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ARAŞTIRMA MAKALESİ **RESEARCH ARTICLE**

The Relationship between Agriculture and Carbon Dioxide Emission in Türkiye: A Non-Linear Evidence

Türkiye'de Tarım Sektörü ve Karbondioksit Emisyonu Arasındaki İlişki: Doğrusal Olmayan Bir Kanıt

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Abstract

Agricultural production has both increased and become more efficient with the development of technology. However, greenhouse gases such as CO_2 released into the air during production cause climate change. This situation also affects agricultural productivity. Therefore, the main objective of this paper is the examine the interaction between agricultural sector activity and CO_2 emissions in Türkiye in a non-linear framework. For this purpose, the Maki cointegration test and the Single Fourier frequency Toda & Yamamoto causality test were used to investigate the interplay between agricultural value added and CO2 using time series data covering the period from 1968 to 2018. In addition to the empirical analysis developed in the paper, our study adds to the literature by studying the relationship between CO_2 and energy consumption in the agricultural sector, as opposed to studies that use aggregate CO_2 emissions as an indicator of climate change. In addition, the short- and long-run interactions between CO_2 and agricultural productivity were investigated by estimating two separate equations where agricultural productivity and CO_2 emissions are used as dependent variables. The Maki cointegration test cointegration test shows the existence of a long-run relationship between agricultural value added and CO_2 emissions under structural breaks. The detected significant breaks are associated with significant events affecting the Türkiye economy. For instance, when agricultural value added is the dependent variable, the break dates of 1971 and 1974 coincide with the oil crisis, while the breaking dates of 2002 and 2008 coincide with Türkiye's 2001 financial crisis and the 2008 global financial crisis. Similarly, the break dates of 1973 and 1977 obtained in the CO_2 equation are associated with the 1970s' global oil crisis. Long-run parameter estimates derived from FMOLS and CCR estimators indicated that CO_2 emissions have a long-run, positive and significant impact on agricultural productivity. In addition, the long-run results support the existence of a positive and significant impact of agricultural productivity on environmental degradation. The gradual shift causality test also supports the presence of one-way causality, running from agriculture output to CO_2.

Keywords: Agriculture sector, Carbon dioxide emissions, Structural break analysis, Nonlinear analysis

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Öz

Tarımsal üretim, teknolojinin gelişmesi ile hem artmıştır hem de daha verimli hale geldiği gerçeği yadsınamaz. Ancak üretim esnasında havaya salınan CO_2 gibi sera gazları iklim değişikliğine neden olmaktadır. Bu durum da tarımsal verimliliği etkilemektedir. Dolayısıyla bu çalışmada Türkiye'de tarım sektörü aktivitesi ile CO_2 emisyonları arasındaki karşılıklı etkileşimi doğrusal olmayan bir çerçevede incelemeyi amaçlamaktadır. Bu amaçla, Maki eşbütünleşme testi ve Tek Fourier frekansı Toda & Yamamoto nedensellik testi, 1968'den 2018'e kadar olan dönemi kapsayan zaman serileri kullanarak tarımsal katma değer ile CO_2 arasındaki etkileşimi araştırmak için kullanılmıştır. Makalede yapılan ampirik analize ek olarak, çalışmamız, toplam CO_2 emisyonlarını iklim değişikliğinin bir göstergesi olarak kullanan çalışmaların aksine, tarım sektöründe CO_2 ve enerji tüketimi arasındaki ilişkiyi inceleyerek literatüre katkıda bulunmaktadır. Ayrıca, CO_2 ve tarımsal verimlilik arasındaki kısa ve uzun vadeli etkileşimler, tarımsal verimlilik ve CO_2 emisyonlarının bağımlı değişkenler olarak kullanıldığı iki ayrı denklemin tahmini ile araştırılmaktadır. Maki eşbütünleşme testi, tarımsal katma değer ile yapısal kırılmalar altındaki CO_2 emisyonları arasında uzun dönemli bir ilişkinin varlığını göstermektedir. Tespit edilen önemli kırılmalar, Türkiye ekonomisini etkileyen önemli olaylarla ilişkilidir. Örneğin, tarımsal katma değerin bağımlı değişken olduğu modelde, 1971 ve 1974 yıllarının kırılma tarihleri petrol kriziyle çakışırken, 2002 ve 2008 yıllarının kırılma tarihleri Türkiye'nin 2001 mali krizi ve 2008 küresel mali krizi ile çakışmaktadır. Benzer şekilde, CO_2 denkleminde elde edilen 1973 ve 1977'nin kırılma tarihleri, 1970'lerin küresel petrol krizi ile ilişkilidir. FMOLS ve CCR tahmincilerinden türetilen uzun dönemli parametre tahminleri, CO_2 emisyonlarının tarımsal verimlilik üzerinde uzun vadeli, olumlu ve önemli bir etkiye sahip olduğunu göstermektedir. Bunun yanında, uzun dönemli sonuçlar, tarımsal verimliliğin çevresel bozulma üzerinde olumlu ve önemli bir etkisinin varlığını desteklemektedir. Kademeli kayma nedensellik testi ise, tarımsal üretimden CO_2'ye kadar uzanan tek yönlü nedenselliğin varlığını desteklemektedir. Bu bulgular Türkiye'de tarımsal verimlilik ve CO_2'nin birbirini desteklediğini göstermektedir. Her ne kadar CO_2'nin tarımsal verimliliği pozitif etkilemesi olumlu görünse de çevreci olmayan bir tarıma işaret etmektedir.

Anahtar Kelimeler: Tarım sektörü, Karbondioksit emisyonları, Yapısal kırılma analizi, Doğrusal olmayan analiz

1. Introduction

Despite recent advances in production technology, agricultural output is adversely affected by a range of variables that reduce yields. These are mostly related to climate change, such as water scarcity, drought, plant pests and diseases, and altered vegetation seasons. Because of its effects on agricultural productivity, global climate change has major implications for food security and international trade. Climate change can adversely affect agriculture including loss of cultivated areas, shifting precipitation patterns, reduced irrigation water, and drought (Adams et al., 1998). Because of agriculture's importance, any climate-change-induced output reductions significantly affect the economy's macroeconomic fundamentals. For example, it may increase consumer prices for domestic produced and imported foods (Dellal, 2011).

At the same time as being affected by climate change, agriculture itself also significantly affects the environment. In particular, it contributes significantly to greenhouse gas emissions due to increasing mechanization, livestock production, soil tillage, and excessive nitrogen fertilizer usage. This suggests that countries must abandon the use of fossil fuels and increase the use of renewable energy in agricultural production (Ben Jebli and Ben Yousef, 2017).

The main objective of this study is to reveal the interaction between agricultural activity and CO_2 in Türkiye. For this purpose, the research question of the study can be stated as follows: Is there a statistically significant relationship between agricultural productivity and CO_2 in Türkiye? Türkiye presents an interesting case to analyze how environmental pollution affects agriculture. Firstly, according to the greenhouse gas inventory, agriculture's CO2 emissions in Türkiye have increased dramatically during the previous three decades. Türkiye's total per-capita greenhouse gas emissions are projected to grow to 6.3 tons of CO2 equivalent in 2020 from 4 tons in 1990. As measured by CO_2 equivalent, energy-related emissions accounted for 72 percent of Türkiye's emissions in 2020, followed by agriculture at 14 percent, industrial processes and product consumption at 12.7 percent, and the waste sector at 3.1 percent. Agriculture was projected to emit 73.2 Mt CO2 equivalent in 2020, a 58.8 percent increase from 1990 and a 7.5 percent increase from 2019 (TURKSTAT, 2021). The second reason Türkiye is an interesting case is that its arable land area has shrunk significantly over the last three decades, from approximately 32% of the total agricultural land area in 1990 to approximately 25% in 2020 (World Bank, 2022). There has been a similar climate-change-induced rise in temperature from an annual average of 12.7 °C in 1991 to 14.5 °C in 2020, according to the Turkish State Meteorological Service (TSMS, 2022). Climate change is universally recognized as having a substantial influence on diverse sectors, with the agricultural industry being arguably more susceptible to its effects compared to other industries. Therefore, in order to effectively address the impact of climate change on the agricultural sector, it is imperative to conduct comprehensive studies at both the national and international levels (Konukcu et al., 2020).

This study provides a novel contribution to the literature in this area. First, it offers a more specific analysis than previous literature on Türkiye, which has primarily concentrated on pollution's impact on overall economic activity, with few studies focusing on the agriculture sector (Bayraç and Doğan, 2016; Pakdemirli, 2020; and Çetin et al., 2020). In contrast, instead of examining CO_2 emissions at an aggregate level, our study examines the relationship between agricultural activities and CO_2 emissions due to the agriculture sector. Similarly, we also consider agriculture's energy consumption as a major determinant of agricultural activity. Second, this study considers the long-run environmentally degrading impact of agricultural activity. Third, our literature review suggests that research examining agricultural activity and pollution has mostly used linear estimation methodologies. However, some researchers have argued that linear models may be inappropriate for analyzing the relationship between emissions and agricultural activity because changes in the economic environment and abnormal climate conditions could create serious parameter instabilities, leading to biased empirical results. Our study therefore addresses these gaps in the literature by using Maki (2012) cointegration and Toda and Yamamoto (2016) causality tests to investigate the nonlinear impacts of local and global economic events on the relationship between agricultural activity and climate change.

The rest of the article is structured as follows. The following section briefly reviews the literature on climate-change-induced effects on agricultural productivity. We then present the study's methods and variables before summarizing the results of the cointegration and causality tests. We conclude with policy suggestions predicated on the estimation results.

2. Literature Review

Table 1 and *Table 2* presents the main findings from the literature analyzing the agriculture-CO_2 emission nexus. Some studies have employed temperature and precipitation data as indicators of climate change. Rosenzweig and Parry (1994) find that changing climate conditions reduce agricultural yields. Using the Ricardian model, Liu et al. (2004) measured how climate change has affected Chinese agriculture economically. They found that temperature increments have led to increasing average net agricultural income. Brown et al. (2010) estimated a panel data model for 133 countries covering 1961 to 2003. They found that increasing precipitation raises agriculture's share in GDP, rising temperatures have the opposite effect. Also, using the Ricardian model, Masud et al. (2014) showed that temperature, precipitation, farm size, educational information, land area, and labor input value all affect rice production in Malaysia.

Table 1. Time series studies.

Study	Country	Period	Variables	Methodology	Findings
Jebli and Youssef (2017)	Tunisia	1980-2011	GDP, CO2, AGR, trade openness, REN and NONREN	VECM causality	There is a bidirectional relationship between agriculture and CO_2.
Zafeiriou and Azam (2017)	France, Portugal and Spain	1992-2014	CO2 and AGR	ARDL, VECM causality	There is unidirectional causality from CO_2 to agriculture variable.
Waheed et al. (2018)	Pakistan	1990-2014	CO2, REN, AGR and forest area	ARDL cointegration, VECM causality	There is unidirectional causality from agriculture to CO2.
Jebli and Youssef (2019)	Brazil	1980-2013	CO2, GDP, CRW and AGR	ARDL, VECM causality	There is no short-run causality relationship. However, there is a bidirectional, long-run relationship between agriculture and CO2.
Ngarava et al. (2019)	South Africa	1990-2012	CO2, AGR, coal and electricity energy	ARDL, Granger causality	There is unidirectional causality from agriculture to CO2.
Pakdemirli (2020)	Türkiye	1961-2018	AGR and CO2	ARDL, VAR	There is a strong relationship between agriculture and CO2.
Çetin et al. (2020)	Türkiye	1968-2016	CO2, GDP, AGR, REN and LAND	Toda-Yamamoto	There is unidirectional causality from agriculture to CO2.
Wang (2022)	China	1985 -2019	AGR, CO2, LAND, Harvested, GDP, AGR export and NONREN	ARDL, Johansen cointegration	CO2 has a positive effect on agriculture.

Notes: AGR (Agricultural Value Added), REN (Renewable Energy Source), AGRE (State's Agricultural Expenditures), AGRPI (Agricultural Production Index), CRW (combustible renewables and waste consumption), EFP (Ecological Footprints), RQ (regulatory quality)

Regarding Türkiye, three studies (Dellal et al., 2011; Başoğlu and Telatar, 2013; Dumrul and Kilicarslan, 2017), have examined whether CO_2 emissions affect agriculture. Based on temperature and precipitation forecasts for seven geographical regions in Türkiye in 2050, Dellal et al. (2011) used both biophysiological and economic models to investigate whether climate change will affect Turkish agriculture. The results suggest that the crop yield will decline significantly in all regions. Shrinking agricultural land and climate change will reduce production by 2.2-12.9%. Başoğlu and Telatar (2013) applied multiple regression analysis to analyze how climate change affected Turkish agriculture from 1972 to 2011. They found that increasing precipitation increased agriculture's share in GDP, whereas rising temperature reduced it. Furthermore, Dumrul and Kilicarslan (2017) reported that temperature increases agricultural GDP over the long run while precipitation reduces it.

The present study aims to address two research gaps in the literature reviewed above. First, previous studies used total CO_2 emissions rather than those of the agricultural sector specifically while examining the relationship between climate change and agriculture. Second, previous studies assumed a time-invariant relationship between agricultural activity and climate change. Our study therefore considers nonlinearity in the relationship in both the long and short run by employing the Maki (2012) cointegration and the single Fourier-frequency Toda and Yamamoto causality tests.

Table 2. Panel Data studies.

Study	Country	Period	Variables	Methodology	Findings
Islam et al. (2014)	Southeast asian countries	1975-2011	CO2, AGR, fertilizer, capital and population	Panel ARDL and PMG	CO_2 has a positive effect on agriculture.
Khalid et al. (2016)	10 countries	1990-2014	AGR, GDP, CO2, capital, AGRE, LAND, AGRPİ, fertilizer	Panel OLS	CO_2 has a positive effect on agriculture.
Hayaloğlu (2018)	10 countries	1990-2016	GDP, AGR, CO2, LAND, population, capital and schooling	Panel OLS	CO_2 has a negative effect on agriculture.
Olanipekun et al. (2019)	African countries	1996-2015	EFP, GDP, REN, population and AGR and RQ	Emirmahmutoglu and Kose Granger causality	There is a bidirectional relationship between ecological footprint and CO2.
Qiao et al. (2019)	G20 countries	1990-2014	CO2, GDP, AGR and REN	Panel VECM causality	There is unidirectional causality from agriculture to CO2.

Notes: AGR (Agricultural Value Added), REN (Renewable Energy Source), AGRE (State's Agricultural Expenditures), AGRPI (Agricultural Production Index), CRW (combustible renewables and waste consumption), EFP (Ecological Footprints), RQ (regulatory quality)

3. Materials and Methods

This study employed annual data from 1968 to 2018. The availability of the data on agriculture-sector CO_2 emissions determined the estimation sample. These were retrieved from the International Energy Agency (IEA) as an indicator of climate change. Real agricultural value added was used to measure agricultural sector activity. In line with previous studies (Wang, 2022), agricultural land, agricultural energy consumption, and fixed capital formations were also included in the model as control variables.[1] Given that the present study aimed to quantify both the short- and long-run interactions between CO_2 and agricultural productivity, two separate equations were estimated, which treated agricultural output and CO_2 emissions as dependent variables. The linear forms of the estimated equations are formulated as follows:

Model 1: $$\boldsymbol{lnAGR_t = \beta_0 + \beta_1 lnCO2_t + \beta_2 LAND_t + \beta_3 lnENG_t + \beta_4 GFCF_t + \varepsilon_t} \quad \text{(Eq.1)}$$

Model 2: $$\boldsymbol{lnCO2_t = \beta_0 + \beta_1 lnAGR_t + \beta_2 LAND_t + \beta_3 lnENG_t + \beta_4 GFCF_t + \varepsilon_t} \quad \text{(Eq.2)}$$

Where $\boldsymbol{lnAGR_t}$ represents the natural log of real agricultural value added; $\boldsymbol{lnCO2_t}$ represents the natural log of agriculture-sector CO_2 emissions in tonnes (Mt); $\boldsymbol{lnENG_t}$ is the natural log of the energy consumption in the agricultural sector. Agricultural land ($\boldsymbol{LAND_t}$) and gross fixed capital formation ($\boldsymbol{GFCF_t}$) are included in their level form as they are defined in percentage terms. Agricultural land is defined as the proportion of total land that

[1] Appendix Table A1 provides detailed descriptions of the variables.

is cultivated. Gross fixed capital formation as a percentage of GDP is included as a control variable to quantify the effect of a change in total value added, i.e., investment on agricultural productivity and environmental quality.[2]

3.1. Maki (2012) Cointegration Test with Multiple Structural Breaks

The Johansen and Juselius (1990) cointegration test were used first to analyze the long-run relationship between agricultural activity and CO2 emissions. The Maki (2012) cointegration test was then used to investigate the long-run relationship between agricultural activity and CO2 emissions given unknown multiple structural breaks. Using Monte Carlo simulations, Maki (2012) demonstrated that the proposed test had better effect size and power than other cointegration with structural break tests (Gregory and Hansen, 1996; Hatemi J., 2008). The Maki (2012) cointegration test is based on the following four specifications:

Model 0: Level shift

$$\boldsymbol{y_t = \mu + \sum_{i=1}^{k} \mu_i D_{i,t}\ \beta' x_t + u_t}, \qquad \text{(Eq.3)}$$

Model 1: Level shift with trend

$$\boldsymbol{y_t = \mu + \sum_{i=1}^{k} \mu_i D_{i,t} + \beta' x_t + \sum_{i=1}^{k} \beta'_i x_t D_{i,t} + u_t}, \qquad \text{(Eq.4)}$$

Model 2: Regime shift and trend

$$\boldsymbol{y_t = \mu + \sum_{i=1}^{k} \mu_i D_{i,t} + \gamma t + \beta' x_t + \sum_{i=1}^{k} \beta'_i x_t D_{i,t} + u_t}, \qquad \text{(Eq.5)}$$

Model 3: Regime shift with trend

$$\boldsymbol{y_t = \mu + \sum_{i=1}^{k} \mu_i D_{i,t} + \gamma t + \sum_{i=1}^{k} \gamma_i t D_{i,t} + \beta' x_t + \sum_{i=1}^{k} \beta'_i x_t D_{i,t} + u_t}, \qquad \text{(Eq.6)}$$

Where $\boldsymbol{y_t}$ represents the dependent variables in Equations 1 and 2, i.e., the natural log of agricultural value added, $\boldsymbol{lnAGR_t}$, and the natural log of carbon emissions, $\boldsymbol{lnCO2_t}$. $\boldsymbol{x_t}$ represents the m-dimension vector of the explanatory variables. $\boldsymbol{x_t' = [lnCO2_t, LAND_t, lnENG_t, GFCF_t]}$ and $\boldsymbol{x_t' = [lnAGR_t, LAND_t, lnENG_t, GFCF_t]}$ are used in Equations 1 and 2, respectively. $\boldsymbol{u_t}$ is the white noise error term while $\boldsymbol{D_{i,t}}$ is a dummy variable taking the value 1 if $\boldsymbol{\tau > T_{Bi}}$ (i=1,.., k) and 0 otherwise, where k is the maximum number of breaks. $\boldsymbol{T_{Bi}}$ represents the time period of the break in the intercept, $\boldsymbol{\mu}$, and the vector slope coefficients, $\boldsymbol{\beta}$.

Based on these settings, the Maki (2012) cointegration test can be applied using the following steps if Model 1 is taken as the benchmark model. First, the maximum number of breaks (k) is determined and the model is estimated:

$$\boldsymbol{y_t = \mu + \mu_1 D_{1,t} + \beta' x_t + u_t}. \qquad \text{(Eq.7)}$$

The null hypothesis with $\boldsymbol{\rho} = 0$ is then tested against the alternative hypothesis with $\boldsymbol{\rho} < 0$ using the equation below:

$$\boldsymbol{\Delta\hat{u}_t = \rho\hat{u}_{t-1} + \sum_{j=1}^{p} \alpha_j \Delta\hat{u}_{t-j} + \varepsilon_t}, \qquad \text{(Eq.8)}$$

Where $\boldsymbol{\varepsilon_t}$ $(0, \sigma^2)$ and $\boldsymbol{\hat{u}_t}$ are the OLS residuals from the model 1. Based on the recursive estimation of the model above, a single break is searched, and t-statistics are computed to test for ρ=0 for all possible periods of the break. The set of all possible partitions and the t-statistics are denoted as $\boldsymbol{T_1^a}$ and τ_1, respectively. In the case of k=1, the minimum t-statistic in τ_1 is used as the test statistic.

In the second step, the first breakpoint is selected by minimizing the sum of the squares (SSR) as follows:

$$\boldsymbol{SSR_1 = \Sigma_{t=1}^{T} (y_t - \hat{\mu} - \hat{\mu}_1 D_{1-t} - \hat{\beta}' x_t)}^2, \qquad \text{(Eq.9)}$$

Where $\boldsymbol{\hat{\mu}}$, $\boldsymbol{\hat{\mu}_1}$, and β are the OLS estimates. Then the first breakpoint is denoted as $\boldsymbol{\widehat{bp}_1 = arg\ min\ SSR_1}$

In the third step, the estimated breakpoint $\boldsymbol{bp_1}$ is included to the regression model. Based on the similar procedure the second breakpoint is searched before t-statistics are used to test for ρ=0 for all possible periods of the second break using the regressions given by

[2] *Figure A1* shows the visual inspection of the series. *Table A2* contains the desctiptive statistics of the variables without natural log form for AGR_t, $CO2_t$ and ENG_t.

$$\boldsymbol{y_t = \mu + \mu_1 D_{1,t} + \mu_1 D_{2,t} + \hat{\beta}' x_t + u_t,} \quad \text{(Eq.10)}$$

$$\boldsymbol{\Delta\hat{u}_t = \rho\hat{u}_{t-1} + \sum_{j=1}^{p} \alpha_j \Delta\hat{u}_{t-j} + \varepsilon_t} \quad \text{(Eq.11)}$$

The set of all possible partitions and the statistics of $\boldsymbol{\rho}$ are denoted as $\boldsymbol{T_2^a}$ and τ_2, respectively. Furthermore, $\boldsymbol{\tau_p^2 = \tau_1 \cup \tau_2}$

In step four, as with estimation of the first breakpoint, the second breakpoint, bp_2, is estimated by minimizing $\boldsymbol{SSR_2}$ in the following equation:

$$\boldsymbol{SSR_2 = \Sigma_{t=1}^{T} (y_t - \hat{\mu} - \hat{\mu}_1 D_{1-t} - \hat{\beta}' x_t)}^2 \quad \text{(Eq.12)}$$

In the last step, the estimated first and second breakpoints are introduced into the model. Finally, steps 3 and 4 are repeated until the maximum number of breaks, k, is achieved. Finally, $\boldsymbol{\tau_{min}^k}$ is adopted as the t test statistic over the set $\boldsymbol{\tau_p^k = \tau_1 \cup \tau_2 \dots \cup \tau_k^2}$.

3.2. Single Fourier-frequency Toda and Yamamoto (2016) causality test

We first examined the agricultural activity–CO_2 emissions relationship using the Toda and Yamamoto (1995) Granger causality test, which estimates the VAR model with (p + d) order, where p is the lag length and d is the maximum integration degree of the variables. It thereby aims to eliminate the constraint of the same degree of integration of the series in the Granger causality test, as in the following VAR (p + d) model:

$$y_t = \alpha + \beta_1 y_{t-1} + \dots + \beta_{p+d} y_{t-(p+d)} + \epsilon_t \quad \text{(Eq.13)}$$

Where y_t represents the matrix of *k* endogenous variables $y_t{}' = [lnAGR_t, lnCO2_t, LAND_t, lnENG_t, GFCF_t]$. a and β represent the vector of the intercept and parameter matrices, respectively, while ϵ_t is the vector containing white noise error terms. Wald statistics with $\chi 2(p)$ degrees of freedom are used, where the null hypothesis of Granger non-causality is that the first *p* parameters are jointly equal to zero i.e., $H_0 : \beta_1 = \dots = \beta_p = 0$.

Some authors (e.g., Enders and Jones (2015), Ventosa-Santaulària and Vera-Valdés (2008)) have argued that if the data-generating process is subject to structural changes, the null hypothesis of noncausality can be rejected despite the lack of a significant causal relationship between the two variables. Hence, if breaks are not accounted for, inferences about the significance of the Granger causality analysis may be incorrect. To address these issues, Nazlioglu et al., (2016) suggested a Granger causality test based on Fourier approximation. This is superior to the alternative nonlinear causality test because the Fourier approximation avoids the need to know the number, dates, and types of breaks. Instead, it uses a few low-frequency elements to represent the structural transitions as a smooth process.

To accommodate structural changes, Nazlioglu et al., (2016) modify the assumption that the intercept terms are constant, such that the VAR model in Equation (13) is redefined as follows:

$$y_t = \alpha(t) + \beta_1 y_{t-1} + \dots + \beta_{p+d} y_{t-(p+d)} + \epsilon_t \quad \text{(Eq.14)}$$

Here, rather than being time variant, the intercept terms, α(t), are functions of time to model smooth structural shifts in y_t. To capture gradual, smooth shifts with an unknown date, number, and form of breaks, α(t) is modeled through one Fourier expansion as follows:

$$\alpha(t) = \alpha_0 + \sum_{k=1}^{n} \gamma_{1k} \sin\left(\frac{2\pi kt}{T}\right) + \sum_{k=1}^{n} \gamma_{2k} \cos\left(\frac{2\pi kt}{T}\right), \quad \text{(Eq.15)}$$

where k stands for the frequency for the approximation and n denotes the number of frequencies and γ_{1k} and γ_{2k} denote the frequency’s amplitude and displacement, respectively. Instead of a higher frequency version of the intercept term, Nazlioglu et al., (2016) use a single frequency component because the number of frequencies is most usually related with stochastic parameter change, which leads to over-fitting by reducing the degrees of freedom. Accordingly, the single frequency component α(t) is redefined as follows:

$$\alpha(t) = \alpha_0 + y_1 \sin\left(\frac{2\pi kt}{T}\right) + y_2 \cos\left(\frac{2\pi kt}{T}\right) \quad \text{(Eq.16)}$$

Hence, the final form of the estimated equation for the gradual-shift causality test is as follows:

$$y_t = \alpha_0 + y_1 \sin\left(\frac{2\pi kt}{T}\right) + y_2 \cos\left(\frac{2\pi kt}{T}\right) + \beta_1 Y_{t-1} + \cdots + \beta_{p+d} y_{t-(p+d)} + \epsilon_t. \quad \text{(Eq.17)}$$

Here, the null hypothesis of Granger non-causality is tested in the same way as in the linear Toda and Yamamoto (1996) test presented in Equation (13), i.e. $H_0 : \beta_1 = \ldots = \beta_p = 0$. In order to increase the power of the test statistic in small samples while maintaining its robustness from the unit root and cointegration properties of the data, Nazlioglu et al., (2016) used the residual sampling bootstrap approach introduced by Efron (1979). The lag length of the VAR model p and frequency k are selected based on the minimum value of the information criterion.

4. Results and Discussion

4.1. Unit root tests

This section first considers the variables' unit root properties as shown in the Augmented Dickey and Fuller (1981), Phillips and Perron (1988), and Zivot and Andrews (1992) unit root test results, presented in *Table 3*. The linear unit root tests indicate that the unit root null hypothesis cannot be rejected for the levels of all series. However, it can be rejected after the first difference transformation of the variables. That is, all series can be treated as first difference stationary, i.e., I(1). In addition to the linear unit root tests, *Table 3* also shows the Zivot and Andrews (1992) unit root test results, which account for endogenous structural breaks. The results confirm the I (1) properties of the variables, as evidenced by the ADF and PP test results. This further indicates that the level of the variables contains a unit root with a significant structural break. The significant breaking dates obtained for some of the variables, namely 1982, 2001, 2007, and 2008, are associated with crisis periods.

Table 3. Unit Root Results

Variable	ADF		PP		Zivot and Andrews	
	I	I/T	I	I/T	Model A	Model C
$lnAGR_t$	1.21119 (1)	-0.87015 (1)	1.80089	-2.39450	-2.41100 (3) (2010)	-4.19287 (3) (2001)
$LnCO2_t$	-2.17432 (0)	-3.27227 (0)	-2.48737	-3.27529	-4.14442 (0) (2001)	-4.01409 (0) (2001)
$LAND_t$	-1.73336 (0)	-1.31479 (0)	-1.83769	-1.44427	-3.16379 (0) (2007)	-3.31020 (0) (1998)
$lnENG_t$	-1.44788(0)	-2.21067(0)	-1.47910	-2.25222	-3.04293 (0) (1982)	-4.06777 (0) (2008)
$GFCF_t$	-1.53217(0)	-2.98077(0)	-1.48054	-3.14246	-4.38833 (1) (1998)	-4.33980 (1) (1987)
$\Delta lnAGR_t$	-12.1163***(0)	-12.3363***(0)	-12.2735***	-27.0988***	-7.3797*** (4) (2005)	-7.2848*** (4) (2005)
$\Delta lnCO2_t$	-7.09263*** (0)	-7.40330*** (0)	-7.09324***	-7.45905***	-8.0732*** (0) (1978)	-8.2745*** (0) (1982)
$\Delta LAND_t$	-6.54591***(0)	-6.54384***(0)	-6.55681***	-6.54839***	-7.7085*** (0) (1984)	-7.6153*** (0) (1984)
$\Delta lnENG_t$	-7.08946***(0)	-7.15296***(0)	-7.08968***	-7.19996***	-7.5304*** (0) (1980)	-7.9341*** (0) (1980)
$\Delta GFCF_t$	-6.60696***(0)	-6.54070***(0)	-6.80615***	-6.71654***	-6.8008*** (0) (1989)	-6.7661*** (0) (1989)

Notes: *** denotes the series is stationary at the 1% significance level; I=intercept; T=trend. In the ADF tests, the SIC (Schwarz Information Criterion) is used to determine the optimum number of lags to a maximum of 10 lags. The bandwidth of the PP test is determined using the Newey-West method using the Bartlett kernel. Likewise, in the Zivot and Andrews test, which takes structural breaks into account, the maximum lag was searched up to 4 lags based on the minimum value of the t statistics. The values in parentheses indicate the optimum number of lags of the augmented part for the ADF and Zivot and Andrews tests.

4.2. Cointegration and causality test results

After applying the unit root tests to demonstrate the variables' first-difference stationarity, cointegration tests were applied to the long-run associations in Equation (1). More specifically, the Johansen and Juselius (1990) cointegration test was implemented to analyze the linear long-run relationship (see *Table 4*). The Maki (2012) cointegration test was used to investigate the variables' nonlinear long-run relationship. The test findings are shown in *Table 5*, panels (a) and (b), respectively.

Table 4. Johansen cointegration results

Hypothesized	Trace result			Max Eigenvalue result		
	Eigenvalue	**Statistic**	**Critical Value (0.05)**	**Eigenvalue**	**Statistic**	**Critical Value (0.05)**
None *	0.618756	101.0401	76.97277	0.618756	47.25142	34.80587
At most 1	0.343437	53.78869	54.07904	0.343437	20.61609	28.58808
At most 2	0.283467	33.17260	35.19275	0.283467	16.33319	22.29962
At most 3	0.201516	16.83941	20.26184	0.201516	11.02696	15.89210
At most 4	0.111856	5.812456	9.164546	0.111856	5.812456	9.164546

* Denotes rejection of the hypothesis at the 0.05 level.

Table 5. Maki Cointegration Test Results

Panel a. Dependent Variable $lnAGR_t$					
Model	**Test Statistics**	**Critical Value**			**Break Date**
		1%	**5%**	**10%**	
0	-5.4538155	−6.856	−6.306	−6.039	1975/1985/1998/2008/2012
1	-8.9773321***	−7.053	−6.494	−6.220	1971/1974/1998/2002/2008
2	-7.6119198	−8.336	−7.803	−7.481	1982/1990/1995/2007/2012
3	-8.0555682	−10.08	−9.482	−9.151	1975/1986/1995/2004/2012
Panel b. Dependent Variable $lnCO2_t$					
Model	**Test Statistics**	**Critical Value**			**Break Date**
		1%	**5%**	**10%**	
0	-6.3435031**	−6.856	−6.306	−6.039	1973/1977/1995/2011/2015
1	-5.4904613	−7.053	−6.494	−6.220	1973/1976/1997/2000/2007
2	-7.0583022	−8.336	−7.803	−7.481	1981/1988/1993/1999/2006
3	-6.4519885	−10.08	−9.482	−9.151	1978/1987/1997/2003/2009

Note: **, *** denote significant at the at 5% and 1%, respectively. The maximum lag length is taken as 3. 1000 bootstrap was used.

The Johansen cointegration results indicate that the null hypothesis of no cointegration can be rejected because the trace and max eigenvalue test statistics show that the variables include at least one cointegrating vector. Given that the statistical significance of long-run relationships indicated by linear cointegration tests may be misleading, the Maki cointegration was also implemented based on Equations 1 and 2. Here, agricultural value-added, and CO_2 emissions were employed as the dependent variables (see *Table 5*), thereby enabling up to five structural breaks to be tested for cointegration.

The test results corroborated the results of the Johansen test by rejecting the null hypothesis of no cointegration. However, *Table 5* indicates that the cointegrating relationships are subject to structural shifts in both models. As already noted, the breaking dates coincide with significant local and global economic events that affected Turkish's economy. When agricultural value added is the dependent variable, the breaking dates of 1971 and 1974 both coincide with the oil crisis, while the breaking dates of 2002 and 2008 coincide with Türkiye's 2001 financial crisis and the 2008 global financial crisis. Similarly, when CO2 emissions are the dependent variable, the breaking dates of 1973 and 1977 coincide with the 1970s' global oil crisis.

Table 6. Long-Run Coefficient Estimates: lnAGR$_t$ dependent variable

	FMOLS		CCR	
Variable	**Coefficient**	**Std. Error**	**Coefficient**	**Std. Error**
$lnCO2_t$	0.367689***	0.028980	0.373403***	0.033002
$LAND_t$	-0.010984***	0.003390	-0.010830**	0.004044
$lnENG_t$	-0.164949***	0.021127	-0.168943***	0.022531
$GFCF_t$	0.007562***	0.001441	0.007421***	0.001713
C	21.65796***	0.249539	21.61835***	0.292924
DUM1971	-0.080809***	0.016012	-0.082545***	0.016799
DUM1974	0.027658*	0.014544	0.027487*	0.015030
DUM1998	0.071604***	0.016758	0.069931***	0.019502
DUM2002	-0.007469	0.014192	-0.006647	0.014432
DUM2008	0.129407***	0.014632	0.129774***	0.017666

Note: *, **, *** denote significant at the at 10%, 5% and 1% respectively.

Table 7. Long-Run Coefficient Estimates: lnCO2$_t$ dependent variable

	FMOLS		CCR	
Variable	**Coefficient**	**Std. Error**	**Coefficient**	**Std. Error**
$lnAGR_t$	0.554916***	0.171254	0.578763**	0.218420
$LAND_t$	0.027145***	0.007672	0.028575***	0.008256
$lnENG_t$	0.535268***	0.047548	0.530739***	0.054319
$GFCF_t$	0.006681*	0.003436	0.006547*	0.003736
C	-7.605921*	4.040726	-8.218490	5.110718
DUM1973	0.106868***	0.037011	0.107688***	0.037351
DUM1977	0.164025***	0.032521	0.161703***	0.033721
DUM1995	0.100781***	0.036002	0.097140**	0.039411
DUM2011	0.122884**	0.047880	0.122268**	0.059637
DUM2015	0.156903***	0.042196	0.152421***	0.046492[3]

Note: *, **, *** denote significant at the at 10%, 5% and 1% respectively.

After confirming cointegration under multiple structural breaks, the long-run coefficients were estimated with full modified ordinary least squares (FMOLS) and canonical cointegrating regression (CCR) estimators (see *Tables 6* and *7*). For the estimation of the long-run parameters, following Ike et al. (2020) and Khan et al. (2020), dummy variables were constructed to determine the impact of structural breaks on the long-run parameters. As *Tables 6* and *7* indicated, these parameters were both statistically significant and yielded qualitatively the same results. Therefore, we interpreted the FMOLS parameter estimates for both equations. It is worth noting that all other structural break dates, with the exception of 2002, were significant at the 1% significance level. This suggests that the break dates from the Maki cointegration test are significant and ought to be included in the long-run parameter estimates.

Regarding the agricultural productivity model results, CO_2 emissions significantly increased agricultural productivity, in line with Wang's (2022) findings for China. All other variables were statistically significant at the one-percent level. An increase in land area devoted to agriculture significantly reduced agricultural productivity ($lnAGR_t$). This suggests that expanding arable farming may not improve agricultural sector efficiency, which may instead depend on rising capital formation.

[3] Diagnostic tests were conducted on the estimated models and are not presented in the text to save space in the paper. For example, the correlogram of residuals for the long-run estimation of model 2 is presented in the appendix.

Regarding the long-run coefficients when the model's dependent variable was CO_2 emissions, agricultural productivity significantly increased CO_2 emissions. This indicates that, in Türkiye, rising agricultural activity reduces environmental quality. The control variables also significantly increased CO_2 emissions. According to the FMOLS estimator, the LAND, ENG, and GFCF parameter coefficients were 0.027, 0.535, and 0.006, respectively, while similar coefficients were obtained from the CCR estimator.

Table 8. Error Correction Model Results

Panel (a): Dependent Variable $lnAGR_t$				
Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Probability**
$\Delta \mathbf{ln}CO2_t$	0.178403*	0.099716	1.789109	0.0805
$\Delta LAND_t$	-0.014309**	0.006772	-2.112893	0.0403
ΔENG_t	-0.100472**	0.041635	-2.413167	0.0200
$\Delta GFCF_t$	0.004677*	0.002343	1.996752	0.0521
ECM_{t-1}	-1.130477***	0.163053	-6.933187	0.0000
C	0.009941	0.006164	1.612650	0.1140
Panel (b): Dependent Variable $lnCO2_t$				
Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Probability**
$\Delta \mathbf{ln}AGR_t$	-0.036636	0.157673	-0.232357	0.8173
$\Delta LAND_t$	-0.011212	0.010221	-1.097022	0.2786
$\Delta \mathbf{ln}ENG_t$	0.127391*	0.065043	1.958554	0.0565
$\Delta GFCF_t$	0.009664***	0.003395	2.846465	0.0067
ECM_{t-1}	-0.338889**	0.127656	-2.654700	0.0110
C	0.041540***	0.007316	5.677594	0.0000

Note: *, **, and *** denotes significant at the at 10%, 5%, and 1% level, respectively.

Having estimated the long-run parameters, we then estimated the error correction models for the agricultural productivity and CO_2 emissions equations to analyze the dynamics of the short-run relationship. Based on Granger's representation theorem, the error correction term indicates how rapidly a dependent variable returns to equilibrium following a change in the other variables (Engle and Granger, 1987). *Table 8*, Panel (a), shows that the error correction term was negative and statistically significant for the agricultural productivity equation. That is, short-run imbalances in the system are corrected in the long run. Regarding the short-run coefficients, the short-run impact of CO_2 emissions is positive and statistically significant, as with the long-run estimates. The remaining variables have similar parameter estimates for both the long-run and short-run coefficients. *Table 8*, Panel (b), shows the error correction results for the CO_2 model. As with the agricultural productivity equation, there is a statistically significant negative error correction coefficient. This indicates that deviations from the long-run equilibrium are eliminated in the short run. Furthermore, increases in energy consumption and gross fixed capital formation have statistically significant positive impacts, similar to the long-run estimates in *Table 7*. However, the agricultural productivity parameter is statistically insignificant in the short run. This indicates that the error correction mechanism is functioning properly in both models.

Following the time series analysis of the agricultural productivity and CO_2 equations, the linear and regime-shifting Toda-Yamamoto causality tests were performed to identify any interactions between the variables (Table 9). Based on the linear causality test results, there is a one-way causal relationship, significant at the 5% level, from agricultural value added to the CO_2 emissions, and a one-way causal relationship, significant at the 10% level, from CO_2 emissions to agricultural land area. Given that the Maki's (2012) cointegration test indicated structural breaks in the data, a gradual-shift causality test was conducted. The results confirmed the linear Toda-Yamamoto causality test findings, i.e. the causal relationship runs from agricultural value added to CO_2 emissions.

Table 9. Causality Tests Results

	Toda & Yamamoto					Single Fourier-frequency Toda & Yamamoto				
Null hypothesis	**Wald st.**	**Bootstrap p-value.**	**d**	**p**	**f**	**Wald ist.**	**Bootstrap p-value**	**d**	**p**	**f**
$lnCO2_t \neq> lnAGR_t$	0.97586	0.64500	1	2	0	0.08880	0.94900	1	2	1
$LAND_t \neq> lnAGR_t$	0.73955	0.71200	1	2	0	0.27930	0.86600	1	2	1
$GFCF_t \neq> AGR_t$	0.00328	0.99700	1	2	0	0.41929	0.81400	1	2	1
$ENG_t \neq> lnAGR_t$	1.02208	0.60900	1	2	0	0.23805	0.88600	1	2	1
$lnAGR_t \neq> lnCO2_t$	9.15924**	0.01700	1	2	0	9.73685**	0.01200	1	2	1
$LAND_t \neq> lnCO2_t$	1.70389	0.44500	1	2	0	0.95943	0.63400	1	2	1
$GFCF_t \neq> lnCO2_t$	3.62570	0.16900	1	2	0	3.77221	0.17100	1	2	1
$lnENG_t \neq> lnCO2_t$	4.21913	0.13200	1	2	0	4.47276	0.13300	1	2	1
$lnAGR_t \neq> LAND_t$	3.63190	0.18000	1	2	0	1.62905	0.43500	1	2	1
$lnCO2_t \neq> LAND_t$	5.61466***	0.07600	1	2	0	3.30327	0.20600	1	2	1
$GFCF_t \neq> LAND_t$	1.42637	0.51300	1	2	0	0.74254	0.70600	1	2	1
$lnENG_t \neq> LAND_t$	1.65944	0.44100	1	2	0	2.68300	0.28100	1	2	1
$lnAGR_t \neq> GFCF_t$	2.40039	0.30900	1	2	0	2.84314	0.22400	1	2	1
$lnCO2_t \neq> GFCF_t$	2.21921	0.35700	1	2	0	2.55863	0.29900	1	2	1
$LAND_t \neq> GFCF_t$	0.29445	0.86500	1	2	0	3.16510	0.21100	1	2	1
$lnENG_t \neq> GFCF_t$	0.91726	0.60000	1	2	0	0.22564	0.90300	1	2	1
$lnAGR_t \neq> lnENG_t$	0.27264	0.88200	1	2	0	0.14066	0.91600	1	2	1
$lnCO2_t \neq> lnENG_t$	2.47495	0.28300	1	2	0	1.77270	0.39700	1	2	1
$LAND_t \neq> lnENG_t$	0.47725	0.76500	1	2	0	1.51865	0.48400	1	2	1
$GFCF_t \neq> lnENG_t$	1.34487	0.48300	1	2	0	0.22335	0.88300	1	2	1

Notes: ** and * denote significance at 5% and 10% level, respectively. The maximum lag length p was selected as 3 for both tests. d=dmax, p= lag length, f= frequency, 1000 bootstrap was used.

5. Conclusions

This study analyzed both the long-run and short-run relationships between CO_2 emissions and agricultural productivity in Türkiye. Our research differed from the literature on several aspects. First, we adopted novel methodologies in which the interactions between CO_2 and agricultural production were presumed to be nonlinear. To this end, we applied both the Maki (2012) cointegration and gradual-shift causality tests developed by Nazlioglu et al., (2016). Second, in contrast with prior studies, CO_2 emissions due to agriculture have been employed instead of total CO_2 in the regression analysis.

The cointegration analysis confirmed the long-run association between CO_2 and agricultural productivity. However, the Maki (2012) cointegration test results indicated that this relationship is subject to structural changes due to local and global events affecting Türkiye's economy. Therefore, a mutually positive relationship between agricultural productivity and CO_2 emissions has been confirmed by the long run parameter estimates. The positive and statistically significant association between CO_2 emissions and the agriculture industry is aligned with the results of some prior studies, e.g. Islam et al. (2014), Khalid et al. (2016) and Wang (2022). The adverse impact of agricultural activity on environmental quality can be linked to important climate change drivers, such as livestock activities, fertilizer use, land use, and soil cultivation methods, which deserve further investigation. The long-run coefficient estimates imply that an expansion in farmland reduces agricultural productivity while raising CO_2 emissions. That is, expanding the arable land area in Türkiye may not be a viable solution for increasing agricultural efficiency. In accordance with the findings of Wang (2022), the adverse environmental effects resulting from the escalation of agricultural activities in Türkiye can be ascribed to the growing reliance on fossil fuels within the agricultural sector, thereby leading to an elevation in greenhouse gas emissions. The aforementioned findings underscore the imperative of transitioning Türkiye's agricultural technologies and energy consumption towards environmentally sustainable practices. Moreover, the outcomes of both the linear and gradual shift causality tests demonstrated a unidirectional causal association running from agricultural productivity to CO_2 emissions. This evidence is consistent with the findings reported by Qiao et al. (2019), Waheed et al. (2018), Jebli and Youssef (2019), Ngarava et al. (2019), and Çetin et al. (2020). This finding suggests that there is a need to enhance the environmental sustainability of agricultural production tools in Türkiye.

In light of our research, it is evident that proactive measures ought to be implemented in order to mitigate the factors that contribute to climate change. Several potential strategies could be contemplated for adoption, encompassing enhanced management practices pertaining to agricultural land utilization, regulation of water supply, collection and reutilization of wastewater, prevention of deforestation, and the cultivation of plant species that exhibit resistance to drought conditions. The implementation of these measures is expected to yield positive outcomes for the advancement of the agricultural sector and the mitigation of climate change. As additional data becomes accessible, forthcoming investigations may incorporate a broader time span to examine the aforementioned variables that influence agricultural productivity.

Ethical Statement

There is no need to obtain permission from the ethics committee for this study.

Conflicts of Interest

We declare that there is no conflict of interest between us as the article authors.

Authorship Contribution Statement

Concept: İbrahim ÜRKMEZ, Ahmet SEVİM Design: İbrahim ÜRKMEZ, Abdurrahman Nazif ÇATIK.; Data Collection or Processing: İbrahim ÜRKMEZ, Abdurrahman Nazif ÇATIK.; Statistical Analyses: İbrahim ÜRKMEZ, Abdurrahman Nazif ÇATIK.; Literature Search İbrahim ÜRKMEZ, Ahmet SEVİM; Writing, Review and Editing: İbrahim ÜRKMEZ, Ahmet SEVİM, Abdurrahman Nazif ÇATIK.

References

Adams, R. M., Hurd, B. H., Lenhart, S. and Leary, N. (1998). Effects of global climate change on agriculture: An interpretative review. *Climate Research*, 11(1): 19–30. https://doi.org/10.3354/cr011019

Başoğlu, A. and Telatar, O. M., (2013). İklim değişikliğinin etkileri: Tarım sektörü üzerine ekonometrik bir uygulama. *Karadeniz Teknik Üniversitesi Sosyal Bilimler Enstitüsü Sosyal Bilimler Dergisi*, 3(6): 7-25. (In Turkish)

Bayraç, H. N. and Doğan, E. (2016). Impacts of climate change on agriculture sector in Turkey. *Eskişehir Osmangazi University Journal of Economics and Administrative Sciences*, 11(1): 23–48.

Ben Jebli, M. and Ben Youssef, S. (2017). Renewable energy consumption and agriculture: evidence for cointegration and Granger causality for Tunisian economy. *International Journal of Sustainable Development and World Ecology*, 24(2): 149–158. https://doi.org/10.1080/13504509.2016.1196467

Brown, C., Meeks, R., Ghile, Y. and Hunu, K. (2010). *An Empirical Analysis of the Effects of Climate Variables on National Level Economic Growth Background Paper to the 2010 World Development Report*. http://econ.worldbank.org (Accessed dDate: 29.11.2022).

Çetin, M., Saygin, S. and Demir, H. (2020). The impact of agricultural sector on environmental pollution: A cointegration and causality analysis for Turkish economy. *Journal of Tekirdag Agricultural Faculty*, 17(3): 329–345. https://doi.org/10.33462/jotaf.678764

Dellal, D., Mccarl, B. A. and Butt, T. (2011). The economic assessment of climate change on Turkish agriculture. *Journal of Environmental Protection and Ecology*, 12(1): 376–385.

Dickey, D. and Fuller, W. A. (1981). Likelihood ratio statistics for autoregressive time series with a unit root. *Econometrica*, 49(4): 1057–1072.

Dumrul, Y. and Kilicarslan, Z. (2017). Economic impacts of climate change on agriculture: Empirical evidence from the ARDL approach for Turkey. *Pressacademia*, 6(4): 336–347. https://doi.org/10.17261/pressacademia.2017.766

Efron, G. (1979). Bootstrap methods: another look at the jackknife. *The Annals of Statistics*, 7(1): 1–26.

Enders, W. and Jones, P. (2015). Grain prices, oil prices, and multiple smooth breaks in a VAR. *Studies in Nonlinear Dynamics and Econometrics*, 20(4): 399–419. https://doi.org/10.1515/snde-2014-0101

Engle, R. F. and Granger, C. W. J. (1987). Co-integration and error-correction: Representation, estimation and testing. *Econometrica*, 55: 251-256.

Gregory, A. W., & Hansen, B. E. (1996). Residual-based tests for cointegration in models with regime shifts. *Journal of Econometrics*, *70*(1), 99–126. https://doi.org/10.1016/0304-4076(69)41685-7

Hatemi-J., A. (2008). Tests for cointegration with two unknown regime shifts with an application to financial market integration. *Empirical Economics*, 35(3): 497–505. https://doi.org/10.1007/s00181-007-0175-9

Hayaloğlu, P. (2018). İklim değişikliğinin tarım sektörü ve ekonomik büyüme üzerindeki etkileri. *Gümüşhane Üniversitesi Sosyal Bilimler Enstitüsü Elektronik Dergisi*, 9(25): 51–62.

IEA (2022). *International Energy Agency*. https://www.iea.org/, (Accessed Date: 20.11.2022).

Ike, G. N., Usman, O. and Sarkodie, S. A. (2020). Fiscal policy and CO2 emissions from heterogeneous fuel sources in Thailand: Evidence from multiple structural breaks cointegration test. *Science of the Total Environment*, 702: 134711 https://doi.org/10.1016/j.scitotenv.2019.134711

Islam, Md. S., Tarique, K. Md. and Sohag, K. (2014). Co2 Emission and agricultural productivity in Southeast Asian Region: A pooled mean group estimation. *A Scientific Journal of COMSATS-SCIENCE VISION*, 18(1–2): 29–38.

Jebli, B. M. and Youssef, S. B. (2019). Combustible renewables and waste consumption, agriculture, CO2 emissions and economic growth in Brazil. *Carbon Management*, 10(3): 309–321. https://doi.org/10.1080/17583004.2019.1605482

Jebli, M. B. and Youssef, S. B. (2017). The role of renewable energy and agriculture in reducing CO2 emissions: Evidence for North Africa countries. *Ecological Indicators*, 74: 295-301.

Johansen, S. and Juselius, K. (1990). Maximum likelihood estimation and inference on cointegration — with applications to the demand for money. *Oxford Bulletin of Economics and Statistics*, 52(2): 169–210. https://doi.org/10.1111/j.1468-0084.1990.mp52002003.x

Khalid, A. A., Mahmood, F. and Rukh, G. (2016). Impact of climate changes on economic and agricultural value added share in GDP. *Asian Management Research Journal*, 1(1): 35–48.

Khan, Z., Hussain, M., Shahbaz, M., Yang, S. and Jiao, Z. (2020). Natural resource abundance, technological innovation, and human capital nexus with financial development: A case study of China. *Resources Policy*, 65: 101585 https://doi.org/10.1016/j.resourpol.2020.101585

Konukcu, F., Deveci, H. and Altürk, B. (2020). Modelling of the effect of climate change on wheat yield in Thrace Region with AquaCrop and WOFOST models. *Journal of Tekirdag Agricultural Faculty*, 17(1): 77-96. https://doi.org/10.33462/jotaf.593883

Liu, H., Li, X., Fischer, G. and Sun, L. (2004). Study on the impacts of climate change on China's agriculture. *Climatic Change*, 65(1–2): 125–148. https://doi.org/10.1023/B:CLIM.0000037490.17099.97

Maki, D. (2012). Tests for cointegration allowing for an unknown number of breaks. *Economic Modelling*, 29(5): 2011–2015. https://doi.org/10.1016/j.econmod.2012.04.022

Masud, M. M., Rahman, M. S., Al-Amin, A. Q., Kari, F. and Filho, W. L. (2014). Impact of climate change: An empirical investigation of Malaysian rice production. *Mitigation and Adaptation Strategies for Global Change*, 19(4): 431–444. https://doi.org/10.1007/s11027-012-9441-z

Nazlioglu, S., Gormus, N. A. and Soytas, U. (2016). Oil prices and real estate investment trusts (REITs): Gradual-shift causality and volatility transmission analysis. *Energy Economics*, 60: 168–175. https://doi.org/10.1016/j.eneco.2016.09.009

Ngarava, S., Zhou, L., Ayuk, J. and Tatsvarei, S. (2019). Achieving food security in a climate change environment: Considerations for environmental kuznets curve use in the South African agricultural sector. *Climate*, 7(9): 108. https://doi.org/10.3390/cli7090108

Olanipekun, I. O., Olasehinde-Williams, G. O. and Alao, R. O. (2019). Agriculture and environmental degradation in Africa: The role of income. *Science of the Total Environment*, 692: 60–67. https://doi.org/10.1016/j.scitotenv.2019.07.129

Pakdemirli, B. (2020). CO_2 Impacts of CO_2 emissions on agriculture: Empirical evidence from Turkey. *Derim*, 37(1): 33–43. https://doi.org/10.16882/derim.2020.700482

Phillips, P. C. B. and Perron, P. (1988). Testing for unit roots in time series regression. *Biometrika*, 75(2): 335-346. https://doi.org/10.2307/2336182

Qiao, H., Zheng, F., Jiang, H. and Dong, K. (2019). The greenhouse effect of the agriculture-economic growth-renewable energy nexus: Evidence from G20 countries. *Science of the Total Environment*, 671: 722–731. https://doi.org/10.1016/j.scitotenv.2019.03.336

Rosenzweig, C. and Parry, M. L. (1994). Potential impact climate change on world food supply. *Nature*, 367: 133–138.

Toda, H. Y. and Yamamoto, T. (1995). Statistical inference in vector autoregressions with possibly integrated processes. *Journal of Econometrics*, 66(1-2): 225-250. https://doi.org/10.1016/0304-4076(94)01616-8

TSMS. (2022). Turkish State Meteorological Service. https://www.mgm.gov.tr/FILES/resmi-istatistikler/parametreAnalizi/2021-ortalama-sicaklik.pdf (Accessed Date: 10.12.2022).

TURKSTAT. (2021). Turkish Statistical Institute. https://data.tuik.gov.tr/Bulten/Index?p=Greenhouse-Gas-Emissions-Statistics-1990-2019-37196 (Accessed Date: 10.12.2022).

Ventosa-Santaulària, D. and Vera-Valdés, J. E. (2008). Granger-Causality in the presence of structural breaks. *Economics Bulletin,* 3(61): 1-14.

Waheed, R., Chang, D., Sarwar, S. and Chen, W. (2018). Forest, agriculture, renewable energy, and CO2 emission. *Journal of Cleaner Production*, 172: 4231–4238. https://doi.org/10.1016/j.jclepro.2017.10.287

Wang, H. (2022). Role of environmental degradation and energy use for agricultural economic growth: Sustainable implications based on ARDL estimation. *Environmental Technology and Innovation*, 25: 1–12. https://doi.org/10.1016/j.eti.2021.102028

World Bank. (2022). World Development Indicators. https://databank.worldbank.org/source/world-development-indicators (Accessed date: 20.11.2022).

Zafeiriou, E. and Azam, M. (2017). CO_2 emissions and economic performance in EU agriculture: Some evidence from Mediterranean countries. *Ecological Indicators*, 81: 104–114. https://doi.org/10.1016/j.ecolind.2017.05.039

Zivot, E. and Andrews, D. W. K. (1992). Further Evidence on the Great Crash, the Oil-Price Shock, and the Unit-Root Hypothesis. *Journal of Business & Economic Statistics* 10(3): 251-270. https://doi.org/10.2307/1391541

Table A1. Description of the variables

Notation	Definition	Unit	Source
AGR_t	Agriculture, forestry, and fishing (Value added)	2015 US$	WB (WDI)
CO_{2t}	Agricultural sector CO_2 emissions	Tonnes	IEA
$LAND_t$	Agricultural land	Percentage of total land area	WB (WDI)
ENGt	Agricultural energy consumption	Kilotonnes of oil equivalent (ktoe)	IEA
$GFCF_t$	Gross fixed capital formation	Percentage of GDP	WB (WDI)

Table A2. Descriptive statistics of the variables

	AGR_t	CO_{2t}	$LAND_t$	*ENGt*	$GFCF_t$
Mean	38500	160890.7	50.71169	2419.262	21.43254
Median	36000	140333.1	50.44762	2409.989	22.80306
Maximum	62000	378628.2	53.5621	5342.634	29.85714
Minimum	26100	31890.07	47.70864	583.4623	11.87302
Std. Dev.	975000	97376.58	1.40838	1404.081	5.550205
Skewness	0.8881	0.5564	0.3291	0.3782	-0.1318
Kurtosis	2.8476	2.2326	2.4418	1.9538	1.6608
Jarque-Bera	6.7537	3.8827	1.5827	3.5416	3.9586
J-B Probability	0.0342	0.1435	0.4532	0.1702	0.1382

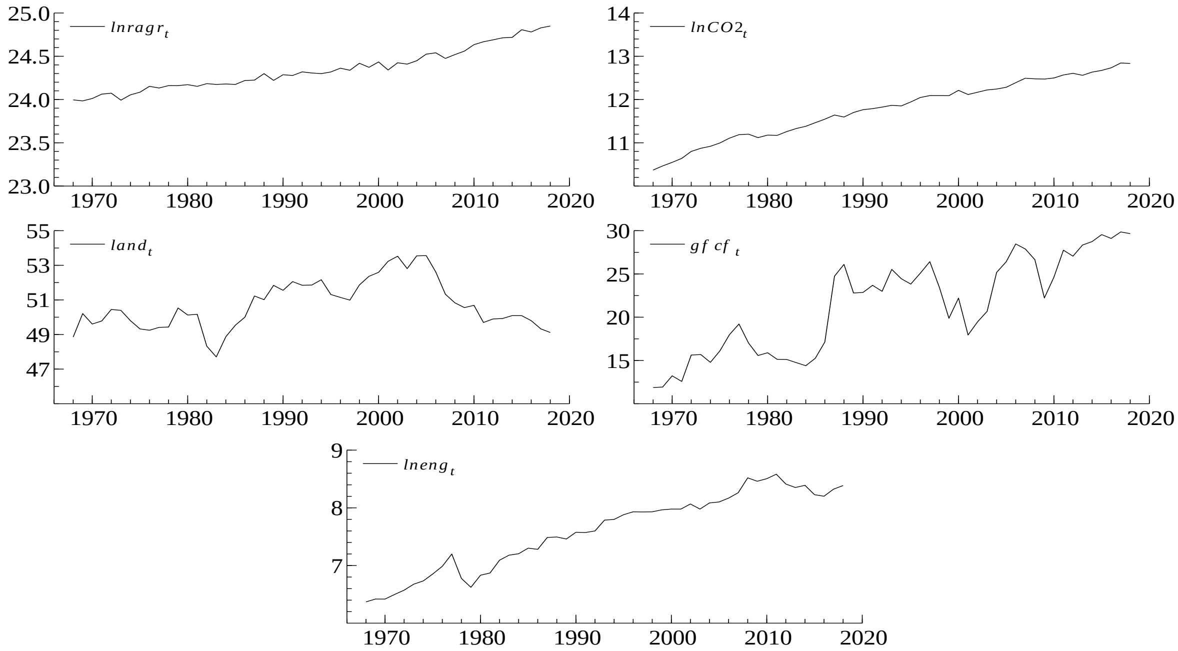
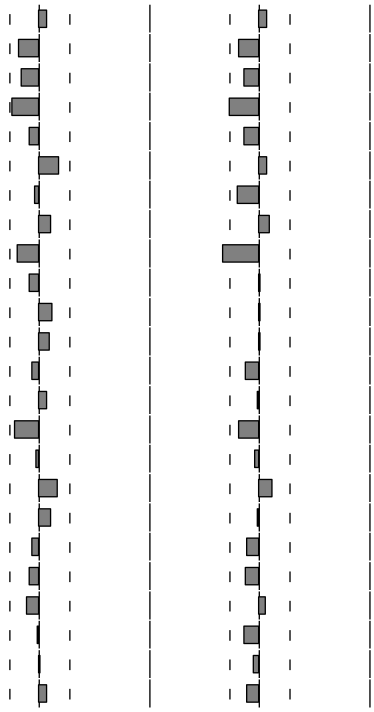


Figure A1. Time series plot of data

Sample (adjusted): 1969 2018
Included observations: 50 after adjustments



Autocorrelation / Partial Correlation	AC	PAC	Q-Stat	Prob*
1	0.078	0.078	0.3215	0.571
2	-0.187	-0.194	2.2189	0.330
3	-0.161	-0.134	3.6495	0.302
4	-0.249	-0.279	7.1533	0.128
5	-0.097	-0.146	7.6940	0.174
6	0.192	0.076	9.8615	0.131
7	-0.035	-0.197	9.9365	0.192
8	0.116	0.094	10.766	0.215
9	-0.198	-0.342	13.247	0.152
10	-0.089	0.004	13.762	0.184
11	0.126	0.008	14.820	0.191
12	0.101	-0.001	15.518	0.214
13	-0.063	-0.125	15.801	0.260
14	0.076	-0.014	16.217	0.300
15	-0.221	-0.190	19.857	0.177
16	-0.032	-0.036	19.935	0.223
17	0.180	0.124	22.489	0.167
18	0.120	-0.011	23.661	0.166
19	-0.062	-0.114	23.986	0.197
20	-0.083	-0.129	24.582	0.218
21	-0.113	0.062	25.722	0.217
22	-0.008	-0.132	25.728	0.264
23	-0.005	-0.048	25.730	0.314
24	0.078	-0.118	26.342	0.336

Figure A2. Model 2 correlogram of residuals