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Predicting Climate Change with Artificial Neural Networks within the Framework of Environmental and Economic Policies: The Case of the G20

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ABSTRACT

The Climate change is a significant issue that directly affects the environment and well-being of every living organism on Earth. In addition to environmental concerns, it exacerbates socio-economic burdens, especially in developing countries, and further worsens ongoing social inequalities. The effects of climate change and the difficulty of reversing these effects necessitate international collaboration and policies that prioritize sustainability. At this point, it is important to predict how climate change and trends will evolve in the future in order to minimize the adverse effects and take necessary measures. The aim of this study is to estimate the course of global climate change, particularly in the G20 countries, which are among the countries most responsible for environmental problems, based on the goals of the United Nations 2030 Agenda for Sustainable Development. For analysis, the Artificial Neural Networks method, which has recently emerged in forecasting studies, is used. The dependent variable in the analysis is the change in temperature, which is an indicator of climate change. The independent variables include per capita CO2 emissions, population, GDP change, consumption of oil, coal, natural gas, nuclear energy, urban population, and carbon tax implementation. Referring to the United Nations Environment Conference, the data range is limited to 1972-2022, and the average temperature change until 2030 is predicted. According to the analysis results, it is found that the average global temperature change by 2030 will exceed the United Nations target of 1.5 degrees Celsius.©**authors**.

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1. Introduction

One of the significant turning points in human history is undoubtedly the Industrial Revolution, which began with the invention of the steam engine. The industrialization that accelerated at the beginning of the 19th century contributed to a high economic growth trend, but it also led to some adverse effects. The changes in production activities during the industrialization process increased the need for energy use and the consumption of fossil fuels. Indeed, the environmental degradation and climate change resulting from this transformation have intensified scientific studies in this field.

Climate change is a significant challenge that directly affects the environment and welfare of all living beings on Earth, including future generations. The magnitude and complexity of climate change, along with growing concerns about current environmental issues, continue to impact many people globally and will do so for generations to come. As a result of climate change, natural disasters leading to significant loss of life and economic damage have increased in recent years. Research on climate change highlights that natural disasters and associated losses are expected to increase in the future. In this context, sustainable development and a sustainable economy that considers environmental benefits make international cooperation inevitable.

When evaluating the relationship between international economic policies and environmental pollution, it is widely accepted that developed countries are largely responsible for both the creation of environmental pollution and the implementation of environmental policies. Statistics show that developed countries, particularly G20 countries, have a significant share in the emission of greenhouse gases into the atmosphere, which causes environmental pollution and climate change.

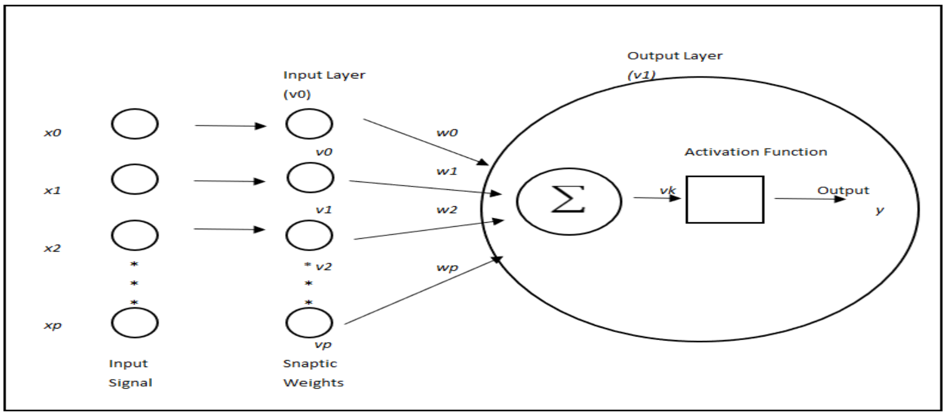
The purpose of this study is to emphasize the importance of this global issue by analyzing the relationship between environmental and economic policies through a comparative study of G20 countries. In this context, the study aims to determine the future trajectory of climate change, particularly within the framework of the United Nations 2030 Sustainable Development Agenda, by adopting its goals as the analytical framework. To achieve this, the study utilizes the Artificial Neural Networks model, which has been frequently used in recent years for predicting climate change and ecological events.

Artificial Neural Network

Artificial Neural Networks (ANN), one of the emerging fields in artificial intelligence, are a mathematical computational model based on biological neural networks, consisting of a group of interconnected artificial neurons that process information using a connectionist approach (Li and Ma, 2010: 211). Defined as an information processing process, ANN is also described as a black-box model that produces outputs in response to given inputs.

The modern view of ANN is considered to have started with the work of Warren McCulloch and Walter Pitts in 1943, which demonstrated that artificial neuron networks could, in principle, compute any arithmetic or logical function (Xu and He, 2018: 347; Hu and Hwang, 2002: 13). In their 1943 work, McCulloch and Pitts mathematically defined the structure of the neuron network, attempting to prove that a neuron could perform logical functions. As shown in Figure 1, a simple ANN, resembling a biological neuron, consists of nonlinear interconnected hidden layers between the input layer and the output layer.

Figure 1. *The Structure of an Artificial Neural Network*



Source: Adapted from Lopez, Lopez, and Crossa, 2022: 382.

According to Figure 1, the mathematical representation of an ANN (vk) is calculated as shown in Equation 1.

(1)

$$\sum_{j=1}^{p} vij\ xj$$

In Figure 1, v(v1, v2, v3) represents the input layer containing independent variable(s). The input layer can be considered as the information coming from the external world (Liu et al., 2010: 3855). The purpose of this layer is to distribute the given external input model vector to the feedforward part of the network (Yegnanarayana, 2005: 203). The different values received by the neuron are then modified by synaptic weights, which come together to produce what is called the net input. The mathematical representation of the net input (vj) is shown in Equation 2 (Lopez, Lopez, and Crossa, 2022: 382).

(2)

$$\sum_{j=1}^{p} wij\ xj$$

The net input (vj) determines whether the neuron is activated or not. The activation of the neuron depends on the activation function. As shown in Figure 1, the activation code (vk) is the area where the output is obtained, evaluated between the net input and the output. The activation function is used to limit the amplitude of a neuron's output (Haykin, 2009: 10). Using appropriate activation function can help prevent underfitting.

There are many different activation functions in the literature. These include the Sigmoid, linear function, step function, sinus function, threshold function, rectified linear unit, and hyperbolic tangent function. The Sigmoid function is the most commonly used in studies and is defined as an increasing S-shaped function (Haykin, 2009: 14).

In the linear function, the input is considered as the output of the cell. It is a linear neuron transfer function (Yadav, Yadav & Kumar, 2015: 22). In the step function, the output of the cell takes a value of 1 or 0, depending on whether the incoming net input is below or above a defined threshold value. The sinus function is defined for y values between 0 and 1, where it converges towards 0 before the x=0 axis and towards 1 after it (Öztemel, 2017: 51).

The threshold function is used when the incoming values are between 0 and 1. Rectified linear unit (reLU), function is defined as f(x) = max (0,x) and returns 0 for negative inputs and the input value for positive inputs (Bhujade & Asthana, 2023: 69). It is computationally simple and performs better in deep networks. The hyperbolic tangent (Tanh) function is calculated by passing the incoming (vj) value through the tangent function. The Tanh function compresses the output to the range −1 to 1. It works better than the sigmoid function because it ensures the output is zero-centered.

The middle layer shown in the middle part of Figure 1 is referred to as the hidden layer (Nielsen, 2013: 11). These layers are called hidden because the calculations performed between the input and the output are not visible to the user (Aggarwal, 2018: 17). They consist of neurons responsible for extracting patterns associated with the analyzed process or system (Silva et al., 2017: 22). In Figure 1, y represents the output layer. The output layer consists of the response variable and varies according to the number of inputs (Shehab et al., 2022: 190).

Advantages and Disadvantages of Artificial Neural Networks: Artificial Neural Networks can vary depending on the application. Neural Network approaches are preferred due to their ability to model nonlinear dynamics and process input signals from different domains (Zecchin et al., 2015: 245). Since many scientific relationships are nonlinear, this is considered a significant advantage (Cartwright, 2008: 6). The other advantages of the model, which led to the preference for ANN in this study, can be expressed as follows:

- Generalization, an intuitive behavior unique to humans, is considered one of the key advantages of ANN (Yegnanarayana, 2005: 372). At its core, machine learning is built on creating models that generalize well and perform well on unseen data (Chollet, 2017: 97).
- With ANN, better prediction performance can be achieved using smaller amounts of data (Walczak and Cerpa, 2003: 641). Advances in artificial intelligence research have become prominent in recent years.
- Compared to traditional models, the advantage of ANN is its ability to work with incomplete information. The impact of working with incomplete information on the model's performance depends on the importance of the missing data (Öztemel, 2017: 32).
- Adaptive learning is one of the most significant advantages of ANN systems. In adaptive learning, ANN mimics the human brain in learning how to perform tasks while learning (Kukreja et al., 2016: 30). For example, the system can learn to recognize the desired information by using adaptability and pattern structure.
- Another advantage of artificial neural networks is their ability to learn from the environment. Environmental learning is beneficial in applications where the complexity of the environment makes other types of solutions impractical (Krenker, Bešter, and Kos, 2011: 13).

Although Artificial Neural Networks have many advantages over traditional systems, there are also some disadvantages that researchers in this field strive to minimize. The known disadvantages and practical challenges of ANNs are expressed as follows:

- The most commonly criticized aspect of ANN in the literature is its "black box" nature. As explained in the section describing the ANN process defined as the process of information processing, produces outputs in response to given inputs. The calculations performed between the input and output in the hidden layer are not visible to the user. Therefore, ANN is often referred to as a black box, and the lack of transparency in the system is criticized.
- An unpredictable gap can form between the training and test data performance, which poses a problem, especially when models are complex, and the dataset is small (Aggarwal, 2018: 25).
- There are no specific rules or guidelines for designing a network for a particular application in ANN. When developing an application with ANN, there is no universal rule for model selection and determining the topology of the networks. Making the right choices entirely depends on the experience of the person using the model.
- To complete the training, it is generally considered sufficient to reduce the error of the network on the samples below a certain value.

Typically, learning is stopped when the user believes the error is small enough (Kriesel, 2009: 59). However, there is no definitive method for deciding how long the training should continue.

Types of Artificial Neural Networks

ANNs can be classified in various ways based on their characteristics. In general, the classification of ANNs is based on the following criteria (Basheer and Hajmeer, 2000: 13); Function the ANN is designed to serve (such as pattern association, clustering, etc.), degree of connectivity of neurons in the network (partial/full) and direction of information flow in the network (recurrent and non-recurrent).

Feedforward Neural Networks are considered the oldest and most widely used network architecture (Silvestrini and Lavagna, 2022: 11). In its most general form, a feedback network consists of a series of processing units where the output of each unit, including the unit itself, is fed as input to all other units (Yegnanarayana, 2005: 142). The term "feedforward" refers to the flow of information within the network. Information flows in a single direction, from input to output, without any feedback loops (Krenker, Bešter, and Kos, 2011: 7). Movement occurs in only one direction from the input layer to the hidden layer (if present) and to the output layer.

Spiking Neural Networks, also known as Ascending Neural Networks, are third-generation artificial neural networks in which each neuron uses separate spikes to communicate within the network (Silvestrini and Lavagna, 2022: 20). Ascending Neural Networks were originally inspired by the communication scheme used by the brain, where neurons transform information over time through action potentials (spikes) via adaptable synapses.

The Recurrent Neural Networks (RNNs) used in this study, designed to learn sequential or time-varying patterns, began to be studied in the 1990s. Artificial neural networks with a recurrent topology are referred to as Recurrent Artificial Neural Networks. Recurrence/reiteration is defined as the process by which a neuron affects itself through any path or connection (Kriesel, 2009: 66).

In a recurrent network, the outputs of some neurons are fed back to the same neurons or neurons in previous layers (Basheer and Hajmeer, 2000: 14). During learning, the recurrent network feeds its inputs through the network, including data feedback from outputs to inputs, and repeats this process until the values of the outputs no longer change (Yadav, Yadav & Kumar, 2015: 25). Unlike a general neural network, Recurrent Neural Networks have input not only in one layer but in all layers. In a network with feedback connections, a nonlinear dynamic system is processed. A recurrent neural network distinguishes itself from a feedforward neural network by having at least one feedback loop (Haykin, 2009: 23). In this type of network, where feedback loops are possible, loops do not cause problems because the output of a neuron affects its input not immediately, but at a later time (Nielsen, 2013: 12).

This type of neural network is commonly used for designing sequential data such as text sentences, time series, and biological sequences (Aggarwal, 2018: 39). The main advantages of recurrent neural networks are as follows: the network memorizes relationships; it has the ability to compute while considering past information (Silva et al., 2017: 139). The loops in the network's topology enable signals to be stored for a certain period after they are generated and reused. It is a universal approach for all nonlinear dynamic systems; any nonlinear dynamic system can be approximated to any desired level of accuracy by a recurrent neural network, provided the network is equipped with a sufficient number of hidden neurons, without any restrictions (Haykin, 2009: 789). It has a model size that does not increase with the size of the input.

2. Literature Review

In their 1996 study, Gopal and Woodcock predicted changes in the forested area in California under a national project by using annual data from the 1988-1991 period with a Multilayer Feedforward Neural Network (MLFNN). Due to the prolonged drought in the region, which led to the extinction of coniferous tree species, the future of the tree species in the area was predicted. In the study, changes in the land structure of the region and forested areas were used as input variables, while the decrease in forested areas and losses in tree species were used as output layers. The number of hidden layers in the model was tested within the range of 5-50. The study proceeded with 15 hidden layers, which provided the best performance. Additionally, the same prediction process was carried out using the Gramm-Schmidt Method, and the results were compared with those of the MLFNN. The findings indicated that the MLFNN provided better predictions than the Gramm-Schmidt Method. The future predictions revealed that there would be significant losses, particularly among coniferous tree species.

In their 2005 study, Thuiller et al. analyzed climate change in Northern and Southern Europe using Neural Network models based on data from shifting plant diversity. The study used data from 1,350 plant species between 1972 and 1996 to predict the future of these species up to 2080. The climate data used included annual average winter and summer precipitation, average temperature, and the minimum temperature of the coldest month. Seven different climate change scenarios were developed, taking into account qualitative variables such as global development, technology, and migration up to 2080. The study found that many plant species are under threat, with more than half of the species expected to become extinct by the end of 2080. In the most severe climate change scenario, it was estimated that 22% of plant species would be critically endangered, and 2% would face extinction.

In their 2014 study, Azid et al. attempted to measure air pollution and air quality in Malaysia using Neural Networks by analyzing regions where the country's 10 air monitoring stations were located. The study examined hourly data from the 2005-2011 period, using measurements of methane gas, non-methane hydrocarbons, tetrahydrocannabinol, ozone gas, sulfur dioxide, carbon monoxide, nitrogen dioxide, and particulate matter. The study employed the XLSTAT 2014 software package. In the analysis, a Multilayer Perceptron and Feedforward Neural Network were used, and the Kaiser-Meyer-Olkin (KMO) Test was applied, considering the root mean square error (RMSE) as a performance metric. It was concluded that the RMSE showed better performance in prediction, and the study highlighted the need to pay attention to methane gas and tetrahydrocannabinol variables, emphasizing the necessity of reducing the usage of these gases.

In their 2019 study, Maleki et al. investigated whether Neural Networks could accurately predict future environmental pollution in Ahvaz, Iran, a city with high levels of air pollution due to dust storms. The study utilized hourly data from the first 9 months of 2009, obtained using the beta attenuation method at four air monitoring stations in the city. The variables used in the study included air temperature, wind, precipitation, ozone, nitrogen dioxide, cobalt, sulfur dioxide, and particulate matter measurements. The study concluded that NN could be an effective model for predicting air pollution. Subsequently, the NN model was used to forecast air pollution from August 2009 to August 2010. The prediction results indicated a significant increase in air pollution over the following year.

In their 2020 study, Javadinejad, Dara, and Jafary predicted changes in groundwater levels in Ramhormoz, Iran, due to climate change using Nonlinear Autoregressive with Exogenous Inputs and Neural Networks. The study utilized data from 1980-2010, where daily precipitation, minimum and maximum daily temperatures were the independent variables, and atmospheric circulation was the dependent variable. To predict the decrease in groundwater levels using the NN model, observations from 23 active piezometric wells in the Marvdashtplain region were included. The input components simulated due to climate change were fed into the neural network model to forecast the aquifer's condition for the next seven years. The analysis revealed that climate change has significant impacts on the groundwater levels in the tested region. The study concluded that, as a result of climate change, groundwater levels in the area are expected to decrease.

In their 2022 study, Maqsood et al. investigated the future of evapotranspiration and temperature on Prince Edward Island, Canada, using Long Short-Term Memory (LSTM) Recurrent Neural Networks and Convolutional Neural Networks (CNN). The study utilized daily maximum and minimum temperature data from the 1989-2005 period to develop different climate scenarios. The dataset was split, with 70% used for training and 30% for validation, and 2 hidden layers were employed. The Levenberg-Marquardt learning algorithm was applied. Initially, the performance of the neural network was evaluated. Subsequently, the study predicted the behavior of evapotranspiration and temperature for the years 2020, 2050, and 2080. According to the neural network predictions, there is an expected gradual increase in both evapotranspiration and the maximum and minimum temperature values in 2020, 2050, and 2080. The highest temperature change is predicted to occur in 2080.

In their 2023 study, Diengdoh et al. aimed to predict the future presence of 59 butterfly species in Australia from 2050 to 2090 using a Feedforward Neural Network (FNN) model in relation to climate change. The analysis predicted a gradual decline in several butterfly species in Australia's interior regions by 2050 and 2090. However, in the coastal regions of Australia, the climate conditions were not expected to worsen, and no decline in butterfly species was anticipated. As a result, the study emphasized the need to increase the number of green conservation areas.

Upon reviewing the literature, it is observed that ANN have been widely used in both social and applied sciences for a long time. A common feature of many studies is the comparison of predicted values from the ANN model with actual values to assess the performance of the method. In most of the reviewed studies, the ANN model has been found to be more successful than other statistical models in predicting climate change and environmental pollution. According to the literature review analyzing climate change and environmental pollution with ANN, the most commonly used variables in the studies are CO2 emissions, SO2, temperature changes, PM10, particulate matter, and plant biodiversity.

3. Method

In this study, the ANN model was used to predict the future trend of climate change, as explained in the previous section. All analyses were conducted using Matlab R2023b, along with the Deep Learning and Neural Network toolbox statistical programs.

***Creation of the Dataset*:** The design of Artificial Neural Networks (ANN) requires the developer to make numerous decisions, such as input values, the sizes of training, validation, and test datasets, the learning algorithm, network architecture or topology, and the activation function. Many of these decisions are interdependent. Designing ANNs involves following a sequence of steps, which can be outlined as follows (Walczak and Cerpa, 2003: 634); Determining the dataset to be used, identifying the input variables, dividing the dataset into training, validation, and testing subsets, defining the network architecture, selecting the learning algorithm, normalizing the data if necessary, transforming variables into network inputs, training the dataset (until the ANN error falls below an acceptable threshold), testing the model. The performance of the designed ANN is determined by various statistical measures, such as absolute error, root mean square error, coefficient of variance, and the best fit of ANN-predicted data, based on the criteria for minimizing errors.

Before conducting the analyses, datasets were prepared for each country, and the dependent and independent variables to be used in the analysis were determined. The dataset consists of variables created based on a literature review, which are considered to be effective in explaining climate change. The steps involved in creating the dataset for use in the analysis are explained below in sequence.

Dataset Analysis: In the data analysis process, the presence of missing and outlier values was first checked. Then, each dataset was examined for outliers. This step is crucial due to the varying units of the variables used. The reason for this is that the variables used have different units, such as millions, tons, and percentages. The presence of outliers in the dataset, indicating abnormality according to standard deviations, has been detected using the Z-score method. The Z-score formula is shown in Equation 3:

$$z = \frac{x-\mu}{\sigma} \tag{3}$$

It was determined that standardization of the data was necessary for all datasets. In summary, the standardization process is used to systematically normalize the dataset features within a [0, 1] range, which facilitates the interpretation of the data (Logeswari, Bose, and Anitha, 2023: 873).

Feature Selection of Variable: After standardization, the statistical significance of the model was determined. This step is essential to prevent unnecessary and irrelevant variables in the dataset from reducing the model's effectiveness and increasing its complexity. In other words, it is necessary to determine whether the independent variables selected to identify the dependent variable, temperature, are significant. Different methods such as correlation analysis, Principal Component Analysis (PCA), and feature selection toolboxes are used to follow this process. In this study, the toolbox available in MATLAB was utilized.

Optimization: The optimization process aims to improve the model's performance by minimizing the loss function. In this study, the Matlab optimization toolbox was utilized for optimizing the datasets. The explanatory power of the independent variables for the dependent variable was determined using regression analysis. Initially, regression analysis was performed for one dependent variable and 11 independent variables considered for inclusion in the analysis. However, the land cover change indicator, which reduced the significance of the model, was removed from the model. In the final model, the dependent (output) variable is the change in temperature, which serves as an indicator of climate change. The independent (input) variables in the model include per capita CO_2 emissions, population, GDP change, oil consumption, coal consumption, natural gas consumption, nuclear energy consumption, urban population, and carbon tax implementation (dummy).

The data used in this study spans annual values from 1972 to 2022. The reason for choosing 1972 as the starting year is that international collaborations (Stockholm Conference) in combating climate change have been tracking their goals since that date. Another important consideration in the study is the assumption that at least 30 years of data are required to determine the climate conditions of a place.

To measure the success of the models created, it is necessary to apply metrics that are widely accepted as standards. The statistical indicators used to evaluate the performance of the models in this study are MSE and R^2.

4. Finding

The application section of the study is divided into two parts. In the first stage, before predicting the temperature change for 2030, the predictive success of the ANN model to be used was measured. For this purpose, the existing temperature change data were re-estimated using ANN. This process was carried out using Matlab's Neural Network Fitting toolbox. The predicted temperature change values found by the model were compared with the actual temperature change values. The application was performed separately for each country.

In the second stage, the temperature change between 2023 and 2030 for G20 countries was predicted. The performance of the dataset created for each country was determined using the coefficient of determination analysis. Summary results for all countries are shown in Table 1.

Table 1. *Summary ANN Regression Analysis Results (R2) Values*

India	Argentina	China	Germany	Indonesia
0,95	0,95	0,96	0,87	0,95
Avustralia	**France**	**Italy**	**U. Kingdom**	**Mexico**
0,94	0,95	0,95	0,98	0,95
Japan	**Russia**	**S. Korea**	**S. Arabia**	**S. Africa**
0,97	0,97	0,93	0,96	0,98
USA	**Canada**	**Brazil**	**Turkey**	**World**
0,97	0,96	0,98	0,94	0,98

It has been observed that the R^2 values in the established model are quite good for all countries. The predicted values are found to be consistent with the actual values. In other words, the performance of the ANN for the study is quite high.

After testing the success performance of the ANN in the first stage, the application moves on to the second part. In the second part, the temperature changes for the G20 countries between 2023 and 2030 will be predicted.

***Future Prediction of Climate Change Using the Nonlinear Autoregressive Exogenous Model: G20 Countries*:** A Nonlinear Autoregressive Exogenous Model (NARX), which incorporates exogenous inputs, is a type of recurrent dynamic network with feedback connections that span various layers of the network (Boussaasa et al., 2018: 3). In this model, feedback connections are allowed, and a nonlinear dynamic system is operational. The autoregressive process is expressed as AR(p), where the current value of the series depends on the previous p values. The defining equation for the NARX model is shown in equation 4.

$$y(t)=f(y(t-1),y(t-2),\ldots,y(t-ny),u(t-1),u(t-2),\ldots,u(t-nu)) \quad (4)$$

In the NARX model, neural learning is used to efficiently combine previous data to predict future values in time series (Ali et al., 2021: 7-8). The external input and subsequent outputs of the time series data are responsible for predicting the next value in the nonlinear model of the NARX neural network.

The NARX model is specifically designed to incorporate exogenous inputs effectively, making it particularly suitable for problems where external variables significantly influence the system dynamics. While models like LSTM and GRU are powerful in handling sequential data, they do not explicitly account for exogenous variables without additional architectural adjustments. NARX offers a relatively simpler structure compared to LSTMs and GRUs, making it easier to interpret and implement for tasks where interpretability is crucial.

This is particularly beneficial in climate prediction, where understanding the role of external factors (e.g. temperature) is as important as making accurate predictions. The NARX model was chosen over LSTM and GRU due to its strength in explicitly handling exogenous inputs, its interpretability, and its computational efficiency.

Since the predicted values in the study are normalized values in the initial stage, the process was reversed, and denormalization was performed. The denormalization process was carried out using Matlab. This process was calculated separately for each country. In all analyses, Levenberg-Marquardt (LM), Bayesian Regularization, and Scaled Conjugate Gradient algorithms were tested sequentially for the selection of the learning algorithm. The analyses continued with the LM algorithm, which provided the most successful and fastest results.

In the model, data from 1972 to 2022 was used to predict how temperature changes will occur by 2030 for all sample countries. Table 2 presents the analysis results and temperature forecasts created by selecting different combinations of features.

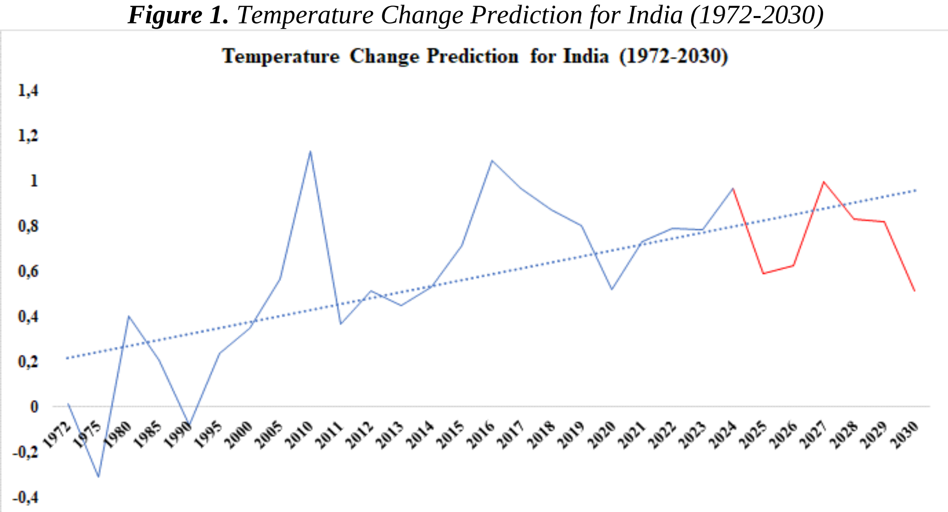
Tablo 2. *G20 - NARX Model Performance Results*

Sample	Model	Learning Algorithm	Split	Epoch	Hidden Layer	Delay Layer	R^2	MSE
India	**NARX	TrainLM	90-10	19	10	2	0,96	0,0003
Argentina	**NARX	TrainLM	90-10	8	10	2	0,89	0,0033
China	**NARX	TrainLM	90-10	35	10	2	0,94	0,0013
Germany	**NARX	TrainLM	90-10	11	10	2	0,97	0,0029
Indonesia	**NARX	TrainLM	90-10	24	10	2	0,96	0,0023
Australia	**NARX	TrainLM	90-10	16	8	2	0,88	0,0081
France	**NARX	TrainLM	90-10	11	10	2	0,96	0,0022
Italy	**NARX	TrainLM	90-10	9	10	2	0,95	0,0041
United Kingdom	**NARX	TrainLM	90-10	11	8	2	0,97	0,0026
Mexico	**NARX	TrainLM	90-10	13	10	2	0,97	0,0028
Japan	**NARX	TrainLM	90-10	11	8	2	0,96	0,0023
Russia	**NARX	TrainLM	90-10	24	10	2	0,99	0,0035
South Korea	**NARX	TrainLM	90-10	11	10	2	0,86	0,0013
Saudi Arabia	**NARX	TrainLM	90-10	12	10	2	0,98	0,0059
South Africa	**NARX	TrainLM	90-10	11	10	2	0,91	0,0017
United State	**NARX	TrainLM	90-10	14	8	2	0,96	0,0038
Canada	**NARX	TrainLM	90-10	10	8	2	0,95	0,0031
Brasil	**NARX	TrainLM	90-10	12	10	2	0,97	0,0034
Turkey	**NARX	TrainLM	90-10	10	10	2	0,98	0,0016
World	**NARX	TrainLM	90-10	9	10	2	0,96	0,0005

For the NARX prediction models in the application, the number of delays, the number of hidden layers, the test-training split of the data set, and the training algorithm to be used were calculated with different combinations. The dataset was partitioned into 90% for training and 10% for testing during the analysis. For each combination, training continued until the specified error target was reached. As a result, models with the highest training and test performance were selected. Subsequently, the analysis proceeded with the model marked with ** in Table 2, which demonstrated the highest level of statistical significance.

- ***India Sample:*** Using the developed model, the temperature changes in India up to 2030 were predicted with NARX. The prediction results are presented in Figure 1.

Figure 1. *Temperature Change Prediction for India (1972-2030)*



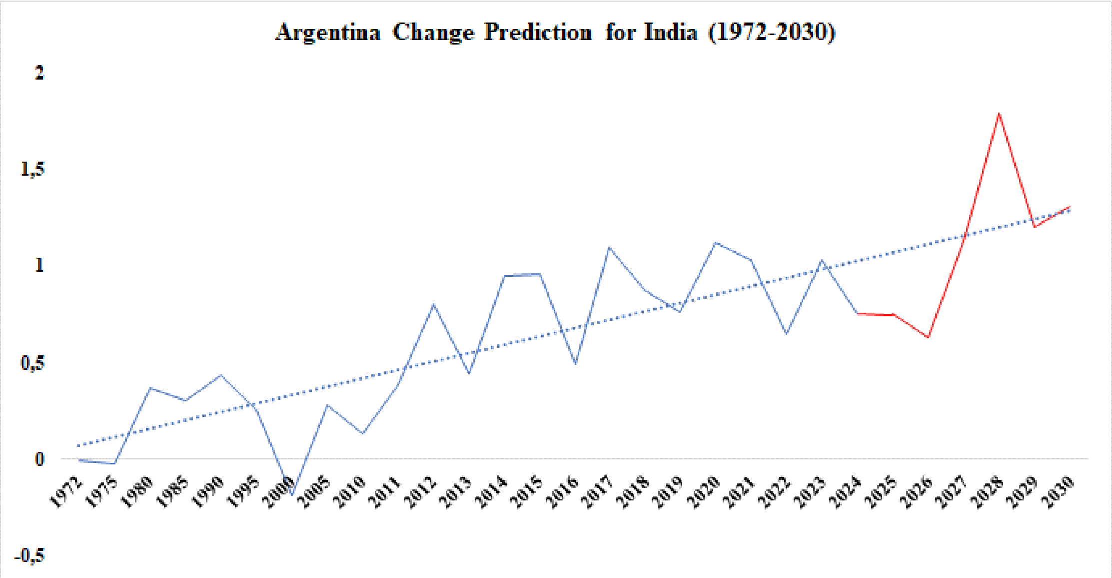
Source: The results predicted by the ANN model have been presented in a graph.

When analyzing the predictions made by NARX in Figure 1, it can be observed that the temperature change in India will increase irregularly until 2030. The average temperature change until 2030 is expected to be 0.76. India ranks as the third highest emitter of methane gas among G20 countries on average, and methane emissions in the country have been steadily increasing. India is also the third highest emitter of nitrous oxide gas among G20 countries on average, with nitrous oxide emissions continuing to rise over the years. Non-renewable energy consumption in India has increased by 972% from 1972 to the present. The country ranks second in the G20 in terms of the highest death rate caused by air pollution and first in terms of the highest death rate caused by water pollution. With a population of 1.4 billion, India is the second most populous country among the G20 nations. The urban population has increased by 72% since 1972.

India ranks third in the G20 for the highest average greenhouse gas emissions over the past 50 years. In summary, the heavy reliance on non-renewable energy and the high population density are the primary factors contributing to greenhouse gas emissions in the country. Considering these data, based on the ANN prediction result, it is reasonable to estimate a temperature change of 0.76 in India by 2030. Under these assumptions, with India not committing to any pledges in the Kyoto Protocol and not being included in the carbon tax implementation, the temperature will continue to rise according to the ANN prediction. According to India's climate change mitigation report, in order to reduce greenhouse gas emissions, India must specifically decrease non-renewable energy consumption and increase renewable energy consumption (International Monetary Fund, 2023a). While energy consumption preferences will have a negative impact on growth in the short term, it should not be overlooked that the cost of climate change will be higher if proper policies are not implemented.

- ***Argentina Sample:*** After the selections made, the changes in temperature in Argentina until 2030 were predicted using NARX. The prediction results are presented in Graph 2.

Figure 2. *Argentina Change Prediction for India (1972-2030)*



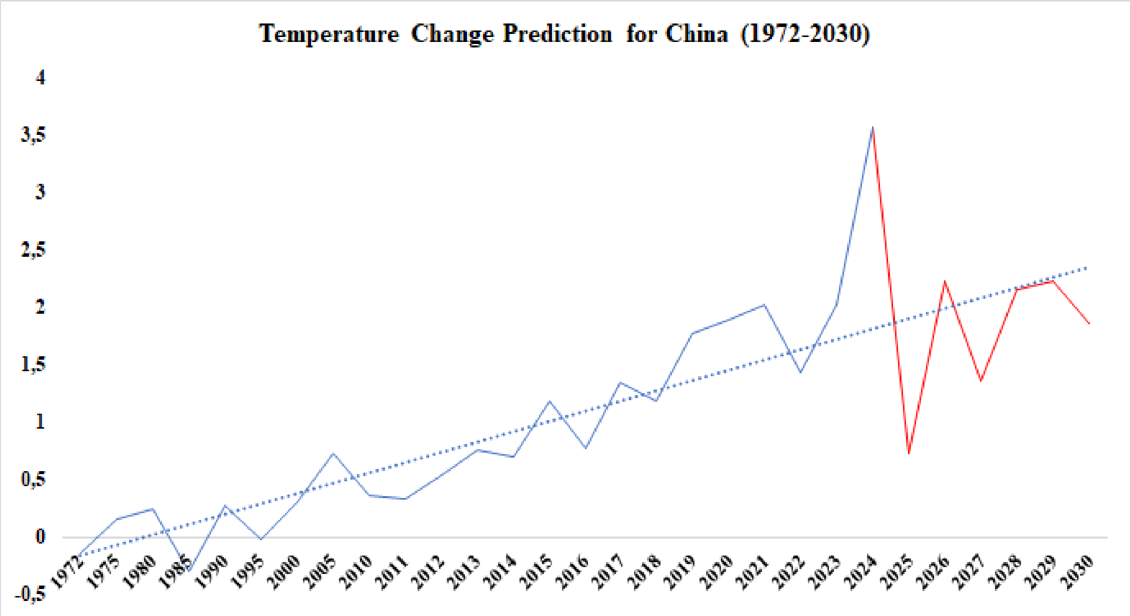
Source: *The results predicted by the ANN model have been presented in a graph.*

When examining the analysis predicted with NARX in Graph 2, it is observed that the change in temperature in Argentina until 2030 will continue to fluctuate irregularly, as it has in previous periods. The sharp irregularity in temperature changes since 1972 also affects the prediction data for the future. According to the ANN prediction, the temperature change will be 1.31 by 2030. The highest temperature increase in

Argentina occurred in 2020. However, in 2020, both total non-renewable energy consumption and carbon dioxide emissions decreased compared to the previous year. The unusual heatwave in the year with the highest temperature over the past 50 years is associated with climate change. Between 1972 and 2022, per capita CO2 emissions in Argentina increased by 4%. Argentina ranks as the 9th highest emitter of methane gas among G20 countries, with methane emissions continuously rising. The country has the highest urban population ratio within the total population among G20 countries. As a result of these factors, greenhouse gas emissions in Argentina have increased by 72% since 1972. Argentina is also ranked 5th in terms of chemical use in agriculture among G20 countries. Considering these data, based on the ANN prediction, it is reasonable to estimate that the temperature change in Argentina will be 1.31 by 2030.

- ***China Sample:*** After the selections made, the change in temperature in China until 2030 was predicted using the NARX model. The prediction results are presented in Graph 3.

Figure 3. *Temperature Change Prediction for China (1972-2030)*



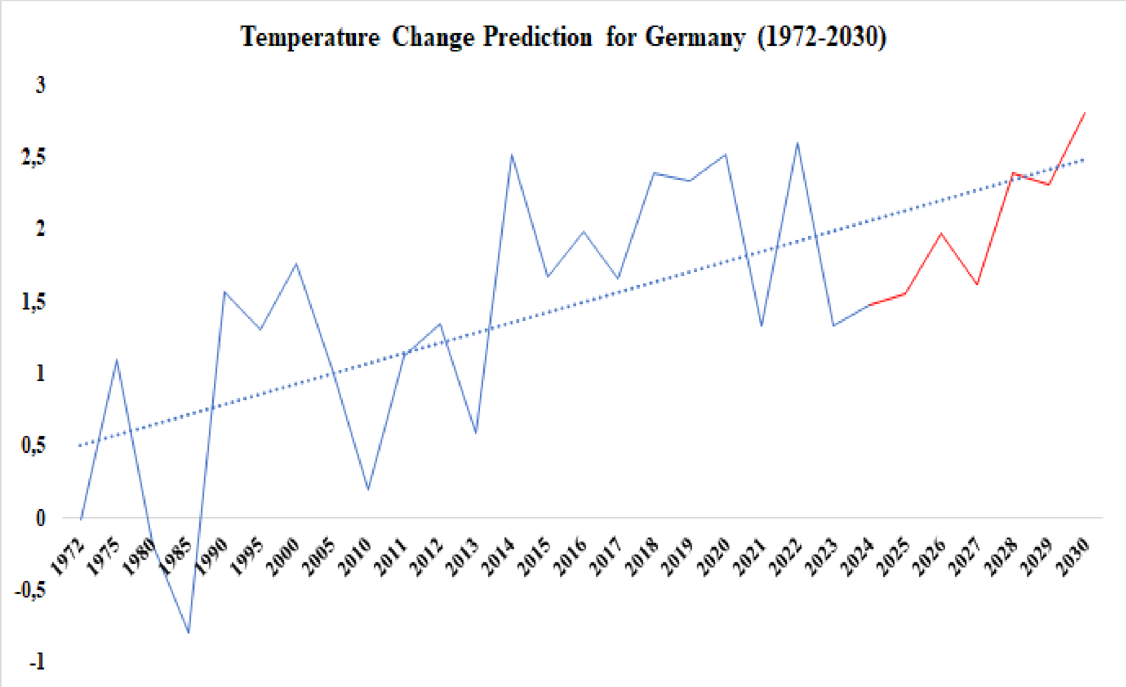
Source: The results predicted by the ANN model have been presented in a graph.

When examining the analysis predicted with NARX in Graph 3, it is observed that the temperature change in China will gradually increase in a positive direction until 2030. According to the ANN prediction, the average temperature change will be 1.86 by 2030. China is the largest emitter of greenhouse gases and the highest consumer of non-renewable energy among G20 countries. It is also the leading emitter of methane gas within the G20, with methane emissions continuously increasing over the years.

China is the highest emitter of nitrous oxide gas in the G20, and this emission has consistently risen over time. With a population of 1.4 billion, China is the most populous country in the G20. The urban population ratio within the total population has increased by 270% since 1972. The country ranks 3rd among G20 nations in terms of chemical use in agriculture. Given these data, based on the ANN prediction, it is reasonable to estimate that the temperature change in China will be 1.86 by 2030. Considering China's current non-renewable energy consumption rate, population, economic activities, and urbanization rate, it stands out as one of the countries that has the most negative impact on global climate change. China's refusal to sign the Kyoto Protocol and its reluctance to cooperate internationally in reducing greenhouse gas emissions is of great significance for the trajectory of global climate change.

- ***Germany Sample:*** After the selections made, the change in temperature in Germany until 2030 was predicted using the NARX model. The prediction results are presented in Graph 4.

Figure 4. *Temperature Change Prediction for Germany (1972-2030)*

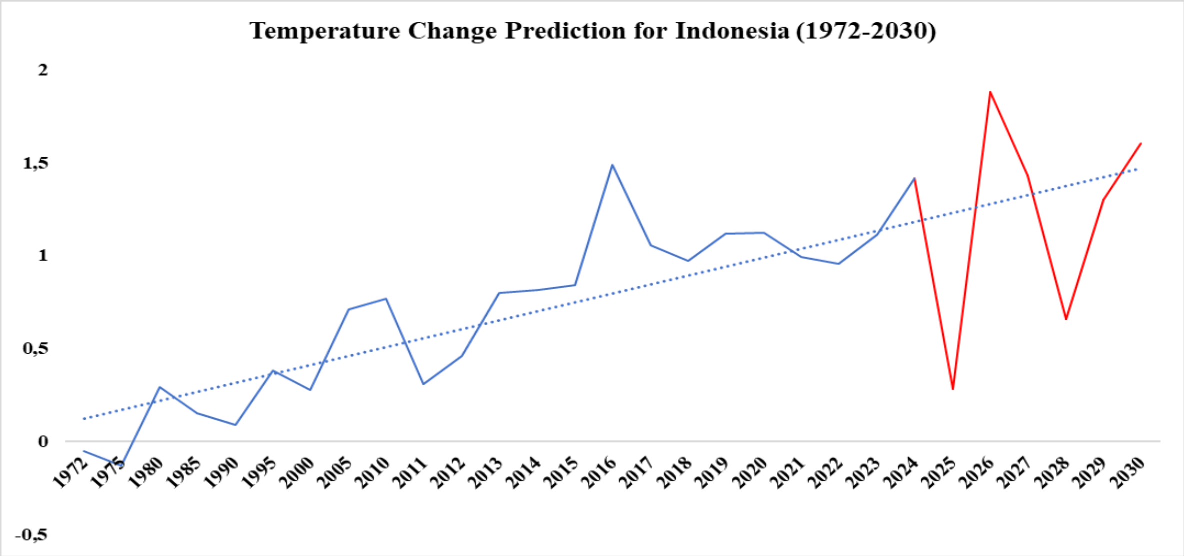


Source: The results predicted by the ANN model have been presented in a graph.

When examining the analysis predicted by NARX in Graph 4, it is observed that the temperature change in Germany will continue irregularly until 2030. The temperature change is expected to be 2.8 until 2030. Germany has reduced its non-renewable energy consumption by 36% from 1972 to the present. Among the G20 countries, Germany is one of the countries with the lowest methane gas emissions. Methane emissions in the country have gradually decreased over the years. The total greenhouse gas emissions have decreased by 37%. Germany is the 9th most populous country among the G20 countries. Temperatures in Germany have been increasing over the years. Despite the policies implemented, improvements in indicators have not had a positive impact on temperature change. In 2023, the temperature change in Germany was 2.44. Considering this, based on the ANN forecast, it is reasonable to estimate a temperature change of 2.80 in Germany by 2030.

- ***Indonesia Sample:*** Following the selections made, the change in temperature in Indonesia until 2030 was predicted using NARX. The prediction results are presented in Graph 5.

Figure 5. *Temperature Change Prediction for Indonesia (1972-2030)*

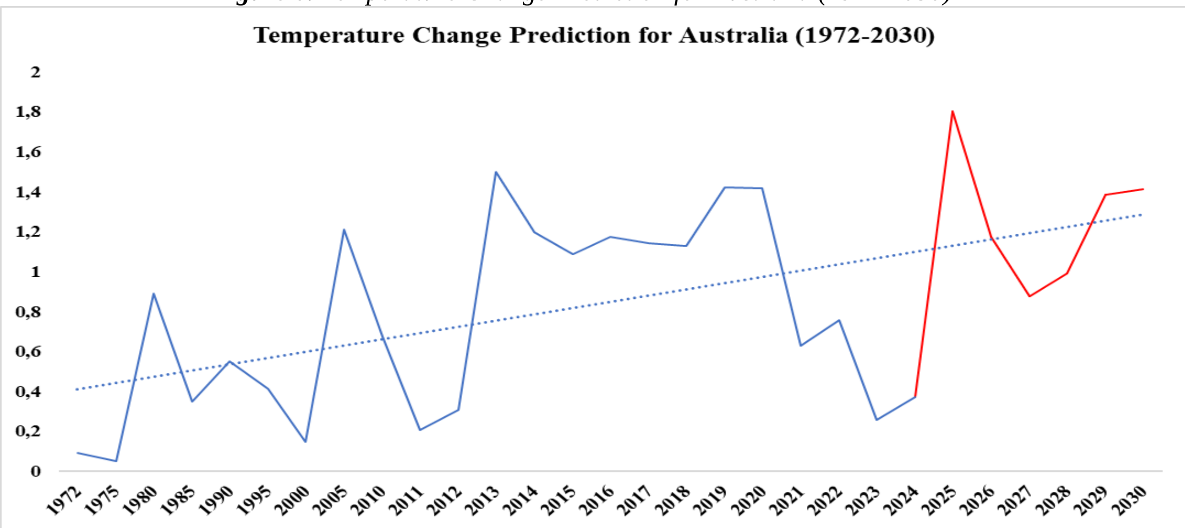


Source: *The results predicted by the ANN model have been presented in a graph.*

When examining the analysis predicted by NARX in Graph 5, it is observed that the temperature in Indonesia will increase steadily. The temperature change is expected to be 1.6 until 2030. Indonesia is the 4th most populous country among the G20 countries. The urban population ratio within the total population has increased by 226% from 1972 to the present. Indonesia ranks 6th among the G20 countries in terms of average methane gas emissions. Non-renewable energy consumption in Indonesia has increased by 819% from 1972 to the present. As a result, net greenhouse gas emissions in Indonesia have been consistently increasing. Considering this, based on the ANN forecast, it is reasonable to estimate a temperature change of 1.60 in Indonesia by 2030.

- ***Australia Sample:*** Following the selections made, the change in temperature in Australia until 2030 was predicted using NARX. The prediction results are presented in Graph 6.

Figure 6. *Temperature Change Prediction for Australia (1972-2030)*

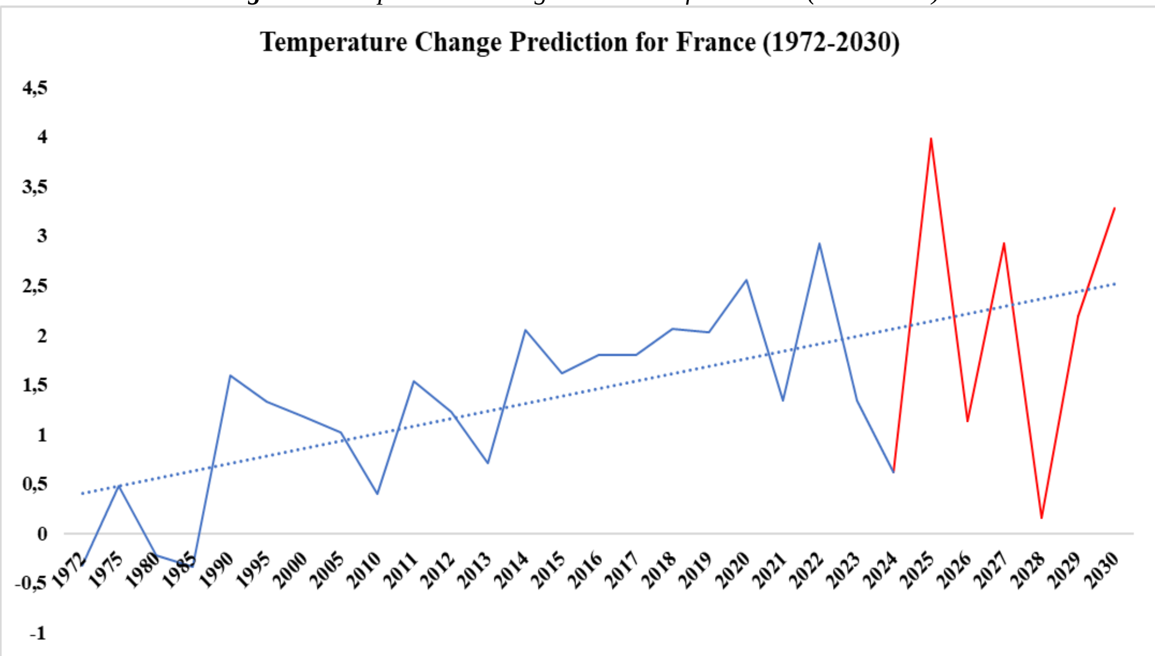


Source: *The results predicted by the ANN model have been presented in a graph.*

When examining the analysis predicted by NARX in Graph 6, it is observed that the temperature in Australia will increase steadily until 2030. The temperature change is expected to be 1.41 by 2030. Australia has a commitment to reduce emissions by 8% under the Kyoto Protocol. However, it has been observed that greenhouse gas emissions in Australia have increased over the years. Non-renewable energy consumption in Australia has increased by 81% from 1972 to the present. Australia ranks 2nd among G20 countries for the highest per capita CO2 emissions between 1972 and 2022. During this period, per capita CO2 emissions in the country have increased by 31%. The use of chemicals in agriculture has increased by 255% in the past 30 years. Considering the factors contributing to climate change, this rise stands out. Given this context, according to the ANN forecast, it is reasonable to estimate a temperature change of 1.41 in Australia by 2030.

- ***France Sample:*** Following the selections made, the change in temperature in France until 2030 was predicted using NARX. The prediction results are presented in Graph 7.

Figure 7. *Temperature Change Prediction for France (1972-2030)*

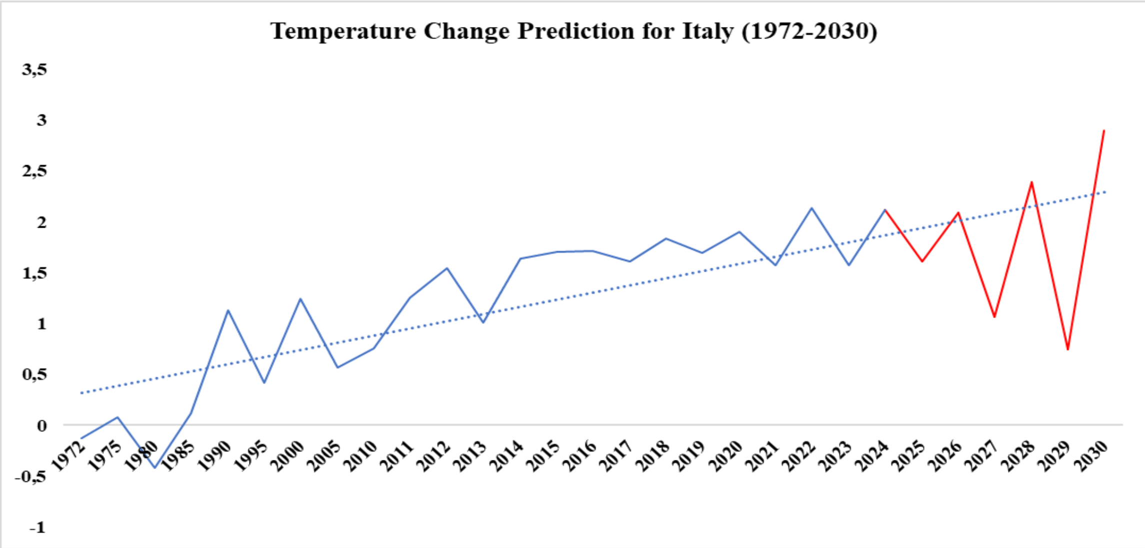


Source: *The results predicted by the ANN model have been presented in a graph.*

When examining the analysis predicted by NARX in Graph 7, it is observed that the temperature change in France will be irregular until 2030. The average temperature change is expected to be 2.61 by 2030. France has a commitment to reduce emissions by 8% under the Kyoto Protocol. As explained in the second section, non-renewable energy consumption in France has decreased by 41% from 1972 to the present, while renewable energy consumption has increased. France ranks 12th among G20 countries for the highest per capita CO2 emissions between 1972 and 2022. Per capita CO2 emissions have decreased by 51% from 1972 to the present. A significant increase in forested areas has been observed over the years in France. Accordingly, France has gradually reduced greenhouse gas emissions since 1990. In 2023, the temperature change in France was recorded as 2.59. Considering this, the ANN forecast suggests that a temperature change of 2.61 by 2030 is a reasonable result.

- ***Italy Sample:*** Following the selections made, the change in temperature in Italy until 2030 was predicted using NARX. The prediction results are presented in Graph 8.

Figure 8. *Temperature Change Prediction for Italy (1972-2030)*



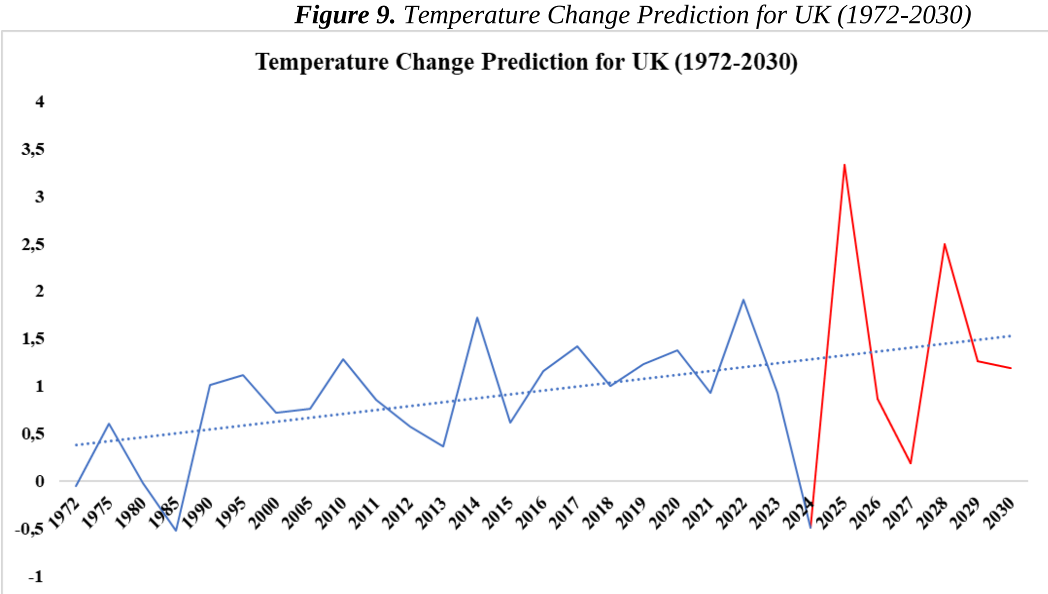
Source: *The results predicted by the ANN model have been presented in a graph*.

When examining the analysis predicted by NARX in Graph 8, it is observed that the temperature in Italy will increase irregularly until 2030. The average temperature change is expected to be 2.90 by 2030. Italy has committed to an 8% emissions reduction under the Kyoto Protocol. Per capita CO2 emissions in Italy have decreased by 11% since 1972. The country has gradually reduced both methane and nitrous oxide emissions over time. Among G20 countries, Italy ranks among those with the lowest average methane and nitrous oxide emissions.

A significant increase in forested areas and a notable decrease in chemical use in agriculture have been observed over the years. Consequently, Italy has gradually reduced greenhouse gas emissions to date. However, non-renewable energy consumption in Italy has increased by 10% since 1972, with the largest increase seen in natural gas consumption. Temperatures in Italy have continued to rise over the years. Despite policy-driven improvements in key indicators, these measures have not positively impacted temperature changes. In 2023, the recorded temperature change in Italy was 2.27. Considering this, the ANN forecast indicates that a temperature change of 2.90 by 2030 is a reasonable projection.

- ***United Kingdom Sample:*** Following the selections made, the change in temperature in the United Kingdom until 2030 was predicted using NARX. The prediction results are presented in Graph 9.

Figure 9. *Temperature Change Prediction for UK (1972-2030)*

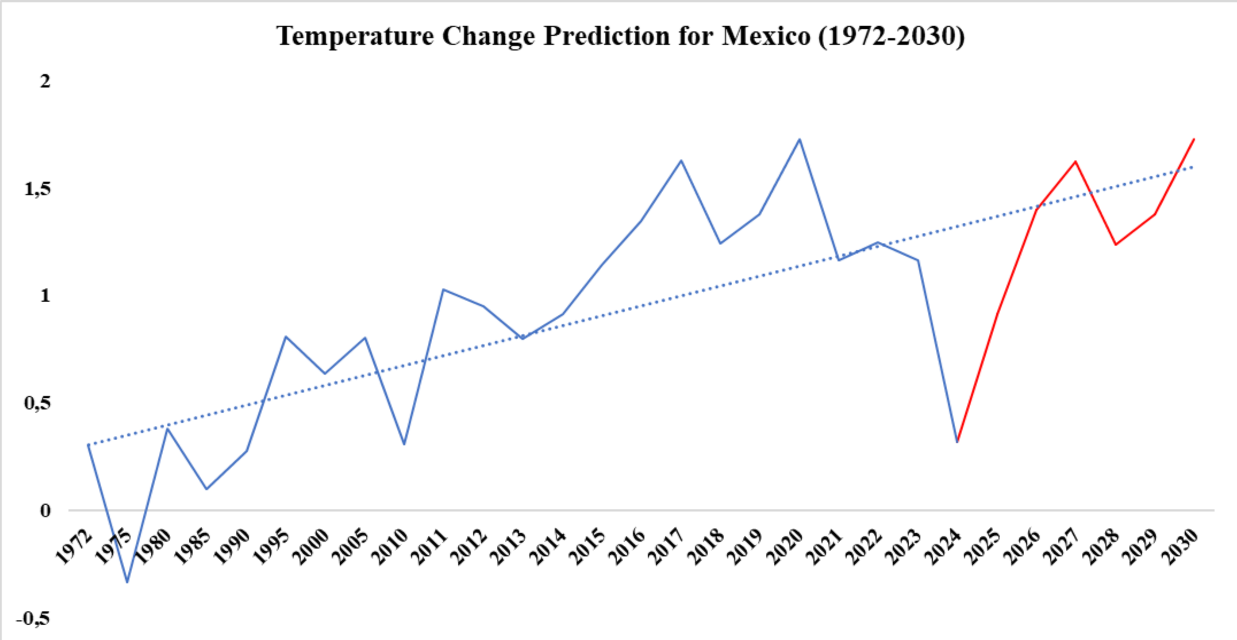


Source: *The results predicted by the ANN model have been presented in a graph.*

When examining the analysis predicted by NARX in Graph 9, it is observed that the temperature in the UK will increase continuously until 2030. The average temperature change is expected to be 1.19 by 2030. The United Kingdom has committed to an 8% emissions reduction under the Kyoto Protocol. Non-renewable energy consumption in the UK has decreased by 41% since 1972, while renewable energy consumption has increased. Per capita CO2 emissions in the UK have decreased by 58% over the same period. Consequently, the UK has gradually reduced greenhouse gas emissions to date. In 2023, the recorded temperature change in the UK was 1.48. Considering this, the ANN forecast indicates that a temperature change of 1.19 by 2030 is a reasonable projection.

- ***Mexico Sample:*** Following the selections made, the change in temperature in Mexico until 2030 was predicted using NARX. The prediction results are presented in Graph 10.

Figure 10. *Temperature Change Prediction for Mexico (1972-2030)*

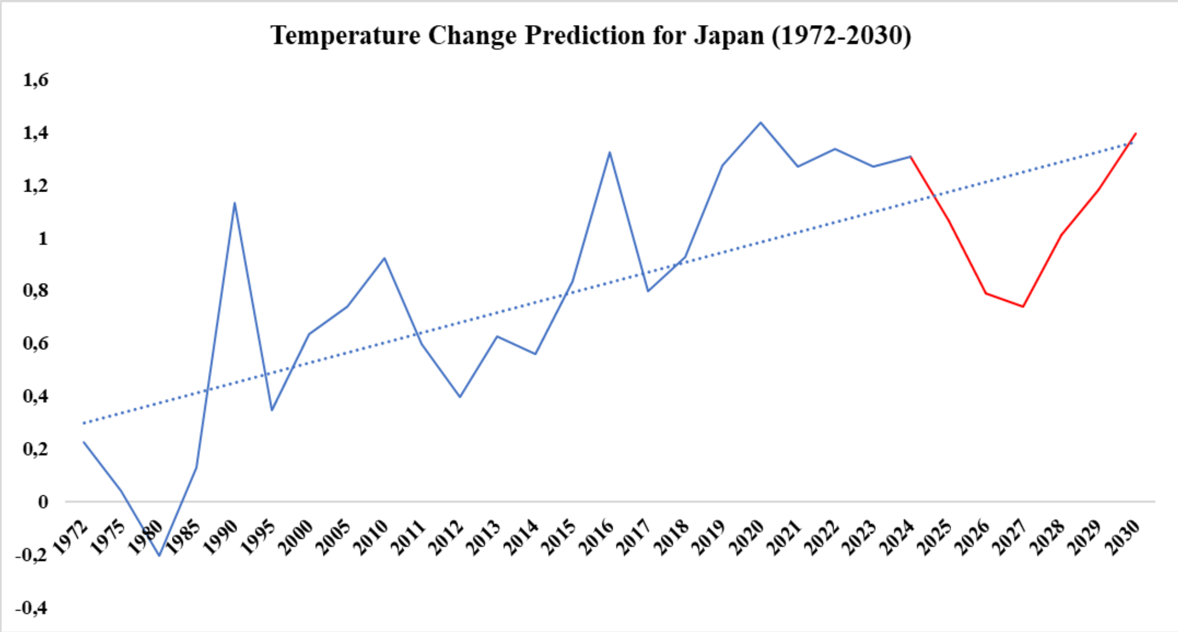


Source: *The results predicted by the ANN model have been presented in a graph.*

When examining the analysis predicted by NARX in Graph 10, it is observed that the temperature in Mexico will continuously increase until 2030. The average temperature change is expected to be 1.73 by 2030. In Mexico, non-renewable energy consumption has increased by 289% since 1972. As shown in Annex 6, per capita CO2 emissions in Mexico have risen by 59% over the same period. A decline in forested areas has been observed in the country over the years. Consequently, greenhouse gas emissions in Mexico have increased by 75% since 1972. In 2023, the temperature change in Mexico was recorded at 1.68. Considering this, the ANN forecast suggests that a temperature change of 1.73 by 2030 is a reasonable projection.

- ***Japan Sample:*** Following the selections made, the change in temperature in Japan until 2030 was predicted using NARX. The prediction results are presented in Graph 11.

Figure 11.*Temperature Change Prediction for Japan (1972-2030)*

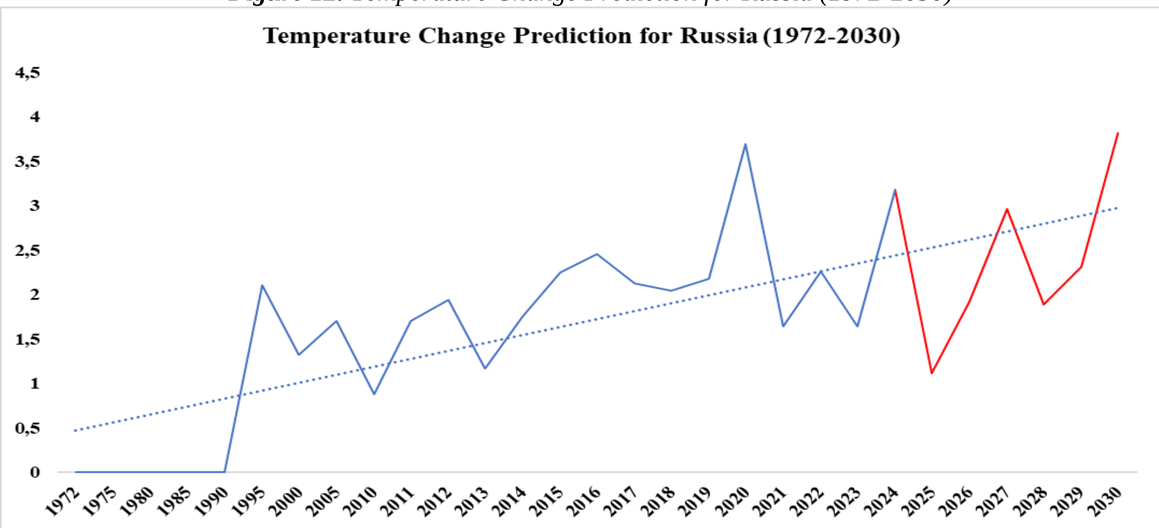


Source: *The results predicted by the ANN model have been presented in a graph.*

When examining the analysis predicted by NARX in Graph 11, it is observed that the temperature in Japan will continuously increase until 2030. The average temperature change is expected to be 1.39 by 2030. In Japan, non-renewable energy consumption has decreased by 35% since 1972. However, Japan ranks as the 3rd highest consumer of non-renewable energy among G20 countries on average. Per capita CO2 emissions in Japan have increased by 7% since 1972. With a current population of 125 million, 92% of the population resides in urban areas, and the population has grown by 117% since 1972. In 2023, the recorded temperature change in Japan was 1.85. Considering this, the ANN forecast suggests that a temperature change of 1.39 by 2030 is a reasonable projection.

- ***Russia Sample:*** Following the selections made, the change in temperature in Russia until 2030 was predicted using NARX. The prediction results are presented in Graph 12.

Figure 12. *Temperature Change Prediction for Russia (1972-2030)*

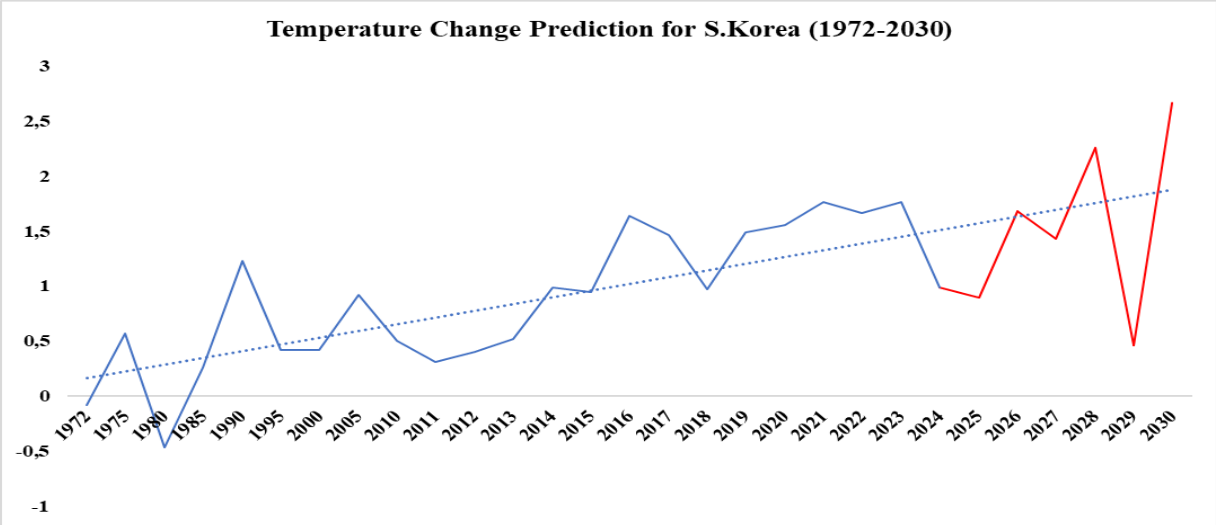


Source: *The results predicted by the ANN model have been presented in a graph.*

When examining the analysis predicted by NARX in Graph 12, it is observed that the temperature in Russia will continuously increase until 2030. The average temperature change is expected to be 3.81 by 2030. Despite the decrease in both non-renewable energy consumption and per capita CO2 emissions since 1985, Russia remains the 4th highest consumer of non-renewable energy among G20 countries. The country predominantly consumes oil and natural gas, with renewable energy consumption being limited and comparatively low within the G20. Data indicate that per capita energy consumption in Russia is steadily increasing. Russia is also among the G20 countries with the highest average methane and nitrous oxide emissions. In 2023, the temperature change in Russia was recorded at 2.53. Considering this, the ANN forecast suggests that a temperature change of 3.81 by 2030 is a reasonable projection.

- ***South Korea Sample:*** Following the selections made, the change in temperature in South Korea until 2030 was predicted using NARX. The prediction results are presented in Graph 13.

Figure 13. *Temperature Change Prediction for S.Korea (1972-2030)*

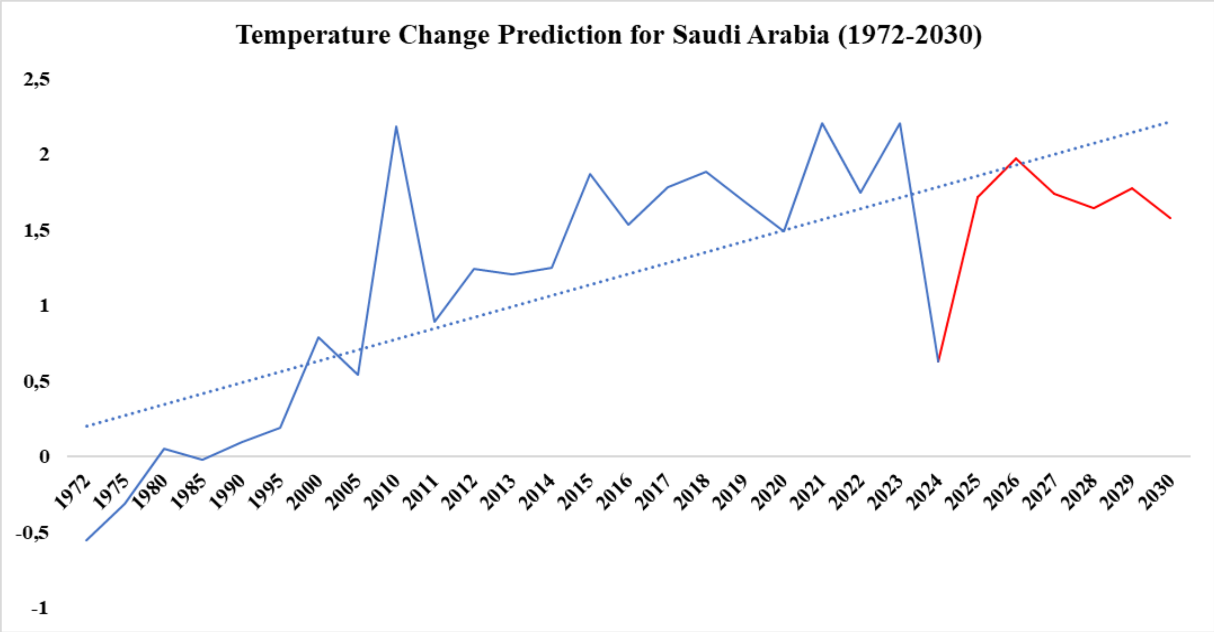


Source: *The results predicted by the ANN model have been presented in a graph.*

When examining the analysis predicted by NARX in Graph 13, it is observed that the temperature in South Korea will continuously increase until 2030. The average temperature change is expected to be 2.66 by 2030. In South Korea, non-renewable energy consumption has increased by 1,153% since 1972, while per capita CO2 emissions have risen by 177% during the same period. Consequently, greenhouse gas emissions in the country have grown by 158% since 1972. In 2023, the temperature change in South Korea was recorded at 2.03. Considering this, the ANN forecast suggests that a temperature change of 2.66 by 2030 is a reasonable projection.

- ***Saudi Arabia Sample:*** Following the selections made, the change in temperature in Saudi Arabia until 2030 was predicted using NARX. The prediction results are presented in Graph 14.

Figure 14. *Temperature Change Prediction for S.Arabia (1972-2030)*

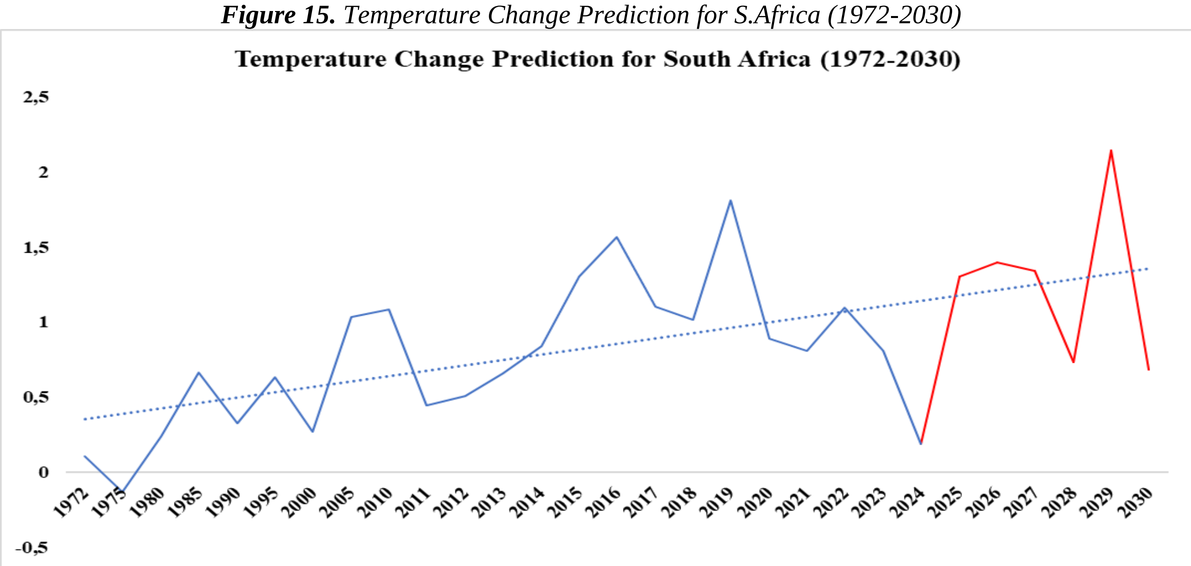


Source: *The results predicted by the ANN model have been presented in a graph.*

When examining the analysis predicted by NARX in Graph 14, it is observed that the temperature in Saudi Arabia will continuously increase until 2030. The average temperature change is expected to be 1.57 by 2030. Saudi Arabia ranks as the 4th highest G20 country in terms of average per capita CO2 emissions between 1972 and 2022. Non-renewable energy consumption in the country has increased by 630% since 1972. During the same period, Saudi Arabia is also among the countries with the highest growth in per capita CO2 emissions. In 2023, the temperature change in Saudi Arabia was recorded at 1.83. Considering this, the ANN forecast suggests that a temperature change of 1.57 by 2030 is a reasonable projection.

- ***South Africa Sample:*** Following the selections made, the change in temperature in South Africa until 2030 was predicted using NARX. The prediction results are presented in Graph 15.

Figure 15. *Temperature Change Prediction for S.Africa (1972-2030)*

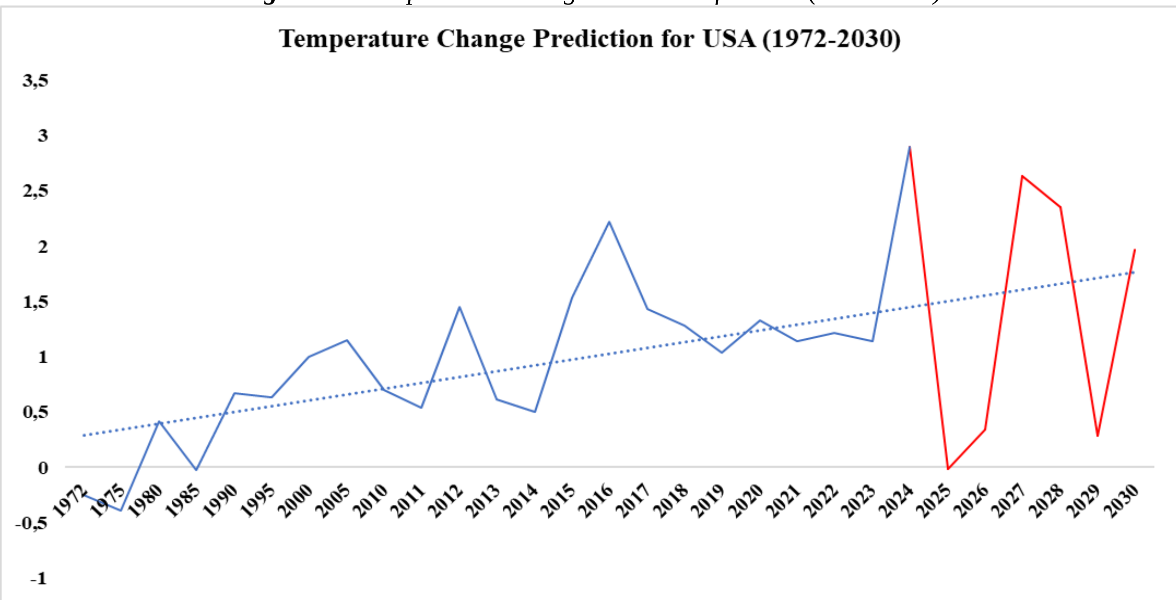


Source: *The results predicted by the ANN model have been presented in a graph.*

Based on the analysis predicted with NARX in Graph 15 and examined in Graph 48, it is observed that the temperature change in South Africa will be irregular until 2030. The average temperature change by 2030 will be 0.88. In South Africa, non-renewable energy consumption has increased by 139% since 1972, while per capita CO2 emissions have risen by 135%. The proportion of the urban population within the total population has grown by 43%. In 2023, the recorded temperature change in South Africa was 1.12. Considering this, the ANN forecast suggests that a temperature change of 0.88 by 2030 is a reasonable estimate. As a developing country, South Africa faces high levels of poverty and unemployment. Consequently, the heavy reliance on non-renewable energy, particularly coal, in economic activities is considered a primary contributor to climate change.

- ***USA Sample:*** Following the selections made, the change in temperature in USA until 2030 was predicted using NARX. The prediction results are presented in Graph 16.

Figure 16. *Temperature Change Prediction for USA (1972-2030)*

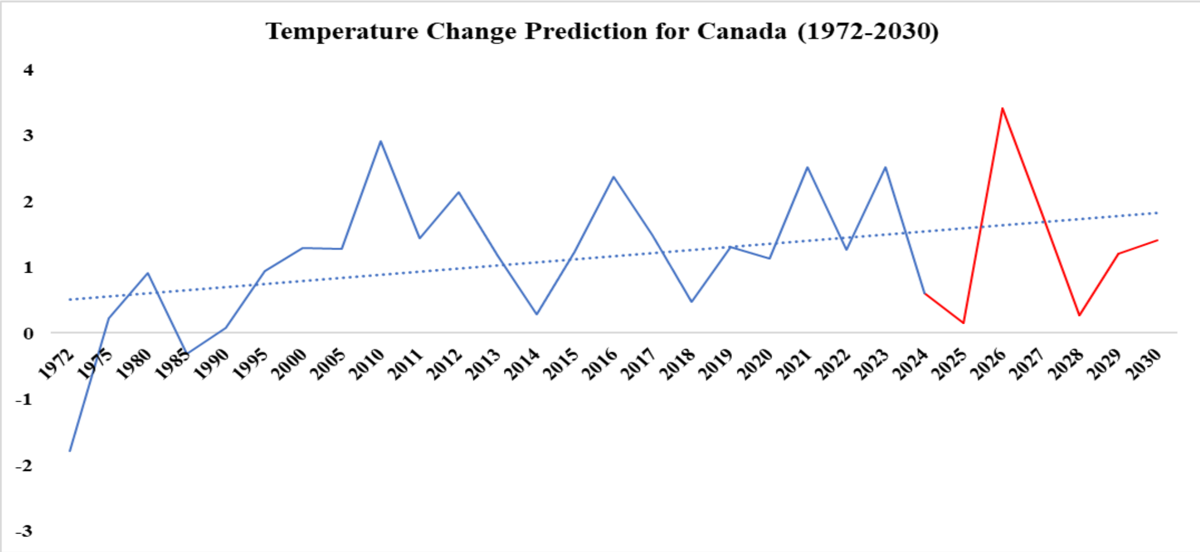


Source: *The results predicted by the ANN model have been presented in a graph.*

When examining the analysis predicted with NARX in Figure 16, it is observed that the change in temperature in The United States will be irregular until 2030. The average temperature change by 2030 will be 1.97. The United States ranks as the second-largest emitter of greenhouse gases and the second-largest consumer of non-renewable energy among G20 countries. Additionally, the U.S. has the highest average per capita CO2 emissions between 1972 and 2022 among G20 nations. It is also the second-largest emitter of methane gas within the G20, with methane emissions continuing to rise steadily. Similarly, the U.S. ranks as the second-largest emitter of nitrous oxide gas within the G20, with nitrous oxide emissions consistently increasing over time. Considering these factors, the ANN forecast suggests that by 2030, a temperature change of 1.97 in the U.S. is a reasonable estimate. The United States, as one of the leading industrialized nations, stands out as one of the countries having the most negative impact on global climate change when considering its current rate of non-renewable energy consumption, population, economic activities, and urbanization rate. Therefore, the policies pursued by the United States play a crucial role in combating climate change.

- ***Canada Sample:*** Following the selections made, the change in temperature in Canada until 2030 was predicted using NARX. The prediction results are presented in Graph 17.

Figure 17. *Temperature Change Prediction for Canada (1972-2030)*

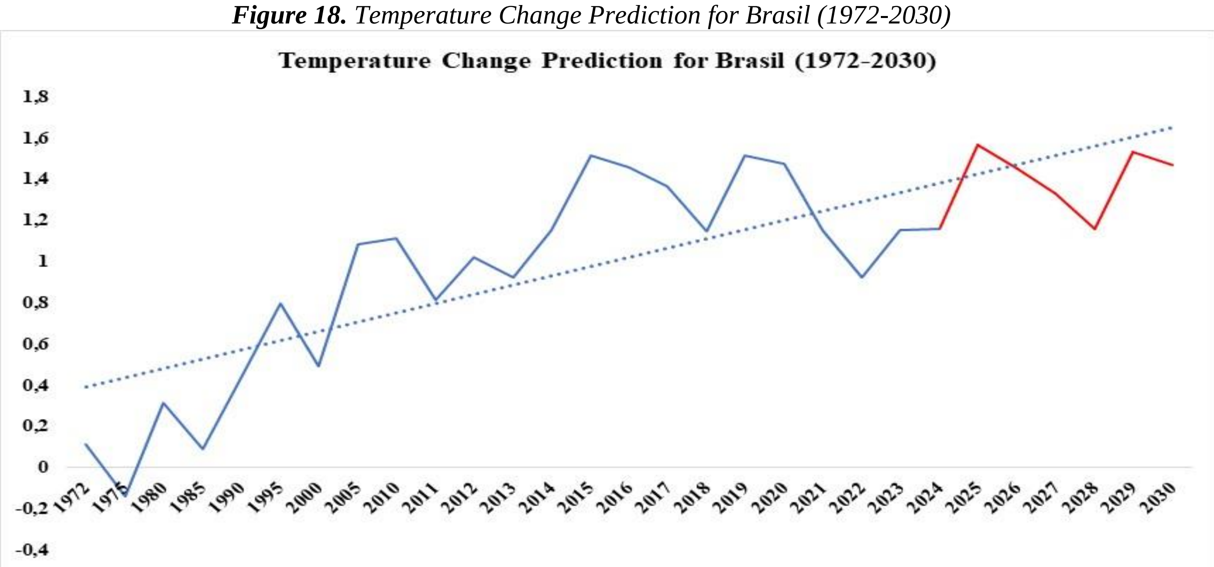


Source: *The results predicted by the ANN model have been presented in a graph.*

When examining the analysis predicted with NARX in Figure 17, it is observed that the change in temperature in Canada will be irregular until 2030. The average temperature change by 2030 will be 1.42. Canada ranks as the 3rd highest country in terms of average per capita CO2 emissions between 1972 and 2022 among G20 nations. Canada is the 9th highest in methane gas emissions within the G20 countries. Methane emissions have been steadily increasing in the country. The use of chemicals in agriculture has increased by 214% over the past 30 years. In 2023, the temperature change in Canada was 2.36°C. Considering this, according to the ANN forecast, it is reasonable to estimate a temperature change of 1.42°C by 2030 in Canada.

- ***Brasil Sample:*** Following the selections made, the change in temperature in Brasil until 2030 was predicted using NARX. The prediction results are presented in Graph 18.

Figure 18. *Temperature Change Prediction for Brasil (1972-2030)*

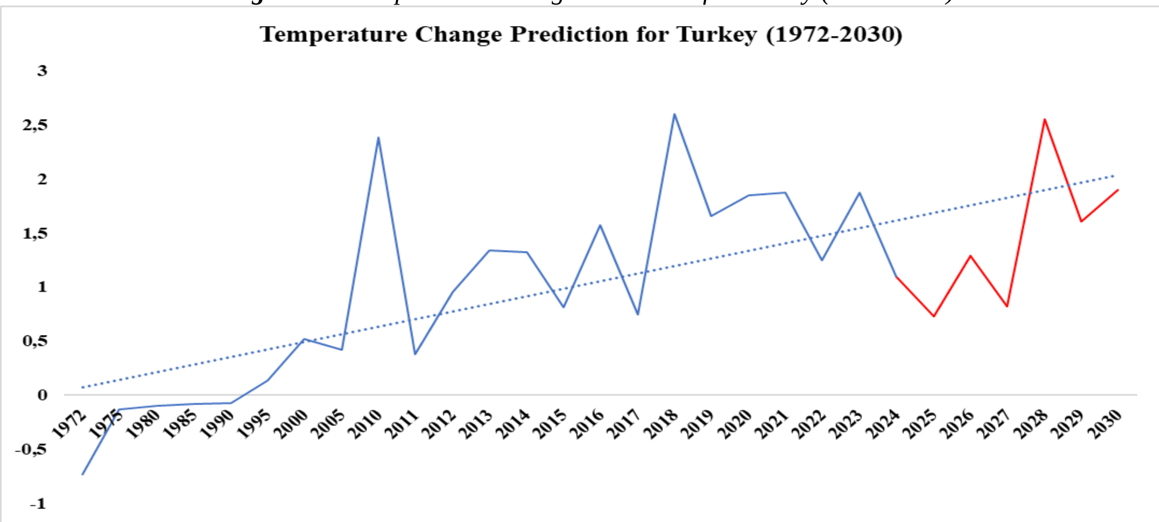


Source: *The results predicted by the ANN model have been presented in a graph.*

When examining the analysis predicted with NARX in Figure 18, it is observed that the change in temperature in Brazil will be irregular until 2030. The average temperature change by 2030 will be 1.47. Brazil ranks as the 6th highest country in terms of average greenhouse gas emissions over the past 50 years among G20 nations. It is the 5th highest in methane emissions within the G20. Methane emissions have consistently increased in the country. Brazil is the 5th most populous country among G20 nations. A significant reduction in forested areas has been observed in Brazil. Additionally, the use of chemicals in agriculture has increased by 1307% over the past 30 years. Given the factors contributing to climate change, this rise is particularly notable. In 2023, the temperature change in Brazil was 1.65°C. Considering this, according to the ANN forecast, it is reasonable to estimate a temperature change of 1.47°C by 2030 in Brazil.

- ***Turkey Sample:*** Following the selections made, the change in temperature in Turkey until 2030 was predicted using NARX. The prediction results are presented in Graph 19.

Figure 19. *Temperature Change Prediction for Turkey (1972-2030)*



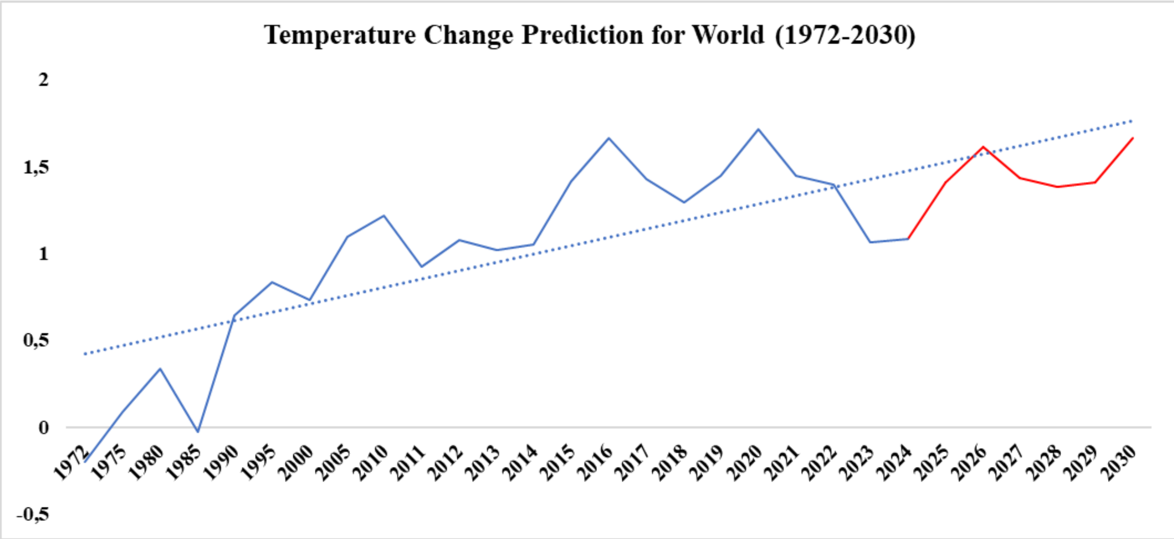
Source: *The results predicted by the ANN model have been presented in a graph.*

When examining the analysis predicted with NARX in Figure 19, it is observed that the change in temperature in Turkey will be irregular until 2030. The average temperature change by 2030 will be 1.90. In Turkey, both methane and nitrous oxide emissions have continuously increased over time. Turkey is the 10th most populous country among G20 nations. The use of chemicals in agriculture has risen by 77% in the past 30 years. In 2023, the temperature change in Turkey was 2.06°C. Considering these factors, according to the ANN forecast, it is reasonable to estimate a temperature change of 1.90°C by 2030 in Turkey.

In the study, after predicting the temperature change for each G20 country using an ANN, an attempt was made to determine the change in temperature on a global scale. A new dataset covering the years 1972-2022 was created for the world. The dependent variable is the change in temperature, while the independent variables are defined as per capita GDP, population, per capita non-renewable energy consumption, urban area, per capita CO2 emissions, and the volume of trade in GDP. In the analysis, the dataset was first normalized, and after the analysis, a denormalization process was performed for the predicted values.

- ***World Sample:*** Following the selections made, the change in temperature in Turkey until 2030 was predicted using NARX. The prediction results are presented in Graph 20.

Figure 20. *Temperature Change Prediction for World (1972-2030)*



Source: *The results predicted by the ANN model have been presented in a graph.*

Based on the analysis predicted with NARX, it is observed that the temperature change globally will increase steadily until 2030. According to the prediction results analyzed with ANN, the average global temperature change will be 1.66 degrees Celsius by 2030. Since 1972, there has been an increase in all factors contributing to climate change globally. From 1972 to the present, non-renewable energy consumption has increased by 73%, methane gas in the atmosphere by 24%, nitrous oxide by 33%, and per capita CO2 emissions by 7%. The total population has increased by 107%, while the urban population within the total population has risen by 54%. As a result, net greenhouse gas emissions have increased by 75.6%. Furthermore, the number of human fatalities due to natural disasters caused by climate change has increased by 299%, while losses in other species are believed to be even higher, though there is no official record.

In summary, as highlighted in the latest Climate Change Report published by the IPCC, the temperature is expected to exceed the 1.5-degree Celsius target by 2030, as predicted in this study (IPCC, 2023: 10). The most recent report indicates that the threshold for temperature rise has already been surpassed, even if greenhouse gas reductions continue. It emphasizes that the measures taken so far have been insufficient and that radical decisions are necessary.

5. Discussion

As explained, the impacts of climate change on natural ecosystems are highly complex and destructive. Therefore, scientists, academics, and policymakers conduct various studies to predict where, when, and to what extent these effects will occur. There is consensus that global warming, as committed to in the Paris Climate Agreement and defined by the Climate Change Panel, must be stabilized at 1.5 degrees Celsius above pre-industrial levels to maintain environmental sustainability. Policies are being developed to achieve this goal, and countries are expected to cooperate on this matter.

As explained with data throughout the study, G20 countries are responsible for approximately 75% of global resource use and 80% of global greenhouse gas emissions. Controlling about 84% of the global economy, G20 countries are considered the driving force of development and growth. However, the diversity and different development paths among G20 countries make them largely responsible for many of the world's environmental problems due to unsustainable production and consumption patterns. Therefore, the energy, chemicals, methods, and other elements used in economic activities by G20 countries play a key role in global climate change. For these reasons, this study examines the G20 countries as a sample and tests the achievability of the 2030 temperature change target agreed upon in the UN's Paris Climate Agreement, specifically within the G20 context.

The study analyzes the course of temperature changes, accepted as an outcome of climate change, for G20 countries in 2030 using the Artificial Neural Networks model, which has recently been frequently used in detecting climate change. The dependent (output) variable of the model is the change in temperature, which is an indicator of climate change. The independent (input) variables of the model include per capita CO2 emissions, population, GDP growth, oil consumption, coal consumption, natural gas consumption, nuclear energy consumption, carbon tax implementation, and urban population. The analysis was determined to cover the period from 1972 to 2030, based on international organizations related to climate change. Temperature changes in G20 countries up to 2030 were predicted using data from the period 1972-2022.

In the temperature change predictions made with Artificial Neural Networks, it was found that the average temperature would continuously increase until 2030 in India, Argentina, China, Germany, Indonesia, Italy, Australia, the United Kingdom, Mexico, Japan, Russia, South Korea, Saudi Arabia, South Africa, the United States, Brazil, and Turkey. In France and Canada, it was predicted that the temperature changes would be irregular. It was estimated that the temperature change in Indonesia, China, Germany, South Korea, the United States, France, Italy, Mexico, Saudi Arabia, Russia, and Turkey would exceed the targeted value. The global temperature change for the G20 countries was found to be an average of 1.85°C. According to the predicted results, the average temperature change in G20 countries will exceed the targeted value. The average global temperature change by 2030 is predicted to be 1.66°C. According to the predicted results, the global average temperature change will also exceed the targeted value. As a result, when the predicted values are examined, it is observed that the temperature change in G20 countries is higher than the global average. This supports the hypothesis that developed countries are the main cause of global climate change.

6. Conclusion

In summary, the study predicts that the UN's 2030 target of limiting global warming to 1.5 degrees Celsius will be exceeded, both in the G20 countries and globally. This indicates that the actions taken so far to limit climate change have been insufficient. Factors such as the total consumption of non-renewable energy, the emission of greenhouse gases into the atmosphere, chemicals used in agriculture, urban population rates, and deforestation continue to increase globally. Consequently, natural disasters, death rates linked to environmental pollution, and ultimately, changes in temperature are expected to continue rising.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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