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The Nexus of Agricultural Efficiency, Renewable Energy Consumption, and Climate Change in Turkey

(Research Article)

Türkiye'de Tarımsal Etkinlik, Yenilenebilir Enerji Tüketimi ve İklim Değişikliği Bağlantısı

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ABSTRACT

Agricultural practices and renewable energy consumption have a major impact on the absorption of heat-trapping greenhouse gases and are closely linked to climate change. The impact of agriculture on climate change is due to the GHGs such as methane, nitrous oxide and carbon dioxide carbon dioxide that are released into the atmosphere during the agricultural practices. Therefore, to avoid undesirable effects of agriculture on climate change, it is important to understand the relationship between agricultural activities and greenhouse gases. In this study, we analyze the long-term effects of agricultural efficiency, fertilizer use, and renewable energy consumption on total carbon emissions in Turkey. The analysis is performed in two steps. In the first step, the values of agricultural efficiency are calculated using the CEE method. In the second step, ARDL and NARDL models are used to estimate the long-term effects of agricultural efficiency, fertilizer use, renewable energy consumption, GDP and population on CO_2 *emissions. The results show that improving agricultural efficiency and increasing the share of renewable energy would reduce carbon emissions, while fertilizer use, GDP, and population have negative long-term effects on* CO_2*. In addition, the results of the Wald test indicate asymmetric long-term effects of renewable energy, agricultural efficiency, and fertilizer use on climate change.*

Anahtar Kelimeler:
İklim Değişikliği, Tarımsal Etkinlik, Yenilenebilir Enerji

ÖZET

Tarımsal uygulamalar ve yenilenebilir enerji tüketimi, ısıyı hapseden sera gazlarının emilimi üzerinde önemli bir etkiye sahiptir ve dolayısıyla iklim değişikliği ile yakından bağlantılıdır. Tarımın iklim değişikliği üzerindeki etkisi, tarımsal faaliyetler sırasında atmosfere salınan metan, azot oksit ve karbondioksit gibi gazlardan kaynaklanmaktadır. Dolayısıyla, tarımsal faaliyetlerin iklim değişikliği üzerindeki istenmeyen etkilerinden kaçınmak için tarımsal faaliyetlerin sera gazları üzerindeki etkisini ortaya koymak önemlidir. Bu çalışmada, Türkiye'de tarımsal etkinlik, gübre kullanımı ve yenilenebilir enerji tüketiminin toplam CO_2 *emisyonu üzerindeki uzun dönem etkileri analiz edilmektedir. Analiz iki aşamada gerçekleştirilmiştir. İlk aşamada CEE yöntemi kullanılarak Türkiye'nin tarımsal etkinlik değerleri hesaplanmıştır. İkinci aşamada ARDL ve NARDL modelleri yardımı ile tarımsal etkinlik, gübre kullanımı, yenilenebilir enerji tüketimi, GSYH ve nüfus gibi değişkenlerin* CO_2 *üzerindeki uzun dönem etkileri tahmin edilmiştir. Sonuçlar, tarımsal etkinliğin iyileştirilmesinin ve yenilenebilir enerjinin payının artırılmasının sera gazı salınımı azaltacağını, gübre kullanımı, GSYH ve nüfusun ise sera gazı salınımı üzerinde olumsuz uzun vadeli etkileri olduğunu göstermektedir. Ek olarak, Wald testinin sonuçları yenilenebilir enerji, tarımsal etkinlik ve gübre kullanımının iklim değişikliği üzerindeki uzun vadeli etkilerinin asimetrik olduğunu göstermektedir.*

1. INTRODUCTION

The amount of greenhouse gases in the atmosphere has increased over the last century, primarily due to human activities. The main contributors to greenhouse gas emissions from human activities include fossil fuels, agricultural practices, and industrial activities (EPA 2023; Sun et al. 2022; Talaei, Gemechu, and Kumar 2020). Agriculture, in particular, is becoming the second largest emitter of greenhouse gases after fossil fuel consumption (Our World in Data 2023). Despite its historical importance and continued relevance, agriculture, which has been the main source of human livelihood since the Neolithic period, can disrupt the Earth's thermal balance through the release of gases such as carbon dioxide (CO_2), nitrous oxide (N_2O), and methane (CH_4) (Tongwane and Moeletsi 2018; Fróna, Szenderák, and Harangi-Rákos 2019). An increase in atmospheric concentrations of these gases is predicted to increase average temperatures, thereby triggering climate change. Within this paradigm, agriculture is responsible for 30% of total greenhouse gas emissions (IAEA 2023; World Bank 2023). This phenomenon is mainly due to the repeated cultivation of crops, the conversion of non-agricultural land into agricultural land, the unintentional fertilization of soils, the energy consumption of agricultural activities, the burning of savannas, the use of pesticides, and the generation of waste (FAO 2018; Tilman et al. 2011). In this context, it is crucial to control greenhouse gas emissions due to climate change, while efforts to increase agricultural and industrial production continue.

Climate change is one of the greatest threats facing our planet today, and its far-reaching effects are being felt in a number of areas, including agriculture and biodiversity (Aydinalp and Cresser 2008; Oliver and Morecroft 2014; Closset, Dhehibi and Aw-Hassan 2015; Yohannes 2016; Ouraich et al. 2019). These threats are exacerbated by the increasing vulnerability of agriculture to climate change. However, it has been shown that the vulnerability between climate change and agriculture is interactive. While climate change poses a serious threat to agricultural productivity, agricultural activities also contribute to the acceleration of climate change through the emission of greenhouse gasses such as CO_2, N_2O and CH_4 (Flessa et al. 2002; Cui, Zhao, and Shi 2018). In particular, CO_2, N_2O and CH_4 have the strongest heat-trapping capacity, and the emission of these gasses is directly linked to agricultural practices (Scialabba and Müller-Lindenlauf 2010). Agricultural practices such as the use of synthetic fertilizers, drainage of organic soils, tillage methods and irrigation systems have been identified as significant contributors to N_2O and CH_4 emissions (Lal 2004). In addition, the production of synthetic fertilizers used to increase agricultural yields releases significant amounts of CO_2 as the manufacturing process requires natural gas (Adger, Pettenella and Whitby 1997). In this context, artificial fertilizers have a direct impact on greenhouse gasses and thus on climate change, as they are an important component of agricultural production (Zhang et al. 2015; Sharma and Singhvi 2017). While increasing agricultural productivity seems to require the use of fertilizers, efforts to increase productivity have brought into the discussion a term on which there is no consensus: "efficiency". In the simplest sense, efficiency -as distinct from productivity- means more output per unit of input (Ogundari 2014; Lovins 2017; Deng and Gibson 2019). While productivity is a non-relative measure of one output obtained from multiple inputs, efficiency is a relative measure of multiple outputs obtained from multiple inputs. From one year to the next, productivity may increase while efficiency may decrease, since the quantity of output is not the only indicator of efficiency. Therefore, efficiency is a much broader concept that includes the notion of productivity (Patterson 1996; Çam, Karataş, and Lopcu 2022). When assessing efficiency in relation to climate change, a number of outputs, such as carbon emission and climate change, should be considered in addition to production output, because inputs used in agricultural production, such as fertilizer, energy consumption, release significant amounts of greenhouse gasses (Adger, Pettenella, and Whitby 1997; Vlontzos et al. 2014). This is where the disagreement over the concept of efficiency begins. While it is not a herculean task to define efficiency theoretically, calculating it as a metric is an arduous task. There are numerous variables that can be used under the concept of efficiency, but not all of them are identifiable or satisfy the factors we aim to explain. With this in mind, it is important to use the minimum number of factors that can accurately reflect efficiency in a mathematical formulation. In addition to the determination of the variables, the mathematical formulation used to calculate the efficiency values is also crucial. Unfortunately, due to the vagueness of the concept, there is no unique method for calculating efficiency. A number of methodological benchmarks based on multi-criteria decision making have been used to compute efficiency (Zhang and Chen 2022; Wang and Wang 2022), which appear to be plausible and highly representative of efficiency values. Therefore, the preferred method and the variables used to calculate efficiency are critical to obtain a representative metric of theoretical efficiency. Consequently, a benign method should be preferred to obtain reliable results with a minimum number of variables. Beyond the methodological debates, it is important to calculate agricultural efficiency due to harmful inputs used in agricultural activities, such as fertilizers and fosil fuel based energy consumption in order to determine impact of efficiency on greenhouse gases and thus climate change (Guo et al. 2022).

This study employes the Cross-Efficiency Evaluation (CEE) method, which is based on the classical Data Envelopment Analysis (DEA), to calculate cross-efficiency scores for the Turkish agricultural sector. Based on the existing literature, we define a set of inputs and outputs that are relevant for the analysis. The selected inputs include the share of agricultural land, agricultural labor, and fertilizer consumption (Shanmugam and

Venkataramani 2006; Nandy and Singh 2020). Outputs include agricultural GDP (Manogna and Mishra 2022) and agricultural greenhouse gas emissions, especially nitrous oxide (N_2O) and methane (CH_4) (Chen, Miao and Zhu 2021). Fertilizer and energy consumption as the main inputs in agricultural production emit significant amounts of CO_2, N_2O, and CH_4. Both production of fertilizers, due to the natural gases involved, and use of fertilizers, due to the methane and nitrous oxide emitted, contribute to climate change (Ramírez and Worrell 2006). Therefore, we believe that examining the impact of agricultural efficiency and fertilizer use on carbon emissions will provide an undeniable guide to tackling the climate crisis. In this context, we have examined the impact of these variables on total carbon emissions for Turkey, where agriculture is an important sector, because Turkey has a great potential for agricultural greenhouse gas emissions. Considering the importance of the agricultural sector for the country, we have studied the impact of agricultural efficiency, fertilizer use, renewable energy consumption, and some control variables, including GDP and population (Zoundi 2017; Namahoro et al. 2021; Raihan and Tuspekova 2022) on CO_2 emissions to provide empirical evidence with the aim of reducing the harmful effects of agricultural activities. The analysis consists of two independent steps. In the first step, we calculated agricultural efficiency using the CEE method. The fertilizer per hectare, share of agricultural land and labor employed in agriculture were utilized as inputs of the model, while agricultural GDP and total agricultural greenhouse gases, including N_2O, and CH_4, were used as outputs. The second step was to examine the long-term and possible asymmetric effects of agricultural efficiency, fertilizer use, renewable energy consumption on Tukey's total CO_2 emissions using ARDL (Autoregressive Distributed Lag) and NARDL (Nonlinear Autoregressive Distributed Lag) models. We strongly believe that this research will fill a significant gap in the scientific discourse on assessing the impact of agricultural efficiency on climate change. This assertion is based on the observation that numerous foundational studies have examined the impact of climate change on agriculture (Adams et al. 1998; Aydinalp and Cresser 2008; Chen, Chen and Xu 2016; Dumrul and Kilicaslan 2017; Arora 2019; Malhi, Kaur and Kaushik 2021), some studies have examined the interactions between agricultural practices and climate change (Uri 2001; Ojha et al. 2014; Yurtkuran 2021). However, our main focus is to describe the impact of increased agricultural efficiency on climate change dynamics. Therefore, our research question is as follows: "Can prudent use of agricultural inputs mitigate the negative impacts of climate change by reducing greenhouse gas emissions?" In line with the research question, our hypothesis is that by increasing agricultural efficiency and using inputs more effectively, we can reduce greenhouse gas emissions from agriculture and mitigate the undesirable effects of climate change.

2. CROSS-EFFICIENCY EVALUATION (CEE) METHOD

The CEE method is a classical technique based on Data Envelopment Analysis (DEA) that calculates the efficiency of all DMUs in order to eliminate the problem of alternative solutions of the DEA method. The optimal weights calculated by classical DEA may have multiple solutions, especially for efficient DMUs, and these solutions may lead to unrealistic weights. Thus, the DMUs may take extreme values due to the unrealistic weights. The method developed by Sexton et al. (1986) to calculate the efficiency of DMUs using cross-scoring (Anderson, Hollingsworth and Inman 2002). The logic of cross-evaluation is to use the DEA as an intermediate step to calculate a peer evaluation instead of a self-evaluation. The peer evaluation refers to an average weight-based score calculated for each DMU using the optimal weights of the other DMUs. The advantages of the cross-efficiency method are that it can generate stable efficiency scores for DMUs and that it is a mathematical method that does not require expert judgement or prior assumptions to overcome undesirable solution problems, such as multiple or unrealistic solutions introduced by DEA (Örkcü and Örkcü 2015). Similar to the other multi-criteria decision making methods, the CEE method also calculates cross-efficiency scores using multi-inputs and multi-outputs. The CEE, in addition to efficiency calculation methods such as DEA, TOPSIS, etc. attempt to calculate optimal weights of mathematical formulas that maximize the ratio of outputs to inputs. The calculation of the cross-efficiency scores of a DMU consists of two steps. In the first stage, the weights of each input and output are determined using the classical CCR model of Charnes et al. (1978). The efficiency structure of the individual DMUs is as follows:

$$E_p = \frac{\sum_{r=1}^{s} u_r y_{rp}}{\sum_{i=1}^{m} v_i x_{ip}} \tag{1}$$

Here, y_{rj} $(r = 1, \dots, m)$ and x_{ij} $(i = 1, \dots, n)$ represent the output and input values of each DMU, respectively. E_p is the efficiency value of the pth DMU, u_r is the weight of the output y_r, and v_i is the weight of the input x_i. Using the above ratio, Charnes et al. (1978) developed the following model, called the CCR model

$$\max\,(E_p) = \frac{\sum_{r=1}^{s} u_r y_{rp}}{\sum_{i=1}^{m} v_i x_{ip}}$$

s.t. (2)

$$\frac{\sum_{r=1}^{s} u_r y_{rj}}{\sum_{i=1}^{m} v_i x_{ij}} \leq 1$$

$$v_i, u_r \geq 0$$

For $j = 1, \dots, n$, $i = 1, \dots, m$ and $r = 1, \dots, s$. This mathematical form is a classical constrained optimization problem. With a few mathematical tricks, the problem can be transformed into a linear programming problem.

$$max\theta_p = \sum_{r=1}^{s} u_r y_{rp}$$

s.t. (3)

$$\sum_{i=1}^{m} v_i x_{ip} = 1$$

$$\sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} \leq 0$$

$$v_i, u_r \geq 0$$

$$j = 1, \dots, n,\ i = 1, \dots, m \text{ and } r = 1, \dots, s$$

The mathematical formulation (3) is the output-oriented CCR model and is structured as a linear programming problem. The CCR model can yield values between 0 and 1, and a DMU is efficient if and only if its efficiency is equal to 1. In the second step, the cross-efficiency of the DMUs is obtained using the weights assigned to the DMUs by the CCR model.

$$E_{dj} = \frac{\sum_{r=1}^{s} u_{rd}^{*} y_{rj}}{\sum_{i=1}^{m} v_{id}^{*} x_{ij}} \quad (4)$$

$$j = 1,2, \dots, n$$

Where (*) represents optimal weights in the CCR model. For DMU_j $(j = 1, \dots, n)$

$$\mathrm{E}[E_j] = 1/n \sum_{d=1}^{n} E_{dj} \quad (5)$$

the average of all $E_{dj}(d = 1, \dots, n)$ referred to as *the cross-efficiency score* for DMU_j (Liang et al. 2008).

3. ARDL AND NARDL MODELS

In econometrics, the study of cointegration dynamics between a dependent variable and independent variables is often based on two well-established techniques: The Autoregressive Distributed Lag (ARDL) model and the Nonlinear Autoregressive Distributed Lag (NARDL) model. While both approaches have the advantage of capturing the lagged effects of the independent variables on the dependent variable, they offer different advantages in elucidating the nature of the relationship between the variables (Arı 2021; Turhan and Arı 2021). The ARDL model is characterized by its ability to identify long-run equilibrium relationships between variables even if they have different orders of integration, with the exception of I(2) stationarity (Menegaki 2019; Arı 2022). This property makes the ARDL model particularly valuable in situations where the underlying data generation process is not readily apparent, or where preliminary unit root tests are inconclusive. In contrast, the NARDL model relaxes the linearity assumption inherent in the ARDL model. This allows the NARDL model to capture potential asymmetries in the response of the dependent variable to positive and negative shocks in the independent variables. For example, the NARDL model could show that a positive change in an independent variable could have a stronger effect on the dependent variable than a negative change of the same magnitude (Shin et al. 2014). This added flexibility can be critical for researchers attempting to model complex relationships where the effects may not be symmetric. The choice between the ARDL and the NARDL model depends on the specific characteristics of the data and the research question. If the focus is on identifying a long-run equilibrium relationship and the data have stationarity properties consistent with the assumptions of the ARDL model, then the ARDL model may be an appropriate choice. However, if the focus is on examining potential nonlinearities or asymmetries in the relationship, then the NARDL model may provide a more complete representation of the underlying dynamics. As a result, this ability of the NARDL model is particularly valuable when analyzing systems in which increases and decreases in the independent variables have different effects. In addition, the NARDL approach can accommodate different orders of integration between the variables, including I(0), I(1) and cointegrated structures.

The general form of the ARDL model can be expressed as follows:

$$CO_{2,t} = c + \sigma CE + \beta REN_t + \theta FR_t + \eta GDP_t + \emptyset POP_t + u_t \quad (6)$$

Where CO_2 is Turkey's total carbon emissions, CE is agricultural efficiency calculated using the CEE method, REN is renewable energy consumption, FR is fertilizer consumption per hectare, GDP is gross domestic product, and POP is the total population of Turkey. In the above context, c stands for a constant, while β, θ, ∅, and η represent the coefficients associated with the explanatory variables. The ARDL model, coupled with the corresponding error correction form, allows for lagged effects. Following the methodology outlined by Pesaran, Shin, and Smith (2001), the conditional error correction form of the ARDL model used to analyze potential cointegration relationships is formulated as follows:

$$\Delta CO_{2,t} = c_0 + \pi_n CO_{2,t-1} + \pi_y CE_{t-1} + \pi_G REN_{t-1} + \pi_E FR_{t-1} + \pi_X GDP_{t-1} + \pi_m POP_{t-1}$$

$$+ \sum_{t=1}^{p} \emptyset' \Delta \mathrm{CO}_{2,t-p} + \sum_{t=0}^{p_1} \omega' \Delta CE_{t-p_1} + \sum_{t=0}^{p_2} v' \Delta \mathrm{REN}_{t-p_2} + \sum_{t=0}^{p_3} \varphi' \Delta FR_{t-p_3}$$

$$+ \sum_{t=0}^{p_4} \vartheta' \Delta \mathrm{GDP}_{t-p_4} + \sum_{t=0}^{p_5} \delta' \Delta \mathrm{POP}_{t-p_5} + u_t \qquad (7)$$

In the above equation, π_n, π_y, π_G, π_E, π_m, and π_X are the long-run coefficients, and $\emptyset'$, ω', v', δ', ϑ', and φ' are the short-run coefficients vectors. In the assessment of cointegration among variables, the examination involves the computation of an F-statistic (denoted as FPSS) within the framework of the null hypothesis asserting that "the long-run coefficients are simultaneously zero." The selection of the suitable model, whether constrained or unconstrained, is contingent upon the presence or absence of trend or constant components within the long-run relationship. Upon validation of the existence of a cointegration relationship, subsequent steps encompass the estimation of the long-run coefficients and the formulation of the error correction model (ECM). The nonlinear ARDL framework, as theorized by Shin, Yu, and Greenwood-Nimmo (2014), is employed to disentangle the positive and negative impacts of the series and to examine potential asymmetric effects. The regression model is structured such that CE, REN, and FR are permitted to exert asymmetric effects on CO_2, and is expressed as follows:

$$CO_{2,t} = c + \eta^+ CE_t^+ + \eta^- CE_t^- + \beta^+ REN_t^+ + \beta^- REN_t^-$$
$$+ \theta^+ FR_t^+ + \theta^- FR_t^- + \emptyset GDP_t + \partial POP_t + \mathrm{v}_t \qquad (8)$$

REN_t^+, REN_t^-, CE_t^+, CE_t^-, and FR_t^+, FR_t^- are the asymmetric variables computed by partial sum processes for renewable energy, cross-efficiency series, and fertilizer consumed in agriculture, respectively. Finally, the asymmetric error correction model can be expressed as equation (9):

$$\Delta CO_{2,t} = \rho CO_{2,t-1} + \alpha^+ REN_{t-1}^+ + \alpha^- REN_{t-1}^- + \lambda^+ CE_{t-1}^+ + \lambda^- CE_{t-1}^- + \varsigma^+ FR_{t-1}^+ + \varsigma^- FR_{t-1}^-$$
$$+ \sum_{j=1}^{p} \gamma_j \Delta CO_{2,t-j} + \sum_{j=1}^{p} \tau_j \Delta GDP_{t-j} + \sum_{j=1}^{p} \pi_j \Delta POP_{t-j}$$
$$+ \sum_{j=0}^{p_1} (\vartheta_j^+ \Delta REN_{t-j}^+ + \vartheta_j^- \Delta REN_{t-j}^-) + \sum_{j=0}^{p_2} (\delta_j^+ \Delta CE_{t-j}^+ + \delta_j^- \Delta CE_{t-j}^-)$$
$$+ \sum_{j=0}^{p_3} (\partial_j^+ \Delta FR_{t-j}^+ + \partial_j^- \Delta FR_{t-j}^-) + \epsilon_t \qquad (9)$$

Here, ρ, α^+, α^-, λ^+, λ^-, ς^+, and ς^- are the long-run, while γ_j, τ_j, π_j, ϑ_j^+, ϑ_j^-, δ_j^+, δ_j^-, ∂_j^+, and ∂_j^- are the short-run asymmetric coefficients. The asymmetric cointegration test follows the same procedure as the bound test approach of Pesaran, Shin, and Smith (2001). Next, the long-run and short-run asymmetries of renewable energy consumption, cross-efficiency, and fertilizer consumption are tested using the Wald test.

4. DATA SET AND MODEL

The calculation of agricultural efficiency and the investigation of the relationship between CO_2 and agricultural efficiency, renewable energy consumption, fertilizer use, population, and GDP were performed separately. Therefore, the analysis was carried out in two steps: Calculating agricultural efficiency with CEE and testing the symmetric and asymmetric coefficients with ARDL and NARDL models. Agricultural greenhouse gases, including N_2O, and CH_4, rural population as a percentage of total population, fertilizer consumption per hectare, percentage of land used for agriculture, and agricultural GDP were used in the CEE model to determine agricultural efficiency. Of the variables, rural population, the land used for agriculture, and fertilizer consumption were used as input variables, while agricultural GDP and total methane gases were used as output variables. As greenhouse gases are considered as outputs of agricultural activities and the objective is to reduce emissions, this variable was included in the model as 1/GRN.

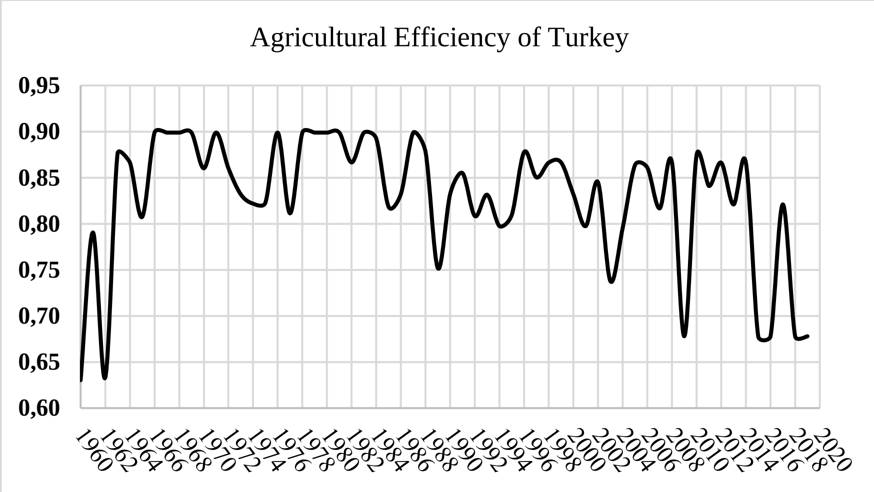

Figure 1. Agricultural Efficiency Values Based on CEE Method

Figure 1 shows the agricultural efficiency values of Turkey for the period 1960-2019*. The most efficient year was 1967 with an efficiency value of 0.8989, while the least efficient year was 1960 with an efficiency value of 0.6303. As discussed in the introduction, the efficiencies evaluated by the CEE method are based on multi-inputs and multi-outputs and thus differ from productivity. In a year in which productivity increased, efficiency may decrease due to its multi-dimensional structure considering multi-inputs and multi-outputs. Carbon emissions, GDP, share of renewable energy in total energy consumption, fertilizer consumption, total population, and agricultural efficiency obtained from the CEE model were used as variables of ARDL and NARDL models. Total carbon emission was the dependent variable of ARDL/NARDL, while others were explanatory variables. The analysis was applied to the set of annual observations for the years 1960-2019. Table 1 lists the abbreviations, sources and definitions of the variables.

Table 1. Abbreviation and Definition of Variables

Variable	*Definition*	*Source*
GDP	Gross Domestic Production (constant 2015 US$)	Development indicator of World Bank database
FR	Fertilizer Used in Agriculture (kg used per hectare)	Our World in Data
CE	Agricultural Efficiency obtained by CEE method	Efficiency values is calculated by authors
POP	Total Population	Development indicator of World Bank database
REN	Rate of Renewable Energy Consumption	International Atomic Energy Agency
CO_2	Carbon Emission (metric tons)	Our World in Data
GRN	Greenhouse Gases from Agriculture (metric tons)	United State Environmental Protection Agency
AGDP	Share of agricultural GDP in total GDP	Development indicator of World Bank database
LBR	Rate of Rural Population in Total Population	Development indicator of World Bank database
LND	Percentage of Land Used for Agriculture	Development indicator of World Bank database

Agricultural efficiency essentially reflects the ability to produce more desirable outputs with less input. In this framework, we used the CEE methodology to calculate agricultural efficiency scores. This methodology uses a composite measure expressed as a weighted sum of outputs divided by a weighted sum of inputs. In particular, the weights assigned to each output and input reflect their relative importance within the agricultural production system. In our specific case, we have defined two outputs: AGDP: This is the desired output and represents the total economic contribution of the agricultural sector. GHGs: This is an undesired output, as the main objective is to minimize greenhouse gas emissions associated with agricultural practices. To account for the undesirable nature of GRN within the CEE model, we have included its reciprocal, (1/GRN), as an output. This mathematical transformation ensures that a reduction in GRN results in an increase in (1/GRN) and thus reflects a more desirable outcome in terms of environmental sustainability. Consequently, using the CEE method, we obtained a set of agricultural efficiency scores. These scores reflect the relative performance of each agricultural production unit within the sample and illustrate its ability to maximize desired outputs (AGDP) while minimizing undesired outputs (GRN) for a given level of inputs. Furthermore, the calculated efficiency series was subsequently included as one of the independent variables in the ARDL and NARDL models. The inclusion of this variable allows us to explore the potential interplay between agricultural efficiency and other factors affecting the dynamics of agricultural production. Table 2 presents the descriptive statistics for all the variables used in the analysis. These

* R software is used to calculate agricultural efficiencies of Turkey.

statistics provide an initial understanding of the distribution and characteristics of the data and form the basis for further statistical investigation.

Table 2. Descriptive Statistics

Variable	Mean	Maximum	Minimum	Std. Dev.
GDP	26.594	27.628	24.957	26.281
FR	65.846	149.642	3.205	36.294
CE	0.829	0.899	0.630	0.071
POP	17.796	18.240	17.129	16.613
REN	23.428	55.841	9.437	12.022
CO_2	18.938	19.868	16.635	18.621
GRN	1.479	1.827	1.155	0.179
AGDP	22.253	54.919	5.776	14.931
LBR	45.164	68.485	24.370	14.235
LND	50.368	53.562	47.447	1.537

The transformed data was used to create the CEE model. LBR, LND and FR are among the commonly used inputs in the calculation of agricultural efficiency (Shanmugam and Venkataramani 2006; Nandy and Singh 2020), while AGDP is a widely used indicator of agricultural output (Manogna and Mishra 2022). The model then assessed the relative efficiency of each decision making unit (DMU) by comparing its resource utilisation in terms of output and environmental impact with the most efficient frontier set by the other DMUs. In essence, agricultural efficiency, as measured by the CEE approach, reflects the ability to achieve a desired level of agricultural output (AGDP) while using less resources (LBR, LND and FR) per unit of output. Lower values for the resource consumption variables and higher values for the output and environmental impact variables indicate higher agricultural efficiency. According to Table 2, the maximum share of renewable energy in total energy consumption was 55.84%, the average fertilizer use per hectare was 65.84 kg, and the highest efficiency had a value of about 0.90, while the lowest efficiency value was 0.63 for the analyzed period. The maximum share of agriculture in GDP was 54.91% and the minimum share was 5.77%.

The application of Autoregressive Distributed Lag and Nonlinear Autoregressive Distributed Lag models requires the determination of the stationarity properties of the variables involved. Stationarity refers to the statistical property that a time series has a constant mean, variance, and covariance over time. In this context, we use the Ng-Peron unit root test to assess the homogeneity or order of integration of the variables. This test is particularly appropriate because it is robust to potential serial correlation and heteroskedasticity within the data. The ARDL and NARDL bounds tests have specific stationarity requirements. Ideally, the dependent variable should be integrated of order one, referred to as I(1), indicating the presence of a stochastic trend. The independent variables, on the other hand, can be integrated of either order zero (I(0)), which represents a stationary process, or order one (I(1)). This flexibility makes it possible to include both stationary and non-stationary independent variables in the models, thus capturing both short-run and long-run dynamics. Table 3 shows the results of the Ng-Peron unit root test for all variables used in the ARDL and NARDL estimations below. These results serve as a guide for model selection and ensure the validity of the estimated coefficients.

Table 3. Ng-Peron Unit Root Test

	Trend and Constant				*Constant Only*			
Variables	***MZa***	***MZt***	***MSB***	***MPT***	***MZa***	***MZt***	***MSB***	***MPT***
CO_2	-2.11	-0.89	0.42	35.84	2.29	3.73	1.63	220.61
CE	-3.02	-1.01	0.34	25.10	-1.82	-0.94	0.52	13.26
REN	0.73	0.35	0.49	62.22	0.37	0.56	1.54	134.73
FR	-4.81	-1.34	0.28	17.75	2.87	3.08	1.07	108.52
GDP	-0.45	-0.18	0.40	41.52	3.83	6.70	1.75	318.78
POP	-2.65	-0.77	0.29	23.41	2.08	3.38	1.63	212.31
ΔCE	-18.31	-3.02	**0.16***	5.04	**-8.63****	**-2.05****	**0.24***	**2.95****
ΔCO_2	**-28.66*****	**-3.56*****	**0.12*****	**4.45****	**-26.76*****	**-3.52*****	**0.13*****	**1.35****
ΔREN	**-27.76*****	**-3.58*****	**0.13*****	**4.13****	**-24.24*****	**-3.29*****	**0.14*****	**1.65*****
ΔFR	**-70.33*****	**-5.88*****	**0.08**	**1.50*****	**-109.58*****	**-7.33*****	**0.07*****	**0.34*****
ΔGDP	**-28.46*****	**-3.72*****	**0.13*****	**3.48*****	**-22.65*****	**-3.37*****	**0.15*****	**1.08*****
ΔPOP	-3.58	-1.31	0.37	24.99	**-8.70****	**-1.98****	**0.23****	**3.21***
	-23.80	*-3.42*	*0.14*	*4.03*	*-13.80*	*-2.58*	*0.17*	*1.78*
	-17.30	*-2.91*	*0.17*	*5.48*	*-8.10*	*-1.98*	*0.23*	*3.17*
Critical Values	*-14.20*	*-2.62*	*0.19*	*6.67*	*-5.70*	*-1.62*	*0.28*	*4.45*

(*), (**) and (***) are significance levels of 10%, 5% and 1%, respectively. Δ represents the difference of variables. The unit root statistic without an asterisk means that the hypothesis is not rejected.

The Ng-Peron unit root test can be performed in two forms: the model with trend and constant and the model with constant only. According to the results in Table 3, the null hypothesis that the variables are nonstationary could not be rejected at the level for both of the models. The other hand, the null hypothesis was rejected for most differentiated variables in the model with trend and constant, while rejected for all first differentiated variables in the model with constant. Thus, the homogeneity assumptions underlying the ARDL/NARDL bounds test were met for all variables. This means that the explanatory variables exhibit zero or first-order homogeneity, while the dependent variable exhibits first-order homogeneity.

Table 4. ARDL Bound Test

VAR Lag Analysis (ARDL)			***ARDL Bound Test***			
Lag	AIC	SC	F Statistic	Signif.	I(0)	I(1)
0	05.584	5.874		10%	2.08	3.00
1	-10.856	-8.252	**10.72*****	5%	2.39	3.38
2	-14.257	**-9.339***		1%	3.06	4.15
3	**-16.491***	-9.257				
Breusch-Godfrey LM Test (Autocorrelation)		Prob.	***Breusch-Pagan-Godfrey (Heteroskedasticity)***		Prob.	
F-statistic	0.025	0.9758	F-statistic	1.54	0.1269	
Obs*R-sq.	0.075	0.9633	Obs*R-sq.	23.01	0.1486	

Breusch-Godfrey LM Test checks for the presence of autocorrelation in the errors (residuals) of a regression model. Autocorrelation means that the errors of one observation are correlated with the errors of the preceding or subsequent observations. The LM statistic is derived from an auxiliary regression in which the residuals of the original model are used as explanatory variables. A statistically significant LM statistic indicates the presence of autocorrelation in the errors of the model. When autocorrelation is present, the assumptions of the model are violated, which can lead to unreliable coefficient estimates and standard errors. Besides, the Breusch-Pagan-Godfrey (BPG) test examines the presence of heteroskedasticity in the errors of a regression model. Heteroskedasticity refers to a situation where the variance of the errors is not constant across observations. In the Breusch-Pagan-Godfrey, the residual values from the original model are used as independent variables. A statistically significant BPG statistic indicates the presence of heteroskedasticity. If heteroskedasticity is present, the efficiency of the model may be compromised, i.e. the estimates may not be as accurate as they could be.

Table 4 contain the lag analysis of the VAR method, ARDL bound test results, and diagnostic test results. The VAR analysis suggested two lags and three lags based on the SC criteria and the AIC criteria, respectively. Since we used the SC information criteria for both the bounds test and the estimation of the long-run coefficients, the lag was set to two. Accordingly, the F-statistic was calculated as 10.72, indicating rejection of the null hypothesis that there is a cointegration relationship between the variables, so it means that the variables move together in the long run. In statistics and econometrics, this means that "even if individual time series are not stationary, a combination of them is". The Breusch-Godfrey LM test for autocorrelation and the Breusch-Pagan-Godfrey test for heteroscedasticity implied the validity of the ARDL bounds test. Since the probability values of the Breusch-Godfrey LM and BPG tests are greater than the conventional significance levels in statistics and econometrics (1%, 5%, and 10%), the results of the VAR model and ARDL Bound Test are valid. Having established that there is a long-run relationship, the next step is to estimate the long-run coefficient of the ARDL model.

Table 5. Long-Run Coefficients of ARDL and Error Correction Models

Long-Run Coefficients of ARDL Model				***Error Correction Model Coefficients***			
Dependent Variable: CO_2				***Dependent Variable: ΔCO_2***			
	Coef.	***Std. Error***	***Prob.***		***Coef.***	***Std. Error***	***Prob.***
CE	-0.640	-2.59	0.0127	***ΔCE***	-0.195	-4.29	0.0001
REN	-0.028	-8.71	0.0000	***$\Delta CE_{(-1)}$***	0.152	3.16	0.0028
FR	0.005	3.52	0.0010	***ΔREN***	-0.024	-12.28	0.0000
GDP	0.209	2.23	0.0306	***ΔFR***	0.001	3.05	0.0038
POP	0.830	2.73	0.0090	***ΔGDP***	0.517	6.88	0.0000
Constant	-3.508	-0.90	0.3746	***ECM****	***-0.399***	-5.59	***0.0000***

Table 5 shows the long run, short run, and error correction coefficients of the ARDL model. In estimating the models in Table 5, the lag of the variables was allowed to vary. All long-term coefficients were statistically significant at conventional levels of significance. The coefficients of CE and REN had negative signs, while the coefficients of FR, GDP and POP had positive signs. The negative sign indicates a positive effect on CO_2 and thus on climate change. A 1% increase in CE would result in an average decrease in CO_2 emissions of 0.64%. Among the estimated coefficients, the one for agricultural production efficiency (CE) stands out as the most negative. This statistically significant result underscores the critical role of increased agricultural efficiency in mitigating climate change. A larger negative coefficient for CE means that an increase in agricultural efficiency leads to a greater reduction in carbon emissions. This result is consistent with our initial hypothesis that optimizing the use of inputs in the agricultural sector can significantly contribute to reducing GHG emissions. Simply put, producing the same amount of agricultural products with fewer resources results in a smaller environmental footprint. By minimizing resource waste and optimizing production processes, agricultural activities can be diverted from their traditional, emissions-intensive paths. Therefore, our analysis underscores the urgent need to implement strategies to promote efficient agricultural production. By encouraging the adoption of new strategies, policymakers and stakeholders can contribute to a more environmentally sustainable agricultural sector that ultimately reduces carbon emissions and mitigates the negative effects of climate change. Renewable energy has become a critical factor in global efforts to combat climate change. Consequently, increasing the use of renewable energy sources is a promising strategy to mitigate climate change, and our empirical analysis supports this notion. The estimated coefficient for REN shows that, on average, a 1% increase in renewable energy consumption leads to a 0.028% decrease in total carbon emissions. This negative coefficient indicates an inverse relationship between REN and carbon emissions, which is consistent with scientific evidence that renewable energy sources such as solar, wind, hydro, and geothermal generate electricity with minimal or no carbon emissions. By displacing fossil fuel generation, increased use of renewable energy can significantly reduce greenhouse gas emissions at the source. This reduction in emissions has a cumulative effect on mitigating the long-term effects of climate change, such as rising global temperatures, extreme weather events, and rising sea levels, but it is important to recognize that this is only one piece of the puzzle. While the positive impact of RENs is undeniable, a comprehensive approach to mitigating climate change requires a multi-faceted strategy. This strategy could include advances in energy storage technologies, improved energy efficiency measures across all sectors, and the development of carbon capture and storage technologies. In summary, our findings highlight the central role of renewable energy consumption in addressing climate change. By accelerating the transition to renewable energy, we can collectively contribute to a more sustainable future for our planet.

The effects of the other independent variables on climate change show a positive relationship. The use of chemical fertilizers, GDP and total population all contribute statistically significantly to the increase in greenhouse gas emissions. The estimated regression coefficients show that the total population has the strongest positive influence on climate change. A 1% increase in population is associated with an elasticity of 0.83%, which means that for every 1% increase in population, carbon emissions increase by 0.83%. This positive relationship between population growth and climate change can be attributed to several factors. A larger population requires higher resource consumption in various sectors, which can lead to higher energy consumption and waste generation. In addition, population growth often requires an expansion of agricultural production, which may be associated with practices that contribute to greenhouse gas emissions, such as the use of chemical fertilizers. The positive coefficient for GDP suggests that economic activity also plays a role in exacerbating climate change. This can be explained by the fact that many economies continue to rely on fossil fuels as their primary source of energy. As economic output increases, so does the demand for energy, which can lead to an increase in greenhouse gas emissions associated with the burning of fossil fuels. In addition, economic growth can lead to increased consumption, which in turn contributes to resource depletion and the associated environmental impacts. It is important to note that while the impact of fertilizer use is statistically significant, it appears relatively small compared to population growth and GDP. Further research is needed to investigate the specific mechanisms by which fertilizer use contributes to greenhouse gas emissions and to identify potential mitigation strategies.

Agriculture accounts for almost 30% of total greenhouse gas emissions. Therefore, efficient use of inputs in agricultural production is critical to avoid the undesirable effects of greenhouse gas emissions such as N_2O and CH_4. Using less fertilizer, land, and labor to produce more agricultural output, i.e., a higher efficiency value achieved through the CEE method, leads to a reduction in greenhouse gases. Since fertilizers are a major source of N_2O and CH_4, which have a tremendous heat-trapping capacity, reducing fertilizer use leads to a reduction in greenhouse gas emissions. REN is another important variable affecting climate change. Fossil fuels account for nearly 70% of total greenhouse gas emissions. In this sense, transitioning to clean energy or using more renewable energy would be a breakthrough in reversing the undesirable effects of climate change. In the context of climate change impacts, the results of the estimated ARDL model meet all a priori expectations for the variables REN, CE, and FR. The error correction coefficient (-0,399*)*, calculated in Error Correction Model (ECM) signalized that 39.9% of a shock to CO_2 is corrected after one period. In other words, the effect of a shock on the dependent variable disappears after about two and a half years.

Table 6. VAR Analysis and Bound Test for NARDL Model

Var Lag Analysis NARDL			*NARDL Bound Test*			
Lag	AIC	SC	F-Stat.	Singif.	I(0)	I(1)
0	7.4246	7.7501	**4.511******	10%	2.26	3.34
1	-10.2586	-7.0036		5%	2.55	3.68
2	-13.8354	**-7.6508****		1%	3.15	4.43
3	**-16.5809****	-7.4668				
Breusch-Godfrey LM (Autocorrelation)		Prob.	***Breusch-Pagan-Godfrey (Heteroscedasticity)***			Prob.
F-statistic	0.6261	0.5423	F-statistic		1.1503	0.3540
Obs*R-squared	2.4820	0.2891	Obs*R-squared		27.4083	0.3358

The NARDL model examines the long-run asymmetric impact of the explanatory variables on carbon emissions. Table 6 shows the results of the VAR analysis and the cointegration test, as well as the diagnostic test including autocorrelation and heteroscedasticity for the NARDL bound test. According to the VAR analysis, the information criteria SC and AIC recommend two and three lags as optimal. As in the ARDL model, we preferred the SC information criterion to test the cointegration relationship between the variables. The F-statistic of the NARDL cointegration test, calculated as 4.511, indicates a long-run relationship between the variables at the 1% significance level. Also, the Breusch-Godfrey LM test for autocorrelation and the Breusch-Pagan-Godfrey test for heteroscedasticity showed the validity of the NARDL cointegration test results because the null hypothesis of both test could not be rejected†.

Table 7. Log-Run and Short-Run Coefficients Asymmetric Tests, NARDL and Error Correction Models

Long-Run Coefficient of NARDL				*Error Correction Model of NARDL*			
Dep. Variable: CO_2	***Coeff.***	***Std. Error***	***Prob.***	***Dep. Variable: ΔCO_2***	***Coeff.***	***Std. Error***	***Prob.***
REN-	-0.0124	0.0050	0.0195	***(Ren+)***	-0.0158	0.0054	0.0067
REN+	-0.0308	0.0026	0.0000	***(Ren-)***	-0.0392	0.0058	0.0000
CE-	-0.4000	0.1321	0.0051	***(CE- $_{(-1)}$)***	-0.5086	0.1721	0.0061
CE+	-0.9647	0.1480	0.0000	***(CE+ $_{(-1)}$)***	-1.2267	0.1891	0.0000
FR-	0.0010	0.0003	0.0082	***(FR- $_{(-1)}$)***	0.0012	0.0007	0.0750
FR+	0.0054	0.0007	0.0000	***(FR+ $_{(-1)}$)***	0.0068	0.0013	0.0000
POP	1.0095	0.3163	0.0034	***(POP$_{(-1)}$)***	1.2837	0.4697	0.0106
GDP	0.6621	0.0794	0.0000	***(GDP$_{(-1)}$)***	0.8419	0.1241	0.0000
Long-Run and Short-Run Asymmetry Tests				***Δ (Ren-)***	-0.0344	0.0025	0.0000
				Δ (Ren- $_{(-1)}$)	-0.0077	0.0024	0.0037
				Δ (Ren- $_{(-2)}$)	-0.0117	0.0023	0.0000
	Wald Test			***Δ (CE- $_{(-1)}$)***	0.4921	0.0693	0.0000
	WLR		***WSR***	***Δ (CE- $_{(-2)}$)***	0.3446	0.0718	0.0000
REN	***6.58*** *(0.0157)*		***Null***	***Δ (CE+)***	-0.5222	0.0694	0.0000
				Δ (CE+ $_{(-1)}$)	0.3485	0.0671	0.0000
CE	***14.22*** *(0.0007)*		***11.27*** *(0.0002)*	***Δ (CE+$_{(-2)}$)***	0.1590	0.0436	0.0010
				Δ (FR+$_{(-1)}$)	-0.0025	0.0004	0.0000
FR	***20.62*** *(0.0001)*		***1.13*** *(0.2973)*	***Δ (FR+$_{(-2)}$)***	0.0029	0.0005	0.0000
				Δ (FR-)	-0.0006	0.0003	0.0825
* WLR is the long-run asymmetric test statistic of the Wald test, WSR is the short-run asymmetric test statistic of the Wald test. The significance level of each test statistic is given in parentheses. The dependent variable of NARDL is CO_2, the dependent variable of Error Correction Model is D(CO_2).				***Δ (POP)***	65.7608	6.0256	0.0000
				Δ (POP$_{(-1)}$)	-72.3947	6.2749	0.0000
				Δ (GDP)	0.7688	0.0513	0.0000
				Δ (GDP$_{(-1)}$)	0.2119	0.0542	0.0005
				Constant	-21.3641	1.6521	0.0000
				@Trend	-0.0405	0.0031	0.0000
* ETC(-1) is error correction term.				***ETC$_{(-1)}$***	**-1.2716**	***0.0980***	***0.0000***

Table 7 contains the NARDL long-run coefficients and the error correction model. The coefficients sign of the NARDL model were consistent with those of the ARDL model. All long-run coefficients had statistically significant effects on CO_2 in Turkey. Accordingly, REN and CE had positive effects on CO_2, while FR, GDP and POP had negative effects. The Wald test for long-run asymmetric effects of REN (WLR) indicated that the effects of increasing and decreasing REN were not equal. A 1% increase in REN resulted in a -0.0308% decrease in CO_2,

† The null hypothesis of the Breusch-Godfrey LM test is "There is no serial correlation" and the null hypothesis of Breusch-Pagan-Godfrey test is "The residuals are distributed with equal variance".

while a 1% decrease in REN resulted in only a -0.0124% decrease in CO_2. In other words, the asymmetric effect of (REN+) on CO_2 was 2.5 times greater than that of (REN-). Therefore, increasing the share of renewable energy in total energy consumption would contribute more to eliminating the long-term undesirable effects of climate change. The short-term asymmetric effects of REN (WRS) could not be tested because the Δ(REN+) coefficient was not included in the error correction model. Both tests implying no difference between long- and short-run asymmetric effects of CE on CO_2 were rejected at all significance levels. Accordingly, (CE-) and (CE+) had negative coefficients, but the coefficient of (CE+) was 2.4 times larger than that of (CE-). The result suggests that increasing agricultural efficiency or using agricultural inputs more efficiently would lead to greater reductions in CO_2 emissions and thus reduce the harmful effects of climate change. Finally, the results of the Wald test showed the asymmetric effects of FR on CO_2 only in the long-run. An increase in fertilizer use had a much greater effect on greenhouse gases than a decrease. The effect of (FR+) was about 5 times greater than that of (FR-). Furthermore, there was no difference between the short-term positive and negative effects of FR on climate change. Therefore, it was concluded that the use of fertilizers in agriculture could have more harmful effects on the climate in the long-term than in the short-term. According to the long-run coefficients of the NARDL model, GDP and POP had positive signs as expected, i.e., negative impacts on greenhouse gases. The main source of carbon emissions is human activities such as fossil fuel consumption, industrial production, and agriculture. An increase in population means more human activity and thus more greenhouse gas emissions, and more population means more GDP production. Therefore, these two variables would create a snowball effect on CO_2.

5. CONCLUSIONS AND DISCUSSIONS

Agricultural inputs, such as chemical fertilizers, play an important role in increasing agricultural production. Increased production is often associated with increased emissions of greenhouse gasses, including CO_2, CH_4 and N_2O. These emissions result from a variety of agricultural practices, including the use of fertilizers and changes in land use, even if they increase agricultural productivity. Therefore, rather than focusing solely on maximizing agriculcural production, agricultural efficiency is increasingly becoming the cornerstone of sustainable agricultural practices, as it has a direct impact on reducing agricultural GHG emissions. It is important to recognize that agriculture is not the only contributor to climate change. Heavy reliance on fossil fuels is another major source of carbon emissions. So, a multi-pronged approach is needed to effectively combat climate change. In this context, to determine the impact of fertilizer use, renewable energy consumption, and agricultural efficiency that is determined by the cross-efficiency evaluation method on climate change, we analyze the long-term relationship between CO_2 and explanatory variables by using the ARDL and NARDL models. This study uses a two-step framework to investigate the complex interactions between agricultural efficiency, renewable energy consumption, and climate change. The first step focuses on the calculation of agricultural efficiency. We utilize the CEE method, a DEA-based approach, to assess the relative efficiency of agricultural production units. This allows us to identify best practices and potential areas for improvement in the agricultural sector. In the second phase, we investigate the long-term relationships between renewable energy consumption, agricultural efficiency, and climate change, represented by total carbon emissions. To do this, we use two econometric techniques: the ARDL and NARDL models. These models are particularly well suited to analyze dynamic relationships and to account for possible non-linearities in the data. The empirical results of both ARDL and NARDL models confirm the existence of statistically significant long-run relationships between the independent variables and carbon emissions. The results show that agricultural efficiency and the share of renewable energy consumption have a positive impact on carbon emissions, indicating their potential to mitigate climate change. Conversely, factors such as fertilizer use, total population, and GDP have a negative relationship with carbon emissions. Interestingly, the coefficient for agricultural efficiency is significantly larger than that for renewable energy consumption and fertilizer use, indicating a potentially more important role for agricultural efficiency in mitigating climate change. Moreover, the coefficients of the NARDL model support the results of the ARDL model. Both models consistently show that increasing agricultural efficiency and renewable energy consumption helps mitigate the negative effects of carbon dioxide emissions, while factors such as fertilizer use, population growth, and economic expansion exert an opposite pressure on climate change. In summary, this study highlights the important role of agricultural efficiency in combating to climate change. While both renewable energy and reduced fertilizer use are promising, optimizing agricultural practices proves to be a far more effective strategy in this battle. The results presented here provide valuable insights for policy makers seeking to formulate effective strategies for sustainable agricultural development and climate change mitigation. Consequently, the need to mitigate climate change requires a multifaceted approach, and the agricultural sector is a critical area for action. In Turkey, increasing agricultural efficiency-the ability to produce more with less input-is emerging as a key strategy. This can be achieved through a combination of technological advances, improved resource management, and the adoption of sustainable agricultural practices. One promising avenue is the exploration of alternative agricultural practices, such as low-emission regenerative or organic agriculture. These approaches are not only about increasing productivity, but also about environmental sustainability. Regenerative agriculture focuses on restoring soil health and ecosystem services, while organic agriculture avoids the use of synthetic fertilizers and pesticides. By implementing these methods, Turkey can potentially achieve a decoupling effect in which agricultural production increases while greenhouse gas emissions decrease. Besides, government policies can play an important role in promoting the transition to more sustainable agricultural practices in Turkey. Financial instruments, such as subsidies for organic fertilizers or cost-sharing programs for the adoption of regenerative techniques, can provide incentives for farmers to shift from conventional, input-intensive methods to the use of renewable energy sources. In addition, educational initiatives and technical assistance programs can provide them with the knowledge and skills necessary for successful implementation. While increasing agricultural efficiency is critical, it must be done in a way that minimizes negative impacts on the environment. For example, the uncontrolled use of chemical fertilizers and the inefficient use of inputs may initially increase production, but contribute significantly to greenhouse gas emissions through processes such as the release of nitrous oxide. The introduction of stricter regulations or the promotion of more targeted fertilizer application techniques can help to mitigate these negative effects. In summary, sustainable agricultural development in Turkey can only be achieved through a multi-pronged approach. By prioritizing efficiency gains through technological advances and sustainable practices, combined with supportive government policies and environmental protection measures, Turkey can help moderate undesired effects of climate change while ensuring long-term food security.

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