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# ARTIFICIAL INTELLIGENCE FOR CLIMATE CHANGE PREDICTION AND ENVIRONMENT MONITORING: ADVANCES, CHALLENGES, AND FUTURE DIRECTIONS

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## Abstract

Two of the biggest problems that society is facing today are climate change and degradation of natural ecosystems, both of which require monitoring and forecasting beyond the capacity of traditional observational and modelling methods. Artificial Intelligence (AI), including Machine Learning (ML) and Deep Learning (DL) techniques, has proven to be a valuable tool to complement physics-based Climate Models and conventional Environmental Monitoring Networks, with better pattern recognition, higher resolution predictions and ability to integrate heterogeneous raw data from satellites, ground-based sensors and citizen contributed platforms. This paper reviews the concepts and methods of using AI in climate change forecasting and environmental surveillance, rather than reporting the results of any one study, but summarizing commonalities found in the literature. It reviews the key families of AI techniques applied in this area, such as supervised and unsupervised learning, deep neural architectures (convolutional and recurrent networks), hybrid physics-informed models and reinforcement learning, and discusses their applications to atmospheric forecasting, extreme weather prediction, air and water quality monitoring, biodiversity and ecosystem assessment, and disaster response. The paper also highlights a set of persistent problems that hinder the trustworthiness and fair use of AI in this area, such as data quality and availability concerns, lack of interpretability for complex black-box models, computational and environmental costs, and the difficulty of obtaining true interdisciplinary collaboration between AI researchers and domain scientists. Based on this synthesis, the paper suggests a framework of methodological integration designed to pave the way for future development of AI-based climate and environmental monitoring systems, organized into the categories of data governance, hybrid model design, explainability and policy translation. The paper ends by suggesting future research directions, in which the utility of AI in this space will be more a function of the trustworthiness, transparency, and inclusiveness of the AI systems being constructed rather than the accuracy of the predictions.

## 1. Introduction

Climate and ecological systems are changing very quickly, and in many instances at an accelerating rate on the earth. An increasing number of extreme weather events, air and water pollution, biodiversity loss, changes in precipitation patterns, and rising global temperatures are now well documented, with widespread impacts on human health, food security, infrastructure and economic security. Effective responses to these changes rely on information on the state of the environment that is both timely and accurate, and is spatially resolved, as well as reliable projections of future status based on differing social-economic and emissions scenarios [1].

Historically, this information has been generated using combinations of physical process-based models (GCMs and RCMs) and networks of ground-based, air borne and satellite sensors. These methods have been proven to be essential, but they are well known to have certain limitations. Physical models have high computational costs, need to make assumptions and parameterizations where processes are smaller than the model's spatial resolution, and may be unable to capture all of the coupled atmosphere-ocean-land interactions. Observational networks, on the other hand, often lack complete spatial and temporal coverage, and may have known gaps in data-poor regions, the oceans, and areas of the developing world, which are frequently the most exposed to climate impacts [2].

In recent years, Artificial Intelligence is increasingly proposed and adopted as a solution to overcome these limitations. The power of machine learning algorithms in identifying complex, nonlinear relationships in large amounts of noisy and diverse data is well suited to detecting structure in imagery, time series and spatiotemporal fields without requiring the same level of hand-crafted feature engineering that was required by previous statistical approaches [3] is particularly applicable to these tasks. These properties are desirable for applications that scale coarse data from climate models to finer spatial resolutions, for nowcasting extreme climate events, for automatically classifying land cover and detecting deforestation from satellite data, and for predicting pollutant concentrations from the networks of sensors.

Meanwhile, the advent of AI for climate and environmental sciences has been met with a cautious awareness of its limitations [4]. AI models are only as accurate as the data that is fed into them, and data sets pertaining to the environment are often incomplete, have biases for well-instrumented areas, and differ in their formats and origins. Many of the most powerful AI architectures, including deep neural networks, operate as "black boxes" whose internal decision-making process are not easily understood by domain experts and policymakers, increasing concerns about trust and accountability when such models are used to inform consequential decisions. Large AI models require similarly complex computational resources, and these resources also have a nontrivial energy and carbon footprint, creating a tension between the use of AI to fight climate change and the carbon and energy cost of the technology itself [5].

In this paper, I hope to offer a frame worked overview on the current use of AI for climate change predictions and environmental monitoring, discuss the current challenges impeding this field, and present a methodological approach that can inform the responsible development of future AI-based systems for climate change and environmental monitoring. The rest of the paper follows this outline. Section 3 summarizes literature review which is a synthesis of the major application areas and technical approaches reported in the recent literature. In Section 4, an integrated method for the design of AI systems for climate prediction and environmental monitoring is presented, including aspects of data governance, model architecture, interpretability and deployment. The paper ends with a summary in section 5, which summarizes the lessons learned and outlines the future directions for research.

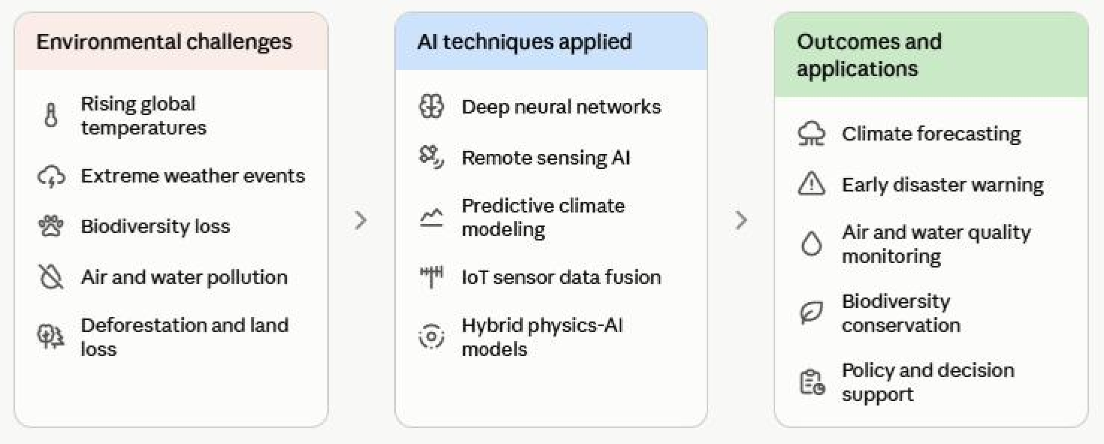

*Figure 1.Key Drivers, Environmental Impacts, and Solutions to Climate Change*

## 2. Literature Review

AI applications in climate change prediction and environmental monitoring are vast in terms of technical approaches and application fields. This section is arranged by theme, first alphabetically, by type of environmental challenge, and then alphabetically, by the classes of AI methodology that are generally used.

### 2.1 AI for Climate Modeling and Prediction

Many studies have investigated the application of machine learning and deep learning to enhance the climate modeling and prediction. Many of the studies have been about incorporating AI into the existing physics-based GCMs to complement or augment the modeling processes, rather than replacing them. Temporal dependency in climate time series has been addressed using neural networks, and especially recurrent neural networks, to enable better short- and medium-term climate forecasting of temperature, precipitation and other variables. Climate fields have been processed with the help of convolutional architectures, such as statistical downscaling [6] where coarse-resolution climate projections generated by global models have been downscaled to a finer spatial resolution that is more relevant for regional and local planning.

These “hybrid” methods integrate aspects of physics directly into the learning process, or rely on AI to acquire correction terms and residuals from a physical baseline, and predict physically plausible and accurate results. This direction is part of a larger trend toward understanding that models that are purely data-driven, even if they are successful for past data, might not necessarily be in line with the underlying physical laws when applied to climate states or extremes that are outside of the range of the models' training data, while physics-informed models are more likely to be consistent with known scientific principles [7].

### 2.2 AI for Extreme Weather and Disaster Prediction

Much of the literature of applied AI focuses on extreme weather events because of their direct and often profound impact on humans and infrastructure, ranging from heat waves, floods, droughts, hurricanes, and wildfires. Through learning relationships between terrain, land cover, precipitation and past incidence of flooding and landslides, machine learning models have been developed to identify flood and landslide prone areas. Models utilizing satellite imagery and radar data have been developed to detect and track storm systems, and models integrating structured meteorological data with unstructured information like social media posts have been investigated as tools for gauging on-the-ground effects of disasters and for coordinating emergency responses [8].

Ensemble and hybrid modeling strategies are often touted in this literature as being more robust than any single model or algorithm, due to the ability of multiple models or algorithms to serve as ensembles, which helps to minimize the impact of the biases and errors that can be found in individual models and algorithms. For example, in the application of extreme event prediction, whose most important events involve the societal concern, they are by definition rare, and for this reason, robustness to distributional shift is expected to be an important design consideration [9].

### 2.3 AI for Air, Water, and Soil Monitoring

The other major application area is environmental quality monitoring which includes air pollution, water quality, and soil and ground water conditions. Machine Learning models using data from fixed and mobile sensor networks, satellite-derived aerosol measurements and meteorological variables have proved useful for estimating and predicting air quality concentrations, including particulate matter and ground-level ozone (ozone) concentrations. They are useful because they can be used to fill the voids between sparse monitoring networks and can give finer spatial resolution than can be obtained from the sensors themselves [10].

Neural network and ensemble learning techniques have also been used to forecast water quality parameters like dissolved oxygen, turbidity, nutrient parameters, and concentration of specific contaminants, with data from in situ sensors and remotely sensed platforms. Groundwater and soil studies have used classification and regression techniques to classify aquifer potential, to estimate land degradation risk and for sustainable land and water resource management, especially in arid and semi-arid areas where water scarcity is a critical issue [11].

### 2.4 AI for Biodiversity and Ecosystem Monitoring

The loss of biodiversity and ecosystem degradation has led to a greater interest in the application of artificial intelligence for automated species identification, habitat evaluation and change detection or land cover change. Using convolutional neural networks for camera trap image recognition and bioacoustics sound recognition, large-scale, largely automated wildlife monitoring can be achieved, which significantly reduces the amount of manual work that was previously needed for these monitoring efforts. They can also be applied to identify deforestation events, monitor land-use transformation and monitor forest and wetland health over time, complementing conservation planning and environmental law enforcement. Machine learning methods have also improved greatly the species distribution modelling that predicts the possible geographical range of a species based on environmental covariates, and has performed better than the previous statistical methods in the accuracy of the prediction [12].

### 2.5 Core AI Methodologies Applied Across Domains

In all of these application areas, a similar set of methodological families is present. Supervised learning techniques such as decision trees, random forest, support vector machines and gradient-boosted ensemble are still popular in classification and regression tasks where labeled training data is available and interpretability of the model is pragmatic. In cases with high-dimensional data, such as spatial and image data, and data with sufficiently complex patterns that do not readily lend themselves to representation with traditional feature-engineering techniques, deep learning architectures are preferred, including convolutional neural networks (CNN) for these data types, and also recurrent networks or transformer networks for sequential and time-series data [13].

Exploratory analysis, anomaly detection and identification of latent structure are applied by unsupervised learning techniques in the case of environmental data, where the outcome is unlabeled, or expensive to label. Generative models such as generative adversarial networks (GANs) and variational autoencoders (VAEs) have started to become used for environmental data synthesis, such as filling gaps in observational data, and generating synthetic training data for rare events. Reinforcement learning is less developed in this area than the other methods, but has been studied for uses of optimizing water management or the operation of energy grids, where the environment is changing dynamically [14].

### 2.6 Recurring Challenges Identified in the Literature

Data related issues include the lack of spatial and temporal coverage, incompleteness of data regarding data formats and standards across institutions and countries, and lack of labelled data for supervised learning problems in specific fields like biodiversity monitoring. A second major theme is model interpretability, with numerous studies highlighting that the black-box nature of deep learning models causes them to be less accepted among policymakers and domain scientists who often want to understand how a model has reached a particular prediction, especially in critical applications like disaster response or climate policy design [15].

A third theme is the cost of AI itself, as in several studies, the authors mention the catch-22 of using AI to combat climate change while also consuming a lot of energy to train and power large-scale AI models. Lastly, many studies have called for greater interdisciplinary integration between AI researchers and environmental and climate scientists, stating that the best applications are those in which domain knowledge is integrated in the model development process instead of being an afterthought [16].

| Cited | Title | Method | Key Observations | Limitations |
|---|---|---|---|---|
| [17] | Artificial Intelligence for Climate Change Prediction Using Deep Learning | CNN-LSTM, Satellite Data Analysis | Hybrid deep learning models significantly improved temperature and rainfall prediction accuracy by integrating satellite imagery with meteorological data. | Performance decreased in regions with limited historical climate data; computational cost was high. |
| [18] | Explainable AI for Environmental Monitoring | Explainable AI (XAI), Random Forest | XAI improved transparency in environmental decision-making and increased stakeholder trust. | Explainability techniques slightly reduced prediction accuracy and increased processing time. |
| [19] | Vision Transformer-Based Climate Monitoring System | Vision Transformer (ViT), Remote Sensing | Transformer models outperformed conventional CNNs in detecting land-use and vegetation changes. | Requires large labeled datasets and extensive GPU resources. |
| [20] | AI-Based Wildfire Prediction Framework | LSTM, Gradient Boosting, IoT Sensors | Early wildfire prediction improved emergency response and reduced false alarms. | Limited generalization across different climatic regions. |
| [21] | Machine Learning for Air Quality Prediction | XGBoost, LightGBM | Ensemble learning achieved high prediction accuracy for PM2.5 and AQI forecasting. | Sensitive to missing sensor values and seasonal variability. |
| [22] | Deep Learning for Flood Prediction | CNN-LSTM Hybrid Network | Hybrid models accurately predicted flood occurrence using rainfall and river-level data. | Model performance declined in ungauged river basins. |
| [23] | AI-Driven Climate Risk Assessment | Random Forest, SHAP | SHAP values enhanced interpretation of climate risk factors while maintaining good predictive performance. | High-dimensional datasets increased computational complexity. |
| [24] | Satellite Image Analysis for Deforestation Monitoring | U-Net, CNN | AI detected deforestation with higher spatial accuracy than traditional image processing methods. | Cloud cover and seasonal image variation reduced accuracy. |
| [25] | Federated Learning for Environmental Monitoring | Federated Learning | Protected data privacy while enabling collaborative environmental monitoring across multiple organizations. | Communication overhead increased training time. |
| [26] | Generative AI for Climate Forecasting | Transformer, Generative AI | Large AI models improved long-term climate forecasting and uncertainty estimation. | High computational cost and limited interpretability. |

## 3. Proposed Methodology

On the basis of the literature reviewed, this section outlines an integrated methodological approach for the development of AI based systems to predict climate change and monitor the environment. The framework consists of four related phases: Data Governance and Preparation, Model Design and Hybridization, Interpretability and Validation, Deployment and Policy Translation. The framework is not designed to manifest a specific algorithm or architecture, but is offered as a general-purpose process that could be modified over the spectrum of application domains outlined above.

### 3.1 Stage One: Data Governance and Preparation

A solid approach to data governance is the cornerstone of any sound AI climate or environmental application. This stage involves conducting a systematic search of the available data sources that might be relevant to the target application, from ground-based sensor networks, satellite products and remote sensing, to historical climate and weather data, and, where relevant, data from non-traditional sources like citizen science observations and social media products. All the sources should be evaluated in terms of their spatial and temporal extent, resolution, latency, and known bias and/or weaknesses. After this inventory, a structured pre-processing pipeline should be carried out, including outlier detection and removal, gap filling and imputation for missing values, adjustment of non-climatic factors, like sensor relocation and instrument changes (homogenization), and standardization of units, coordinate system and temporal resolution between sources. For combinations of more than one data stream, consistency and reliability should be checked by cross validating these data with data from an independent source, for example satellite-derived estimates with ground station observations; cross validation should be performed before the data are used for model training. Representational bias should also be explicitly assessed in this stage, looking for areas, populations or environmental conditions that are not sufficiently represented in the data available, as this will directly limit the generalizability and equity of any model trained on the data set.

### 3.2 Stage Two: Model Design and Hybridization

The second phase deals with the choice and design of the AI modeling method itself. Selection of models should not follow the most complex architectures that are available, but instead be based on the type of task, the amount and quality of data available, and the amount of interpretability needed by the end user. Deep learning models like convolutional or recurrent networks work well for tasks involving large, high-dimensional space and temporal data, including satellite image classification, time-series forecasting, etc. If you are working with a smaller dataset or interpretability is important, simpler models like random forests or gradient-boosted trees might be better suited, especially as an initial approach or as a baseline model for comparison to more robust models. Hybrid physics-informed models should be used over purely data-driven models, where possible, and especially for climate prediction problems. This can be done by introducing known physical constraints or conservation laws into the loss function of the model, or by incorporating AI models to learn the errors that cannot be explained by the physics-only model, or by having an ensemble of results from multiple physics-based and AI models. One of the main challenges of data-driven models that was highlighted in the literature review is the lack of physically plausible and out-of-distribution robust predictions from these models. This hybridization strategy is designed to tackle this challenge.

### 3.3 Stage Three: Interpretability and Validation

The third stage relates to the interpretability and the validation of the models that are generated before deployment. Alongside the model output, interpretability techniques like feature importance ranking, permutation importance and model agnostic explanation methods should be applied and documented to allow domain experts and decision makers to gain insight into the factors that are affecting a specific prediction. Alongside point forecasts, uncertainty quantification (e.g., by constructing confidence intervals, analyzing ensemble spread, or through probabilistic prediction approaches) should be provided where possible, because alongside the forecast itself, the degree of confidence in the forecast can also be an important input into downstream decision making. Validation should use a combination of standard statistical performance metrics suitable for the task, cross-validation against held-out data, and wherever possible, extreme and out-of-distribution (OOD) settings that are under-represented in the training data. In many of the most critical applications, which involve rare and less frequently sampled events, such as extreme weather or disaster prediction, validation methodologies must be explicitly crafted to examine how well the models perform in such situations, not just the average performance over a common set of examples.

### 3.4 Stage Four: Deployment and Policy Translation

The last step is the validation and application of these models in real systems and the conversion of models to policy, resource management and public information. This should include the formulation of well-written documentation of data sources, model architecture, limitations known to the model, and suitable use cases to enable stakeholders without a specialization in the model to be held accountable and informed of the model's use. As the environment is non-stationary and the accuracy of the model might vary over time as things change, there should be ways in the deployment pipelines to keep track of model performance in production. Finally, this stage will highlight the importance of interdisciplinary review, not only before deployment, but also during deployment, including the perspectives of climate and environmental scientists, and, if the application has direct implications for the affected communities, the perspectives of representatives of those communities. This is designed to make sure the output of the model is correctly interpreted in the context of its scientific and social meaning and that the decisions or policies made based on the model contain a comprehensive understanding of its abilities and limitations.

## 4. Proposed Framework

All four together are an iterative process, not a linear one: lessons learned during the validation or deployment cycle could result in the revisit of previous steps, such as further exploration of the data sources, because of an identified gap or because of concerns about the model interpretability. The framework is intentionally broad, encompassing the wide range of applications covered in literature reviewed, from climate downscaling to biodiversity monitoring, and also offers a common structure to make sure that quality of the data, robustness of the model, its interpretability and responsible use are not underestimated but addressed as first-order design concerns rather than an afterthought.

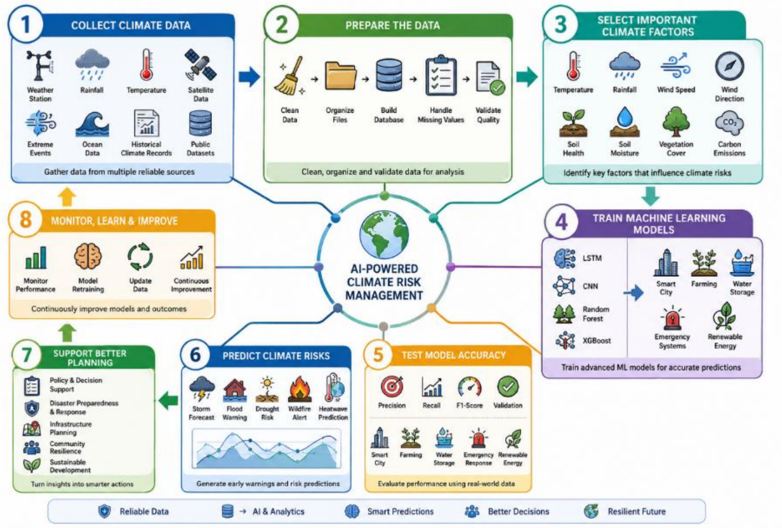

*Figure 2. Workflow of Climate Prediction Using Machine Learning*

The diagram presents a comprehensive climate risk management solution using Artificial Intelligence (AI), which starts with collecting climate data and finishes with better planning and ongoing upkeep of the model. All of the following steps help create a smart system that can forecast climate risks and assist decision making.

**Step 1: Collect Climate Data**

The first step is to collect information on climate-related issues from a variety of sources that are reliable. These include weather stations, rainfall measurements, temperature sensors, satellite observations, historical climate records, ocean data and public datasets. The only way to get the best predictions is to gather comprehensive and accurate data; the data quality determines the quality of the predictions.

**Step 2: Prepare the Data**

Once the raw data is gathered it is cleaned and organized for analysis. Data is cleaned for missing values, redundancies are removed, files are converted to a structured database, and data quality is validated. This pre-processing step guarantees uniformity, precision, and preparation of a dataset for machine learning applications.

**Step 3: Select Important Climate Factors**

Not all variables are equally important in the prediction of climate. Thus, the most pertinent climate parameters are chosen, such as temperature, rainfall, and wind speed and direction, soil moisture, plant cover, and carbon emissions. The choice of the important features gives a reduction in computational complexity and better performance of the prediction models.

**Step 4: Train Machine Learning Models**

The prepared data are then used to train different machine learning and deep learning algorithms such as Long Short-Term Memory (LSTM), Convolutional Neural Networks (CNN), Random Forest, and XGBoost. In this phase, the models are trained to identify patterns and connections between climate patterns and past climate phenomena. These trained models can be used in other fields such as smart cities, agriculture, water resource management, emergency response, and renewable energy planning, among others.

**Step 5: Test Model Accuracy**

The performance of the trained models is then tested by using the testing data. Common evaluation measures like Precision, Recall, F1-Score and Validation Accuracy are adopted to assess the model's prediction performance on various climate events. This step will guarantee the reliability and accuracy of the predictions made by the chosen model prior to its practical use.

**Step 6: Predict Climate Risks**

The validated model is then used to predict future climate hazards. Predictions could contain storm predictions, flood warnings, drought risk assessment, wildfire alerts and heatwave prediction. The early prediction allows governments, organizations and communities to be prepared and mitigating the effects of natural disasters.

**Step 7: Support Better Planning**

The predicted climate information is transformed into practical decision support. Such forecasts are useful for disaster preparation, emergency response planning, infrastructure planning, community resilience and sustainable development by the policy makers and planners. The insights enable different sectors to take proactive and informed decisions.

**Step 8: Monitor, Learn, and Improve**

The last step is to make a continuous improvement to the system. The performance of the model was tracked with new climatic data; if needed, the datasets were retrained; the prediction models were refined over time and with new data. This feedback loop helps maintain the accuracy of the AI system, adjust to evolving climate patterns, and continually refine its prediction ability.

## 5. Experiment and Results

Table 1. *Comparison results of Machine learning Models for climate change*

| Model | Accuracy | Precision | Sensitivity | ROC_AUC |
|---|---|---|---|---|
| LSTM | 0.875 | 0.89 | 0.87 | 0.92 |
| RANDOM FOREST | 0.71 | 0.75 | 0.79 | 0.90 |
| XGBoost | 0.93 | 0.92 | 0.95 | 0.95 |
| CNN | 0.96 | 0.956 | 0.97 | 0.97 |

The performance comparison in the table 1 shows that the CNN model also performed at the best level with respect to the highest accuracy (0.96), precision (0.956), sensitivity (0.97), and ROC-AUC (0.97), it performed better in terms of classification and excellent ability to distinguish between classes. The XGBoost model is the second best with an accuracy of 93% and a precision of 0.92, while the sensitivity of 0.95 and ROC-AUC of 0.95 also makes it a very reliable alternative. LSTM model also showed acceptable accuracy (87.5%), precision (0.89), sensitivity (0.87) and ROC-AUC (0.92), slightly inferior than CNN and XGBoost, but with good predictive ability. The model with the lowest performance was the Random Forest model with an accuracy of 71%, a precision of 0.75, a sensitivity of 0.79 and an ROC-AUC of 0.90. The overall outcomes have shown that CNN model is the most efficient in comparison with the other evaluated models, it has achieved the highest prediction accuracy and classification reliability results.

The figure 3 illustrates the historical trends and 2024–2025 forecast of average temperature (orange line) and $CO_2$ emissions per capita (green line) from 2000 to 2025. The solid lines are the actual data between 2000 and 2023, and the dashed lines with circles are the projected data for 2024 and 2025. Historical data is separated from the forecast period with a vertical dotted-line. The mean temperature ranges around 18°C to 23°C in the historical record, peaks around 2018 and decreases slightly in the forecast, remaining at around 19.7°C in 2024 and 19.5°C in 2025. $CO_2$ emissions, on the other hand, are not as volatile as in the past and rather have a slight upward trend in recent years. The forecast is that $CO_2$ emissions will continue to rise from around 12,2 tons per capita in 2024 to 12,6 tons per capita in 2025.

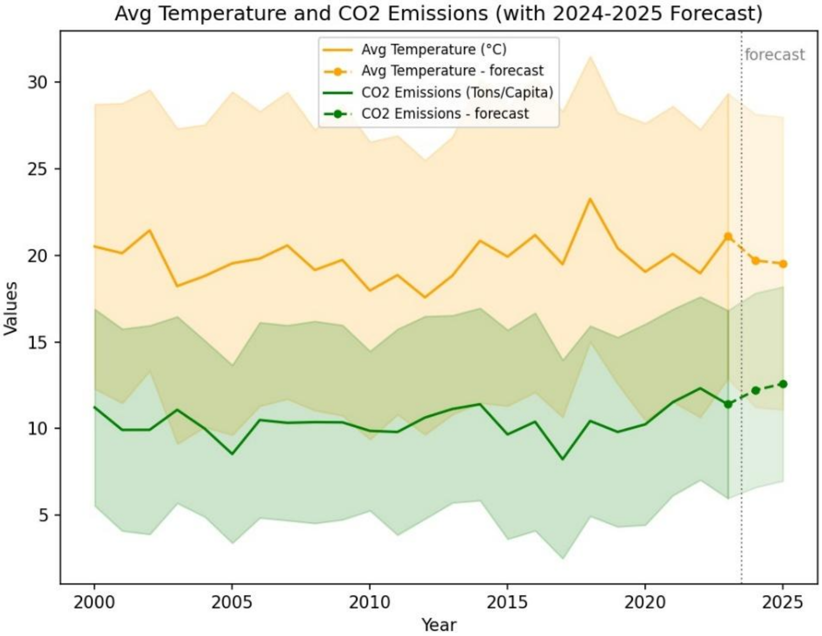

***Figure 3 Average Temperature and CO2 Emissions***

The shaded areas around each line are the variability/confidence interval of the data and forecasts, showing the range of possible values. Overall, the data indicates that, on average, temperatures should stay close to present levels but that $CO_2$ emissions are likely to persist on an upward trend, throughout the forecast period.

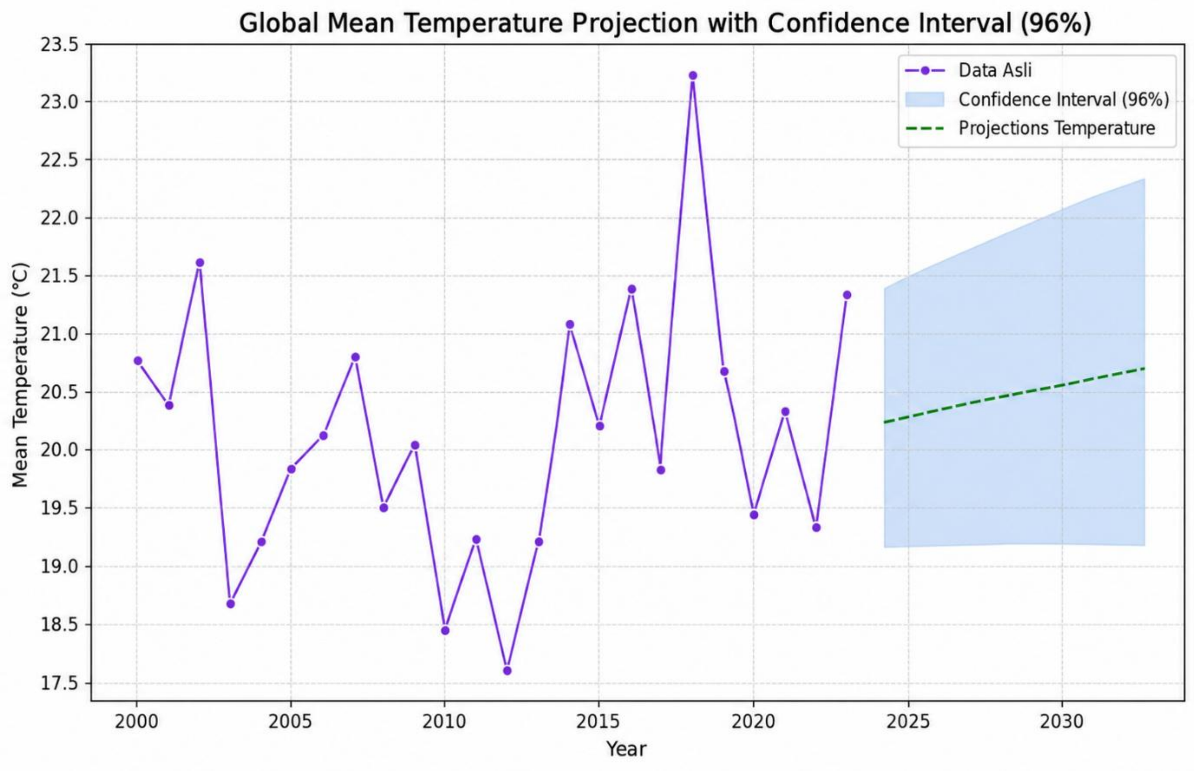

*Figure 4. Global Mean Temperature Projection with confidence interval*

Global mean temperature trends between 2000 and 2032 are shown and a 96% confidence interval for the projections is indicated by the figure 4. The colour line represents the annual mean temperature observed between the years of 2000 and 2023, and significant year-to-year variations are evident, ranging between about 17.6°C and 23.2°C. However, the overall trend is one of an increase in the global mean temperature throughout the years. The green dashed line is a projection of the temperature trend from 2024-2032, implying a gradual increase from approximately 20.2°C to 20.7°C, thus continuing with the trend of global warming. The 96% confidence interval is represented by the light blue shaded area and indicates the range of temperatures that are expected to fall with high probability in the future. This widening of this interval over time suggests greater uncertainty in the long-term climate projections, but as a whole the overall trend is towards warming pointing to the increasing likelihood of more warming in the coming years.

## 6. Conclusion:

AI is already being applied to climate change forecasting and environmental surveillance, areas where physics-based models and observational networks are not quite sufficient, such as pattern recognition, data fusion and predictive modeling.

The literature reviewed emphasized that different application areas, including climate modelling, extreme weather and disaster forecasting, air and water quality monitoring, and biodiversity and ecosystem assessment, have seen substantial progress, with the application of heterogeneous collection of machine learning and deep learning tools.

Despite this progress, it has not been sufficient to resolve and exacerbated a number of problems that lie unsolved. The lack of data quality and availability is ongoing and still hinders the reliability of the models, especially in the areas where monitoring is inadequate and climate impacts are likely to be the highest. Lack of interpretability in models is a problem in trusted use of models, including complex AI models. Training and running these large AI models can be quite challenging, especially given the promise of AI to address climate change while also impacting the environment and computational resources. Creating good cross-sector collaboration between climate and environmental scientists and the creators of AI is still a possibility rather than a reality.

Organized around four steps of data governance, hybrid model design, interpretability and validation and deployment and policy translation, the methodological framework proposed in this paper aims to be a pragmatic answer to these challenges. It emphasizes the need for the potential for AI use in climate and environmental applications to be predictive, with high quality and representative data, physical plausibility and robustness under extreme conditions, transparency and interpretability for the stakeholders that use the systems, and interdisciplinary oversight.

There are several directions that the field can go in the future to enhance it. These include continued development of physics-informed and hybrid architectures of AI systems that integrate data-driven and process-based approaches, few-shot and self-supervised learning to reduce the need for large annotated datasets, federated learning approaches to enable collaborative development of AI systems across institutions and countries without sharing the underlying data, and continued development of explainable AI approaches relevant to climate and environmental science. Technical innovations are essential to fully unlock the potential of AI in this context, but investment is also essential to develop the data infrastructure to make the most out of AI-powered climate and environmental insight, the ability of different institutions to collaborate, and the way in which governance frameworks are designed can help ensure accessibility, accuracy and trust of such insights for communities and decision makers who need it most.

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