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ESTIMATIONS OF GREEN HOUSE GASES EMISSIONS OF TURKEY BY STATISTICAL METHODS

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Highlights

- Estimations of CH_4, N_2O nnd CO_2 Emissions of Turkey are aimed.
- Predictions are evaluated by of GM, ARIMA and DES methods.
- Prediction performance is decided by mean absolute percentage error (MAPE).

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ABSTRACT: The way of life, consumption habits, urbanization rate, type of energy production and increasing energy need with growing economies and population progressively promote the GHGs emissions to Earth's atmosphere. GHGs consisting of CH_4, N_2O, CO_2, H_2O and HFCs cause the climate change, disrupting ecological balance, melting glaciers with global warming in the last decades. Therefore, the issues of future prediction and reduction of GHGs emissions became crucial for policy makers of Turkey and other countries under the international protocols and agreements. This article aims to present the prediction and 8-year future forecasting of CH_4, N_2O and CO_2 emissions of Turkey using past annual data between years 1970 and 2018 with grey, autoregressive integrated moving average and double exponential smoothing models. Based on the results, the best prediction performance is reached by DES model followed by ARIMA and GM for all the emissions. MAPEs calculated from the available data and prediction by DES model from 1970 to 2018 are 0.285, 0.355 and 0.408 for CH_4, N_2O and CO_2 in turn. DES future estimations of CH_4, N_2O and CO_2 at 2026 year are determined as 50700 kiloton of CO_2 eq., 38100 thousand metric ton of CO_2 eq., and 512000 kilotons.

Keywords: *Greenhouse gases, Emission, Forecasting, Environment, Turkey*

1. INTRODUCTION

Green House Gases (GHGs) causes global warming as a serious factor that changes the earth's climate [1]. The emissions of GHGs, such as methane (CH_4), carbon dioxide (CO_2), and nitrous oxide (N_2O) have a great effect on anthropogenic climate warming phenomena according to the assessment of Intergovernmental Panel on Climate Change in 2013 [2]. Although CO_2 emission is higher than other GHG emissions, CH_4 and N_2O emissions are more effective 28 and 256 times than CO_2 emissions on global warming [3]. On the other hand, if no action is taken to reduce these hazardous emissions, annual median temperature will be expected to increase by 4 to 5 degrees Celsius by 2100 [4].

GHGs are emitted to the atmosphere by both human-based and natural ways [5]. From these gases, N_2O emerges from the reaction of NO and O_3 in atmosphere air and depletes O_3 [6]. NO and CO_2 are mostly produced at the end of combustion by vehicle's engines, heating and electricity energy production systems using hydrocarbon-based fuels as natural gas, diesel, gasoline, and coal, etc [7, 8]. CH_4 emission comes from agriculture activity, farm animals, organic decays, and gas leakages from underground and volcanos [9, 10].

To combat the predictable effects of GHGs over bios, atmosphere and climate of earth, Kyoto Protocols and Paris Agreement were signed in both1997 and 2015. However, GHG emissions have been desperately increased by great demand of countries to hydrocarbon-based energy consumption. For this reason, the countries led by the G7 have increased their GHGs forecasting studies related to the decrease of energy consumption [11]. Moreover, the usage of renewable energy types as wind, solar, wave, waste recycle and

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combustion systems emitting less GHGs are to be recommended for energy production [12, 13].

Turkey is a developing country as a terrestrial bridge among Europe, Asia and Africa continents. GHGs emissions of Turkey has been increasing since 1980s [14] because the growing trend of Turkey has a deep impact on its energy consumption. After Turkey joined Kyoto in 2009 and signed Paris Agreement in 2015, Turkey was expected to decrease its GHGs emissions to 21 %. Even though Turkey aimed not to exceed 929 million tone (MT) CO_2 equivalent emissions by 2030 [15], its GHGs emissions have risen up to 520.9 MT in 2018 [16]. Because of this reason, studies about the forecasting GHGs emissions of Turkey has begun to gain significance more and more.

Time series data of GHGs emissions of countries are able to be obtained in hourly, daily, monthly and annual terms. Forecasting techniques on past univariate or multivariate data generally include methods of artificial neural networks [17], fuzzy logic [18] support vector machine [19], machine learning [20] and classic statistical models as regression [21], autoregressive integrated moving average [22] and grey [23], etc. Statistical methods are more appropriate for future predictions of short univariate time series in regard to other methods preferred more for long univariate and multivariate data.

In this study, CH_4, N_2O and CO_2 greenhouse gas emissions of Turkey are predicted by grey, autoregressive integrated moving average, and double exponential smoothing models from statistical techniques using past annual univariate time series data [24] of CH_4, N_2O and CO_2 between 1970 and 2018 years. Besides, next 8-year data are forecasted up to 2026. The calculations of train, test, and prediction of models are realized using Python codes.

In the literature, according to authors knowledge, the studies about the estimation of Turkey's green gas emissions are presented less. Main contribution of this study is to forecast future greenhouse gases emissions by statistical methods. Besides, the study is suitable for future planning of decreasing GHGs emissions because new arrangements and regulations to minimize GHGs are forced by developed countries in the world. In addition, EU countries have been planning to put new restrictions to countries where they import goods and services from. For realizing this purpose, real data and statistical results are compared by error criterion (MAPE). Error criterion increases the reliability of future emission data for the next years and thus, more accurate results are obtained.

2. LITERATURE OVERVIEW

Prediction is an important issue for determination of the reduction targets of GHGs emissions because countries have been scheduling annual GHGs emissions using predictions to achieve the aimed limits. There are many studies that include estimation methods forecasting future data from former time series data in literature. [4] forecasted total GHGs emission between 2018 and 2050 in Romania. [7] estimated heavy-duty vehicle emissions (CO_2) for future 9 years of Semarang City, Indonesia. Şahin [8] predicted Turkey's GHGs emission between years 2017 and 2025 using Grey methods. [9] used machine learning method with regression models, shallow learning, and deep learning for predicting greenhouse gas emissions from agricultural soils. [11] predicted CO_2 emissions in the G7 countries. [12] utilized a recursive structural vector autoregression method to forecast GHGs in Montenegro. [13] constructed a novel multi-variable grey forecasting model based on the smooth generation of independent variable sequences with variable weights and new multivariable grey prediction model with structure compatibility for forecasting of CO_2 with the effect of renewable energy in Turkey. [14] predicted the energy-related CO_2 emission between years 2013 and 2025. [15] estimated GHGs in Turkey with grey wolf optimizer algorithm-optimized artificial neural networks. [16] forecasted of GHGs caused by electricity production in Turkey with deep learning, support vector machine and artificial neural network algorithms. [17] compared actual and predicted GHGs emissions by artificial neural networks of Bulgaria and Serbia. [19] applied Support Vector Regression, Artificial Neural Networks, and Box-Jenkins method to model CO_2 emissions. [21] studied on CH_4 emissions for Tibetan Plateau between years 2006 and 2100. [22] used autoregressive integrated moving average to model and forecast CO_2 emissions in Bangladesh.[23] used generalized accumulative grey model to predict GHGs emissions in China. [25] forecasted methane emissions from tropical and subtropical areas by using artificial neural networks. Ammar et. al. [26] predicted Tunisian greenhouse gas emissions from different species. [27] forecasted the methane percentage in the air for the future 10 years using autoregressive integrated moving average model, self-existing threshold autoregressive model, and smooth logistic transition autoregressive model for the methane data of Pakistan, China, and India from 1970 to 2012. [28] estimated CO_2 emissions in the eight Asian countries between years 2019 and 2023 by grey model. [29] compared actual and predicted CO_2 emission values by grey method between years 1995 and 2009.[30] studied the controlling and monitoring of CO_2 in Oman by linear regression prediction. [31] predicted the CO_2 emissions of the developed countries by using multi-layer artificial neural networks. [32] analyzed total GHGs emission between years 1990 and 2016. [33] forecasted total CO_2 emission from paddy crops in India for coming next six years by using prediction methods. [34] predicted the effect on GHGs emissions of the end-of-life vehicles (ELV). [35] estimated CH_4 emissions by combining wavelet transform and artificial neural networks on the Belyy Island, Russia. [36] studied GHGs emissions in Turkey consistent with energy, industrial products, agribusiness, and barren sectors by using time series models as moving average, exponential smoothing, exponential smoothing with trend. [37] predicted GHGs during the period at LTO (landing /take off) of aircrafts at Kahramanmaraş Airport in Turkey. [38] forecasted CO_2 emissions in China between years 2011 and 2020. [39] estimated direct and indirect total CO_2 eq. emissions of a family in Turkey. [40] studied with purpose of the evolution of GHGs emissions in 12 developed economies by using time series data between 1970 and 2018 years applying the exponential smoothing state-space model (ETS), the Holt–Winters model (HW), the TBATS model, the ARIMA model, the structural time series model (STS), and the neural network autoregression model (NNAR). [41] predicted CO_2 eq. emissions reaching 728.3016 metric tons in the year 2030. [42] predicted a 30% increase in the total CO_2 emissions of Iran by 2030 with multiple linear regression (MLR) and multiple polynomial regression (MPR) analysis. [43] proposed multi-agent intertemporal optimization model (MIOM) based on forecasting trends of 13 products in Liaoning Province, China from 2018 to 2030. [44] compared ARIMA and Verhulst model predicting CO_2 emissions in Russia and China. [45] studied the forecasting of CO_2 emissions based on energy planning in Shanxi Province from 2019 to 2035.

3. METHOD

There is no only one forecasting model that is appropriate in the same time for all of data. The determination of model is a very significant step for prediction and future estimation with past univariate or multivariate time series data. Classical statistical models are mostly able to present better solutions in acceptable limits for short time series data according to models as machine learning, artificial neural network, deep learning, etc. In the present study, statistical models preferred for annual estimations of CH_4, N_2O and CO_2 from greenhouse gases emitted by Turkey are as follows: Grey, autoregressive integrated moving average, and double exponential smoothing models.

3.1. Grey Model

Grey theory is compatible with the discrete small number data series and incomplete information [46]. Beyond of this, easily it can be applied to forecast future series f for a time interval. GM (1,1) is a kind of Grey model that first "1" specifies that this model is a first order Grey model, and corresponding "1" shows that Grey model depends on univariate time series.

$x^{(0)}$ = x(0) (1), $x^{(0)}$ (2),…, , $x^{(0)}$ (n) is a representation of non-negative original sequence where n represents length of data. $x^{(1)}$ = $x^{(1)}$ (1), $x^{(1)}$ (2),…, , $x^{(1)}$ (n) represents new accumulated sequence. Accumulated generating operator (AGO) of $x^{(0)}$ is calculated as [47]:

$$x^{(1)}(k) = \sum_{i=1}^{k} x^{(0)}(i) \tag{1}$$

Adjacency mean generating sequence of $x^{(1)}$ (1) is $z^{(1)} = z^{(1)}$ (1) , $z^{(1)}$ (2),…, , $z^{(1)}$ (n) and $z^{(1)}$(1)is defined as $z^{(1)}$(1) = z(1)(1), x(1)(k) = 0.5[x(1)(k)- x(1)(k-1)] where k denotes 2,3,…,n. First-order grey differential equation model is calculated as[48]:

$$\frac{dx^{(1)}(t)}{dt} + ax^{(1)}(t) = b \tag{2}$$

where t is independent variables, a represents grey developed coefficient and b is named as grey controlled variable.

Basically grey difference equation of GM(1,1) model is given by,

$$x^{(0)}(k) + az^{(1)}(k) = b \tag{3}$$

$[a,b]^T$ (T is transpose of the inner brackets matrix) parameter satisfies least square equation and is estimated as [49]:

$$[a, b]^T = (B^T B)^{-1} B^T Y \tag{4}$$

where B is denoted as:

$$B = \begin{bmatrix} z^{(1)}(2) & 1 \\ z^{(1)}(3) & 1 \\ \vdots & \vdots \\ z^{(1)}(n) & 1 \end{bmatrix} \tag{5}$$

and Y is given by,

$$Y = \begin{bmatrix} x^{(0)}(2) \\ x^{(0)}(3) \\ \vdots \\ x^{(0)}(n) \end{bmatrix} \tag{6}$$

AGO sequence is predicted by Eq(7) and AGO sequence is denoted as [50]:

$$\hat{x}^{(1)}(k+1) = \left(x^{(0)}(1) - \frac{b}{a}\right) e^{-ak} + \frac{b}{a}, \text{k} = 1,2,3, \ldots \tag{7}$$

Similarly predicted original sequence is defined as:

$$\hat{x}^{(0)}(k+1) = \hat{x}^{(1)}(k+1) - \hat{x}^{(1)}(k) \tag{8}$$

3.2. Autoregressive Integrated Moving Average Model (ARIMA)

ARIMA methodology is an appropriate technology which is progressed by Box and Jerkins for short series and forecasting. [51]. The ARIMA(p,q,d) is based on the autoregressive (AR), moving average (MA), and the combination of AR and MA (ARMA) models [52]. Future value variable is as a kind of function that has a property of linearity and depends on several past observations and random errors. Nonseasonal time series are composed of past values and errors so nonseasonal time series are defined by [53]:

$$X_t = \theta_0 + \phi_1 X_t - 1 + \phi_2 X_t - 2 + \cdots + \phi_p X_t - p + e_t + \theta_1 e_t - 1 + \theta_2 e_t - 2 + \cdots + \theta_q e_t - q \tag{9}$$

where X_t, et re value and random error at time t respectively. θ_i(i=1,2,..,p) and ϕ_j (j=1,…,q) are model parameters. p is named as order of autoregressive polynomial and q is denoted as order of moving average polynomial. d is the difference process that converts non-stationary times series to stationary time series. d can be selected as 0,1 and 2 [54]. If q is equal to zero, X_t becomes an autoregressive (AR) model of order p. Besides if p is equal to zero, X_t becomes a moving average (MA) model of order q. In this study p,q,d are selected as 0,1 and 2 respectively. As a result, ARIMA(0,1,1) is used.

3.3. Double Exponential Smoothing Model (DES)

Another naming of double exponential smoothing (DES) model is Holt's linear exponential model that is used to forecast time series of which trend is known. DES is based on three equations: Equations (10), (11) and (12) [55]:

$$L_i = \alpha X_i + (1-\alpha)(L_{i-1} + b_{i-1}) \tag{10}$$

$$b_i = \beta(L_{i-1} + b_{i-1}) + (1-\beta)b_{i-1} \tag{11}$$

$$Y_{i+m} = L_i + m b_i \tag{12}$$

Where X_i is the input raw data of original times series at sample i, L_i is an estimation of the data series at the sample number i and bi is estimation of the data series trend at the sample number i.α and β are weighting coefficients that could be selected between 0 and 1. Finally, Y_{i+m} is used for forecasting for specific interval (m>0). To specify initial Li and bi. Equations (13),(14) ,(15) and (16) are applied.

$$L_1 = X_1 \tag{13}$$

$$b_1 = 0 \tag{14}$$

$$b_1 = X_2 - X_1 \tag{15}$$

$$b_1 = (X_n - X_1)/(n-1) \tag{16}$$

For b_i which minimum forecast error is obtained, is selected.

3.4. Mean Absolute Percentage Error (MAPE)

To evaluate the performance of statistical forecasting models is used MAPE equation as follows:

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{X[i]-P[i]}{X[i]}\right| \times 100\% \tag{17}$$

where X[i] is present data, P[i] is the forecasted data and n is the test length.

4. RESULTS AND DISCUSSION

The prediction results of GM, ARIMA and DES methods for observed emissions of CH_4, N_2O and CO_2 between years 1970 and 2018 are presented in Figure 1-3. ARIMA and DES predictions are able to track the observed time data better. The prediction performance is to be mostly decided by MAPE in literature. The best MAPEs are achieved with DES model following by ARIMA and GM given in Table 1. MAPEs calculated for GM, ARIMA and DES methods after train, test and prediction processes are 6.426%, 3.167%

and 0.285% for CH_4; 7.304%, 3.829% and 0.355% for N_2O; 7.503%, 5.503% and 0.408% for CO_2 emission in turn.

Table 1. MAPEs for predictions obtained between years 1970 and 2018.

	CH_4			N_2O			CO_2		
	GM	ARIMA	DES	GM	ARIMA	DES	GM	ARIMA	DES
MAPE %	6.426	3.167	0.285	7.304	3.829	0.355	7.503	5.503	0.408

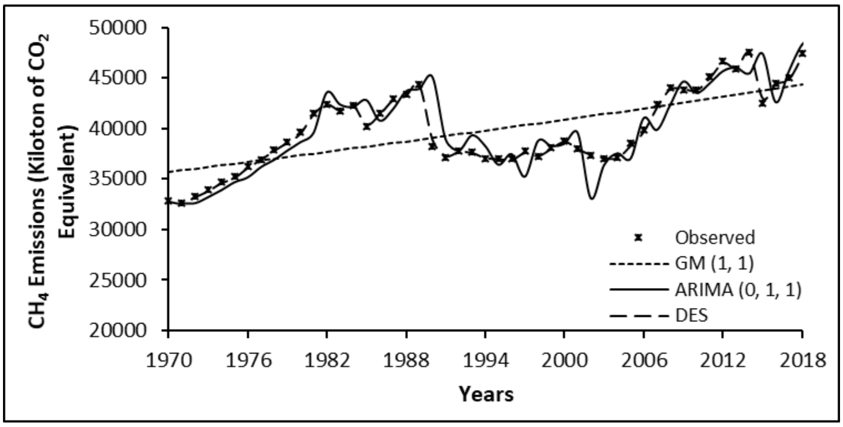

Figure 1. CH_4 Emissions versus Time

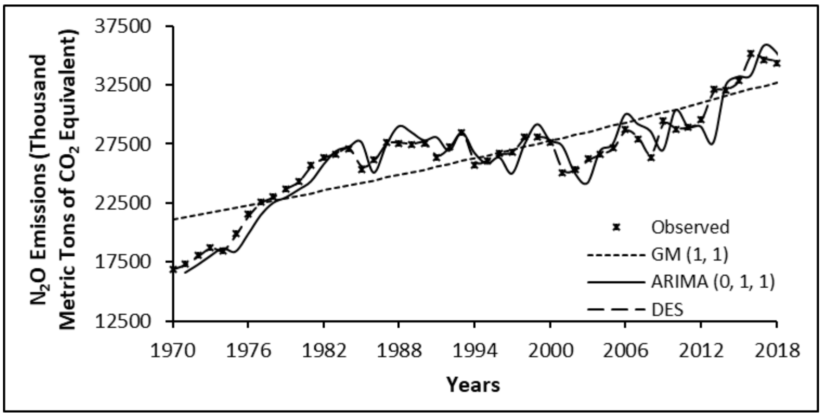

Figure 2. N_2O Emissions versus Time

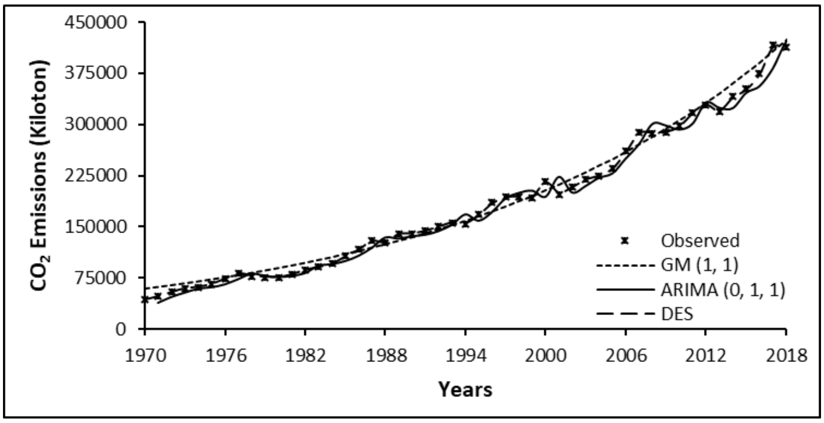

Figure 3. CO_2 Emissions versus Time

Table 2 presents the forecasted values for future 8 years based on the past time data of the 49-year emissions between years 1970 and 2018. The estimated emission values for CH_4, N_2O and CO_2 at year 2026 are 50700 kiloton of CO_2 eq., 38100 thousand metric ton of CO_2 eq., and 512000 kilotons. An upward trend goes on for all the emissions. According to forecasting figures of DES model, it is clarified that the emissions of CH_4, N_2O and CO_2 ascend 6.9%, 10.8% and 23.9% between years 2019 and 2026. The increments between years 1970 and 2026 are found as 54.6%, 125.5% and 1100.7%, respectively. From these results, it is concluded that CO_2 emission indicates a bigger increasing rate in years and has a significant share in the emissions of the other greenhouse gases. Moreover, the forecasted values for next 8 years are also illustrated in Figure 4-6.

Table2. Future 8-year forecasted values between years 2019 and 2026

	CH_4 (CO_2 equivalent in kt)			**N_2O (CO_2 equivalent in kt)**			**CO_2 in kt**		
YEAR	**GM**	**ARIMA**	**DES**	**GM**	**ARIMA**	**DES**	**GM**	**ARIMA**	**DES**
2019	44600	49137.1	47600	33000	33604.3	34900	441000	433373	427000
2020	44800	50474.6	48100	33300	32282.3	35400	459000	436016	439000
2021	45000	50162.5	48500	33700	34367.3	35800	479000	440277	451000
2022	45200	50319.4	49000	34000	33813.4	36300	498000	448828	463000
2023	45400	51447.7	49400	34300	34301.7	36700	519000	464220	476000
2024	45600	52662.6	49800	34600	34847.3	37200	541000	472634	488000
2025	45800	52251.0	50300	34900	37353.9	37700	563000	465039	500000
2026	46000	53035.4	50700	35200	37248.7	38100	587000	481444	512000

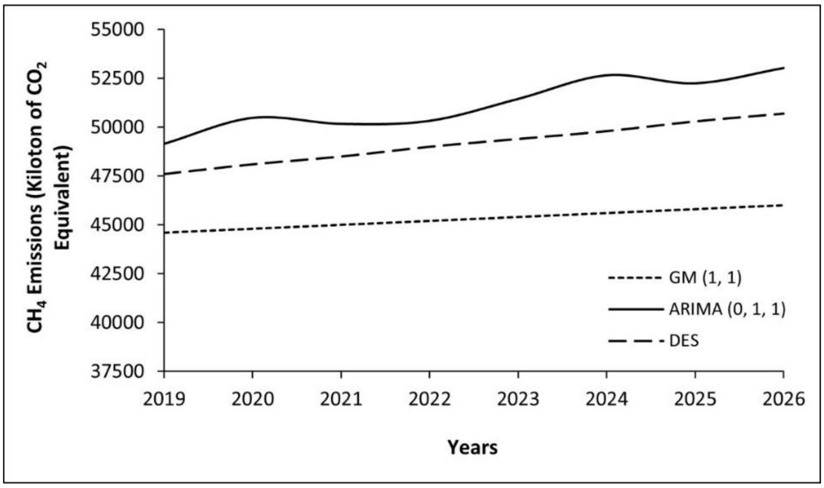

Figure 4. Future CH_4 Emissions versus Time.

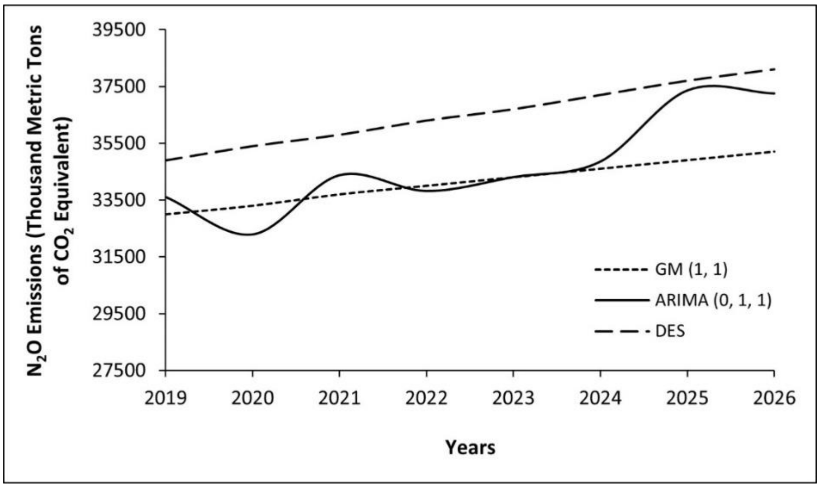

Figure 5. Future N_2O Emissions versus Time.

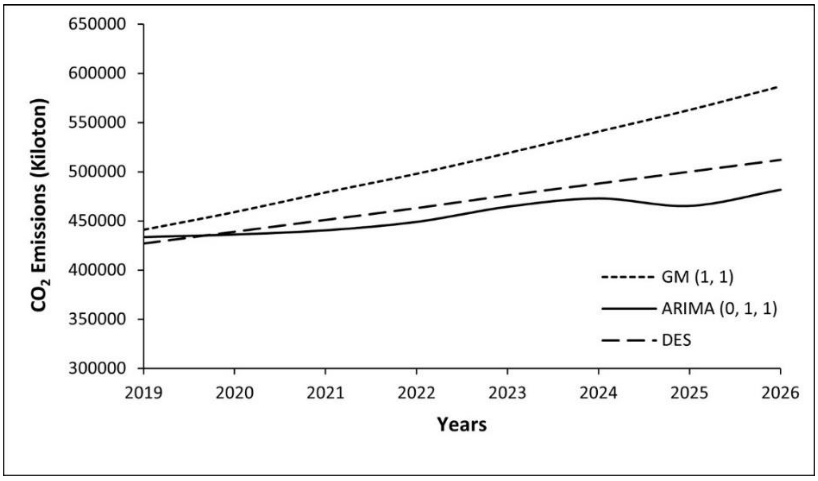

Figure 6. Future CO_2 Emissions versus Time.

CO_2 can substantially be reduced by using cleaner fuels as hydrogen in present transportation, heating and energy production systems based on combustion in Turkey. Both CO_2 and N_2O linked with NO largely formed by fuel combustion can be diminished by the use of renewable energy production systems as wind, solar, wave in place of combustion-based systems. The decrease of CH_4 emitted by livestock, manure and agriculture activities can be realized by building the methane gas aggregation and transformation facilities on location with the technique of mass production.

5. CONCLUSION

GHGs emissions are serious factors over environmental pollution and global warming. Turkey signed the Paris Climate Agreement and Kyoto protocols to decrease greenhouse gas emissions in compliance with the termed rates. Predictions of GHGs emissions are very crucial for policy makers of Turkey to reach the targeted annual emission values by establishing the balance between the environmental policies and sustainable economic development. Furthermore, the forecasting studies of GHGs gases are able to present contributions to organize and to predict the national inventory of GHGs emissions.

In this study, the estimations of annual emissions of CH_4, N_2O and CO_2 greenhouse gases in Turkey are realized by three statistical models: GM, ARIMA and DES. The univariate time series data between years 1970 and 2018 are used for trains, tests and predictions of models. with the aim of evaluating the performance of models, MAPE values are calculated between annual observed and predicted emissions of 49 years. Finally, 8-year future forecasting is determined from 2019 to 2026. The following results are obtained by the study: DES model represents the best prediction performance according to ARIMA and GM models above available emission data of greenhouse gases. MAPE values for DES prediction is 0.285, 0.355 and 0.408 for CH_4, N_2O and CO_2. GHGs emissions continues to rise in the near future. The emissions of CH_4, N_2O and CO_2 increase 6.9%, 10.8% and 23.9%, respectively between years 2018 and 2026. The forecasted values of CH_4, N_2O and CO_2 for 2026 year are 50700 kiloton of CO_2 eq., 38100 thousand metric ton of CO2 eq., and 512000 kilotons, respectively.

CO_2 holds an important place in GHGs emissions and its emission is relatively easier to be reduced by not using fossil fuel based combustion systems. The usage of hydrocarbon based fuels can gradually be decreased and be replaced with cleaner hydrogen fuels. Policy makers can increase the investments for renewable energy production types such as wind, solar, geothermal and biomass. Nuclear energy is still appropriate option for intense energy production with minimum GHGs emissions. In addition, other statistical methods, forecasting approaches of machine learning or hybrid models can also be utilized to achieve more accurate estimations in future studies.

Declaration of Ethical Standards

Authors declare to comply with all ethical guidelines, including authorship, citation, data reporting and original research publication.

Credit Authorship Contribution Statement

Suat ÖZTÜRK: The author has done research, analyzed and written the article.
Ahmet EMİR: The author has analyzed, written and edited the article.

Declaration of Competing Interest

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

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Data Availability

Research data has not been made available in a repository.

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