The Contribution of AI in Climate Modeling and Sustainable Decision-Making

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Abstract:
The dual challenge of the climate crisis and increasing anthropogenic pressure highlights an urgent call for collaborative global governance for the management of sustainability to safeguard collective wellbeing. Addressing the climate change dilemma entails shared collective responsibility for ecological and social justice and, thus, provides an important context for decision-making on governance for societal transitions towards political, economic, and cultural systems that are socially inclusive, equitable, and environmentally safe. Such societal-level decisions are often abstracted by model representations of increasingly sophisticated climate models, which remain heavily reliant on numerical simulations. Particularly at local scales, bottom-up models that utilize site-specific datasets for vulnerable communities can provide estimates of climate change worldwide. However, the requirements for high-fidelity climate simulation models are the frequency and prevalence of model outputs relative specific areas of interest, such as cities and regions, as well as at the decision-support time scale of local climate mitigation and adaptation policy.

Keywords: Artificial Intelligence (AI), Machine Learning, digital technology, Climate, historical data, AI prediction model.

1. INTRODUCTION

With the recent proliferation of Artificial Intelligence (AI), digital technology enabled bottom-up models are now capable of predicting climate variables at unprecedented temporal and spatial resolutions. While the technical prerequisites of machine learning are big data, fast computers, and new algorithms for associative data pattern mining, the historical lack of big site-specific datasets, especially on weather, makes the utilization of prediction models for localized decisions support an elusive goal. The recent creation of global and local multi-attribute tracking datasets enables the construction of site-specific datasets of historical climate variables, together with data on influencing environmental, economic and social factors. The novel local solutions to historical data limitations in fact open the path for the potential of localized AI prediction models, not just to fill in gaps for site-specific climate variables at the monthly-level decision-support timescale, but also to aid with training climate forecasting models at different aggregational levels.

2. OVERVIEW OF CLIMATE CHANGE

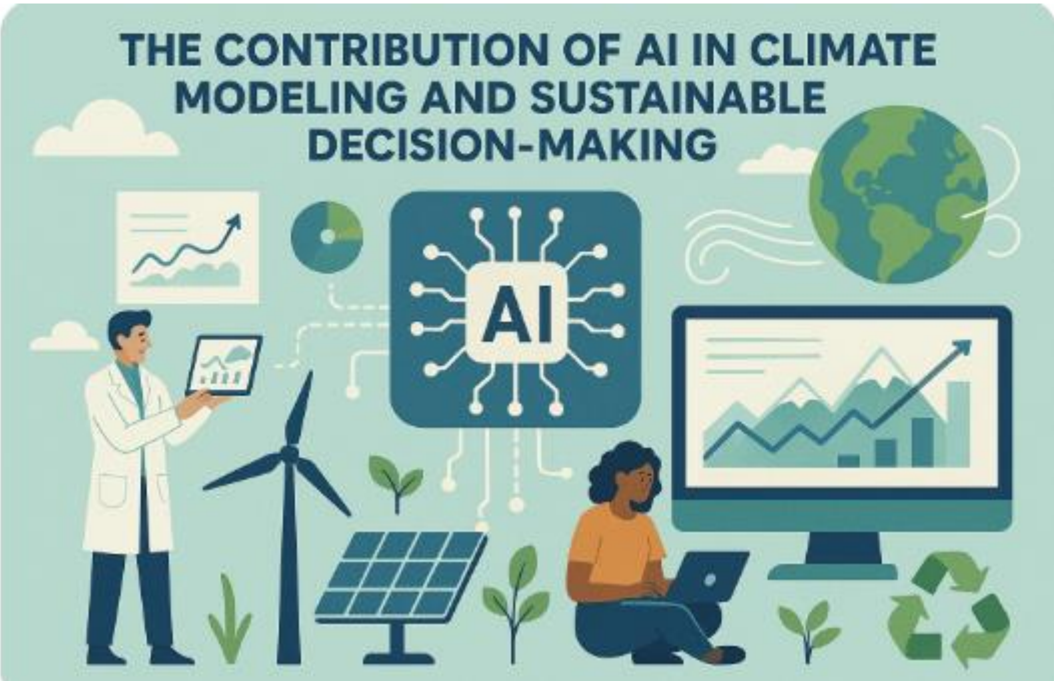
Climate change is a long-term shift in temperature and weather patterns, both globally and regionally. Although climate change is a natural phenomenon, since the 1800s, human activities, particularly fossil fuel combustions, have been acting as a “forcing” factor enhancing the natural greenhouse effect by releasing greenhouse gas emissions into the atmosphere, leading to climate warming. Extreme weather events, such as droughts, cyclones, floods, or heatwaves, can result from climate change. Some regions may also experience cooling, perhaps due to the disruption of ocean currents and the transfer of heat from the tropics to high latitudes. As these weather events grow in intensity and regularity, the demand for climate adaptation rises, as does the call for climate mitigation. When focusing on disruptive climate effects, the needs for disaster response and recovery also gain importance. We often forget about slow-onset effects, such as loss of biodiversity, acidification, or increases in sea level, temperature, and desertification but human and life-system adaptation and resilience-building to such ongoing changes are critical.

Concerned about the human-induced speed and scope of climate change, the scientific community convinced politicians of the environmental problems that could result from climate change, particularly as these problems could spread globally. New scientific fields were created, such as Earth system science, climate impact research, and sustainability research, focusing on climate change as a conceptual link between computers. In the 1980s, the realization emerged that actions were needed to avoid the most severe effects of climate change. However, the estimates of the degree of anthropogenic influence started with large uncertainties. Also, the interactions of climate change with other sustainability challenges, such as biodiversity loss and poverty, were not well understood yet.

3. THE ROLE OF AI IN CLIMATE SCIENCE

Much of the modeling applied to climate data is done through the prism of physics-based models, where the governing equations are derived from first principles, or statistical techniques, which attempt to identify and fit empirical relationships in the data. The contribution from informed computing applied almost exclusively through machine learning has, until recently, been limited, with many climate modeling presentations at major conferences with focus on cosmology or Earth observation. Recently however, this has started to change, with the climate science community more willing to build collaborations with computer scientists pushing innovation in ML.

ML is now used in a wide range of applications in climate science and climate-related fields: from forecasting severe weather events like hurricanes, typhoons and floods, through improved representation of physical processes like convection in models, downscaling the coarse resolution of general circulation models to produce regional and higher resolution climate projections, identifying climate variability and narrowing down the sources of extreme weather events, to using climate models to better understand climate's role in infectious diseases spread or using climate and social data to predict climate-related migration. Opportunities obviously exist in many more areas, and new promising ML techniques for areas like bias correction and model emulation have been developed that address the inherent challenges in applying ML in climate science. The research climate scientists and machine learning specialists have opened the door to new climate research opportunities, but much work remains to fairly test and validate the ML techniques, secure the essential lengthy climate model integrations necessary to analyze long-term climate change, and interpret the results physically and statistically.



3.1. Machine Learning Techniques

Traditionally, climate modeling has relied on explicit physics to drive our understanding of climate feedbacks and climate processes, hence the phrase "physics-guided" models. However, essentially all physics-guided models have physical parameters that must be interpreted and/or constrained. Machine learning is playing an increasing role in interpreting these parameters and learning new parameterizations. There is great promise in exploring our understanding of climate and weather as an explicit input-output function, or system. Therefore, the concept of learned systems is becoming more popular. Several recent reviews detail the use of machine learning in improving or enhancing long-standing climate models, or component parts thereof, with machine learning. For example, they review applications in which machine learning is used to replace subgrid parameterizations such as for deep convection, boundary layer processes, and turbulence in the atmosphere, rain formation and the development of clouds and precipitation, evapotranspiration and budget, ocean mixing and eddy variability, inflow or outflows from glaciers, snow and ice dynamics, and carbon processes for ecosystem and land surface models. Other experts have examined more broadly the intersection of machine learning and the geophysical sciences.

For the specifics of climate projections, training of neural networks often uses covariance data transfer via longitude-latitude from a high-resolution simulation and maps it to a coarser domain neural network. Machine learning could alleviate the shortcomings for bias and variance reduction, and information transfer between scales while currently enhancing primarily the Grand Challenge Parameterization Problem. However, the boundary conditions that make climate a unique system with seasonal to decadal predictability rest on specific generally chosen domain configurations, needed biases, untrained types of neural networks, and variable scales for a range of variables associated with climate-atmosphere interactions that can significantly influence parameterization error and climate sensitivity.

3.2. Data Analysis and Interpretation

Climate modeling is based on qualitative and quantitative analysis of observable variables, specific assumptions or hypotheses and physical equations that regulate climate behavior. The available climate-related data are usually monitored with great resolution in the time domain but lower in the space domain. Furthermore, climate measurements sometimes show a high degree of noise. For these reasons, data processing is essential in climate science.

Modern climate science mostly relies on the use of sophisticated data analysis techniques. Rarely qualitative or merely statistical analysis is sufficient, and physics-based models are required to describe the processes that underlie the variability of climate observables. The models can be in some case very complex. Other times a simpler model, able to capture the essential features that one intends to extract from the data, is preferred. A non-linear 1D advection and diffusion physical model of the time series of surface temperature anomalies is used as the template to analyze climate data. More ambitious studies attempting to invert a more complicated dynamical model of the Earth’s climate system to extract information starting from temperature anomalies are also being considered.

Machine Learning and Artificial Intelligence are an emerging discipline that aims to develop schemes able to improve their performance by learning from data, without being explicitly programmed. Their ideas and methods are providing novel, powerful approaches for scientifically inspiring problem-solving questions. They have been successfully applied in a variety of different problems and fields, showing great success in both supervised and unsupervised paradigms.

Machine Learning algorithms rely on robust statistical and probability theoretical principles and offer the possibility to replace or improve some of the traditional approaches in a scientifically inspiring way. The inherent parallel processing capabilities of Machine Learning algorithms enable to efficiently train models with a very large number of free parameters that allow them to represent the underlying data in a highly flexible way.

4. AI APPLICATIONS IN CLIMATE MODELING

Artificial intelligence, including its derivatives, such as machine learning, reinforcement learning, and deep learning, have emerged as some of the most important enablers in various climate prediction endeavors, especially in terms of data processing capabilities and speed. Earth system models consist of complex mathematical models of the Earth’s environment, which rely on numerical methods and physical equations to simulate climate dynamics. Traditionally, the predictive skill of an Earth system model had been low on localized variables and at high spatiotemporal resolutions. Advanced computing technologies, including supercomputers and cloud computing, have enabled the training of large and complex numerical Earth system models that have superior skill on localized climate variables, such as temperature, precipitation, etc. Continuous improvements and innovations in both the design of the model architectures and global initialization preparatory processes have made the model hierarchies reach unprecedented capabilities in physically recognizing how climate variables interrelate at multiple timescales, from the synoptic and the seasonal to the decadal and the centennial, along with better recognition of climate shift and misbehavior patterns. Various types of AI-driven climate and weather prediction top benchmark performance in multiple centers across the world.

4.1. Predictive Modeling

The contribution of AI is indispensable for the optimal mapping between input and output data of climate models, as these maps often need to be approximated in a prediction model. For this purpose, AI techniques including Machine Learning and Deep Learning leverage state-of-the-art methods. Climate modeling is often executed based on physically-based Mathematical Models, which require knowledge of how to solve a set of complicated interconnected non-linear equations. Alternatively, statistical Machine Learning techniques minimize the number of assumptions on how to approximate the statistical dynamics of the unknown predictor of climate properties and use the abundance of climate data to learn possible approximations. While those Mathematical Models and Machine Learning techniques are often considered entirely separate, in recent years there has been increased interest in Hybrid Modeling approaches that combine Mathematical Models with data-driven Machine Learning techniques. In this approach, the Mathematical Model of the climate properties is used to train a low resolution model based on Machine Learning. There are multiple tasks in climate prediction including Numerical Weather Prediction, seasonal forecast, weather of the following summer and climatological prediction.

The predicted data are provided in different time resolutions, which differ according to the modeled climate actions. The time resolution of the output data ranges from data corresponding to basic predictions based on high-resolution niche models used only at basic points through empirical downscaling supported by the Machine.

4.2. Simulation of Climate Scenarios

As stated earlier, AI relies on data input, and there are numerous sources that generate climate data from AMMs. AMMs have long been valuable tools used for producing dynamic climate data based on various driving inputs such as Solar radiation, Greenhouse gas emissions, and terrestrial forces. However, AMMs can take a hefty computational toll when generating high-resolution results over long time periods and do not support the generation of data with varying choices of parameters or driving inputs. AI is valuable in this process as it can offer speed up AMMs and produce novel outputs never computed by AMMs.

For example, GANs have been used for producing high-fidelity climate data which are statistically indistinguishable from the data produced with AMMs. Coupled with methods such as transfer learning, GANs can imitate the behavior of AMMs without running them at high computational cost, thus allowing researchers and policymakers to quickly simulate and explore an array of climate scenarios. Traditionally, AMMs are run to provide an infrequent number of per-grid historical reanalysis products. However, GANs can quickly be used to produce multiple fine-resolution outputs for the same grid and desired time period which can be used for exploring the sensitivity of variation in model outputs to changes in input parameters.

Novel GANs such as VarGAN and real-value GANs can be directly trained on actual physical model outputs. Due to the couple temporal and spatial correlation in temperature and precipitation variables, fine-tuning both GANs using the two-step training process has allowed researchers to produce historical fine-resolution climate data useful for various climate applications such as agriculture, hydrology, and tourism study. For example, GANs have been used for combining spatiotemporal datasets and downscaling precipitation variables for hydrological studies.

5. INTEGRATION OF AI WITH TRADITIONAL CLIMATE MODELS

The predictions of future climate state and change are typically generated through global numerical models, known as General Circulation Models (GCMs). These models are based on physical principles, such as the conservation of mass, momentum, energy, water, etc., as formalized through the Navier-Stokes equations of fluid motion and energy conservation principles known in meteorology as the equations of motion, thermodynamic energy equation, and equations of continuity and state. Everybody agrees that they are based on solid physics principles. However, because of the coarseness of GCM spatial grids (between 10 km and 100 km), the parameterization of microphysics processes and feedbacks is needed for what cannot be directly resolved by a given GCM (typically, turbulent motion), as formalized through the so-called parameterization schemes. Parameterization schemes are also the crux of the problem, as they introduce considerable uncertainty in the GCM climate-response-to-CO2-increases that is used to calculate changes in future climate by forcing it with different pathway-specific scenarios of the rate-at which CO2 is released into the atmosphere.

6. AI FOR SUSTAINABLE DECISION-MAKING

We are at a crucial junction of the climate crisis, in which we need to accelerate climate action and change decision-making at all levels of society quickly and radically. Several recent calls to move beyond business as usual across public, private, and academic sectors highlight the need to address the issues of human and social behavior, as climate inertia cannot be simply explained by a lack of awareness about climate risks. The convergence of technological, economic, political, and sociocultural factors is pushing towards a transition in decision-making, an area where AI can provide solutions to complement climate modeling. AI can help us move beyond enabling technology that automates processes or tasks towards better decision support systems by manipulating unstructured data at a massive scale to extract information that can enhance awareness of climate change effects. Furthermore, data can be utilized to better develop instruments and mechanisms for decision-making that can drive a more effective transition to a sustainable future. In this section, we review selected applications of AI, such as those based on big data, machine learning, and agent-based modeling, in two of the areas that we believe AI can best contribute to. Specifically, we discuss resource management, while focusing on policy formulation.

AI-based systems can help us devise a proper energy transition strategy by creating models that can accurately reproduce data regarding electricity demand, production, and exchange. These models can, in turn, be exploited to verify possible transition scenarios, such as a faster and larger introduction of renewable energy sources and related technologies, the introduction of dynamic pricing, demand-side management measures, or the use of batteries or demand response. Moreover, unlike traditional modeling methods, AI-based systems can naturally integrate the huge amount of unstructured information contained in social media. In particular, user-generated content allows for a much wider scope than is possible with traditional sources, such as household energy accounts or specialized surveys. AI can help to gather the will of the people, aggregating sentiments and opinions regarding the energy scenario, and bridging the gap between electricity supply and demand modeling to create more resilient social-technical systems.

6.1. RESOURCE MANAGEMENT

The traction gained by AI has ignited interest in deploying it to advance multiple spheres, climate resilience being one, as it requires prediction of extreme conditions in sufficient spatio-temporal resolution to influence climate-sensitive decisions. For example, agricultural yield prediction is crucial for a country, as crop failures could culminate to scarcity of food and later increase poverty, famine, and loss of lives. Earlier approaches based on dynamical models suffered from the disadvantage of being computationally expensive.

AI models have proposed methodologies to address a variety of challenges for yield prediction, including handling large datasets, being independent of prior physical considerations about data; automation of the time-consuming task of hyperparameter tuning for complicated neural network-based models over tailored metrics; uncertainty quantification, and handling sparsely sampled data comprising of only few seasons with successful crop yields. Similar AI-driven models have been developed for the estimation of above-ground biomass and crop water requirement. AI models are not limited to crop prediction alone but have also been deployed for estimating the soil moisture in the US Corn Belt, which impacts the sowing and harvesting activities for crops.

6.2. Policy Formulation

Motivated by the recent developments in AI and the ever-increasing need for urgent responses to growing imbalances and disruptions in the climate system, there is a new wave of investments in AI for Climate. A significant share of these investments is currently targeting applications of AI that support the design and implementation of climate policies, especially those that are particularly critical for climate mitigation. For instance, funding organizations active in supporting climate-related scientific research have initiated partnerships with AI companies in order to facilitate the development of AI-informed monitoring assessments for national-level emissions inventories as well as regional and international policy scenarios analysis. Other knowledge system use cases for AI include climate feedback mapping for coastal cities; temporally high-resolution urban-gravity modeled carbon emissions; emissions of marine traffic; carbon fluxes of oil and gas companies; observations data driven supply chain carbon footprints; and near real time satellite-based power grid and energy generation monitoring.

From the perspective of policy modeling itself, recent years have witnessed a significant growth in the number of AI models developed for the task of estimating social-science-model-indicating Policy Meta-Parameters, like Elasticities. Both Data-Driven AI Approaches and Model-Based AI Approaches have been applied for increasing the quantity of available empirical knowledge on System-Wide Meta-parameter Uncertainties and Estimation Coverage of Structural Macro-economic Models, bearing the ambition of improving Policy Ex-ante Evaluation and Model Updating Utility, which could potentially lead to spillover effects on Climate Policy Formulation and Political Decisions. Similarly, AI has also been applied for the task of Empirical Risk Reduction When Modeling the Macroeconomics for International Climate Cooperation within the framework of an Intertemporal General Equilibrium Approach to Solving Dynamic Games.

7. CASE STUDIES OF AI IN CLIMATE INITIATIVES

The use of artificial intelligence in climate action is innovative, and practitioners have recently taken steps to explore its potential. Some significant examples are described and categorized into Urban Planning Initiatives and Agricultural Practices Initiatives.

7.1. Urban Planning

Urban Perception utilizes deep learning and computer vision methods to extract urban land use characteristics from aerial and satellite images. Land use in the built-up environment is a significant contributor to energy, carbon, and water footprints. Their model automatically identifies buildings with saturation of energy and tourist movement. They concluded that policymakers should use high-resolution imagery for sustainable development. The system was thoroughly trained to quantitatively segment and recognize geo-spatial zones corresponding to carbon emission distributions. They found a perfect match at parking lots, Zhongdian, and airports, which are land use types that produce most of the distributed carbon emissions in West Coast cities. Urban Heat Islands create higher average city temperatures than surrounding rural areas because of heat retention by the artificial fruits of urban areas. Their predictive model for future heat islands showed that effective decision-making could require planting 10% more trees than predicted.

7.2. Agricultural Practices

AI has been introduced in precision agriculture and is often fused with agricultural drones. All these advanced technologies for farming by drones. Drones in precision agriculture improved efficiency, accuracy, and quality of crop strategizing and management. Drones on demand from drones are beyond any other channel of distribution. UAVs are convenient to sow seeds, create maps, check for plant illness, and locate weeds. The advanced UAVs have embedded sensors to check for crop maturity, real-time fertilizer prescription mapping, real-time weather monitoring, and UAV deliveries.

7.1. Urban Planning

Increased urbanization is drawing nearly 70% of the global population into urban clusters, which produce more than 80% of global emissions while having a smaller footprint compared to rural areas. These areas are also more vulnerable to climate change impacts like flooding, heat stress, and sea-level rise. AI has started to make significant contributions towards climate-informed decisions in urban planning policy. However, AI can unintentionally worsen this complex affair if applied irresponsibly. Urbanization is more than just physical movement from rural to urban clusters; it involves a fundamental change in society's approaches towards modes of production, consumption, family structures, and political ideologies, among others. Therefore, climate change and urbanization are reciprocally related and must be strategically integrated to create climate-resilient urban-planning policies, and speed up the transition towards a net-zero world. Moreover, integrating climate change into urban planning can also ensure long-term resilience of cities to the worst impacts of climate change. Urban planning can also affect how quickly cities can achieve their net-zero targets and how well they can accomplish the inevitable transition to a carbon-neutral economy.

7.2. Agricultural Practices

Keyword search: AI, agriculture, crop yield, decision-making, irrigation.

Climate change is one of the factors affecting agricultural activities and increasing the food security gap. Droughts, floods, desertification, salinization, pests, and diseases not only contribute to crop yield loss but also destroy the long-borne eco-balance of the agricultural ecosystem. Besides, an excessive or unintended application of agricultural inputs also affects soil health, which is vital for sustainable food production. Precision farming can help reduce both these impacts and optimize crop production. So, the development of precision farming technologies through upscaling AI in agriculture would be the natural way to promote replenishment in food production.

AI is being used for real-time and precise crop yield prediction that can help the authorities in promoting food security and help the organizations engaged in financial investments in estimating future returns. A highly relevant study highlighted that machine learning can predict crop yield as accurately as econometric models while enabling the use of various data sources. Some researchers even used machine learning-based approaches to determine more precisely the yield gap. According to some researchers, machine learning can be used for rice yield prediction using remote sensing data while another research methods used the Random Forest algorithm to predict cotton yield. Research has also applied a proprietary commercial agricultural AI to carry out wheat yield prediction in the United States through modeling and found great accuracy with various machine learning algorithms. Hence, machine learning and AI can be very useful for predicting crop yield accurately.

8. CHALLENGES IN IMPLEMENTING AI IN CLIMATE SOLUTIONS

AI remains at a nascent stage for many climate solutions. It has great potential, but a long way to go before mainstream deployment. The large computational needs for implementing some of the more promising solutions also hinder deployment for all but the richest organizations and companies.

Data Quality and Availability

The reliance on comprehensive, robust datasets is crucial. Data that is inaccurate or susceptible to biases can negatively impact models and subsequent results. The AI models need to be calibrated carefully to address the complexities in climate science where there are many unknowns or difficult-to-quantify uncertainties. AI is often considered a “black box” where only limited insights can be obtained with LLMs, deep reinforcement learning techniques, or other stochastic frameworks with limited explainability for the models. Therefore, deploying ML/DL without domain knowledge raises concerns about the reliability of predictions. An often-cited issue with ML concerns the bias–variance dilemma: the inability to generalize to unseen situations is due, in part, to overfitting of the functions to very little data concerning previous weather system states. These concentrate on a small area relative to the amount of input variables available; thus, accurate transfer functions to climate models are very challenging.

Ethical Considerations

The importance of accuracy as well as explainability of AI models has broader implications. Deploying errant models can risk lives in the case of severe weather, natural disasters, predicting air quality, or prolonged effects on health from heatwaves, floods, and drought with possible economic impacts for regions without sufficient resources. The energy intensity of model training for the new class of LLMs deploying a large number of parameters that need to be optimized not only consume the allocated energy for the cloud or AI service user but also have cascading energy requirements that include internet data usage, cooling of servers, as well as a prolonged demand for electricity in areas relying on fossil fuels which trigger spikes in carbon emissions.

8.1. Data Quality and Availability

Advances in AI, data, and computing power offer the possibility of untangling complex systems. The relationship between greenhouse gas emissions and climate change is far from the simple correlations observed between the increase in one and the other, and AI holds the potential to support modeling and understanding of the climate system, even to the discontent of researchers who have previously struggled to explain climate dynamics with simple models. But AI requires data, and the data requirements of AI typically far exceed for what is available on climate. For example, the data must be numerous enough to allow for statistical learning but also rich enough to represent the finer details of climate, such as the enormous amount of geographical surface heterogeneity and the clouds.

To infer climate relationships, a relatively short historical observational record in the context of the long historical residence time of climate compared to the much slower historical pace of change in the underlying boundary conditions must be supplemented. Understanding climate and modeling predictions require different – often contrary – approaches to uncertainties compared to more tangible impacts such as agriculture or health, where AI is now widely deployed. Although agriculture and health services could offer the necessary training and learning opportunities, the scientific explanation of turnover times in climate could hinder motivation to produce good data to train AI. Generating accurate forward climate models often involves meeting assumptions of homogeneity, ergodicity, stationarity, or, in the absence of fundamental laws such as thermodynamics, assumptions of Gaussianity, known in statistics to be at odds with the nature of natural phenomena. Various degrees of inaccessibility due to provably hidden or transient variables may introduce additional problems.

8.2. Ethical Considerations

Despite the immense potential of AI to help mitigate climate change and its consequences, there are considerable challenges to its successful development and deployment in this realm. Apart from the issue of poor-quality and sparse data (which could result in poor predictive performance and potentially unsafe deployment), there are additionally specific ethical considerations that the field must necessarily focus on, such as responsibility and accountability, bias and discrimination, transparency, or privacy and data protection.

Firstly, who is responsible if a climate model fails to make an accurate prediction and a region suffers from food desertion due to crop failure or suffers from devastating floods because of poor management of rivers? Who should be liable for this? A tech company offering services to mitigate this prediction error? The governmental agency deploying such solutions? Or the researchers developing the forecast model? Centering responsibility around one entity does not seem doable, given the many actors involved in such a complex decision and action chain. Rather, it seems prudent to agree on shared responsibility between the parties involved in the different stages of model development and deployment. However, this also requires clear channeling of liability, which may be more difficult in practice. Similarly, accountability seems difficult to transpose in this context. Climate crises can have impacts over various levels of society in each country, and people have little control over whether any party involved has made a climate-related decision that was unethical or wrong, affected the lives of those people, or even incurred substantial losses. Data-centered AI solutions increasingly demonstrate discriminatory flaws based on sensitive attributes, such as age, gender, ethnicity, or skin color. However, people victimized by these discriminatory algorithms currently have no right to inquire whether AI systems developers have identified or successfully reduced or mitigated sensitivity attributes. At the moment, there are no clear rules on the verification of AI systems functioning and predictions, whether for AI-based predictive climate models, or for AI-based cloud management functions, for instance.

9. FUTURE TRENDS IN AI AND CLIMATE RESEARCH

As AI-enabled systems scale rapidly to unprecedented levels of generality, capability, and accessibility to global talent, and traversing the deep uncertainty and multiscale challenges that define decision making in response to climate change, it is worth considering what future research trajectories in climate, land use, and oceans call upon on AI's growing capabilities. A current trend in model design is to expand self-organizing models in terms of complexity and dimensionality. AI's growing abilities to learn models of images along with state of the art geodetic point cloud models in the forecasting of a diverse space of phenomena leads to expectation that self-organization with more model dimensions will increase the utility of AI-enabled models in regions of real space that receive little attention by physical models. The convergence of more sophisticated AI algorithms and breakthroughs in self-organizing model designs that can generate many accurate emergent solutions is likely to underpin success in AI-enabled modeling of extreme events. Recent results, combining advances in design, training, and inference of generative process rather than adversarial senior organizing models suggest that the capacity to capture the complexity of Asia's monsoon system will similarly increase. More generally, given the increasing forecastable complexity of changes to the climate, land systems, biosphere, and oceans, an unanticipated success will be the creation of AI-enabled models that generate emergency sets of solutions for catastrophic and existential risk events, for policymakers and pluralistic decision-making systems use.

10. COLLABORATION BETWEEN AI EXPERTS AND CLIMATE SCIENTISTS

One critical step in ensuring successful collaboration between AI and climate scientists is interdisciplinary education and training. As the AI field matures, climate research collaborations demand different educational pathways to develop specialists who can facilitate communication, create innovations, and advance important discoveries. Moreover, collaborative research design must counteract the entrenched traditions, incentives, and evaluation structures associated with each field through new approaches that reward community engagement, sharing credit, and, where possible, building of shared resources and infrastructures. Negative historical experiences, and in some cases, differences in workplace cultures between fields may necessitate careful negotiation before research can begin, and long-standing relationships should be cultivated to further build trust and encourage knowledge sharing. AI and climate scientists also must work together to explore potential technical limitations of existing AI approaches for climate research. Ideally, such assessments should take place during the initial phases of collaboration, when there is adequate time for discussion and brainstorming of innovative, interdisciplinary solutions and novel applications to complex climate questions. One of the most common critiques of contemporary AI approaches in niche domains is that they can be “black boxes” that offer little or no explanation of their categorizations or predictions. These “black boxes” can be problematic for AI experts. They may be wary of a wider implementation of AI methods in climate science, particularly in high-stakes decisions, such as those related to safety and policy, unless AI specialists were to thoroughly explain their rationale for the choice of methodology and the results of their prediction and lay bare its uncertainties and failure modes. At best, climate and AI scientists might jointly develop areas with a sound theoretical basis, so that AI “black box” methods could be implemented carefully for specific tasks, with appropriate considerations of uncertainty.

11. FUNDING AND INVESTMENT IN AI FOR CLIMATE SOLUTIONS

AI can have an important role in helping to solve climate problems. But this requires investment in the AI research required to deliver that potential. It emphasized the need for investment or funding needed to enable these AI-driven climate solutions. It notes that “disruptive innovations in mitigation technologies” will not happen automatically, but that there is a need for “urgent, economy-wide and currently available strategies” to tackle climate change, and these strategies need to be carefully designed to make the most of rapidly developing new technologies.

This echoes the earlier findings about the importance of investment in basic AI research. Addressing climate issues requires long-term investment and funding in new climate-focused AIs, as well as research and innovation ecosystems that promote the building of AI tools and services which specifically support climate action plans, which often vary in scope from national down to local levels. Recent comments from influential figures regarding the need for more focus and investment argue additionally for funding bodies and investment

enterprises to focus more on AIs that can specifically be used to address climate challenges. AI's importance for solving climate concerns is evidenced by the substantial work on climate models.
Investment areas should also aim to increase the adoption and dissemination of these AI tools. These efforts can contribute significantly to the global release of greenhouse gases, as well as emissions by other sectors that adversely affect the climate and the physical environment, such as tourism and biodiversity protection. AI-driven climate solutions must also seek to increase climate resilience in lower-income countries and communities.

12. PUBLIC AWARENESS AND EDUCATION ON AI AND CLIMATE CHANGE

The last chapter of this report underscored that awareness of the climate change problem and education on the power to harness technology, including AI, can positively impact decision-making that contributes to the climate agenda. The potential of AI for climate conscious decision-making is sizeable but not fully taken advantage of. Changing the way people view the new digital ecology that involves AI could be developed through awareness and educational programs. AI can assist climate change and members to track their footprint on this new connectivity model. Contributing positively to the climate agenda through the use and development of decentralized technologies and systems should become a social norm. Sharing power back to the people through positive advancement in trusted systems on the climate crisis can be a key component in helping more people think about decision-making and actions that can positively impact climate change. Society is continuously evolving. Viewing the way new technologies spend the limited resources of our world through the lens of contributing to minimizing its impact on the climate crisis should be developed, becoming social, educational, and corporate stages that influence individuals to fuse their self-interest with climate conscious choices. Making such choices should become an ethos.

AI should be included in educational agenda policies to build a responsible generation of creators and consumers. Such initiatives should increase visibility of AI and what it can or cannot do, to prevent people from blindly giving in to AI’s capability. The hope is to develop a healthy relationship in the future generation. Finally, enhancing the relationship between AI and people through education can help people attain a better work-life balance while using AI in their everyday lives.

13. INTERNATIONAL POLICIES AND AGREEMENTS

This is a matter of science governance at the global level, regulating the issues inherent to our advances in earth system science, modeling and artificial intelligence. In doing innovative research and development of products in machine learning, deep learning and AI algorithms employing earth system data and engaging in their applications to climate and weather highly sensitive and policy relevant sectors, scientists need to adhere to ethical principles about how they represent the results of their work to the scientific community and beyond it. The scientific process and the use of scientific information for navigating the transitions needed for adaptation to climate change and mitigation to achieve the targets set are equally dependent on responsible policies, capacity, and infrastructure to help Investment. Transitioning Investment needs to be directed towards building climate and weather resilience, enabling high emitters globally and nationally to convert their economies sustainably through specific outlines in their NDCs. Acceleration in the transfer of technology and financial resources to help developing countries and potential achieve the targets in their NDCs in a manner that is realistic and commensurate to their situation is critical for determining success in preventing global temperature rise surpassing 2 oC and setting a lower threshold encouraging more ambitious reductions towards 1.5 oC.

Execution of NDCs emission targets require deep decarbonization modeling of specific emitting sectors, along with specific processes within them, what to policy makers and climate scientists means specific physical representations of the way these processes interact, develop and evolve under the influences of local and regional socioeconomic aspects when subjected to global warming climate changes. The specific representations of processes and their interactions for sector and development pathway deep decarbonization modeling are inherently multiscale and must connect appropriately and reliably from general circulation model scale to the scales at which the processes and their interactions are represented for global to national to regional to sector to process specific development pathway climate change monitoring and projections.

14. TECHNOLOGICAL INNOVATIONS IN AI FOR CLIMATE ACTION

Artificial intelligence has provided several new technological innovations to address climate mitigation and adaptation. Several AI-based climate products or services have already been developed and tested in various parts of the world. For instance, artificial intelligence is being used to support weather modeling and prediction at a finer geographical resolution with minimal costs. Weathering is vital for agriculture production in terms of assessing crop suitability, planning for optimal agricultural activities, forecasting pest and disease outbreaks, and improving digital agro-advisory services. Artificial intelligence is being used to provide accurate, high-resolution, and hyper-local weather forecasts for different sectors. The weather-as-a-service platform offers businesses access to critical weather data. The AI model trains and combines multiple neural networks to deliver weather forecasts that are more precise and can last up to 15 days with temporal granularity.

There has also been a partnership to improve weather forecasting using AI. In another instance, AI is being leveraged to enhance weather modeling and improve forecasts using high-resolution data. The machine learning model predicts hourly precipitation up to 12 hours in advance, and it is claimed to perform better than existing standard methods. Climate change is causing the patterns of climate and weather conditions to change, resulting in more extremes and erratic patterns than before. Such changing cycles will add noise to our climate and weather predictions if predictive models are not retrained in tandem with the changing cycles. Consequently, substantiating the trusted forecasts, accurate analysis, and results provided by AI is crucial, as models also have their uncertainties and would be subject to errors.

15. ROLE OF NON-GOVERNMENTAL ORGANIZATIONS

As stated above, the entire world is in the race against climate change and NGOs also play an important part in this. Bridging the gaps between communities, grassroots action, decision-makers and climate scientists, is the first main task taken on by NGOs. The role of NGOs is mainly to assist in smooth transitions when all other methods for gathering data or taking actions fail. There is a lot of work done to take the initiative to raise awareness, add more voices against climate change, connecting communities who are working at a local level to connect with each other, etc. Organizations are working hard to carry out research tasks at a regional scale and perform climate modeling analysis at particular locations to assist local communities. Our better understanding of how climate science topics are perceived is due to an extensive body of research conducted by social scientists and NGOs.

The third main task is mobilizing as these organizations have extensive networks that can motivate widespread societies that cannot cope up with climate change anymore. These organizations shall help promote fear-appeal material, since generally the non-climate NGO community remains unaware of how these factors might influence social interest in climate change. Integrating and sharing climate data related specifically to biodiversity can help bridge the gap and benefit both the climate and the environment NGOs, while providing the NGOs and Civil Society Organizations with motivation to foster climate data collection and sharing. The organizations operating around the world shall work to establish equitable relationships with the scientists in order to increase mutual understanding about climate data work and to develop routes for dissemination of climate data to the broader public. The scientific process must be open and transparent, allowing different priorities and concerns to be aired and debated in public forums where the possible ruptures and modifications in the relationships can be made explicit.

16. INTERDISCIPLINARY APPROACHES TO CLIMATE CHALLENGES

Translating knowledge into practice requires institutional mechanisms for collaboration and interdisciplinary study that presently do not exist, yet are necessary to discover new solutions bridging modern society with the natural world, and to encourage their widespread adoption. At several higher education institutions, interdisciplinary research centers unite scientists from diverse fields to study the methodological questions posed by the climate crisis - questions impossible to answer without contributions from multiple fields. The answers provided by this open discourse lay the foundation for new significant advances in the constituent disciplines. Achieving these advances, and then applying them to the resolution of specific difficulties, necessitates effective communication between researchers in the various disciplines and effective organization of student involvement. By forcing the world to adapt, climate change will create complex ethical dilemmas requiring collaboration by experts in diverse fields. People will be displaced; old jobs rooted in natural cycles will disappear; new ways of living will be imposed on our society.

17. CONCLUSION

In this chapter, we summarized the key ideas and findings of the present work, concerning the contributions of AI in climate modeling and in creating tools to support Sustainable Decision-Making (SDM). We first presented the background of the research and proposed a concise overview of the climate change context and a description of the phenomena of Climate Change and Global Warming (CW), presenting key concepts and definitions. Artificial Intelligence (AI) and its branches were also introduced, some more relevant concepts related to the use of AI in climate modeling and SDM were also presented, such as the Urban Heat Island (UHI) phenomenon, Explainable AI (XAI) and Fairness, and SDM using Integrated Assessment Models (IAMs), aimed mainly at policy makers. We pointed to the public perception of climate addressing the importance of how the CW problem has been communicated to all and how we must evolve in a way that reframes the CW decision-making problem. The contribution of Artificial Intelligence (AI) and its branches, focusing on Machine Learning (ML) and Deep Learning (DL), were then organized and discussed regarding Climate Modeling (CM) and Policy Making (PM) to reduce the impacts of climate change mainly from the Sustainable Development Goals (SDGs) perspective.

Research on climate modeling by using AI techniques has recently been gaining ground, with many applications being proposed in the literature. Regardless of that, climate modeling is still highly demanding in computational terms, and some connections with PM continue lacking, which limits the use of AI techniques in SDM addressed to CW prevention or mitigation. The junction between climate modeling and philosophy of science is still underestimated, although many benefits, such as better modeling, understanding, use, and acceptance of AI and ML models, can emerge from that. AI techniques can be also used to support the configuration of models focusing on complex phenomena, or even at policy configurations related to CW.

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