Research Paper on SecurityThreats from Temperature Changes Occurrence by using Artificial Intelligence (AI) and Machine Learning (ML)

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Abstract
In the past, climate change has been a significant problem all over the world; nonetheless, it has been challenging to mobilize collective action in response to the problem. In spite of the knowledge that climate change is a threat to our species as well as the life that already exists on our planet, this continues to be the case. The researchers who have looked into this phenomenon have come to the conclusion that effective communication regarding climate change is predicated on messages that are both emotionally charged and personally meaningful, and that pictures, in particular, are essential in order to generate awareness and concern about the subject. In spite of the widespread belief that this is the case, the majority of the conventional modes of communication that professionals employ when interacting with members of the general public are frequently founded on discoveries made in the scientific community. These studies, on the other hand, typically fail to convey either the urgency or the relevance of this huge occurrence. Utilizing Artificial Intelligence (AI) and Machine Learning Is the Purpose of Our Report So That We Can Help Bridge This Gap And Build A Tool To Promote Awareness About The Effects Of Climate Change The purpose of our report is to use AI and ML so that we can help bridge this gap and build a tool to promote (ML).
Keywords: Climate change, Environment, Artificial Intelligence (AI), Machine Learning (ML).

I. Introduction

The various alterations that have taken place in our perspectives on life and technology can be regarded to be a direct result of the effect of artificial intelligence, sometimes known as AI. The advancement of artificial intelligence (AI) and machine learning (ML), both of which have applications that are continuously revolutionizing the ways in which we interact with our electronic devices, other people, and the natural world, is going to usher in some very exciting times in the not-too-distant future. [1, 2] These developments are going to bring about some very exciting times.

Only 33 percent of customers, according to the findings of surveys, are fully aware of all of their connections with AI. Since the 1950s, when Alan Turing computerized the game of chess, which later served as the foundation for robots that defeated world-class chess players [3,] artificial intelligence has made its way out of research labs and into our everyday lives. Since that time, artificial intelligence has been put to use in a wide variety of settings, ranging from medical diagnostics to uses in the military. Turing made the discovery six years prior to the establishment of the phrase "artificial intelligence," which is used to characterize the reasoning and cognitive capabilities of a machine and is detailed in Figure 1. In other words, Turing made the breakthrough in the field of artificial intelligence.

In 1951, researchers Allen Newell and Herbert Simon presented the Ferranti Mark 1 to the world. The Ferranti Mark 1 was a remarkable computer that was able to conquer the game of checkers and as a result achieved international notoriety. Since that time, there has been a significant increase in the momentum behind the development of AI, and the breadth of the technology has broadened to include applications that are useful in day-to-day life. Every single individual in the world who currently owns a smartphone uses AI in some form or another [4].

On a regular basis, users of social networking sites like Facebook, LinkedIn, and YouTube engage in conversations with computer programs that are powered by artificial intelligence. The majority of us are probably already familiar with one of the typical applications of AI, which is the development of personalized recommendations for videos to watch. In order to do things like adjust the color of a tunnel or estimate traffic along a route, Google Maps uses artificial intelligence (AI) and machine learning. In order to target client preferences more precisely, artificial intelligence (AI) is being employed in search engine marketing. In the field of medicine, artificial intelligence (AI) and machine learning are finding applications in the process of accelerating the development of novel pharmaceutical combinations and the enhancement of medical imaging for diagnostic reasons. In agriculture, artificial intelligence is used to create predictions about a variety of outcomes associated to the fertility of the soil and the conditions of the atmosphere. These forecasts can help farmers plan more effectively and increase their crop yields. The incorporation of artificial intelligence (AI) into the field of automobile manufacturing, as demonstrated by Tesla, has made it possible for automobiles to operate without human intervention. There are many different ways that artificial intelligence (AI) can be put to use [5].

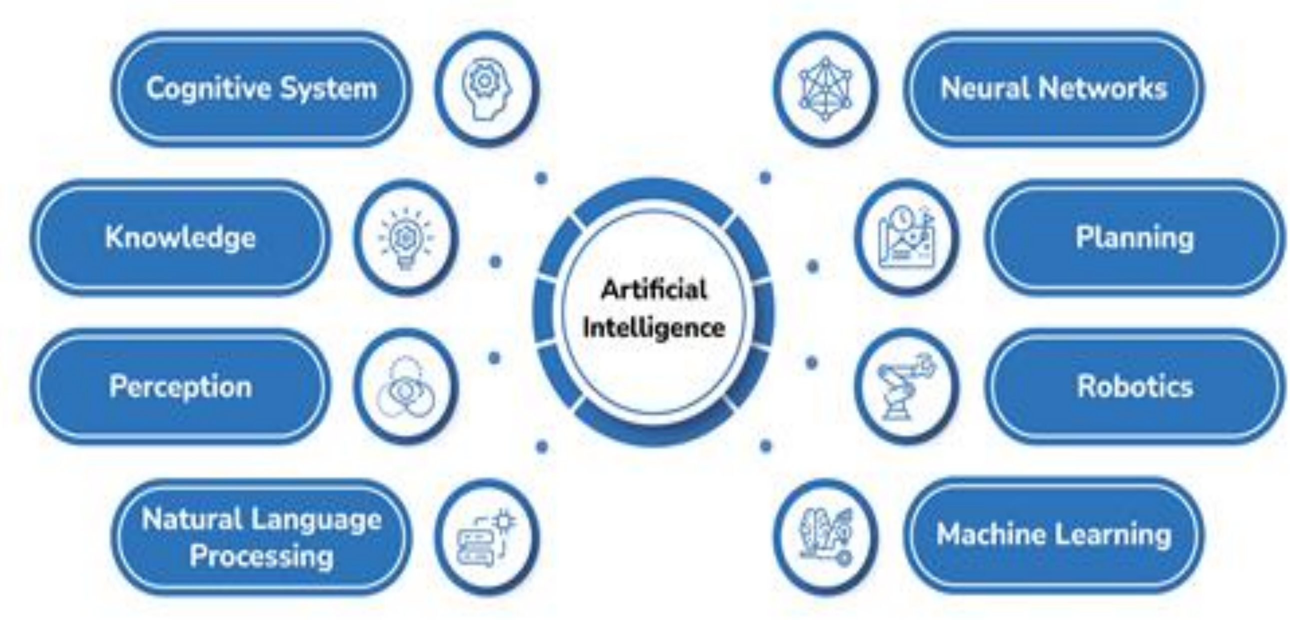


Figure 1: Field of AI

In recent years, there has been a precipitous rise in the number of businesses that incorporate artificial intelligence (AI) as part of their enterprise information technology (IT). Consumers and businesses alike are turning to applications that are powered by artificial intelligence in order to find solutions to problems that occur in the real world. The government use artificial intelligence for a variety of tasks, including the management of traffic, the analysis of social data, the preparation for natural catastrophes, the evaluation of economic activities, and more. Companies that provide financial services are increasingly turning to artificial intelligence in order to tailor new product offerings in response to anticipated shifts in consumer preferences and market conditions. As a direct outcome of the implementation of AI in customer service, the development of conversational bots and intelligent interactive voice response systems (IVRs) that exhibit nearly human-like behavior has taken place. There are a lot of different ways that algorithms for artificial intelligence can be applied, and the benefits that come along with them are significant [6].

In this article, we will study the ways in which the field of environmental intelligence may profit from the application of artificial intelligence, as well as the ways in which it may assist save lives. The use of artificial intelligence to address key concerns, such as climate change and carbon emissions, brings the human race one step closer to accomplishing the sustainability goals it has set for itself.

At the turn of the 21st century, everyone started becoming aware of the financial benefits that artificial intelligence may provide. Because of continual innovation, such as the creation of new algorithms, enhancements, and research that breaks new ground, artificial intelligence (AI) is growing more intelligent. This is due to the fact that AI is becoming more intelligent. As AI grows increasingly adept at automating a wider variety of jobs and as its capabilities continue to increase, the sphere of AI's influence and the number of applications it has will continue to expand. Unresolved problems such as bias, job losses, a lack of transparency, and malevolent uses of AI such as autonomous weapons are examples of some of the hazards that are associated with artificial intelligence [7].

The evolution of artificial intelligence will have to face greater challenges as it shifts its focus from being "human friendly" to being "earth-friendly." As the need to respond to social, economic and health implications at scale develops, AI has the potential to alter the problem of our growing environmental problems. AI has the ability to change the problem of our worsening environmental problems. [Here are a good example:] [Here are a good example:] [Here's a good example:] [This is a prime example] We now have the ability to modify legacy institutions and old methods in order to find solutions to critical problems such as long-term food and water shortages, inadequate urban planning, the loss of biodiversity, climate change, and a direct focus on the overall wellbeing of humans. These problems have been plaguing the world for quite some time. [7].

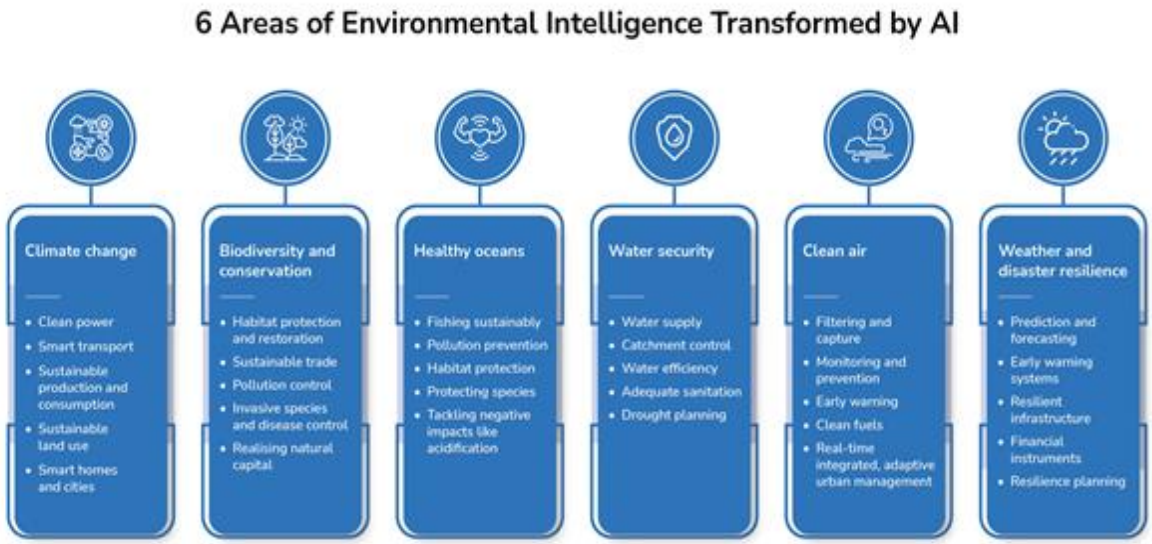


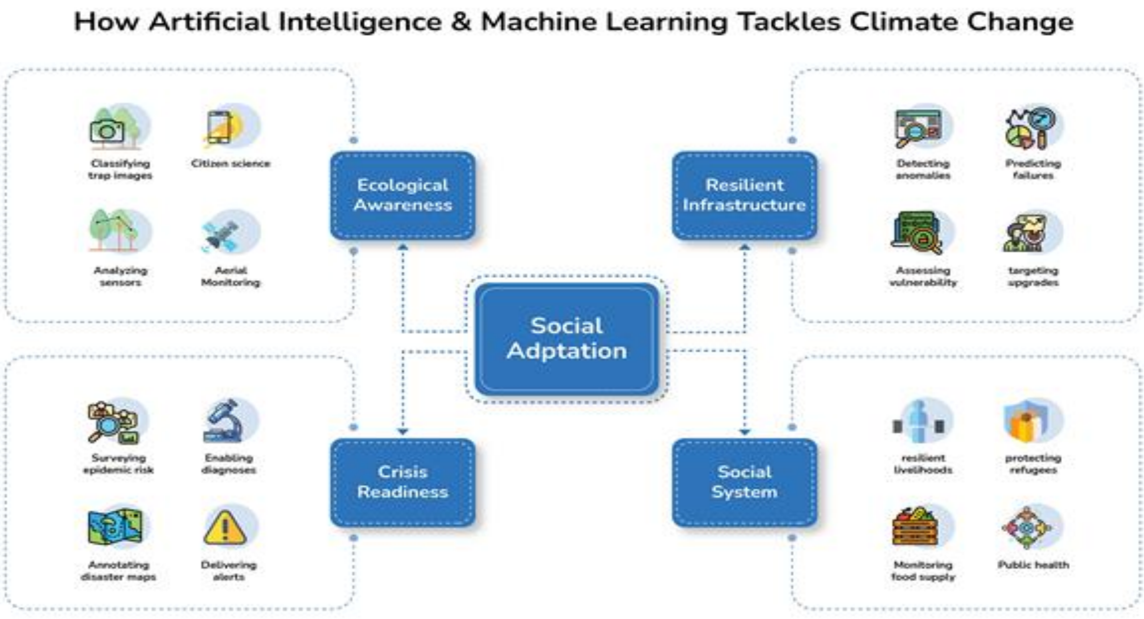
Figure 2: 6 ways of AI for Climate Change

II. 6 Ways of AI (Artificial Intelligence) for Temperature Change:

1. Intelligent transportation, such as self-driving and electric vehicles: Artificial intelligence (AI)-powered autonomous vehicles (AVs) are hastening the transition from high-carbon modes of transportation to sustainable, on-demand mobility. This is due to the fact that AVs are able to drive themselves. By lowering emissions of greenhouse gases caused by the combustion of fossil fuels, eco-driving algorithms, traffic optimization, autonomous public transit, and other methods could help cities improve the efficiency with which they run their transportation systems. Electric vehicles will have a significant impact on reducing carbon emissions and minimizing the effects of global warming when they are utilized to replace cars that are powered by fossil fuels [8].

2. Energy grids that are more energy-efficient: By utilizing distributed power networks that are energy-efficient, AI improves the capacity to forecast the supply and demand of renewable energy. Accelerating the process of resource allocation and management can be accomplished by increasing the effectiveness of load management, energy storage systems, the integration of renewable energy, and dynamic energy exchange. Technology that is

powered by artificial intelligence has helped find and implement climate-conscious solutions, which has led to progress being achieved in the field of renewable energy.
3. Agricultural endeavors and intelligent food systems: Agriculture that is powered by AI makes use of automated data gathering systems, corrective measures, predictive analysis, and fundamental decision-making abilities. The evaluation of soil fertility, animal nutrition, crop disease control, and resource efficiency can all be improved as a result of this for agricultural businesses. The management of land, the conservation of water, and the decrease of fertilizer use are all things that will contribute to the preservation of natural ecosystems while also ensuring a healthy harvest throughout the year. AI can also detect genetic makeups that help crops resist pests and adverse weather [9]. [citation needed]
4. Analysis of climate trends and weather forecasting Climate informatics is a field driven by artificial intelligence that makes use of technology to improve weather forecasting and our overall understanding of the effects of climate change. Deep learning networks enable artificial intelligence algorithms and climate data to be processed more rapidly and in real-time, all while making more optimal use of the computer resources available. Because of this, we are able to gain a deeper comprehension of the dynamics behind climate patterns and projections.
AI will assist in the forecast of extreme weather scenarios through increased data modeling approaches[10]. This will be accomplished by lowering the expenses of research and accelerating the discovery of new information.
5. Effective catastrophe response systems:
Using real-time data analysis, artificial intelligence is able to analyze enormous volumes of data coming from a number of sources in real-time, which enables it to forecast potentially disastrous weather events in advance. AI can assist in the construction of a disaster response system that is more adaptable if it is used to analyze the nature of climatic changes and determine hazards in particular locations. AI systems have the ability to build effective disaster response strategies by using data from early warnings, simulations, and emergency situations. This is analogous to how artificial intelligence is utilized in the video game Alpha Go to select and implement the optimal move[11].
6. Artificial intelligence-driven smart cities that are interconnected Zoning limitations, building designs, urban infrastructure, sewage control, floodplains, and a great deal more may all be simulated and built using AI. It is possible that humans may be able to develop the most technologically connected and efficient cities by combining virtual reality (VR) with augmented reality (AR). It may be possible to improve the quality of life in cities by investigating real-time data on topics such as energy usage, water use, traffic statistics, carbon emissions, social demography, and meteorological conditions. The use of artificial intelligence to environmental intelligence is the key to achieving sustainable urban design and a life that is networked [11].
The use of artificial intelligence in environmental intelligence is on the rise as a result of a growing worldwide attention to time-sensitive concerns such as climate change.



III. Multiple climate hazards hitting India together

India is both a significant contributor to the production of greenhouse gases and one of the countries that is most at risk from the effects of climate change. Water scarcity, heat waves and drought, severe storms and flooding, and the negative health and economic effects that arise from these extreme weather events are already having an impact on the country as a direct result of climate change. It is anticipated that climate change would have a significant negative impact on India due to the country's large population (1.2 billion people) and substantial reliance on agriculture. Despite the inherent unpredictability, global climate models forecast significant shifts in India's future climate, including the following:

• Glaciers are receding at an average rate of 10–15 meters per year, based on data taken from throughout the world, which indicates that glaciers are melting at a faster rate. It is projected that river basins that are supplied by these glaciers may flood if the rate picks up. This will be followed by decreased flows, which will lead to water shortages for drinking and agriculture. All of the models indicate that there will be an overall increase in the mean annual temperature throughout the Indian subcontinent, as well as a reduction in the diurnal temperature fluctuation and an increase in the amount of precipitation. The entire country of India is expected to experience warming of 0.5 degrees Celsius by the year 2030 (which is roughly equivalent to the warming that occurred during the twentieth century), and a warming of 2-4 degrees Celsius by the end of the century, with northern India experiencing the greatest rise. It is anticipated that the levels of other types of air pollution, in addition to the levels of tropospheric ozone pollution, would increase in major cities as the world warms.

• It is anticipated that increased precipitation, particularly monsoonal rains, will lead to fewer wet days and more days of high rainfall events, each with larger volumes of rain, which will result in catastrophic floods. It is anticipated that the amount of drizzle precipitation, which tops off the soil's water supply, would decrease. The majority of models from around the world anticipate that the Indian summer monsoons will become more powerful. It is also possible that the timing could shift, which will result in an extended period of dry weather in the late summer. The climate models are predicting early snowmelt, which could have a negative influence on agricultural production. Increased aerosol emissions can cause a decrease in rainfall, which can lead to drier conditions with more dust and smoke from drier vegetation burning, which can affect regional and global hydrological cycles, as well as agricultural output. These aerosol emissions can be caused by the production of energy as well as other sources.

The unpredictability of the monsoon's path will have a negative impact on farmers' production by affecting their decisions about which crops to plant and when to plant them. In addition, earlier seasonal snowmelt and receding glaciers will both contribute to a reduction in the quantity of river flow that is necessary for irrigation. It's possible that the population with the lowest incomes, such as smallholder farmers and landless agricultural laborers, would be hit the hardest, which will require massive aid programs from the government. Last but not least, migration, particularly from Bangladesh, has the potential to impose a strain on both the resources and the connections that bind India and Bangladesh together.

4. The Impact of Artificial Intelligence and Machine Learning on Climate Change

Strong artificial intelligence (AI) and machine learning technologies could bring policymakers and engineers one step closer to achieving their sustainable development goals. Artificial intelligence (AI) has the potential to help organizations develop resource management systems that are both more functional and automated. A number of organizations, including those mentioned above, are already using artificial intelligence (AI) and machine learning in their efforts to combat climate change. In the field of environmental intelligence, early users of artificial intelligence include companies like Google, Microsoft, and IBM.

In the coming years, it is anticipated that AI will foster good change and raise awareness of the necessity of conducting operations in a sustainable manner across all industries and countries.

The application of artificial intelligence (AI) in the conservation of biodiversity and the restoration of ecosystems across the globe holds great potential. However, the technology and its many applications for it are just the tip of the iceberg.

Important Considerations Regarding Climate Change:

There are nine primary components involved in climate modeling. Geographical location, unique Earth System Model (ESM) configurations, and possible future paths for emission policies are some of these factors.

Table 1: Key Facts of Climate Change

Facts	Comments
Time	On periods ranging from millennia to days, all climate models anticipate both human-caused change and natural variability for location and height.
Different climate models	In the CMIP5 (Coupled model intercomparison project version 5) database, roughly 40 ESM versions are generated by around 20 climate research centres across the world.
Longitude	Even at the same latitudes, there are significant regional differences in climate.

direction	
Latitude direction	Temperature and rainfall, for example, differ significantly depending on latitude.
Vertical direction	Height has an impact on all meteorological factors, including interactions with atmospheric radiative fluxes and clouds.
Perturbed physics runs	Rather of fully comprehending processes, potential ranges of related factors are comprehended. Some ESM groups have done simulations with various parameterizations to explore how parameter ranges impact future estimates.
Different future emissions	Various future emission scenarios will result in varying changes in atmospheric greenhouse gas levels, resulting in varying climate conditions.
Climate model ensembles	Even if the ESM is the same, the climate system's chaotic unpredictability in any particular decade might lead to drastically divergent estimates. Ensembles are produced by using the same model structure but changing the beginning circumstances somewhat.
Different initial state	In a number of start-up settings, ESMs (Earth system models) are often employed. It's probable that, prior to the industrial revolution, the status of the seas was unknown.

Emergent constraints (ECs) are a fourth novel strategy for improving predictions by lowering the inter-ESM dispersion dimension. This method looks for regressions between simulated climate system variables and those that can be measured right now, as well as other climate system properties that are useful for projecting future change, across ESM ensembles. The present measurement is used to limit forecasts of the future variable in these regressions. Physical climate system components, such as lowering uncertainty regarding equilibrium climate sensitivity, and geochemical or biological factors, such as refining the threat of Amazon "die-back," are examples.[12]– [14].

IV. Existing applications of AI(Artificial Intelligence) and ML(Machine Learning) for climate- change

Many climate scientists have turned to machine learning (ML) to learn more about certain Earth System components, as seen in table 2. We now propose that employing machine learning methodologies to discover the more interrelated behaviours across multiple Earth System components, as well as how they aggregate to overall climate responses, has a lot of potential[15].

Table 2: Model for ML Contributing to Learn about Climent change

Climate-Change Research Topic	Changes or Development	Technologies	References
Climate datasets	In a number of start-up settings, ESMs (Earth system models) are often employed. It's probable that, prior to the industrial revolution, the status of the seas was unknown.	GP model fitted with a MCMC method.	[1]
Teleconnections	Determine the terrestrial tropical	Empirical Orthogonal	[8]

	linkages of the Pacific Decadal Oscillation.	Functions, Clustering.	
Climate datasets	To explore hydrological trends and variability, create a long-term, globally consistent runoff dataset.	RF.	[16]
Earth System modelling	Emulate climate models to expand the parameter space that can be handled by a climate model.	MCMC	[15]
Teleconnections	Assess the influence of SST indicators on terrestrial climate.	SRNN, Graph-based Approaches.	[17]
Weather forecasting	Use AI to post-process weather forecasts to aid human forecasters.	RF, GBRT.	[18]
Future climate scenarios	Climate models that are weighted based on their skill outperform ensemble averages.	Generalized HMM.	[19]
Climate impacts	Investigate how climate change will impact above-ground biomass.	SVM, ANN, GRNN.	[20]
Climate datasets	Improving temperature estimations in the absence of missing timeseries. Improve daily maximum and minimum temperature calculations by using data from other nearby observations and recording at the proper time.	GP model fitted with a MCMC method.	[21]
Climate extremes	Precedent meteorological information is utilised in Ethiopia to anticipate meteorological droughts.	ANN; SVR; Wavelet Transforms.	[22]

GP - Gaussian Process, MCMC - Markov Chain Monte Carlo, RF - Random Forest, ANN - Artificial Neural Networks, SRNN- Shared Reciprocal Nearest Neighbours, RF - Random Forest, GBRT - Gradient Boosted Regression Trees, HMM - Hidden Markov Models.

Each box in the first column depicts simulations for the same model framework and forcings, evolving through time and for different ESMs, illustrating the first five features of table 2. The two different boxes (background yellow or green) represent two different sets of simulations chosen to span one of table 1's four extra dimensions: ensemble members capturing internal chaotic features, large-scale estimates of initial state, perturbed-physics experiments, and different socio-economic estimates of GHG emissions, as indicated in the grey column. The four most prevalent machine learning and artificial intelligence approaches are illustrated in the third column. In the fourth column, you'll find potential application diagrams.

Functional responses, such as ecosystem attribute temperature responses, may be determined using the gradient descent method. Gridded datasets of historical weather characteristics may be created by extrapolating sparse weather station data (black dots) using Gaussian processes. Nonlinear non-Gaussian inferences, which may be updated progressively as new data becomes available, can be used to adjust key ESM parameters. Deep learning systems (e.g. NNs) can simulate computationally costly components of ESMs that alter vertical profiles of predicted variables like temperature, for example. This sort of emulation allows for longer simulations, bigger ensembles, and extra capabilities. A improved ML-based knowledge of ESM diagnostics and performance evaluation against data, as shown by the bottom right-to-left arrow, would then support better simulations by the next generation of climate models.

V. Discussion and conclusions

It is becoming increasingly clear, in line with the predictions of a large number of experts, that the consumption of fossil fuels has an effect on the climate. In order to formulate an appropriate response, accurate estimations are required. Estimates of climate variability are generated with the help of discretized equations that are used to characterize the Earth System in ESMs. The pooling of ESM models is a key milestone in climate research because there are large disparities between them; this is true even for scenarios with identical concentrations of greenhouse gases (GHG). The absence of consensus makes it more difficult to implement anticipated adjustments. It is difficult to appreciate the underlying computations, feedbacks, teleconnections, and most significantly, model differences, because of the widespread notion that ESMs are "black boxes," as well as the expectation that researchers will spend time building new model versions on a regular basis. This method departs from standard scientific practices, which call for the construction of numerical models to be backed by analytical information. Using this method, however, the opposite is true. On the other hand, due to the high level of complexity of the Earth System, it is difficult to accomplish the dimension reduction that is required to locate the dominant processes. We believe that the field of climate research is an excellent application for machine learning. This advice, however, is contingent on the algorithms being utilized correctly, with the ideal solution for each study issue, and a comprehensive comprehension of any underlying assumptions that may be involved. The majority of the summarized applications are specialized to climatic system components, which is a limitation placed on a large number of currently available applications. We recommend going even farther and applying machine learning techniques to the entire Earth System, which would include gridded datasets (like ECMWF) and the CMIP5 ensemble. This would be a significant step forward.

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