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FORECASTING THE WORLD'S QUARTERLY GREENHOUSE GAS EMISSIONS VIA MULTI-LAYER PERCEPTRON

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ABSTRACT

This study investigates the dynamics of environmental and economic indicators by examining time series data to understand their impact on sustainable development and environmental management. This study analyzes the data obtained from different sectors by determining the trends of the main variables such as Agriculture, Forestry and Fishing (AFF), Construction (C), Electricity, Gas, Steam and Air Conditioning Supply (EGSACS), Manufacturing (MAN), Mining (MIN), Other Services Industries (OSI), Total Households (TH), Total Industry and Households (TIH), Transportation and Storage (TS), Water supply; sewerage, waste management and remediation activities (WSSWMRA) and uses Artificial Neural Networks for data analysis. The results show that; it can be said that the artificial neural network produces results very close to the real values.

1. INTRODUCTION

The concept of "Sustainable development," which addresses a global crisis, is becoming an increasingly important issue. As the world grapples with the consequences of rapid industrialization and urbanization, the need to balance economic growth with environmental stewardship has never been more urgent. Economic growth strategies employed in recent decades, particularly those driven by fossil fuel consumption and industrialization, have intensified environmental degradation. This has led to heightened conflicts surrounding environmental protection, especially as global consumption rates continue to rise. Moreover, the tension between sustainable development and economic growth has become more pronounced due to the high levels of energy consumption and material usage that contribute to significant emissions (Saraçlı & Boca, 2021; Saracli et al., 2023).

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At the heart of this challenge is the pressing need to integrate sustainable development more effectively into education systems. Education plays a pivotal role in shaping individuals' perceptions and behaviors towards sustainability, providing them with the tools to foster environmental stewardship. By including sustainability in curricula and providing students with practical opportunities to promote sustainable practices, education can become a powerful vehicle for addressing environmental issues and cultivating a culture of responsibility towards the planet.

Climate change has emerged as one of the most critical global environmental issues. The primary driver of this phenomenon is the increase in greenhouse gas emissions, which disrupt the Earth's energy balance. These emissions are responsible for the rise in average global temperatures, a process widely known as global warming. The consequences of this warming are far-reaching, affecting not only environmental systems but also economic, social, and health structures across the globe (IPCC, 2021). The impact of climate change is not uniform, with some regions experiencing more severe effects than others. These effects include rising sea levels, more extreme weather events, shifts in agricultural patterns, and threats to biodiversity. Addressing these challenges requires urgent action at both the individual and institutional levels, as well as a concerted effort to transition to more sustainable practices across all sectors of society.

Human activities, particularly since the Industrial Revolution, have been the principal drivers of greenhouse gas emissions. The widespread burning of fossil fuels, deforestation, and industrial processes have all contributed to the accumulation of carbon dioxide, methane, and other greenhouse gases in the atmosphere. These gases trap heat, leading to global warming and exacerbating the instability of the climate system (Edenhofer et al., 2014). As the planet continues to warm, the consequences become more severe, including disruptions to weather patterns, loss of biodiversity, and threats to human livelihoods. To mitigate these effects, reducing greenhouse gas emissions through sustainable energy practices and lifestyle changes is critical.

In this context, the transition towards a more sustainable global economy requires a collective effort that includes the rethinking of energy production and consumption patterns, the promotion of green technologies, and the widespread adoption of sustainable practices at all levels of society. Achieving this goal demands not only technological innovation but also significant behavioral and societal changes, which will be facilitated through education and awareness.

2. LITEREATURE REVIEW

2.1. Greenhouse Gases

2.1.1. Definition and Properties of Greenhouse Gases and Emissions

Greenhouse gases are gases that allow sunlight to enter the Earth's atmosphere but trap outgoing radiation, thereby retaining heat and contributing to the greenhouse effect. Common greenhouse gases include carbon dioxide (CO_2), methane (CH_4), nitrous oxide (N_2O), hydrofluorocarbons (HFCs), perfluorocarbons (PFCs), and sulfur hexafluoride (SF_6). CO_2, which is primarily released through the combustion of fossil fuels, is the most prevalent greenhouse gas. Methane and nitrous oxide are also significant contributors and are released through agricultural and industrial activities (Gordon et al., 2008).

Each greenhouse gas has a different global warming potential (GWP), which measures its heat-trapping ability relative to CO_2. For example, methane has approximately 25 times the warming potential of CO_2, and nitrous oxide has nearly 298 times the warming potential of CO_2 (Myhre et al., 2013). Despite being less prevalent, gases like methane and nitrous oxide have a substantial warming effect due to their higher GWPs.

Greenhouse gases also vary in their atmospheric lifetimes. While CO_2 can remain in the atmosphere for about 100 years, methane has a much shorter lifespan of around 12 years. These variations impact the strategies needed to address each gas's specific role in climate change and highlight the importance of prioritizing certain gases in climate mitigation policies (Hansen et al., 2013).

Greenhouse gas (GHG) emissions, primarily comprising carbon dioxide (CO_2), methane (CH_4), and nitrous oxide (N_2O), are closely tied to industrialization and human activities, especially fossil fuel combustion and land use changes. These emissions trap heat in the atmosphere, contributing significantly to the greenhouse effect and global warming. CO_2, mainly produced by the burning of coal, oil, and natural gas, is responsible for the majority of anthropogenic GHG emissions. The energy sector, which includes electricity generation and transportation, is one of the largest contributors to global GHG emissions, followed by sectors like agriculture, forestry, and industry (IPCC, 2021).

Methane emissions, although less abundant than CO_2, have a far higher global warming potential, making them a critical target in climate mitigation efforts. Agricultural activities, such as livestock production and rice cultivation, are major sources of methane, as is the extraction and distribution of fossil fuels. Nitrous oxide, often emitted through the use of nitrogen-based fertilizers in agriculture, contributes to both climate change and stratospheric ozone depletion. Given their high global warming potentials and longer atmospheric lifetimes, reducing methane and nitrous oxide emissions is as important as curbing CO_2, despite their lower quantities (Saunois et al., 2020).

Global GHG emissions have shown a persistent upward trend since the pre-industrial era, with a marked acceleration in the past century. This trend poses serious challenges to international climate goals, such as those outlined in the Paris Agreement, which aims to limit global warming to below 2°C above pre-industrial levels. Despite efforts by countries to adopt cleaner energy sources and improve energy efficiency, current policies are often insufficient to meet reduction targets. Addressing greenhouse gas emissions thus requires transformative changes in energy production, transportation, agriculture, and waste management to achieve meaningful climate progress (UNFCCC, 2015).

2.1.2. Sources of Greenhouse Gases

Greenhouse gases originate from both natural and anthropogenic sources. Natural sources include volcanic eruptions, plant respiration, ocean evaporation, and microbial activity in soils. For instance, volcanic activity releases significant amounts of CO_2 into the atmosphere as part of the natural carbon cycle. Plants release CO_2 through respiration, although this process is generally balanced by photosynthesis. Additionally, oceans release dissolved CO_2 into the atmosphere during evaporation (Friedlingstein et al., 2020).

Human-induced emissions, however, are the primary contributors to increased greenhouse gases, directly driving climate change. The main sources of anthropogenic emissions are fossil fuel combustion, agriculture, industrial processes, deforestation, and waste management. In particular, the energy sector accounts for the largest share of CO_2 emissions globally, with significant contributions from electricity generation, transportation, and industry (Edenhofer et al., 2014).

Agricultural practices contribute to methane and N_2O emissions. For example, livestock production emits methane through enteric fermentation, while nitrogen-based fertilizers lead to

N_2O emissions. Deforestation is another major contributor, reducing carbon sinks and releasing CO_2 into the atmosphere. Forests act as carbon sinks by absorbing CO_2, so increased deforestation disrupts the carbon balance and further exacerbates climate change (Saunois et al., 2020).

2.1.3. Climate Impacts of Greenhouse Gases

As greenhouse gases accumulate in the atmosphere, more heat is trapped, leading to a rise in global temperatures. This phenomenon disrupts climate systems and triggers various environmental issues, including melting polar ice caps, rising sea levels, and an increase in the frequency and severity of extreme weather events. CO_2 and CH_4, due to their high heat-trapping capacities, are among the most significant contributors to long-term global warming (Hansen et al., 2013).

The impacts of global warming extend beyond environmental concerns, affecting economic and social systems as well. Agricultural production may decline, and water resources may become scarcer as a result of shifting climate conditions. Extreme weather events, such as hurricanes and wildfires, pose a direct threat to infrastructure and economic stability, leading to substantial financial losses worldwide (IPCC, 2021).

Climate change also has severe social implications. Heatwaves, floods, and other extreme events impact public health, while climate-induced displacement disrupts communities and ecosystems. These consequences emphasize the importance of reducing greenhouse gas emissions and adopting effective climate policies to mitigate the adverse effects on both natural and human systems (Rogelj et al., 2016a; Rogelj et al., 2016b).

2.1.4. Global Emission Trends and Data

Since the industrial revolution, greenhouse gas emissions have shown a consistent upward trend. Data from the International Energy Agency (IEA) reveal that fossil fuel consumption has led to significant increases in atmospheric CO_2 concentrations. Although global emissions saw a temporary decline in 2020 due to the COVID-19 pandemic, emissions have since rebounded, particularly in the energy and transportation sectors (IEA, 2021).

Developing countries are contributing to rising emissions due to rapid industrialization and urbanization. As these nations grow economically, their energy demands—and consequently, their fossil fuel consumption—also rise. Deforestation and agricultural expansion further exacerbate the carbon imbalance, contributing to increased global emissions (Saunois et al., 2020).

The annual growth rate of global greenhouse gas emissions is a critical indicator for tracking climate progress. Following the Paris Agreement, many nations have committed to reducing their emissions. However, current trends suggest that limiting global warming to 1.5°C or even 2°C remains a challenge, highlighting the urgent need for mitigation efforts and a transition to renewable energy sources (UNFCCC, 2015).

2.2. Artificial Neural Network

Artificial Neural Networks (ANN) are powerful artificial intelligence algorithms inspired by the synaptic connections in the human brain and used to model complex relationships in the field of machine learning. Today, thanks to the increasing data volume, processing power and widespread use of open-source libraries, ANNs offer effective solutions in many areas such as image processing, natural language processing, financial forecasting and health. Especially with deep learning approaches, ANNs provide very successful results in modeling nonlinear relationships and extracting meaningful patterns from large data sets (Goodfellow et al., 2016). In this context, ANNs are widely preferred both in academic research and industrial applications today.

Many different architectures have been developed in the artificial neural network literature and optimized for various data types. While one of the most basic structures, the Multilayer Perceptron (MLP), is frequently used especially in structured data; Convolutional Neural Networks (CNN) stand out with their superior performance in image processing and computer vision problems (Krizhevsky et al., 2012). On the other hand, Recurrent Neural Networks (RNN) and especially Long Short-Term Memory (LSTM) networks produce effective results on sequential and time series data (Hochreiter & Schmidhuber, 1997). In recent years, Transformer-based models, which stand out with their parallel processing capabilities and attention mechanism-based structures, have revolutionized many areas, especially natural language processing (Vaswani et al., 2017). These different architectures provide flexibility in ANN applications by offering structures that vary according to the data type and problem.

Multi-Layer Perceptron (MLP) is one of the most widely used and basic forms of artificial neural networks (Rumelhart et al., 1986). MLPs are feed-forward neural networks consisting of an input layer, one or more hidden layers, and an output layer, which enables them to model nonlinear relationships effectively. The network uses nonlinear activation functions, such as ReLU (Rectified Linear Unit), sigmoid, and tanh, allowing the network to learn complex patterns from data. Among these, ReLU is particularly favored in deep learning architectures due to its ability to mitigate the vanishing gradient problem (Glorot et al., 2011). An example of MLP visual is as in Figure 1.

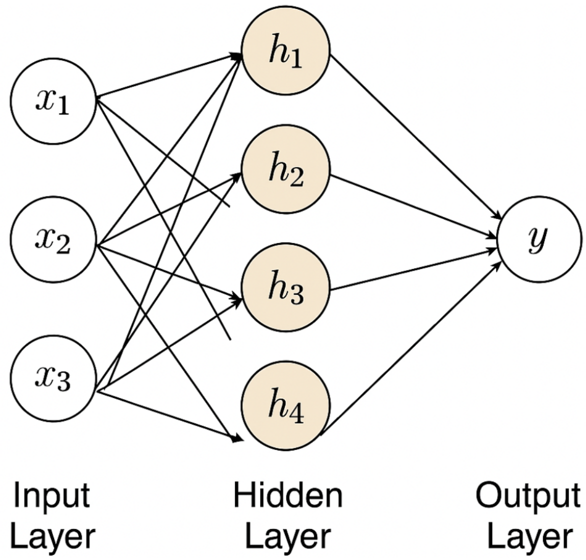

Figure 1. Graph for MLP

The training process of MLPs typically utilizes the backpropagation algorithm and gradient descent methods, which adjust the weights and biases in the network to minimize the error between predicted and actual outputs. The input data in an MLP model is passed through the layers, with each layer processing the input through a set of weights, biases, and an activation function. The output of each layer is passed to the next, ultimately leading to the prediction at the output layer.

The general mathematical expression for the output y of an MLP model with L layers can be represented as:

$$y = f_L(w_L . f_{L-1}(w_{L-1} \dots f_1(w_1 . x + b_1) + b_2 \dots + b_L) \quad (1)$$

Where: x represents the input vector, w_i and b_i are the weights and biases of layer i, f_i represents the activation function applied at layer i, y is the final output prediction of the model.

The learning process of MLP updates all weights by computing the gradient of the error function with the backpropagation algorithm. A loss function such as MSE or cross-entropy is usually used to minimize the difference between the target variable y and the predicted value $\hat{y}$. For example, the MSE used in regression problems are as follows:

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2 \quad (2)$$

The process of updating the weights with the gradient descent algorithm is:

$$w_{ij}^{t+1} = w_{ij}^{t} - \eta.\frac{\partial L}{\partial w_{ij}} \quad (3)$$

It is defined as, where η is the learning rate and L is the loss function.

Thanks to this structure of MLP, linear and nonlinear multivariate problems can be modeled effectively. However, the classical MLP architecture may be limited in data with spatial or temporal dependencies (e.g. images). Although special structures such as CNN or RNN are preferred in such cases, MLP is still a very powerful and reliable method, especially in data containing structured and independent observations.

In this study, MLP, one of the artificial neural network architectures widely used in literature, was preferred. MLP was used to model the changes in greenhouse gas emissions over time and to learn the nonlinear relationships between the factors affecting these changes. The multivariate data structure at the input of the model was processed effectively thanks to the inter-layer learning capacity of MLP; thus, high performance was achieved in estimating greenhouse gas emissions. In this context, it was evaluated that the MLP architecture offers a suitable and successful approach in modeling greenhouse gases.

3. METHODOLOGY

In this study, multiple artificial neural network (ANN) models were developed to forecast the quarterly greenhouse gas (GHG) emissions of various industrial sectors over time. ANNs are widely utilized in time-series forecasting due to their ability to capture nonlinear relationships within complex datasets (Zhang, 2003). A separate model was trained for each dependent variable to produce sector-specific forecasts for Q3 and Q4 of 2023 and Q1 and Q2 of 2024.

Dataset and Variables

The dataset was obtained from the International Monetary Fund (IMF) climate data portal (https://climatedata.imf.org) and includes quarterly GHG emissions across ten sectors:

- Agriculture, Forestry and Fishing (AFF)
- Construction (C)
- Electricity, Gas, Steam and Air Conditioning Supply (EGSACS)
- Manufacturing (MAN)
- Mining (MIN)
- Other Services Industries (OSI)
- Total Households (TH)
- Total Industry and Households (TIH)
- Transportation and Storage (TS)
- Water Supply; Sewerage, Waste Management and Remediation Activities (WSSWMRA)

Among the five available GHG types (Methane, Nitrous Oxide, Carbon Dioxide, Fluorinated Gases, and Greenhouse Gas), "Greenhouse Gas" was selected as the target emission type for all sectors due to its broader representation and more consistent values across industries. The only independent variable used was "Date_index", representing time in quarters. Each dependent variable reflects the sector's total greenhouse gas emissions for a given quarter.

Data Preprocessing

To ensure consistency in model input and output, both independent and dependent variables were standardized using the "StandardScaler" function from the "Scikit-learn" library. This process transforms the data to have a mean of zero and a standard deviation of one, which is particularly recommended when working with ANNs to improve convergence (Goodfellow et al., 2016). The preprocessing and modeling steps were implemented in Python 3.11, with key libraries including:

- TensorFlow 2.15
- Pandas 2.1
- Numpy 1.26
- Matplotlib and Seaborn for visualization

Model Architecture

In this study, the Multi-Layer Perceptron architecture was preferred as an artificial neural network-based prediction model. The model consists of only Dense (fully connected) layers and aims to learn non-linear relationships between input data and target variables. Due to the relative simplicity of the structure and the high performance it provides, especially on structured data sets, the MLP architecture was a suitable choice for this study.

Four different ANN architectures were tested to identify the best-performing model. The performance was evaluated based on the mean squared error on the test set given in Table 1.

Table 1.
Actual values and model forecast values for AFF, C, EGSACS, MAN, MIN emissions

Model	Hidden Layers	Activation	Epochs	Batch Size	MSE (Test)
M1	32 neurons	ReLU	100	16	0.0281
M2	64 neurons	ReLU	200	16	0.0215
M3	128 neurons	Tanh	150	32	0.0334
M4	64 + 32 neurons	ReLU	200	16	0.0268

Examining Table 1, among these, Model 2 (M2) yielded the best performance. It featured a single hidden layer with 64 neurons using the ReLU activation function and a single output neuron. The model was compiled using the Adam optimizer and mean squared error (MSE) as the loss functional standard approach in continuous variable prediction tasks (Chollet, 2018).

Model Training and Validation

The dataset was divided into training (80%) and test (20%) subsets to allow for model evaluation on unseen data. The model was trained for 200 epochs with a batch size of 16. To improve model accuracy and prevent overfitting, 20% of the training data was further allocated as a validation set during training. Increasing the epoch count facilitated the model’s learning of complex relationships, while the validation set helped to monitor and mitigate overfitting (Zou et al., 2020).

Model Evaluation and Forecasting

The model's performance was evaluated using the mean squared error (MSE) between the predictions on the test data and the actual values. Additionally, predictions were generated for the entire dataset and compared with actual values to assess the model's predictive accuracy. The model’s outputs, normalized through the “scaler_y” function, were inversely transformed to their original scale to enhance interpretability. For future projections, values of "Date_index" 55, 56, 57, and 58 were used to assess the model’s ability to generalize to new data points. Forecasts were individually computed for each dependent variable and saved to Excel files for further analysis. These results were compared with existing literature in time-series forecasting to evaluate the accuracy and robustness of the model’s predictions (Bontempi et al., 2013).

4. FINDINGS

The graph of the quarterly values of the variables is given in Figure 2.

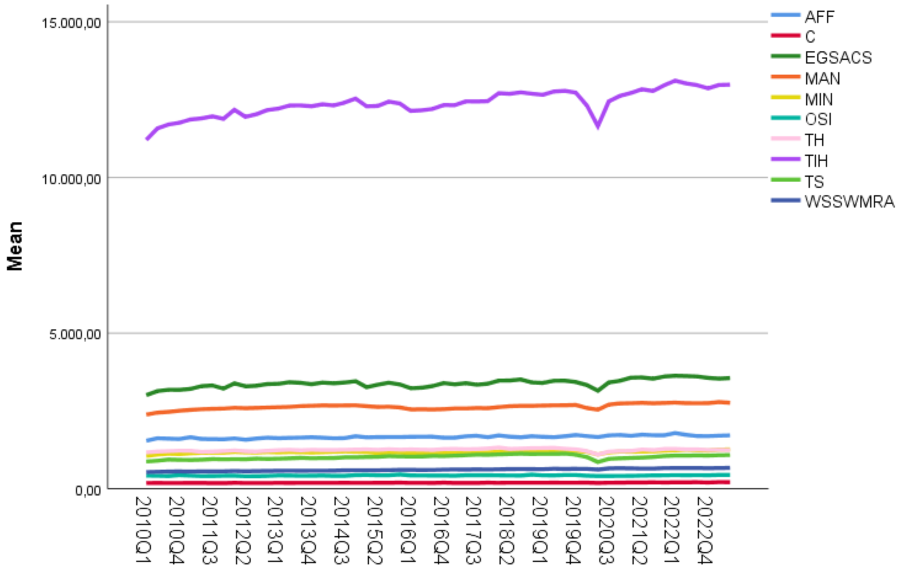

Figure 2. Mean Graph for variables

Figure 2 shows the average values of various emissions and measurements in terms of time series analysis. The averages of the AFF and C variables generally show an upward trend, suggesting that they increase over time and may be associated with a potential environmental problem or economic activity. In particular, the fact that AFF remains at a constant value above 15,000 indicates a continuous increase trend in this emission. Fluctuations can be observed in the average values of other variables, especially for EGSACS, MAN and MIN, but these fluctuations are less pronounced; this requires evaluating whether there is a specific seasonal or cyclical effect. The OSI, TH, TIH and TS variables generally follow a flat course, indicating that these emissions are more stable and under control. The average of the TIH variable in particular may show higher variance over time; this may require a deeper examination with time series analysis.

The forecast and actual values of the established model are given in Table 1 and Table 2.

Table 1 presents the actual values and model forecast values of AFF, C, EGSACS, MAN and MIN emissions by years and quarters. While a general increasing trend is observed in emission values, for example, the AFF value increased from 1548.40 in the first quarter of 2010 to 1708.43 in the first quarter of 2023. Model forecasts give results close to the actual values in most quarters, but there are significant differences in some periods; for example, in the fourth quarter of 2017, the actual AFF value was 1658.81, while the forecast was 1680.05. A similar situation applies to C, EGSACS, MAN and MIN emissions, but in some quarters the model forecasts may be lower or higher than the actual values. In the second quarter of 2020, the actual value for C emissions was 190.30, while the forecast was 201.73; this situation shows that the model may give inconsistent results in certain periods. The table shows that fluctuations in emission values may be due to economic and environmental factors and also indicates that the predictive power of the model needs to be improved. According to this information, monitoring emission data provides important information for determining environmental policies and developing better prediction models.

Table 1.
Actual values and model forecast values for AFF, C, EGSACS, MAN, MIN emissions

Year/ Quarter		AFF Actual	ANN Forecast	C Actual	ANN Forecast	EGSACS Actual	ANN Forecast	MAN Actual	ANN Forecast	MIN Actual	ANN Forecast
2010	I	1548,40	1599,05	186,82	186,96	3011,15	3206,62	2386,96	2503,02	1058,33	1128,64
	II	1624,48	1601,32	188,81	187,25	3141,33	3212,61	2448,50	2507,16	1102,09	1130,06
	III	1613,17	1603,59	187,80	187,54	3180,89	3218,60	2472,01	2511,30	1126,02	1131,49
	IV	1601,39	1605,86	188,54	187,82	3179,91	3224,59	2510,33	2515,44	1120,05	1132,92
2011	I	1658,37	1608,13	188,94	188,11	3210,43	3230,58	2536,05	2519,58	1141,65	1134,35
	II	1603,25	1610,40	189,10	188,39	3297,61	3236,57	2558,22	2523,72	1155,36	1135,77
	III	1596,55	1612,67	186,77	188,68	3322,99	3242,55	2570,62	2527,85	1162,38	1137,20
	IV	1592,63	1614,98	183,75	188,97	3220,08	3248,54	2577,79	2531,99	1164,37	1138,63
2012	I	1620,67	1617,44	193,57	189,26	3387,22	3254,53	2602,61	2536,13	1187,07	1140,05
	II	1577,55	1619,99	186,87	189,56	3293,28	3260,52	2590,16	2540,27	1171,11	1141,48
	III	1617,15	1622,64	187,67	189,86	3312,79	3266,51	2599,83	2544,41	1168,12	1142,91
	IV	1643,90	1625,30	188,46	190,15	3365,68	3272,50	2613,85	2548,55	1180,73	1144,34
2013	I	1629,04	1627,96	192,73	190,45	3374,11	3278,49	2623,42	2552,69	1172,91	1145,76
	II	1637,02	1630,62	189,84	190,75	3426,81	3284,48	2633,40	2556,83	1181,77	1147,18
	III	1644,45	1633,28	193,19	191,05	3407,15	3290,47	2658,14	2560,96	1177,04	1148,59
	IV	1657,12	1635,93	192,34	191,35	3361,56	3296,46	2667,04	2565,10	1168,31	1150,00
2014	I	1641,77	1638,59	192,53	191,64	3414,29	3302,45	2679,94	2569,24	1177,55	1151,41
	II	1625,30	1641,27	191,97	191,94	3390,99	3308,43	2674,42	2573,38	1190,04	1152,82
	III	1630,34	1644,04	195,52	192,24	3416,29	3314,42	2679,38	2577,11	1200,46	1154,23
	IV	1692,04	1646,82	193,41	192,54	3458,97	3320,38	2683,07	2580,71	1189,73	1155,64
2015	I	1655,69	1649,68	191,87	192,84	3265,83	3326,26	2653,97	2584,28	1183,85	1157,06
	II	1662,15	1652,54	195,95	193,18	3342,54	3332,14	2631,13	2587,84	1153,37	1158,47
	III	1665,07	1655,48	195,83	193,52	3409,90	3338,02	2638,52	2591,40	1163,02	1159,87
	IV	1664,15	1658,64	199,61	193,86	3355,60	3343,90	2615,21	2594,96	1168,56	1161,27
2016	I	1671,06	1661,82	192,09	194,21	3231,19	3349,78	2552,32	2598,53	1145,60	1162,68
	II	1674,03	1664,87	193,03	194,53	3248,09	3355,66	2557,65	2602,09	1150,61	1164,08
	III	1675,57	1667,86	190,90	194,75	3302,74	3361,54	2552,44	2605,65	1138,35	1165,49
	IV	1641,97	1671,17	201,00	194,85	3398,56	3366,73	2561,77	2609,21	1150,09	1167,55
2017	I	1642,82	1673,84	190,74	194,95	3355,97	3373,82	2583,08	2611,97	1156,31	1171,31
	II	1689,70	1675,92	190,20	195,31	3395,79	3383,03	2583,14	2613,83	1170,03	1175,08
	III	1705,21	1677,98	191,16	195,78	3344,05	3391,98	2596,89	2616,75	1169,11	1178,86
	IV	1658,81	1680,05	199,86	196,31	3376,08	3401,08	2592,03	2622,66	1169,98	1182,39
2018	I	1717,07	1682,11	193,45	196,85	3477,88	3409,14	2626,45	2630,04	1196,39	1185,52
	II	1676,58	1684,18	197,43	197,40	3478,97	3416,67	2654,79	2638,24	1215,98	1188,59
	III	1656,47	1686,24	197,77	197,95	3513,58	3423,90	2663,88	2646,00	1216,69	1190,98
	IV	1691,06	1688,31	197,78	198,51	3418,62	3431,12	2665,01	2652,94	1200,32	1192,49
2019	I	1673,45	1690,38	198,32	199,05	3401,85	3438,35	2675,50	2659,15	1209,82	1193,97
	II	1660,41	1692,44	200,16	199,59	3472,10	3445,58	2682,73	2665,02	1225,48	1195,46
	III	1692,57	1694,51	197,69	200,12	3475,71	3452,92	2683,92	2670,86	1227,41	1196,94
	IV	1732,31	1696,58	197,93	200,66	3431,86	3460,32	2693,86	2676,71	1214,48	1198,42
2020	I	1693,59	1698,64	199,66	201,19	3333,46	3467,73	2596,58	2682,56	1191,53	1199,91
	II	1665,44	1700,71	190,30	201,73	3151,54	3475,14	2543,45	2688,41	1102,95	1201,39
	III	1719,18	1702,78	197,42	202,26	3421,70	3482,54	2708,12	2694,26	1174,41	1202,87
	IV	1731,55	1704,84	201,49	202,79	3472,59	3489,95	2744,75	2700,11	1196,17	1204,35
2021	I	1705,29	1706,91	204,72	203,33	3572,11	3497,35	2752,36	2705,96	1190,96	1205,84
	II	1740,69	1708,97	205,34	203,86	3579,92	3504,76	2765,14	2711,81	1198,46	1207,32
	III	1723,58	1711,01	208,47	204,40	3539,27	3512,17	2749,57	2717,66	1200,98	1208,80
	IV	1720,67	1713,00	205,08	204,93	3608,12	3519,57	2760,08	2723,51	1224,51	1210,28
2022	I	1792,30	1714,99	211,22	205,46	3633,69	3526,98	2770,88	2729,36	1237,84	1211,77
	II	1735,68	1716,97	209,19	205,99	3624,51	3534,39	2753,82	2735,21	1257,42	1213,25
	III	1697,77	1718,96	213,72	206,52	3611,05	3541,79	2751,84	2741,06	1239,48	1214,73
	IV	1693,68	1720,95	204,35	207,03	3563,94	3549,20	2752,84	2746,82	1227,81	1216,22
2023	I	1708,43	1722,94	216,84	207,51	3540,19	3556,61	2789,42	2752,52	1262,76	1217,70
	II	1719,73	1724,92	215,94	208,00	3559,47	3564,01	2762,95	2758,20	1265,55	1219,18
	III	1731,27	1726,91	212,15	208,48	3702,35	3571,42	2798,77	2763,88	1300,98	1220,66
	IV	1728,67	1728,90	211,93	208,96	3722,78	3578,83	2813,92	2769,56	1308,01	1222,15

Table 2.
Actual values and model forecast values for OSI, TH, TIH, TS, WSSWMRA emissions

Year/Quarter		OSI	OSI Forecast	TH	TH Forecast	TIH	TIH Forecast	TS	TS Forecast	WSSWMRA	WSSWMRA Forecast
2010	I	427,30	414,01	1171,44	1193,32	11207,93	11676,96	879,24	898,55	538,29	548,63
	II	420,54	414,67	1196,97	1196,18	11575,31	11702,48	904,40	904,23	548,19	550,60
	III	413,14	415,33	1209,79	1199,04	11701,02	11728,00	941,26	909,90	556,95	552,58
	IV	443,38	415,99	1224,51	1201,90	11758,08	11753,52	930,81	915,58	559,16	554,55
2011	I	424,27	416,65	1222,70	1204,76	11864,29	11779,04	927,06	921,25	554,82	556,55
	II	409,60	417,31	1187,95	1207,62	11897,47	11804,56	936,08	926,93	560,31	558,55
	III	411,77	417,97	1197,20	1210,49	11964,55	11830,08	954,84	932,68	561,42	560,56
	IV	420,63	418,63	1211,91	1213,39	11882,66	11855,60	947,62	938,73	563,89	562,56
2012	I	422,30	419,29	1235,59	1216,29	12174,53	11881,12	952,74	944,78	572,77	564,60
	II	404,98	419,95	1207,32	1219,23	11947,35	11906,64	951,03	950,93	565,04	566,65
	III	407,26	420,75	1199,46	1222,23	12032,92	11932,16	969,22	957,38	571,43	568,69
	IV	415,40	421,68	1222,97	1225,30	12167,97	11957,68	961,99	963,86	574,99	570,77
2013	I	429,52	422,61	1242,88	1228,39	12212,99	11983,20	969,02	970,38	579,36	572,90
	II	426,23	423,54	1253,89	1231,51	12312,01	12008,72	980,20	976,95	582,84	575,06
	III	420,64	424,47	1238,27	1234,63	12315,07	12034,24	996,08	983,53	580,10	577,34
	IV	420,88	425,40	1254,65	1237,77	12287,83	12059,76	983,10	990,16	582,83	579,64
2014	I	425,82	426,33	1248,31	1240,92	12351,91	12085,28	988,71	996,92	582,99	581,96
	II	416,66	427,25	1246,98	1244,06	12314,24	12110,80	991,15	1003,67	586,74	584,36
	III	418,51	428,18	1255,10	1247,21	12405,09	12136,32	1013,80	1010,48	595,70	586,88
	IV	441,15	429,11	1263,04	1250,39	12534,70	12161,89	1014,97	1017,31	598,32	589,42
2015	I	445,81	430,04	1266,08	1253,77	12285,99	12187,44	1024,83	1024,13	598,07	592,07
	II	434,21	430,97	1254,04	1257,17	12297,25	12213,79	1028,23	1030,96	595,62	594,80
	III	436,72	431,90	1274,00	1260,52	12437,38	12240,14	1051,84	1037,79	602,48	597,73
	IV	463,01	432,78	1260,50	1263,16	12377,31	12266,13	1041,87	1044,07	608,82	601,00
2016	I	431,45	432,97	1265,63	1265,67	12138,78	12291,97	1038,12	1049,93	611,34	604,67
	II	429,70	433,12	1260,18	1267,92	12158,64	12317,28	1039,22	1055,90	606,13	608,58
	III	426,14	433,35	1251,03	1269,75	12202,02	12344,48	1057,20	1061,87	607,67	612,49
	IV	426,49	433,65	1277,44	1270,93	12327,76	12386,55	1052,37	1067,70	618,07	616,40
2017	I	422,30	433,96	1284,39	1271,74	12323,64	12415,40	1066,36	1070,62	621,67	620,32
	II	438,41	434,28	1273,36	1272,55	12443,33	12434,40	1081,58	1071,91	621,14	623,91
	III	436,60	434,37	1276,89	1273,35	12440,34	12453,39	1096,95	1073,20	623,49	626,75
	IV	436,30	434,15	1299,40	1273,90	12450,20	12471,23	1094,59	1074,49	623,15	629,17
2018	I	434,48	433,93	1327,77	1272,23	12707,00	12488,66	1105,96	1075,78	627,55	631,22
	II	430,03	433,72	1282,50	1270,54	12687,57	12504,34	1117,92	1076,52	633,37	632,93
	III	426,82	433,51	1294,48	1268,85	12734,90	12519,68	1128,09	1075,42	637,13	634,60
	IV	457,07	433,30	1307,75	1267,16	12690,86	12535,02	1119,44	1073,12	633,81	636,29
2019	I	434,72	433,09	1310,33	1265,47	12656,88	12550,36	1121,22	1070,82	631,67	637,98
	II	433,26	432,88	1315,84	1263,77	12762,03	12565,70	1125,21	1068,51	646,85	639,68
	III	444,85	432,67	1289,50	1262,08	12782,35	12581,04	1130,13	1066,21	640,58	641,26
	IV	444,18	432,46	1269,86	1260,39	12723,42	12596,38	1095,64	1063,90	643,30	642,77
2020	I	423,69	432,24	1212,52	1258,70	12316,09	12611,72	1023,40	1061,60	641,66	644,28
	II	411,17	432,03	1101,07	1257,01	11649,07	12627,06	862,04	1059,30	621,11	645,80
	III	411,63	431,82	1195,90	1255,31	12450,64	12642,40	962,80	1056,99	659,48	647,31
	IV	414,49	431,61	1213,65	1253,62	12620,27	12657,74	981,66	1054,69	663,90	648,82
2021	I	416,38	431,40	1218,72	1251,93	12713,36	12673,08	992,64	1052,39	660,19	650,33
	II	424,54	431,19	1263,63	1250,24	12835,00	12688,42	1005,05	1050,08	652,24	651,84
	III	431,87	430,98	1245,82	1248,55	12776,94	12703,76	1026,07	1047,78	651,31	653,35
	IV	434,61	430,77	1280,52	1246,85	12955,94	12719,10	1055,80	1045,47	666,53	654,86
2022	I	439,32	430,55	1285,23	1245,16	13109,72	12734,43	1069,42	1043,17	669,80	656,37
	II	435,60	430,34	1266,77	1243,47	13021,13	12749,77	1068,31	1040,87	669,83	657,89
	III	439,03	430,13	1266,70	1241,78	12964,78	12765,11	1075,24	1038,56	669,94	659,40
	IV	436,20	429,92	1249,15	1240,08	12864,54	12780,45	1070,92	1036,26	665,66	660,89
2023	I	446,84	429,71	1254,88	1238,39	12971,86	12795,74	1082,60	1033,96	669,91	662,34
	II	447,90	429,50	1247,29	1236,70	12978,53	12810,98	1086,55	1031,65	673,16	663,78
	III	439,08	429,29	1271,78	1235,01	13281,20	12826,23	1142,13	1029,35	682,69	665,23
	IV	435,23	429,08	1303,70	1233,32	13363,51	12841,48	1152,70	1027,04	686,57	666,68

Table 2 shows the actual values of OSI, TH, TIH, TS and WSSWMRA emissions by years and quarters and the model forecasted values; in general, an increasing trend is observed in emission values, for example, while the OSI value in the first quarter of 2010 was 427.30, it increased to 464.19 in the fourth quarter of 2019. Although the model forecasts generally give results close to the actual values, significant differences are observed in some periods; for example, while the actual OSI value in the fourth quarter of 2016 was 445.13, the forecast was 433.55, indicating that the model may be inadequate in certain periods. There are differences between different emission types; especially TH and TIH values generally show higher forecast. While fluctuations in emissions may vary depending on economic and environmental factors, the increase in emissions in the years after 2015 may indicate increased industrialization or human activities. According to this information, the model's predictions appear to be consistent with the emissions data, but differences in some quarters indicate that the model needs to be optimized, and these data provide important information for monitoring environmental emissions, paving the way for the development of better prediction models.

Table 3.
MSE values for AFF, C, EGSACS, MAN, MIN, OSI, TH, TIH, TS, WSSWMRA

Variables	MSE	RMSE	R^2	MAPE (%)	MAE
AFF	563.33	23.73	0.75	1.09	18.18
C	13.51	3.68	0.80	1.40	2.79
EGSAXS	8138.73	90.21	0.61	2.11	71.42
MAN	3221.62	56.76	0.61	1.78	46.61
MIN	1080.05	32.86	0.48	2.19	26.11
OSI	123.09	11.09	0.19	2.03	8.73
TH	1081.99	32.89	0.33	1.80	22.21
TIH	60492.56	245.95	0.68	1.52	188.56
TS	2177.33	46.66	0.56	2.93	30.18
WSSWMRA	61.50	7.84	0.96	0.94	5.91

Table 3 presents the performance metrics for the modeled variables, revealing that the lowest error values were obtained for the *WSSWMRA* variable, with a Mean Squared Error (MSE) of 61.50, Root Mean Squared Error (RMSE) of 7.84, Mean Absolute Percentage Error (MAPE) of 0.94%, and Mean Absolute Error (MAE) of 5.91. Additionally, the R^2 value for *WSSWMRA* is 0.96, indicating the highest accuracy in prediction among the variables. The *C* variable also demonstrates low error metrics (MSE: 13.51, RMSE: 3.68, MAPE: 1.40%, MAE: 2.79) and a high R^2 value (0.80), indicating good model performance. On the other hand, the *OSI* variable shows the weakest model performance with a low R^2 value of 0.19. The *EGSAXS*, *MAN*, and *TIH* variables exhibit relatively high MSE and MAE values, suggesting lower prediction accuracy for these variables compared to others. Overall, while the model performs well for some variables, the prediction accuracy for others is more limited, which may be due to the nature of the variables or the structure of the data.

5. DISCUSSION AND CONCLUSION

This study aimed to examine the changes in environmental and economic indicators over time, evaluating their potential impacts on sustainable development and environmental management. The findings reveal trends in the mean values of different variables, contributing to a better understanding of environmental and economic dynamics. Notably, the continuous increase in the AFF and C variables signals the growing burden of industrialization, energy consumption, and resulting environmental challenges (Yılmaz, 2021). This trend underscores the need to balance industrial sustainability with environmental concerns.

Fluctuations in the EGSACS, MAN, and MIN variables can be interpreted as reflections of the challenges faced by these sectors and the seasonal impacts on their performance. For example, the agricultural sector is significantly affected by macroeconomic factors like climate change. Studies using artificial neural networks (ANN) have developed various models to predict the impacts of climate change scenarios on agricultural productivity. Aydın et al. (2022) employed ANNs to examine these impacts, highlighting the strong relationship between climate change and yield. Such findings emphasize the importance of sector-specific management strategies for environmental sustainability.

While the OSI, TH, TIH, and TS variables exhibit more stable trends, this stability may indicate effective environmental management practices or compliance with relevant policies. ANN techniques serve as powerful tools for analyzing and predicting such time series data. Specifically, a study by Merve and Duman (2023) investigated the effects of water quality parameters, concluding that ANNs could successfully predict these parameters. Such results reinforce the significance of utilizing ANNs in developing environmental management strategies.

Moreover, the high variance in the TIH variable indicates a need for further research and strategic planning. Korkmaz et al. (2021) conducted an ANN analysis focusing on water consumption, which yielded significant insights into determining and managing consumption patterns. Controlling emissions is critical for mitigating environmental risks and achieving sustainable development goals.

In this study, methodology section appears to focus on using Artificial Neural Networks (ANN) for forecasting greenhouse gas (GHG) emissions across various industrial sectors. The study employs a Multi-Layer Perceptron (MLP) architecture, which is a type of ANN that works well with time-series forecasting. The data is standardized, and the model is tested using various configurations of hidden layers, neurons, and activation functions. The results suggest that Model 2 (with 64 neurons, ReLU activation, and 200 epochs) performs the best in terms of minimizing the Mean Squared Error (MSE).

Additionally, the study provides a detailed explanation of how the model training and validation process was carried out, including the use of training, test, and validation subsets of data. The evaluation metric for performance is the MSE, and forecasted values for future quarters are generated and compared with the actual data.

Suggestions for Enhancements or Clarifications:

Explain the choice of ANN architecture: You might want to expand on why the Multi-Layer Perceptron architecture was chosen, specifically in comparison to other types of neural networks (e.g., LSTM, RNN) that might be better suited for time-series data.

Model evaluation comparison with benchmarks: It could be beneficial to add a comparison of your model's performance with traditional forecasting methods (e.g., ARIMA, linear regression) or even other machine learning techniques, especially if the MLP model outperforms them significantly.

Overfitting and regularization: Since overfitting is a common issue with ANNs, did you consider techniques such as dropout, early stopping, or L2 regularization to mitigate it? You may want to mention how overfitting was controlled beyond splitting the data into training, validation, and test sets.

Time-series data handling: For time-series forecasting, the temporal aspect of data (seasonality, trend) is crucial. Consider discussing whether any temporal feature engineering or transformation (such as lag variables or differencing) was used to help the model learn time-dependent patterns better.

In conclusion, this study demonstrates the importance of analyzing time series data to understand the dynamics of environmental and economic variables. The findings provide valuable guidance in formulating environmental management strategies and developing relevant policies. Future research could delve deeper into the examination of these data and perform more comprehensive analyses of potential relationships. Additionally, comparing the findings on an international scale could contribute to developing broader strategies for addressing global environmental issues.

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