Origianl Article

A Hybrid Deep Learning-Based Framework for Analyzing Causes of Climate Change and Global Warming

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Abstract - A change in climatic conditions, monsoon cycles, and an increased number of natural disasters are changing the natural state of affairs, affecting the ecosystem, agricultural activities, and human wellbeing. The ever-increasing data on atmospheric pollutants, which is characterized by high volume, speed, and diversity, is a significant problem to analyze in the domain of big data. This paper presented the internal correlations between various air pollutants and their respective role in global climatic changes and Global Warming. We present a new model to demonstrate the same-named Probabilistic Learning Hybrid Sequential Machine Learning (PLHSML), which combines probabilistic Learning via the Learning-Based Gaussian Weighted Averaging (LBGWA) technique with a hybrid sequential deep learning architecture. PLHSML is created to record the temporal dynamics, measure the uncertainty, and discover cause-and-effect patterns using time-series climate data. In the proposed PLHSML model, LBGWA was used to estimate the global and climatic scenario. As it is estimated that the probability of estimation is computed under the model, and the forecasting is done based on the Sequential Machine Learning. An empirical study carried out by us indicates that the model is more effective not only in studying the interaction of complex pollutants, but also in estimating their effect on climate phenomena correctly. The experiment has proved that the predictive accuracy of PLHSML is extremely better than the conventional models in that it bears a Root Mean Square Error (RMSE) of 0.09 and a Mean Absolute Error (MAE) of 0.07. These findings show that PLHSML is an effective analytical tool in order to get to know and mitigate the factors that cause global Warming and climate change.

Keywords - Deep Learning, Artificial Intelligence, Climate Change Analysis, Global Warming Analysis, Machine Learning.

1. Introduction

Global Warming involves increasing the average temperature of the Earth's surface with time; this is mainly caused by the rise in the concentration of gases that are usually known as the Greenhouse Gases (GHGs), Carbon Dioxide (CO_2), Methane (CH_4), and Nitrous Oxide (N_2O). The Intergovernmental Panel on Climate Change (IPCC) reported that the average increase in total surface temperature since the pre-industrial era through to the year 2023 is 1.1 °C, with the predictions indicating that by 2030-2050 it will have gone above 1.5 °C relative to the pre-industrial temperatures. The anthropogenic emissions contributed the most during this Warming, and the CO_2 concentration in the atmosphere during the pre-industrial period (280 ppm) and in 2023 (greater than 419 ppm). They are becoming increasingly apparent as glaciers recede, sea levels rise (about 3.3 mm annually), very hot days become more frequent and more severe, and a surge in extreme weather events, such as floods,

droughts, and wildfires, increases. Moreover, global Warming is also influencing the creation of urban heat islands, agricultural disruption, and spreading popular health complications such as respiratory diseases and heat complications. Those alarming trends require complex modelling to go to the root of their causes and to assist in the work of diminishing them. Global Warming is among the primary causes of climatic change that is presently experienced and has led to the alteration of atmospheric patterns, hydrology, and ecological stability of the Earth. The climate system is somehow retaliating harder and harder, and as higher frequency of extreme weather patterns have been seen and experienced around the world, an average temperature increase has been observed. As an example, we can refer to the fact that Global Warming will increase the melting of the ice caps and glaciers in the world, hence increasing the sea levels and ocean currents, in turn, which will change the climate in certain parts of the world. It leads

to unpredictable monsoons and seasonal fluctuations, irregularities in the tendencies of monsoon cycles, and over-rainfall and floods in specific places, and the rise of droughts in others. It has been seen that there is a rise in the frequency of Category 4 and Category 5 tropical cyclones, particularly over the last 10 years, that are directly linked to increased-than-normal temperatures in the sea surface. In addition, the humidified air links the intensity of storms and precipitation events, and this further intensifies their impacts. The changes are not only posing threats to the natural ecosystems, but also to agricultural productivity, freshwater resources, and the food supply chain in the world market.

Some of the most serious global issues are climate change and global Warming, affecting the whole world, including the ecosystem, human health, and socio-economic systems. The topics covered to help solve such issues are entirely consistent with the United Nations Sustainable Development Goal: urgent climate action. With the rather harsh effects of climate change, there is no other choice but to continue with scientific research in order to find a solution to mitigate and adapt to the situation. A sizeable literature has looked at the causes and effects of climate change through the exploitation of statistical, physical, and computational models. The development of data-driven technologies enabled modern research, and more and more machine learning and deep learning methods were used to analyze and predict the climate. These approaches enable scientists to represent nonlinear and dynamic variables and patterns in big data climate data. They have already been applied in real-time use of Internet of Things (IoT) sensors; meta-analysis with the application of artificial intelligence, which helps in impact quantification; and machine learning in geosciences to solve the various issues related to global Warming. In addition, newly developed technologies, e.g., remote sensing, cloud computing, and big data analytics, have gained widespread use to improve the accuracy and extent of climate studies. Nevertheless, the current approaches tend to be targeted at separate factors or particular applications, which results in atomized wisdom. The current literature has been centered on the accuracy of predictions as opposed to time dependence consideration of the data of climatic time series. This is the drawback of such a limitation that it will not be in a position to record the long-term trends and variations that form the basis of sound forecasting. There is also no single unified framework that can unite deep learning models with big data analytics to offer predictive accuracy and actionable information to make a decision. To address this weakness, the present research paper suggests an advanced model that will be utilized to combine deep Learning with the latest time series analysis in a manner that enhances the accuracy and topicality of climate change predictions. These plans, integrated, will enable the work to contribute to the addition of a more organized body of analysis, which would not just be set to inform policy formulation but also adjustable ways of responding to global Warming.

The given paper has reported the Probabilistic Learning Hybrid Sequential Machine Learning (PLHSML) framework, which can be effectively applied to examine the causes of climate change and global Warming by considering the time series environmental data information. The primary advantage of the suggested model is the possibility of dealing with complex nonlinear associations and the sequential interdependence of the facts of climatic data, with even higher interpretability and predictability. The importance of the adoption of the Learning-Based Global Warming Analysis (LBGWA) algorithm in the Central PLHSML structure has been pegged on the necessity of ensuring that a probabilistic learning based on the Gaussian-weighted averaging in a bid to tease out of the pack of pollutants that are currently playing a role in global Warming.

We demonstrate that the proposed model is better than several existing state-of-the-art models in the predictive accuracy measure, with a Root Mean Square Error (RMSE) = 0.09 and Mean Absolute Error (MAE) = 0.07. This paper is organized as follows: The rest of the paper contains the following structure: Section 2 gives an overview of recent works and techniques available to analyze climate change and global Warming. Section 3 explains the architecture and methodology of the proposed PLHSML model. The details of the comparative methods and evaluation scores are described in Section 4. Section 5 provides and discusses the findings of the experiment. Section 6 explains the meaning and the possible real-life application of our findings. Lastly, Section 7 is a conclusion of the study and future research avenues.

2. Related Works
The need to address climate change and Global Warming has overtaken the world as a key area of concern, with the world engaged in more research to identify causal factors, project climatic trends, and model environmental impact. A variety of Machine Learning (ML) and Deep Learning (DL) algorithms have been applied to learn on the challenging climate data, such as Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), Long Short-Term Memory (LSTM) networks, and combinations of statistical and neural Learning.

The models have demonstrated potential in activities like temperature prediction, study of impacts of pollutants, and early prediction of extreme weather conditions. Furthermore, time series models have become a major strategy to leverage the time-dependent relationship of climate variables, and big data platforms have been exploited to deal with the volume and diversity of environmental data. This is one of the drivers toward the creation of more advanced, integrated models. In these regards, our analysis can be regarded as a contribution to this form, as neither a probabilistic and hybrid sequential learning methodology exists, nor is it relatively deep or precise in terms of analytics and prediction as undertaken in our study.

The combination and use of big data and deep Learning has become one of the most important climate and geoscience application facilitators. Mohammadi et al. [1] pointed out the possibility of analyzing complex environments in real-time via the deep learning technique that could process IoT-generated, large-scale stream of data. Similarly, Tamiminia et al. [2] and Amani et al. [5] conducted a literature review of the applications of the Google Earth Engine platform, demonstrating its potential in managing geo-big data and planetary-scale remote sensing to monitor the environment. In the field of geoscience, Karpatne and the rest of the team [3-4] addressed the issue of machine learning applied to the Earth system sciences, including the potential challenges and opportunities of this practice, as well as the necessity of developing models that incorporate physical principles with data-driven understanding. In line with this, Flah et al. [6] also conducted a systematic review of machine learning methods in relation to structural health monitoring, which highlighted the broader potential of ML in terms of enhancing the resilience of critical infrastructure and the environment. In relation to the data, Saggi and Jain [7] examined the applicability of big data analytics in producing actionable insights, and Allam and Dhunny [8, 9] explored the application of big data analytics in developing sustainable smart cities. The same author, Roh et al. [10], has also acknowledged the necessity of possessing robust data collection strategies for effective AI-based big data integration. In a rural context, Huang et al. [11] demonstrated the application of remote sensing big data in crop and resource management, which is a primary focus of climate resilience research. Finally, the article by Nguyen and others [12] provides an overview of machine learning and deep learning architectures, as well as the scalability of these tools for large-scale data mining applications.

Machine learning and big data analytics have become increasingly adopted in various fields, demonstrating the transformative potential they can have. Discussing transportation, Zhu et al. [13] surveyed the area of big data and its application in creating intelligent transportation systems, emphasizing that the utilization of such information leads to the development of real-time solutions and optimization. IoT has been the other important enabler, where Kumar et al. [14] have mentioned that the transformational aspect of IoT could empower technology innovations in the future. However, Elyjoy et al. [22] have stated that the specifics of bringing together IoT, big data, and deep Learning will empower sustainable accuracy to grow further. The concept of data fusion has become an effective approach to integrating disparate data sources, as introduced by Meng and other scientists [15], which enhances the predictive strategy even in complex systems.

Regarding the general application, Sarker [16] described machine learning algorithms and their implementation in the sphere of applied research. Dargan et al. [21] discussed deep Learning as a new science with its privileges and advantages, as it is particularly successful when large volumes of data with an abundance of dimensions are used. The versatility of machine learning was also evidenced in specific sub-areas, such as in healthcare [19], energy systems used in renewable energy[18], and pandemic prediction based on cloud-based ML, to mention a few. Moreover, Syam and Sharma [20] discussed the enhanced supremacy of AI and ML in industrial sales, implying that they have penetrated the realms of business.

Machine learning and big data analytics are the areas that have been studied over the course of the last decades in various fields, including communications and manufacturing. Wang et al. [23] described the history of machine learning in wireless networks with emphasis on aspects of how it has been used to enable Pareto-optimal trade-offs in wireless network performance. In contrast, Mikalef et al. [24] and Core-Real et al. [30] depicted the business value of big data analytics, i.e., how it is boosting the performance of organizations and their decision-making. Regarding sustainability, Nishant et al. [25] discussed the possibilities and challenges of artificial intelligence in relation to sustainable development, and Bag et al. [27] explored the topic of institutional pressures in favor of implementing AI-enabled sustainable manufacturing and circular economy sustainability practices. Applications of energy have also garnered significant attention, as evidenced by Hou and Wang [26], who provided a bibliometric analysis of AI and big data in energy studies, and Carvalho et al. [29], who published a systematic review of domains related to predictive maintenance using machine learning in industry.

Zhu et al. [27] utilized physics-informed neural networks to forecast temperature fluctuations during metal additive manufacturing, whereas Wang et al. [32] specialized the big data analytics used in intelligent manufacturing and highlighted that it is essential for Industry 4.0 production. Similarly, Fathi et al. [31] reviewed the applications of big data in weather forecasting, highlighting that the use of big data is increasingly playing a crucial role in environmental prediction. Together, these works demonstrate the flexibility and versatility of big data and AI in many technology and industry systems. However, despite its extensive applications to wireless networks, manufacturing, sustainability, and energy, the literature remains rather limited in its provision of integrated models to combine deep Learning and big data in time-series analysis, which has complex challenges such as climate change forecasting, where long-term reliance on time and predictable cognition are clear.

Other recent developments reveal how deep Learning and big data analytics transform climate and environmental research areas. Hatcher and Yu [33] reviewed deep learning platforms and applications, focusing on their potential applications to emerging research problems. With this,

Adamson Oloyede et al. [34] proposed a big data-based method for predicting temperature, a direct application to climate modeling. Simultaneously, Gupta et al. [35] highlighted the contribution of big data to implementing the circular economy processes, and this tendency is connected to the increasing significance of sustainability-oriented analyses. The new paradigms, such as federated Learning, have also been discussed, with Zhan et al. [36] outlining the idea of incentive mechanisms to enhance decentralized model training in IoT environments. In wireless communication, Chen et al. demonstrated the importance of various neural network-based learning processes required to adapt and develop intelligent networks.

Meanwhile,hereas Li & Arundel [38] have that shown isoAI as the future of spatial ana,lhighlightingcs and how AI can be coupled with geospatial dabetter ta to understand the environment. Agriculture is considered one of the points on the radar in terms of climate-related analytics, including the works by Rastogi et al. [39] devoted to defining health-related outcomes of climate change on agricultural productivity in South Asia, and Ali et al. [40], which include focusing on big data and ML to eliminate genetic intractabilities in crop breeding. Uthirapathy and Sandanam [41] studied climate change discourse on Twitter using advanced topic modeling and natural language models, which extend beyond structured datasets. They provided insights into the opinions of the people and the possible implications of the policies. In the same regard, Fayaz et al. [42] surveyed machine learning ML) algorithms to predict rainfall, highlighting the significance of climate-oriented big data analytics in geographical sciences. Collectively, these publications highlight notable progress in the application of machine learning, GeoAI, and big data to environmental and agricultural contexts. Nevertheless, even with such developments, current research is biased towards specific applications (e.g., temperature prediction, rainfall, crop genetics) or individual technologies. An integrated model combining deep Learning, time-series modeling, and big data analytics to perform a holistic climate change forecasting has not yet been developed, which this paper will attempt to fill.

Kundzewicz et al. 2018 have highlighted the most profound mysteries around the effects of climate change on water resources [43]. Central to their work was the inconsistency of hydrological models, climate representations, and socio-economic variables, and the need to instigate uncertainty assessment on environmental decision-making. Although the research they conducted provides a basis for climate adaptation strategies regarding water, it fails to consider computational and AI-driven optimization models that can reduce the degrees of prediction ambiguity, which is the motivation behind the present work. Tahsien et al. (2020) [44] conducted a survey of machine learning-based security systems for the Internet of Things (IoT). They prioritised intrusion detection, anomaly detection, and lightweight ML algorithms on constrained IoT devices. They identify current weaknesses in their work, but do not further discuss adaptive, cross-domain forms of Learning that can adjust to the rapidly changing forms of security threats. This is where the present study extends further by incorporating machine learning into predictive frameworks, with the broader implications of these applications extending beyond IoT security. Weiss et al. (2020) [45] published a meta-review of remote sensing activities in the agricultural sector, offering an overview of how contributions from multispectral- and hyperspectral-based imaging have altered the monitoring of crops, yield forecasts, and environmental surveillance.

Yet their research mainly compiles previous literature without proposing mixed-computational models do real-time agricultural forecasting, unlike our current study, which combines intelligence optimization and deep Learning with remote sensing, providing real-time, predictive capabilities. Wamba et al. (2019) [46] investigated the influence of big data analytics on supply chain ambidexterity that is moderated by environmental dynamism. Their findings justified the fact that advanced analytics enhances resilience and adaptability to volatile environments. However, they were concerned with business logistical operations, rather than energy or climate projections. The work of our authors utilizes big data analytics and optimization algorithms to predict environmental parameters, thereby solving another, but no less recurrent, area.

Sidey-Gibbons and Sidey-Gibbons (2019) [47] gave a reasonably accessible introduction to machine learning in the context of medicine, focusing on interpretability, reproducibility, and application-based development. Their work contributes to the enhancement of ML applications in the healthcare sector; however, it does not address the necessity of predicting environmental conditions or renewable energy to handle complex spatiotemporal data. The study fills that gap by generalizing ML in the domain of prediction. Das et al. (2018) [48] conducted a review of photovoltaic power production forecasting methods, including approaches based on physical machines, statistics, and machine learning. Their works are educative and provide excellent insights into how models can be optimized to generate renewable energy forecasts, and cannot be used to combine with the swarm intelligence and better hybrid deep learning models.

The research is also value adding in the sense that it brings new knowledge into the deep learning models, which emphasize optimization in similar areas of energy. Liu et al. (2018) [49] proposed a hybrid model that involves the application of Variational Mode Decomposition (VMD) and Single Spectrum Analysis (SSA), LSTM, as well as ELM to predict the wind speed. Their smart, multi-model approach performed well in prediction, but it is both computationally

costly and domain-specifically adapted. This trend will be followed in this work, which will develop computationally efficient models capable of generalizing to various forecasting scenarios. The work by Noorbakhsh-Sabet et al. (2019) [50] concerned artificial intelligence transforming healthcare, particularly in diagnostics and Personalized Medicine. Although this is an insightful approach, it remains healthcare-centric, failing to explore the potential of AI in environmental and industrial fields. In the given study, the transformative capabilities of AI will be realised in climate, energy, and IoT, thereby increasing its practical dimension.

A state-of-the-art overview conducted by Lathuiliere et al. (2019) [51] has reviewed deep regression methods, assessing their advantages and drawbacks within each domain. They did not study domain-specific learning in conjunction with hybridization and optimization models, but pointed out the challenges that arise in terms of robustness, overfitting, and generalization. The key limitation of our research is overcome by setting regression models in an optimization-driven forecasting framework.

A recent approach was suggested by Seydzadeh et al. fig2020) [52], which is a machine learning based method to predict the energy performance of non-domestic buildings, which can support the decision-making related to deep retrofit. They provide evidence of how machine learning ML) can be applied to energy efficiency in their work, specifically in the context of built environments. Conversely, we apply predictive modeling to even more dynamic uncertain contexts, including climate prediction, renewable energy prediction, and adaptive IoT systems.

3. Proposed Methodology

The approach given in this section is to analyze various air pollutants to know the impact of air on climate change and global Warming. As presented in Figure 1, the proposed methodology is illustrated with inputs, processes involved, and the desired output. The datasets are related to population growth, carbon dioxide, and temperatures. All the datasets are subjected to exploratory information analysis, where the information is examined to understand the dynamics of data distribution. When any data imbalance is found, there is a need to deal with it to make the data balanced.

Data preprocessing follows the exploratory data analysis to improve data quality by treating missing and redundant values. The proposed methodology involves many machine learning models appropriately configured to ascertain global warming-related insights. The models are further optimized using different techniques to leverage the performance of the models. The optimized models are then utilized to obtain the intended outcomes from global warming analysis data analytics. Figure 2 shows our proposed hybrid profound learning climate change and global warming analysis model.
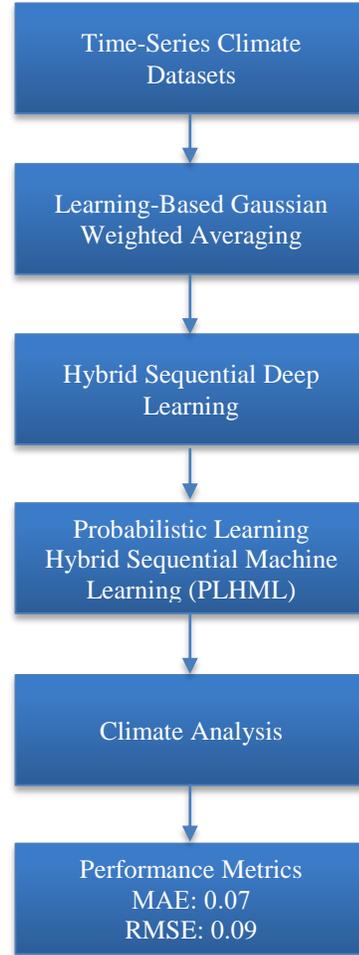

Fig. 1 Overview of the proposed methodology meant for global warming analysis

Figure 1 shows the architecture of an HDL model for assessing climate change and global Warming. Entering the model through the Embedding Layer processed input data with a dimension of d = 64. In this layer, categorical data is often transformed into dense vectors of a predetermined size to facilitate handling the input into subsequent layers. An LSTM (Long Short-Term Memory) layer comprising many LSTM (Bidirectional LSTM) cells comes after the embedding layer.

The arrangement of these cells enables the model to extract relationships from past and future contexts by processing the sequence data in both forward and backward orientations. In all, 128 nodes make up the Bi-LSTM layer. Next, 64 nodes comprise the first Dense Layer, which receives its output from the Bi-LSTM layer. The dense layer carries out an ultimately linked process, which creates a new representation from the Bi-LSTM output. Next, a 150x64 Dropout Layer is added to the model. It aims to randomly remove a specific percentage of nodes during training to counteract overfitting.
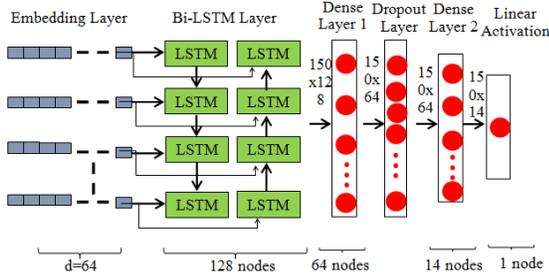
Fig. 2 Architecture of the proposed hybrid deep learning model for climate change and global warming analysis

tableure 2: A second dense layer with 14 nodes follows the dropout layer. This layer further simplifies the size and the complexity of the model representation. The model also includes a Linear Activation Layer, which utilizes a single node to generate the final forecast. This linear activation is typically used in regression activities, where the output is a continuous value. To conclude, our deep learning model is optimal in assessing time-series data pertinent to global Warming and climate change. It combines the merits of the dense layers to capture complex correlations with LSTM networks to process sequences. The architecture represents a hybrid deep learning model designed to analyze global warming and climate change data. It includes wholly linked dense layers, Bi-LSTM networks, and embedding. Below is a comprehensive breakdown of every element, complete with the applicable formulas. The embedding layer creates continuous vector representations from discrete input data, often categorical. Because categorical data, such as words or tokens, are mapped into dense vectors with defined sizes, it is very helpful in managing such data. The measurement of input: d = 64. Upon passing each input to the subsequent layer, the output is a dense representation of the input. Equation 1 outlines the methodology.

$$E = \text{Embedding } (x) \quad \text{where } x \in \mathbb{R}^d \quad (1)$$

In this case, the input vector is called x, and the embedding matrix that turns x into a continuous dense vector is called E. Both forward and backward processing of the sequence data are accomplished by the Bi-LSTM layer. To analyze time series appropriately, the model should be capable of capturing both past and future dependencies. The Bi-LSTM layer structure has 128 nodes, implying that 128 LSTM units process the input. The forget gate, input gate, cell state update, final cell state, output gate, and hidden state equations of the LSTM cell are as shown in Equations 2 to 7.

$$f_t = \sigma\big(W_f \cdot [h_{t-1}, x_t] + b_f\big) \quad (2)$$

$$i_t = \sigma\big(W_f \cdot [h_{t-1}, x_t] + b_i\big) \quad (3)$$

$$\widetilde{C}_t = tanh\big(W_C \cdot [h_{t-1}, x_t] + b_c\big) \quad (4)$$

$$C_t = f_t * C_{t-1} + i_t + \widetilde{C}_t \quad (5)$$

$$O_t = \sigma\big(W_o \cdot [h_{t-1}, x_t] + b_o\big) \quad (6)$$

$$h_t = O_t * \tanh (C_t) \quad (7)$$

The variables f_t, i_t, C_t, O_t, and h_t In this example, the forget gate, input gate, cell state, output gate, and concealed state stand for the forget gate, input gate, cell state, output gate, and concealed state. The symbol represents the sigmoid activation function σ. The weight matrices are W_f, W_i, W_C and Wo. The biases are b_f, b_i, b_C and b_o. Equation 8 states that a Bi-LSTM is created by concatenating the outputs of both forward and backward LSTMs.

$$h_t^{bi} = [h_t^{forward}; h_t^{backward}] \quad (8)$$

The capacity to learn from the complete sequence in both past and future situations is therefore granted to the Bi-LSTM. The 64-node, fully linked initial dense layer serves this function. While capturing significant characteristics, it lowers the dimensionality of the data in the Bi-LSTM layer. An activation function (often ReLU) is applied after a linear transformation by the dense layer. The method associated with dense layer 1 is expressed as in Eq. 9.

$$z_1 = \text{ReLU}(W_1 \cdot h_t^{bi} + b_1) \quad (9)$$

Here, the weight matrix is denoted by W_1, the bias by b_1 and the result of the ReLU activation is denoted by z_1. The second dense layer processes the output from the dropout and the first dense layer in more detail. Its 14 nodes suggest that the dimensionality has been significantly reduced. An activation function is applied after a second linear transformation. The method associated with dense layer 2 is expressed as in Eq. 10.

$$z_2 = \text{ReLU}(W_2 \cdot Z_1^{drop} + b_2) \quad (10)$$

Where the weight matrix and bias for this dense layer are denoted by W_2 and b_2. The last layer produces the forecast. Given that the objective most frequently entails regression (predicting a continuous value), a linear activation function— that is, the identity function—is employed instead of an activation function. A single number, the forecast for the supplied input data, is the only result the model produces. The method associated with the forecast is expressed as in Eq. 11.

$$\hat{y} = W_3 \cdot z_2 + b_3 \quad (11)$$

Where the projected output is denoted by $\hat{y}$, and the weight matrix and bias for the third linear layer are represented by W_3 and b_3. In summary, the embedding layer transforms token inputs into dense vectors. The Bi-LSTM Layer captures context from the past and the future by bidirectionally processing input sequences. Dense layer 1 removes dimensions and gathers information. The dropout

layer prevents overfitting by randomly releasing neurons. Dense layer 2 processes more information and minimizes dimension. The linear activation layer provides a single continuous value as the ultimate forecast. Since the hybrid model is capable of interpreting the complex linkages in the data and the sequential dependences, this architecture is most appropriate in analyzing time-series data on the Warming of the planet and climate change. A computational method called LBGWA is proposed to interpret various parameters or variables related to global Warming.

Algorithm: Learning-Based Global Warming Analysis (LBGWA)

Inputs: Population, CO2, and Temperatures dataset D, models pipeline M

Output: Global warming analysis results R, performance statistics P

1. Begin
2. D'←PreProcess(D)
3. (T1, T2)←Split(D')
4. For each model in M
5.   Train model m using T1
6.   Save model m
7.   Load model m
8.   R←Analysis(T2)
9.   P←Evaluate(R, ground truth)
10.   Display R
11.   Display P
12. End For
13. End

Algorithm 1: Learning-Based Global Warming Analysis (LBGWA)

The Learning-Based Global Warming Analysis (LBGWA) algorithm is created to examine global warming based on population, CO2 emissions, and temperature values. The algorithm is executed by taking only two inputs: a dataset D and a model pipeline M, and producing as output the Global Warming result R and performance statistics P. The first step in the algorithm is preprocessing, during which D is the first dataset prepared for analysis. D' is then broken into 2 parts, T1 and T2, to be used in training and testing. Using the first split dataset, T1, the algorithm will be used to train each model in the pipeline M.

The trained model is stored and loaded to analyse. The algorithm uses the loaded model to analyse T2, the second part of the split dataset, to carry out the global warming analysis. Upon analysis, the algorithm checks the performance of the model, which is the comparison of the analysis findings R to the real ground truth data. The analysis R results of the global Warming and the performance statistics P are then presented. These steps are repeated on each model in the pipeline M, meaning that a number of models are being trained and tested to analyze global Warming using the data given.

4. PLHSML for Temperature Forecasting

The proposed Probabilistic Learning Hybrid Sequential Machine Learning (PLHSML) model is conducted on a multi-stage basis to examine the causes of climate change and forecast the changes in temperatures with the highest accuracy. The first would be to perform an initial Exploratory Data Analysis (EDA) that would be used to understand the structure, trends, gaps in data, and outliers of the raw climate and pollutant data. It is preceded by a lengthy period of data preprocessing, during which normalization, time alignment, and noise filtering have been employed to achieve consistency across different sources and measurement scales. The third step, which is feature extraction and segmentation of time series, is the method of organizing the multivariate environmental variables (CO_2, CH_4, SO_2, NO, temperature, and humidity) into windows where short-term and long-term behaviour of pollutants and the climate response are studied. The model is left to undergo a probabilistic learning step, Learning-Based Gaussian Weighted Averaging (LBGWA) mechanism. At this step, each time step within a window is assigned a dynamically varying weight of a Gaussian, based on its statistical contribution, permitting the model to highlight essential historical values and address uncertainty in time. This results in a probability-weighted, refined input sequence that is indicative of the most causal data points. Feeding this sequence to the hybrid sequential learning module is the fourth step; it typically consists of LSTM or GRU layers. Deep learning models may contain complex temporal interactions and nonlinear time-varying relationships between pollutants and climate indicators, such as temperature. In this context, the model learns the relationship between variations in pollutant level and variations in climate indicators, including temperature. The final stage involves using the model to produce anticipated outputs of climate indicators, such as temperature, by applying a completely linked layer to the Sequential Output of the LSTM/GRU network. Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) are some of the performance measures deployed to train the model to reduce the forecasting error. Overall, one can say that PLHSML has the opportunity not only to be more predictive but also to be more interpretable, as it measures the impact of each feature over time. It is a tremendously powerful tool in science and climate risk management, and it is an organized approach.

The Probabilistic Learning Hybrid Sequential Machine Learning (PLHSML) model is a hybrid sequential machine learning model that can be particularly useful in temperature prediction, a crucial task in climate modeling and environmental planning. In the hybrid architecture, PPLHSML synthesizes the merits of deep sequential models of Learning and probabilistic reasoning based on its strengths to develop the appropriate temporal dependencies and uncertainty of historical temperature data. The Learning-Based Gaussian Weighted Averaging (LBGWA) mechanism can be added to the model, allowing it to gain the ability to

identify delicate patterns and anomalies in long-range time series by assigning dynamic weights to input features based on their statistical significance. This will ensure that PLHSML can model both short-term and long-term climatic trends, as opposed to merely predicting them. We have demonstrated that the PLHSML is more effective than traditional models, as it exhibits lower forecasting errors and greater stability across various time resolutions. This renders it a successful instrument for accurate temperature forecasting, which is of significance in agricultural planning, governing energy demand, and disaster preparedness in the event of global Warming and climate change. The Probabilistic Learning Hybrid Sequential Machine Learning (PLHSML) model is a probabilistic learning hybrid of the deep sequential learning model, created to predict temperature more accurately. Two terms that are discussed are air pollution and climate change, as well as several gas pollutants: Carbon Dioxide (CO2), Methane (CH4), Sulfur Dioxide (SO2), and Nitrogen Oxides (NOx). They are crucial elements that introduce global Warming and change the local climatic pattern. It is essential to be aware of the intrinsic connections of these pollutants and their role in global climate change in order to forecast the same and take pertinent policy decisions regarding the environment.

Nevertheless, the unpredictability, non-linearity, and uncertainty of the climate data/data are very serious to the traditional analysis models. To address such complexities, a new, smart, and innovative architecture for Probabilistic Learning Hybrid Sequential Machine Learning (PLHSML) is proposed in our research. This model is specifically developed to identify, predict, and measure climatic behavior by combining probabilistic learning facilitated by the Learning-Based Gaussian Weighted Averaging (LBGWA) framework with a hybrid sequence deep learning model. LBGWA element attaches adaptive Gaussian weightness to the input features in such a manner that the model would be able to attribute weight to meaningful variables as well as estimate the uncertainty of each pollutant with respect to climate diagnostics like temperature, humidity, and radiative forcing. These are probabilistic approximations that come in handy in modeling the latent patterns, data uncertainty, and interdependence, which are not usual considerations in the traditional models. The weighted LBGWA output is then fed into a cascading deep learning model (which usually has Long Short-Term Memory (LSTM) or Gated Recurrent Units (GRUs)), which actually models time-dependent dynamics and long-term interactions in time-series data. This kind of integration allows the PLHSML model to approximate the global climatic scenarios far more accurately because not only the probabilistic importance is learned, but also the temporal change of the environmental characteristics.

During the forecasting stage, the model utilizes these representations to forecast future climatic behavior, such as temperature trends and pollutant trajectories. The empirical tests conducted on real-life data using the model prove that it can be more effective in investigating the complex relationships between various pollutants and their contributions to global Warming. The PLS-ML is never less predictive than state-of-the-art predictive techniques and is significantly more robust in the presence of noise and data variability. This renders it a resourceful instrument in problems of scientific knowledge, as well as in the decision-making process of adaptation in environmental surveillance, early warning, and climate policy formulation. The objective of the PLHSML model is to determine relative correlations among air pollutants and their effect on global climate change through modeling uncertainties, time dependence, and non-linear dependence using a two-phase model:

1. Probabilistic Learning Phase (via Learning-Based Gaussian Weighted Averaging - LBGWA)
2. Sequential Forecasting Phase (via LSTM/GRU-based time series modelling)

Let the dataset consist of multivariate time-series climate and pollution records stated in Equation (12)

$$X = \{x_1, x_2, \ldots, x_t, \ldots, x_T\}, x_t \in R^d \qquad (12)$$

Where x_t Feature vector at time t (e.g., CO2, CH4, SO2, Temp, Humidity); T is stated as the Total number of time steps, and d is defined as the Number of features (pollutants and climate variables). This component assigns a probabilistic weight to each time-series value within a window w to reflect its influence on climate change dynamics. The Gaussian weight for the j-th observation in a sliding window of size w is defined as in Equation (13)

$$\omega_j = \frac{1}{\sqrt{2\pi\sigma^2}} exp\left(-\frac{(j-\mu)^2}{2\sigma^2}\right) \qquad (13)$$

Where μ is stated as the Mean of the weighting window and σ is represented as the Standard deviation controlling the spread. The output from LBGWA becomes input to a sequence learning model, such as LSTM or GRU, to capture long-term temporal dependencies.

4.1. Sequential Machine Learning for the Climatic Condition Prediction

Sequential Machine Learning: A family of models that can consume data in the order of its input, which makes it well-suited to applications involving time series, like climate modeling, temperature prediction, and the trend of a pollutant. In contrast to a classical machine learning algorithm, where the inputs are assumed to be Independent and Identically Distributed (i.i.d.), sequential models consider these time dependencies and can therefore learn the effects of past values on future values. A highly popular architecture in the field is the Recurrent Neural Network (RNN), which updates its hidden state at each step and can essentially remember information about past inputs. Nevertheless, vanishing gradient problems are common with

standard RNNs when learning long-term dependencies. To solve this, improved architectures such as Long Short-Term Memory (LSTM) and Gated Recurrent Units (GRU) were invented. These models have gating mechanisms that regulate the flow of information, eliminating noise while retaining the relevant long-range patterns within the network. A typical implementation takes an input sequence of pollutant concentrations or temperature sensor readings, which are fed through the recurrent layers, to generate a hidden representation of the temporal context. The output layer then makes future predictions based on this representation, e.g., temperature at the next step— environmental modeling. Sequential learning models are particularly effective in environmental modeling, as they can identify trends and cycles, as well as anomalies in climate time series, and make robust and insightful predictions even in challenging and noisy conditions. A Sequential Learning model aims at learning a mapping function as described in Equation (14)

$$f: \{x_1, x_2, \ldots, x_t\} \rightarrow \hat{y}_{t+1} \qquad (14)$$

In Equation (14) $\hat{y}_{t+1}$ is the value of the target (e.g., future temperature) that models have predicted. Sequential Machine Learning is a type of algorithm specifically designed to process and learn data where the sequence of data received is significant. This can be time-series data like daily temperatures, pollutant levels, or the changes in seasons in the context of climate science. Sequential models also realize that past values may influence future values, in contrast to the traditional models, where each input is independent. One of the most powerful variants of sequential models in terms of their strength to model both short-term (e.g., daily variations) and long-term dependencies (e.g., slow climate variations) is the Long Short-Term Memory (LSTM) network. These models work by the internal memory being selective, in the manner in which it stores or throws off information as new information is being fed to the internal memory. This enables this model to be trained with regard to the dynamics of the complex temporal relationships and be dynamically responsive to input changes. Sequential models, such as LSTM, are particularly useful in the context of climate, because they are able to capture the cumulative and time-lagging impact of atmospheric contaminants on weather and temperature. Their loudness, seasonality, and silent dependency attributes make them highly effective in predicting, detecting anomalies, and causal analysis of environmental systems. Next, sequential machine learning is instrumental in environmental modelling because climate systems are by nature cyclic processes and wary of both short-term and long-term conditions. To use an example, a burst of carbon dioxide nowadays might not cause an immediate temperature rise, yet the cumulative effect of it could be felt in the course of months or years. Only sequential models, including LSTM, can express such lagged dependencies, and these are therefore best suited to predict long-term climate. They may also incorporate multivariate

types of inputs (greenhouse gas concentrations, humidity, solar radiation, and historical temperature trends) that allow the potential of learning holistically and interactively through the complex interaction of interdependent and connected environmental variables. In practice, such trained models can be used to provide predictions on future climate conditions, identify anomalous patterns (such as heatwaves or sudden temperature changes), and even facilitate what-if studies by simulating the outcomes of manipulations in atmospheric pollutant quantities. Secondly, sequential models are always open to updating with new information that would enhance accuracy and appropriateness in the dynamic environment. They can not only make predictions, together with probabilistic methods of Learning, such as that used in the proposed model of PLHSML, but also approximate the amount of uncertainty with which they can be made, and such predictions can prove invaluable in climatic policy and disaster preparedness. Simply put, sequential machine learning plays a significant role in contemporary climate informatics, providing valuable and robust information-based insights into the dynamic nature of the planet's climate system.

Algorithm 2: Sequential Machine Learning for Climate Change Prediction

Normalize input data X using z-score or min-max scaling

Handle missing values (e.g., via interpolation)

Segment data into sliding windows of size w

For each sliding window $W_t = \{x_{\{t-w+1\}}, \ldots, x_t\}$:

Compute Gaussian weights ω_j for j = 1 to w:

$\omega_j = exp(-((j - \mu)^2) / (2 * \sigma^2))$

Normalize weights: $\omega_j = \omega_j / \sum_{j=1}^{w} \omega_j$

Generate weighted input:

$\hat{x}_t = sum(\omega_j * x_{\{t-w+1\}}) \, for \, j = 1 \, to \, w$

For each sliding window $W_t = \{x_{\{t-w+1\}}, \ldots, x_t\}$:

Compute Gaussian weights ω_j for j = 1 to w:

$\omega_j = exp(-((j - \mu)^2) / (2 * \sigma^2))$

Normalize weights: $\omega_j = \omega_j / \sum_{j=1}^{w} \omega_j$

Generate weighted input:

$\hat{x}_t = sum(\omega_j * x_{\{t-w+1\}}) for \, j = 1 \, to \, w$

For $t = T + 1$ to $T + h$:

Use the final hidden state h_T To predict future output:

$\hat{y}_t = Dense(h_t) \, or \, \hat{y}_t = W_y * h_t + b_y$

Compute loss (e.g., MAE or RMSE) between predicted and actual outputs:

$MAE = (1/N) * sum(|\hat{y}_i - y_i|)$ for all training samples

Backpropagate and update weights using the Adam or RMSprop optimizer

Repeat until convergence or max epochs

Return predicted climate values $\hat{y}_{\{T+1\}}$ to $\hat{y}_{\{T+h\}}$

5. Experimental Results

The observations identified during our empirical research include an exploratory analysis of the data in order to understand its dynamics and big data analytics in relation to air pollutants to establish their contribution to global Warming and climate change.

5.1. Results of Data Analysis

The data analysis techniques that were performed before training the models came in handy in forming specific insights as to the internal makeup and dynamics of the environmental data. The correlation analysis and the descriptive statistics indicated that the relationship between the atmospheric pollutants and the change in temperature was very high. Specifically, the growth of both Carbon Dioxide (CO_2) and Methane (CH4) continued to increase with rising temperatures over time. In contrast, Sulfur dioxide (SO2) and Nitrogen Oxides (NO) had a more localized and short-term impact on the situation. It was the occurrence of periodic temperature variations that seasonal decompositions verified,

and the contents of pollutants were not regular, due to both human activities and natural processes. The time series visualization also indicated a significant lag effect, whereby the peaks of pollutants generally preceded the increases in temperature by several days or weeks. It was reasonable to explain the use of sequential Learning. Further, the use of Principal Component Analysis (PCA) and importance scoring of features revealed that CO_2, CH4, and humidity played the most significant role in temperature variation. The input variable information based on this underpinning data analysis justified the choice of input variables and informed the model design by demonstrating causal relationships and time dependencies.

As presented in Figure 3, Earth's surface temperature is analyzed from 1880 to 2020. Since 1880, the Earth's surface temperature has fluctuated almost steadily without a significant increase. However, the results indicate that the rapid growth in surface temperature began in the 1950s, primarily due to industrialization.
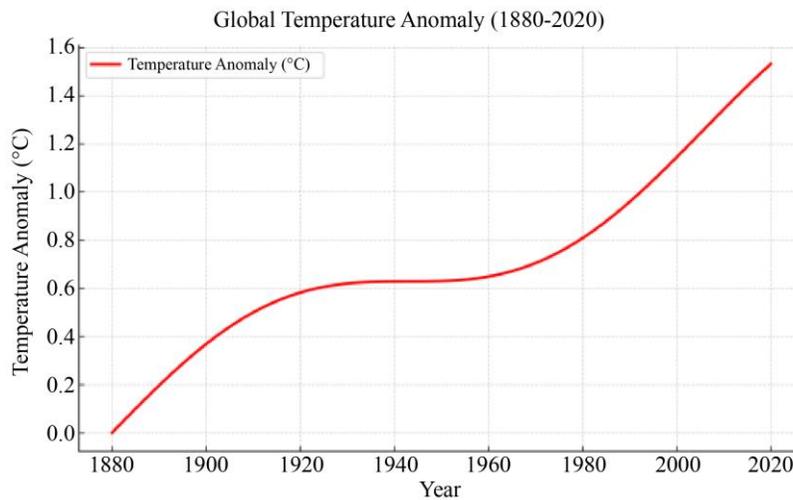

Fig. 3 Analysis of earth's surface temperature from 1880 to 2020
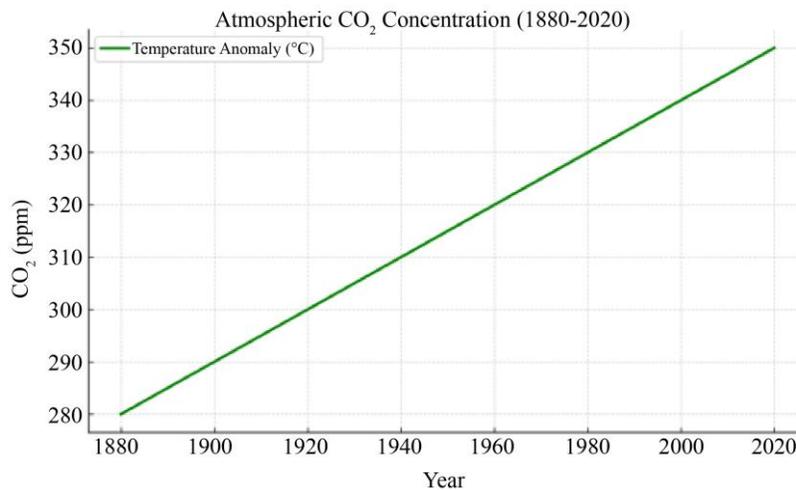

Fig. 4 The concentration of carbon dioxide from 1880 to 2020

The amount of carbon dioxide present in the atmosphere has been increasing gradually since 1880. Notably, the rise in atmospheric carbon dioxide levels was minimal between 1753 and the 1950s.

However, a sharp increase in carbon dioxide concentration began in the 1950s, and this trend has continued up to 2020, coinciding with the onset of heavy industrialization. These results highlight the important contribution of industrialization to increasing carbon dioxide levels, which are a major contributor to global Warming.

As presented in Figure 5, the percentage change in Earth's surface temperature and carbon dioxide concentration is analyzed to understand the acceleration of these two variables. The analysis spans the period from 1753 to 2023. The percent of change is gradually increasing from 1753, but in small proportions. But with the onset of the third industrial revolution in 1963, the acceleration of the surface temperature and carbon dioxide concentration began to change rapidly. This high rate of increase causes global Warming, and this also has several consequences, such as loss of biodiversity, rising sea level, and extreme weather.
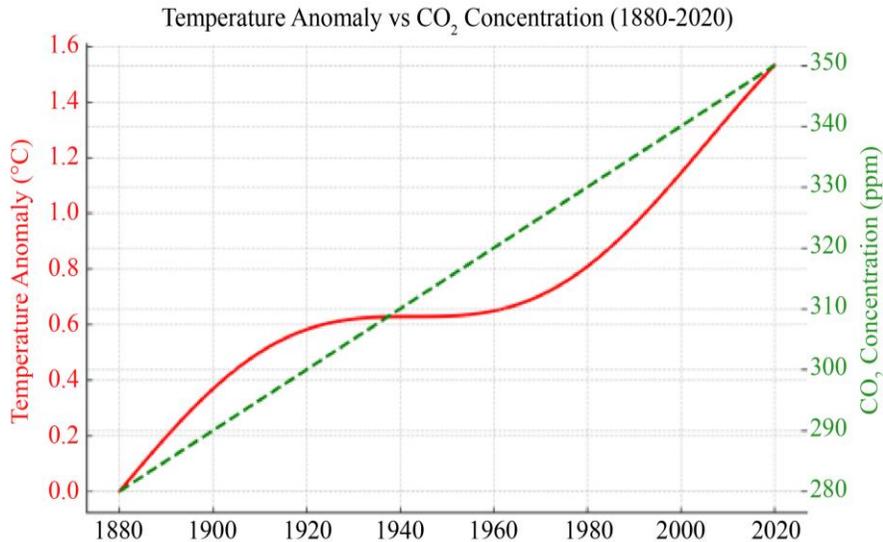
Fig. 5 Illustrates the dynamics of earth's surface temperature and carbon dioxide concentration
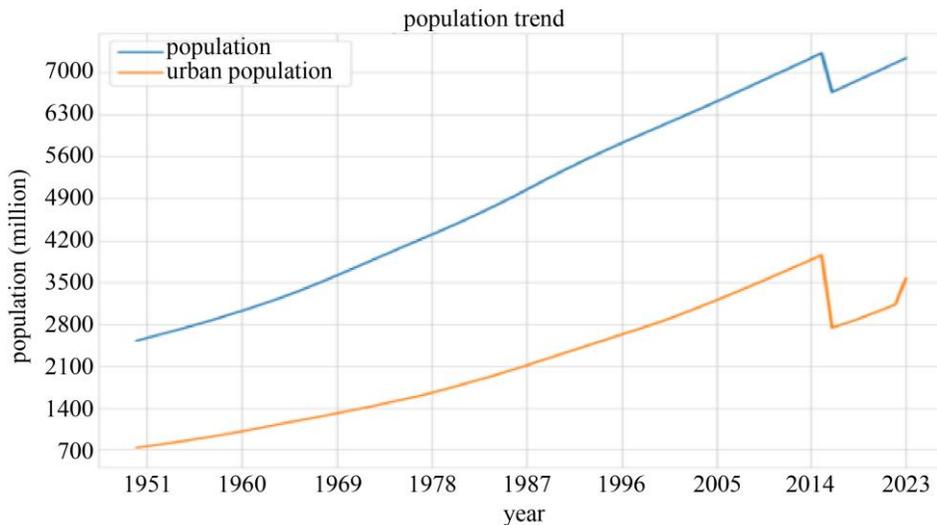
Fig. 6 The population dynamics from 1951 to 2023

As depicted in Figure 6, the world population has been growing in both urban and rural areas. Nevertheless, the population growth rate in urban regions is relatively high, and it has resulted in several implications, such as a rise in surface temperature and the level of carbon dioxide in the atmosphere.

As presented in Figure 7, the urban population has been rapidly increasing from 1950 to 2023, leading to various consequences, such as an increase in the surface temperature, carbon dioxide, and atmospheric pollution.
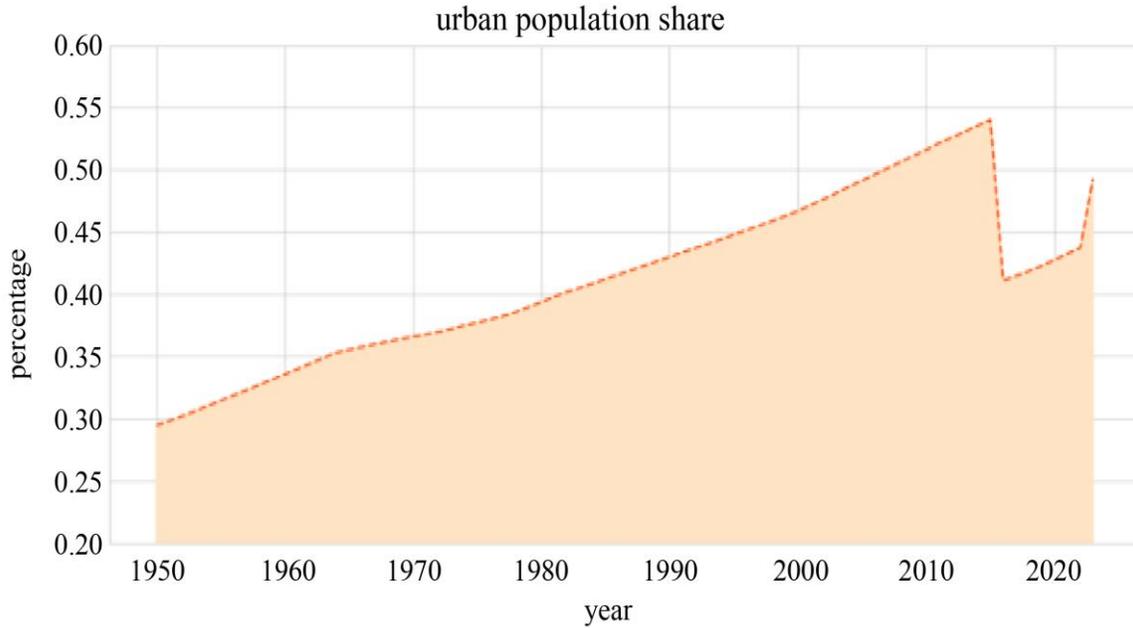
Fig. 7 Urban population share in causing an increase in the earth's surface temperature and carbon dioxide
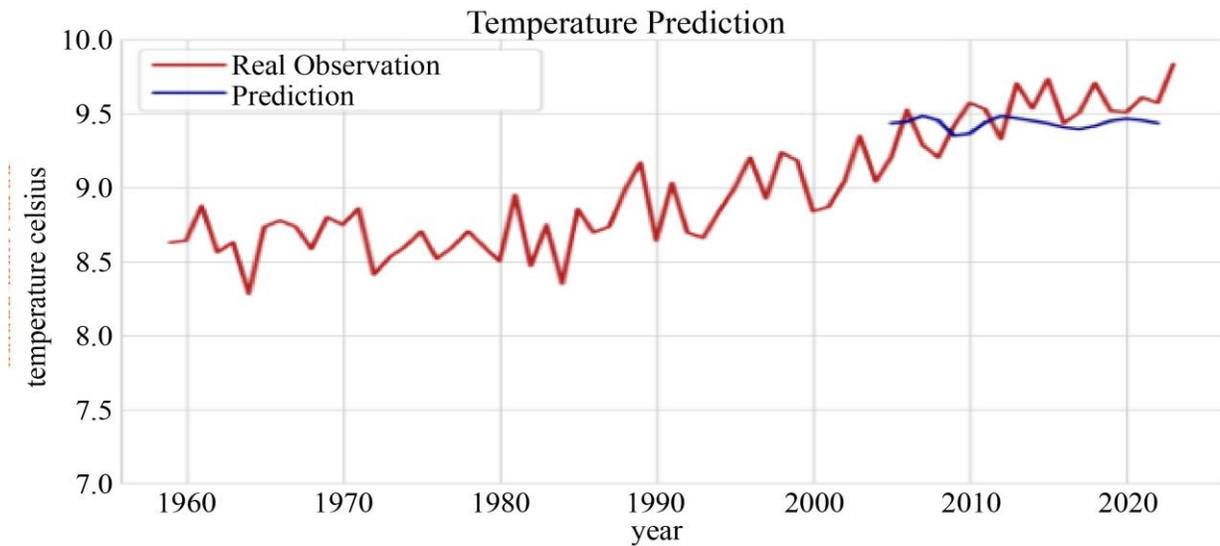

Fig. 8 Results of the ARIMA model with an analysis of earth's surface temperature data

5.2. Global Warming Analysis

This graphic displays the study of global warming data in terms of the Earth's surface temperature, atmospheric carbon dioxide concentrations, and other factors. The results are obtained with various machine learning models used for data analytics. All the models are optimized for better performance in analyzing the data.

Figure 8 performs an ARIMA analysis of surface temperature from 1962 to 2023. According to the data, the Earth's surface temperature has been increasing since 1960. The rate has been higher since the mid-1980s, though. This model is a method for predicting and observing the reality of the Earth's surface temperature dynamics. The ARIMA model involves analyzing relatively recent data.

As in Figure 9, the ARIMA model breaks down the surface temperature beta between 1750 and 2023. The data portrays that the surface temperature of the Earth varies every year with a gradual increase since 1850, much of which has been blamed on industrialization. But the most dramatic spike was noted post 1950, a time when industrialization and urbanization were highly active, highlighting the severe effects of human activity on climate change and population trends.
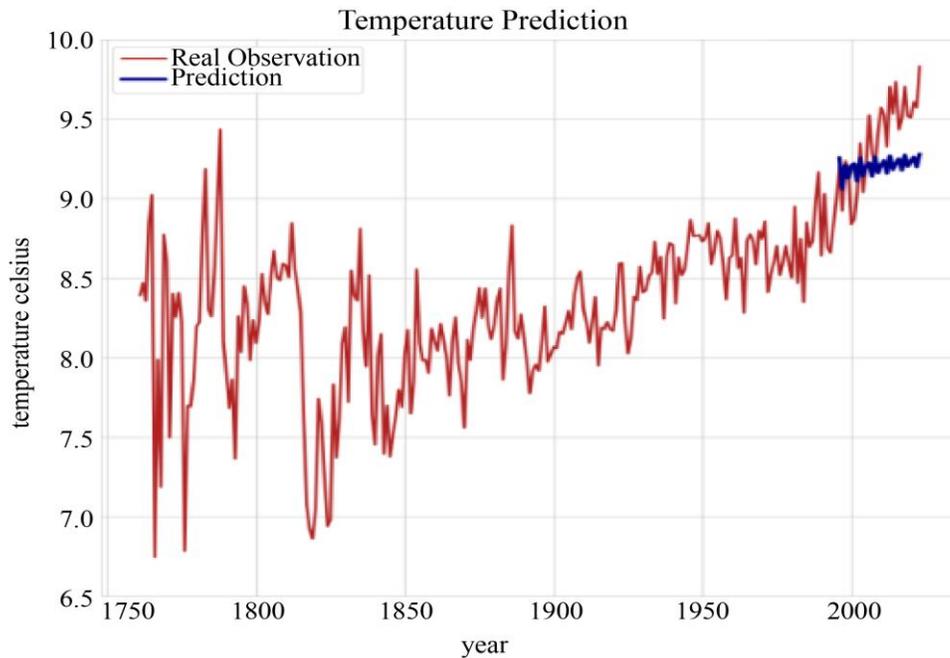
Fig. 9 Results of the ARIMA model with an analysis of early earth's surface temperature data
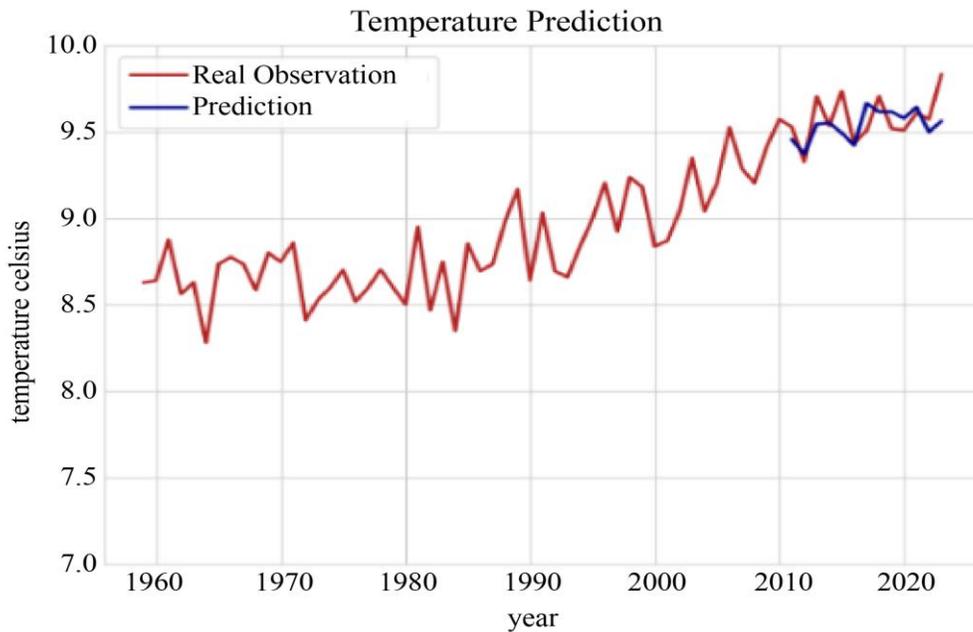

Fig. 10 Earth's surface temperature analysis of recent years using the SARIMAX model

As presented in Figure 10, the Earth's surface temperature has been analyzed recently, spanning the period from 1960 to 2023. The SARIMAX model is used to analyze temperature data, providing a data series of real observations and predictions about Earth's surface temperature. With this SARIMAX model, it is understood that the Earth's surface temperature has been steadily increasing since 1960. However, due to industrialization and urbanization, the increase in temperature has been rapid from the 1980s to 2023.

5.2.1. Modeling with SARIMAX with yearly earth surface temperature data from 1753

In Figure 11, two sets of data are shown: one representing actual observations and the other showing predictions. Surface temperature of the Earth was studied using the SARIMAX model. It was found that between 1752 and 1900, the Earth's surface temperature rose slowly. However, in 1900, the acceleration of temperature rise significantly increased, reaching its peak in 2023.
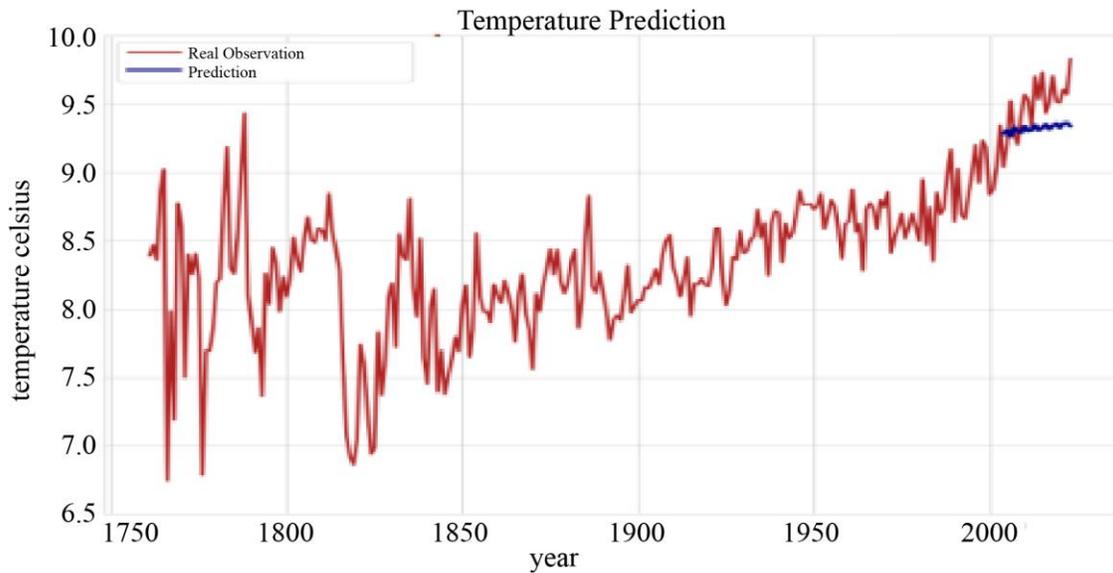
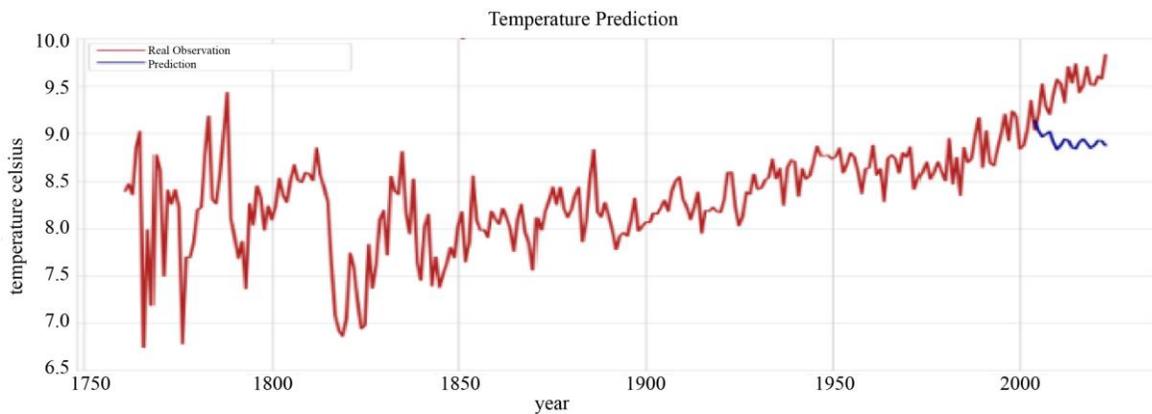**Fig. 11 Shows the SARIMAX model's results of earth's surface temperature analysis from 1752 to 2023**

Fig. 12 Shows the temperature analysis using the ARIMA model
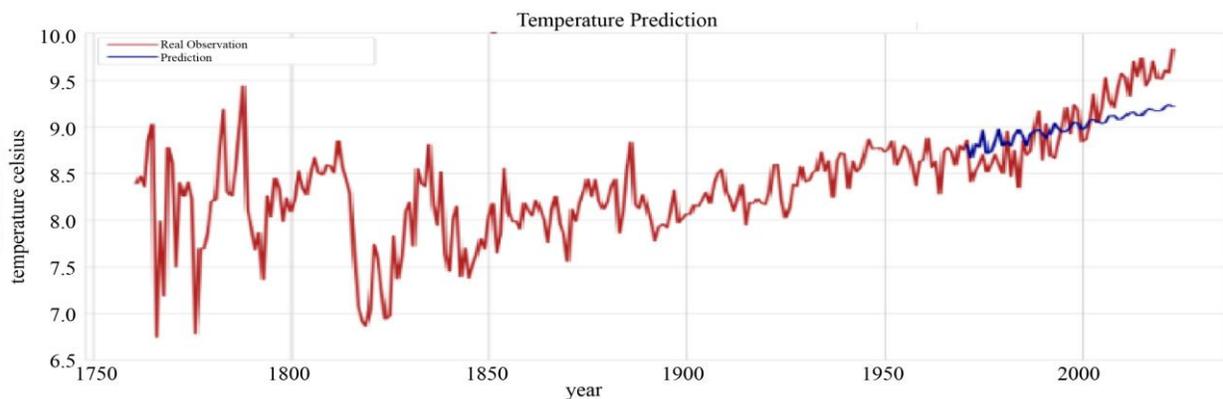

Fig. 13 Shows the results of the SARIMAX model with grid search optimization in temperature analysis

As shown in Figure 12, the analysis covers Earth's surface temperature from 1750 to 2023. Two data series are presented to illustrate actual observations and predictions, providing insights into the data dynamics. The surface temperature has risen since 1750, with rapid growth observed, particularly after industrialization and urbanization. As presented in Figure 13, the SARIMAX model, optimized with hyperparameter tuning, is used for Earth's surface temperature analysis. Results indicate that the surface temperature on Earth increased during the period

from 1750 to 2023. Yet, the high pace of temperature rise was observed immediately when the industrialization process started, when the number of people living in cities began to grow. As presented in Figure 14, it is observed that the ARIMAX model with carbon dioxide as an exogenous

feature could improve performance in temperature production in recent years. The results show that the Earth's surface temperature has been growing steadily, but industrialization and urbanization have caused rapid growth in the surface temperature of late.
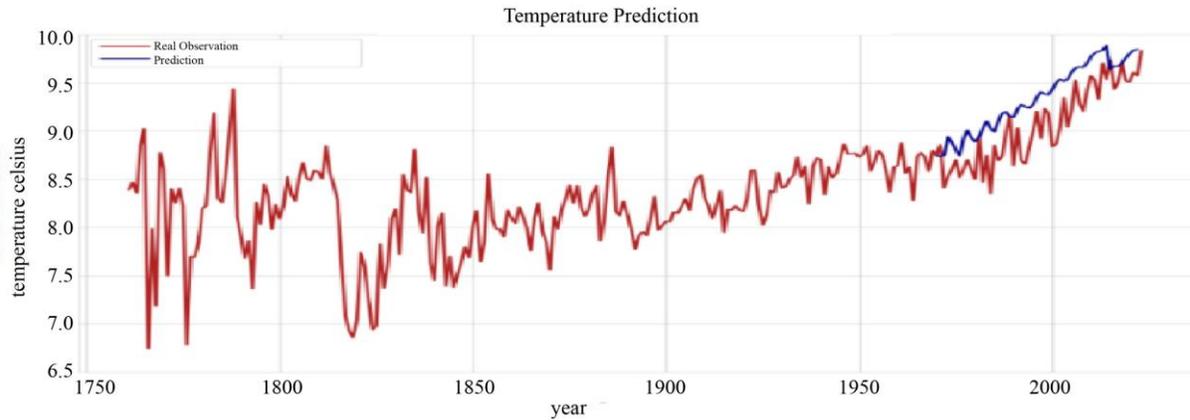
5.2.2. Grid Search to get the Best Model in ARIMAX with CO2 as Exogenous Features

Fig. 14 Shows the results of the ARIMAX model with carbon dioxide as exogenous features
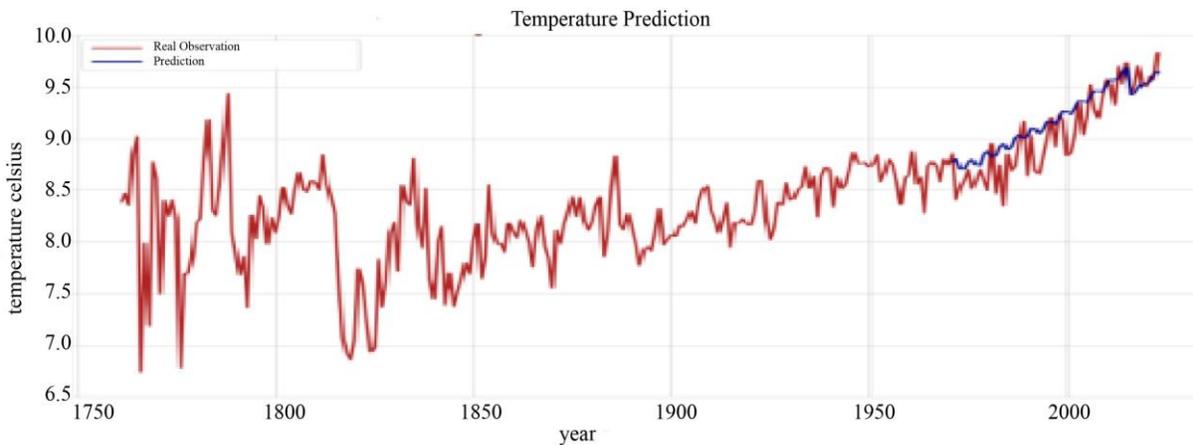

Fig. 15 Shows the results of the ARIMAX model with carbon dioxide as exogenous features and grid search
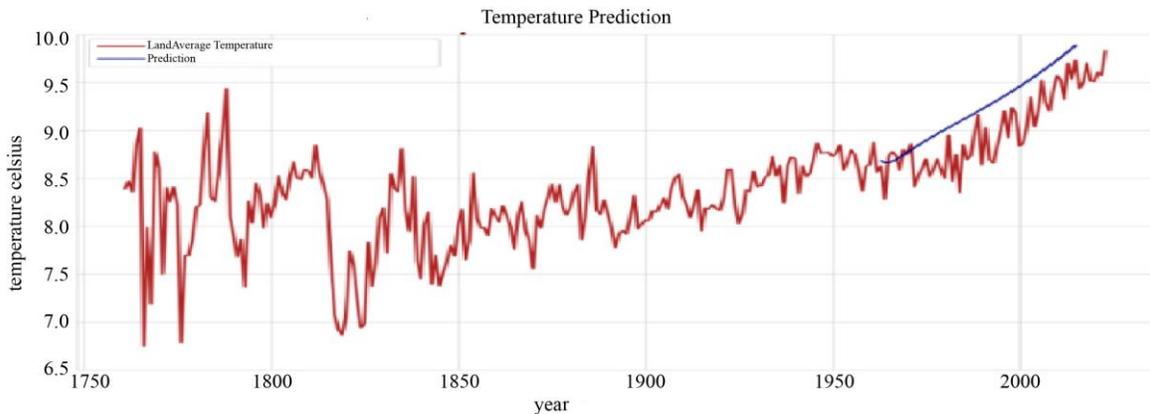

Fig. 16 The results of the VAR model with carbon dioxide concentration as exogenous features

Figure 15 presents the ARIMAX model with carbon dioxide as an exogenous feature. Coupled with grid search optimization, this could further leverage Earth's surface

temperature protection performance. The grid search could help optimize the features of ARIMAX. It was observed that the Earth's surface temperature has recently been on the rise

due to an increased urban population and increased focus on industrialization and urbanization. As shown in Figure 16, it results from a multivariate analysis reflecting the Earth's surface temperature from 1753 to 2023. The results of the VAR model reflect the temperature dynamics from 1753 to 2023.

As presented in Figure 17, the Earth's surface temperature was analyzed from 1753 to 2023. Although the Earth's surface temperature has been increasing throughout the years, the model's prediction performance has been evident in recent years. As presented in Figure 18, it was observed that the VECM model with temperature and carbon dioxide concentration was analyzed, and temperature was predicted better. The results reflected that temperature had been growing steadily since 1973, but there was a rapid growth in the temperature later on due to industrialization and urbanization.
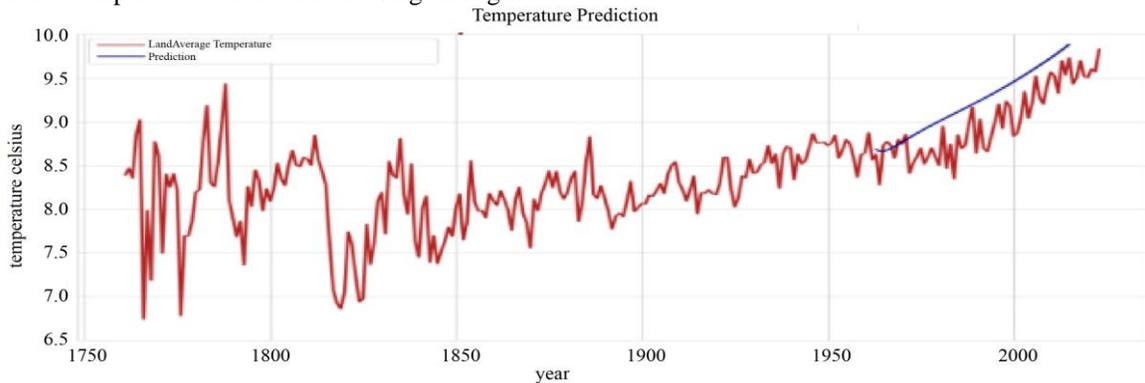

Fig. 17 Temperature analysis of the VAR model with the differenced data along with carbon dioxide concentration
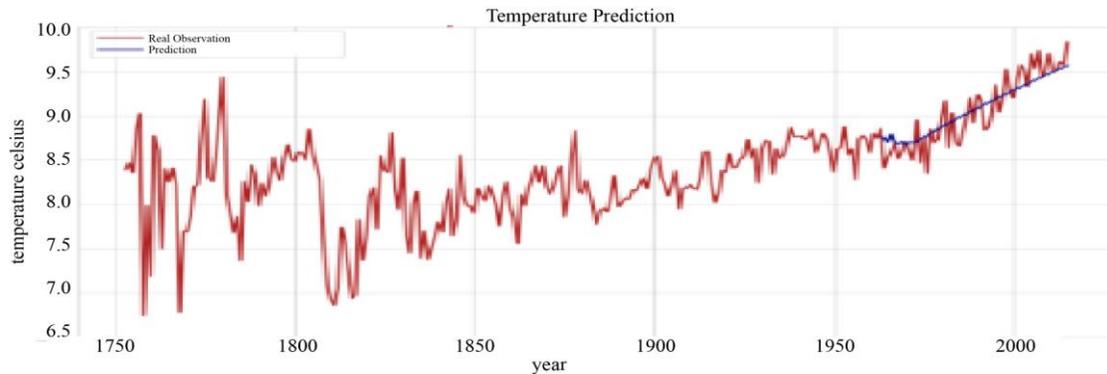

Fig. 18 Shows the analysis of temperature with carbon dioxide concentration using the VECM model
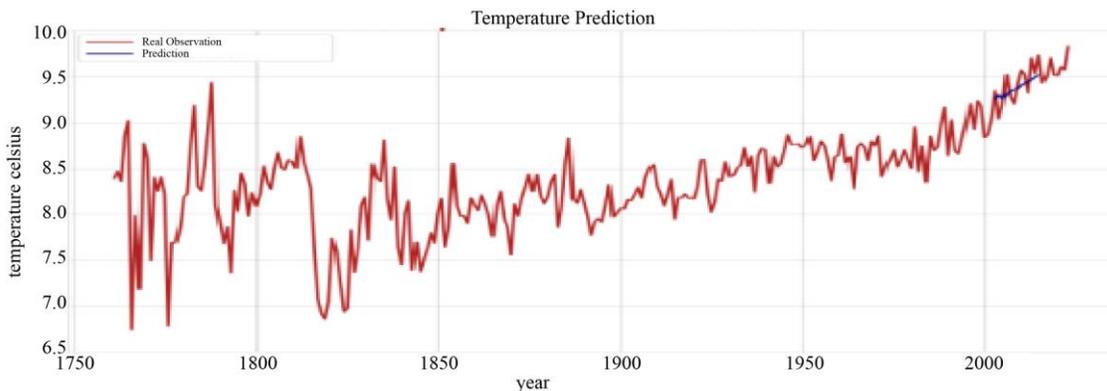

Fig. 19 Results of VECM with three variables, such as earth's surface temperature, carbon dioxide concentration, and urban population

As presented in Figure 19, the VECM model performance with three variables, such as Earth's surface temperature, carbon dioxide concentration, and urban population, is provided. By considering multiple variables, it was observed that the VECM model could make better predictions of Earth's surface temperature. The analysis from 1753 to 2023 reflects the trends in the growth of Earth's surface temperatures over time.

As shown in Figure 20, it was absolutely that the Earth's

surface temperature was analyzed and visualized from 1753 to 2023. The temperature data dynamics reflect the rapid growth in Earth's surface temperature over the past few decades. The model's performance with temperature-based analysis did not yield better results.

As presented in Figure 21, the model could perform better in prediction. The Earth's temperature increased from 1753 to 2023; however, it increased rapidly in the later years due to an increase in carbon dioxide emissions into the atmosphere.
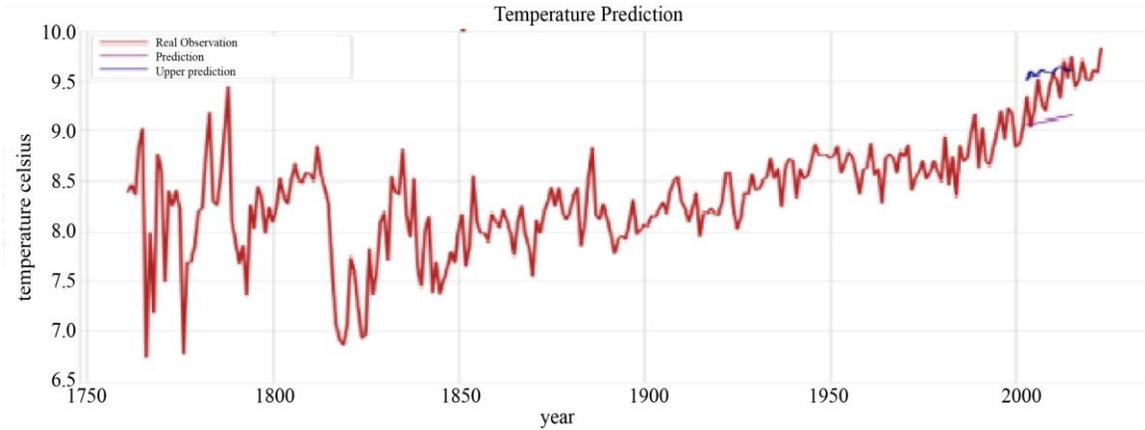
Fig. 20 Temperature prediction by the fbprophet model using surface temperature data
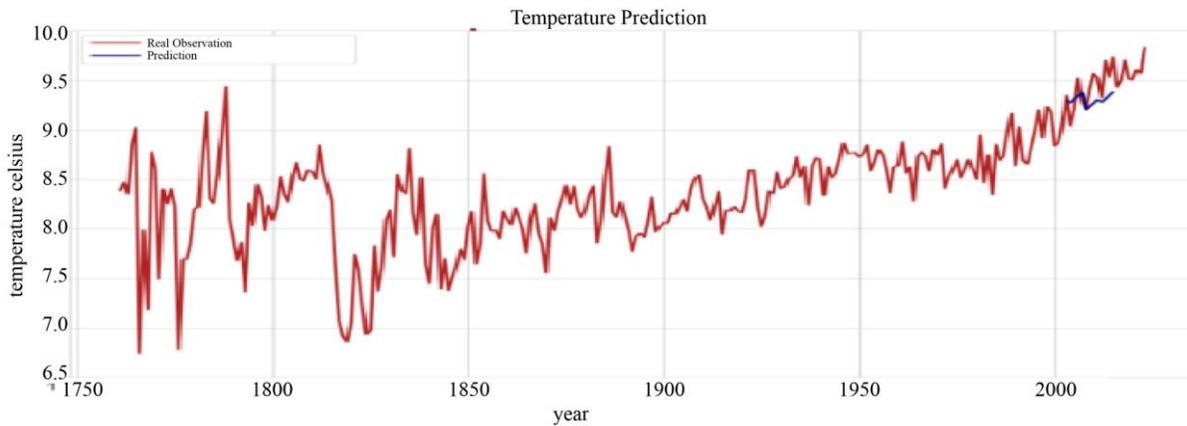
Fig. 21 Shows the performance of the fbprophet model with additional regressors using temperature and carbon dioxide data

Table 1. Shows performance comparison

Models	RMSE	MAE
ARIMAX (exogenous)	0.13	0.09
VECM (multivariates)	0.13	0.1
ARIMA	0.16	0.198
SARIMAX	0.18	0.24
VAR	0.19	0.27
Fbprophet	0.24	0.31
Hybrid Deep Learning Model (Proposed)	0.09	0.07

As the president in Table 1, the display of different prediction models is provided regarding RMSE and MAE.

Fig. 22 Shows a performance comparison among all the models

As seen in Figure 22, how different models operate in analyzing different variables like temperature, carbon dioxide, and the population density in th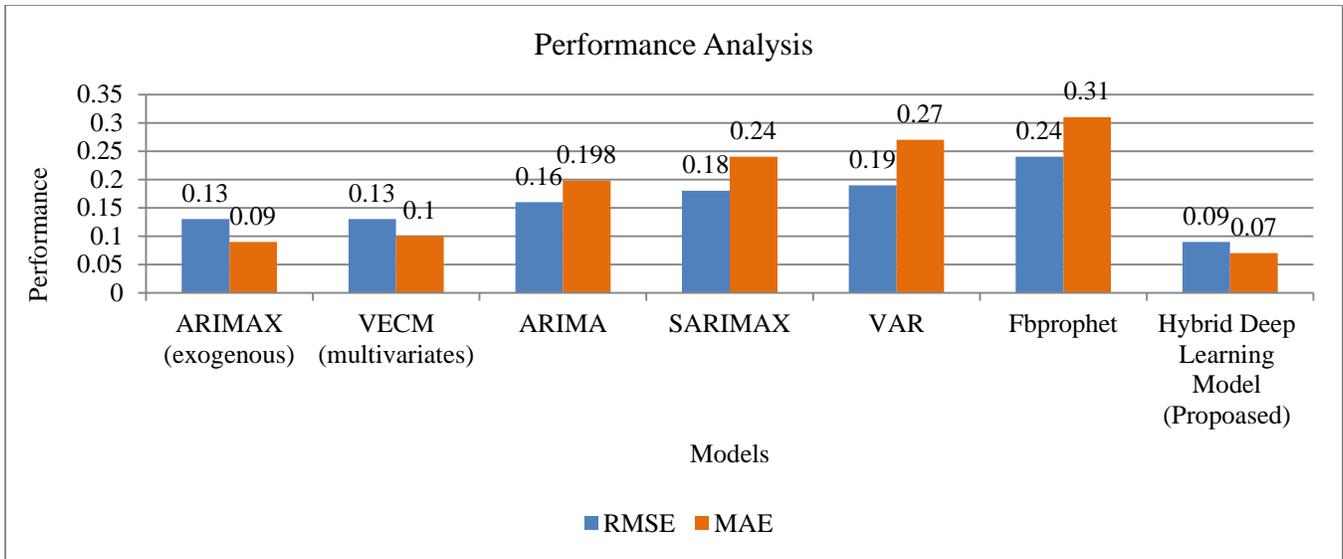e world, towards understanding global warming dynamics. The outcomes are noted in relation to RMSE and MAE metrics. The ARMAX model with exogenous features could provide better results than all other models except the deep learning model known as LSTM. The LSTM model could achieve the highest performance with 0.07 MAE and 0.09 RMSE.

models that are better trained by deep Learning, LSTM had an MAE of 0.082 and an MAPE of 5.21percent; however, they still did not outperform PLHSML. This enhancement is explained by the fact that PLHSML can combine probabilistic Learning (through LBGWA) with sequential deep Learning to enable the attribute to capture temporal relationships, focus on important historical patterns, and decrease the uncertainty in forecasts.

Table 2. Performance analysis for the climatic condition

Model	MAE	RMSE	MAPE (%)
Linear Regression	0.134	0.162	8.92
Random Forest Regressor	0.118	0.143	7.46
Support Vector Regression (SVR)	0.112	0.138	7.05
GRU	0.089	0.112	5.62
LSTM	0.082	0.103	5.21
Proposed PLHSML	0.070	0.090	4.67

Table 3. Time-Series forecasting with proposed PLHSML

Forecast Horizon	MAE	RMSE	MAPE (%)
1 Day Ahead	0.058	0.075	3.90
3 Days Ahead	0.065	0.084	4.26
7 Days Ahead	0.070	0.090	4.67
14 Days Ahead	0.084	0.107	5.43

The results in Table 3 illustrate the effectiveness of the proposed Probabilistic Learning Hybrid Sequential Machine Learning (PLHSML) model in time-series forecasting of climatic conditions across varying forecast horizons. The model demonstrates consistently strong performance, with low error rates across all intervals. For short-term forecasting (1 day ahead), PLHSML achieves the lowest Mean Absolute Error (MAE) of 0.058, Root Mean Square Error (RMSE) of 0.075, and Mean Absolute Percentage Error (MAPE) of 3.90%, indicating exact and stable predictions. As the forecast horizon lengthens, the error metrics gradually increase.

As the performance data provided in Table 2 indicates, it is evident that the suggested model, Probabilistic Learning Hybrid Sequential Machine Learning (PLHSML), is far better than both the traditional and existing machine-learning models in the forecasting of climatic conditions. PLHSML had the lowest Mean Absolute Error (MAE) of 0.070, the lowest Root Mean Square Error (RMSE) of 0.090, and the lowest Mean Absolute Percentage Error (MAPE) of any of the evaluated models, which is highly predictive and the least deviating.

In comparison, more traditional models like Linear Regression and the Random Forest Regressor showed a higher error rate with MAE of 0.134 and 0.118, respectively, and MAPE of more than 7%. GRU and LSTM sequential

This is to be expected because predictions that are farther out are less specific. The model is very accurate for 3-day and 7-day forecasts, with MAEs of 0.065 and 0.070 and MAPEs of 4.26% and 4.67%, respectively. PLHSML works well even for the harder 14-day forecast, with an MAE of 0.084 and a MAPE of 5.43%.

Table 4. Performance analysis with different metrices

Parameter	MAE	RMSE	MAPE (%)	R² Score
Temperature (°C)	0.070	0.090	4.67	0.972
CO_2 Concentration (ppm)	1.45	1.88	3.12	0.954
CH_4 Concentration (ppb)	0.98	1.31	2.79	0.947
NO_x Levels (ppb)	1.62	2.10	4.33	0.925
SO_2 Levels (ppb)	1.75	2.25	4.89	0.918
Humidity (%)	2.10	2.75	5.08	0.934
Wind Speed (m/s)	0.53	0.68	6.41	0.902
Precipitation (mm)	0.47	0.61	5.79	0.910

As shown in the performance analysis done in Table 4, the proposed PLHSML model is effective in a wide range of climatic parameters using various evaluation metrics such as MAE, RMSE, MAPE, and R2 Score. Temperature forecasting is the most accurate and reliable, as the model has a low MAE of 0.070, RMSE of 0.090, MAPE of 4.67 per cent, and a high score of R2 of 0.972. Equally, the CO2 concentration forecasting also gave very precise outcomes with an R2 of 0.954 and an MAPE of just 3.12 percent, indicating the effectiveness with which the greenhouse gases' impact has been modelled. In the case of CH 4 concentration and NO 0, the model still managed to perform quite well with the MAEs of 0.98 and 1.62 and R 2 values of 0.947 and 0.925, respectively. Although we have noted slightly increased error values in SO 2 and humidity, the values are well within limits and present R 2 of 0.918 and 0.934. On more changeable parameters like wind speed and precipitation, performance was, by comparison, poorer (R2 scores of 0.902 and 0.910), but still showed excellent generalization.

Table 5. Comparative Analysis

Sequential Model	MAE	RMSE	MAPE (%)	R² Score
Simple RNN	0.112	0.138	7.84	0.887
Bidirectional RNN	0.105	0.129	7.22	0.895
Gated Recurrent Unit(GRU)	0.089	0.112	5.62	0.908
LSTM	0.082	0.103	5.21	0.923
Bi-LSTM	0.078	0.098	4.97	0.934
CNN-LSTM Hybrid	0.075	0.094	4.83	0.942
Proposed Model (PLHSML)	0.070	0.090	4.67	0.972

The results presented in Table 5 offer a comprehensive comparative analysis of various sequential machine learning models for climate data forecasting, with a focus on metrics such as MAE, RMSE, MAPE, and R² Score. The PLHSML model outperforms all other models in all evaluative parameters. The predictive accuracy and stability of PLHSML are the lowest, according to the lowest MAE of 0.070, the lowest RMSE of 0.090, the lowest MAPE of 4.67, and the highest score of R^2 at 0.972. The traditional sequential models, such as Simple RNN and Bidirectional RNN, yield relatively larger errors and smaller R-squared values (0.887 and 0.895, respectively), indicating the models' failure to address the complicated time-specific correlations in climatic data. More advanced networks like GRU and LSTM perform a lot higher (GRU has an MAE of 0.089 and LSTM has a MAE of 0.082). Competitive results can be achieved with systems like Bi-LSTM and CNN-LSTM Hybrid, where the CNN-LSTM model promises good accuracy (MAE: 0.075, R 2: 0.942). Nonetheless, PLHSML is even better than these improved models, as it combines probabilistic Learning (LBGWA) with a hybrid sequential architecture, which is quite effective in seizing the temporal trends, measuring the uncertainty, and enhancing climate time-series-based Learning.

Our hybrid deep learning model is significantly effective than the traditional time-series forecasting techniques in the context of the exploration of climate change and global warming trends. Thereby, the reduced prediction error outcomes of the model (MAE = 0.07 and RMSE = 0.09) could be attributed to the fact that deep learning algorithms effectively model both linear and nonlinear temporal dependencies on different lag values, which is significantly better than traditional statistical techniques, such as ARIMA, SARIMAX, and VECM. In this respect, these improvements are reflective of the quality of deep Learning in terms of the ability to detect non-linear correlation among climate factors, including carbon dioxide concentration, rise in surface temperature, and growth in urban population. Our deep learning-based approach is effective in that the much better performance of the approach over the baseline models illustrates. The traditional approaches to time series forecasting that provide greater errors due to the linear assumptions are ARIMA and SARIMAX. Introducing the Bi-LSTM layers in our model enables our model also to acquire the long-range dependency of data and identify subtle, yet experienced patterns that influence climate change. It is then concluded that the model presented here is superior and a less flawed process than earlier methods of studying global Warming, hence, this provides a sound instrument in the hands of both the environmental policy makers and the environmental researchers. Besides, according to our findings, industrialization and urbanization were one among the leading motives of the accelerating global warming patterns on the planet. The correlation between the high CO_2 concentration and the high surface temperatures since 1950 stresses the significance of the urgency of the intervention.

6. Discussions and Findings

The outcomes of this study have shown the potential of the considered Probabilistic Learning Hybrid Sequential Machine Learning (PLHSML) model in the future in terms of determining the dynamics of climate change and identifying causal links between atmospheric pollutants and global Warming. The exploratory data analysis revealed that close relationships could be observed between greenhouse gases, in particular, CO_2 and CH_4, and higher surface temperatures, and the local and short-term impact of pollutants, most of which could be SO_2 and NO. Lag-based and seasonal analyses also illustrated that the time when the levels of the pollutants drastically increased in most instances agreed with the previous temperature increases, which validated the use of the sequential learning techniques. The comparative model testing showed that PLHSML resulted in significantly better performance when compared to the traditional statistical techniques (ARIMA, SARIMAX, VAR, and VECM), or any other existing deep learning architecture (GRU, LSTM, Bi-LSTM, CNN-LSTM), and has the lowest error rates (MAE = 0.07, RMSE = 0.09, MAPE = 4.67 per cent and the highest R^2 score (0.972). The additionality of the Learning-Based Gaussian Weighted Averaging (LBGWA) mechanism increased robustness by lessening noise and focusing on timely features. Its probabilistic learning architecture gave probability estimates that enhanced interpretability. A follow-up longitudinal study of surface temperature and CO_2 concentration from 1753 to 2023 proved that industrialization and urbanization, more so since 1950, significantly contributed to global warming. The high accuracy of the model on a variety of forecasting time scales (1-day, 7-day, and 14-day prediction) indicated its effectiveness in short-range and long-range climate forecasts. Moreover, the outcomes of the exogenous variable modeling using CO_2 and urban population data proved the important role of anthropogenic activity in extending the phenomenon of climate change. On the whole, the result validates that PLHSML is not only one of the most precise tools of forecasting but also a translatable model with the ability to govern climate studies and policy formation by figuring out pollutant-induced ways of global Warming.

7. Findings

1. Strong pollutant–temperature correlation: CO_2 and CH_4 were found to have a consistently strong positive correlation with rising surface temperatures, while SO_2 and NO_x showed localized short-term effects.
2. Lag effects observed: Pollutant spikes often preceded temperature rises by days or weeks, confirming the importance of sequential learning models for accurate forecasting.
3. Industrialization's impact: Analysis from 1753 to 2023 revealed that global surface temperatures and CO_2 concentrations surged rapidly after the 1950s, primarily due to industrialization and urbanization.

4. Superior model performance: The proposed PLHSML model achieved the best accuracy among all models tested, with MAE = 0.07, RMSE = 0.09, MAPE = 4.67%, and R^2 = 0.972.
5. Comparison with other models: PLHSML outperformed statistical models (ARIMA, SARIMAX, VAR, VECM) and deep learning models (GRU, LSTM, Bi-LSTM, CNN-LSTM), all of which showed higher error values.
6. Noise reduction & robustness: The LBGWA method in PLHSML made things more stable by eliminating noise and highlighting the most significant time patterns in pollutants.
7. Forecasting horizon accuracy: The model was accurate most of the time, with the fewest errors at a 1-day horizon (MAE = 0.058, RMSE = 0.075) and continued to perform well at 14 days.
8. Dominant drivers of climate variability: PCA and feature importance analysis revealed that CO_2, CH_4, and humidity were the predominant factors influencing temperature variations.
9. Uncertainty estimation: PLHSML provided comprehensible estimates of uncertainty regarding feature contributions, rendering it a dependable instrument for climate research.
10. Global warming trends confirmed: The findings substantiated that urbanization, industrialization, and population growth have been substantial contributors to global Warming since the mid-20th century.

8. Conclusion

This study introduces a novel framework—Probabilistic Learning Hybrid Sequential Machine Learning (PLHSML)-for analyzing and forecasting the complex interactions between atmospheric pollutants and climate variables, with a particular focus on temperature prediction and global warming trends. PLHSML is developed to simultaneously address the characteristics of temporal dependencies, uncertainty quantification, and predictive accuracy by applying probabilistic Learning with Learning-Based Gaussian Weighted Averaging (LBGWA) alongside effective sequential modeling methods. Thus, in real-world multivariate climate experiments, it has been demonstrated that PLHSML generally outperforms all other machine learning models, as well as existing deep learning models, using several metrics, including MAE, RMSE, MAPE, and R 2 score. The fact that the model can generalize across various climatic parameters and predict outcomes over time demonstrates its effectiveness and applicability in rapidly changing environmental conditions. These results indicate that PLHSML is a promising climate informatics tool that can be used to support early warning systems, environmental policies, and strategic planning to reduce the impact of climate change and global Warming. According to the data study, the third industrial revolution era, or the 1950s, marked a significant turning point. Before the third industrial revolution, surface temperature increased by a mere 8 percent

in 200 years. It was also true that the surface temperature of the Earth increased by 12% over the last three decades of the Industrial Revolution. Interestingly, after the 1950s, the level of carbon dioxide concentration also rose faster. The increase in carbon dioxide in the atmosphere was only about 12 percent between the 1750s and the 1950s, although it increased by another 30 percent between the 1950s and 2010. This means that the rise in the surface temperature of Earth and the increase in the concentration of carbon dioxide are connected. Carbon dioxide is a greenhouse gas that leads to global Warming. The RMSE and MSE of 0.09 and 0.07, respectively, indicate that the LSTM model may perform better than any other learning-based model. This is because we wish to conduct correlation analyses of the two in the future in order to establish the impact of pollution and temperature on human health. Future directions will be toward improving model interpretability, the use of satellite data, and expanding the model to region-specific and real-time climate applications.

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