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Determination with Gene Expression Programming of the Relationship Between Socio-Economic Variables and Greenhouse Gas Emissions in Turkey

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Abstract

One of the most important indicators of economic development is environmental quality. One of the most important sources of environmental pollution and climate change is greenhouse gas emissions. In this work, a new approach based on Gene Expression Programming (GEP) was used to forecast greenhouse gas (GHG) emissions depending on energy consumption, economic development (GDP), and population. The reliability of the GEP model was determined using several statistical indicators. In the relationship between energy consumption-GDP- population and GHG emissions, R2, MAPE, and RMSE values were found as 0.99337, 0.06987, and 7.1355, respectively. Sensitivity analysis seen that energy consumption have the highest effect on greenhouse gas emissions. The results obtained, it is showing that Gene Expression Programming can be successfully used to model greenhouse gas emissions.

Keywords: Gene expression programming, greenhouse gas emissions, energy consumption, economic development, population.

Article Type: Research Article

Türkiye'de Sosyo-Ekonomik Değişkenler ve Sera Gazı Emisyonları Arasındaki İlişkinin Gen İfade Programı ile Belirlenmesi

Öz

Ekonomik kalkınmanın en önemli göstergelerinden biri çevre kalitesidir. Çevre kirliliği ve iklim değişikliğinin en önemli kaynaklarından biri sera gazı emisyonlarıdır. Bu çalışmada, enerji tüketimi, ekonomik kalkınma (GSYİH) ve nüfusa bağlı olarak sera gazı (GHG) emisyonlarını tahmin etmek için Gen İfade Programlamasına (GEP) dayalı yeni bir yaklaşım kullanılmıştır. GEP modelinin güvenilirliği, çeşitli istatistiksel göstergeler kullanılarak belirlenmiştir. Enerji tüketimi-GSYİH-nüfus ve GHG emisyonları arasındaki ilişkide R2, MAPE ve RMSE değerleri sırasıyla 0.99337, 0.06987 ve 7.1355 olarak bulunmuştur. Duyarlılık analizi sonucunda enerji tüketiminin sera gazı emisyonları üzerinde en yüksek etkiye sahip olduğu görülmüştür. Elde edilen sonuçlar, Gen İfade Programlamanın sera gazı emisyonlarını modellemek için başarılı bir şekilde kullanılabileceğini göstermektedir.

Anahtar Kelimeler: Gen ifade programı, sera gazı emisyonları, enerji tüketimi, ekonomik kalkınma, nüfus.

Makale Türü: Araştırma Makalesi

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1. INTRODUCTION

With the start of the industrial period, it has been understood that greenhouse gas production due to human activity is the main reason for the abnormal increase in world temperature. One of the most important indicators of economic development is environmental quality. One of the most important causes of environmental pollution and climate change is greenhouse gas emissions. Greenhouse gases formed as a result of economic activities cause climate changes and global warming (Ashrafi et al., 2012; Quesada-Rubio et al., 2011).

Targets are set by conducting studies to reduce greenhouse gas emissions in our country and the world. For these reasons, it is also important to accurately estimate the expected greenhouse gas emissions in the future. Table 1 shows Turkey's total greenhouse gas emissions between the years 1990 - 2019. Carbon dioxide (CO2) constitutes the largest share of greenhouse gases that cause global warming and climate change.

Table 1. Turkey's Greenhouse gas emissions (CO2 equivalent -Million tonnes) (Turkish Statistical

Year	Total	CO2	CH_4	N_2O	F-gases
1990	**219.6**	151.5	42.5	25.0	0.6
1991	**227.0**	158.0	43.4	24.7	0.9
1992	**233.2**	163.9	43.3	25.3	0.7
1993	**240.5**	171.0	43.1	26.0	0.4
1994	**234.5**	167.4	42.8	23.6	0.7
1995	**248.0**	180.9	42.6	23.9	0.6
1996	**267.6**	199.5	43.0	24.5	0.6
1997	**278.9**	212.0	42.2	24.0	0.6
1998	**280.4**	212.0	42.4	25.3	0.6
1999	**277.8**	207.8	43.8	25.6	0.6
2000	**299.0**	229.8	43.7	24.8	0.7
2001	**280.5**	213.5	42.9	23.3	0.8
2002	**286.2**	221.0	41.0	23.3	1.0
2003	**305.3**	236.5	43.0	24.6	1.2
2004	**314.8**	244.5	43.5	25.4	1.5
2005	**337.3**	264.2	45.2	26.2	1.7
2006	**358.6**	281.6	46.6	28.4	1.9
2007	**391.7**	312.7	49.0	27.6	2.3
2008	**387.9**	309.3	49.9	26.2	2.4
2009	**395.8**	315.4	49.6	28.5	2.4
2010	**399.1**	314.4	51.4	29.8	3.6
2011	**428.1**	339.5	53.7	30.9	4.0
2012	**447.6**	353.7	57.1	32.1	4.7
2013	**439.7**	345.2	55.5	34.1	4.8
2014	**459.0**	361.7	57.5	34.6	5.3
2015	**473.3**	381.3	51.6	35.4	5.0
2016	**498.9**	401.2	54.5	37.7	5.5
2017	**525.0**	425.3	54.8	39.1	5.7
2018	**522.5**	419.4	58.1	39.3	5.7
2019	**506.1**	399.3	60.3	40.2	6.2

Some studies in the literature on the relationship between economic development, energy consumption and environmental pollutants are available. Previous studies exploring the impact of energy consumption and economic factors on GHG emissions using different approaches are summarized in Table 2.

Table 2. Summary of related earlier studies

Authors	Country	Variables	Methodology
Ahmadi et al., 2019	Middle Eastern	Carbon emissions, consumption of fossil fuels, GDP	Artificial neural networks
Ozturk and Acaravci, 2010	Turkey	Carbon emissions, employment ratio, energy consumption, economic growth	Granger causality
Wu et al.,2019	China	Carbon emissions, economic growth	Log Mean Divisa Index
Sözen et al., 2009	Turkey	GHG emissions, energy consumption, GDP, GNP	Artificial neural networks
Sözen et al.,2007	Turkey	GHG emissions, sectorial energy consumption	Artificial neural networks
Antanasijevic et al.,2014	European countries	GHG emissions, GDP, energy consumption	Artificial neural networks
Radojević et al., 2013	Serbia	GHG emissions, GDP, energy consumption	Artificial neural networks
Liu and Hao, 2018	Different countries	CO_2 emissions, energy consumption, economic development	Granger causality
Antanasijevic et al., 2015	European countries	GHG emissions, energy consumption	Artificial neural networks
Acheampong and Boateng, 2019	Australia, Brazil, China, India, USA	Carbon emissions, energy consumption, economic growth, foreign direct, financial development, investment, trade openness, urbanization, industrialization	Artificial neural networks
Du et al., 2019	China	Carbon emissions, economic growth	Standard deviational ellipse
Ohlan, 2015	India	CO_2 emissions, economic growth, trade openness, population, energy consumption	Autoregressive distributed lag bounds (ARDL)
Behrang et al., 2011	Different countries	CO_2 emission, coal, oil, natural gas, and energy demand,	Artificial Neural Network
Marjanović et al., 2016	European Union countries	Economic growth, CO_2 emission	Extreme Learning Machine
Mardani et al., 2020	Argentina, Australia, Brazil, Canada	Carbon dioxide emissions, economic growth, energy consumption	Fuzzy neural network
Shahbaz et al., 2013	Indonesia	Carbon dioxide emissions, economic growth, energy consumption, trade openness	Granger causality
Salahuddin et al., 2018	Kuwait	Carbon dioxide emissions, economic growth, financial development, electricity consumption, foreign direct investment	Granger causality
Amarante et al., 2021	Brazil	Carbon dioxide emissions, economic growth, renewable - nonrenewable energy use	Granger causality

As seen in Table 2, studies on the relationship between socioeconomic variables and GHG emissions with the GEP model in the literature were not found. This paper is different from the literature relationships between greenhouse gas emissions (GHG), energy consumption (E), gross domestic product per capita (GDP), and population (P) in Turkey by using the GEP model were examined.

2. ESTIMATING GHG EMISSIONS BY GEP ALGORITHM

GEP was developed by Ferreira (2001) using the essential principles of genetic algorithm (GA) and genetic programming (GP). The method used by GEP to assess knowledge is similar to biological assessment (Ozbek et al., 2013; Ferreira, 2001). Figure 1 shows the GEP algorithm. The algorithm starts by selecting five elements like function set terminal set adaptive function control parameter and stop condition. The GEP algorithm randomly composes a preliminary chromosome representing a mathematical characteristic after which converts it into an expression tree (ET). To find the ideal topology is used different GEP parameters. The best GEP parameters for predicting GHG emissions are shown in Table 3. Automatic problem solver software was used in this study (Teodorescu and Sherwood, 2008)

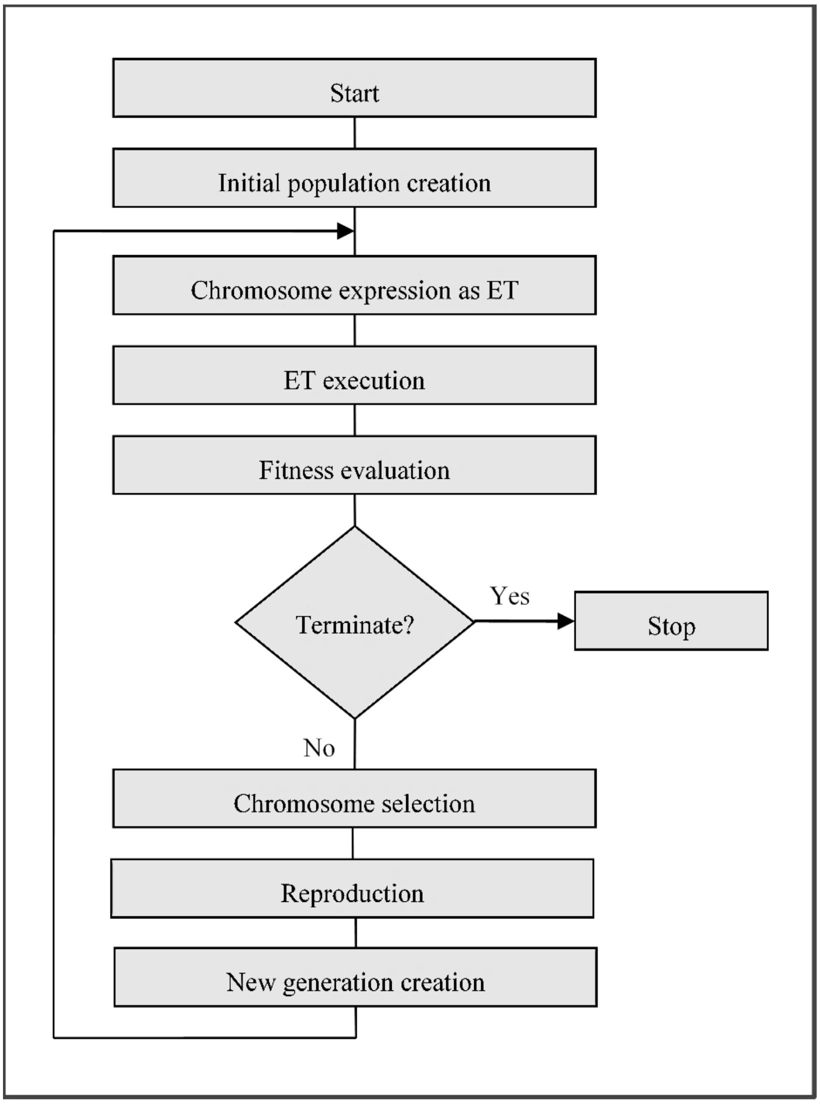

Fig. 1. The algorithm of Genetic Expression Programing (Teodorescu and Sherwood, 2008).

Table 3. The parameters of the GEP algorithm

Parameters of GEP models	**Energy consumption- GDP- Population**	**Energy consumption**	**Population**	**GDP**
Number of generations	877519	514891	7532896	21804855
Number of chromosomes	50	50	50	50
Number of genes	2	2	3	3
Head size	6	4	6	8
Linking function	Addition	Addition	Addition	Addition
Mutation rate	0.044	0.044	0.044	0.044
Inversion rate	0.1	0.1	0.1	0.1
One-point combination rate	0.3	0.3	0.3	0.3
Two-point combination rate	0.3	0.3	0.3	0.3
Gene combination rate	0.1	0.1	0.1	0.1
Gene transposition rate	0.1	0.1	0.1	0.1
Function set	$+, -, \times, \div$, *power*, √, ln, sin, cos, tan, 1/x	$+, -, \times, \div$, *power*, √, 10^x, sin, cos, tan, 1/x	$+, -, \times, \div$, *power*, √, 10^x, sin, cos, tan, 1/x	$+, -, \times, \div$, *power*, √, ln, sin, cos, tan, 1/x
R^2	0.9934	0.9849	0.9749	0.8646

Variable data are taken Turkish Statistical Institute. Fig. 2 shows the trend in each series for the period 1998–2019. As can be seen in Fig. 2, GHG emissions, energy consumption, GDP, and population in Turkey have been steadily increasing from 1998 to 2019. This indication implies that energy consumption, population and GDP could are major drivers of Turkey’s GHG emissions.

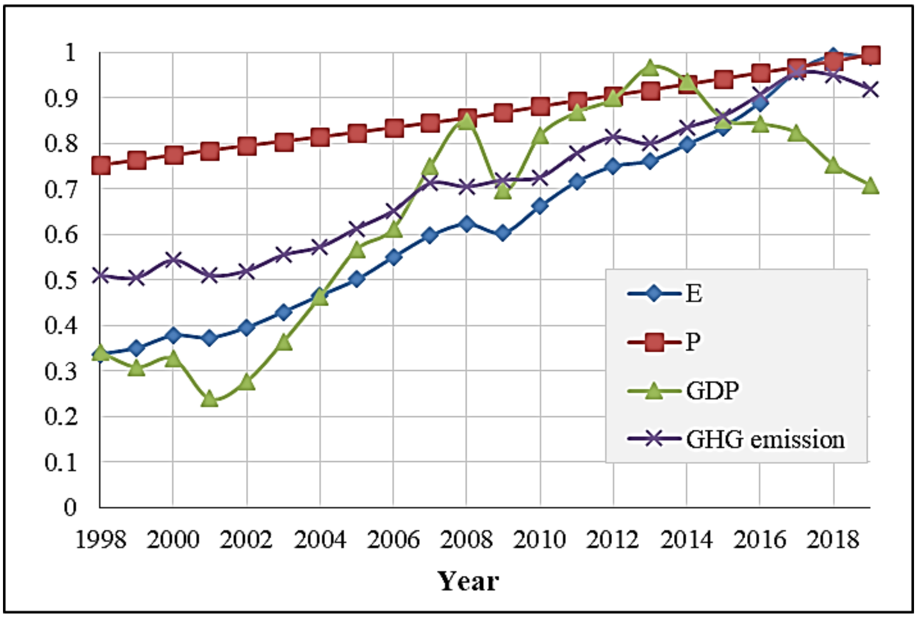

Fig. 2 Trends in GHG emissions, energy consumption, GDP and population

In the study, the general functional form of the GEP model for predicting the impact of economic growth (GDP), energy consumption (E) and population (P) on greenhouse gas emissions (GHG) is given as Eq. (1).

$$GHG_t = f(E_t, GDP_t, P_t) \quad (1)$$

Three statistical parameters are used to evaluate the performance of the model, namely Mean Absolute Percentage Error (MAPE), Root Mean Square Error (RMSE), and R-squared (R^2), which are defined as follows:

$$MAPE = \frac{1}{n}\left[\frac{\sum_{i=1}^{n}|t_i - o_i|}{\sum_{i=1}^{n} t_i} x100\right] \quad (2)$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(t_i - o_i)^2}{n}} \quad (3)$$

$$R^2 = \frac{\left(n\sum t_i o_i - \sum t_i \sum o_i\right)^2}{\left(n\sum t_i^2 - \left(\sum t_i\right)^2\right)\left(n\sum o_i^2 - \left(\sum o_i\right)^2\right)} \quad (4)$$

where the t in Equations (2), (3), and (4) represents the actual GHG emission in Turkey, while o in the model represents the predicted value of Turkey GHG emission.

3. RESULTS AND DISCUSSION

3.1. Energy consumption - GHG emissions

Studies in the literature show that energy consumption has an important impact on GHG emissions. Studies in the literature indicated that energy consumption increases carbon emissions (Shahbaz et al., 2013; Salahuddin et al., 2018; Zhang and Cheng, 2009). The correlation between energy consumption and GHG emissions derived from the GEP model is given in Eq.5. Depending on the energy consumption, the comparison between the actual and the GEP model GHG emission for the period 1998–2019 is given in Fig. 3. The comparison of the results of model with the actual GHG emissions data for the test dataset is given in Fig. 4. The R^2 value for actual and predicted GHG emissions is 0.98049. The high R^2 values indicate that is the strength of the relationship between the developed model results and the actual results.

$$GHG = tan\big(tan(E) + cos(E)\big) + \sqrt{E} - 1 \tag{5}$$

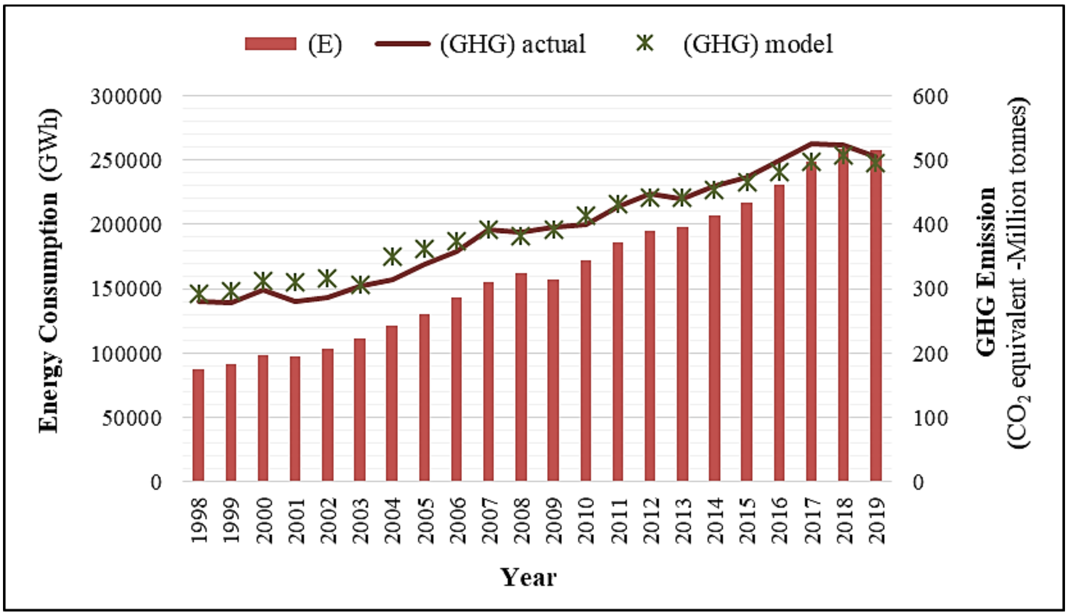

Fig.3. The comparison between the actual and the model GHG emission depending on the energy consumption

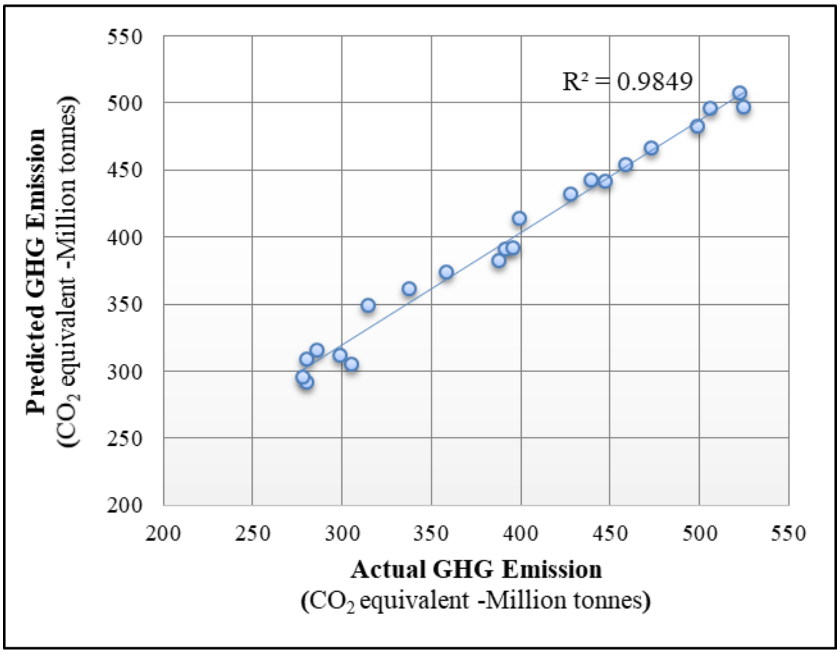

Fig.4. Scatter chart of actual and predicted GHG emissions

3.2. Economic growth (GDP) - GHG emissions

Economic growth (GDP) is another factor affecting GHG emissions. When the studies in the literature are examined, it is seen that the economic growth in general increases the GHG emissions (Liu and Bae, 2018; Tamazian et al., 2009; Stern, 2004). The correlation between GDP and GHG emissions derived from the GEP model is given in Eq.6. Depending on the GDP, the comparison between the actual and the GEP model GHG emission for the period 1998–2019 is given in Fig. 5. The comparison of the results of model with the actual GHG emissions data for the test dataset is given in Fig. 6. The R^2 value for actual and predicted GHG emissions is 0.8646. The high R^2 values indicate that is the strength of the relationship between the developed model results and the actual results.

$$GHG = tan\big(2\,GDP + tan(GDP)\big) + \frac{2\,GDP}{\sqrt{GDP}} + \tan(\tan\,(\sin(GDP))) + (\ln\,(GDP^2) - 1) + tan\big(GDP \times tan(GDP)\big) + \frac{2GDP}{\sqrt{GDP}} \quad (6)$$

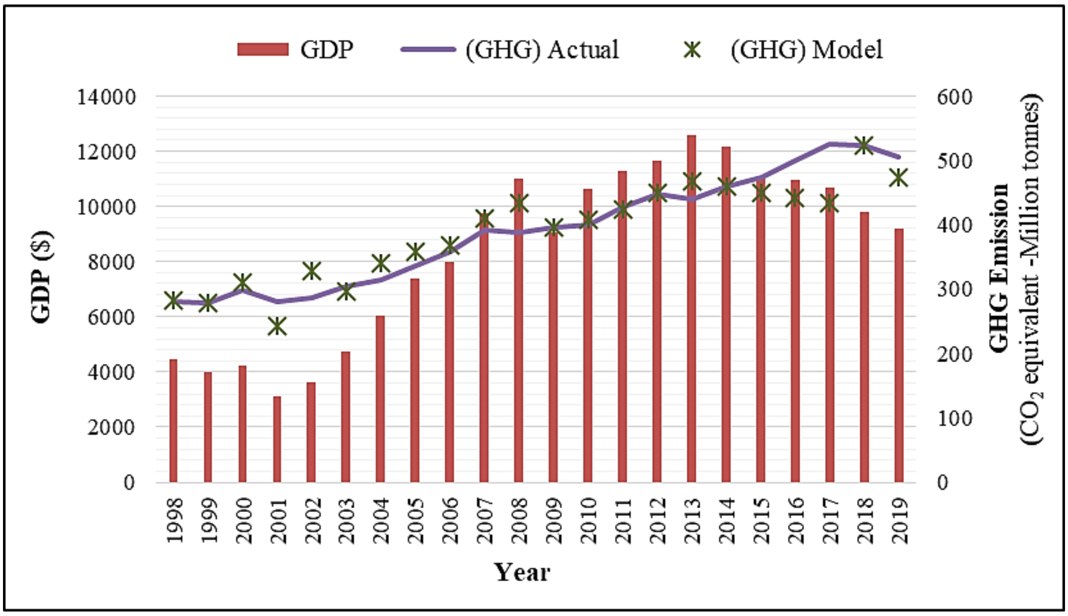

Fig.5. The comparison between the actual and the model GHG emission depending on the GDP

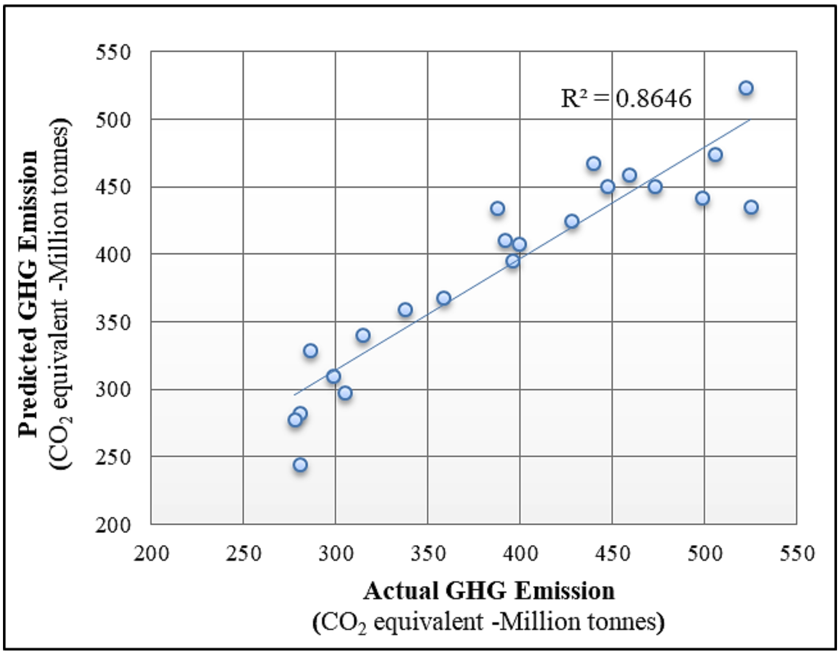

Fig.6. Distribution of actual and predicted GHG emissions

3.3. Population - GHG emissions

The population has a significant impact on GHG emissions. The population could influence energy consumption, therefore increasing GHG emissions. Zhu and Peng (2012) and Shi (2003) reported that population is related to the increase of GHG emissions. Dong *et al. (2018)* reported that population contributes significantly to the increase of GHG emissions. The correlation between population and GHG emissions derived from GEP model is given in Eq.7. Depending on the population, the comparison between the actual and the GEP model GHG emission for the period 1998–2019 is given in Fig. 7. The comparison of the results of model with the actual GHG emissions data for the test dataset is given in

Fig. 8. The R^2 value for actual and predicted GHG emissions is 0.9749. The high R^2 values indicate that is strength of the relationship between the developed model results and the actual results.

$$GHG = tan(P\,tan(P)) + \sqrt{2P} + \sqrt{2P} * \left(\cos\left(\sqrt[4]{P}\right)\right) + \sqrt{\left(\frac{P}{sin\left(cos\left(\frac{1}{P}\right)\right)}\right)} \tag{7}$$

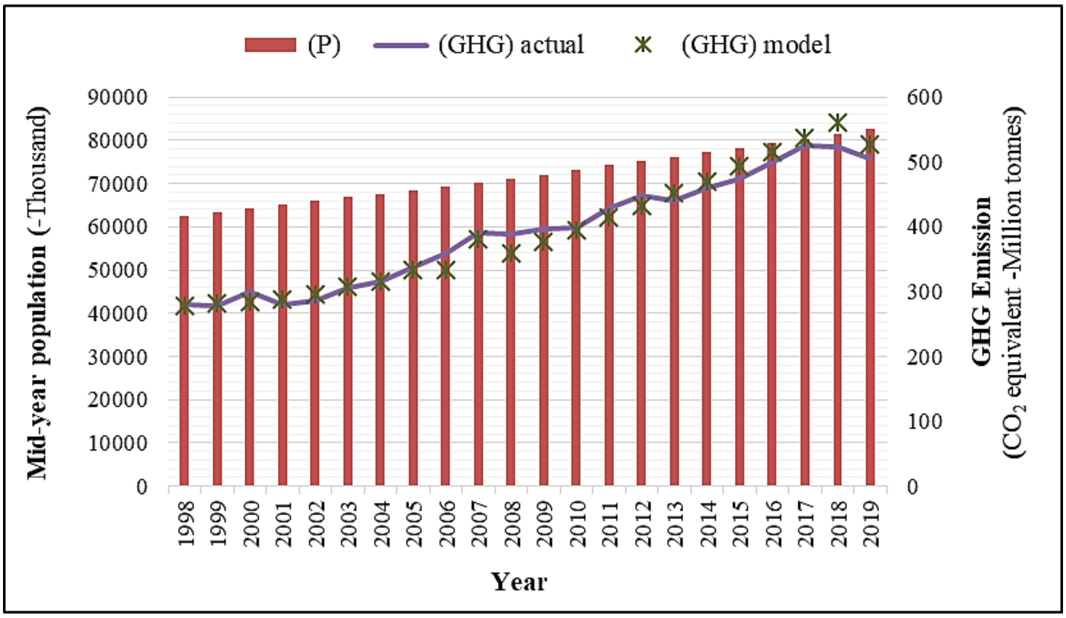

Fig.7. The comparison between the actual and the model GHG emission depending on the population

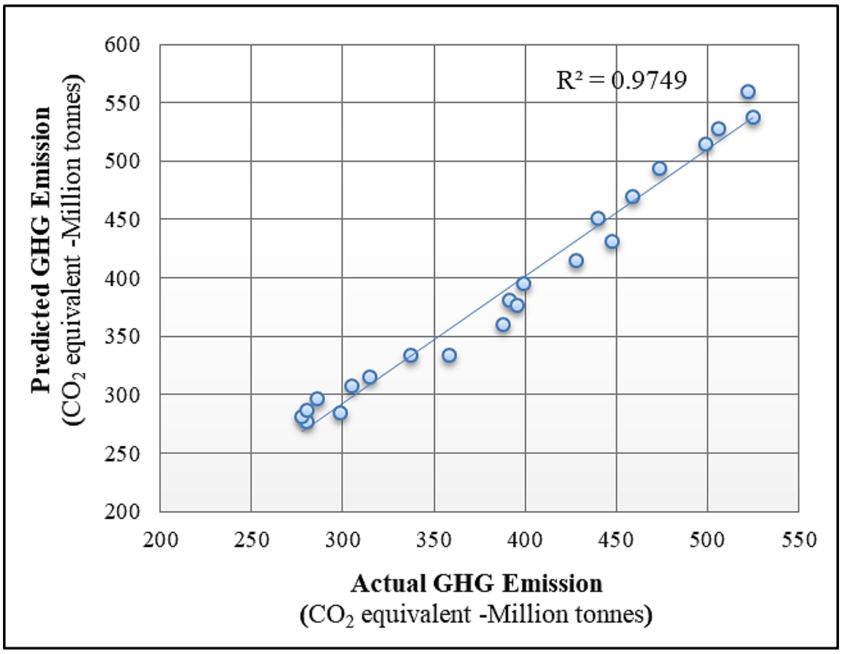

Fig.8. Scatter chart of actual and predicted GHG emissions

3.4 Energy consumption, GDP, population - GHG emissions

In addition, the effects of all three variables on GHG emission at the same time were investigated. The correlation between years, energy consumption, economic growth, population, and GHG emissions derived from the GEP model is given in Eq.8. The angle functions in Eqs. (5) - (8) were calculated in radians. Fig. 9 demonstrates the performance of the GEP model on the test dataset by comparing the results given by the predicted and the actual GHG emission. The R^2 value for actual and predicted GHG emissions is 0.9934. In Table 4, the actual GHG emissions are compared with the GHG emissions predicted by the equation derived from the GEP model. It can be seen that the error is very small. The maximum percentage difference is 3.177 %, which is very acceptable.

$$GHG = \left(sin\left(\frac{E}{P}\right) * \left(\frac{GDP-P}{t_{year}}\right)\right) + \left(tan\left(\frac{GDP(1+t_{year})}{t_{year}}\right) + \sqrt{GDP+E}\right) \quad (8)$$

Table 4. Comparison of actual GHG emissions and obtained with the GEP model

Year	Energy Consumption (GWh)	Mid-year Population (person – thousand)	GDP ($)	GHG Emission (CO_2 equivalent -Million tons)			
				Actual GHG	GEP predicted GHG	Error	Percentage difference (%)
1998	87705	62464	4445.253573	280.4194542	273.3103576	7.109097	2.535165
1999	91202	63364	4010.465188	277.8408780	279.9020313	-2.061150	-0.741850
2000	98296	64269	4249.100697	298.9542288	291.0031567	7.951072	2.659629
2001	97070	65166	3107.502117	280.5032346	283.5221795	-3.01894	-1.076260
2002	102948	66003	3608.095838	286.2273531	295.4761120	-9.24876	-3.231260
2003	111766	66795	4739.291448	305.2901548	312.0476711	-6.75752	-2.213470
2004	121142	67599	6021.106526	314.8431524	317.3247028	-2.48155	-0.788190
2005	130263	68435	7375.667084	337.3446455	341.9517449	-4.60710	-1.365700
2006	143071	69295	7971.236812	358.5711046	358.2144798	0.356625	0.099457
2007	155135	70158	9735.457673	391.6642608	386.8456588	4.818602	1.230289
2008	161948	71052	11018.19763	387.8532135	393.0243880	-5.171170	-1.333280
2009	156894	72039	9044.314888	395.8438884	383.2673707	12.57652	3.177141
2010	172051	73142	10629.46749	399.1430617	405.8352970	-6.692240	-1.676650
2011	186100	74224	11289.12866	428.1203857	426.6098424	1.510543	0.352831
2012	194923	75176	11674.94433	447.5820849	438.3841058	9.197979	2.055037
2013	198045	76148	12582.40925	439.6943821	442.9919689	-3.297590	-0.749970
2014	207375	77182	12178.00628	458.9538778	455.8058588	3.148019	0.685912
2015	217312	78218	11085.31803	473.3358240	467.6181704	5.717654	1.207949
2016	231203.7	79278	10964.46144	498.8867787	483.9369481	14.94983	2.996638
2017	249022.6	80313	10696.34158	524.9809150	513.3936869	11.58723	2.207171
2018	258232.0	81407	9791.834138	522.4766283	521.3689368	1.107692	0.212008
2019	257273.1	82579	9212.734842	506.0804181	515.1380232	-9.057610	-1.789760

Table 5 shows the statistical parameters in the prediction for various socio-economic indicators of Turkey's GHG emission, such as MAPE, RMSE, and R^2. The statistical parameters listed in Table 5 are the results of the best GEP model.

Table 5. Statistical parameters for predicting GHG emission for various socio-economic indicators

Socio-economic indicator	MAPE	RMSE	R_2
Energy consumption	0.155807	16.73919	0.984938
GDP	0.247336	30.8741	0.864631
Population	0.152785	16.04764	0.974906
Energy consumption- GDP- Population	0.069870	7.13550	0.993370

In addition, sensitivity analysis was carried out to determine the rate at which each input mutable contributes to the GHG emissions in Turkey. Sensitivity analysis was made using the partial rank correlation coefficient (PRCC) (Mishra, 2004). Fig. 10 shows the normalized sensitivity weight of each input variable for Turkey. Fig. 10 shows that energy consumption has the highest sensitivity weight, followed by economic development (GDP). As can be seen in Fig. 10, the PRCC results show that energy consumption (0.98) and economic development (GDP) (0.625) increase GHG emissions while population (-0.685) reduce GHG emissions in Turkey.

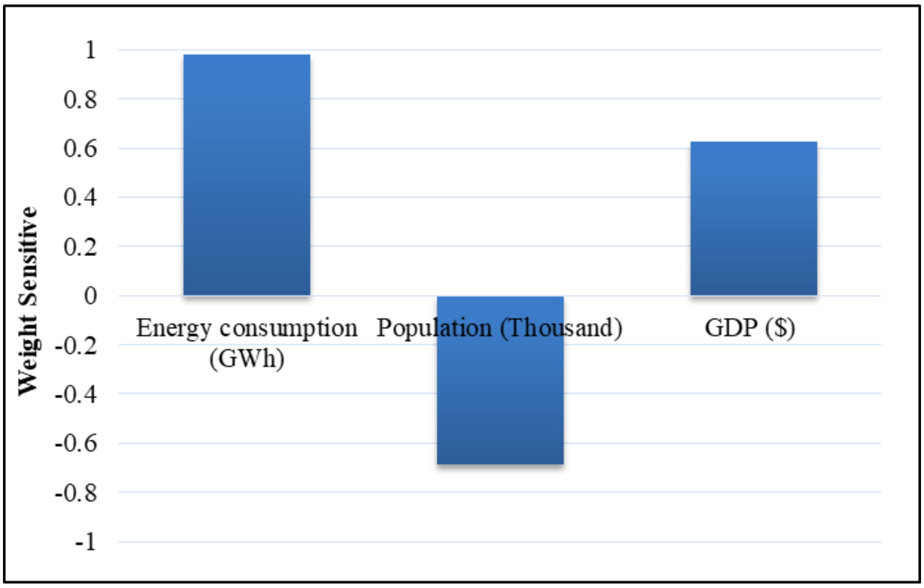

Fig. 10. Sensitivity analysis of various inputs on GHG emissions

4. CONCLUSION

The increase in GHG emissions, especially the increase in carbon dioxide emissions, is the cause of global warming and climate change and is one of the most important issues in the environmental and economic fields.

This paper investigates the relationship between energy consumption, economic growth, and population and GHG emissions in Turkey by using the GEP model for 1998–2019 periods. The developed GEP models are very practical to use. These new formulas can be used with any spreadsheet program or programming language to estimate GHG emissions, as described in this study, it may not be necessary to use dedicated GEP software. The GEP model was successfully trained for the prediction of GHG emissions by the statistical assessment of the model. In the relationship between energy consumption and GHG emissions; R_2, MAPE, and RMSE values were found as 0.984938, 0.155807, and 16.73919, respectively. In the relationship between GDP and GHG emissions; R_2, MAPE, and RMSE values were found as 0.864631, 0.247336, and 30.8741, respectively. In the relationship between population and GHG emissions; R_2, MAPE, and RMSE values were found as 0.974906, 0.152785, and 16.04764, respectively.

In the relationship between energy consumption- GDP- population and GHG emissions; R_2, MAPE, and RMSE values were found as 0.99337, 0.06987, and 7.1355, respectively. The highest correlation in GHG emission estimation has been obtained in this model.

Additionally, sensitivity analysis based on partial rank correlation coefficient (PRCC) showed that energy consumption have the highest effect on GHG emission.

The results presented in this study ensure useful insights about the energy system and GHG emissions control modeling. They also play an important role for scholars and policymakers as potential tools to develop an energy plan.

Ethical Statement

During the writing and publication of the study titled "Determination with Gene Expression Programming of the relationship between socio-economic variables and greenhouse gas emissions in Turkey", the rules of Research and Publication Ethics were complied with and no falsification was made in the data obtained for the study. Ethics committee approval is not required for the study.

Contribution Rate Statement

All of the authors in the study contributed to all processes from the writing of the study to the drafting and read and approved the final version.

Conflict Statement

This study did not lead to any individual or institutional/organizational conflict of interest.

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