The impact of economic growth, renewable energy, non-renewable energy and trade openness on the ecological footprint and forecasting in Turkey: An case of the ARDL and NMGM forecasting model

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The impact of economic growth, renewable energy, non-renewable energy and trade openness on the ecological footprint and forecasting in Turkey: An case of the ARDL and NMGM forecasting model

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ABSTRACT

In this study, the effects of economic growth, renewable and non-renewable energy production and trade openness on ecological footprint for Turkey were investigated. By using the annual data for the period 1980-2016, the short- and long-term relationship with the Autoregressive Distributed Lag Model (ARDL) was examined. In addition, a prediction model is presented with the Multivariate Gray Prediction Model (NMGM) method. According to the findings obtained from the ARDL model, economic growth, renewable and non-renewable energy production have a positive effect of 0.166, 0.1431 and 0.1118, respectively, on the ecological footprint in the long run. In the short run, economic growth, renewable energy production and non-renewable energy production has the same effect of 0.1941, 0.1673 and 0.1308 on the ecological footprint. In addition, no effect of trade openness on the ecological footprint has been detected, both in the long and short run. The originality of this study is to investigate the short- and long-term effects of economic growth and trade openness on the ecological footprint, in addition to the amount of renewable energy production and non-renewable energy production in Turkey, using the ARDL model. In addition, another originality of this study is a dynamic evaluation of the ecological footprint for Turkey and the determination of the impact values of the variables that affect the ecological footprint. ARIMA models, in which the dependent variable is estimated with its own past values, are generally used as estimation models. Likewise, univariate gray estimation models also make estimations with the dependent variable's own past values. Another unique aspect of this study is the use of a gray estimation model, in which the variables that have been shown to have a significant short- and long-term relationship with ARDL are also included in the model.

Keywords: Ecological Footprint, ARDL, Gray Estimaiton, Renewable and Non-Renewable Energy Production.

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1. INTRODUCTION

The industrial revolution, along with the change in production and consumption patterns, has led to an increase in pressure on the environment. When factors such as rapid population growth, urbanization and technological developments were included in this process, this pressure increased even more. Eventually, the environmental problems have become a priority issue as a result of production processes in which the environment has not been taken into account for the sake of increasing economic growth and prosperity. Therefore, we require tools to determine to what extent the demand of mankind remains within or exceeds the limits that the natural capital of the Earth can provide, and also to detect early warning signs and potentially predict the consequences of man-made pressures (Mancini et. al., 2016: 390). At the same time, the limited resources make it mandatory to ensure sustainability by operating within the limits of these resources.

Measuring the current situation is essential for planning sustainability effectively. While it is necessary to maintain the quality of life of people, it is necessary to monitor whether the consumption is within our ecological possibilities or above these limits, that is, at a level where the natural capital of the biosphere is consumed. Therefore, footprint analyses provide a benchmark for ecological sustainability. These energy and resource output measurements can help policymakers assess the ecological impact of the population and compare this impact with nature's capacity to regenerate. In other words, footprints compare human load with nature's carrying capacity. (Wackernagel, 1998: 8).

There are several types of footprints used in monitoring ecological sustainability. These include environmental footprints (carbon footprint, water footprint, energy footprint, emission footprint, nitrogen footprint, land footprint, biodiversity footprint, other environmental footprints), social footprints (social footprint, other social footprints), economic footprints (financial footprint, economic footprint), combined environmental, social and/or economic footprints (exergy footprint, chemical footprint), composite (composite) footprints (ecological footprint, sustainable process index, sustainable environmental performance indicator). Most of the counted footprints have limited data availability and data uncertainty. In addition, performing footprint analyses can be costly in terms of data and resources, and can also take a long time. These reasons make it difficult to measure footprints (Čuček et.al., 2012: 10-13).

Among the composite footprints, the ecological footprint is a widely used indicator to measure environmental sustainability. This indicator was first proposed by Rees (1992) and later developed by Wachernagel and Rees (1996). The ecological footprint is a composite indicator that combines six footprints. These footprints are built land footprint, carbon footprint, fishing area footprint, forest area footprint, cropland footprint, grassland footprint. The carbon footprint (CO2 emissions) covers more than half of the ecological footprint. The ecological footprint has a number of advantages for measuring environmental sustainability. These are (Borucke et al, 2013: 519):

- Offers a potential tool for measuring planetary boundaries and the extent to which humanity has transcended these boundaries.
- Can be used to explore issues such as the limits of resource consumption, the international distribution of the world's natural resources, and how to address the sustainability of natural resource use around the world.
- Provides a basis for assessing current ecological supply and demand as well as historical trends, setting goals, identifying action options, and monitoring progress towards stated goals.

Another important concept used in ecological footprint analysis is biocapacity. The biocapacity, which can also be called the ecological budget or the capacity of nature to regenerate, is a measure of the amount of biologically efficient, usable land and seahorses that provide ecosystem services consumed by humanity (Borucke et.al. , 2013: 519). An ecological deficit/deficiency occurs if the ecological footprint exceeds the biocapacity. A region with an ecological deficit satisfies demand by importing ecological assets, since it has destroyed its own resources. If the biocapacity of a region exceeds its ecological footprint, the region is said to have a biocapacity reserve (Global Footprint Network, 2021).

The world's resources are being consumed at a rate well above the sustainable level. Since 1975, the natural resource production and carbon sequestration capacities of the planet have been significantly exceeded every year. Therefore, problems such as climate change, climate crises, resource depletion and food shortages are faced more frequently. So much so that in 1961 the number of planets necessary to meet human activities on a global scale was 0.73, while by 2017 the number of planets required had increased to 1.73 planets (Global Footprint Network, 2021).

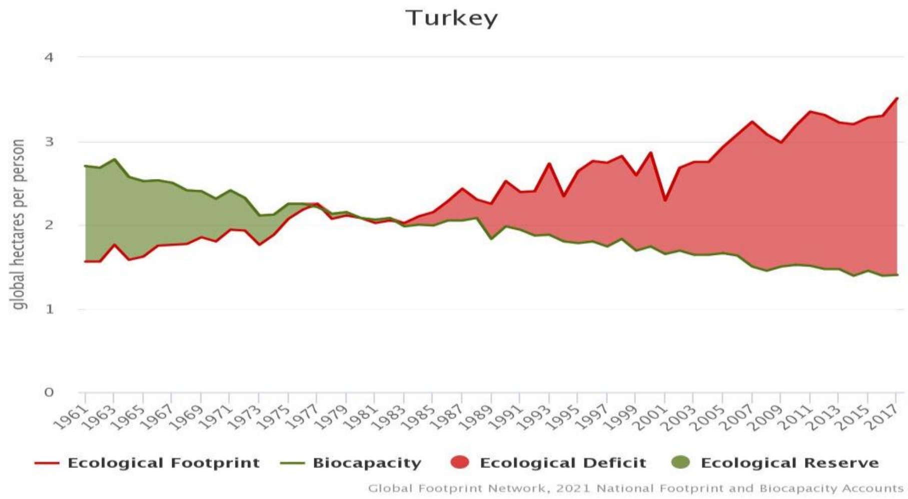

Fig 1. Ecological Footprint and Biocapacity in Turkey (1961-2017) (footprintnetwork.org, 2021).

Turkey's ecological footprint and biocapacity ratio is given in Figure 1. As can be seen from the figure, between 1961 and 1988, Turkey has been an exporter of biocapacity, albeit in a small amount, almost every year. In other words, the biological capacity sent out of the country is more than that received from outside. 1988 is the last year when Turkey became a net exporter of biological capacity. Turkey has been an importer of net biological capacity since 1989. In this sense, it can be expressed that Turkey has used its natural resources in an unsustainable way. While the number of planets required to meet human activities in Turkey was 0.5 in 1961, the number of planets required increased to 2.2 in 2017. This situation shows that Turkey has used its resources more than the world average. The most important reason for Turkey's becoming a country with an ecological deficit is population growth (WWF, 2012; Global Footprint Network, 2021). As a matter of fact, Turkey's population, which was 27.4 million in 1961, reached 81.1 million in 2017 and 84.3 million in 2020.

In line with the above, it is seen that the ecological footprint is significant and has become a subject worth researching. In this context, it is considered important to investigate the determinants of ecological footprint in Turkey. In the first stage of the research, the long and short term effects of economic growth, renewable and non-renewable energy production and trade openness on the ecological footprint in Turkey were tried to be determined by using the ARDL model. In the second stage, it was aimed to develop a prediction model using the determinants of the ecological footprint herein For this purpose, the gray estimation model proposed by Deng (1982) and based on the gray system theory, which partially refers to systems containing known information, was used. Gray system theory is widely used in many different fields (Deng, 1989; Chang and Tseng, 1999). Gray prediction models, which are an important part of the theory of gray systems, have gained popularity in time series forecasting due to their simplicity and ability to characterize an unknown system using at least four data points (Wang and Meng, 2008). Gray prediction models use the Cusum (cumulative sum) operator to extract the exponential characteristic hidden in the original time series and then continuous time dynamics (ordinary differential equations) to fit the Cusum series (Wei and Xie, 2020). In this study, the new multivariate gray prediction model, which is one of the gray prediction models, was used. These models are named as New Multivariable Gray Prediction Models by Zeng et al (2019) and expressed as NMGM (1, N). With the gray prediction model, a model related to the ecological footprint in Turkey will be developed. In the NMGM (1,N) multivariate gray estimation model, ecological footprint shall be used as the dependent variable, and renewable energy production, non-renewable energy production, economic growth and trade openness data shall be used as independent variables. The model, on the other hand, shall be referred to as the NMGM (1.5) model.

The general contribution of this study to the literature can be listed as follows:

1. The main contribution of this study is to investigate the short- and long-term effects of economic growth and trade openness on the ecological footprint, especially in the amount of renewable energy production and non-renewable energy production in Turkey, using the ARDL model.

2. Another contribution of this study is to conduct a dynamic assessment of the ecological footprint for Turkey and to determine the impact values of variables affecting the ecological footprint. ARIMA models, where the dependent variable is estimated with its own historical values, were generally used as prediction models. Likewise, univariate gray prediction models make predictions with the dependent variable's own historical values. In this study, unlike other studies, a gray prediction model was used, where the variables that were found to have a significant short- and long-term relationship with ARDL were also included in the model. This prediction model is expressed as the NMGM (1, 5) model.

3. This study will be the first one in which the ecological footprint for Turkey is modeled by the multivariate gray prediction method (NMGM(1,N)).

2. LITERATURE

The relationship between energy consumption and economic indicators was pioneered by the study of Kraft and Kraft (1978). In the study examining the relationship between gross energy consumption and GNP in the USA during the 1947-1974 period, the main empirical findings were that causality was only unidirectional from GNP to energy and there was no causality from energy to GNP in the post-war period. Following this study, studies were also conducted on economic growth and energy consumption (Akarca and Long, 1980; Eden and Hwang, 1984). Then, the relationship between environmental indicators and economic indicators was investigated within the framework of the Environmental Kuznets Curve (EKC) hypothesis (Holtz-Eakin & Selden, 1995; Lim, 1997; Galeotti & Lanza, 1999; Cole, 2004; Lee et al., 2009; Narayan & Narayan, 2010; Yılancı & Pata, 2020; Pata & Caglar, 2021). The Kuznets curve was originally conducted to test the relationship between income distribution and economic growth (Kuznets, 1955). Then, the measurement of the relationship between environmental pollution and economic growth was emphasized and studies were carried out under the name of EKC. The EKC hypothesis states that environmental degradation will increase with the increase in economic growth up to a certain point, but after a certain turning point, environmental degradation will decrease. In other words, he states that there is an inverted U-shaped relationship between economic growth and environmental degradation (Grossman and Krueger, 1991;1995).

In recent years, besides economic growth, the effects of renewable-non-renewable energy (Menyah & Wolde-Rufael, 2010; Farhani, 2013; Apergis et al., 2010; Apergis & Payne, 2012; Shafiei & Salim, 2014; Dogan & Ozturk, 2017; Kahia et al., 2016; Çetin & Sezen, 2018; Akay et al, 2015) and trade openness (Sebri and Ben-Salha, 2014; Kızılkaya et al., 2015; Shahzad et al., 2017) on environmental indicators have been investigated. In studies on this subject, CO_2 emissions are generally used as an indicator of environmental degradation. However, in these studies, it has been observed that the ecological footprint variable is used relatively less as an indicator of environmental degradation. This variable is a broader indicator that also includes CO_2 emissions. In addition, this variable measures the overall impact of human activities on the environment in terms of water, soil and air and is more comprehensive compared to other emissions (CO_2, NO_x etc.). Therefore, the use of ecological footprint in studies will provide a wider framework (Kihombo et al., 2021). For this reason, the relationship between the ecological footprint variable and economic and social indicators has been the subject of many studies in recent years. In these studies, different models and variables were used for country groups or for a single country. In studies where the ecological footprint is used as a dependent variable, the independent variables differ. It is seen that renewable and non-renewable energy consumption is generally used as an independent variable. In these studies, it is observed that there is an inverse relationship between renewable energy consumption and ecological footprint, and a direct proportional relationship between non-renewable energy consumption and ecological footprint. (Support et al., 2018; Wang and Dong, 2019; Sharif et al., 2020; Support and Sinha, 2020; Nathaniel and Khan, 2020). Some of the studies measuring the impact of trade openness on the ecological footprint say that trade openness has a negative impact on the ecological footprint (Al-Mulali and Ozturk, 2015; Charfeddine, 2017; Mrabet et al., 2017; He et al., 2019), while others say the opposite is true (Destek et.al, 2018). The direction of impact is determined by the level of development and industrialization of countries. In industrialized and developed countries, it is possible to import advanced technologies and cleaner production processes. Therefore, trade openness exerts the technical impact on the environment. Thanks to this effect, the environmental quality is improved during the production process. On the contrary, in the early stage of development, the primary concern of any country's policy makers is to drive growth, even at the expense of the environment. Therefore, cheap and polluting technologies are imported in these countries to increase production, and in this case, the technical impact of trade openness deteriorates environmental quality (Destek and Sinha, 2020: 4).

In addition, it has been observed that multivariate gray prediction models were also used in the literature to investigate the effect of determinants of ecological footprint. These prediction models are based on gray system theory. (Deng, 1989; Chang and Tseng, 1999). Wang (2008) estimated the ecological footprint and ecological capacity of Zhejiang for the period 1997-2003 using the gray prediction model, GM(1,1). Peng et al. (2018) used the data of 2013-2017 and estimated the ecological footprint per capita with the gray prediction model for the period 2018-2022. They estimated ecological safety in Chinese provinces through emergency-ecological footprint hybrid indicators with gray prediction models using 2006-2015 data. (Yang et.al. 2018). In the literature for Turkey, no study was found where multivariate gray prediction models were applied for the estimation of the ecological footprint.

3. METHODOLOGY AND DATA

3.1. Data

In this study, the relationship between ecological footprint (EFC), economic growth (GDP), non-renewable energy (NRE), renewable energy (RE) and trade openness (TA) for Turkey was investigated. Empirical analyzes were made using annual data for the period 1980-2016. EFC variable (per capita consumption, gha) was measured in terms of the GDP variable (GDP growth per capita, current USD), the NRE variable (net electricity generation from fossil sources), the RE variable (net electricity generation from renewable resources), and the TA variable (trade open to GDP ratio). The EFC variable was retrieved from Global Footprint Network database while the GDP and TA variables were retrieved from the World Development Indicators database and the NRE and RE variables were retrieved from the BP Statistical Review database. All variables were used in natural logarithmic form.

3.2. ARDL Model

In this empirical study, long-run and short-run relationships were investigated using a distributed lag autoregressive model (ARDL). This model was developed by Pesaran et al (2001). The ARDL model has several features over models Johansen and Juselius, 1990, and Engle and Granger, 1987. Firstly, this model allows us to investigate the cointegration relationship even in the case of series (I(0) or I(1)). Secondly, by adding the error correction parameter to the cointegration equation, long-term and short-term relationships can be obtained at the same time (Pesaran et.al., 2001). The last one is that it can produce effective prediction results even in small sample situations. Because of these advantages, ARDL model was used in the study. The ARDL model created for the variables discussed in the study is as follows:

$$\Delta EFC_t = \alpha_0 + \sum_{i=1}^{p} \beta_1 \Delta EFC_{t-1} + \sum_{i=1}^{q} \beta_2 \Delta GDP_{t-1} + \sum_{i=1}^{q} \beta_3 \Delta NRE_{t-1} + \sum_{i=1}^{q} \beta_4 \Delta RE_{t-1} + \sum_{i=1}^{q} \beta_5 \Delta T_{t-1} + \lambda_1 EFC_{t-1} + \lambda_2 GDP_{t-1} + \lambda_3 NRE_{t-1} + \lambda_4 RE_{i-1} + \lambda_5 T_{t-1} + e \quad (1)$$

If the error correction parameter is added to the above equation, the error correction model will be obtained (ECM):

$$\Delta EFC_t = \alpha_0 + \sum_{i=1}^{p} \beta_1 \Delta EFC_{t-1} + \sum_{i=1}^{q} \beta_2 \Delta GDP_{t-1} + \sum_{i=1}^{q} \beta_3 \Delta NRE_{t-1} + \sum_{i=1}^{q} \beta_4 \Delta RE_{t-1} + \sum_{i=1}^{q} \beta_5 \Delta T_{t-1} + \lambda_1 EFC_{t-1} + \lambda_2 GDP_{t-1} + \lambda_3 NRE_{t-1} + \lambda_4 RE_{t-1} + \lambda_5 T_{t-1} + \omega ETC_{t-1} + \varepsilon_t \quad (2)$$

Here Δ is the difference operator showing the short-term dynamics. Level values indicate long-term information. t is the time, and p and q are the lag lengths. ECT is the error correction parameter and ε is the error term. Lag lengths are generally determined by the Akaike (AIC) or Schwarz (SIC) information criteria.

In the ARDL model, first of all, the stationarity levels of the series are determined. Because this method can be used if the series are I(0) or I(1) but not I(2). Second, the null hypothesis $(H0: \lambda 1 = \lambda 2 = \lambda 3 = \lambda 4 = \lambda 5 = 0)$, demonstrating that there is no cointegration is tested against the alternative hypothesis $(H1: \lambda 1 \neq \lambda 2 \neq \lambda 3 \neq \lambda 4 \neq \lambda 5 \neq 0)$ demonstrating that there is cointegration. This hypothesis is tested with the F-statistic. The calculated F-statistic value is compared with the lower I(0) and upper I(1) critical table values calculated by Pesaran et al (2001) or Narayan (2005). If the F-statistic is greater than I(1), the null hypothesis is rejected and it is decided that there is cointegration. Third, a number of diagnostic tests (normal distribution, autocorrelation, varying variance) of the ARDL model are checked. The fact that these diagnostic tests are at desired values proves that the model is set up correctly and can be used for prediction purposes.

3.3. Gray Prediction Model

The following steps are followed when applying the Multivariate Gray Prediction Model, namely NMGM(1, N), to the structural compatibility (Zeng et al., 2019).

Step 1. Creating dependent and independent variable sequences

$$X_1^0(n) = (X_1^0(1), X_1^0(2), X_1^0(3), \ldots, X_1^0(n)) \quad (3)$$

$$X_i^0(n) = (X_i^0(1), X_i^0(2), X_i^0(3), \ldots, X_i^0(n)), i = 2,3, \ldots . N \quad (4)$$

(n=sample size)

Step 2. While AGO is a cumulatively produced series, with the 1-AGO operator, monotonously increasing series are obtained.

$$X_1^1(n) = (X_1^1(1), X_1^1(2), X_1^1(3), \dots, X_1^1(n)) \quad (5)$$

$$X_i^1(n) = (X_i^1(1), X_i^1(2), X_i^1(3), \dots, X_i^1(n)), i = 2,3, \dots . N \quad (6)$$

1-AGO operatörü aşağıdaki şekilde hesaplanır.

$$X_1^1(k) = \sum_{t=1}^{k} X_1^0(t),\ k = 1,2, \dots, n \quad (7)$$

$$X_i^1(k) = \sum_{t=1}^{k} X_i^0(t),\ k = 1,2, \dots, n \; and \; i = 2,3, \dots, N) \quad (8)$$

Step 3. NMGM (1, N) model is established.

$$X_1^1(k) = \sum_{i=2}^{N} b_i X_i^1(k) + \beta_1 X_1^1(k-1) + \beta_2(k-2) + \beta_3 \quad (9)$$

Step 4. Its parameters $\hat{P} = [b_2, b_3, \dots, b_N, \beta_1, \beta_2, \beta_3]^T$are calculated with the Least Squares method.

$$B = \begin{bmatrix} X_2^1(2) & X_3^1(2) & \dots & X_N^1(2) & X_1^1(1) & 1 & 1 \\ X_2^1(3) & X_3^1(3) & \dots & X_N^1(3) & X_1^1(2) & 2 & 1 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ X_2^1(m) & X_3^1(m) & \dots & X_N^1(m) & X_1^1(m-1) & m-1 & 1 \end{bmatrix} \quad (10)$$

$$Y = \begin{bmatrix} X_1^1(2) \\ X_1^1(3) \\ \vdots \\ X_1^1(m) \end{bmatrix} \quad (11)$$

Then the least squares estimate of the sequence of parameters satisfies,

(i): $if\ m = N + 3\ ve\ |B| \neq 0\ ise\ \hat{P} = B^{-1}Y;$

(ii): $if\ m > N + 3\ ve\ |B^T B| \neq 0\ ise\ \hat{P} = (B^T B)^{-1} B^T Y;$

(iii): $if\ m < N + 3\ ve\ |BB^T| \neq 0\ ise\ \hat{P} = B^T (BB^T)^{-1} Y;$

Step 5. To simulate the value of $\hat{X}_1^1(k)$, the time response function is calculated as follows.

$$\hat{X}_1^1(k) = \sum_{u=1}^{k-1} [\sum_{i=2}^{N} \beta_1^{u-1} b_i X_i^1(k-u-1)] + B_1^{k-1} \hat{X}_1^1\ (1) + \sum_{v=0}^{t-2} \beta_1^{k-2} [(k-v-1)\beta_2 + \beta_3\ ], k = 2,3, \dots, m. \quad (12)$$

Step 6. To determine the exact value $\hat{X}_1^0(k)$, the following equation is used.

$$\hat{X}_1^0(k) = \hat{X}_1^1(k) - \hat{X}_1^1(k-1), k = 2,3, \dots, n \quad (13)$$

Step 7. The% deviation in the training set and test set estimates is calculated as follows.

$$\Delta(k) = \frac{|\hat{X}_1^0(k) - X_1^0(k)|}{X_1^0(k)} * 100, k = 1,2, \dots, n \quad (14)$$

4. RESULTS AND DISCUSSION

4.1. ARDL Model

Before proceeding to the ARDL method, it is necessary to determine the stationarity degrees of the variables. Therefore, Augmented Dickey-Fuller (ADF) (Dickey and Fuller, 1979) and Phillips and Perron (PP) unit root (Perron, 1990) tests were used in this study to determine the stationarity levels of the variables. According to the test results in Table 1, the EFC variable is I(1) in the fixed model and I(0) in the fixed and trended model according to ADF and PP. While GDP and RE variables are I(1) according to both unit root tests, NRE variable is I(1) according to the ADF test, I(0) in the fixed model according to the PP test, and I(1) in the fixed and trended model. Finally, while the variable T is I(0) according to ADF, it is

I(0) in the fixed model and I(1) in the fixed and trended model according to PP. Based on this information, none of the variables are I(2). Therefore, there is no hesitation in applying the ARDL model to investigate the relationship between the variables.

Table 1: Unit Root Test Results

	Augmented Dickey–Fuller		**Phillips–Perron**	
Variable	**Intercept**	**Intercept+Trend**	**Intercept**	**Intercept+Trend**
EFC	-1.1153	-4.9344***	-0.7970	-5.0139***
GDP	-0.4711	-2.8906	-0.4711	-2.9376
NRE	-1.4695	0.2255	-3.5049**	-1.2035
RE	-1.0374	-3.1123	-0.5997	-3.1123
T	-3.5616**	-4.0697**	-3.5805**	-3.9102
ΔEFC	-6.5236***	-	-12.111***	-
ΔGDP	-6.1470***	-6.0514***	-6.1470***	-6.0514***
ΔNRE	-6.3068***	-4.8145***	-	-15.6152***
ΔRE	-7.5913***	-7.4822***	-8.7858***	-8.5495***
ΔT	-	-	-	-6.2249***

Note: While *Δ* denotes the difference operator, *** and ** indicate 1% and 5% significance levels. The latency length was determined automatically based on the Akaike information criterion.

Pesaran et al. (2001) proposed the F statistic in their study to test the existence of a cointegration relationship between the variables. If the F statistic is greater than the upper bound at the relevant significance level, it is decided that there is a cointegration relationship between the variables. In Table 2 below, the statistical value of F has been presented. Accordingly, it is seen that the F statistical value (19.958) at the 5% significance level is greater than the upper limit value (3.49). Therefore, this result confirms the existence of a cointegration relationship between the variables.

Table 2: Bounds Test

			Critical Values	
Statistik		**Probability**	**I(0)**	**I(1)**
F	19.958	%5	2.56	3.49

Note: The F statistic for k=4 has been obtained from the relevant program output.

After determining the cointegration relationship, the long and short term coefficients of the ARDL model can be interpreted. In this context, the short and long-term estimation results of the ARDL (1.0.0.0.0) model have been presented in Table 3. In the long run, GDP, NRE and RE variables are significant at the 1% level. From this point of view, a 1% increase in the GDP variable in the long term will increase the EFC by 0.166%. Similarly, it was determined that a 1% increase in NRE and RE in the long term would increase EFC by 0.1118% and 0.1431%, respectively. Finally, it was found that the T variable did not have any statistically significant effect on EFC in the long term.

Table 3: ARDL (1.0.0.0.0) Model Results

Variable	**Short Run Coefficient**	**Std. Error**	**t-Statistics**
C	0.1903***	0. 2002	9.5058
EFC(-1)	-1.1688***	0.1203	-9.7095
GDP	0.1941***	0.0407	4.7717
NRE	0.1308***	0.0432	3.0290
RE	0.1673***	0.0321	5.2057
T	5.2056	0.0724	1.3549
ECT	-1.1689***	0.0989	-11.8197
Variable	**Short Run Coefficient**	**Std. Error**	**t-Statistics**
GDP	0.1660***	0.0324	5.1187
NRE	0.1118***	0.0335	3.3377

RE	0.1431***	0.0246	5.8092
T	0.0839	0.0611	1.3720
C	162777.9***	2710.477	60.0551
DiagnosticTests	**Statistics**		
Breusch-Godfrey otokorelasyon testi	1.3087 (0.286)		
White değişen varyans testi	0.5474 (0.896)		
Ramsey RESET testi	0.5538 (0.462)		
Jarque-Bera normallik testi	2.1380 (0.343)		

Note: While *Δ* denotes the difference operator, *** and ** indicate 1% and 5% significance levels. The latency length was determined automatically based on the Akaike information criterion. Values in () represent probability values.

Looking at the short-term results in Table 3, it is observed that the error correction term (-1.1689) is negative and statistically significant as expected. The fact that this term is negative and statistically significant means that the short-term deviations will stabilize in the long-term after approximately (1/1.1689 = 0.85) 1 year. The short-term results, in parallel with the long-term results, state that GDP, NRE and RE were significant at the 1% significance level, while T was not. These results reveal that a 1% increase in GDP in the short term will increase EFC by 0.1941%. In addition, it has been determined that a 1% increase in NRE will have an increasing effect of 0.1308% on the EFC in the short term. Finally, it was found that a 1% increase in RE would increase the EFC by 0.1673% in the short term.

In order for the ARDL model to be used for prediction , it must meet some conditions. These conditions can be counted as the absence of autocorrelation and varying variance problems in the model, the normal distribution of the model, and the correct establishment of the model. The results in Table 3 show the diagnostic test conditions for the predicted ARDL (1.0.0.0.0) model. According to these results, the ARDL (1.0.0.0.0) model satisfies all the conditions stated above. Therefore, this model can be used for prediction purposes.

4.2. Grey Prediction

In this application, the data between 2004-2013 was used as training data and the data between 2013-2016 was used as test data, and a prediction model was created for the Ecological footprint through the NMGM (1.5) model.

After applying the data set application steps given in Annex 1, the parameter prediction results have been obtained (Table 4).

Table 4. Parameter Predictions

b2	b3	b4	b5	Beta1	Beta2	Beta3
0.084	0.481	0.352	0.147	-0.423	22.411	14.245

The weights between the ecological footprint and the 4 different control parameters (GDP, T, NRE and RE) are as follows: T (0,481) > NRE (0,352) > RE (0,147) > GDP (0,084).

In Table 5, the simulation and prediction values for the ecological footprint for the NMGM(1.5) model have been presented.

Table 5. NMGM (1,5) Simulation Outputs

Year	Real Value	NMGM(1,4) Simulation value	Simulation Deviation	
2004	19.05	19.05		Training Data
2005	19.12	19.12	0.00	Training Data
2006	19.18	19.20	0.08	Training Data
2007	19.24	19.20	0.21	Training Data
2008	19.21	19.25	0.20	Training Data
2009	19.19	19.17	0.08	Training Data
2010	19.26	19.27	0.03	Training Data
2011	19.33	19.34	0.02	Training Data
2012	19.34	19.33	0.06	Training Data
2013	19.33	19.34	0.04	Training Data
Training Data Mean Simulation Deviation				**0.08**
2014	19.34	19.36	0.08	Test Data
2015	19.38	19.34	0.20	Test Data
2016	19.40	19.36	0.23	Test Data
Test Data Mean Simulation Deviation				**0.17**
General Error				**0.09**

5. CONCLUSİONS

Turkey has been a country with an ecological deficit since 1989. The most important factor revealing this deficit is the ecological footprint. Within the scope of this research, the effects of GDP, renewable energy sources, non-renewable energy sources and trade openness variables, which are claimed to be the determinants of the ecological footprint in the literature, were examined with regard to Turkey.

In the long term, GDP, NRE and RE variables are significant at the 1% level. From this point of view, a 1% increase in the GDP variable in the long run will increase the EFC by 0.166%. Similarly, it has been determined that a 1% increase in NRE and RE in the long run will increase EFC by 0.1118% and 0.1431%, respectively. Finally, it was concluded that the T variable did not have any statistically significant impact on EFC in the long run. In addition, it has been understood that the deviations that will occur in the short term will stabilize in the long term after approximately (1/1.1689 = 0.85) 1 year. These results reveal that a 1% increase in GDP in the short term will increase EFC by 0.1941%. In addition, it has been determined that a 1% increase in NRE will have an increasing effect of 0.1308% on the EFC in the short term. Finally, it was found that a 1% increase in RE would increase the EFC by 0.1673% in the short term.

For the gray prediction model in this study, the period of 2004-2013, which constitutes the data set, was used as the training data while the period of 2013-2016 was used as the test data. A prediction model for the ecological footprint was created through the NMGM (1.5) model. This prediction model obtained showed a very low deviation with a value of 0.9%.

A part of the results of this study are compatible with other studies in the literature. Dumrul and Kılıçaslan (2020) determined a cointegration relationship between ecological footprint and international trade, energy consumption and GRP variables for Turkey and concluded that there is a proportional relationship between these variables. Dogan et al. (2019) showed in their study that fossil fuel energy consumption, export, urbanization and financial development are the most common causes of anthropogenic pressure on the environment in MINT countries, including Turkey, for the period 1971-2013. They also revealed that the effects of exports and imports have negative and positive effects on environmental degradation, respectively. Kutlar et al. (2021), again looking at the 1976-2016 period data for these countries, concluded that the increase in energy consumption increases the flexibility of the ecological footprint. Similarly, Bulut (2021) revealed that there is an inverse relationship between ecological footprint and renewable energy consumption for Turkey in the period 1970-2016. Sharif et al (2020), using quarterly data for the 1965-2017 period, showed that renewable energy reduces ecological footprint in the long run. In addition, according to the results of the study, economic growth and non-renewable energy affect the ecological footprint in the same direction in the long and short term.

According to the results of our research, as the GDP in the country increases, the footprint also increases. In order to reduce the ecological footprint, it is the right approach to use renewable resources instead of fossil fuels and increase the production of renewable energy for this purpose. However, as can be seen from the coefficients in the prediction model, in the long run, the 0.166 coefficient of the GDP is more effective than the 0.143 coefficient of the renewable energy production. The same also applies for the short term, where GDP has a coefficient of 0.194 and renewable energy production has a coefficient of 0.167. In other words, the impact of the country's economic growth on pollution is greater than the impact of renewable energy production. Therefore, the effect of renewable energy production rate on pollution cannot reach the rate of growth on pollution. Therefore, taking a broader perspective on the issue, the issue of energy production using renewable energy sources, which are the only substitutes for fossil fuels, should be discussed by stakeholders. On this occasion, by encouraging the production of renewable energy, the ecological footprint, which is one of the indicators of the damage to the environment, will increase relatively less. In this way, Turkey's sustainable development will be enhanced. With the impact of GDP, NRE, RE and T variables used in the prediction model obtained by gray prediction, it will be possible to predict the future values of the EFC.

This study can be extended by using different variables, different country groups and different periods. In addition, a prediction model can be developed with different prediction methods.

Ethical approval and consent to participate

Not applicable.

Consent for publication

Not applicable.

Authors contributions

Serhat Çamkaya: Investigation, Writing – review & editing, Conceptualization, Methodology.

Özlem Karadağ albayrak: Investigation, Visualization, Writing – original draft., Proof reading.

Conceptualization.

Samet Topal: LCA calculation, Writing – review & editing.

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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.

Availability of data and materials

The datasets used and/or analyzed during the current study are available from the corresponding author on reasonable request.

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