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The Role of Artificial Intelligence in Climate Modeling

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ABSTRACT

Climate modeling has evolved significantly with the advancement of computational techniques, moving from traditional numerical methods to increasingly sophisticated models leveraging Artificial Intelligence (AI) and Machine Learning (ML). This paper explores the integration of AI into climate modeling, highlighting how neural networks, predictive analytics, and machine learning algorithms can improve the accuracy, speed, and robustness of climate forecasts. While traditional models rely heavily on physics-based simulations and empirical parameterizations, AI offers novel approaches to deal with the multiscale, nonlinear, and data-intensive nature of climate systems. Case studies demonstrate AI's capabilities in emulating complex Earth system models, forecasting extreme weather events, and processing vast observational datasets. Nevertheless, challenges such as data availability, model interpretability, and ethical considerations remain significant hurdles. The paper concludes by discussing the need for multidisciplinary collaboration and the development of hybrid frameworks that combine physics-based modeling with AI-driven insights to better predict and respond to the urgent threats posed by climate change.

Keywords: Climate Modeling, Artificial Intelligence, Machine Learning, Predictive Analytics, Earth System Models, Climate Emulation, Data Assimilation.

INTRODUCTION

Computers have been used to study the climate for some time, but technological advancements have transformed the tools available to climate scientists. Modern computation is more parallel and optimized, with nonlinear solvers evolving from costly methods to multi-grid solvers that utilize spatially varying time-stepping. New discretization techniques, like the discontinuous Galerkin method on unstructured elements, have replaced older methods. GPU technology has also advanced significantly, enabling code optimization for Cloud Computing and TPUs. Moreover, open-source software for geophysical and climate modeling has surged. These ongoing changes present a mix of opportunities and challenges for scientific communities. In one session, climate scientists must articulate the uniqueness of their issues, while engineers are urged to engage in climate modeling. Papers exploring neural networks for jet stream prediction, machine learning for extreme rainfall events, and neural network performance comparisons are encouraged. Contributions can range from theoretical innovations to practical experiments or applications of theory to real-world issues. Researchers will be prompted to contemplate the true contributions of their work. Climate dynamics are influenced by multi-scale and multi-physics processes, such as the rapid cloud microphysics affecting slower storm track formation and the gradual equatorial heat transport and atmospheric thermodynamics, with varying model resolutions informing these interactions [1, 2].

Overview of Artificial Intelligence

There exists a nebulous line of demarcation between statistics and the more modern form of analysis, artificial intelligence (AI). The emergence of machine learning (ML) has complicated things even more. Though AI and ML methods rely on statistics, the nature of the algorithms is more diverse than what is typically seen in statistics. It is useful to examine the fundamental components of AI. AI relies on four foundational components: a model, data, a cost function, and a method for updating the model based on the data. AI's modeling techniques are pervasive in our society, ranging from casting a recommendation for a particular television show to scanning a photo for a face and highlighting it. Conversely, climate models seek to represent key processes in the climate system that drive variability. Because climate modeling is multiscale in terms of both space and time, the physical representation is typically based on equations of first principles, some of which are linear and therefore amenable to analytical solutions, while some are highly nonlinear and highly disparate in both timescales and spatial scales. Because of the sheer number of processes involved, the high dimensionality of the solution space, and the imbalance in scales, these equations are typically solved using more parsimonious models. These models generally exhibit inputs that excite the modeled system and outputs that are the realization of the modeled system scaled through a complicated nonlinear transformation. Model uncertainty can arise due to the structural imperfections in the equations as well as from the use of simplifications that attenuate some aspects of the modeled processes. The difference between the true system and the model is not zero, and an error is generally cast at scales comparable to the input covariance. Standard stochastic approaches try to emulate the input uncertainty based on covariance, while physics-based methods do so based on equations; so far, the two approaches have been rather isolated from each other. Integration of AI with physics and stochastic modeling approaches can provide tremendous opportunities to understand the climate system, thereby alleviating the problem of climate change [3, 4].

Historical Context of Climate Modeling

Understanding natural and anthropogenic climate change processes involves using computational models that represent the main components of the Earth system: the atmosphere, ocean, sea ice, and land surface. These models have become increasingly computationally expensive as resolution is increased and more complex process representations are included. To gain robust insight into how the climate may respond to a given forcing, and to meaningfully quantify the associated uncertainty, it is often required to use either or both ensemble approaches and very long integrations. Here, a comprehensive overview of the suite of climate models based on the HadCM3 coupled general circulation model is provided. This model was developed at the UK Met Office and has been heavily used during the last 15 years for a range of future (and past) climate change studies, but has now been largely superseded for many scientific studies by more recently developed models. However, it continues to be extensively used by various institutions, including the BRIDGE research group at the University of Bristol, which has made modest adaptations to the base HadCM3 model over time. In modern environmental and climate science, it is necessary to assimilate observational datasets collected over decades with outputs from numerical models. During the twentieth and twenty-first centuries, numerical modelling became central to many areas of science. A great deal of time and effort is devoted to developing, evaluating, comparing, and modifying numerical models that help us synthesise our understanding of complex natural systems. Here, an assessment of the contribution of past (palaeo) climate modelling to multidisciplinary science and society is provided. Complex climate models, and latterly Earth System Models (ESMs), are in the vanguard of attempts to assess the effects, risks, and potential impacts associated with the anthropogenic emission of greenhouse gases. Since then, it has become apparent that to fully appreciate the complex interactions between climate and the environment, it is necessary to adopt multidisciplinary scientific approaches capable of robustly testing long-standing hypotheses [5, 6].

Traditional Climate Modeling Techniques

Advances in Earth system model development focus on reducing costs through improved parameterizations of process models, leading to a modular framework where costly components can be swapped for emulators during runtime. This study addresses how to adjust CAM emulator performance through temperature perturbations, with findings indicating the crucial role of vertical mass flux adjustments linked to convection and cloud in response to these changes. The necessity for higher-resolution analogs for accurately depicting these processes underscores the potential of diagnostic machine learning techniques to enhance model efficacy. Hybrid frameworks could effectively simplify emulation, transferring atmospheric scaling to different or less complex models. Model emulators represent a significant computational task in ML, and recent efforts aim to utilize approximations to ease this burden. Existing data-driven methods often overlook necessary constraints and have not been evaluated in this context. Emulators operating on daily or hourly scales should leverage multi-scale physics-based data and regularization strategies. A notable advancement is ACE, a deterministic surrogate for the FV3GFS model, known for its stability and physical consistency over long simulations. ACE's framework relies on meticulous data ingestion and design, alongside Sphere Fourier Neural

Operator architecture, but its deterministic nature may introduce systematic uncertainties in climate modeling. A generative modeling approach is suggested to not only assess this uncertainty but also enhance data-rich climate model inference [7, 8].

Integration of AI in Climate Models

In terms of expertise, AI and climate are worlds apart. Past climate epochs extended over millions of years and were driven by tectonic processes and the variability of Earth's orbital parameters. In contrast, anthropogenic climate change is, for the first time in Earth's history, a direct consequence of human activities. The rate of change is unprecedented, and the impacts of climate change are widespread, making it more relevant than ever to predict future climate at a range of time scales. Given the important implications for our societies, a wide range of assessments has been performed in the past. However, considerable uncertainty remains, and mitigation measures often are based on simplified models, which generally cannot simulate all scales of motion. Crutzen famously speculated on manipulating the climate system for counteracting global warming; should this more radical approach be considered, the ability to monitor such a deliberate intervention hinges on a deep understanding of the climate system. The projected temperature before the Paris Agreement has been a subject of worldwide concern, and more than 90 efforts have been devoted to projecting future climates since the mid-1990s. Different steering mechanisms, known as representative concentration pathways, have been suggested to drive the models. Major efforts have been devoted to identifying and excluding outliers among the projections based on climate models, which differ widely in their realization of associated sea surface temperature changes. These diversities result in considerably different responses of atmospheric circulation, one of the commanding drivers of regional climate change. However, incorporating AI techniques beyond standard statistics ultimately can extract information close to the truth from multiple projections based on imperfect models [9, 10].

Machine Learning Algorithms in Climate Science

Climate science is an inherently difficult problem needing the diagnosis of multiple underlying processes across a range of timescales. These processes are crudely parametrized in climate models, adding uncertainty to Climate Sensitivity predictions and future simulations. Characterizing and reducing these uncertainties is a central element of climate science. Ensemble climate forecasts can generate large pools of climate model output, and uncertainties need to be robustly quantified. To meet the need for uncertainty quantification in a computationally efficient and interpretable manner, existing techniques were examined, and a new approach was proposed based on quantifying uncertainty through a two-parameter mixture of Gaussians fit to ensemble prediction distributions. These simple model forms were found to predict uncertainty in predictions more robustly than from established max-min entropy methods and more effectively capture subtle features in ensemble distributions. As the horizon for climate predictions lengthens, computational burdens are ever more pronounced for high-resolution emissions and socio-economic scenarios. There is thus growing interest in the emulation of climate models or their robust statistical analogs with a view to geoengineering and other future scenarios. Great strides are being made in this field using machine learning, notably a new technique based on neural networks that can be trained very rapidly to reproduce the Taylor principles of climate physics. This turns several hours of prediction in a supercomputer into only a few seconds on a laptop. Examples of the new ML techniques currently being tested are dynamically generating maps of British rainfall, India-Monsoon, and Asperity distribution for Rayleigh number homogeneity. Dynamical emulators, by definition, are not interpretable as they attempt to capture chaos directly. However, methods to translate their predictions into the context of simpler statistical models exist, e.g., investigating the scale-invariance of sea-level pressure output from dynamical emulators for the Andrew Wright model of sedimentation. There exists a more subtle challenge, namely, how predictions of a dynamical emulator can be used to constrain the uncertainties on proxy records without recasting them as statistical models in a sparse-feeling approach [11, 12].

Data Sources for Climate Modeling

Climate prediction relies on a high level of technicity and requires a vast amount of computing and simulation resources. Due to the complexity of interactions (between and inside the climate domains), a series of parametrizations need to be introduced into climate models, which will limit the price of the model. Moreover, this stratification leads to very computationally expensive physical processes. Therefore, climate predictions need to be performed using supercomputers able to handle the necessary numerical operations in several days, or even weeks, of calculation. Accordingly, even these supercomputers are not able to make systematic long-term predictions at a high resolution. The response of a model (e.g., the climate) to a set of climate forcings is mostly described by its physical parameters. These parameters are obtained from human expert knowledge or pre-existing subjective analytical formulations. Thanks to supercomputers, the plausible ranges of physical parameters (the model forcings) of GCMs are becoming less and less uncertain, which makes the role and estimation of the new, more sophisticated parameters based on new Earth observations. As a consequence, the design of cheaper climate emulators (typically called Integrated Assessment Models) becomes increasingly necessary. The computing difficulties of GCMs imply considering new data mining and statistical methods able to tackle Big Data and real-time challenges, if not possible through other numerical methods. GCM outputs depend on a very high number of (unknown) complex parameters (which are called the emissions). This makes it very hard to build emulators able to map the logic of the responses of GCMs to the corresponding emissions. Therefore, conventional and memory requesting methods are to be replaced by other Machine Learning methods during the first stages of GI mechanisms. In forcing relevant climate model simulations, the pressure on computing resources and supercomputers will grow tremendously, and for this reason, new, cheaper models are to be learned and designed. Conversely to GCMs, which attempt to map the climate physics, climate emulators are data-driven, parsimonious learning models able to reproduce the GCM outputs with an acceptable uncertainty without referencing the physics of the systems [13, 14].

AI and Predictive Analytics in Climate Modeling

Artificial Intelligence (AI) is a powerful technology that has found widespread adoption in a variety of applications. With an umbrella definition that refers to machines mimicking human intelligence by acquiring, aggregating, and evaluating data, AI offers a wide array of data analysis and prediction techniques, explanatory tools for complex systems type discovery, and automated decision-making models. Since climate modeling requires the application of a variety of data-driven techniques, explanatory tools and methods, as well as mathematically-based optimization in prediction and simplification, there is potential that AI can impact the climate modeling effort. Earth System Models (ESMs) are used for simulations of the climate system. However, the simulations have limited accuracy and rely on compute nodes for inference and projections, monitoring, and understanding. The climate-targeted small adjustment simulation methodology combines transfer learning with adaptive exploration of parameters for training a surrogate AI/ML model for emulating and accelerating the simulations of the complex problem regarding the collapse of the Atlantic Meridional Overturning Circulation (AMOC) in ESMs. Surrogate models promise to speed up such simulations using a dimension-reduced approximation. While there are many possibilities of surrogate modeling techniques, especially considering ESMs, a proper choice does not sacrifice performance and accuracy, which is essential for prediction. Recent advances in AI/ML in improving simulation speed and acceleration are inspiring in the exploration of climate modeling as a testbed application. A hybrid AI/ML modeling approach has been proposed, which enables climate modelers in scientific discovery based on a climate-targeted simulation methodology. Focusing on the need to discover climate tipping points, the combination of a surrogate AI/ML model with an exploration of natural modes can be used on large datasets on critical biophysical processes at land-atmosphere and ocean-atmosphere interfaces [15, 16].

Case Studies of AI Applications in Climate Research

In recent years, researchers have begun employing AI methods to address climate research questions. These AI methods generally fall into three categories: climate emulation, data science and observation, and power forecasting. Climate emulators refer to machine learning methods that concisely approximate climate models, allowing faster predictions as needed in future impact assessments. These emulators have been applied with great success to a variety of offline climate models, and AI's capability to predict impacts in the future that a climate model has not been trained on has begun to be explored. The second major avenue of research has focused on using AI to ingest and exploit climate data. Within this avenue, methods used in many high-impact areas have been explored about how to best observe and quantify climate observations, such as precipitation, temperature, snow cover, and carbon concentrations. In one notable application, a deep learning model was employed to measure atmospheric snow by interpreting clouds. Within climate science, there is an additional category devoted to the application of AI methods for power forecasting, ushering in AI-driven growth in the energy sector. In the wake of notable power outages in Texas and across Europe, and with solar and wind buildings being brought online without sufficient investment in energy storage, many studies are currently working to build and develop AI models capable of more accurate power consumption forecasting. The vast majority of the above-listed climate AI research raises many critical and notable ethical challenges—one of many which conceiving, constructing, and utilizing a climate emulator would raise is the existence of a novel technology that indirectly allows for speedier climate model projection. AI hence raises questions of liability and empirical process re-evaluation, with fair imitation and competitive climate modeling samples already garnering attention. With regards to downstream equity, the price of computing resources will need to be monitored with a focus on avoiding negating any improvements brought forth to the entirety of humanity by AI's charm and cost. To improve these efforts, there is less understanding than current scrutiny with regards to how climate data can be assimilated and estimated, and whether best practices that have been elucidated in endeavors across disciplines are transferable to the climate domain. As AI simultaneously poses challenges and unlocks amazing opportunities on both fronts, AI can show major potential in overall climate and understanding in a space facing growing attention and disclosed information incentive [17, 18].

Challenges In Implementing AI in Climate Models

One of the main challenges in implementing AI within climate models is the lack of access to high-quality datasets essential for AI-driven model development across various disciplines. Climate action often focuses on specific regions, relying on limited datasets, which restricts efforts to particular aspects of climate modelling or geopolitical areas. Addressing the complexities of the Earth system requires global collaboration to nurture the knowledge ecosystem while ensuring datasets are interpretable across modelling groups, even with AI models. A key next step is curating openly accessible datasets in these critical areas. The codebases for numerical simulations in Earth and climate sciences are often complex and accompanied by extensive libraries. Advances in simulation handling and modelling languages are hard to adopt without significant investment and collaboration. Because AI frameworks can draw from similar domains, a collective effort is crucial for engaging the community and ensuring AI is leveraged effectively in climate models. Although clear use cases exist for generating Earth system models that replicate existing behaviors accurately, much variability remains poorly understood. It is essential to define initial steps and conduct impact assessments to avoid poorly-framed AI questions in the Earth system [19, 20].

Ethical Considerations in AI and Climate Modeling

As AI shapes climate modeling, ethical concerns become essential, focusing on representation, fairness, accountability, and explainability in training data and model implementation. The justice of an AI system relies on the quality of data it receives. AI climate models hinge on what data is considered relevant, raising issues of data justice concerning how individuals are represented and treated based on digital data. Bias in this context can obscure key contributors to climate change, leading to the exclusion of specific locations or timeframes and an underestimation of carbon emissions from certain sectors. This inadequate representation can neglect populations adversely affected by climate change, exacerbating existing inequities. When regional authorities are omitted from AI models, it compromises climate and energy transformation goals. Such exclusion can also enable regional governments or sectors to engage in harmful fossil fuel usage without considering future consequences, leading to broader negative impacts. Moreover, insufficient AI climate accounting might trigger skepticism or counterproductive actions. Those included in AI models wield influence, while those excluded become disempowered, creating a moral imbalance that perpetuates injustice in global climate responses. Instances of exclusion stem from relying on narrow training datasets or using accessible datasets that fall short in representation. Without comprehensive, globally representative datasets, AI climate models struggle to reliably forecast climate change impacts and solutions in both the short and long term. Private datasets controlled by governmental and influential organizations could prevent AI models from accurately assessing the real consequences of climate dynamics [21, 22].

Future Directions in AI For Climate Science

In today's generational moment, the global race for AI is set to significantly impact society and the environment, transforming job markets and governance structures relevant to climate action. Current AI systems, trained on biased datasets, may interact adversely with other datasets, destabilizing political agencies involved in climate negotiations. Additionally, operational AI infrastructures could exacerbate inequality, hindering climate initiatives. Therefore, it is crucial to design less biased AI systems that address the distinct social and planetary challenges faced today. A human-in-the-loop AI model is proposed with three design goals aimed at enhancing global climate action through data-centric knowledge generation: fostering a planetary epistemic web that aids climate efforts; facilitating climate mitigation and adaptation by understanding social tipping elements; and alleviating data injustices tied to pretraining datasets used in AI systems. The rise of generative models like GPT-4 and DALL•E2 has sparked public interest in AI's potential and limitations, urging the development of systems that can support and sustainably enhance human intelligence and creativity. These systems should tackle climate change, biodiversity loss, and pandemics within the Digital, AI, and Internet of Things frameworks, all vital for human coexistence. However, achieving these intertwined objectives is challenging due to the climate system's complexity, which is modeled by partial differential equations with inadequate data. Climate decision-making requires years to gather, analyze, and integrate datasets, while climate data assimilation from sensors can only occur hours later, and patrol planning takes a week. The AI's capability on these timelines remains uncertain [23, 24].

Collaboration Between AI Researchers and Climate Scientists

Climate modeling is complicated and time-consuming, necessitating a deep knowledge of the climate physics principles to use it effectively. Involving AI researchers and potentially outside experts in the development and nurturing of climate modeling frameworks is a viable approach for climate modelers who need help discovering novel science with climate models. AI climate modeling is an emerging discipline that uses AI technologies and tools in climate modeling. A climate-targeted simulation methodology that uses a novel combination of deep neural networks and mathematical methods for modeling dynamical systems is proposed. This methodology is demonstrated by climate models for scientific discovery related to tipping points in the climate system. Getting stakeholders directly involved in climate modeling will likely increase the effectiveness and efficiency of climate model development and provide new climate-modeling-inspired ideas and thoughts in AI and climate sciences. There is a strong impetus behind such an approach. AI climate modeling is a new discipline that uses climate models in novel ways to tackle daunting climate physics problems using technologies and tools from AI research. Many climate scientists have established solid reputations in AI research, producing high-level ideas, frameworks, platforms, and groundwork papers. Combining the knowledge from climate physics, climate modeling, and climate science with the AI question by involving AI researchers in the modeling of climate models is a secure avenue for current climate modelers. Efforts to increase diversity, equity, and inclusion in climate modeling at all levels will also introduce voices from underrepresented groups, stakeholders outside climate modeling, and industries to expand the perspectives and knowledge in this otherwise relatively closed field [25, 26].

Policy Implications of AI-Enhanced Climate Models

The increasing recognition of climate change as one of the most crucial issues of our time is prompting further exploration of the role of AI-related developments for digitization, such as machine learning (ML), neural networks (NNs). AI-enhanced climate modeling could bypass traditional limits on gridding and spatial resolution of climate models and make insights from climate models available for real-time predictive insights. Earth system modeling is of central importance to understanding the Earth's future climate. Earth system models are massively complicated computer codes. The approach currently pursued has three main approaches: Downscaling climate simulations using supervised learning workflows and accuracies, and qualitatively improving predictions. Generating new climate model architectures is explored with 100 % new concepts and accuracy retrievals. The production and simulation concept assembly (sufficient) for empirical testing are explored or executed in parallel with last approaches—accuracy retrievals can be attempted with new physics attribution concepts. The nature of ESRs and the data obtained from them pose substantial challenges for AI/ML techniques. The level of ocean temperature should be compared. As the boundary between AI/ML and climate modeling can no longer be drawn cleanly, the data geo-informatics community needs to quickly align with the climate community. There is much to learn from AI/Mysticism approaches that render ESMs as probabilistic models. Investigating approximations that exploit advantageous anesthesized ESM components is of immediate research interest, and continues research for determining whether and precisely where an AI/Mysticism attack on Earth system modeling is appropriate and in what form [27, 28].

Public Engagement and Awareness

Public engagement in climate modeling sounds like a logical way to include more voices and minds in climate science, but it has proven difficult to implement effectively. The challenges have partly arisen from the complexity of climate modeling, partly from the caution and complexity of the scientific process itself, and partly from the controversial nature of climate science. Nevertheless, public participation should remain an important goal for AI researchers involved in climate modeling. Exploration of a warm world involves considerable uncertainties, including different kinds of extreme risks tied to well-known and poorly understood feedbacks. These include the important yet uncertain feedbacks that create the greatest climate-related risks for humans and ecosystems. In the case of global warming beyond 3 degrees Celsius, the most important feedbacks involve the irreversible decline of the Amazon forest, large and poorly understood carbon cycle feedbacks in the West Antarctic and Greenland ice sheets, and climate model uncertainty feedbacks. An operational question is how to tackle the task of selecting important yet uncertain feedback and exploring its consequences. It may be possible to harness some combination of expertise from scientists, AI, and the public. However, as with many AI-augmented challenges, the desired output (the exploration) may be easier to define than how best to produce it (the calculation). Rather than downplay the strangeness of the challenge, the creation of a new class of AI approaches to modeling could be viewed as entering a new frontier in which understanding and cooperation are paramount [29, 30].

CONCLUSION

Artificial Intelligence is transforming the landscape of climate modeling, offering powerful new tools to tackle the inherent complexity, high dimensionality, and computational intensity of simulating Earth's climate system. AI techniques such as neural networks, surrogate modeling, and machine learning-driven emulators have demonstrated significant potential in enhancing prediction capabilities, reducing computational costs, and uncovering hidden patterns in massive climate datasets. However, the integration of AI into climate science is not without challenges; issues related to data quality, model transparency, interpretability, and ethical use must be systematically addressed. Collaborative, interdisciplinary efforts that merge traditional physics-based approaches with advanced AI methodologies are critical for future breakthroughs. By embracing these innovations while carefully navigating their limitations, the scientific community can create more resilient, accurate, and actionable climate models, essential for informing policy decisions and mitigating the impacts of global climate change.

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