AI-empowered next-generation multiscale climate modelling for mitigation and adaptation

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Earth system models have been continuously improved over the past decades, but systematic errors compared with observations and uncertainties in climate projections remain. This is due mainly to the imperfect representation of subgrid-scale or unknown processes. Here we propose a next-generation Earth system modelling approach with artificial intelligence that calls for accelerated models, machine-learning integration, systematic use of Earth observations and modernized infrastructures. The synergistic approach will allow faster and more accurate policy-relevant climate information delivery. We argue a multiscale approach is needed, making use of kilometre-scale climate models and improved coarser-resolution hybrid Earth system models that include essential Earth system processes and feedbacks yet are still fast enough to deliver large ensembles for better quantification of internal variability and extremes. Together, these can form a step change in the accuracy and utility of climate projections, meeting urgent mitigation and adaptation needs of society and ecosystems in a rapidly changing world.

Climate change poses an unprecedented risk for humans and Earth's sustainability¹. This grand challenge threatens civil infrastructure, agriculture, water availability, public health, economic security and international peace². Climate mitigation is urgently required to reduce the magnitude of the climate crisis by decreasing and offsetting anthropogenic emissions. In addition, climate adaptation strategies need to be developed to prepare for the negative impacts and consequences of climate change while mitigation efforts are ongoing.

Mitigation

Atmospheric concentration of CO₂ has risen to ~420 parts per million (2023), ~50% above its pre-industrial level. Consequently, the global surface temperature was 1.09 °C warmer in 2011–2020 compared with 1850–1900³. The speed of this warming is rapid, and it has been unprecedented for more than 2,000 years. To limit global warming to 1.5 °C

above pre-industrial temperatures, we would need to cut today's CO₂ emissions by ~43% by 2030, and they would need to continue to decline further to achieve net-zero emissions by 2050, followed by negative CO₂ emissions throughout the rest of the century^{1,4}. Immediate, deep and sustained reductions of methane and other greenhouse gases would also be required. Otherwise, limiting warming to 1.5 °C or even 2 °C will be beyond reach. This requires moving towards the phase-out of fossil fuel use, with a 'transitioning away' and 'accelerated action in this critical decade' now being called for in the first Global Stocktake of the 28th Conference of the Parties.

Adaptation

In every region of the world, we are experiencing the impacts of climate change, with many extreme events becoming more frequent and more severe and high-temperature records regularly being broken.

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Box 1: Emerging Earth system processes and feedbacks

In addition to uncertainties in climate projections arising from subgrid-scale processes, uncertainties arise from the ocean and terrestrial carbon cycle response to climate change and increased atmospheric CO₂ concentrations⁴, as well as from other important Earth system components (for example, cryosphere) and feedbacks (for example, chemistry and aerosols)¹⁷. Indeed, the effects of anthropogenic climate change depend not only on the levels of greenhouse gases that humanity continues to emit, but also on how the Earth can absorb some of those emissions. Mitigation pathways to reach the Paris Agreement require large-scale transformation of our industrial, energy and transport systems and large-scale deployment of CO₂ removal through land, ocean or direct captures towards a net-zero world and negative emissions¹³. Reliable simulation of the carbon cycle and other Earth system feedbacks is therefore critical to correctly assess the effectiveness of climate mitigation strategies, including the effectiveness of nature-based carbon dioxide removal strategies such as re/afforestation, bioenergy with carbon capture and storage, and sustainable agriculture⁹⁶. It also requires addressing climate mitigation together with air quality improvements related to methane emissions and aerosol emission reductions³. As we highlight in our proposed approach, it is therefore important to complement kilometre-scale climate modelling activities with coarser hybrid ESMs that can interactively simulate these feedbacks such as permafrost^{97,98}, wildfire⁹⁹ and biological processes (for example, photosynthesis, transpiration and soil respiration)¹⁰⁰. AI can help to further enhance understanding of important climate and Earth system processes and feedbacks and their representation in hybrid ESMs (Fig. 1), for example:

- **Radiation:** AI can help better represent radiation and its interactions with the atmosphere, including reflection, absorption and scattering processes with clouds. It can speed up the expensive and infrequent radiation computation in atmospheric models, allowing for more frequent calls and, thus, for more accurate radiation and cloud–radiation interactions. This can help to elucidate the feedback mechanisms influencing Earth’s energy balance and the climate system in hybrid ESMs.
- **Clouds, convection and microphysics:** exploiting satellite data, ground sensors and high-resolution atmospheric models, AI can help analyse and better predict cloud feedbacks and cloud–aerosol interactions, uncovering their roles in climate regulation and weather patterns, which enhances understanding of cloud dynamics and their impact on global and regional climate. ML-based parameterizations implemented into hybrid ESMs can reduce systematic biases, for example, in precipitation compared with traditional ESMs.
- **Gravity waves:** AI can analyse high-resolution model data and observations that resolve gravity waves to better represent waves in the atmosphere, connect the wave activity and deposited momentum to the gravity-wave sources and learn to predict the gravity-wave drag, leading to a better understanding of gravity-wave processes and their influence on atmospheric dynamics. AI can thus enable hybrid ESMs that better represent gravity-wave drag and its various effects, helping to eliminate some long-standing biases (for example, gravity-wave drag).
- **Turbulence:** AI can analyse high-frequency atmospheric data from various sources, including aircraft, satellites and ground-based stations, along with high-resolution turbulent resolving simulations to more accurately model turbulence in the atmosphere with unprecedented spatial and temporal resolution.

This enables the identification of modes of atmospheric turbulence that can be incorporated into hybrid ESMs, improving the representation of, for example, energy transfer processes and mixing in the atmospheric boundary layer.

- **Terrestrial carbon cycle:** land processes are not likely to improve through high-resolution simulations as many processes cannot explicitly be resolved, so the main ways to improve models are through the use of observations and process representation. AI can analyse vast amounts of satellite imagery and meteorological data to identify patterns and trends in ecosystems at high spatial and temporal resolution. This enables improved prediction of the timing of events across diverse ecosystems, enhancing the predictive capacity of ecosystem responses to climate change and informing conservation and agricultural practices.
- **Land–atmosphere interactions:** AI can process and analyse large and complex datasets from various in situ or remote-sensing sources to identify and model land–atmosphere feedbacks and processes with high spatial and temporal accuracy. This can enable a detailed understanding and prediction of how vegetation and soil moisture interact with the atmosphere, influencing surface carbon, water and momentum fluxes, and climate and weather at multiple scales.
- **Wildfire:** worsening fires in a warming climate are of utmost importance to our understanding of climate impacts, but fire in ESMs is treated simplistically and does not, for example, account for the possible climate feedback rising from changing fire aerosol emissions. AI can harvest terrain information, weather conditions, fuel loads and satellite estimates of burned area and emissions to develop AI-based fire ignition, burned area and emissions parameterizations that can be used to more accurately represent fire in a changing climate.
- **Permafrost climate–carbon feedback:** the permafrost carbon stores that are today ‘locked’ in the frozen ground are not represented in most models, and no models represent abrupt thaw processes that have the potential to dramatically increase permafrost carbon emissions and, thereby, projections of permissible emissions. AI can be used to establish connections between climate, vegetation, soil thermal and fire conditions and trends, along with landscape type and vulnerability, that can be used to predict the probability of abrupt thaw and carbon release so that abrupt thaw can be incorporated into ESMs.
- **Hydrological processes:** leveraging remote sensing, historical snow information, streamflow and groundwater data, and meteorological inputs, AI can forecast hydrological processes, including snowpack dynamics, soil moisture and river flows. This provides insights into water variations across space and time, enhancing resource management, flood forecasting and climate models with detailed, spatially explicit forecasts of water availability.
- **Ocean dynamics and cryosphere:** harvesting satellite data, ocean buoys and atmospheric models, AI can help decipher dynamic interactions between ocean currents, temperature and the atmosphere as well as improve the representation of unresolved turbulent processes and subsurface flow, allowing for improved modelling of how these interactions influence global climate patterns. In the cryosphere, processes are not likely to improve in higher-resolution simulations, but AI can integrate complex data sources to improve process understanding and refine model parameterizations, enhancing simulations of ice dynamics and feedback processes.

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- Salinity heat and momentum exchange: AI can improve the representation of salinity heat and momentum exchange in climate models by analysing vast datasets of oceanic and atmospheric interactions from in situ measurements and high-resolution simulations that can help identify patterns and relationships. These algorithms can then inform the development of more accurate parameterizations, improving the fidelity

of salinity heat and momentum exchange in climate model simulations.

Another challenge lies in accurately representing biodiversity, ecological, adaptation and evolutionary processes and their role in ecosystem functioning¹⁰¹. For further examples of important Earth system feedbacks, we refer to ref. 17.

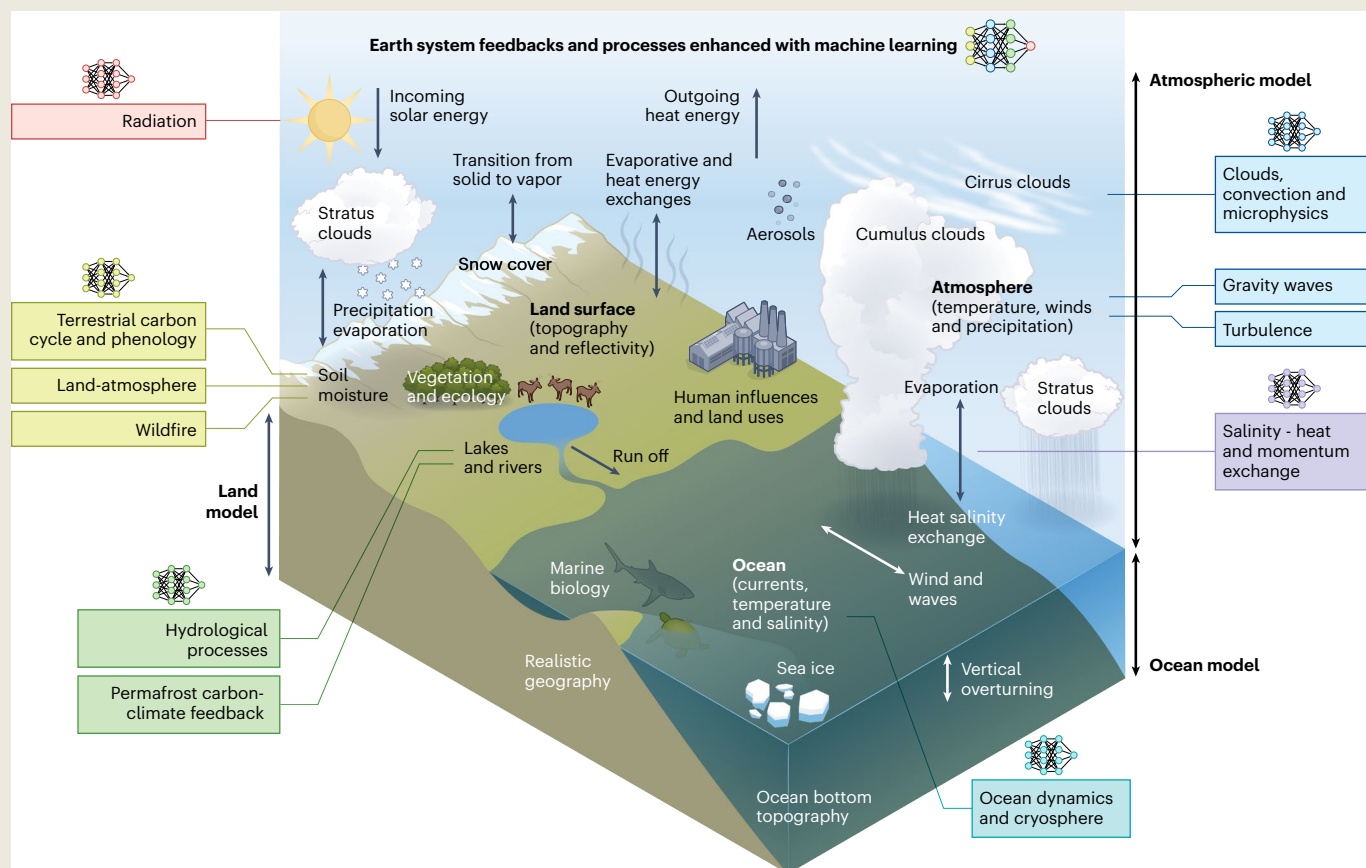


Fig. 1 | Feedback mechanisms across the Earth's system introduce uncertainties in climate projections, affecting carbon cycles and climate change responses. Many feedbacks are poorly understood or resolved, which calls for sustained research towards improved coarse-scale ESMs, exploiting AI/ML along with emerging data streams to help overcome barriers

to understanding and representing them in hybrid ESMs. The interplay of natural processes and human-induced emissions underscores the complexity of mitigating climate change, necessitating innovative solutions such as AI for effective climate strategies.

Many recent extreme events would have been highly unlikely without human-induced climate change⁵. Across sectors and regions, the most vulnerable people and ecosystems are disproportionately affected by these changes. The rise in extremes has led to some irreversible impacts as nature and humans are pushed beyond their ability to adapt¹. Early investments can maximize the resiliency and cost-effectiveness of adaptation strategies but require reliable climate projections for various plausible future socioeconomic scenarios at a scale relevant to actions, which is typically regional or local.

Climate modelling for mitigation and adaptation

Climate and Earth system models (ESMs) provide a fundamental source of information for climate mitigation and adaptation decisions. Applying these models to understand climate change and to provide multimodel climate simulations is internationally coordinated by the World Climate Research Programme's Coupled Model Intercomparison Project (CMIP), with simulations of the most recent phase, CMIP6⁶, just being completed. CMIP has supported climate research since the

early 1990s, while careful analysis of CMIP model output has provided a fundamental basis for Intergovernmental Panel on Climate Change assessment reports and climate policy negotiations over the past several decades (for example, the Paris Agreement⁷).

However, due to their complexity and computational costs, ESMs typically have a coarse resolution (~40–160 km (ref. 8)). These models still exhibit systematic errors compared with observations^{9,10}, and large uncertainties in their projections remain, such as on precipitation changes, the jet stream and ocean circulation changes^{11,12}. These climate projection uncertainties may deter policy decisions regarding adaptation, investment, security and resiliency. Climate mitigation and adaptation decisions could benefit from more reliable projections of the Earth system, not only globally but also increasingly on regional and local scales, where adaptation and resilience take place. Different mitigation pathways involve strategies that differ in when they achieve net-zero emissions and vary in the distribution of mitigation efforts between short-lived and long-lived climate forcers, reliance on land-use strategies and the scope and timing of carbon removal¹³.

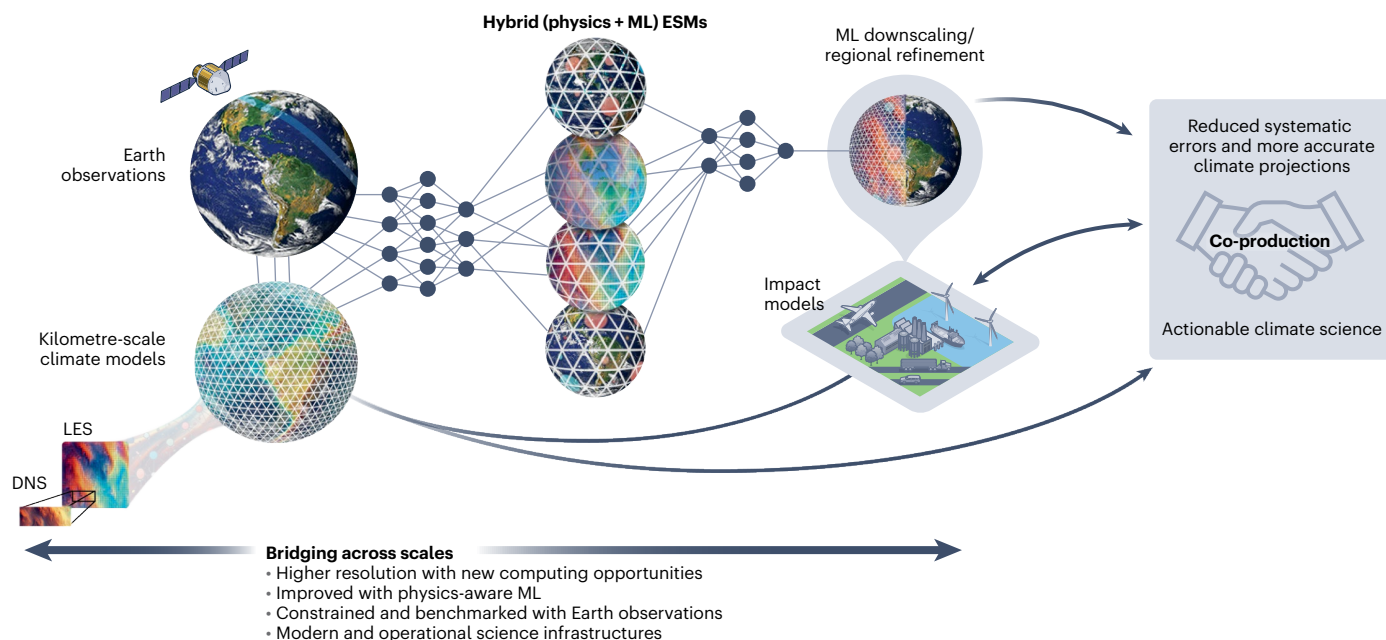


Fig. 2 | Schematic of the proposed AI-empowered multiscale climate modelling approach for urgent mitigation and adaptation needs. This approach bridges across scales and process complexity for faster and more accurate climate information also on regional and local scales. We note that LES

and Earth observations are also used to directly refine kilometre-scale climate models and coarser-scale ESMs. DNS, direct numerical simulations. Credit: globes, NASA/Visible Earth.

Therefore, ESMs must depict coupled cycling of greenhouse gases, encompassing both natural processes and human-induced influences for a broad range of policy-specific scenarios (Box 1).

In this Perspective, we call for a hybrid multiscale Earth system modelling approach, bringing the artificial intelligence (AI) revolution to climate modelling. Machine learning (ML) provides great potential to improve some of the limitations apparent in coarse-resolution ESMs^{14,15} and high-resolution global kilometre-scale climate models. Our proposed approach provides the potential for a step change in model performance and climate data utility while bridging across scales and process complexity and utilizing the full hierarchy of models.

Current state of climate modelling

Comprehensive ESMs not only represent the physical climate but also include interactive carbon and other biogeochemical cycles¹⁶ and components such as ice sheets, as well as many other features of the Earth system that are important for climate change and its impacts¹⁷. Compared with earlier generations, CMIP6 models have increased spatial resolution and improved physical process representation⁸. Another advance in CMIP6⁶ is the increasing number of large ensembles, which have provided important new insights into the relative contribution of internal climate variability and external forcing to projected changes^{18,19}. The simulation of mean climate and its variability has improved for many large-scale key indicators of climate change, but long-standing systematic errors compared with observations remain^{9,10} in addition to a large spread in climate projections¹² and sensitivity²⁰. At regional scales, the intensity and frequency of climate extremes such as extreme rainfall, droughts and heatwaves are often not accurately modelled^{21,22} yet are critical for accurate resilience and adaptation planning. This has motivated the development of techniques to constrain uncertainties with the help of observations, emulators and palaeoclimate information¹¹.

A large contribution to systematic errors and the large spread in climate sensitivity and projections stems from processes occurring at scales smaller than the model grid resolution⁸, such as convection, microphysics, aerosol–cloud interactions, or ocean eddies²³, and

dynamical²⁴ processes. These processes need to be empirically approximated in models by parameterizations. This has motivated the development of kilometre-scale climate models²⁵ or more regional large eddy simulations (LES) at even finer resolution²⁶. These models can simulate key small-scale and fast physical processes with improved accuracy²⁵, resolving many of the biases of coarse-resolution simulations, such as better global precipitation distributions²⁷, more realistic representation of extremes²⁸ and better equatorial wave dynamics²⁹. However, due to their staggering computational costs, kilometre-scale climate models cannot currently be run at climate timescales for multiple decades or longer. Further, large ensembles with coarser-scale ESMs that include important Earth system processes and feedbacks are required (Box 1). Simulations with multiple ensemble members as well as careful calibration and tuning³⁰ are beyond the reach of kilometre-scale climate models. More fundamentally, even kilometre-scale climate models exhibit biases, for example, in precipitation²⁵, because they still rely on parameterizations for even smaller-scale processes. These challenges present fundamental roadblocks to more useful climate projections, whether with high- or coarse-resolution climate models.

An AI-empowered approach for faster and more accurate hybrid climate modelling

We argue that a holistic approach to climate and Earth system modelling that fully integrates AI will be a productive path forwards to make progress in climate modelling. Our proposed approach (Fig. 2) is based on four pillars: (1) higher resolution across scales with new computing opportunities: next-generation climate models and ESMs need to fully leverage modern and evolving hardware to enable simulations at higher resolution that better resolve important processes such as deep convection or ocean eddies. Given the shortcomings of even high-resolution simulations and the continued need for coarser ESMs to represent Earth system complexity, this needs to be complemented by (2) Hybrid ESMs improved with physics-aware ML where parameterizations or subcomponents of the models are replaced with ML to improve the representation of subgrid-scale or poorly known physical and biological processes. We also need to (3) harness the wealth of Earth observations

to evaluate, constrain, calibrate and improve models. This needs to be supported by (4) modern and operational science infrastructures to define common experiments and standards, to provide annual updates of climate forcings and climate feedbacks that relate forcings to the Earth's energy imbalance and to operationalize policy-relevant climate model simulations and output, including regionally downscaled³¹ or regionally refined³² output.

An important component of this approach is that coarser-scale ESMs are enhanced to hybrid models, in which parameterizations and subcomponents are improved with ML informed by kilometre-scale climate model simulations or even higher-resolution LES and direct numerical simulations, and by Earth observations. Hybrid ESMs promise to have substantially reduced systematic errors and enhanced projection capability compared with current ESMs. In contrast to kilometre-scale climate models, ESMs incorporate important Earth system processes and feedbacks (Box 1) while still being fast enough to provide large ensembles important to simulate internal variability and extremes¹⁸ and to improve attribution and understanding¹⁹. These models can be brought to actionable climate scales using ML-based downscaling or regional refinement that can also be used to drive impact models. They can themselves be increased in resolution through new computing opportunities. Since even kilometre-scale climate models still require parameterizations of even smaller-scale processes and for processes that are not likely to improve just through increased resolution (for example, land and cryosphere), they can also be enhanced to hybrid kilometre-scale climate models using the same approach. We argue that modernized infrastructures are required that utilize AI towards the operationalization of policy-relevant simulations and model outputs to a broad range of stakeholders. This approach could substantially enhance the applicability of climate modelling and projections also on the regional to local scale to tackle urgent mitigation and adaptation needs. It requires co-production as indicated with the handshake in Fig. 2 with stakeholders that ensures that services utilize the most advanced capabilities available, while the scientific community promptly addresses any service gaps³³.

High resolution across scales with new computing opportunities

Today's ESMs operate predominantly on parallelized centralized processing units, limiting their ability to fully harness the potential of advanced new hardware such as graphical processing units and tensor processing units³⁴. The use of highly parallelized hardware has played a pivotal role in driving the AI revolution³⁵, so we believe that the same transition to modern hardware and new codes that are more agile and agnostic to different hardware is a critical step for accelerating ESMs to allow for higher resolution across scales^{34,36}, and for fully harnessing the capabilities of ML algorithms^{37,38}.

To employ ML and leverage modern hardware infrastructure within ESMs, barriers posed by languages such as Fortran and C need to be overcome, but this requires substantial code modifications, taking many years of development. Further, the integration of ML algorithms remains ad hoc, with specific language bridges between Fortran or C and Python, in which most ML algorithms are written. These bridges also do not readily permit 'online' learning, that is, the training and tuning of the embedded ML subcomponents online when data become available in sequence and are used to update the ML on the fly, which is critical to utilize Earth observations.

Refactoring codes with modern high-level languages, such as Python/JAX³⁹ or Julia⁴⁰, offers transformative possibilities³⁴. These languages can flexibly leverage modern hardware (for example, graphical processing units or tensor processing units)^{41–43} and support differentiable programming^{44,45}, which is the capacity to take the derivative to a variable of interest within numerical precision and at very limited computational cost⁴⁵. It is one of the backbones of the ML revolution to efficiently compute gradients of nonlinear functions and could

be applied to model code to tune physical or ML parameters and initial conditions, creating seamless ML physical model integration^{44,46}. NeuralGCM, the first fully differentiable hybrid atmospheric model combining physics and neural networks in an end-to-end trainable fashion, is a breakthrough in that direction, written in Python/JAX⁴⁷. We expect differentiable programming with modern languages such as Python/JAX to play an important role.

All these advances would accelerate the transition to exascale computing to run high-resolution ESMs that explicitly resolve more processes, enhancing model accuracy and more easily integrating ML. These advances will benefit from collaboration with the computer science community and the private sector⁴⁸, potentially leveraging large language models to accelerate code refactorization⁴⁹.

Hybrid ESMs improved with physics-aware ML

To reduce systematic errors in coarser-scale ESMs, ML trained on short high-resolution climate model simulations has been successfully substituted for conventional parameterizations of deep convection, cloud cover and ocean turbulence, thereby enhancing the fidelity of the host ESM, for example, for ocean transport, cloud-cover distribution, sea surface temperature biases or precipitation distributions and timing^{50–56}. ML can also be used to replace parameterized processes that do not have a clear physical basis and that are still unresolved in high-resolution simulations, such as warm rain or ice microphysics, photosynthesis, vegetation phenology, or land-atmosphere or ocean-atmosphere interactions, as long as sufficient Earth observations are available (Fig. 1). For example, for land, ML has been used to find the optimal regulation of land-atmosphere flux exchange, such as canopy or aerodynamic resistance and its dependence on atmospheric stability^{57,58} or to unravel the role of microbial carbon-use efficiency for soil carbon storage⁵⁹. These hybrid approaches are, however, not without limits, and several ML challenges need to be overcome⁴⁸. First, ML struggles with extrapolation beyond the training regime (out-of-distribution prediction). New approaches to improve those predictions, such as by incorporating climate invariant variables⁶⁰ or multi-fidelity approaches that merge traditional parameterization with ML trained on historical data, are showing promising progress^{61,62}. ML approaches can also lead to numerical instabilities when integrated into a host climate model⁶³. Combining causal discovery and deep learning can help mitigate instability problems by learning the physical drivers of subgrid-scale processes and improving numerical stability during temporal roll-out⁶⁴. Trust and generalizability of ML models can be further enhanced by introducing more interpretable latent dimensions^{28,53} or equation discovery^{52,65,66}.

We argue that even kilometre-scale climate models could be improved with such a hybrid ML-based approach by being able to learn from ultra-high-resolution simulations (for example, direct numerical simulations and LES) and Earth observations (Fig. 2). This is because even kilometre-scale climate models exhibit biases as they still require parameterizations of even smaller-scale processes (for example, microphysics and turbulence) as well as parameterizations for land (for example, photosynthesis, ecosystem respiration and wildfires), ocean, sea-ice and land-ice processes. Land and cryosphere processes and biases, for example, are not likely to improve through just increased resolution as many processes are not explicitly resolved even at high resolution or because they involve complex biological systems whose structural form is currently unknown⁶⁷.

Harnessing the wealth of Earth observations

Numerical weather prediction fuses model trajectories with observations via data assimilation that corrects the model trajectory as an initial condition problem and, sometimes, adjusts physical parameters of the model to better predict weather. Data assimilation has been immensely successful^{68,69}. Yet the model's inherent biases appear again in longer simulations as the data assimilation does not correct them. For example, on subseasonal to seasonal timescales, a model similar to the ones

used to predict weather tends to be less accurate than a climatology⁷⁰. These issues reveal that the model structure and parameterizations of high-resolution weather models are also imperfect.

A wealth of Earth observation data from satellite, in situ and ground-based measurements are now available, with data volumes already well beyond hundreds of petabytes⁷¹, as well as palaeoclimate proxies⁷². They are routinely used to guide manual climate model tuning^{30,73} and for model evaluation⁷⁴, supported by modern evaluation packages^{75,76}. However, these datasets are only starting to be used to drive automated model tuning and parameterization refinement yet offer tremendous potential for placing observational constraints on many subgrid-scale physical and biological processes, in particular because of the increasing spatial resolution of observational systems alongside new observations with a focus on Earth system processes (for example, hydrology, biology and cryosphere)³³.

We advocate a new model–data fusion approach in climate modelling that relies on ML-based parameter estimation (inference), which, unlike in traditional data assimilation, corrects model structure (parameterizations, whether physically based or ML based) instead of model trajectories (initial conditions)⁷⁷. Traditional data assimilation is limited in its applicability to climate because it addresses primarily the production of accurate initial conditions⁷⁷, whereas climate is impacted mainly by boundary conditions. Instead, we support efforts to focus on inferring model structure, including physical or ML-based parameterizations based on sparse, noisy and indirect observations. This approach targets not individual state trajectories, as day-to-day matching is impossible for freely evolving climate models, but rather statistics of variables. Statistics are more directly relevant to climate, which focuses on changes in statistics rather than on single trajectories, and because often, exact initial conditions are unknown and matching conditions on specific days is impossible because of internal variability. There are now new algorithmic developments that can accelerate progress on that front. For example, generative AI and diffusion models can help define and constrain statistics and are already starting to be applied in climate modelling⁷⁸.

This approach for model–data fusion requires substantial algorithmic developments, merging traditional data assimilation and ML techniques⁷⁹ and targeting statistics⁸⁰, also utilizing differentiable computing. Challenges include handling high-dimensional data, developing new frameworks for statistics' evolution or fine tuning deep neural networks in the presence of uncertainty⁸¹, due to observational error, process uncertainty and inherent stochasticity. Current ML approaches face difficulties in the presence of sparse, noisy and indirect observations, typical of Earth observations such as from satellites⁸¹. While ML has been used for climate model parameter tuning⁸², it often lacks uncertainty quantification⁸³. Recent advances in Bayesian inference and probabilistic numerics can advance the field^{84,85}.

Modern and operational science infrastructures

CMIP has been very successful over the years in developing an efficient infrastructure with common standards for climate model output, dramatically facilitating and expanding the analysis and use of multimodel climate simulations. These guidelines and standards, coupled with the long-term viability of the overall CMIP process, have allowed and encouraged the parallel evolution of data and evaluation infrastructures.

Nevertheless, because of the changing needs of a range of stakeholders, including climate services such as the Copernicus service of the European Union and emerging efforts from the National Oceanic and Atmospheric Administration in the United States, more timely climate projection updates are required so that the impact of changes to past and likely future emission trajectories due to global events such as pandemics, wars, climate policy changes, global economic disruptions or natural shocks such as a major volcanic eruption can be accounted for so that the best climate information is available for events such as the annual Conference of the Parties and the Global Stocktakes. Such

a process should include yearly updating and quality control of forcing datasets based on historical and near-real-time observations⁸⁶, a process to produce rapidly updatable policy-relevant scenarios that reflect actual emissions, recent events and climate policy changes^{87,88}, as well as the operationalization of policy-relevant climate simulations and the provision of corresponding output to users. The opportunities of ML in this regard should be further explored⁸⁹.

A key component that we advocate is interactivity to enable users to explore, understand and extract relevant simulated climate data easily, much in line with digital twins⁹⁰. Cloud computing and modern ML techniques offer promising solutions for enhancing user interactions. For example, active learning⁹¹ and causal inference^{66,92} can help optimize, analyse and embed users in the simulation loop while addressing causal (for example, counterfactual) queries. ML can also support making the data available to users at scale with effective data compression tools⁹³.

Conclusions

Long-standing systematic errors in coarse-scale ESMs have motivated the development of kilometre-scale global climate modelling efforts with the goal to provide more accurate near-term climate predictions⁹⁴. However, these models are too expensive to be run on century time-scales and are often limited in their representation of the complexity of the Earth system complexity. Climate projections with coarser ESMs that comprehensively simulate emerging Earth system processes and feedbacks (Box 1) will continue to be required to reliably project the long-term forced climate change response and extreme events in the face of intrinsic climate variability. However, a step change in the models' performance is required.

In this Perspective, we share a vision of an AI-empowered next-generation multiscale climate modelling approach based on four pillars: acceleration, hybridization of ESMs, full integration of Earth observations and improvements of infrastructure. With this integration, we expect substantial reductions of systematic errors in new ESMs compared with the current generation. Such ML approaches blending Earth observation and domain knowledge effectively will provide the benefits of increased resolution and improvements across scales. Today's results on parameterization and physics-data integration are promising and suggest that interaction between ML and physics-based models will yield hybrid models that produce improvements in process representation and ESM fidelity, even when run at a coarser resolution, still allowing century-long simulations, many ensemble members and the tuning of models against observations. On the basis of this potential, we believe that the future of climate modelling will involve hybrid ESMs, where ML approaches replace many model subcomponents that advance towards process understanding and model interpretability, not just ML emulation. We note that so far, hybrid developments have been largely restricted to specific subcomponents of the atmosphere, ocean or land models, yet the integration of ML-based hybrid approaches into a fully coupled ESM to perform CMIP-type simulations remains a daunting task.

This approach must be fully embedded into a modernized and operationalized infrastructure to be maximally impactful, delivering critical information about climate change in a broad and accessible format for targeted adaptation and mitigation to a wide group of stakeholders. This multiscale climate modelling vision would provide a step change in providing accurate climate information to serve emerging mitigation and adaptation needs at more frequent intervals than is currently possible, allowing interactivity for users through enhanced ML techniques. It will also provide the foundation for more realistic digital twins of the Earth system⁹⁰ that are scalable, user interactive and adaptive. This holistic approach to hybrid climate and Earth system modelling could form an integral part of international activities such as World Climate Research Programme's CMIP⁶ and high-resolution activities such as Destination Earth (<https://destination-earth.eu/>) or Earth Visualization Engines (EVE⁹⁵).

To achieve this vision, the international community must tackle several challenges on the ML side⁴⁸, the algorithmic part, the operationalization of policy-relevant simulations and forcing, and the broad and inclusive accessibility of climate model data, as we outline here. Challenges lie ahead, but this objective has never appeared to be as much within reach as it is today. We believe that the debate of future modelling should not be centred around high-resolution climate modelling versus complex, coarser-resolution ESMs. Instead, a new ML-empowered multiscale climate modelling approach that integrates Earth observations through modernized code, hardware innovations and adaptive international science infrastructures is required. Indeed, we argue that climate modelling needs to be approached within a hierarchy of models going across complexity and resolution ranging from high-resolution to coarser ESMs that are enhanced with ML and downscaled or regionally refined to drive impact models, as described in this Perspective. This way, we will be able to better project the full complexity of future Earth's climate and extreme events at unprecedented accuracy, also improving climate information and technology assessments for sustainable developments of sectors such as transport, energy and aviation. It is incumbent on the whole Earth system modelling community to join forces to offer the best and most accurate climate information for urgent mitigation and adaptation needs in a rapidly changing world. Time is of the essence.

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Author contributions

V.E. led the writing and developed the multiscale climate modelling approach with AI for urgent mitigation and adaptation needs jointly with P.G. and all co-authors. All authors contributed to the writing of the manuscript and the development of the proposed approach.

Competing interests

The authors declare no competing interests.

Ethics

This study has been conducted in full conformity with Nature's research ethic policies and principles of scholarly freedom and responsibility.

Consent to participate

All the authors have actively accepted an invitation from the corresponding author to participate in this study.

Consent for publication

All the authors have been notified by the corresponding author that this study has been submitted for consideration for publication.

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