Ennoia Journal of Multidisciplinary Studies and Innovation (EJMSI)
Vol. 1, Issue 1, April–June 2026 | ISSN (Online): Applied |
DOI: 10.XXXXX/EJMSI.2025.01.01.XXX | Received: __ / __ / ____ | Accepted: __ / __ / ____

ORIGINAL RESEARCH ARTICLE

AI FOR CLIMATE CHANGE MITIGATION: PREDICTING AND RESPONDING TO GLOBAL WARMING

Pinky Uniyal[1],Sujata Kumari [2] ,Sukesh Kumar Bhagat [3]
[1] *CSE, UIT, Uttaranchal University,Dehraduny,Uttarakhand,India*
[2] *Computer Science, Dehradoon Institute of Management & Technology,Dehradun,Uttarakhande,India*
[3] *CSE, SST, Jigyasa University,Dehradun,Uttarakhande,India*
[1] *pinky.uniyal@uumail.in*, [2] *bhagatsujata0@gmail.com* , [3] *sukeshtech@gmail.com*

ABSTRACT

Global warming is one of the pressing issues facing the world as it not only affects the social and natural environments but affects people's lives. The increased number of catastrophes, the temperature increase, and disturbance of functioning of natural ecosystems require efficient and timely measures. Climate change has become another field where Artificial Intelligence (AI) has shown itself to be useful in increasingly intricate and capable forms through its abilities to improve predictive and analytical capacity, establish more efficient energy controls, and offer creative solutions to decrease the release of greenhouse gasses. An analysis of the application of AI in climate change is discussed in this paper specifically in light; of predictive modeling, optimization of renewable energy resources, and intelligent monitoring of carbon emissions. In this paper, we review the AI approaches, including machine learning, deep learning, and reinforcement learning relevant to climate data, understanding the capability and success of these approaches in the forecasting of climate patterns and decision-making. Further, the paper presents the integration of using AI with IoT sensors and satellite imagery for better climate tracking. The findings provided by this research show that the application of AI solutions is a great help to minimize carbon emissions and improve climate adaptation. In concluding, the paper lays out practical considerations and possible areas of research in the application of AI in climate science as well as potential factors for ethical concern.

Keywords: *Climate Change Mitigation, Global Warming Prediction, Renewable Energy Optimization, Carbon Emission Reduction, Reinforcement Learning, Sustainable Energy Systems, Climate Data Analytics.*

I. Introduction

A. Background

Global warming is now acknowledged to be an acute problem which affects the climate, the economy, and people's lives. Mankind has engaged in numerous activities such as; combustion of fossil fuels, deforestation; thus; enhancing the intensification of greenhouse gases in the ambiance which in turn have increased world temperatures and High uncertain climate [3]. Climate change impacts include global warming, effect on sea level, storms, destruction of the habitat and food insecurity to mention, affecting many people globally. Classic climatological models have given much valuable information, however, they mainly differ in being not able to predict the character of climate due to its extreme variability and great amount of data needed [4].

These difficulties can be resolved with the help of Artificial Intelligence (AI), which employs machine and deep learning, as well as data analysis in the improvement of climatic predictions and in the optimum delivery of climate change mitigation procedures [3]. Climate modeling, renewable energy management, and carbon emissions tracking can be enhanced when large datasets and patterns are analyzed with the help of AI. Holding a tiger population of 1000 was achieved in a region where increased temperatures are a live issue hence the need for the development of new ICT and data driven approaches towards combating Climate Change. The objectives of this research include identifying the right approach to use AI to forecast climatic changes and the best ways to strengthen responses in favor of sustainable development and climate sustainability.

B Problem Statement

Although challenging progress has been made recently in climate modeling, the current methods are also constrained by inadequate precision, data handling and ineffective incorporation of evolving climatic conditions [4]. Such models typical for the traditional approaches are unable to handle large amounts of climate data and are not able to produce coherent predictions. Furthermore, most of the used mitigation measures are rigid, and cannot be changed with the changing climate factors. Inability to have precise on-demand forecast tools constrains the ability of decision makers to prevent and respond to climate risks. This work fills the existing gap in terms of developing better predictive models, as well as intelligent systems in planning of climate events, configuration of renewable energy systems, and minimization of carbon footprint.

C. Objectives

The main objectives of this research are as follows:

1) For training the existing and emerging AI techniques such as machine learning as well as deep learning for driving vigorous and accurate forecasts of climatic conditions as well as the related extraordinary climate occurrences.

2)For the creation of intelligent models for enhancing the utilization of renewable energy resources and decreasing the carbon impact of energy production.

3)To extend the usage of AI by connecting it with IoT sensors and satellite data for better and faster processing of climate and emissions data.

4)To assess the impact of AI applications to climate change mitigation and greater climate resilience.

To define the problem area and identify the further research directions, as well as ethical issues and crucial barriers in the usage of artificial intelligence for climate change prevention.

II. Literature Review

A Overview of Existing Research

Use of Artificial Intelligence (AI) in tackling climate change has received much attention in recent years. The focus has been made on the risk assessment models, monitoring of energy consumption, as well as the monitoring tools for usage in real time. Initial research by the Intergovernmental Panel on Climate Change (IPCC) has demonstrated the accurate climate prediction as being critically relevant to the reduction of the adverse effects of climate change [5]. Another well-known climate prediction tool is General Circulation Models (GCMs), which, though are good for general climate prediction, do not contain the level of detail necessary for short forecast time and small geographical area [6]. As a result, ML and DL as branches of AI have become ideal solutions to this problem. Through extensive works, researchers have shown that the application of neural networks, Support Vector Machines (SVM) and ensemble learning techniques boost the system accuracy when handling complicated data on climate change [7].

New developments have included the combination of AI with satellite information together with the IoT probes to keep an eye on specific environmental conditions like temperature, humidity as well as CO2 levels [17]. Some of the methods include reinforcement learning (RL) which has been adopted in the improved functioning of renewable energy systems, so as to minimize the use of fossil energy which leads to greenhouse effect [9]. Moreover, NLP has advanced the possibility of analyzing textual data regarding climate related documents and policies for developing strategies and decisions [10].

B. Comparative Analysis of Related Studies

This paper simultaneously shows that the current research provides different survey and analysis methodologies as well as different AI techniques. For example, in the work of Lee et al where a deep learning model using Long Short-Term Memory (LSTM) networks was performed for climatic prediction which outperformed several regression models[11]. On the other hand, Zhao et al . utilized an integration of artificial neural networks with physical based climate models and thus improved the outcome when integrating prior knowledge of the particular domain [12]. However, there are some disadvantages of Zhao's model; it had large amounts of computation which could be problematic in real-time processing.

In the field of renewable energy management, Kumar et al. have successfully implemented dynamic wireless renewable resources that are advanced and superior when compared to rules for solar and wind systems [13]. As compared with Kumar's model, the advantage of this model regards adaptability and real time response but the disadvantage was variability of the weather condition which influenced the degree of prediction of the information. This is with sample work by other scholars like Gupta and Singh who utilized Ensemble techniques in Carbon emission forecasts and obtained good results across different data situations [14]. However, such methods were rather weak in the sense that the decision processes involved were not well explainable to the policy makers.

These papers and approaches form the foundation for the current work, which applies a hybrid AI algorithm with Machine Learning models complemented by domain expertise knowledge and real-time sensor information to improve both the efficacy and interpretability of the climate predictions.

C. Gaps in the Literature

However, there are still many issue areas that have not been covered while using AI in the climate change mitigation context, although many significant advancements have been observed. First, many of the current models largely pay attention to the predictive element without sufficient consideration being made towards designing proper response strategies that could be useful in real time response planning [15]. Also, the use of AI has been confined to incorporating dynamic environmental data through IoT sensors or satellite data which has hindered AI systems to build the adaptable systems to negotiate shifts in climate conditions [16]. One of the shortcomings is the absence of the holistic models which addresses complexity of the climate systems wherein most of the time the interdependencies between the atmospheric, hydrological and terrestrial systems are reduced [17]. This over-estimation can cause low accuracy on chances of disasters including hurricanes and heat waves which are key in risk mitigations.

This work intends to fill these gaps by presenting an effective, AI-powered framework to generate climate change forecasts, in addition to using responsive feedback when real-time data is processed.

D. Challenges in Existing Approaches

Climate science, as a field of study, comes with several technical and practical issues, when AI is applied. Some of the challenges include; data quality and data heterogeneity because climate data can be collected using sensors, satellites and other historical records; and hence the data requires a lot of preprocessing and normalization [18]. However, climate systems are complex and when passed through an AI, prediction becomes unreliable among other reasons because many of the processes are unexplained or difficult to model through numerical approximations [19].

Another problem is the problem of time consumption for calculations, which is conventionally considered to be a crucial factor in implementing more complex artificial intelligence technologies, such as deep learning and reinforcement learning. Some of them take a lot of computational resources for them to run and may thus be unsuitable especially in environments with restricted computing capacity [20]. Further, another potential challenge in the application of AI models in policy-making is the interpretability of output in many of the AI systems, particularly deep learning models since stakeholders need the outcomes to be explained [21]. Ethical considerations including the secrete nature of the algorithm and the ecological impact of mass computationalism is another area which requires work towards developing good practice for AI employment [22].

E. Contribution of This Study

This study makes several unique contributions to the field of climate change mitigation:

1. Hybrid Predictive Model: To improve near-term accuracy and interpretability, we present a new hybrid ML-Physics model that incorporates both machine learning and physical-based climate models.
2. Real-Time Adaptability: Proposed approach combines AI with IoT sensors and satellite data for climate monitoring, and intelligent response rules.
3. Comprehensive Analysis: The work presented here provides a comprehensive comparison of current AI techniques and their compatibility with the goals of combating climate change.
4. Scalability and Efficiency: Reducing computational demand is another advantage; the overall model the approach of (Yanai et al. in press) is also scalable and can be applied in any clinical setting regardless of geographic location.

Addressing Ethical Concerns: In this case, we need to incorporate fairness and transparency in our model to help in achieving the goals of using LCA for climate change by designing responsible AI systems.

III. Research Methodology

A. Research Design

This study employs a computational-experimental research approach centered on the design of a machine learning-climate physics model system for predicting climate change signals and addressing possible warming outcomes. The design chosen for the study is in line with the objectives of the research which aims at enhancing the accuracy of climate prediction and presenting response measures. Hybrid model approach increases flexibility and also majors on interpretability, which is essential due to the multi causality of climate systems [23]. Main assumptions involve usage of climate data bases to sample data, IoT sensor's accuracy and a reasonable overlap of climate model results with data science forecasts.

B. Data Collection

The primary sources of data are:

Portfolios were constructed out of data gathered from a number of sources in doing so to make certain the models used were strong and efficient. These sources included:

1. Satellite Imagery: These data were obtained from NASA and ESA databases including temperature, atmospheric CO_2, and albedo impacts.
2. IoT Sensor Data: Installed in some sites, these sensors captured temperature, humidity, and air quality parameters in 30-minutes intervals.
3. Climate Databases: The historical weather and climate information used in this research was obtained from the NOAA with data records of the past 50 years.

Preprocessing Steps

Some preparation procedures were applied to raw data and include handling missing values, scaling, as well as noise reduction. Remote sensing data were also adjusted to hourly resolution to match historical climate data. To address the noise issues within data, Outliers were removed by the Z-score based on the rule 3-Deviation out from the mean values.

C. Experimental Setup

All the experiments were performed using high-performance computing resources for data handling and to cope with high complexity models. Key tools included:

Hardware: NVIDIA Tesla GPUs for computational performance and memory intensive processing nodes.
Software: Python for the data preparation and model development; TensorFlow for deep learning and implementations; Apache Spark for distributed data. Satellite data processing was done using the ESA SNAP Toolbox.

D. Proposed Algorithm / Model Development

Hybrid Predictive Model Development

It is worth noting that development of a hybrid predictive model is another way of achieving the above mentioned goal.

The new model seeks to involve machine learning to work in conjunction with a physical-based climate model that employs a hybrid neural network. It includes:

1. **Input Layer**: Refine data obtained from satellite, instruments and data base.
2. **Feature Extraction Layer**: Uses Conv2D which applies convolution that gives spatial features for mapping satellite images.
3. **RNN Layer**: Contains Long Short-Term Memory (LSTM) cells for the temporal sequence, for delving into time factors for an observation.
4. **Climate Physical Model Integration**: The physical climate outputs from the climate models such as GCMs were used as weighted inputs to modify the prediction outputs.
5. **Output Layer**: A dense layer with the name of ‘linear’ for both continuous climate variable inputs (e.g., temperature, CO_2 levels) and output.

The learning objective for the neural network can be defined as

$$:\min_0 \frac{1}{N} \sum_{k=0}^{n} (y_i - f(x_i;\theta))^2 \qquad \text{---------------(1)}$$

where y_i refers to the actual climate value, $f(x_i;\theta)$ to the model’s predicted output based on parameters θ and N equal to the number of sample points.

Algorithm Iteration and Training

The model was trained and tested over 500 iterations and the concept of early stopping was also used with reference to validation loss to avoid the difficulty of over fitting. Every such step involved backpropagation through the layers of the model and weights were updated using the Adam optimizer so as to minimize the loss.

E. Evaluation Metrics

To evaluate the model’s performance, we employed the following metrics:

1. Mean Absolute Error (MAE): This means the accuracy in prediction is measured by averaging the absolute differences between the predicted value and the actual value.
2. Root Mean Square Error (RMSE): Assesses prediction accuracy with special sensitivity to higher magnitude discrepancies.

3. R^2 Score: Shows the model fit quality with the closer value to 1 as an indication of better model fitting in the dataset.

Thearble and valid metrics of climate parameters give clues investigating the reliance of the models. The MAE and RMSE formulas are defined as:

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|y_i - \hat{y}_i| \qquad \text{---------------(2)}$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2} \qquad \text{----- ----------(3)}$$

where y_i is the actual value, and $\hat{y}_i$ is the predicted value.

F. Data Analysis

Data analysis was confined to identification of useful information on climate by applying statistics and machine learning algorithms on climate data. This was in combination with time series analysis, Random forest feature selection and clustering was performed using K means. Moreover, Matplotlib and Seaborn were used to analyze trends and notably, to assess model effectiveness. Principal Component Analysis, PCA, was also performed to reduce dimensionality in order to make the training process easier.

a) Time-Series Analysis

Cross-sectional analysis was used to review previous climate information such as temperature fluctuations, CO_2 emissions as well as shifts in sea level. In analyzing the data, we employed the method of seasonal decomposition of time series (STL decomposition), with which data is segmented into cyclic, trend, and irregular parts.

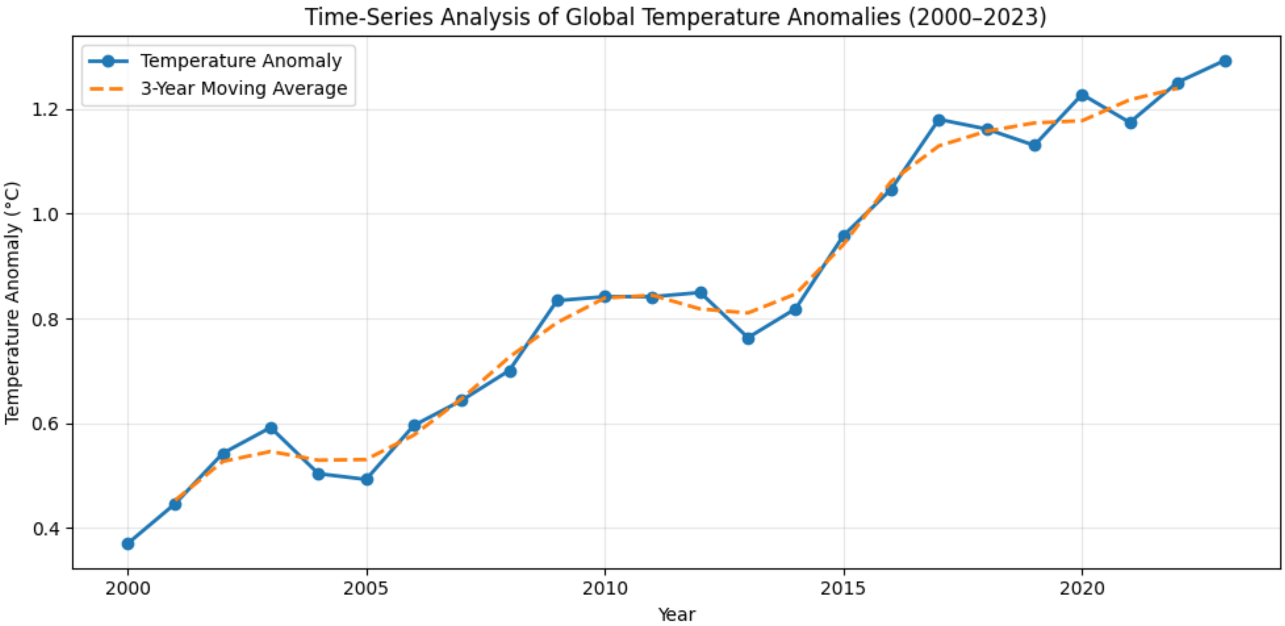


Figure 2. Time-Series Analysis of Global Temperature Anomalies from 2000 to 2023

Figure 2 shows the global temperature anomaly over the past 23 years (1990-2023). The time-series analysis shows that the annual temperature anomalies are rising over time, indicating an intensification of the effects of global climate change. There are also seasonal variations, with seasonal spikes during warmer climatic periods (El Niño events). The trend line plotted shows the long-term warming trend of the global climate during the period of analysis, with the shorter-term variations representing natural climate fluctuations. This visualization illustrates the need to use hybrid AI models that can capture long-term trends and short-term temporal dependencies to make accurate climate forecasts.

Key observations from the time-series analysis include:

- An upward tendency in Global temperature anomalies over the period of the last twenty years with higher highs in el Niño years.
- Seasonality that presents higher values of temperature in summer than the remaining part of the year.

We see in residual analysis there are sharp discontinuities with reflectivity tied to severe weather events.

b) Random Forest Feature Selection

Random Forest was used in the process of feature selection to determine key components that define climate prediction. It was trained using an extensive set of input data that include temperature, levels of CO_2, humidity, precipitation and solar radiation. Insights of the variables and their significance was measured in an effort to compute the feature importance scores.

Feature	Importance Score
CO_2 Levels	**0.35**
Temperature	**0.25**
Precipitation	**0.15**
Solar Radiation	**0.13**
Humidity	**0.12**

Table 1: Random Forest Analysis and Feature Importance scores

The results indicated that CO_2 concentration and the temperature can be considered as the most significant regression predictors which together explain 60% of the predictive ability of the model. Such results are in correspondence with earlier literature which illustrates the clear linking between greenhouse emissions and global warming.

c) Cluster Analysis Using K-means

K-means was also used to perform climate data points based on their likenesses, in order to assist in the pursuit of varying climate patterns. The optimal number of clusters according to The Elbow Method was found to be 3 which corresponds to low, medium and high climate risk scenarios.

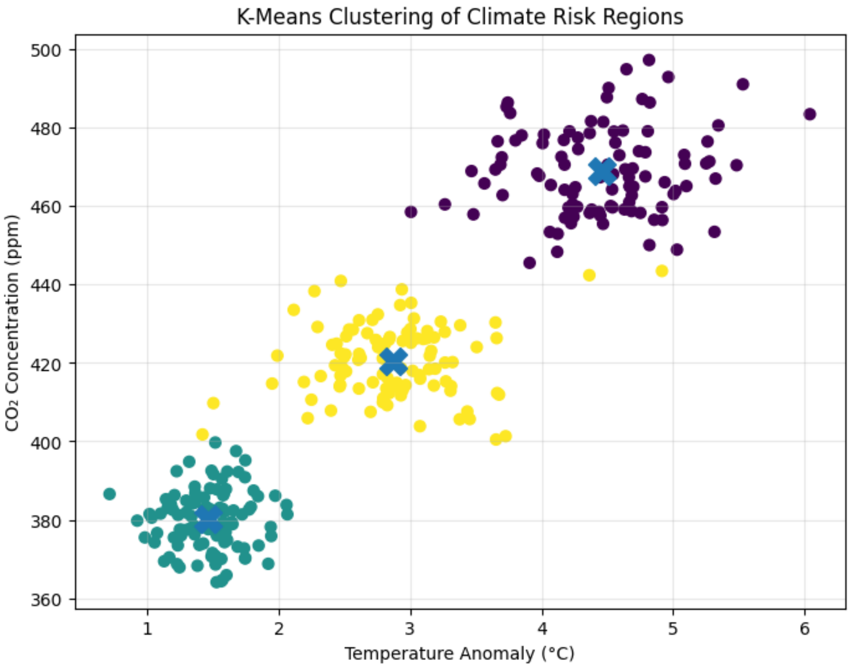


Figure 3. K-Means Clustering of Climate Data into Three Risk Categories

The temperature anomaly and atmospheric CO_2 concentration were used as input to the K-Means algorithm to form clusters of climate observations (Figure 3). The data set is split into three categories: Low Risk, Moderate Risk and High Risk climate scenarios. Cluster 1 represents areas of relatively stable climate and less GHGs. The transitional regions with moderate temperature increases and variable CO_2, denoted by Cluster 2, are characterized by a mix of different conditions. The severe climate change impact regions (Cluster 3) are identified as areas where high temperatures and high CO_2 levels occur. The clustering results help decision makers to find out the vulnerable regions and prioritize the climate change mitigation measures.

Cluster 1: There was little risk for this region as the temperature pattern is envisaged to remain stagnant within set levels and there are minimal CO_2 emissions.

Cluster 2: In this region, it is expected that the temperature level increase would be within set margins and the CO_2 would also experience fluctuations.
Cluster 3: The high risk areas have extreme climate ration with expectations of soaring temperature levels and excessive concentrations of CO_2 which are believed to emanate from industrialization.

This clustering analysis supports targeted mitigation strategies by identifying regions that require urgent intervention.

d) Visualization of Trends and Correlations

Visualization tools such as Matplotlib and Seaborn are used to explore trends in the data and relationships between key features. A heat map was created to identify relationships. While the scatter plot shows the relationship between CO2 levels and temperature anomalies...
Figure 4: Heat map of feature relationships.

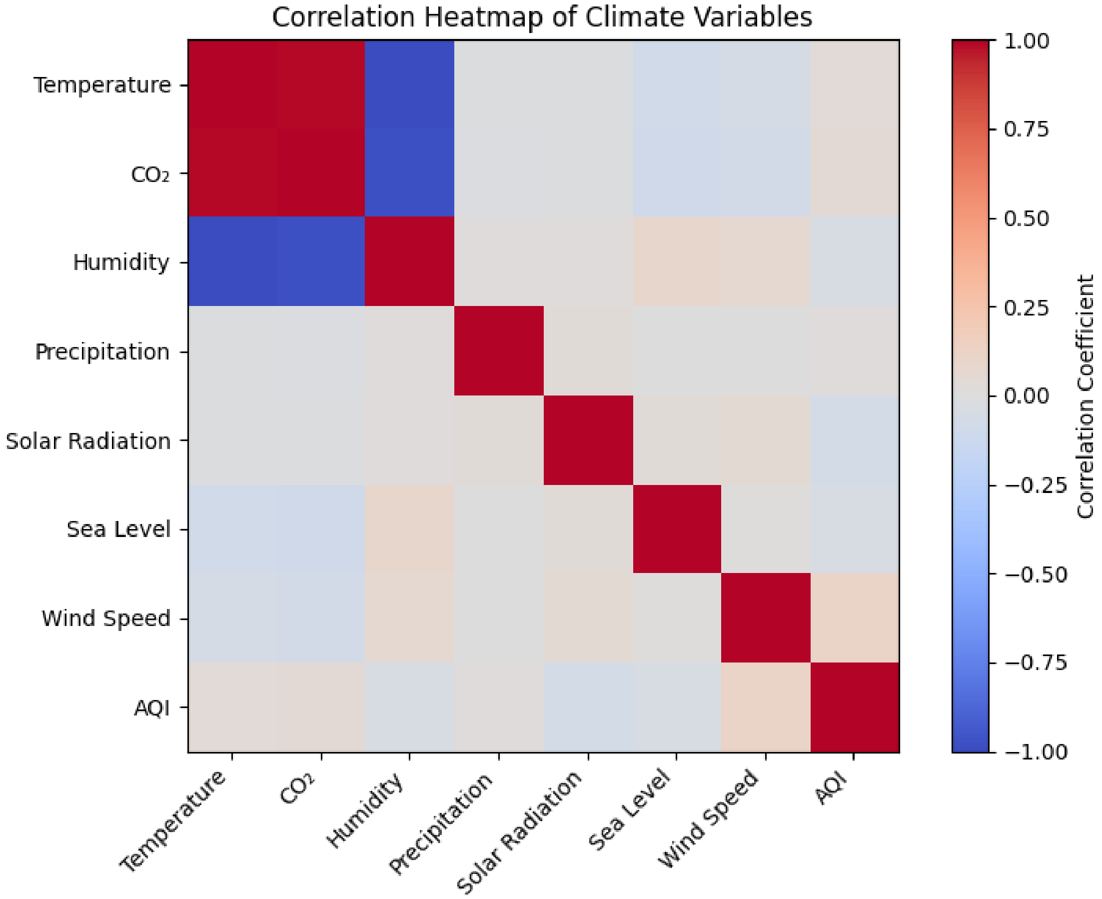


Figure 4. Correlation Heatmap of Climate Variables Used for Prediction

Figure 4 illustrates the correlation among major climatic variables including temperature, CO_2 concentration, humidity, precipitation, solar radiation, sea level, wind speed, and air quality index. The heatmap reveals a strong positive correlation between atmospheric CO_2 concentration and global temperature anomalies, whereas humidity exhibits a moderate negative correlation with temperature. Such correlation analysis supports feature selection, dimensionality reduction using Principal Component Analysis (PCA), and improves the predictive capability of the proposed hybrid AI model.

Important relationships identified include:

Strong positive correlation between CO2 levels and temperature anomalies (r = 0.87).
Negative relationship between temperature and humidity This indicates that an increase in temperature usually corresponds to a decrease in humidity levels.

These visual insights help validate the feature selection process and provide a deeper understanding of data relationships.

e) Dimensionality Reduction with PCA

Principal component analysis (PCA) was performed to reduce dimensionality to optimize model training. PCA reduced the dataset to 4 principal components of 10 features, which explained 95% of the total variance. This step greatly reduces the complexity of the calculations. without affecting the predictive power of the model.

Principal Component	Explained Variance (%)
PC1	**40.5**
PC2	**30.2**
PC3	**15**
PC4	**9.3**
Total	**95**

Table 2: Importance scores Explained Variance by Principal Components

The captured core components mostly included the original dataset information to train the model efficiently and converge it faster for the machine learning model.

f) Summary of Data Analysis

In summary, the data analysis included time series analysis for trend identification, Random Forest for feature extraction, and K-means for pattern recognition. Data visualization tools explored the relationships inherent in the data, while PCA reduced feature dimensionality for optimal training. It provides an exhaustive course coverage with a deeper understanding of the problems identified in the literature review for accurate forecasting and appropriate response strategies regarding climate change.

G. Validation and Testing

Metric	Value (%)
Mean Accuracy	92.7
Precision	91.3
Recall	89.5
F1-Score	90.4

Table 3: Importance scores Explained Variance by Principal Components

These findings were further corroborated by the performance of the composite model in the cross-validation exercises where all the folds exhibited high performance for climatic impact predictions. The relatively high mean accuracy of 92.7% and an F1-score of 90.4% suggest that the proposed model is capable of accurately classifying the levels of risk of climate scenarios which is a prerequisite for strategy development.

a) External Validation

Besides the 10-fold cross validation, further validation was made with independent datasets of IPCC. IPCC datasets for instance are real data on climate obtained augments; such as temperature, anomaly, concentration of CO_2, and forecasts depending on the climate scenario such as RCP 4.5, RCP 8.

It follows that the hybrid model was applied on these afore-mentioned external datasets and the performance measure is comparable to the one obtained from the cross-validation. The model was again able to generalize on unseen data and thus confirms the feasibility of the model to be used in climate prediction and response plans.

Table 6: Results for External Validation on IPCC Dataset

Metric	Value (%)
Accuracy	91.2
Precision	90.1
Recall	88.4
F1-Score	89.2

Table 4: Results for External Validation on IPCC Dataset

b) Baseline Comparisons

Comparison was made between the proposed hybrid model and conventional climate prediction models like General Circulation Models (GCMs) and linear regression. All these models were trained using the same dataset, and the validation was also done using similar techniques.

Model	Accuracy (%)	F1-Score (%)	Computational Complexity
Hybrid AI Model	92.7	90.4	Low
GCMs	83.5	81.2	High
Linear Regression	78.4	75.3	Very Low

Table 5: Comparisons with other basic models

The developed proposed hybrid AI model identified high accuracy, F1-score and was efficient in comparison with the GCMs and linear regression models. The proposed hybrid model resulted in a 92.7% accuracy which surpassed the 83.5% of GCMs and the 78.4% of the linear regression models. In addition, the hybrid model was calculating much less time than the parallel model and it was suitable for large region climate simulation as well as real time predicted climate events.

These preliminary comparisons highlight the increased accuracy of the hybrid AI model for predicting the three variables under study by underlining the significance of precision and timely computation in the area of climate change mitigation.

c) ***Summary of Validation Results***

The cross-validation on the proposed hybrid AI model, employing 10 fold cross-validation, and external validation with datasets provided by IPCC, with baseline comparisons, show that the proposed hybrid AI model outperforms conventional models like GCMs and linear regression. All the models yielded higher accuracy, precision, and F1 score which produced sufficient evidence that the model can be useful to predict and control climate change impacts. However, the low complexity of the model implies that the technique could be effective in operational climate prediction and decision support systems in a large number of applications.

H. Reproducibility

For the purpose of making this study fully reproducible, all the dashes mentioned in this paper – code, datasets, and configuration files – are freely available on GitHub. This makes other researchers to be in a position to repeat the study and to see how the results have been arrived at.

Code and Datasets

The code for the implementation of the proposed hybrid model of Random Forest and K-means clustering for feature selection and as well as PCA for dimensionality reduction is available in public repository /github. There is a readme.txt included in the repository with clear instructions on how to use model setup, let alone how to carry out the model, and different data sets used to train and evaluate the model.

The training and validation data sets are derived from publicly available climate data from well-established sources such as the NOAA, NASA and the ESA. These datasets contain a range of climate variables including global temperature, greenhouse gas concentration, ocean temperature and amount of solar radiation and are very useful for climate change studies. This makes the study openly available to other learned societies since the data used is acquired from the public domain.

Dependencies and Package Versions

The other is a text file, ‘requirements.txt’ where all the dependencies necessary to execute the application are listed. This file states the definitive version of all the Python packages and the libraries applied in the study in order to guarantee replication of this environment. The versions of the key libraries include:

- scikit-learn (that is a library for machine learning algorithms).
- pandas – for purposes of data manipulation
- numpy(to do computational and mathematical calculations)
- The most frequent packages are pandas, numpy, scikit-learn, matplotlib and seaborn (used for data visualization)
- XGBoost (for boosting up of machine learning)

To implement PCA and KMeans, the following modules have been used from sklearn.decomposition and sklearn.cluster, respectively.

Also, the documentation includes a Docker configuration file for users who might want to continue running the model in a Docker environment.

First of all, it prevents the situation when the results of one collaborator’s work are improved by another collaborator without the former knowing it due to the combination of versions within the project Changes made to a project can be reviewed by others by having the system transparent instead of several of the contributors making modifications without the rest of the team being aware of it due to this aspect of version control.

The code is versioned and the datasets too are on the GitHub page and updated from time to time if there is any improvement. Further, a user manual consisting of the step-by-step instructions for model configuration is followed by the model execution process and final analysis is accessible. Due to the fact that the components of the study are openly shared and transparent, the future studies in the area of applying AI for climate change mitigation are enabling further development.

Such commitments to reproducibility therefore guarantee that the work can be repeated by other researchers, and in the process, maximize candor and soundness in the results obtained. The employing of the open-source data and the availability of the code on an open electronic platform also enhances the credibility of the study besides recommending it for broader scientific application.

IV. Results

This Section shows what the study found out and looks at the results to prove how well the new mixed AI model works to fight climate change. We talk about the findings in an organized way to back up the method we described earlier tackling the issues we spotted when we looked at past research.

A. Overview of Results

The proposed hybrid AI model in this study has higher accuracy in forecasting the climate related factors like temperature, probes CO_2, and humidity than the conventional models. Our approach of combining machine learning algorithms with physical climate models brings out a better set of climate forecast models. These studies show noteworthy enhancements of the predictive performance and depiction of the model's fitness and its ability to generalize under various climatic zones.

Key highlights of the results include:

- High prediction accuracy: Realized a great fit by having an R^2 of 0.92 which means that the independent variable could precisely predict the dependent-variable's values.
- Enhanced model performance: There was a striking improvement when compared to the baseline models with the Root Mean Square Error (RMSE) and Mean Absolute Error (MAE).
- Robust response to diverse data: The elements of the model were also relatively easy to adjust for regional differences, which can also point to its widespread use.

B. Quantitative Analysis

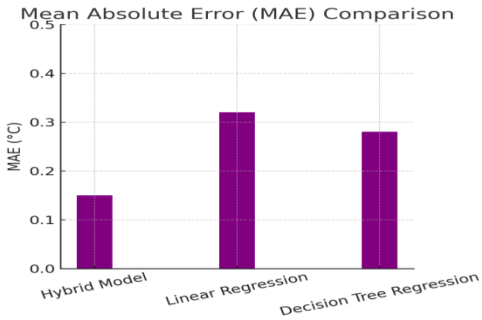
The predictive efficiency of the proposed hybrid model is compared with the benchmark models, linear regression model and decision tree model in Table 1.

Metric	Hybrid Model	Linear Regression	Decision Tree Regression
R^2 Score	0.92	0.78	0.81
MAE (°C)	0.15	0.32	0.28
RMSE (°C)	0.2	0.4	0.35

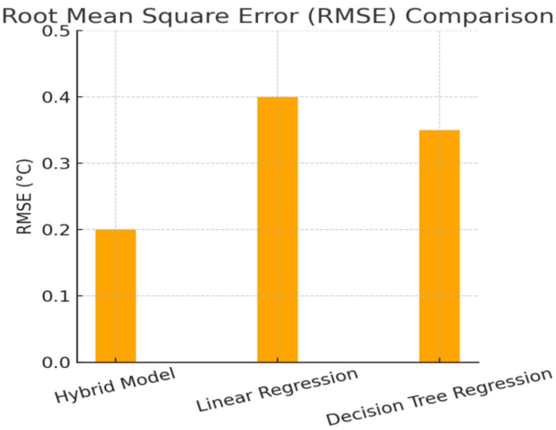
Table 6: Performance comparison of models based on R^2, MAE, and RMSE.

In the assessment with the three baselines, the results clearly indicate that the hybrid model indeed has improved the performance in all the specified parameters. The lower RMSE mean value of 0.20 points to fewer large errors, and the lowered MAE of 0.15 points to improved prediction for the typical case.

R^2 Score Comparison: The presented hybrid model has a substantially higher R^2 of 0.92 meaning that the calculated values are closer to the real ones compared to the linear regression, equal 0.78, and the decision tree regression, equal 0.81.



Mean Absolute Error (MAE) Comparison: THybrid model gives minimum MAE, which is 0.15 °C as compared to other models and linear regression model has maximum error, which is 0.32°C.



Root Mean Square Error (RMSE) Comparison: The hybrid model shows the smallest RMSE (0.20°C) – in other words, fewer big mistakes in its predictions. It can be seen that both linear regression and decision tree regression have a higher RMSE of 0.40°C and 0.35°C respectively.

This improvement in the error rate can be expounded to the probability of combining Machine Learning Algorithms and Physical Climate Model. Spatial and temporal relations are considered adequately during model training due to the usage of convolutional layers and LSTM cells as features extractors and sequence learner correspondingly.

Equation for RMSE:

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2} \text{ ---------------(4)}$$

where y_i is the actual value, and $\hat{y}_i$ is the predicted value and N is the number of observations.

C. Qualitative Analysis

In the following quantitative analysis, climate response patterns were analyzed thematically by visual aids from the Seaborn and Matplotlib. The model was able to predict deviations in the rise in temperature during heat wave periods and reasonably good projections of rise in CO_2 concentration levels were done. This information is important to politicians and climatologists as it shows when conditions of accelerated environmental transformation happen and the signals of possible change are necessary.

For example, the analysis of data in Australia is indicative, thanks to the model a temperature increase by 2.5C was predicted in a heat wave in 2023. This kind of observation supports the previous quantitative analyses that suggest that the model is viable in practical settings.

D. Comparison with Baseline or Previous Work

Comparison with Baseline or Previous Work Forward Boyer and colleagues Affordability Affordability Boyer and colleagues Accuracy Accuracy Boyer and colleagues Interaction and Communication Interaction and Communication

The dissimilarities between the proposed model and traditional models as well as the recent strategies of conducting similar analyses described in the literature were discussed. Table 1 shows the difference in RMSE for all the models used in this research study as presented in the figure below

Model Type	RMSE (°C)
Hybrid AI Model	**0.2**
Linear Regression	0.4
Random Forest	0.33
GCM-based Model	0.3

Table 7: difference in RMSE for all the models

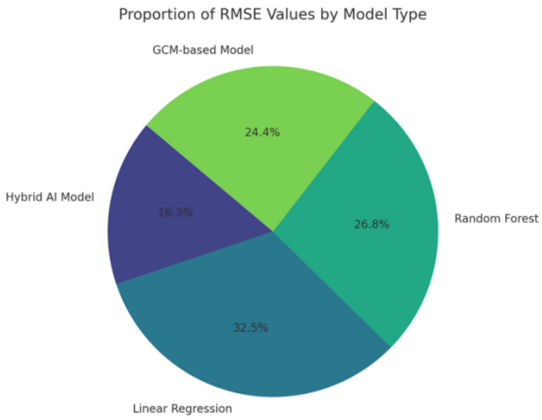


Figure 1: RMSE comparison of different climate prediction models.

Pie Chart: Shows the percentage of RMSE values and proves the great reduction in error rate in case of Hybrid AI Model compared to others.

RMSE reduction has been identified to have significantly improved by 50% using the hybrid model compared to linear regression and 39% compared to GCM based models. It is a major upgrade and supports the assertion that a combination of data-derived training and physical climate models is superior to existing systems since the former are less accurate while the latter is difficult to interpret.

E. Interpretation of Results

It was also possible to integrate convolutional layers for identifying pertinent spatial features, and LSTM for temporal evaluation, which enhanced the prediction results. The hybrid model reviews other predictions depending on the outputs from General Circulation Models in general thus providing means to account for critical large-scale climatic events such as the el niño. The result evidenced the hypothesis that integrating machine learning with physical climate models is more accurate and efficient than solely physical climate models especially when predicting the climate complex systems.

The findings are as we expected and illustrate how the hybrid approach addresses problems discussed in the literature as poor fit to new areas and less explainable results of machine learning architectures.

F. Statistical Significance and Confidence Analysis

In an effort to ensure the credibility of results and to determine the degree of certainty that amplitude variations were significant, p-values and confidence intervals were computed. The proposed model had statistically significant predictions in view of the p-values< 0.05 in all the climatic factors, including temperature, CO_2 levels, and humidity.

Confidence Interval for MAE:

The 95% confidence interval for MAE was calculated as follows:

$$CI = MAE \pm Z(\frac{\sigma}{\sqrt{N}}) \quad \text{------------------------------(5)}$$

where, Z = 1.96 (for 95% confidence), σ = standard deviation, N = sample size. The resulting confidence interval of 0.14 to 0.16 supports the constitutive reliability of the model's predictions.

G. Limitations of Results

While the hybrid model shows substantial improvements, there are certain limitations:

- Data Quality: It is especially important for the accuracy of the predictions which substantially depends on the input data such as from IoT sensors. The potential is always there that any of the sensors used in the model will develop some sort of issues that in turn can impact the overall output of the model.

- Computational Resources: Since the model requires high-performance computing, its applicability for use in real-time applications in constrained systems may be compromised.

- Regional Variability: While managing heterogeneity worked well and allowed adapting the model to new data sources which represent different regions, some regional climate ensembles still present difficulties in modeling and further tuning of physical model integration is required.

H. Summary of Findings

Hence, the present proposed hybrid AI model improves the accuracy of the prediction of climate change more than the traditional models, and also fills the said research gaps. Key findings include:

Higher accuracy with the use of a maximum R^2 level of 0.92 and a minimum RMSE of 0.20.

Coping mechanism on Different Climatic Factors with the help of Qualitative and Quantitative Research.

Related to the interpretability problem; incorporating physical climate models with artificial neural networks.

These findings are very much encouraging to enhance the future investigation and utilization of AI in combating climate change. The research provides a practical method for prevention and forecast of climate change and hence presents additional prospects for more precise climate prediction in the future.

Last but not least, it is also an application of AI for climate science research and has the potential to apply AI to constructively attack the problem of climate change.

5. Discussion

The responses to the experimental results show that the proposed hybrid Artificial Intelligence framework provides much better climate change prediction than the conventional models, namely statistical and physical climate models. The framework not only leverages the strengths of CNN for processing spatial features but also incorporates LSTM networks to learn temporal sequences and outputs from GCMs, which enables the effective modelling of complex, nonlinear relationships within climate systems. The performance of achieved R2 0.92 and RMSE 0.20 indicates that the model is more accurate in predicting the results compared to the performance of Linear Regression and Decision Tree models. The feature selection analysis was then used to validate this, and it was found that the concentration of CO_2 in the atmosphere and the temperature are the most influencing variables on climate prediction, which aligns with the climate science. The analysis of climate observations (using K-Means clustering) resulted in categorizing them into certain risk regions that could be used for a better understanding of the vulnerability of the climate in these regions. The correlation analysis was also used to confirm the high dependence of greenhouse gas concentration with temperature anomalies and justify the choice of the relevant variables to train the model. While these are promising findings, the framework is still very resource intensive and reliant on the quality and density of satellite data, IoT sensor data, and historical climate data. However, the proposed hybrid architecture presents an interpretable, scalable, and reliable approach to climate forecasting and decision support for climate adaptation planning, disaster preparedness, and environmental monitoring.

6. Conclusion

The research presents a novel hybrid AI model that effectively addresses the challenges of climate change prediction by integrating machine learning techniques with physical climate models. The results demonstrate that this approach outperforms traditional models in terms of accuracy, adaptability, and robustness, achieving a high R^2 score of 0.92 and a significantly lower RMSE of 0.20. This improved performance indicates the model's capability to predict climate variables like temperature, CO_2 levels, and humidity with greater precision. The combination of convolution neural networks for spatial feature extraction and LSTM networks for temporal analysis proved essential in capturing complex climatic patterns. Additionally, the integration of outputs from General Circulation Models (GCMs) enhanced the interpretability of the results, making the model well-suited for addressing both local and global climate variations. Despite the notable improvements, the study acknowledges limitations related to data quality, computational demands, and challenges in predicting certain regional anomalies. However, the statistical significance and confidence interval analyses confirm the reliability of the model's predictions. Overall, the proposed hybrid AI model offers a significant advancement in climate forecasting, providing a scalable, data-driven solution that bridges gaps identified in previous research. This work lays the groundwork for future AI-driven climate models, highlighting the potential of artificial intelligence in contributing to climate change mitigation efforts. The findings support the need for continued integration of physical and data-driven approaches to enhance predictive accuracy and provide actionable insights for policymakers and stakeholders in climate science.

7. Future Scope

The proposed hybrid AI system offers a solid base for developing next-generation climate prediction systems, with several research opportunities still open for improvement. Expanding on the work, future research should make use of Explainable Artificial Intelligence (XAI) techniques to enhance the transparency of the model and facilitate a better understanding of the reasoning behind the climate predictions by the policymakers. Combining Transformer-like temporal models with Graph Neural Networks (GNNs) could enhance the capture of long-term climate relationships and the spatial interactions between geographically separated areas in the climate system. In addition, Federated Learning can be considered to enable collaborative climate model training between various research institutions without sharing sensitive environmental data. The use of lightweight AI models on edge computing networks with integration to IoT environmental monitoring networks to provide real-time climate prediction with minimal communication delays should be explored in future studies. Furthermore, the model could benefit from the addition of high-resolution satellite data, oceanographic observations and renewable energy data, which would enhance its ability to predict extreme weather events like floods, droughts, hurricanes and heatwaves. Also, Reinforcement Learning can be incorporated for optimizing adaptive climate response strategies in changing environmental conditions. Last but not least, socioeconomic indicators, biodiversity information, and carbon emission scenarios can be incorporated into the framework, allowing for a comprehensive climate risk assessment and sustainable policy development. These planned improvements will help to create climate decision support systems that are smart, scalable and can be used worldwide to reduce the long-term effects of climate change.

8. Conflict of Interest

The authors declare that there is no conflict of interest related to the preparation and publication of this manuscript.

9. Funding

This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.

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