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RESEARCH ARTICLE

# Investigating global surface temperature from the perspectives of environmental, demographic, and economic indicators: current status and future temperature trend

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## Abstract
Anthropogenic activities have increased atmospheric concentrations of greenhouse gas emissions, which have observably increased global temperature. Recognizing it as one of the most critical issues caused by human activities, this study investigates the effects of environmental, demographic, and economic indicators on global and regional temperature. For this purpose, advanced and powerful machine learning techniques, such as ANN, CNN, SVM, and LSTM, are employed using the data from 1980 to 2018 of the aforementioned regions to predict and forecast global and regional temperatures in Africa, Asia, Europe, North America, and South America. First, the predicted results were found very close to the actual surface temperature, confirming that environmental, economic, and demographic indicators are critical drivers of climate change. Second, this study forecasted global temperature from 2023 to 2050 and regional temperature from 2022 to 2050. The results also predicted a considerable increase in global temperature and regional temperature in the forthcoming years. Particularly, Asia and Africa may experience extreme weather in the future with an increase of more than 1.6 °C. Based on the findings of this study, the major implications have been that maintaining greenhouse gas emissions, balancing economic development, urbanization, and environmental quality while reducing fossil fuel energy consumption will ensure climate mitigation. The findings demand an alteration in human behavior regarding fossil fuel energy consumption to control greenhouse gas emissions, which is the most significant contributor to climate change.

**Keywords** Energy consumption · Greenhouse gas emissions · Population · Economic growth · Temperature · Forecasting

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## Introduction

Extreme temperature events have become more frequent due to global climate change. This warming will likely continue for the foreseeable future until effective strategies are not implemented to curb increasing environmental issues (Qin et al. 2021; Khan et al. 2022c). It has been evident that the magnitude and rate of warming are rising at a frightening pace, which poses a severe threat to the survival and development of human society. In this regard, the Paris agreement was set to limit the increase in temperature beyond pre-industrial levels below 2 °C (Sun et al. 2019) because the continued growth in greenhouse gas emissions will change temperatures, precipitation, and rain in the future (Chen et al. 2021). Heat stress usually results from higher average temperatures (Ahmadalipour et al. 2017); therefore, bringing global warming below 1.5 °C would result in a 50% reduction in extreme temperatures (Nangombe et al. 2018). Similarly, if global warming is kept below 1.5 °C, there is

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the potential to restrain 46% of the increase in high temperature in the East Asia region (Li et al. 2018).

Reducing adversarial effects of global warming and climatic shift requires understanding its various critical determinants concerning environmental (Khan et al. 2022a), demographic, and economic perspectives (Shen et al. 2020). For instance, industrial and commercial sectors dependent on non-renewable energy consumption are directly responsible for greenhouse gas emissions, and this concern changes climate change behavior significantly. Similarly, anthropogenic activities, such as deforestation, are the leading causes of the temperature rise. Human activities, which are increasing the amount of greenhouse gases in our atmosphere, contribute significantly to the enhancement of the greenhouse gas effect because increased gases are absorbed by the earth's surface, trapping more infrared rays and thus increasing the temperature of the atmosphere. There is also evidence that cities in big economies are expanding their boundaries for economic development. This practice widely affects climate change because most developing and emerging economies depend on non-renewable energy consumption (Mele et al. 2021). Also, more significant environmental degradation and urban sprawl are caused by urban agglomeration and development in metropolitan cities (Surya et al. 2021). Other types of human activity are linked with industry, which uses coal, petroleum, and oil to generate electricity in power stations. When these fuels are burnt, greenhouse gases are released into the atmosphere, enhancing the greenhouse gas effects.

Following the arguments, the primary drivers for the greenhouse gas effects and climate change are human activities, energy consumption, and releases of hazardous pollutants into the atmosphere. These critical factors carry a significant contribution to global and regional climate change. Despite the adverse effects of climate change worldwide, the impact of increasing greenhouse gas emissions produced by fossil fuels for energy generation has not been appropriately addressed. Also, to the best of the authors' knowledge, economic and demographic consequences are not widely discussed in the context of climate change. Therefore, this study aims to explore the environmental, economic, and demographic influences on temperature. More specifically, this study is directed to find the impact of environmental, demographic, and economic variables on global temperature and regional temperature in Africa, Asia, Europe, North America, and South America.

This paper focuses on global and regional temperatures and comprehensively analyzes the association between environmental, economic, demographic, and temperature variables. Investigating the association between these variables paves the way to examine its trend in the global and regional environment, which can be the pivotal step to taking some urgent measures. Furthermore, estimating the impacts of climate change from environmental, economic, and demographic perspectives is a step forward in rethinking adaptation and mitigation policies. The key findings from work suggest that long-term environmental, economic, and demographic effects can be the major cause of climate change. These estimates can invite to accelerate global and regional efforts, providing fresh evidence to respond to the temperature changes so that the detrimental impacts of anthropogenic activities on climate change can be avoided. Aside from reducing environmental effects, this study's results will help shape the economic structure by transitioning from brown growth to green growth and towards sustainable development.

Overall, this study used ten influencing factors, namely, energy consumption, $CO_2$ emissions, $N_2O$ emission, CH4 emissions, energy consumption per GDP, population, urbanization, population density, $CO_2$ emissions (per capita), and per capita fossil fuel energy consumption, as input variables to predict their influence on the global temperature and regional temperature in Africa, Asia, Europe, North America, and South America for the period between 1980 to 2018. Furthermore, this study critically examines growing global temperatures (2023 to 2050) and compares regional temperatures by forecasting their trend from 2022 to 2050. This study employs advanced machine learning models to predict the association between environmental, economic, demographic, and temperature variables and to forecast temperature trends by analyzing the dataset globally and regionally. Machine learning models provide better results than statistical techniques and are popular in forecasting related problems (Abbas et al. 2022; Ahmed et al. 2022). Furthermore, due to the capability to analyze complex relationships, machine learning techniques have received significant attention in prediction and forecasting related problems, such as $CO_2$ emissions prediction (Altikat 2021), energy consumption prediction (Liu et al. 2019), economic development forecasting (Sokolov-Mladenović et al. 2016), and water quality forecasting (Joslyn 2018). Since this study is interested in estimating the connection between environmental, economic, and demographic variables and temperature, it also aims to forecast future temperature trends; therefore, machine learning approaches can be suitable method for the study.

The contribution of the present study lies in many ways. After reviewing past studies, the previous studies lack in estimating the association between environmental, economic, demographic, and temperature effects. This study contributes to the literature by exploring the environmental, economic, and demographic impacts on temperature and employs advanced methodological approaches. Furthermore, this research contributes to presenting the current and future temperature trends. Also, one of the unique characteristics of this empirical analysis, which differentiates it from previous research work, is the causal connection between energy consumption, $CO_2$ emissions, $N_2O$ emission, CH4 emissions, energy consumption per GDP, population, urbanization, population density, $CO_2$ emissions (per capita), per capita fossil fuel energy consumption, and temperature. The scope of this work is limited to the global and regional temperature investigation; furthermore, the study is limited to the sample choice, such as it uses a yearly dataset of temperature construct.

This paper can be structured as follows: The next section discusses the theoretical framework and existing literature and presents the research gap. The third section presents a methodological selection and justifies the model in light of the literature. The fourth section provides empirical results, followed by conclusions, implications, and limitations of the study.

## Literature review

Extreme weather events such as heatwaves, droughts, and flooding are being exacerbated by climate change. In this context, climate change has become a serious concern in the scholarly literature (Magazzino et al. 2021b, 2022). Here, we review the existing studies on the association between environmental, economic, demographic, and climate change and highlight the research gap.

### Environmental impact on global warming and climate change

Energy consumption, particularly non-renewable energy sources, significantly contributes to environmental degradation (Khan et al. 2021b, 2022b). The dominant energy sources like coal, petroleum, and natural gas have a variety of applications, from electricity production to transport fuels. Also, these fuels are used to produce manufacturing goods, such as cement and iron. Coal, oil, and diesel fuel heavy automobiles and jets increase $CO_2$ in the atmosphere. As a consequence of these pollutants, today, global warming is a prominent issue (Rehman et al. 2022). Among other types of fossil fuels, coal is the primary energy source for economies (Jamil 2022). When coal is burnt, $CO_2$ is emitted into the atmosphere. As a major contributor to $CO_2$ emissions and global warming, coal-fired power plants are the largest emitters of greenhouse gases. Oil, petroleum, and natural gas are other excessively used energy fuels globally. According to the International Energy Agency, over 80% of energy is produced by fossil fuels, of which oil (33%), coal (27.3%), and gas (24%) were the dominant energy fuels in 2019 (BP 2020; IEA 2021). Unfortunately, most developing and emerging economies rely on these fossil fuels for energy consumption; therefore, the global temperature is continued to rise.

A significant part of global warming that is caused by greenhouse gases is due to carbon dioxide ($CO_2$), methane (CH4), and nitrous oxide ($N_2O$) emissions (Shakoor et al. 2020). These greenhouse gases have been emitted rapidly in the last few decades, which is considered the primary cause in the global temperature (Touma et al. 2021). Recent statistics show that approximately 41.1% of greenhouse gas emissions increased between 1990 and 2016 (NOAA 2018). Accordingly, the average surface temperature worldwide has risen by about 0.57 °C across the globe. According to Intergovernmental Panel on Climate Change (IPCC), global surface temperatures have increased by more than half over the past 50 years because of anthropogenic increases in greenhouse gas concentrations combined with other anthropogenic activities (IPCC 2021). $CO_2$, CH4, and $N_2O$ concentrations today have exceeded the highest concentrations that have been recorded in ice cores during the past 800,000 years (IPCC 2021). This evidence suggests that greenhouse gas emissions are the primary driving forces in global warming and climate change.

Many empirical studies examine the impact of energy consumption, economic development, greenhouse gas emissions, and climate change (Khan et al. 2021a, 2022d). For instance, Khan et al. (2021a, b) investigated the impact of non-renewable and renewable energy sources on environmental quality. The authors reported that non-renewable energy use significantly and positively impacts $CO_2$ emissions. Particularly, coal and oil degrade environmental quality. Similarly, Weili et al. (2022) researched the effect of financial development, energy use, and information communication technology on environmental quality from 2000 to 2019. Their findings revealed that energy consumption and economic growth are the primary drivers of environmental degradation. More recently, Khan et al. (2022b) explored the effect of natural resources, renewable energy use, and economic growth on $CO_2$ emissions in belt and road countries. Their findings also confirmed that economic growth and natural resources significantly degrade environmental quality. However, the study reported that renewable energy consumption improves environmental quality. Ahmed and Shuai (2022) attempted to explore the energy consumption and greenhouse gas emissions trend in the top four major $CO_2$-emitting countries. The authors pointed out that coal, oil, and natural gas are the major driving factors in environmental degradation. Moreover, Rehman et al. (2020) used an autoregressive distributed lag approach to explore the influence of methane, nitrous oxide, and $CO_2$ emissions on agriculture production in China. The results revealed that greenhouse gas emissions have a significant negative impact on agriculture.

## Economic impact on global warming and climate change

The economic-climate relationship largely determines climate change's impact on the economy and the markets (Newell et al. 2021). The relationship between economic growth and global warming is robust across a wide range of specifications (Henseler and Schumacher 2019). Undoubtedly, economic practices promote capital production but negatively impact the environment (Khan et al. 2020). For instance, in many developed countries, the current manufacturing processes result in vast amounts of waste and emissions, leading to the natural environment's degradation (Rehman et al. 2022). On the other hand, information communication technology and an increase in financial development influence environmental quality (Weili et al. 2022). Besides, the severe effect of overusing natural resources, such as agriculture, deforestation, and mining, can cause environmental degradation. Many studies have reported that economic development increases energy consumption and $CO_2$ emissions (Bamisile et al. 2021; Nasir et al. 2021). In line with these findings, other studies also confirmed that economic growth is the primary driver of environmental degradation, whereas renewable energy consumption improves environmental quality in global-income countries (Khan et al. 2022d). Khan et al. (2020) concluded that economic growth and tourism contribute to environmental degradation. Moreover, another study examined the role of economic development on $CO_2$ emissions in the case of ASEAN economies (Nasir et al. 2019). The authors used fully modified ordinary least squares and dynamic ordinary least squares approaches to interpret the results. Their findings demonstrated that financial development and economic growth are the major driving sources of climate change. More recent research by Magazzino et al. (2021b) explored the heterogenous effect of temperature and $CO_2$ emission on income through an econometric approach. Their results demonstrated that an increased temperature decreases income; an increase in emissions significantly raises income.

## Demographic impact on global warming and climate change

Apart from energy, economic, and environmental indicators, demographic variables like population growth, urbanization, and population density also directly impact the environment. For instance, performing more activities in a dense population may result in environmental degradation (Rehman et al. 2022). A more dense population per square kilometer will result in higher sulfur dioxide emissions (SO2) when these people burn coal and other contaminated fuels for cooking and heating purposes (Panayotou 1997). On the other hand, population growth and urbanization are likely to increase energy consumption (Martínez-Zarzoso et al. 2007). Urbanization surpassed the rural population in 2007, and it reached 54% of the global population in 2014. It is also estimated that the world's urban population will reach 54 to 68% by 2050 (UN 2018). Today, around 82% of the population of North America, 81% of the population of Latin America, and 74% of the population of Europe are living in urban areas. In contrast, the level of urbanization in Asian and African countries are 50% and 43%, respectively (UN 2018). Developing economies do not have the same capabilities as developed economies, so they are more susceptible to climate change. For instance, unplanned urban agglomeration increases consumption patterns, such as water usage, and energy consumption per capita, resulting in environmental degradation (Hanberry 2022). Urban populations are more vulnerable to extreme temperature conditions and greater exposure to heat waves from urban heat islands (Estrada et al. 2017). Moreover, the existence of urban heat islands is the most prominent example of climatic changes, in which urban areas experience more substantial increases in temperature than rural areas (Vinayak et al. 2022).

In the context of demographic's impact on climate change, Hall et al. (2017) researched the effect of population on climate change. Their findings suggest that population growth is a crucial determinant of climate change. Jones et al. (2018) projected heat extremes at the regional and global levels. Their findings demonstrated that the changing climate, as well as the changing demographics, is essential factors that contribute to climate change. Additionally, the findings indicate that temperature has a more substantial influence among urban areas than in rural areas, which may result from increased heat wave days in urban areas in response to urban heat effects. Lyu et al. (2019) studied the impact of urbanization on climate change in China. More specifically, the authors evaluated five ecosystem services in a spatially explicit manner. Their findings suggest that compact urban growth can reduce the trade-offs among ecosystem services.

## Literature gap

Overall, climate change has become a problem that must be accepted and dealt with urgently for environmental, social, and economic development. With fast economic and demographic growth, human behavior heavily depends on energy use. Meanwhile, fossil fuels, anthropogenic activities, and many greenhouse gas emissions into the atmosphere have changed climate change. Although, the existing studies have analyzed the impact of energy consumption, population, urbanization, financial development, GDP, and non-renewable energy consumption on environmental quality. However, the majority of existing studies have focused on specific energy types (Khan et al. 2020; Okumus et al.

2021; Fareed and Pata 2022) and the association between economic development and environmental pollution (Saud et al. 2019; Hao 2022; Khan et al. 2022b). Conversely, some studies predict $CO_2$ emissions (Acheampong and Boateng 2019; Huang et al. 2019; Wang et al. 2020) and greenhouse gas emissions (Javanmard and Ghaderi 2022). In contrast, the contribution of the present study is not limited to the specific type of energy and economic variables on environmental quality. But this study adopts environmental, economic, and demographic characteristics and assesses their relationship with climate change (temperature), which has not been explored extensively in previous studies. Thus, this study contributes to the literature that analyzes the association between environmental, demographic, economic, and temperature, discusses its impact on climate change, and comprehensively analyzes global and regional temperature trends in the forthcoming years.

## Methodology

### Datasets

This study used ten influencing factors, namely, energy consumption, $CO_2$ emissions, $N_2O$ emission, CH4 emissions, energy consumption per GDP, population, urbanization, population density, $CO_2$ emissions (per capita), and per capita fossil fuel energy consumption, as input variables for the period between 1980 and 2018. A series of yearly global data (1880 to 2022) and regional data (Africa, Asia, Europe, North America, and South America) were considered between 1910 and 2021 for forecasting purposes. Data on energy consumption and energy intensity by GDP is expressed in quad BTU and GDP (1000 BTU/2015$ GDP PPP), respectively (EIA 2018). Population refers to the total number of people, and urbanization relates to people living in urban regions. At the same time, population density is expressed in people per square kilometer of land area. These demographic indicators were taken from World Bank indicators (WorldBank 2021). Data on $CO_2$, methane, and $N_2O$ emissions are expressed in kt, kt of $CO_2$ equivalent, and thousand metric tons of $CO_2$ equivalent, respectively (WorldBank 2021). Annual $CO_2$ emissions here refer to emissions per capita, measured in tones, whereas per capita fossil fuel energy consumption is expressed in kilowatt-hour (Ourworldindata 2021). Lastly, the outcome indicator, temperature, refers to land temperature and is expressed in degree Celsius (NCEI 2022).

### Theoretical framework

The link between global temperatures and greenhouse gas concentrations has existed throughout history, especially concerning $CO_2$ concentrations (Lacis et al. 2010). $CO_2$ can be emitted by direct impacts caused by human activity on natural forests and other land uses, such as deforestation and burning contaminated fuels. Other greenhouse gas emissions, such as CH4 emission, are responsible for global warming. Also, the primary sources of $N_2O$ emissions come from agricultural activities, such as cultivating crops. $N_2O$ is a long-lived greenhouse gas, one of the dominant ozone-depleting substances (Ravishankara et al. 2009; Tarin et al. 2021). Compared to $CO_2$, $N_2O$ has an estimated global warming potential of approximately 265 times greater than $CO_2$ over a 100-year timeframe (Massara et al. 2017). A significant amount of $N_2O$ can be emitted by wastewater containing organic-based nitrogen materials, such as waste animals (Kampschreur et al. 2009). $N_2O$ concentrations in the atmosphere in 2018 reached 331 parts per billion. Approximately 60% of global $N_2O$ emissions were attributed to natural sources (forests, wetlands, and oceans). Therefore, it contributes to climate change and negatively impacts human health (Fluegge 2016). Furthermore, energy consumption has accompanied economic development, particularly due to industrialization, population growth, and urbanization; non-renewable energy consumption has increased subsequently. In addition to witnessing substantial economic growth over the past few years, most developing and emerging countries have relied on fossil fuel energy consumption. Besides, an unplanned expansion of cities leads to rapid sprawl, degradation of the environment, as well as high consumption patterns have increased environmental concerns (Jarah et al. 2019). For instance, in low-density metropolitan and suburban areas, urban and suburban dwellers consume more energy and resources per capita than rural dwellers, largely due to their low density. Considering those mentioned above, environmental, economic, and demographic characteristics, which are primarily dependent on non-renewable energy consumption, and have an association with greenhouse gas emissions, may contribute to climate change. In this view, this study finds its detrimental impact on temperature.

### Estimated models

This study used the LSTM, ANN, CNN, and SVM models to accomplish the goal. This study estimates the connection between environmental, economic, and demographic variables and temperature and also aims to forecast future temperature trends; for this purpose, machine learning techniques are used due to their popularity and high accuracy. The application of these advanced machine learning algorithms has been proved in many fields, including energy, environment, and medicine. Machine learning algorithms are used for regression, classification, forecasting, and image detection-related problems (Mele and Magazzino 2020; Ahmed et al. 2022). These techniques deal with complex issues, provide more accurate results than traditional methods, and better forecast time series-related tasks (Magazzino et al. 2021a; Ahmed and Shuai 2022). These ML algorithms can be used to interpret parameters and are suitable for modeling global warming and ecosystems (Dai et al. 2019). Many studies have been conducted using ML techniques to examine the future trend of $CO_2$ emissions and greenhouse gas emissions. For instance, Javanmard and Ghaderi (2022) recently used machine learning algorithms to forecast greenhouse gas emissions. Their results demonstrated that ML algorithms have a strong capability in predicting outcome variables. In the case of Turkey, Bakay and Ağbulut (2021) attempted to forecast greenhouse gas emissions based on electricity production. According to the findings, the algorithms used in their study produced individual, satisfying results for predicting greenhouse gas emissions. Other studies also report that ML algorithms, specifically LSTM, ANN, and SVM, have a wide range of capabilities (Acheampong and Boateng 2019; Huang et al. 2019; Gürel et al. 2020). Other possibilities for using these advanced ML techniques could be assessing the patterns in the datasets. These ML algorithms solve the problems unbiasedly and provide consistent and more accurate results than traditional ML algorithms and statistical techniques (Elmaz et al. 2020; Ahmed and Shuai 2022).

## LSTM

The LSTM technique is increasingly used in predicting output and is widely accepted as an effective way of solving problems. An LSTM consists of three layers, namely, input, hidden, and output. A node represents an input layer representing the features from the dataset that we will pass to the model as inputs; furthermore, the hidden layer is connected to each of these inputs. Hence, the hidden layer connects the input layers to the output layers. Figure 1 represents the LSTM architecture. First, we can go with the three gates, input gate, forget gate, and output gate, represented with $(i_t)$, $(f_t)$, and $(O_t)$, respectively, can be computed through Eqs.1-3. Each of its gates and each of the cell's gates has its corresponding weights; for example, $(i_t)$, $(f_t)$, and $(O_t)$ have their own weights. $(f_t)$ decides which information has to be retained or dropped. $(i_t)$ decides which information should be saved to the cell or dropped; next, $(O_t)$ represents which information should be sent to the next hidden state. Equations 1 and 4 show that the $(i_t)$ selectively records new information in the cell state $(c_t)$ whereas through Eq. 5, the $(f_t)$ selectively discards information from the previous cell state. $c_{t-1}$ and $ct$ represent the cell state at times $t-1$ and $t$, respectively, whereas $g_t$ puts on information to the cell state. Finally, $O_t$ generates the information for the next cell as presented in Eq. 6. The following equations are used that describe the driven process of the LSTM approach.

$$i_t = \sigma\ (W_i x_t + R_i h_{t-1} + b_i) \tag{1}$$

$$f_t = \sigma\ (W_f x_t + R_f h_{t-1} + b_f) \tag{2}$$

$$o_t = \sigma\ (W_o x_t + R_o h_{t-1} + b_o) \tag{3}$$

$$g_t = tanh\ (W_g x_t + R_g h_{t-1} + b_g) \tag{4}$$

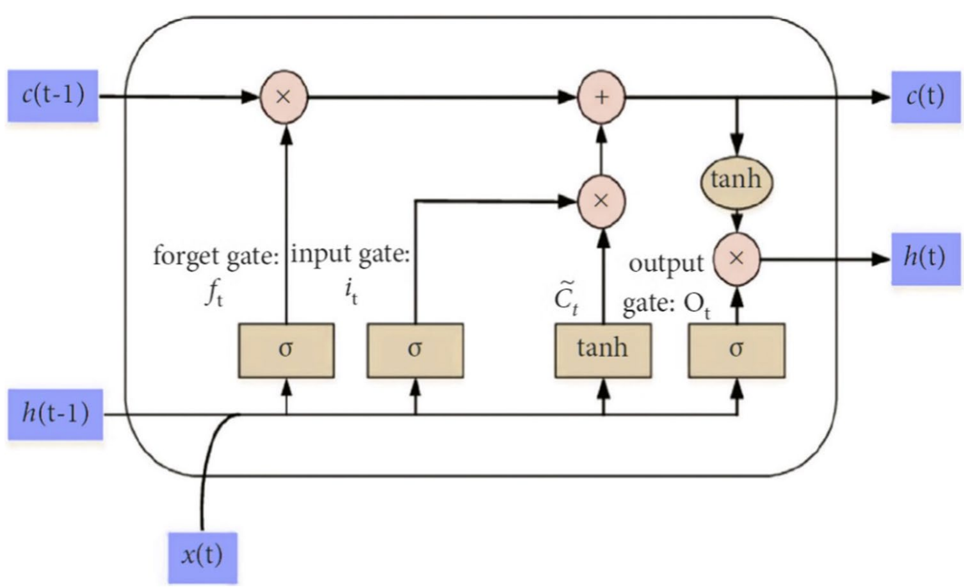
$$c_t = f_t * c_{t-1} + g_t * i_t) \tag{5}$$

$$h_t = o_t * \tanh(c_t) \tag{6}$$

where

$\sigma$ sigmoid function

**Fig. 1** LSTM structure



$W$ input weight

$R$ recurrent weight

$h_{t-1}$ old state

$x_t$ input

$b$ bias

### ANN

The ANN algorithm is one of the most popular algorithms working similarly to a biological nervous system. A neural network can learn the pattern and predict non-linear and complex problems within a limited time. This model can solve a wide range of problems with a biological neural network, so it has some advantages over other models, such as the ability to continue the process when an element of the neural network fails by its parallel nature. Furthermore, ANN learns by itself and does not require reprogramming multiple times. The ANN network comprises three layers: the input layer, the hidden layer, and the output layer. An input layer identifies input and then forwards that signal to the following layer. Essentially, hidden layers act as the weight for the input data and make the connection between them before displaying the decision in the output layer. In addition to the other features of ANN, it can find patterns between input and output data; therefore, it works by tuning the weights in the multilayer perception (Fig. 2).

### CNN

CNN is one of the preferable machine learning models used for feature extraction, prediction, classification, and regression purposes. The important feature of CNN for being able to understand the patterns. The hidden layers of this model are also called convolutional layers, which are the base of this model. The function of the convolution layer is to receive the inputs, transform the inputs, and then pass the output to the next layer. The learning process acquires some kernel metrics to capture the key features used in forecasting. Furthermore, the activation function was performed on the neurons, generally referred to as ReLU. Some studies pointed out that the CNN model has overfitting and underfitting issues. Some modifications were performed to overcome and avoid these problems, such as reducing the number of layers when the results were satisfactory.

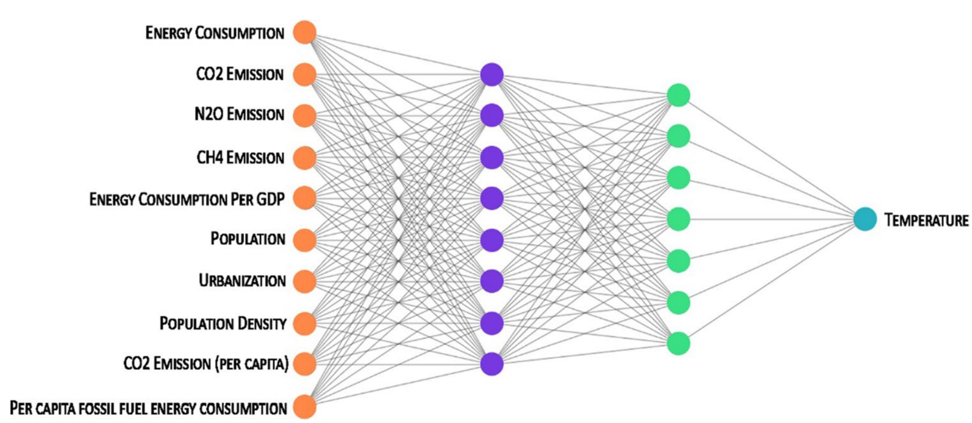
### SVM

As a family of supervised machine learning algorithms, SVM applies to various categories and problems, including classification, regression, and prediction. Besides regression and image classification-related problems, SVM is used for face recognition and text recognition. The SVM uses a mixture of computational and statistical learning techniques and can handle basic parameters such as quadratic, radial, neural, epilson, kernel functions, and C values. This technique makes it possible to minimize the errors from the training data while at the same time maintaining the structure of the decision boundary. Thus, SVM provides essential analysis for the selection of features and models. A study by Torabi et al. (2018) suggests that SVM is a powerful and generic machine learning tool compared with other machine learning techniques; one of its important characteristics is the ability to deal with sizeable dimensional space kernel calculations.

### Data preprocessing and descriptive statistics

Processing raw data is one of the most essential and crucial steps in applying machine learning algorithms because inputting non-processed data may lead to inaccurate, unstable, and confusing predictive results. Therefore, data must be standardized to make it readable for machine learning models. Thus, data processing transforms data into a uniform scaling, which reduces biases, noise, anomalies, outliers, or skewness (Jayalakshmi and

**Fig. 2** ANN architecture



Santhakumaran 2011). A growing body of evidence confirms the importance of data normalization for assessing the accuracy and performance of machine learning models, for instance, ANN (Abbas et al. 2022), SVM (Li et al. 2008), deep learning (Ağbulut 2022), and CNN and LSTM algorithms (Selvin et al. 2017). Because there is a difference between the magnitude scales of each parameter, it is more efficient to scale the respective parameter for conversion; therefore, the parameters were converted to normalized forms (ranging from 0 to 1).

An original dataset is transformed linearly through the normalization technique. This formula (Eq. 7) replaces each value according to its minimum and maximum value.

$$X_{1(normalized)} = \frac{X_1 - X_{1(min)}}{X_{1(max)} - X_{1(min)}} \quad (7)$$

The results of normalized data are presented in Fig. 3, where Fig. 3a indicates raw data and Fig. 3b indicates the normalized data, which is transformed between 0 and 1 values.

Table 1 presents the descriptive estimation of variables of source data. The summary provides the minimum and maximum, mean, standard deviation, skewness, and kurtosis. The results of the skewness and kurtosis demonstrate that the data of input variables are not skewed, and kurtosis statistics are also within the range between −1 and + 1, which confirms the normal distribution of data.

Moreover, we have performed multiple experiments with hyperparameter tuning machine learning models (ANN, LSTM, CNN, and SVM). We performed tunning with epochs, learning rate, and number of neurons in ANN, LSTM, and CNN. The inner nature/architecture of SVM is different from ANN, LSTM, and CNN models. Therefore, for SVM, there are various other parameters, such as kernel type, kernel cache, and max iterations. We performed many experiments on the available dataset using the specific parameters mentioned above. Tables 2 and 3 indicate the various parameters used to determine the model's diagnostics. The robustness and accuracy of results were checked with route mean square error (RMSE), mean square error (MSE), mean absolute error (MAE), and mean bias error (MBE). From the available dataset, 15% of the total data was separated for testing purposes, and we repeated many experiments to determine the performance of these four models. After various trials and checking the number of epochs, learning rate, and accuracy of the models, the best results were noted.

## Results and discussion

### Diagnostic tests and robustness outcomes

We used the dataset between 1980 and 2018 in the present study to predict temperature. ANN, CNN, SVM, and LSTM were trained on a randomly selected dataset with 15% of the total samples. In other words, 85% of the data was used for training and 15% for testing. Figure 4 exhibits each model's training and selection errors. The blue and red lines indicate training and validation errors in each iteration, respectively. Figure 4a, b, and d shows that the plot of training and validation errors is lower to the point of stability with minimal generalization gap, indicating a good fit model. In Fig. 4c, we can observe that the ANN model is underfitting the data until epoch 80; however, from epoch 80 onwards, the model starts learning the training data and reaches the point of stability at epoch 100 with minimal generalization gap.

Furthermore, we performed each model's test to confirm the goodness of fit of ANN, CNN, LSTM, and SVM algorithms through training, testing, and selection criterion. Table 4 exhibits the prediction errors in different scenarios, clearly indicating that the errors are less than one. At the same time, training errors are also lower compared to selection errors. Besides, we employed statistical metrics such as MSE, RMSE, MAE, and MBE to check the robustness of the built ANN, CNN, SVM, and LSTM models. These metrics are used to confirm the robustness and accuracy of the performance of machine learning models in predicting outcomes (Ağbulut 2019, 2022; Ağbulut et al. 2021b; Ahmed and Shuai 2022). It is recommended that small values, close to zero, are desirable, which define the successful results of machine learning models (Bakay and Ağbulut 2021; Ağbulut et al. 2021a; Ağbulut 2022). The results indicate that the MSE, RMSE, MAE, and MBE values are close to zero; the highest and lowest values were noted at 0.074 and 0.003 (see Table 5).

### Analysis of linkage between environmental, demographic, economic variables and temperature

After confirming the accuracy of all these models, the next step was performed to predict the outcome variable (temperature). As this study employed ANN, CNN, SVM, and LSTM models, which used multiple input variables, like energy consumption, $CO_2$ emissions, $N_2O$ emission, CH4 emissions, energy consumption per GDP, population, urbanization, population density, $CO_2$ emissions (per capita), per capita fossil fuel energy consumption for predicting and forecasting global temperature, we trained machine learning models with 15% of the total data on the global dataset. The actual and predicted results of temperature are presented in Table 6. The results with four machine learning models indicate that the predicted temperature values are close to actual temperature results. For instance, together, all ten inputs contribute a value of 0.289 compared to 0.18 to the real temperature (see no. 1 of predicted


**Fig. 3** Results of normalization of variables

temperature by LSTM in Table 6). Similarly, compared to actual temperature of 0.46, 0.46, 0.76, 0.55, and 0.43, LSTM model predicts 0.461, 0.451, 0.646, 0.539, and 0.449, respectively. This implies that the LSTM model has a better capability of predicting outcomes accurately. Apart from the LSTM model, we compared predicted results with other machine learning models. With CNN model, we noted predicted temperature values of 0.335, 0.504, 0453, 0.798, and 0.619, compared to actual temperature values of 0.18, 0.46, 0.46, 0.76, 0.55, and 0.43. Consequently, ANN and SVM model was performed on the same global dataset to analyze the best results. The

**Table 1** Descriptive statistics of variables

| Variables | Minimum | Maximum | Mean | Std. deviation | Skewness | Kurtosis |
|---|---|---|---|---|---|---|
| Energy consumption | 0.00 | 1 | 0.425 | 0.327 | 0.439 | − 1.271 |
| $CO_2$ emission | 0.00 | 1 | 0.390 | 0.342 | 0.589 | − 1.256 |
| $N_2O$ emission | 0.00 | 1 | 0.509 | 0.296 | 0.043 | − 1.123 |
| Methane emission | 0.00 | 1 | 0.497 | 0.292 | 0.137 | − 1.002 |
| Energy consumption per GDP | 0.00 | 1 | 0.355 | 0.306 | 0.954 | − 0.488 |
| Population | 0.00 | 1 | 0.500 | 0.299 | -0.019 | − 1.176 |
| Urban population | 0.00 | 1 | 0.455 | 0.299 | 0.214 | − 1.147 |
| Population density | 0.00 | 1 | 0.502 | 0.298 | -0.024 | − 1.170 |
| $CO_2$ emissions (per capita) | 0.00 | 1 | 0.390 | 0.356 | 0.536 | − 1.366 |
| Per capita fossil fuel energy consumption | 0.00 | 1 | 0.435 | 0.362 | 0.497 | − 1.549 |
| Temperature | 0.00 | 1 | 0.450 | 0.211 | 0.188 | 0.305 |

**Table 2** Parameters of LSTM, ANN, and CNN models

| Parameters | LSTM | ANN | CNN |
|---|---|---|---|
| No. of hidden layers | Hidden layer 1 (50 neurons) | Hidden layer 1 (12 neurons) | Hidden layer 1 (10 neurons) |
| | Hidden layer 2 (20 neurons) | Hidden layer 2 (8 neurons) | Hidden layer 2 (5 neurons) |
| Learning rate | 0.001 | 0.01 | 0.001 |
| Epochs | 1500 | 100 | 300 |

**Table 3** Parameters of the SVM model

| Parameters | SVM |
|---|---|
| Kernel type | Neural |
| Kernel cache | 300 |
| C | 700 |
| Conv. eps | 0.1 |
| Max iterations | 100,000 |
| Shrinking | True |
| Verbose | False |

results presented in Table 6 indicate that ANN and SVM predicted values are close to actual values. Overall, the four models have a better capability in predicting output; however, the LSTM model provides more accurate results.

The above results show that LSTM provides better results; therefore, this study applied the LSTM algorithm for forecasting temperature. Before formal analysis of the forecasting temperature trend, we divided the dataset into training (1880–2012) and tested forecasting (2013–2022) to obtain more robust results. The results demonstrated that the LSTM model provides close values between actual and tested forecasting. After confirming the excellent accuracy of the LSTM model, we forecasted the forthcoming global temperature trend from 2023 to 2050.

It can be seen from Fig. 5 that global temperatures have increased dramatically over the past few decades, reaching a height of 0.7 °C above the 1961–1990 baseline. Extending the baseline to 1850, temperatures were 0.4 °C colder; however, the temperature rose after 1950, subsequently. As a result, the world can expect an average temperature rise of 0.75 °C in the future. This is primarily due to fluctuations in temperature from year to year, which causes the temperature rise to be in the range of 0.50 to 1.5 °C. In addition to the fact that a consistent temperature trend influences the climate systems significantly, it should also be noted that this stable temperature trend marks enormous global warming variations. In the long term, land areas change temperature much more than ocean areas, both warming and cooling to a much greater degree. According to the National Center for environmental information, 2013 to 2021 have remained the warmest years (NCEI 2021). 2005 broke the record for the first time in the twenty-first century and is the 10th warmest year. On the other hand, 2010 ranks as the ninth warmest year. Our results with the LSTM model indicate a consistent trend over the years globally, suggesting that the world may experience more extreme weather in the future. Figure 5 gives the historical record of temperature along with LSTM predicted forecasting and future forecasting globally.

In the past many decades, we have seen increasing changes to the climate due in part to global greenhouse gas emissions, specifically, $CO_2$, $N_2O$, and methane emissions that trap the sun's heat in the atmosphere. Moreover, a change in industrialization and electricity from fossil fuels have drastically increased climate change. Energy demand for industrialization, urbanization, construction,

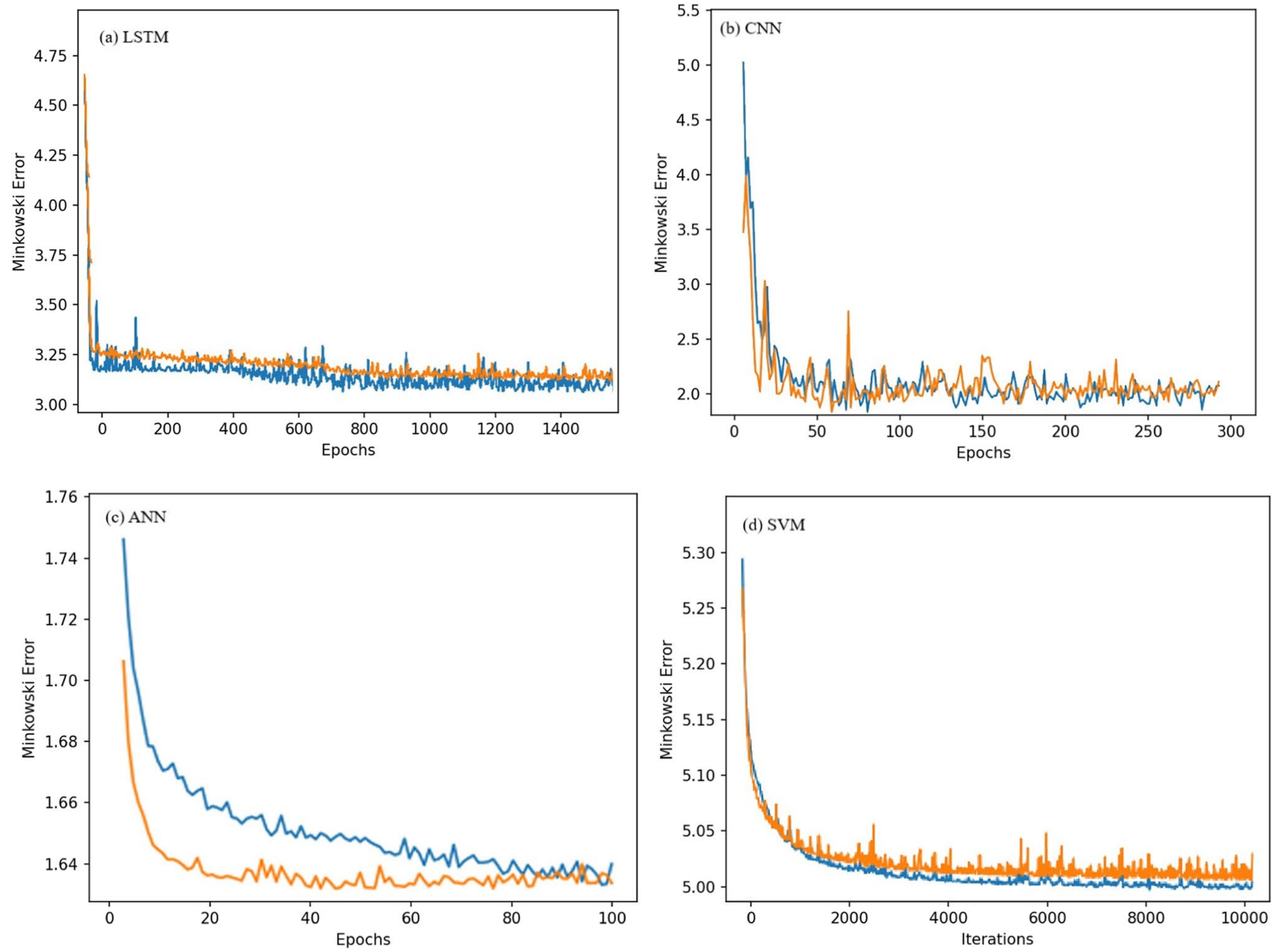



**Fig. 4** Error history of machine learning models

**Table 4** Errors' test for machine learning models

| | Model | Training | Selection | Testing |
|---|---|---|---|---|
| MSE | ANN | 0.000 | 0.002 | 0.003 |
| MSE | CNN | 0.000 | 0.021 | 0.053 |
| MSE | SVM | 0.000 | 0.009 | 0.058 |
| MSE | LSTM | 0.000 | 0.011 | 0.056 |

**Table 5** Robustness and accuracy of results

| Model | RMSE | MSE | MAE | MBE |
|---|---|---|---|---|
| ANN | 0.059 | 0.003 | 0.041 | 0.003 |
| CNN | 0.074 | 0.053 | 0.057 | −0.055 |
| SVM | 0.058 | 0.058 | 0.049 | −0.044 |
| LSTM | 0.056 | 0.035 | 0.038 | −0.025 |

and economic development is increasing at a pace that is currently faster than the ability to produce it with clean energy sources. The climate change effect from greenhouse gas emissions and the burning of fossils fuel to meet energy demands have created an overabundance. Global carbon dioxide emissions have increased by 90% over the past 4 decades, with the increase in emissions stemming primarily from fossil fuel combustion and industrial processes. On the other hand, from the perspectives of economic sectors, agricultural, forestry, and other land use (24%), industry (21%), and transportation (14%) produce the most greenhouse gases. Replacing a higher carbon energy source, such as coal, with lower carbon natural sources like natural gas can have a lower rung of carbon emissions. Similarly, renewable energy sources are proven eco-friendly for the environment. Therefore, world economies need to reduce fossil fuel burning and accelerate eco-friendly energy sources.

Lastly, we analyzed the regional temperature (Africa, Asia, Europe, North America, and South America) and its trend in forthcoming years. Based on available datasets (1910–2021), we trained the LSTM model on the datasets (Africa, Asia, Europe, North America, South America, and

**Table 6** Actual and predicted temperature results with ANN, CNN, SVM, and LSTM models

| No | Actual temperature | Predicted temperature by CNN | Predicted temperature by ANN | Predicted temperature by SVM | Predicted temperature by LSTM |
|---|---|---|---|---|---|
| 1 | 0.18 | 0.335 | 0.292 | 0.263 | 0.289 |
| 2 | 0.46 | 0.504 | 0.476 | 0.546 | 0.461 |
| 3 | 0.46 | 0.453 | 0.416 | 0.453 | 0.451 |
| 4 | 0.76 | 0.798 | 0.680 | 0.818 | 0.646 |
| 5 | 0.55 | 0.619 | 0.553 | 0.539 | 0.539 |
| 6 | 0.43 | 0.463 | 0.421 | 0.483 | 0.449 |

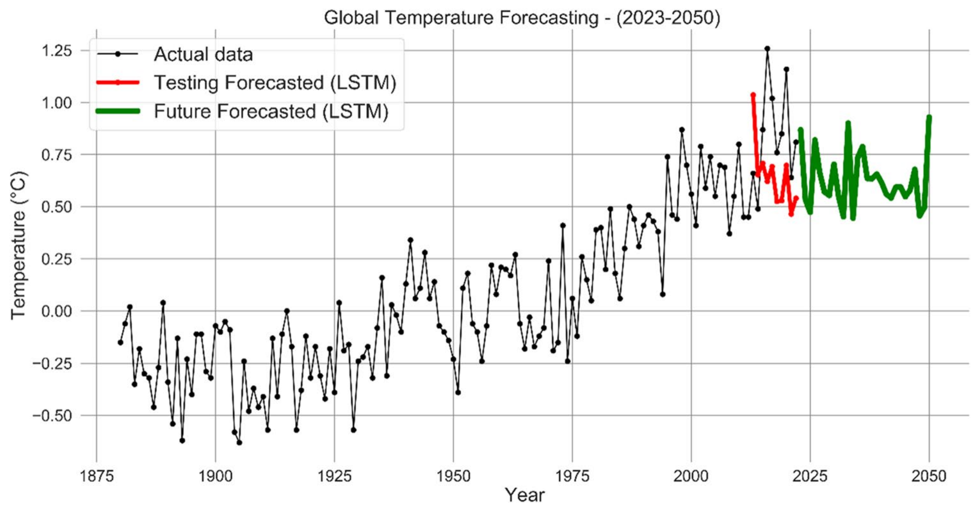



**Fig. 5** Global temperature forecasting

Oceana) from 1910 to 2011 for training and 2012 to 2021 for testing. The tested forecasting results of temperature (2012 to 2021) were found very close to the actual temperature results. This implies that the LSTM model has a better capability in forecasting results. The final step was to forecast the regional temperature trend from 2022 to 2050. The same procedure and algorithm were performed on other regional datasets. Figure 6 gives the historical temperature, tested forecasting, and future forecasting for the African region.

Most of the regions experienced warmer temperatures than usual in the last years. The historical temperature trend provides evidence that surface temperature has increased over the years in Africa. Furthermore, LSTM forecasts of the temperature also indicate a stabilizing trend over the years, suggesting that the temperature is likely to increase significantly in the forthcoming years. More importantly, the trend shows consistently upward from 1980 to 2020. Due to its high vulnerability and low adaptability, Africa, the second-most populous continent, is one of the most vulnerable to climate change. The historical trend in the context of the Africa region shows that among the ten warmest years in Africa, all have occurred since 2005, with the five warmest years occurring since 2010. With an average temperature of 1.44 °C, the years 2010 and 2016 are tied for the warmest years in Africa. Figure 7 indicates the yearly percentage change in temperature of the African region. These results also demonstrate that yearly percentage change in temperature is higher, which employs serious climate concerns in Africa. Considering the year 2022 as the temperature baseline, the trend also suggests that African countries will survive at least 1 °C.

There is a growing risk that West African countries will be exposed to deadly heat stress as a result of global warming (Diedhiou et al. 2018). Also, the effects of global warming in the region are expected to increase the frequency and length of heat waves. Consequently, there is evidence of climate change in northern Africa and the Middle East region adjacent to the Mediterranean, identified as the hotspot areas of climate change (Almazroui et al. 2020). Overall, the forecasted results suggest that temperature has an influencing impact on global warming in African countries.

Following the above procedure, this study examined the forecasting trend of temperature in Asia. Figure 8 indicates the historical temperature, tested forecasting, and forthcoming forecasting for the Asia region. It can be seen clearly that the historical temperature trend in Asia has remained consistent throughout the century. Extending the baseline to 1980, we can see that the temperature in Asia was recorded

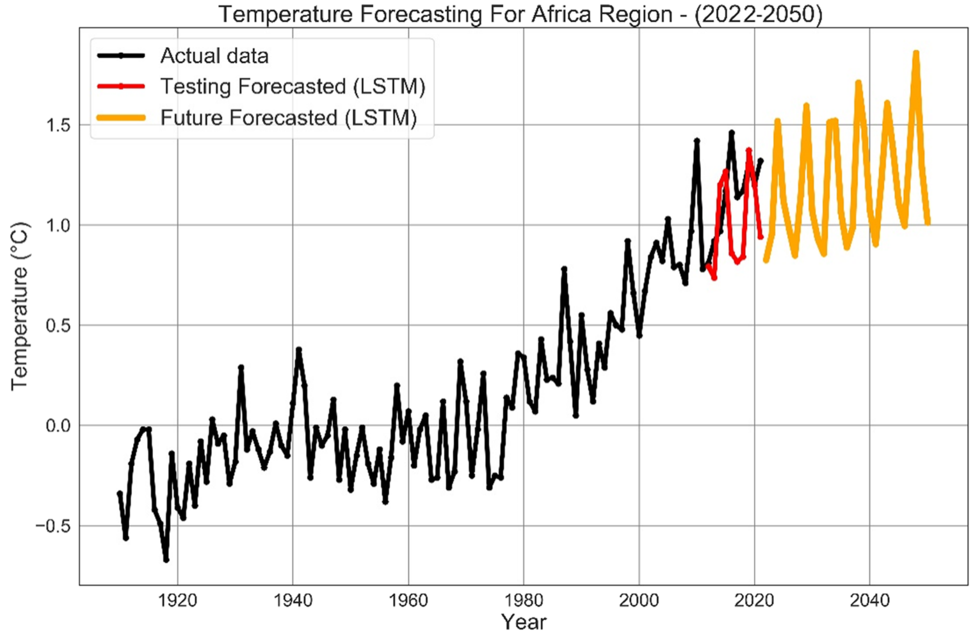



**Fig. 6** Temperature forecasting (Africa region)

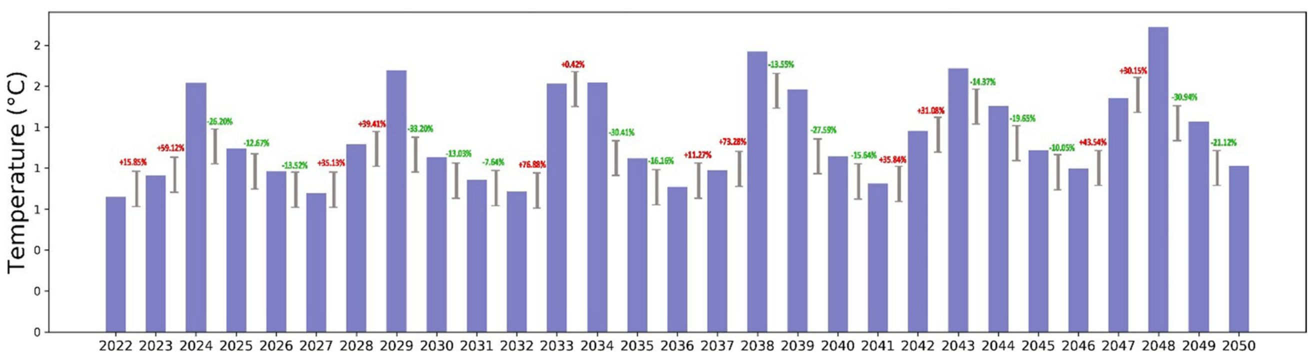



**Fig. 7** Yearly percentage change in temperature (Africa region)

at about 0.5 °C. However, in the forthcoming years, the temperature will cross 1 °C in the next 20 years. The LSTM forecasted trend from 2022 to 2050 also warns of a stable and increased temperature over the years, and the effects are pretty clear with the forecasting trend. Additionally, Fig. 9 presents the yearly percentage change in temperature for the Asia region. Annual percent change in temperature (Fig. 9) is also higher in Asia, indicating that the Asian countries will likely face high temperatures in the forthcoming years. The trend also suggests that the temperature surpasses 1.5 °C in most years. Almost one-fifth of the world's population lives in South Asia, where summer heatwaves could hit if protective measures are not adopted. North India, Bangladesh, and southern Pakistan, which contribute 1.5 billion people, are some of the hardest-hit regions in Asia. Additionally, these countries are among the poorest in South Asia. Many people in these countries rely on subsistence farming, which often requires long hours of hard labor working outside in extreme temperatures. Asia region is also home to many emerging economies. However, most countries in Asia depend on fossil fuel energy consumption, which has subsequently increased global warming. Many developing and emerging countries in Asia use coal, oil, petroleum, and natural gas to produce energy. The adverse effects of these fuels have changed climate change in Asia. Recently, extreme weather events and various impacts of climate change have caused the death of thousands of people, forced millions of others to refugee, and resulted in the loss of billions of dollars while severely impacting infrastructure and ecosystems across Asia (WMO 2020). The weather and climate hazards, including floods, storms, and droughts, affected the agriculture and food security of many Asian countries and have increased the vulnerability of migrants, worsened health conditions, and impacted natural ecosystems.

Apart from Africa and Asia regions, we analyzed the temperature trend of Europe with the LSTM model

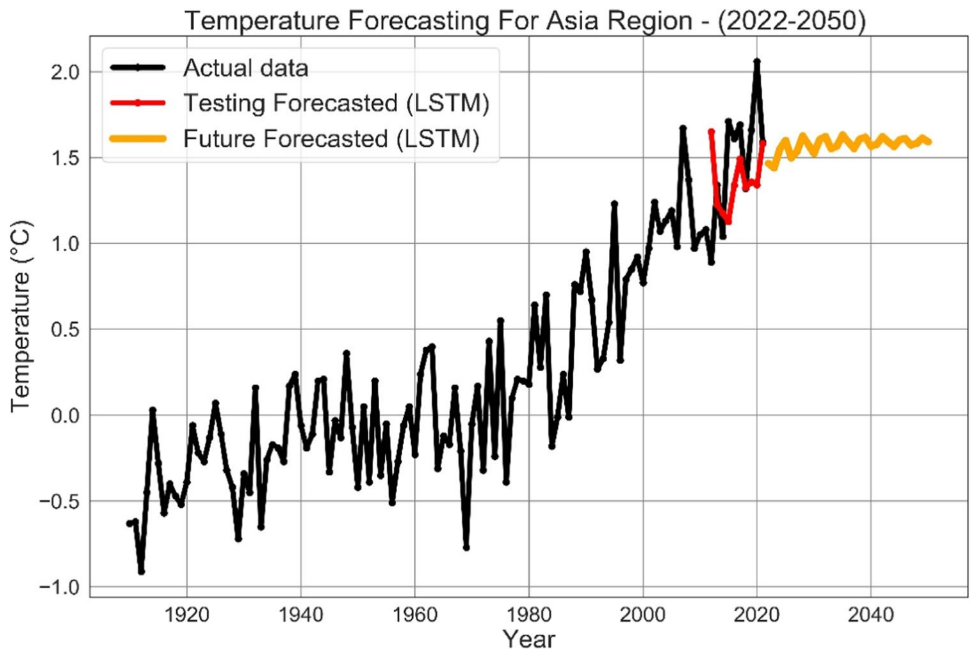



**Fig. 8** Temperature forecasting (Asia region)

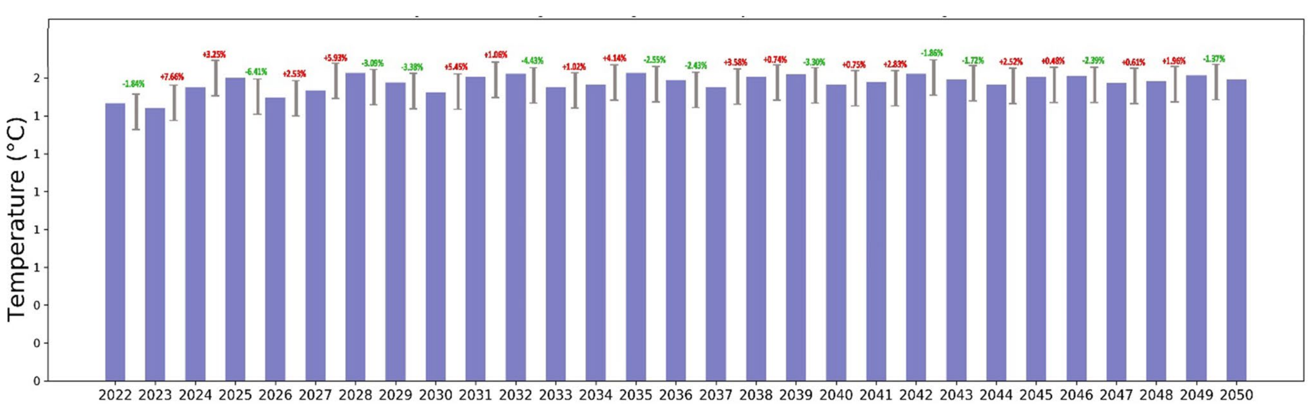



**Fig. 9** Yearly percentage change in temperature (Asia region)

from 2022 to 2050. Figures 10 displays historical temperature trend, tested forecasting, and future forecasting in Europe. The evidence in Europe's case also indicates that this region has been experiencing high temperatures for a few years. Figure 11 displays the yearly percentage change in temperature in Europe. Our forecasted results with the LSTM model demonstrate that European countries will survive at least 0.4 °C. The temperature trend shows that Europe will less likely suffer than Asia and Africa regions. However, the historical trend in the case of Europe shows an increasing temperature trend from 2000 to 2020. The recent two heatwaves of record-breaking intensity hit Europe in 2019. These heatwave events in 2019 were classified as one of the deadliest disasters in the world (Vautard et al. 2020). The LSTM predicted results for Europe indicate that the region is warming faster. As a consequence of the high temperature, the heat waves broke the historical temperature record of many European countries, including Italy, Spain, Australia, Switzerland, and Germany.

It was noted that the historical temperature record of Paris reached 42.6 °C, while a temperature of 43.6 °C was recorded in Paris suburbs. Similarly, the temperatures reached more than 40° in Belgium and the Netherlands for the first time. The 14 stations in Germany have surpassed the historical record above 40.3 °C, with one station exceeding the temperature by 42.6 °C. This evidence shows that recent temperature changes exhibit extreme weather hit the European region.

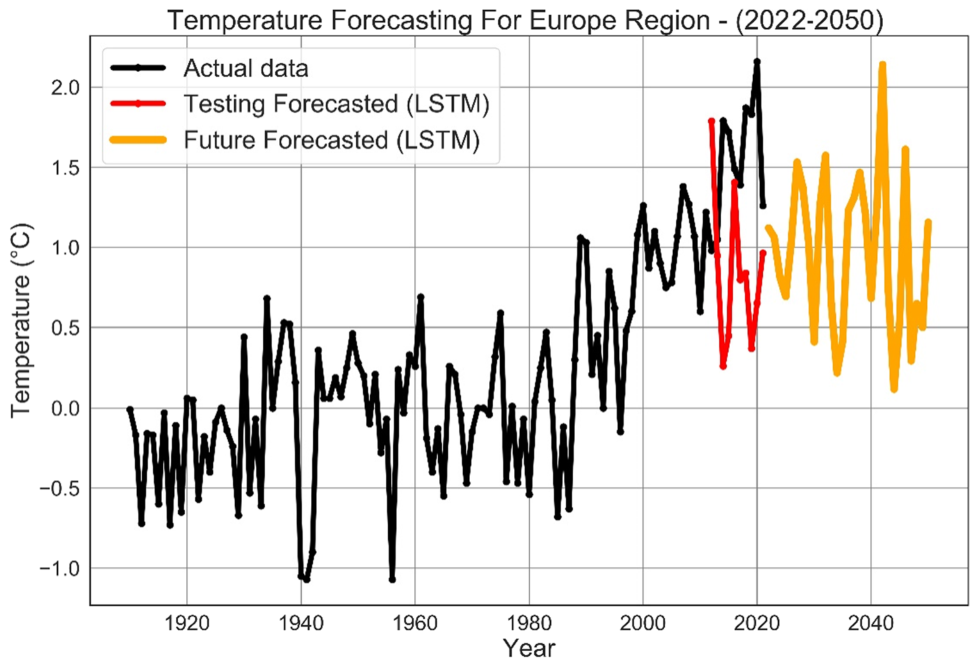



**Fig. 10** Temperature trend (Europe region)

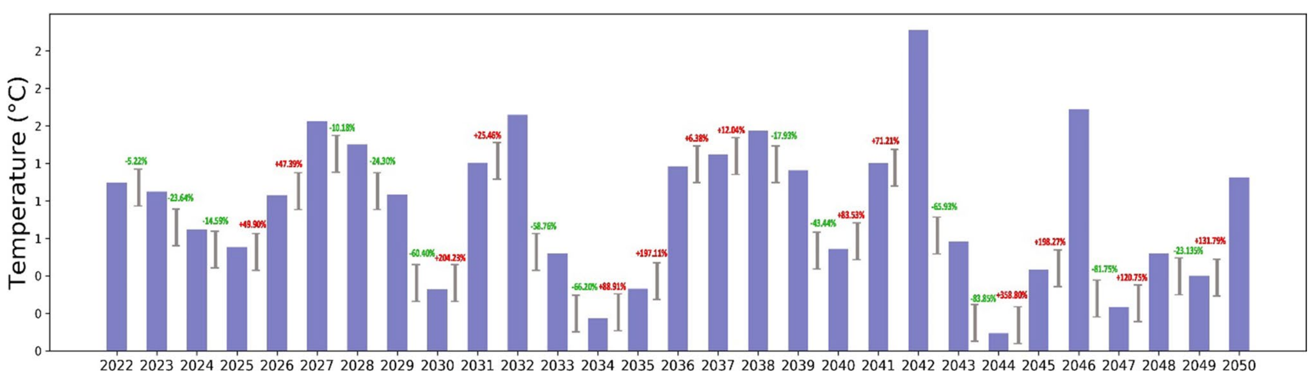



**Fig. 11** Yearly percentage change in temperature (Europe region)

Finally, we forecasted temperature trends in North America and South America. LSTM algorithm was performed on a dataset of North America and South America. Figures 12 and 13 indicate actual temperature, tested forecasting, and forthcoming forecasting in North America and South America, respectively, whereas Figs. 14 and 15 present the yearly change in temperature in North America and South America, respectively.

North America has experienced nine of its ten warmest years in recent decades; the year 1998 ranked as one of the ten warmest years ever. In North America, 2016 was the warmest year, with a temperature deviation of 1.92 °C. It is also estimated that the average temperature in North America has increased by 0.13 °C a year on average. More recently, the Canadian government announced the year 2020 as a disastrous year in terms of weather; due to that, the country lost around 2.5 Canadian dollars (NCEI 2021). Similarly, South America has experienced nine of its ten warmest years in the past 15 years, while the five warmest years have been recorded since 2015. Our forecasted results with the LSTM model indicate a consistent stabilized temperature trend over the years in North America and South America, which implies that both regions will survive at least at 0.5 °C and above. The event of wildfires in South America in 2020 was higher than in 2019. The increased rate of wildfires in 2020 has caused irreversible damage to ecosystems. Therefore, North America and South America regions see the hazardous impacts of increasing temperature as a threat. Besides the hazards above, the report in the context of Latin America shows the increasing threats posed by ocean acidification and rising sea levels to small island developing states, wetlands, coastal ecosystems, and

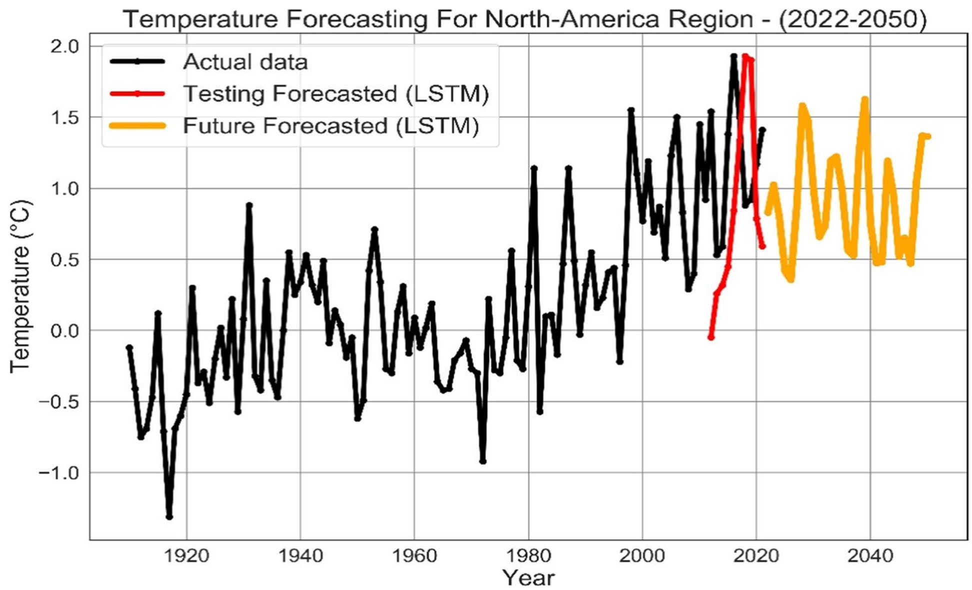



**Fig. 12** Temperature forecasting (North America)

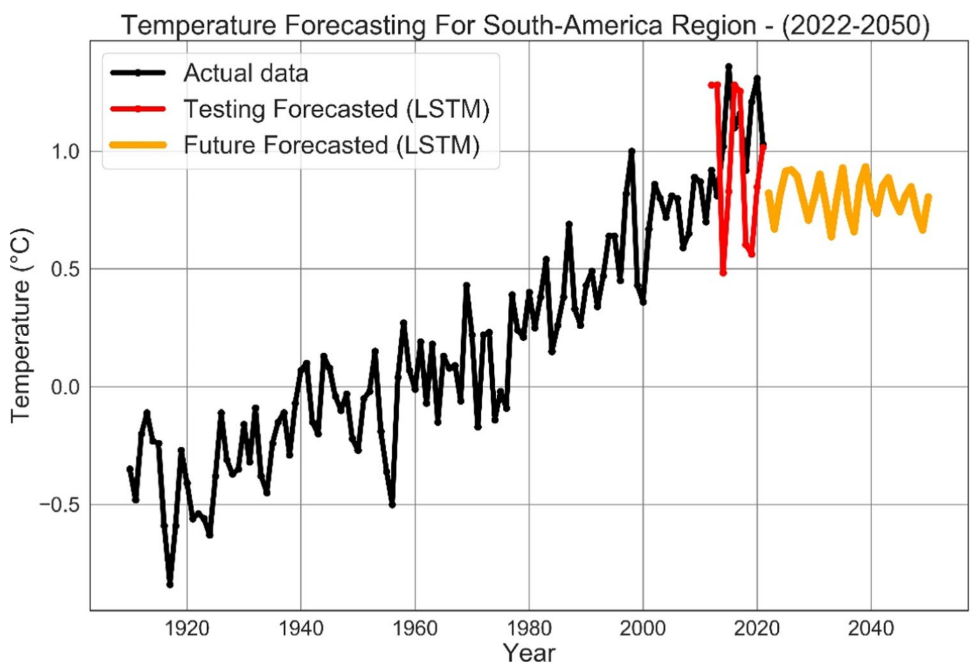



**Fig. 13** Temperature forecasting (South America)

the human communities that depend on them (State of the Climate 2020). A wave of drought sweeping across most of North and South America has significantly impacted inland shipping routes, crop yields, and food production, worsening food insecurity in many areas.

Our results with the LSTM model in forecasting temperature across Africa, Asia, Europe, North America, and South America demonstrate a stabilized temperature over 0.5 °C and above. Particularly, Asia and Africa regions may suffer more where the temperature is estimated to reach around 1.6 °C. Overall, the findings imply that the world would experience heatwaves and a stable temperature over the years. As discussed in the beginning, there has been an enormous increase in the $CO_2$, methane, and $N_2O$ emissions over the years, particularly a rise in $CO_2$ emissions since industrialization began. It is also important to recall that most countries use fossil fuels for industrial purposes. Coal, oil, petroleum, and natural gas contribute largely to total energy consumption. These fuels are proved dangerous for the climate and global warming. Asia and Africa contribute the majority of the world's population. Both regions already experience extremely hot weather. Besides, most countries in Asia and Africa face energy poverty and power issues with a lack of basic facilities (Abbas et al. 2020,

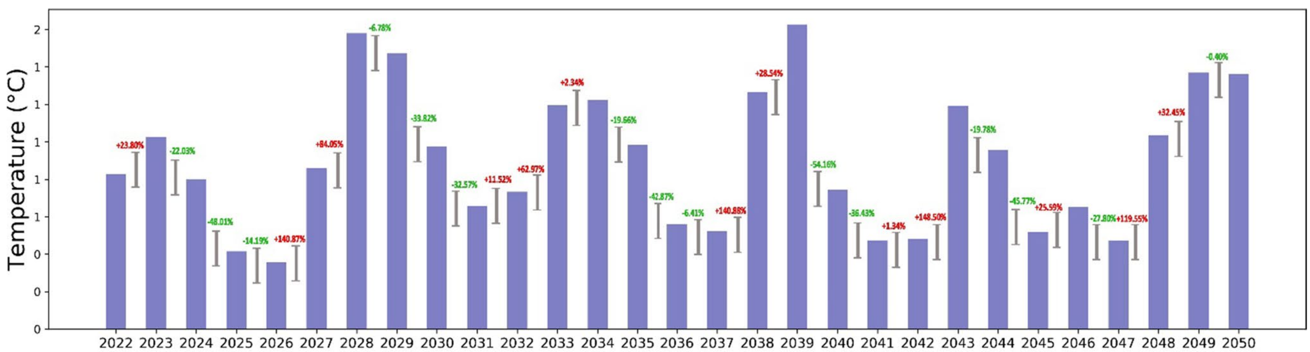



**Fig. 14** Yearly percentage change in temperature (North America region)

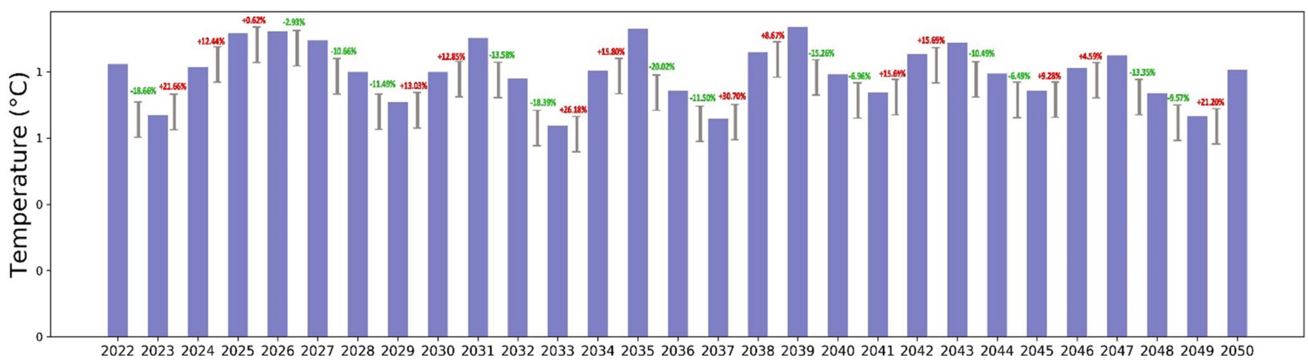



**Fig. 15** Yearly percentage change in temperature (South America region)

2021, 2022). Developing countries in Asia and Africa are the most affected by climate change as most people depend on natural environments and these countries have the least technological advancement to cope with climate change and other environmental issues. Thus, living in extremely hot weather without basic facilities endangers health risks in Asia and Africa. On the other hand, most people in Europe, North America, and South America are not used to surviving in extreme weather, even though most countries in these regions have enough facilities. Thus, these regions may face more extreme consequences of climate change if urgent measures are not taken to curb environmental issues.

### Comparison of findings with other studies

The global average temperature is a significant concern at the current rate and will likely rise in the forthcoming years. Our forecasted results are consistent with previous studies. For instance, the findings of the previous studies demonstrate that the world will likely experience high temperatures, including in European countries (Jacob et al. 2018). Arshad et al. (2020) reported their findings that as a preliminary comparison of current temperatures with historical records, it would seem likely that heatwaves will likely occur twice over the next decade, as well as an increase in extreme weather events and their frequency and intensity. Other studies found that changes in population influence climate change significantly (Rohat et al. 2019). Similar to these findings, Brans et al. (2018) conclude the urban-driven warming in the study. Furthermore, the study's results (Fatima et al. 2021) revealed that anthropogenic activities and greenhouse gas emissions cause the temperature to rise. Our study supports these findings and presents a more robust analysis with multiple economic, environmental, and demographic indicators, extending the new findings on the association between these variables and warning future temperature consequences.

## Conclusion and policy implications

The present study analyzes the global environment in terms of temperature. This study used ten influencing factors (energy consumption, $CO_2$ emissions, $N_2O$ emission, methane emissions, energy consumption per GDP, population, urbanization, $CO_2$ emissions, and per capita fossil fuel energy consumption) as input variables for the outcome variable, temperature. Additionally, this study forecasted global temperature and regional temperature (Africa, Asia, Europe, North America, and South America). This study used CNN, SVM, ANN, and LSTM models to predict and forecast temperature. All the models exhibited excellent capability to predict temperature; however, the LSTM model provides more accurate results than other models. This study forecasted the temperature trend from 2023 to 2050 globally. The forecasted results with the LSTM model demonstrated a stable temperature trend over the years. The results of regional temperature forecasting (2022 to 2050) were an increasing trend in the forthcoming years. Particularly, Asia and Africa regions may experience more extreme weather in the future. It is evident that one of the primary reasons behind global warming is greenhouse gas emissions. It is also widely acknowledged that $CO_2$ is the most significant contributor to climate change among greenhouse gases. As a result, its relative role is expected to grow.

The findings demonstrate that environmental, economic, and population indicators affect climate change. The influence of these factors on climate change indicates that many regions are dependent on non-renewable energy sources. Burning fossil fuels to meet energy demands for industrial and commercial sectors increases greenhouse gas emissions, impacting climate. Most of the temperature spikes can be attributed to greenhouse gases, which trap heat and prevent it from leaving the earth's atmosphere. Clearly, the earth's climate has been changing for decades, and human activities and their influence on the climate system are questionable. The evidence suggests that human actions drive climate change. Therefore, world economies should reduce greenhouse gas emissions, and policymakers and government personnel should focus on environmental issues.

There is no doubt that the planet's warming can devastate both human communities and wildlife habitats. The effects of global warming/climate change can be seen in both increasing and decreasing local temperatures. Additionally, in combination with habitat destruction and pollution, climate change has caused massive wildlife losses, forests, human settlements, glaciers, and coastal heritage sites. Living organisms like plants and animals depend on ecosystems that relatively narrow temperature ranges can only sustain. Meanwhile, human activities are responsible for the recent swift increase in global and regional average temperature over the past few years. From the environmental perspective, coal, petroleum, and oil contribute significantly to greenhouse gas emissions. Without other cleaner options such as nuclear and solar energy, the power industry will emit large $CO_2$. Therefore, there is a dire need to shift energy sources from non-renewable to renewable energy. Developing and emerging economies must reduce petroleum products in the industrial and transportation sectors because a large proportion of greenhouse gas emissions cause global climate. As a result of rising global temperatures, rising sea levels, and more extreme weather caused by greenhouse emissions, human societies are experiencing a greater risk of adverse health effects and reduced economic strength, which will consequently impose high costs on our generation. The responsibility of promoting climate-friendly policies lies with commitment and dedication to reducing greenhouse gases, maintaining economic growth, and supporting innovation simultaneously. In this context, carbon taxes can reduce greenhouse gas emissions and limit $CO_2$ emissions. Moreover, there is a great deal of potential to reduce carbon emissions quickly by switching to fuels that are less carbon-intensive for power plants and vehicles. $CO_2$ emissions can be significantly reduced by switching from coal to natural gas combined cycle plants.

From the demographic perspective, it is expected that migration from hot areas will be triggered by climate change. It is also considered that hundreds of millions of people can move to urban cities, and this move is likely to be a burden on the environment if adequate measures are not taken to mitigate climate change issues. For instance, there is a tendency for humans to adapt to heat by using air conditioning units; however, if the energy used in the air conditioning unit is not renewable, then this use will exacerbate climate warming. Despite the numerous benefits of using renewable energy, communities, residents, nations, and the global community have delayed implementing mitigation strategies to reduce their vulnerability to climate change and shift their reliance from fossil fuels to renewable energy. Besides, urban development is a major contributor to climate change. It is crucial to reduce climate change effects through transportation (public transport, electric vehicles), energy (recycling, solar energy panels, and investment in energy-efficient appliances), and green investment (green construction and greening urban environment). Similarly, households and industries contribute to greenhouse gas emissions mainly through waste disposal, combustion of fossil fuels, and the use of certain substances containing greenhouse gases. The government should raise awareness to reduce waste by choosing reusable products instead of disposables. For example, buying products with minimal packaging can reduce waste.

On the other hand, since the industrial revolution emerged, economic development has accompanied fossil fuel consumption, contributing to greenhouse gas emissions. It is reasonable to consider that pursuing economic development and addressing the problem of climate change are not inherently incompatible; therefore, world economies should balance economic growth and environmental quality. For instance, the price of all machinery or technology that causes carbon emissions should be increased. This will reduce the use of machinery and increase the focus on inventing new environmentally friendly technologies. Also, organic abolition of fuel subsidies can create a competitive trend in the market and give equal opportunities to other technologies.

## Limitations and future work

This study has certain limitations. The results demonstrate the sensitivity of estimated temperature impacts by environmental, economic, and demographic indicators, suggesting a greater need for further investigation into the relationship between climate change and its influencing factors, particularly at the sectoral level. Future studies may extend this work by exploring anthropogenic activities, the impacts of agriculture, deforestation, and food insecurity on climate change. Exploring climate change at the sectorial level can advance new insights into key sources of greenhouse gas emissions contributing to climate change. Our findings are based on the available dataset (1980–2018). If data allows, future work should explore the temperature impacts seasonally, which can provide a more detailed analysis in investigating climate change effects.

**Author contribution** Mansoor Ahmed: conceptualization, investigation, data curation, methodology, writing original draft.
Huiling Song: investigation, results interpretation and editing.
Hussain Ali: writing, review and editing.
Chuanmin Shuai: formal analysis, supervision, review and editing.
Khizar Abbas: methodology, results analysis, policy suggestions.
Maqsood Ahmed: methodology, software, visualization.

**Data availability** Supplementary data to this article will be provided on request.

## Declarations

**Ethics approval** Not applicable.

**Consent to participate** Not applicable.

**Consent for publication** Not applicable.

**Competing interests** The authors declare no competing interests.

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