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LOW-CARBON TECHNOLOGY TRADE AND CLIMATE DYNAMICS: A MACHINE LEARNING-BASED INVESTIGATION*

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Abstract

This study examines the relationship between low-carbon technology trade and climate change indicators by employing a data-driven, machine learning–based analytical framework. Using long-term, multi-country data covering the period from 1958 to 2020, the research investigates how environmental trade dynamics, carbon emissions, and selected economic variables interact with key climate indicators. Unlike traditional econometric approaches, the study adopts advanced machine learning techniques to capture complex and nonlinear relationships that are difficult to model using linear methods. Specifically, the Nonlinear Autoregressive Neural Network with Exogenous Inputs (NARX) is utilized to forecast climate-related outcomes, while SHapley Additive exPlanations (SHAP) are applied to improve the interpretability of the model results. This integrated approach enables both reliable predictive performance and a transparent evaluation of the relative importance of explanatory variables. The findings suggest that low-carbon technology trade plays a meaningful role in shaping climate indicators, although its effects vary across countries and over time. In addition, carbon emissions and trade-related variables exhibit pronounced nonlinear impacts, highlighting the necessity of flexible modeling strategies. Overall, the study contributes to the literature by demonstrating the usefulness of machine learning-based approaches for analyzing long-term and multi-dimensional climate and trade data. The results offer policy-relevant insights for designing sustainable trade and climate strategies.

Keywords: Atmospheric Co_2 concentrations, Climate change, Machine learning, Sea level change.

Jel Classification: *C45, Q54, Q55*

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DÜŞÜK KARBONLU TEKNOLOJİ TİCARETİ VE İKLİM DİNAMİKLERİ: MAKİNE ÖĞRENİMİNE DAYALI BİR ARAŞTIRMA

Öz

Bu çalışma, veri odaklı, makine öğrenimine dayalı analitik bir çerçeve kullanarak düşük karbonlu teknoloji ticareti ile iklim değişikliği göstergeleri arasındaki ilişkiyi incelemektedir. 1958-2020 dönemini kapsayan uzun vadeli, çok ülkeli verileri kullanan araştırma, çevresel ticaret dinamiklerinin, karbon emisyonlarının ve seçilen ekonomik değişkenlerin temel iklim göstergeleriyle nasıl etkileşimde bulunduğunu araştırmaktadır. Geleneksel ekonometrik yaklaşımlardan farklı olarak, çalışma, doğrusal yöntemlerle modellenmesi zor olan karmaşık ve doğrusal olmayan ilişkileri yakalamak için gelişmiş makine öğrenimi tekniklerini benimsemektedir. Özellikle, iklimle ilgili sonuçları tahmin etmek için Dışsal Girişli Doğrusal Olmayan Otoregresif Sinir Ağı (NARX) kullanılırken, model sonuçlarının yorumlanabilirliğini iyileştirmek için SHapley Toplamsal Açıklamaları (SHAP) uygulanmaktadır. Bu entegre yaklaşım, hem güvenilir tahmin performansı hem de açıklayıcı değişkenlerin göreceli öneminin şeffaf bir şekilde değerlendirilmesini sağlamaktadır. Bulgular, düşük karbonlu teknoloji ticaretinin iklim göstergelerinin şekillenmesinde anlamlı bir rol oynadığını, ancak etkilerinin ülkeler ve zaman içinde farklılık gösterdiğini göstermektedir. Ayrıca, karbon emisyonları ve ticaretle ilgili değişkenler belirgin doğrusal olmayan etkiler sergilemekte olup, esnek modelleme stratejilerinin gerekliliğini vurgulamaktadır. Genel olarak, çalışma, uzun vadeli ve çok boyutlu iklim ve ticaret verilerinin analizinde makine öğrenimine dayalı yaklaşımların yararlılığını göstererek literatüre katkıda bulunmaktadır. Sonuçlar, sürdürülebilir ticaret ve iklim stratejilerinin tasarlanması için politika açısından önemli bilgiler sunmaktadır.

Anahtar Kelimeler: Atmosferik CO_2 konsantrasyonları, Deniz seviyesi değişimi, İklim değişikliği, Makine öğrenimi.

***Jel Kodları*:** *C45, Q54, Q55*

INTRODUCTION

Climate change is a great long-term change in world, regional as well as on a local weather patterns as a result of natural and human activities. Whereas weather represents the short run trends in the atmosphere, climate change represents the long run changes-that span decades or more-that affect ecosystems, economies, and even human societies. Such changes are due to the complicated interplay of the systems in the earth: atmosphere, oceans, the landscapes on the earth, and the ice sheets (Baker et al., 2008). Human activity is one of the major causes of climatic change particularly after the Industrial Revolution. The excessive consumption of fossil fuels (coal, oil and gas) has resulted in a dramatic increase in the emission of the greenhouse gases (GHGs), which includes carbon dioxide (CO_2), methane (CH_4) and nitrous oxide (N_2O). These gases trap the heat in the atmosphere of the Earth and global temperatures increase-a phenomenon also referred to as global warming (Shukla et al., 2019). The research paper particularly examines the correlation between a number of environmental variables, which include carbon emission per million of the population, country greenhouse gas emission, the CO_2 emission in domestic production and in the international trade, and the exchange of environmental goods. These are considered to be independent variables. Conversely, the major dependent variables-indicators of climate change development are atmospheric concentrations of CO_2 and sea level rise (Singh et al., 2011).

Iraq is a good example case because it is more susceptible to the effects of the climate. The changing patterns of precipitations, rising temperatures and water shortages, and environmental degradation coupled with socio-political instability make mitigation and adaptation efforts difficult. These circumstances are reflections of problems observed in most developing countries (Adamo et al., 2022). Scientific predictions, with leadership by bodies such as IPCC, combine both climate model data and empirical data to make a prediction of future climate. Such predictions are used to make policy choices, and to identify knowledge gaps that are being searched with data science to a greater extent. Recent advances in empirical data availability and computational methods have enabled researchers to analyze multi-country climate datasets more effectively. The increasing use of data-driven and machine learning-based approaches has made it possible to capture complex and nonlinear relationships between environmental, economic, and climate-related indicators that are difficult to model using traditional econometric methods. In this context, the integration of advanced analytical techniques with longitudinal climate and trade data provides valuable insights for climate prediction and policy formulation.

Climatic changes have implication in many sectors. The destruction of infrastructure and food security of populations with low adaptive capacity are threatened by flooding, agricultural damages, changes in biodiversity, and extreme weather events. Meanwhile, economic systems such as buying and selling environmental products can either reduce or increase the emissions. It is imperative to understand these interrelations or sheep in order to develop an effective global climate policy (Trexler, 2015). The importance of weather and climate to agriculture is emphasized by the attempts to predict the productivity of crops with the help of weather variables. The importance of resolution and data quality is displayed by models like CERES and EPIC, which demonstrate the difference in predictions made by varying climate inputs. In the same way, such a phenomenon as El Niño, or the North American Oscillation, highlights the influence of internal climate variability on water resources and agricultural output.

Recent developments in data-driven climate research have created new opportunities and challenges for climate modeling and prediction. The complexity of climate systems often limits the effectiveness of traditional linear modeling approaches. However, recent methodological developments have encouraged closer collaboration between climate researchers and quantitative analysts. Carbon emissions, GHG emissions, environmental trade and atmospheric indicators are multi-faceted at their intersection. Combined modeling, advanced analytics, and collaborative policymaking will allow responding to the challenge of global climate in a more efficient way. This paper also adds to that debate and analysis of essential relations between data in environmental and economic spheres, where the immediate necessity is to take action on climate informed and data-driven (Liu et al., 2023).

Objectives of the Research

In this research, the aim is to predict climate change trends through the analysis of global atmospheric CO_2 concentration and sea level change using machine learning-based and data-driven modeling approaches. This research aims to analyze long-term, multi-country climate and environmental trade data using machine learning-based and data-driven modeling approaches in order to improve climate change forecasting and support environmental planning. Finally, it provides instruments in enhancing climate science in the world and predicting an environmental change better.

Problem of the Research

Climate change is a burning and sophisticated international problem that is motivated by increasing CO_2 levels, leading to global warming and rising sea level. Nonetheless, the existing forecasting tools frequently can not cope with the complexity and magnitude of climate data that prevents correct predictions. Conventional models can make changes slow or distorted, which may hamper the process of controlling climate risks. Due to the fact that the association between CO_2 emissions and sea level rise constitutes a number of dynamic elements, the more sophisticated data-driven and machine learning methodologies are urgently required to enhance predictions. Unless there is improved prediction, then there is a risk that societies will not be ready to deal with the long-term consequences of climatic changes.

Importance of the study

Climate change prediction is crucial in the realization of the effects of global warming and how to respond effectively to the changes. Scientists aid in the preparation of communities to environmental hazards such as floods and erosion by observing the level of carbon dioxide in the atmosphere and forecasting sea level increase. Making right predictions allows the policy makers to design superior adaptation and mitigation strategies and assist the early warning mechanism to curb disaster losses. Application of data-driven and machine learning-based analytical methods boosts the accuracy of climate predictions by capturing complex and nonlinear relationships among variables.

LITERATURE REVIEW

Operational weather and climate forecasting commenced well before the advent of computer numerical modeling. Throughout history, efforts have consistently been made to comprehend weather and climate patterns and forecast forthcoming conditions by assessing their implications for human life and activities (Robertson and Vitart, 2018). Experiments attempting to decipher the forces governing weather patterns have long been intertwined with astrology and folklore over centuries. Substantial progress in understanding meteorological phenomena emerged in the early decades of the 19th century, with a particular emphasis on elucidating the attributes and dynamics of atmospheric storms. It was during the late 20 th century when formalized efforts to systematize the collection of observational data to forecast weather events began. In the 1850s and 1860s, especially the work of Admiral Fitzroy can be considered one of the landmark events that gave birth to the concept of weather forecasting. In 1860, the issuance of gale warnings to seafarers was inaugurated by the Admiral Fitzroy and the following year he released general weather predictions. The first meteorological prediction was publicized through being published in the Times newspaper as of August 1, 1861. The rapid expansion of the telegraph communication system significantly facilitated the investigative work of Fitzroy because it gave him an opportunity to collect data on different observatories and make a simple analysis of the common atmospheric conditions. Also, he came up with the words forecast and prediction that replaced the term prediction that was formerly used BBC News (2015).

Bulkeley (2002) This is a ground breaking work that sets out to exhaustively examine the challenges that lie ahead in the world of global climatic change. It also provides useful insights into the scientific and political side of this widespread environmental problem in the world, noting how it has become one of the key elements of the urban policy. It also explores the complexity of the city policy dilemmas, including economic, social, and structural resolutions that were imposed by the need to address the issue of climate change in the city setting. The monograph takes part in an extensive discussion of the new urban practices to tackle the two-fold needs of mitigation and adaptation of climate change. At the same time, this paper analyzes the implications of climate change on the notion of equity, both in terms of how society operates and in environmental aspects, and justifies these findings through the use of case studies which focus on the urban setting.

Peter (2011) says that A deeper understanding of urbanism at the community level gives a stronger foundation on which the complexities that are involved in mitigating climate change can be addressed. In his research, the author emphasizes on the necessity of adoption of green urbanization concept at the local scale to reduce CO_2 emissions within a particular geographic area. Peter also examines the synergy between green urbanization, as well as technological advancements and how these two factors can coexist and be put to use in ensuring sustainable living initiatives. Instead of the list of new energy sources and single-dimensional land-use options, Peter integrates these aspects into his prospective national growth scenario in the year 2050 quite smoothly. This integrative method enables him to elaborate their future effects in a wholesome manner. Therefore, his work emphasizes the importance of an integrated methodology that includes land-use change, policy changes, and new technologies to ease the process of transition to a low-carbon economy.

Selvan et al. (2022) also, an attempt was made to examine the suitability of the neurofuzzy and neural network models as distinct and viable machine learning platforms in the climate change prediction scenario. The results indicated that the model was effective in the prediction of data under particular parameter usage, which supports the advantage of the ANFIS model compared to other artificial networks in making climate predictions. Moreover, the data retrieved by the ANFIS system had a significant margin of accuracy with little variation upon comparing the actual and estimated outcome data.

In another research, Rasp (2019) studied the statistical and machine-learning-based applications in the field of weather and climate modeling. The result of this study means that the approach to the investigation has high levels of flexibility to solve various post-processing issues. In addition, the growing computational powers, and the ever-growing datasets, together with the significant progress of the deep learning approaches, make this research area an exceptionally promising place to pursue the research activity in the future.

Kuligowski and Barros (1998) collected the meteorological data of the Lebanon National Climate Data Center in a study and applied an artificial neural network model to make localized climate predictions. The results of their study explain that the results of the use of the neural network method depict significant enhancements, especially in the field of medium/high intensity precipitation cases. These developments are especially relevant in the operational hydrological application, and the importance of these developments cannot therefore be understated.

Mohammed et al. (2016), the main aims of this research project are to clarify and investigate the tendency of the historical temperature during the period between 1950 and 2100 with specific references to the geographical setting of Iraq. The information used to conduct this study was collected on the site (http://www.meteoseism.gov.iq/index.php) of the period between 1950 and 2014 and the Community Climate System Model (CCSM) version 4. The statistical procedures which were applied included the Pearson Coefficient of correlation and the linear regression. The research results imply that the mean air temperature will portray an increasing trend every year in four different scenarios of Representative Concentration Pathway (RCP) with different levels of emissions. The RCP2.6 scenario also has the least aggressive rate of temperature rise, as the anticipated temperature change is between 0.5 and 0.8 degrees Celsius above historical average. On the other hand, the scenario of the RCP8.5 shows the highest escalation of 4.1 to 6 degrees Celsius. Contrastingly, the RCP4.5 and RCP6.5 outlooks are associated with an increase in temperature of between 1 and 2 degrees Celsius and 2 to 4 degrees Celsius respectively as indicated in the context in question. Moreover, the distribution of this rise in temperature with regions shows that there is a dominant trend that stretches to the south and wraps up to the central, western, and northern parts of Iraq.

MATERIALS AND METHODS

This study aims to estimate the relationship between atmospheric CO_2 concentrations, and average sea level change mm in Türkiye, Iraq, China, America, and Germany by analyzing carbon emissions, greenhouse gas emissions, and environmental trade data from these countries. The selected countries-namely the United States, China, Germany, Türkiye, and Iraq-represent heterogeneous economic structures, emission profiles, and roles in international trade. This selection allows the analysis to capture diverse climate-trade dynamics across advanced industrial economies, emerging markets, and energy-intensive developing countries. The focus is not on cross-country comparison per se, but on understanding nonlinear climate–trade interactions across different economic contexts. Carbon emissions per million people, national greenhouse gas emissions, CO_2 emissions embodied in domes, and trade in environmental goods were the study's independent variables. The study also includes dependent variables such as atmospheric CO_2 concentrations (world), change in mean sea level in millimeters (earth).

The data used in the study average global surface temperature, atmospheric CO_2 concentrations, and average sea level change mm data cover the years 1958–2020. Our data on CO_2 emissions embodied in the domes covers the years 2005–2020. Land cover and average surface temperature data cover the years 1992–2018. In light of these data, it is aimed to predict atmospheric CO_2 concentrations, and average sea level change mm for the next 10 years with machine learning algorithms. The data used in the study were also obtained from the International Monetary Fund (IMF). The IMF database was preferred as it provides harmonized and internationally comparable climate-related indicators compiled from multiple authoritative sources.

Given the multi-country and multi-variable structure of the dataset, advanced data-driven modeling techniques were employed to capture nonlinear relationships and temporal dependencies among climate and trade variables. Our data, which will be collected by various methods, will be arranged in a way that is suitable for our analysis. The NARX and SHAP algorithms will be used in the analysis we will perform with Python. These algorithms are well suited for modeling complex and nonlinear relationships in multi-variable longitudinal datasets. The SHAP algorithm will be used to train the models with NARX, and the relationship between the variables will be examined and an estimation made. The methods used in the study are given in detail under the headings below. It is important to emphasize that SHAP values do not imply causal relationships. Instead, they reflect the relative contribution of each explanatory variable to the model's predictions within a purely model-based framework. Accordingly, the results are interpreted in terms of associations and predictive importance rather than causal effects.

Machine Learning

Machine learning (ML) is one of the fundamental branches of artificial intelligence (AI) that allows machines to learn on the basis of data and make decisions with the minimum human intervention (Dunjko and Briegel, 2018). ML was developed during the 1956 Dartmouth Conference, based on algorithms such as decision trees, support vectors machines, and neural networks, and was based on the quality of the data, selection of features, and learning techniques. ML research includes both taskoriented, cognitive and theoretical research. The model that is developed is an ML model, which includes data preparation, algorithm selection, trains, and is applied to new data. Python has the strongest tools because it has strong libraries, and big tech firms are to invest in ML heavily, which facilitates innovation (Mohri et al., 2018).

Data Collection Process

Once the research objective is identified, it follows data collection, which in turn can be defined in terms of choosing a sample population depending on the scope and objectives of the study. The data used should be relevant, reliable and adequate to be able to make generalizable conclusions. Decisions on data type and volume can be made statistically. It is important that there is consistency among the data sources because inconsistencies-including the difference in the number of observations- may result in the absence of data and inaccuracy. Poor data may lead to poor analysis and expenses associated with corrections. Thus, the process of data collection can be performed carefully and accurately, meaning that the following stages of research will be successful (Özdemir, 2021).

Data Preparation Process

During data preparation stage all data obtained should be standardised and prepared to be analysed. The dissimilarities in data type, measurements, and format-particularly when information is collected of several sources-has to be reconciled, in most cases, by normalizing. The importance of missing data should be evaluated, and it should be analyzed or eliminated. Any outliers that may influence the results of the models must be identified and dealt with carefully. The quality of data needs to be maintained as mistakes made at this point in time may affect the whole analysis. It is important to provide, interpret, and systematize data to construct a model accurately, interpret it, as well as make the research a success (Özdemir, 2021).

Nonlinear External Input Autoregressive Network (Narx)

ANNs are mathematical models and are based on the human brain structure and functionality. They can learn, store and retrieve information and are particularly applicable to solve complex, nonlinear problems in clustering, classification, regression and optimization. The Nonlinear AutoRegressive with eXogenous inputs (NARX) is one particular model, which is common in the modeling of nonlinear dynamic systems and time series data (Boussaada et al., 2018). The primary objective of this study is forecasting and pattern recognition rather than formal statistical inference or causal identification. For this reason, machine learning-based models are preferred over traditional econometric approaches that rely on strict assumptions such as stationarity or parameter stability. The NARX framework is particularly suitable for capturing nonlinear and dynamic relationships in long-term time-series data without requiring explicit pre-testing for structural breaks. While structural changes may exist over extended periods, the model is designed to learn such variations implicitly through its nonlinear architecture. NARX networks are a type of recurrent neural networks (RNNs), where the former takes past outputs as inputs and incorporates feedback between many layers, enhancing the performance of time-dependent prediction (Khaleghi et al., 2021). The architecture consists of input layer, hidden layer and the output layer, all the initial random weights are optimized throughout the training. The hidden layer usually takes the sigmoid activation effect with a linear effect in the output layer to help scale the output correctly before learning. Time delays, the number of hidden layer, type of feedback as well as the training functions are all elements that need to be determined prior to learning. NARX can be used with open-loop (serial-parallel) and closed-loop (parallel) feedback. The model is fed by the predicted outputs and the relationship between the inputs and the outputs is defined mathematically in the parallel structure (Boussaada et al., 2018).

$$\hat{y}(t) = F(\hat{y}(t-1), \hat{y}(t-2), \dots, \hat{y}(t-d_y), x(t), x(t-1), \dots, x(t-d_x) \tag{1}$$

When the real target can be reached, unlike the parallel type, in the NARX design with the serial-parallel type, the feedback to the delay line of the feedforward neural network is made with the real target instead of the predicted target. The mathematical expression for the serial-parallel type is given in Equation 2 to express the actual output data at the time $y(t)$ (Boussaada et al., 2018).

$$\hat{y}(t) = F(y(t-1), y(t-2), \dots, y(t-d_y), x(t), x(t-1), \dots, x(t-d_x) \tag{2}$$

The schematic representation of parallel and serial-parallel NARX structures. Various performance measures can be used to monitor NARX training performance and minimize error. In the context of this research endeavor, the selection of the mean square error (MSE) function is favored. The MSE function is shown in Equation 3.

$$MSE = \frac{1}{n}\sum_{i:1}^{n}(\hat{y}_i - y_i)^2 \tag{3}$$

The backpropagation algorithm is commonly used to make weight adjustments to minimize MSE but is not very fast. Levenberg-Marquardt (LM) method has the advantage of making small networks more efficient by integrating both gradient descent and Gauss-Newton. A probabilistic weight distribution is employed by the Bayesian arrangement (BD), which is more accurate with small data sizes but requires more time to train (Khaleghi et al., 2021).

Shapley Additive Explanation (SHAP)

Machine learning has made life much easier but it is a black box and it is difficult to understand how the results are achieved as the logic behind the results is not always understood. SHAP (SHapley Additive exPlanations) is one tool that can be used to resolve this problem by making models more interpretable and transparent (Kelle, 2021).

SHAP, uses game theory to explain machine learning models, which can be defined as the use of Shapley values that are originally introduced by Lloyd Shapley in 1953 to quantify the contribution of each feature to a model prediction (Hausken et al., 2001). Practically, Shapley values of every data point are computed separately and summed to indicate the cumulative effects of a featur. These combined contributions in the form of SHAP visualizations can be used to make models more interpretable.

$$\emptyset_i = \sum_{S \subseteq N\{i\}} \frac{|S|!\,(M - |S| - 1)!}{M!} [f_x - (S \cup \{i\}) - f_x(S)] \tag{4}$$

Where:

$\emptyset_i$: Shapley value of instance i

S: Subsets of the set N

M: Number of features

$f_x - (S \cup \{i\}) - f_x(S)$: Contribution of the feature

The computation of the SHAP value, which signifies the extent of an attribute's influence on the model, is derived through the amalgamation of Shapley values. The SHAP value is obtained by averaging the Shapley values (Lundberg and Lee, 2017). The diagram below is a visualization of a sequential example. For non-linear models, the order in which features are added is important (Kelle, 2021). Although SHAP was originally developed under independent observation assumptions, recent applications have demonstrated its usefulness in time-series contexts when interpreted cautiously. In this study, SHAP values are employed as a diagnostic tool to enhance model transparency rather than as a formal inferential method. The temporal dependence inherent in the data is therefore acknowledged, and the SHAP results are interpreted accordingly.

Calculating SHAP values in decision trees is more complex than linear models. If our machine learning model is based on a decision tree, the TreeExplainer method in the SHAP library should be used. Below is visualized how the SHAP value is obtained from a decision tree model (TreeSHAP, 2022).

Some machine learning algorithms have functions that calculate the importance values of the features used in the model. Especially in decision tree-based algorithms, importance values are calculated according to the formation of the tree, and the most important attributes are used in the nodes while creating the tree (Al Iqbal et al., 2012).

In the decision tree-based XGBoost algorithm, the importance values of the features can be calculated by different methods (Mitchell and Frank, 2017). Different methods give different results and it is difficult to answer the question of which method is correct (The Multiple faces of 'Feature importance' in XGBoost (The Multiple faces of 'Feature importance' in XGBoost, 2022).

ANALYSIS AND FINDINGS

In this study, by analyzing the greenhouse gas emission, carbon emission, and environmental trade data of Iraq, Türkiye, America, China, and Germany, it is aimed to estimate the relationship between surface temperature, air temperature, or climate-related disasters in these countries. The independent variables used in the study were carbon emissions per million people, national greenhouse gas emissions, CO_2 emissions embodied in domes and trade in environmental goods. Dependent variables used in the study were: Change in mean sea level in mm (Earth), atmospheric CO_2 concentrations (World).

The data used in the study-average global surface temperature, Atmospheric CO_2 concentrations, and Average sea level change mm data cover the years 1958–2020.

In light of the presented data, the primary objective of this investigation is to employ machine learning algorithms for the purpose of forecasting climate change-related disasters, atmospheric CO_2 concentrations, as well as land and sea temperatures for a decade. The data used in the study were obtained from the International Monetary Fund (IMF).

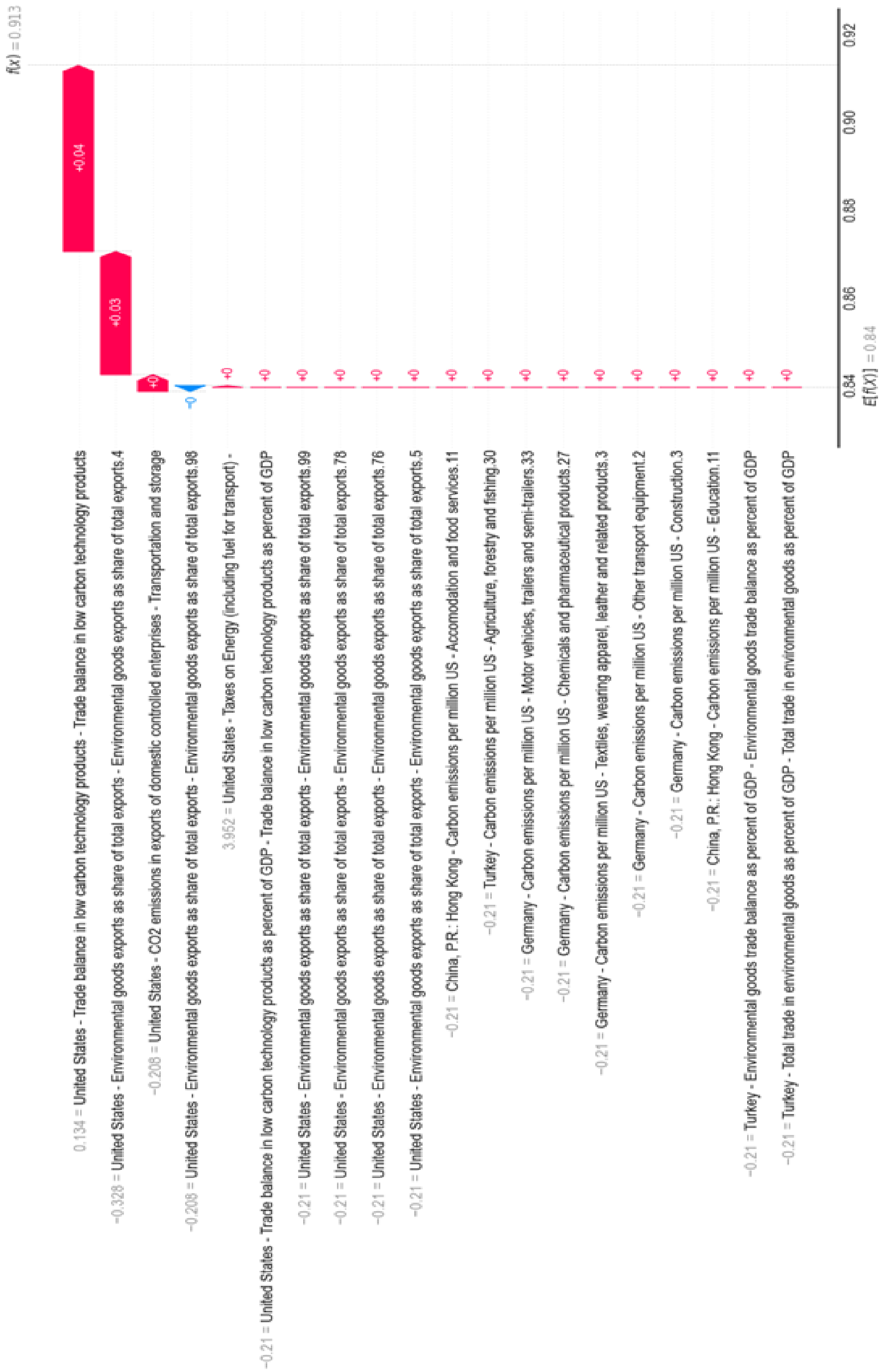
The dataset consists of time-series climate and trade indicators from selected countries, analyzed using machine learning-based modeling techniques. Our data, which will be collected by various methods, will be arranged in a way that is suitable for our analysis. The NARX and SHAP algorithms were employed due to their effectiveness in analyzing complex, high-dimensional, and multi-variable datasets commonly encountered in climate and environmental economics research. The SHAP algorithm used to train the models with NARX and the relationship between the variables examined and the estimation made Below, each dependent variable is evaluated separately, and the outcomes of the analysis are given in detail, both numerically and visually.

Mean Global Surface Temperature

MSE: 0.0906

The variables used in the analysis to explain the change in the mean global surface temperature variable and the contribution of these variables to the change are given in the graphic below.

Figure 1. Variables used for mean global surface temperature



The Variables used for Mean Global Surface Temperature

These results were obtained from the analysis of variables used for the mean global surface temperature:

A one-unit change in the low-carbon technology products trade balance variable in the United States is associated with an approximate increase of 0.042 units in the predicted global mean surface temperature within the model framework

The relationship between environmental goods exports as a proportion of total exports in the United States and the Mean Global Surface Temperature variable is characterized by a positive association. Within the model framework, a one-unit increase in the former is associated with an approximate increase of 0.028 units in the predicted global mean surface temperature. We can interpret that there is no change in our other variables because our values are small. In addition, the effect values of each variable are given in detail in the table below.

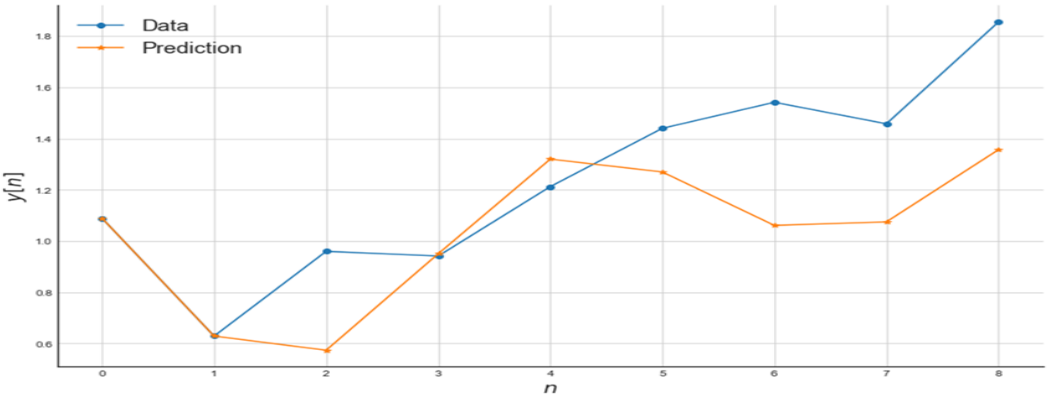
Table 1. Variables used for mean global surface temperature

	Feature	Feature-value
0	China, People's Republic: Hong Kong - Carbon emissions per million US - Accomodation and food services.11	0.000
1	China, People's Republic: Hong Kong - Carbon emissions per million US - Education.11	0.000
2	Germany - Carbon emissions per million US - Construction.3	0.000
3	Germany - Carbon emissions per million US - Other transport equipment.2	0.000
4	Germany - Carbon emissions per million US - Textiles, wearing apparel, leather and related products.3	0.000
5	Germany - Carbon emissions per million US - Chemicals and pharmaceutical products.27	0.000
6	Germany - Carbon emissions per million US - Motor vehicles, trailers and semi-trailers.33	0.000
7	Türkiye - Carbon emissions per million US - Agriculture, forestry and fishing.30	0.000
8	Türkiye - Environmental goods trade balance as percent of Gross Domestic Product - Environmental goods trade balance as percent of Gross Domestic Product	0.000
9	Türkiye - Total trade in environmental goods as percent of Gross Domestic Product - Total trade in environmental goods as percent of Gross Domestic Product	0.000
10	United States - Environmental goods exports as share of total exports - Environmental goods exports as share of total exports.4	0.028
11	United States - Environmental goods exports as share of total exports - Environmental goods exports as share of total exports.5	0.000
12	United States - Environmental goods exports as share of total exports - Environmental goods exports as share of total exports.76	0.000
13	United States - Environmental goods exports as share of total exports - Environmental goods exports as share of total exports.78	0.000
14	United States - Environmental goods exports as share of total exports - Environmental goods exports as share of total exports.98	-0.001
15	United States - Environmental goods exports as share of total exports - Environmental goods exports as share of total exports.99	0.000
16	United States - Trade balance in low carbon technology products - Trade balance in low carbon technology products	0.042
17	United States - Trade balance in low carbon technology products as percent of GDP - Trade balance in low carbon technology products as percent of Gross Domestic Product	0.000
18	United States - CO_2 emissions in exports of domestic controlled enterprises - Transportation and storage	0.003
19	United States - Taxes on Energy (including fuel for transport) -	0.000

The estimation of the Mean Global Surface Temperature variable in the NARX model

According to the findings depicted in Figure 2, for the real data, it was found that the estimates of the global mean surface temperature variable within the NARX model showed a remarkable degree of closeness to the actual values. It is plausible to emphasize that the model gives good results.

Figure 2. The estimation of the mean global surface temperature variable in the NARX model



The Prospective Estimated Values of the Mean Global Surface Temperature Variable for the Years 2018-2031

Table 2 explains when the estimated values for the years 2018–2031 are examined. It was observed that the Mean Global Surface Temperature variable showed a decrease between the years 2018–2022, then increased until 2028, and decreased after 2028.

Table 2. The prospective estimated values of the mean global surface temperature variable for the years 2018-2031

Year	Prediction
2018	1.855*
2019	1.855*
2020	1.058*
2021	0.663*
2022	0.663
2023	1.013
2024	1.286
2025	1.425
2026	1.490
2027	1.606
2028	1.670
2029	1.646
2030	1.584
2031	1.550

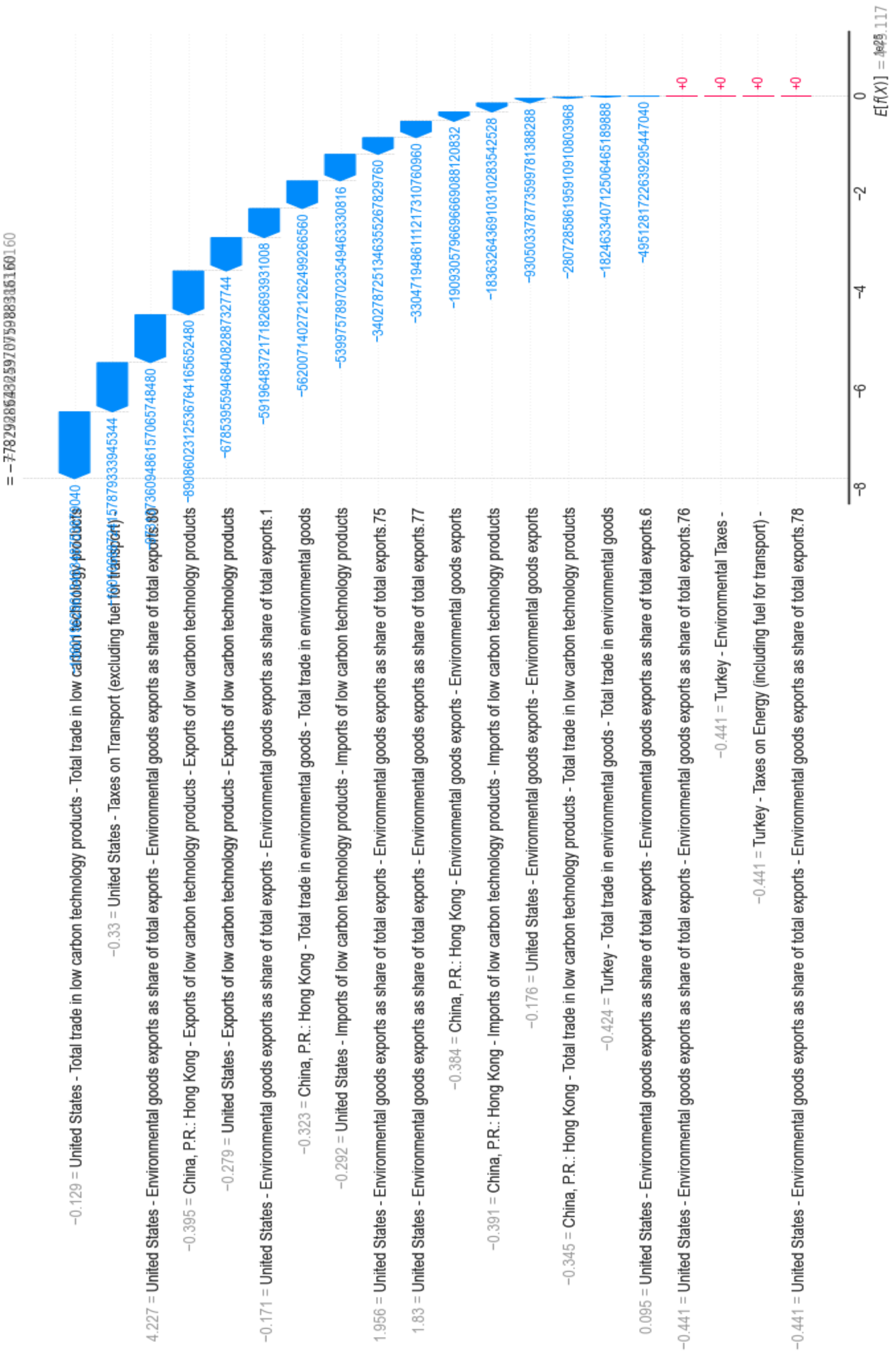
*Real data

Atmospheric CO_2 Concentrations

MSE: 6854.312

The variables chosen to explain the change in the Atmospheric CO_2 Concentrations variable and the contribution of these variables to the change are given in the graphic below.

Figure 3. Variables used for atmospheric CO_2 concentrations



The Variables Used for Atmospheric CO_2 Concentrations

Table 3 explains all the variables used for atmospheric CO_2 concentrations:

We can interpret that there is no change in our other variables because our values are small. In addition, the effect values of each variable are given in detail in Table 3 below.

Table 3. Variables used for atmospheric CO_2 concentrations

	Feature	Feature - value
0	China, People's Republic: Hong Kong - Environmental goods exports - Environmental goods exports	-1.909
1	China, People's Republic: Hong Kong - Total trade in environmental goods - Total trade in environmental goods	-5.620
2	Türkiye - Total trade in environmental goods - Total trade in environmental goods	-1.824
3	United States - Environmental goods exports - Environmental goods exports	-9.305
4	United States - Environmental goods exports as share of total exports - Environmental goods exports as share of total exports.1	-5.919
5	United States - Environmental goods exports as share of total exports - Environmental goods exports as share of total exports.6	-4.951
6	United States - Environmental goods exports as share of total exports - Environmental goods exports as share of total exports.75	-3.402
7	United States - Environmental goods exports as share of total exports - Environmental goods exports as share of total exports.76	0.000
8	United States - Environmental goods exports as share of total exports - Environmental goods exports as share of total exports.77	-3.304
9	United States - Environmental goods exports as share of total exports - Environmental goods exports as share of total exports.78	0.000
10	United States - Environmental goods exports as share of total exports - Environmental goods exports as share of total exports.80	-9.731
11	China, People's Republic: Hong Kong - Exports of low carbon technology products - Exports of low carbon technology products	-8.908
12	China, People's Republic: Hong Kong - Imports of low carbon technology products - Imports of low carbon technology products	-1.836
13	China, People's Republic: Hong Kong - Total trade in low carbon technology products - Total trade in low carbon technology products	-2.807
14	United States - Exports of low carbon technology products - Exports of low carbon technology products	-6.785
15	United States - Imports of low carbon technology products - Imports of low carbon technology products	-5.399
16	United States - Total trade in low carbon technology products - Total trade in low carbon technology products	-1.360
17	Türkiye - Environmental Taxes -	0.000
18	Türkiye - Taxes on Energy (including fuel for transport) -	0.000
19	United States - Taxes on Transport (excluding fuel for transport) -	-1.001

China, People's Republic: Hong Kong - An augmentation of one unit in the Environmental goods exports variable results in a reduction of -1.909 units in the Atmospheric CO_2 Concentrations variable, as stipulated in the cited context.

China, People's Republic: Hong Kong - A augmentation of one unit in the Total trade in environmental goods variable results in a decrement of -5.620 units in the Atmospheric CO_2 Concentrations variable.

Türkiye - A one-unit increase in the environmental goods total trade variable It becomes a -1.824-unit decrease in the atmospheric CO_2 concentration variable, as explained in the reference framework.

A 1-unit increase in the United States environmental goods exports variable is associated with an approximate 9.305-unit decrease in the predicted Atmospheric CO_2 Concentrations within the model framework.

A 1-unit increase in the United States - Environmental Goods Exports as Share of Total Exports variable is associated with an approximate 5.919-unit decrease in the predicted Atmospheric CO_2 Concentrations within the model framework.

A 1-unit increase in the United States - Environmental Goods Exports as Share of Total Exports variable is associated with an approximate 4.951-unit decrease in the predicted Atmospheric CO_2 Concentrations within the model framework.

A 1-unit increase in the United States - Environmental Goods Exports as Share of Total Exports variable is associated with an approximate 3.402-unit decrease in the predicted Atmospheric CO_2 Concentrations within the model framework.

A 1-unit increase in the United States - Environmental Goods Exports as Share of Total Exports variable is associated with an approximate 3.304-unit decrease in the predicted Atmospheric CO_2 Concentrations within the model framework.

A 1-unit increase in the United States - Environmental Goods Exports as Share of Total Exports variable is associated with an approximate 9.731-unit decrease in the predicted Atmospheric CO_2 Concentrations within the model framework.

China, People's Republic: Hong Kong - A 1-unit increase in the Exports of Low Carbon Technology Products variable is associated with an approximate 8.908-unit decrease in the predicted Atmospheric CO_2 Concentrations within the model framework.

China, People's Republic: Hong Kong - A 1-unit increase in the Imports of Low Carbon Technology Products variable is associated with an approximate 1.836-unit decrease in the predicted Atmospheric CO_2 Concentrations within the model framework.

China, People's Republic: Hong Kong - A 1-unit increase in the Total Trade in Low Carbon Technology Products variable is associated with an approximate 2.807-unit decrease in the predicted Atmospheric CO_2 Concentrations within the model framework.

A 1-unit increase in the United States - Exports of Low Carbon Technology Products variable is associated with an approximate 6.785-unit decrease in the predicted Atmospheric CO_2 Concentrations within the model framework.

A 1-unit increase in the United States - Imports of Low Carbon Technology Products variable is associated with an approximate 5.399-unit decrease in the predicted Atmospheric CO_2 Concentrations within the model framework.

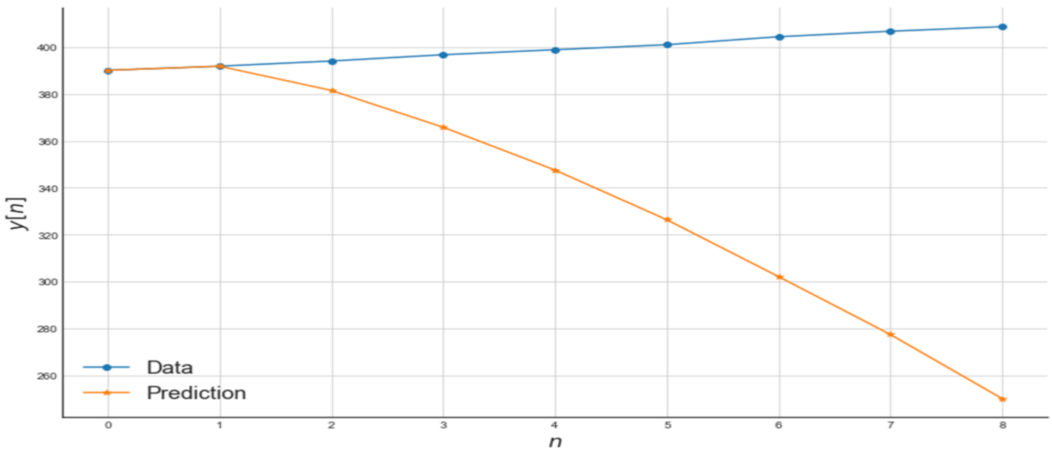
The United States - A 1-unit increase in the Total Trade in Low Carbon Technology Products variable is associated with an approximate 1.360-unit decrease in the predicted Atmospheric CO_2 Concentrations within the model framework.

A 1-unit increase in the United States - Taxes on Transport (excluding fuel for transport) variable is associated with an approximate 1.001-unit decrease in the predicted Atmospheric CO_2 Concentrations within the model framework.

The estimation of the Atmospheric CO_2 Concentrations Variable in the NARX model

In the other hand, in graphic 4.4, it has been observed that the estimation of the Atmospheric CO_2 Concentrations variable in the NARX model differs according to the real data.

Figure 4. The estimation of the atmospheric CO_2 concentrations variable in the NARX model



The Prospective Estimated Values of the Atmospheric CO_2 Concentrations Variable for the Years 2018-2031

According to the results in Table 4, when the estimated values for the years 2018–2031 are examined, it is observed that the Atmospheric CO_2 Concentrations variable shows a decrease between 2018–2031. The sharp decline observed in long-term CO_2 projections should be interpreted with caution, as it may partly reflect data normalization, model sensitivity to recent trends, or structural assumptions inherent in machine learning-based forecasting rather than a physically realistic emission pathway.

Table.4. The prospective estimated values of the atmospheric CO_2 concentrations variable for the years 2018-2031

Year	Prediction
2018	408.714*
2019	408.714*
2020	400.274*
2021	380.877*
2022	371.227
2023	352.959
2024	331.985
2025	310.986
2026	287.779
2027	258.553
2028	223.050
2029	183.014
2030	138.013
2031	87.440

*Real data

Change in Mean Sea Level (Mm)

MSE: 20.486

The variables chosen to explain the change in the Change in mean sea level (mm) variable and the contribution of these variables to the change are given in the graphic below.

Figure 5. Variables used for change in mean sea level (mm)

The Variables Used for Change in Mean Sea Level (Mm)

As shown in Table 5, indicating the variables used for changes in mean sea level (mm):

Table 5. Variables used for change in mean sea level (mm)

	Feature	Feature-value
0	China, People’s Republic: Hong Kong - Carbon emissions per million US - Electricity, gas, water supply, sewerage, waste and remediation services.11	0.000
1	China, People’s Republic: Hong Kong - Carbon emissions per million US - Telecommunications.26	0.000
2	China, People’s Republic: Mainland - Carbon emissions per million US - Computer, electronic and optical products.12	0.000
3	United States - Carbon emissions per million US - Machinery and equipment n.e.c.	0.000
4	United States - Carbon emissions per million US - Other business sector services.27	0.000
5	United States - Carbon emissions per million US - Public administration and defence; compulsory social security.26	0.000
6	United States - Environmental goods exports as share of total exports - Environmental goods exports as share of total exports.1	5.124
7	United States - Environmental goods exports as share of total exports - Environmental goods exports as share of total exports.3	0.000
8	United States - Environmental goods exports as share of total exports - Environmental goods exports as share of total exports.6	13.341
9	United States - Imports of low carbon technology products - Imports of low carbon technology products	0.822
10	United States - Total trade in low carbon technology products - Total trade in low carbon technology products	4.060
11	China, People’s Republic: Hong Kong - CO_2 emissions per unit of output for foreign controlled multinational enterprises - Explicit Fossil Fuel Subsidies - Petroleum.1	0.000
12	China, People’s Republic: Hong Kong - CO_2 emissions per unit of output for foreign controlled multinational enterprises - Fossil Fuel Subsidies - Total Implicit and Explicit - Coal.1	0.000
13	China, People’s Republic: Hong Kong - CO_2 emissions per unit of output of domestic controlled enterprises - Implicit Fossil Fuel Subsidies - Electricity.1	0.000
14	China, People’s Republic: Mainland - CO_2 emissions per unit of output for foreign controlled multinational enterprises - Explicit Fossil Fuel Subsidies - Natural Gas.1	0.000
15	China, People’s Republic: Mainland - CO_2 emissions per unit of output of domestic controlled enterprises - Implicit Fossil Fuel Subsidies - Road Damage.1	0.000
16	Türkiye - CO_2 emissions in output of domestic controlled enterprises - Public admin. and defence; compulsory social security	-0.168
17	United States - CO_2 emissions per unit of output of domestic controlled enterprises - Public admin. and defence; compulsory social security	0.000
18	Türkiye - Environmental Taxes -	0.000
19	Türkiye - Taxes on Energy (including fuel for transport) -	0.000

United States - Environmental goods exports as a share of total exports: A one-unit increase in environmental goods exports as a share of total exports is associated with an approximate increase of 5.124 units (5.124 mm) in the predicted change in mean sea level within the model framework.

United States - Environmental goods exports as a share of total exports: A one-unit increase in environmental goods exports as a share of total exports is associated with an approximate increase of 13.341 units (13.341 mm) in the predicted change in mean sea level within the model framework.

A one-unit increase in the United States - Imports of Low Carbon Technology Products variable is associated with an approximate increase of 0.822 units (0.822 mm) in the predicted change in mean sea level within the model framework.

United States - Total trade in low carbon technology products: A one-unit increase in the total trade in low carbon technology products variable is associated with an approximate increase of 4.060 units (4.060 mm) in the predicted change in mean sea level within the model framework.

Türkiye - CO_2 emissions in output of domestically controlled enterprises (administration and defense; compulsory social security): A one-unit increase in the compulsory social security variable is associated with an approximate decrease of 0.168 units (–0.168 mm) in the predicted change in mean sea level within the model framework. We can interpret that there is no change in our other variables because our values are small. In addition, the effect values of each variable are given in detail in the table below.

The Estimation of the Change in Mean Sea Level (Mm) Variable in the NARX Model

According to the outcome of graphic 4.6, On real data, it was observed that the estimation of the change in mean sea level (mm) variable in the NARX model is similar. This indicates that the estimation is strong.

Figure 6. The estimation of the change in mean sea level (mm) variable in the NARX model

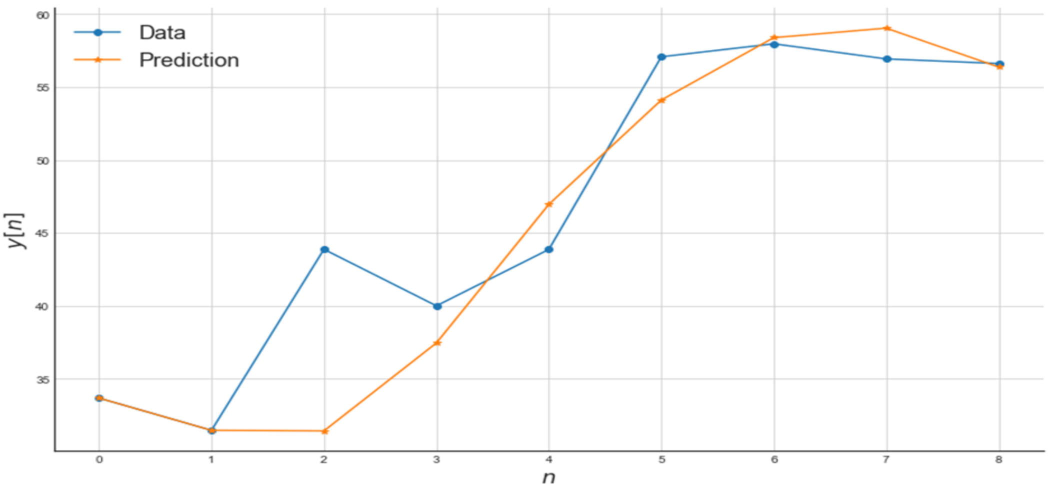


Table 6 showing the estimated values for the years 2018–2031, is examined. It was observed that the change in the mean sea level (mm) variable showed a general increase between the years 2018–2031.

The Prospective Estimated Values of the Change in Mean Sea Level (Mm) Variable for the Years 2018-2031

Table 6 showing the estimated values for the years 2018–2031, is examined. It was observed that the change in the mean sea level (mm) variable showed a general increase between the years 2018–2031.

Table 6. The prospective estimated values of the change in mean sea level (mm) variable for the years 2018-2031

Year	Prediction
2018	56.614*
2019	56.614*
2020	45.994*
2021	37.594*
2022	37.594
2023	42.633
2024	50.994
2025	57.956
2026	60.085
2027	61.912
2028	64.797
2029	67.011
2030	67.709
2031	67.045

*Real data

DISCUSSION AND CONCLUSION

This study analyzed the relationships between environmental indicators and climate change variables across five countries using using machine learning-based and data-driven analytical methods (NARX and SHAP). Results showed that trade in low-carbon technologies and environmental goods was strongly associated with global surface temperature, atmospheric CO_2 levels, and sea level changes. For global surface temperature, certain U.S. environmental trade variables showed a modest increase effect, while other variables had negligible influence.

Therefore, predictions of CO_2 concentration in the atmosphere showed that the expansion of trade in environmental goods and low-carbon technologies is associated with a significant decrease in predicted CO_2 concentrations within the model results. It is worth noting that the U.S. export of low-carbon technology reduced the CO_2 levels significantly. The effects of U.S. trade in environmental goods and the import of low-carbon goods on changes in mean sea level were significant, but the variables of Türkiye were insignificant. On the whole, the NARX model was very accurate in the estimation of true values and in the prediction of the future trends until 2031, which proves the relevance of sustainable trade practices in reducing the effects of climate change.

The findings of this study are based on the analysis of long-term climate and environmental trade data covering the period from 1958 to 2020. The use of machine learning-based models enabled the identification of nonlinear relationships among emissions, trade variables, and key climate indicators. The results indicate that trade-related environmental variables, especially in the United States and China can be said to have a significant impact on climate outcomes. To illustrate, an increase in the trade balance of low-carbon technology products in the United States is associated with higher predicted mean surface temperature values, whereas exports of environmental goods exhibit a negative association with atmospheric CO_2 levels within the model results. In the same way, total trade in low-carbon technologies was found to have a role in increasing the sea level, which is a subtle and even counterintuitive impact of green trade. Surface temperature and sea level change were well modeled by the predictive models, which supports the usefulness of machine learning in predicting the course of climate change. This study does not aim to provide an exhaustive comparison across all possible forecasting models. Instead, the focus is placed on demonstrating the applicability of the NARX framework in capturing nonlinear climate-trade dynamics. Future research may extend this analysis by comparing the predictive performance of alternative machine learning and econometric models. Interestingly enough, the levels of CO_2 in the atmosphere were estimated to reduce drastically within the next ten years, which may reflect model-based projections under assumed conditions, including potential policy shifts and technological developments. It should be noted that long-term forecasts are inherently subject to uncertainty, particularly in the presence of potential policy shifts, technological advancements, and structural changes in economic and environmental systems. Therefore, the projected trends should be interpreted as scenario-dependent predictive outcomes rather than precise future realizations. As a result, it is crucial for policymakers to continue investing in green technologies and strengthening international cooperation to mitigate climate change risks.

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