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Impacts of CO_2 emissions on agriculture: empirical evidence from Turkey

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Abstract

There are ongoing debates around the world regarding the effects of climate change on agriculture. All sectors are known to be affected by climate change, and the agricultural sector is no exception. The present study investigates the effects of climate change on agriculture in Turkey in the 1961-2018 period. In order to determine the link between the variables, an Autoregressive Distributed Lag (ARDL) bounds testing approach to co-integration and Vector Autoregressive (VAR) analysis are applied. Results of the study show that CO_2 emissions have a significant impact on agriculture. Thus, as Turkey's population increases, food sufficiency and security will emerge as more important issues over the next decade, it is vital to take adaptive measures to cope with climate change and its impact on agriculture.

Keywords: Agricultural output; CO_2 emissions; Climate change; VAR analysis; ARDL

CO_2 emisyonlarının tarım üzerindeki etkileri: Türkiye örneği

Öz

İklim değişikliğinin tarım üzerindeki etkileri konusunda dünya çapında devam eden tartışmalar bulunmaktadır. Tüm sektörlerin iklim değişikliğinden etkilendiği bilinmektedir ve tarım sektörü bu etkiden istisna değildir. Bu çalışma, iklim değişikliğinin Türkiye'de tarım üzerindeki etkilerini 1961-2018 dönemi için araştırmaktadır. Değişkenler arasındaki bağlantıyı belirlemek için, eş-bütünleşmeye bir gecikmesi dağıtılmış otoregresif (ARDL) sınır testi yaklaşımı ve vektör otoregresif (VAR) analiz uygulanmıştır. Çalışmanın sonuçları, CO_2 emisyonlarının tarım üzerinde önemli bir etkiye sahip olduğunu göstermektedir. Dolayısıyla, Türkiye'nin nüfusu artışı ile beraber, gıda yeterliliği ve güvenliği önümüzdeki on yıl içinde daha önemli konular olarak ortaya çıkacak ve iklim değişikliğinin etkilerini göz önünde tutan önlemlerin alınması elzem olacaktır.

Anahtar Kelimeler: Tarımsal üretim; CO_2 emisyonları; İklim değişikliği; VAR analizi, ARDL

1. Introduction

Carbon dioxide (CO_2) emissions affect all sectors around the world. For this reason, economic analyses have been made of its effect on many different sectors, such as agriculture, industrial production and services (Wang et al., 2018). Kyoto Protocol and European Union (EU) Decision 280/2004/EC report on greenhouse gas emissions. Under the Kyoto Protocol, new EU member states and candidate countries are given different targets for different base years. The available statistics relating to the environment include; water, wastewater, solid waste, air emission, air quality, biodiversity, environmental expenditures, environmental employment, climate statistics, soil pollution, sea pollution, noise pollution and sustainable development indicators (Sahinli, 2013).

The effects of climate change on agriculture and natural ecosystems have been a subject of significant debate, and studies regarding the effects have been made using several statistical and econometric models. Studies in this field have investigated the rising temperature and its possible effect on agricultural products and production. Parry et al. (2004) analyses the global effects on production, crop yields and the risk of hunger relating to these socio-economic and climate scenarios. The DSSAT-Peanut model has been employed to examine the impact of climate change on peanut production and the oil sector. This model is calibrated primarily through the use of climate data from a 31-year period (1981-2011) as well as soil and agronomy data. The calibrated model is subsequently applied to simulate future peanut yield on the basis of 20 climate scenarios extracted from the 5 Global Circulation Models

(GCMs) developed by the InterSectoral Impact Model Intercomparison Project (ISIMIP), accelerated by 4 Representative Concentration Pathways (RCPs) (Xuab et al., 2017).

In a study by Cline (2008), it is asserted that developing countries are at greater risk than industrial countries as the impacts of global warming worsen. Using general circulation and agricultural impact models, Cline (2008) boldly examines the 2070–2099 period with a view to estimating the economic impact and effects of global warming. The results have shown that agricultural production in developing countries may fall by between 10 and 25 percent if global warming continues unabated (Cline, 2008). Farmers, as the primary agricultural stakeholders, face the greatest risk from climate vulnerability (Abid et al., 2015). Abid et al. (2015) analyze how farmers perceive climate change, and the manner of adapting their farming activities in response to the perceived changes in climate in areas of Punjab province of Pakistan. Their results reveal that awareness of climate change is widespread throughout the area, and that farming households are making the necessary adjustments to adapt their agricultural activities to respond to climatic change. In total, some 58 percent of farm households have adapted their farming activities to changes in climate (Abid et al., 2015). The increase in population and the associated increase in consumption will affect global demand for food. In addition to the over-exploitation of the fishing sector, countries are competing with each other for land, water and energy, and this situation will later be reflected on the food system and on the environment. The effects of climate change represent a particular global threat, and a global strategy is needed if sustainable and equitable food security is to be assured (Godfray et al., 2010).

In another study, the Cobb-Douglas production function was employed in a quantitative examination of the impact of climate change on winter wheat yield in Northern China, with the impact of climatic factors on wheat production being assessed through a time-series analysis of agricultural production data and meteorological observations for the 1981-2016 period (Zhang et al., 2006). Several studies have been conducted in agriculture modelling literature emphasizing the effects of CO_2 emissions on economic growth, output, productivity, agricultural crops, energy consumption and rural population (Abbas and Choudhury, 2013; Alam, 2013; Huang, 2014; Amponsah et al., 2015; Ali et al., 2017; Chandio et al., 2018; Dong et al., 2018; Chandio et al., 2019). Li et al. (2011) claims that climate change will not have a universally negative effect on maize yield in the United States and China. The results of a climate change simulation on maize yields for the 2008-2030 period indicated that a combination of changes in temperature and precipitation will have either positive or negative impacts on maize yield.

The impacts of climate change on agriculture and human well-being include, but are not limited to, biological effects on crop yields, price fluctuations, reduced production potential and per capita calorie consumption, and child malnutrition. There are also a number of biophysical effects of climate change on agriculture, such as changes in production trends and prices, which directly affect the economic system, as farmers and other market players are compelled to make autonomous adjustments, leading to fluctuations in crop mix, input usage, production, food demand, food consumption and trade (Nelson et al., 2009).

For the 1980-2003 period, Lobell et al. (2007) analyzed the relationship between crop yield and three important climatic variables, namely minimum temperature, maximum temperature and precipitation, for 12 important crops grown in California, namely wine grape, lettuce, almond, strawberry, table grape, hay, orange, cotton, tomato, walnut, avocado and pistachio. According to the results, recent climatic trends have had mixed effects on crop yields.

Philips and Loretan (1991) proposed the Autoregressive Distributed Lag (ARDL) model to identify the co-integration relationship between related variables. In the assessment of the relationship between agricultural output, CO_2 emissions, temperature, rainfall, area under cereal crop cultivation, fertilizer usage, energy consumption and rural population variables to establish evidence of long-run and short-run relationships, Chandio et al. (2020) utilized the ARDL bounds testing approach and the Johansen co-integration test. Bessler and Babula (1987) examined the impact of exchange rate shocks on individual commodity exports. Other empirical studies of the impacts of the exchange rate using traditional econometric studies including Chambers and Just (1982), Batten and Belongia (1986) and Carter et al. (1990) revealed a significant direct impact of the exchange rate on agricultural prices and/or exports.

In VAR models, first, the statistical model is described, after the structural model is determined (Spanos, 1990). Although both the VAR approach and traditional econometric approaches require identification restrictions, these restrictions are quite distinct in nature (Orden and Fackler, 1989). The present study, which makes use of a VAR analysis and ARDL approximations, may be the first to determine the effect of climate change on agriculture in the Turkish context.

In this study, firstly, stationarity of CO_2 emissions and agricultural output are tested by using Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) unit root tests. Furthermore, Vector Autoregressive (VAR) and Autoregressive Distributed Lag Model (ARDL) bounds testing approximations are applied to identify any associations between the two variables, using data obtained from the World Development Indicators (WDI) database.

2. Material and Method

2.1. Data source

The present study is based on a data set comprising 57 annual observations covering the 1961-2018 period. The data can be viewed in two blocks: an environmental block (CO_2 emissions) and an agricultural block (agricultural value added). The data was obtained from the World Development Indicators (WDI) database (WDI, 2020), and the variables used were agriculture value added (AGR) (current US$), and total greenhouse gas emissions (CO_2), (kt of CO_2 equivalent).

2.2. Package program

The estimated model is created using EViews version 7.0 econometrics package software. The unit root test analysis is estimated through Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests. The VAR and ARDL coefficients are estimated from an OLS regression.

2.3. Vector Autoregressive (VAR)

The VAR model can be referred to as a system of dynamic simultaneous equations. By definition, the dependent variables are all endogenous in nature, while the independent variables are the set of lagged observations of all the variables in the system. Within the period in question, all of the observed variables in the system are found to affect one another. The VAR approach utilizes all endogenous variable lags in each behavioral equation in a reduced form. In placing identifying restrictions on the matrix of contemporaneous coefficients, the variance matrix of the residuals is used to identify the economic structure. For instance, a Cholesky decomposition of the covariance matrix results in orthogonal behavioral shocks and a contemporaneous coefficient structure that implies a recursive ordering between variables.

Agriculture value added and CO_2 emissions are important variables in the agriculture sector, with different techniques employed in the assessment of the relationships between them, alongside structural econometric models and time series approaches. One of the most important statistical methods used in this field of research is vector autoregressive (VAR) modelling. The VAR model is an alternative to the structural and conventional econometric approach, being a dynamic simultaneous equation model. To execute this model, it is necessary to review the simultaneous equations model (Sahinli, 2019).

2.4. Auto Regressive Distributed Lag (ARDL)

Philips and Loretan (1991) proposed the Autoregressive Distributed Lag Model (ARDL) as a co-integration relationship. The following equation can be followed to explain the ARDL model.

$$Y_t = \alpha + \sum_{j=1}^{k} \alpha_i Y_{t-j} + \sum_{j=0}^{k} \beta_i X_{t-j} + \varepsilon_t \qquad (1)$$

The number of lags to be added to the Equation 1 is determined with the help of such criteria as AIC, SIC and LM, and especially the significance of the lags. A stable situation would be as follows in a long-term equilibrium relationship:

$$Y_t = \frac{\alpha}{1-\sum_{j=1}^{k}\alpha_i} + \frac{\sum_{j=1}^{k}\beta_i}{1-\sum_{j=1}^{k}\alpha_i}X^* = \alpha^* + \beta^* X^* \quad (2)$$

3. Results and Discussion

3.1. VAR Results

The first step in the process is to create a time series plot of the data displaying the annual AGR and CO_2 for each year against within the years from 1961 to 2018. The original data is transformed by taking natural logarithm in order to reduce the effect of outliers. The annual time series are coded as LNAGR (Natural Logarithm of Agricultural Value Added) and $LNCO_2$ (Natural Logarithm of Total Greenhouse Gas Emissions) (Table 1).

In the following Figures 1 and 2, the nonstationary shape of the time series is seen. These series randomly fluctuate, indicating the observation of a global trend or seasonal variations (Figure 1).

Table 1. Descriptive statistics of the LNAGR and $LNCO_2$ variables

	LNAGR	$LNCO_2$
Mean	23.720200	0.835690
Median	23.741840	0.980851
Maximum	24.967070	1.684547
Minimum	22.142350	-0.483082
Standard deviations	0.797636	0.550522
Skewness	-0.203769	-0.550899
Kurtosis	2.051882	2.427776
Jarque-Bera	2.573787	3.725043
Probability	0.276127	0.155281
Sum	1375.772	48.470
Sum of squared deviations	36.26473	17.27522
Observations	58	58

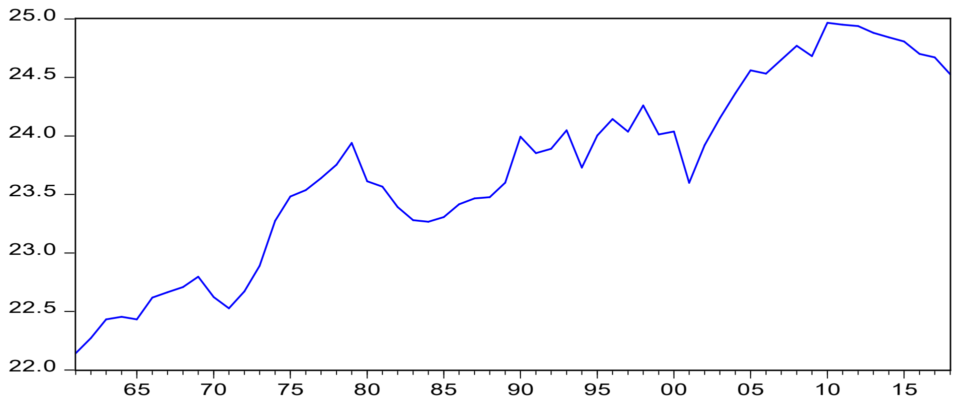

Figure 1. Time plots series of LNAGR (X: Year; Y: LNAGR: Natural logarithm of agricultural value added)

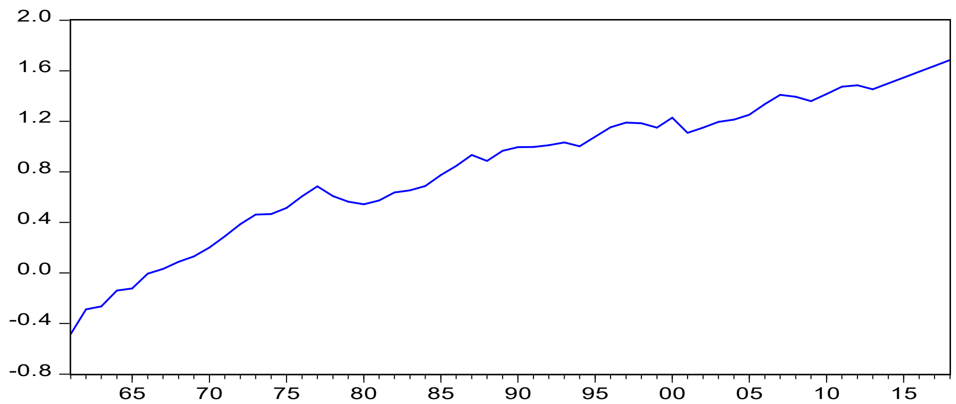

Figure 2. Time plots series of $LNCO_2$ (X: Year; Y: $LNCO_2$: Natural logarithm of total greenhouse gas emissions)

Table 2. Covariance analysis

Correlation [t-statistic] (Probability)	LNAGR	$LNCO_2$
LNAGR	1.000000	
$LNCO_2$	0.950888 (22.98871) (0.0000)	1.000000

Table 3. Unit root tests results

Variables	Deterministic component	ADF	PP
LnAGR	Intercept	-1.750263	-1.746184
$LnCO_2$	Intercept	-2.966119	-3.109835
LnAGR	Trend and intercept	-2.414466	-2.741336
$LnCO_2$	Trend and intercept	-3.798386	-3.850069
ΔLnAGR	Intercept	-7.530148*	-7.538009*
$\Delta LnCO_2$	Intercept	-7.859412*	-7.851323*
ΔLnAGR	Trend and intercept	-7.587972*	-7.592725*
$\Delta LnCO_2$	Trend and intercept	-8.080570*	-8.102711*

ADF and PP represent the unit root tests, being the Augmented Dickey-Fuller and Phillips-Perron tests, respectively.
(*) denote 1%, 5% and 10% levels of significance, respectively.

Table 4. VAR lag order selection criteria

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-44.3888	NA	0.017456	1.627679	1.699365	1.655538
1	118.2484	308.1548*	6.68e-05*	-3.93854*	-3.72348*	-3.85496*

Table 2 shows the correlation between the variables. The correlation coefficient is 0.95, which implies a strong relationship. For the stationary test, an Augmented Dickey-Fuller (ADF) test, the most well-known test in literature, is applied. Test results are easy to interpret and quite efficient. This test is based on the following equation:

$$\Delta Y_t = \beta_1 + \beta_2 t + (\rho - 1)y_{t-1} + \sum_{i-1}^{m} \alpha_i \Delta Y_{t-i} + \varepsilon_t \qquad (3)$$

Where,

ε_t = pure white noise error term

ΔY_{t-i} = difference of Y_{t-i}

The Augmented Dickey Fuller (ADF) and the Phillips-Perron (PP) tests are used to determine the stationary of time series. In the present study, if there is a unit root, namely, if the null hypothesis is ρ=1, we can conclude from this result that the time series is nonstationary. The alternative hypothesis is $|\rho|$<1, indicating the time series is stationary. If ρ>1 then the original time series will be explosive.

As (it) can be seen from Table 3, a test for unit root in level is carried out. Once again, there is a unit root, and LNAGR and $LNCO_2$ are nonstationary. In the first difference model, the hypothesis, DLNAGR and $DLNCO_2$ have no unit root is rejected, and the time series is thus stationary. The Phillips-Perron test yielded similar results. In the event of the LNAGR and $LNCO_2$ series being stationary, a VAR analysis can be made, for which an appropriate lag length must first be determined. There are many criteria when determining lag length, being AIC, SIC, FPE and HQ, and the results related to these criteria are presented in Table 4. From the values given in Table 4, the proper lag length ρ=1 (Table 4) can be identified. All of the results for the estimated VAR (1) model are presented in Table 5.

The results of all eigenvalues for the stability of the VAR (1) model are presented in Table 6. It is worthy of note that all of the roots are complex. Considering the absolute value, all of the calculated modules are smaller than the unit value (Figure 3). Furthermore, all of the characteristic roots fall within the unit circle, from which it can be concluded that the VAR (1) model is stable and fulfils the stationary conditions (Table 6).

The impulse response functions are calculated and presented below. Until now, two variables are discussed: the LNAGR and the CO_2 series. When a unit of random shock (both their own and the other variable's shocks) is applied to these variables, the responses of relevant variables can be shown for 10 periods in Figure 4.

Table 5. Results of vector autoregression estimates

	LNAGR	$LNCO_2$
LNAGR (-1)	0.747349 (-0.09519) (-7.85114)	-0.04701 (-0.02607) (-1.80327)
$LNCO_2$ (-1)	0.209266 (-0.19084) (-1.09655)	0.848333 (0.05226) (16.2316)
C	5.760539 (2.13863) (2.69356)	1.100109 (0.5857) (1.87829)
@TREND	0.00341 (0.00613) (0.55645)	0.006097 (0.00168) (3.63267)
R-squared	0.957754	0.993107
Adj. R-squared	0.955362	0.992717
F-statistic	400.5147	2545.314
Log likelihood	24.25292	98.07484

Table 6. Roots of characteristic polynomial

Root	Modulus
0.797841-0.085370i	0.802395
0.797841+0.085370i	0.802395

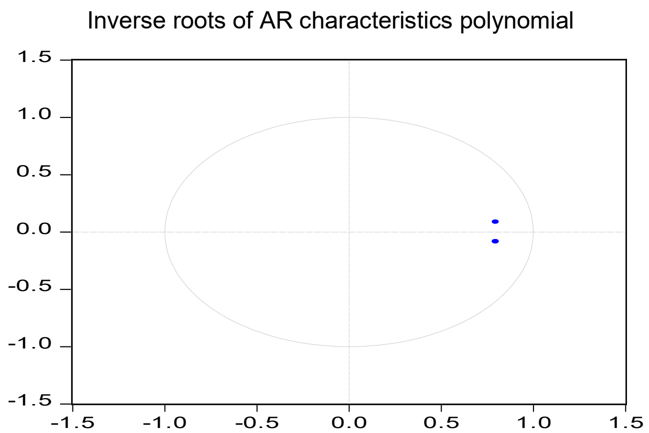

Figure 3. Inverse roots of AR characteristic polynomial

When the figure is examined (a), the panel shows the response of LNAGR to LNAGR, which means the reaction to itself. When a unit of random shock is given to the error term of LNAGR, this shock variable is shown to be affected by itself. Accordingly, when LNAGR is subjected to a shock, a random shock that will have a positive effect on LNAGR will occur. In other words, this shock is the effect of increasing LNAGR, and the effect increases over 10 years (Figure 4). When the figure is examined in the panel (b), LNAGR is presented as a reaction to $LNLNCO_2$. Accordingly, when random shocks are applied to $LNCO_2$ in the panel (b), the effect of the shock on LNAGR is considered. The results show that $LNCO_2$ shocks significantly affect LNAGR, that and LNAGR maintains a stationary condition. In other words, it can be said that a linear interaction exists between LNAGR and $LNCO_2$. In this case, LNAGR increases $LNCO_2$ for three periods, although the effect is slowly decreased. If the LNAGR increases (or decreases), so does the $LNCO_2$ value, and vice versa. That is, the impulse response functions provide clues to causality, although interpretations must consider random shocks rather than being based on causality (Figure 4). Panel (c) of Figure 4 shows, the response of $LNCO_2$ to LNAGR. There is an inverse relationship between $LNCO_2$ and LNAGR. Accordingly, random shocks that occur in the LNAGR can decrease $LNCO_2$ for five periods and the response is fading slowly (Figure 4).

Panel (d) presents the response to the $LNCO_2$ itself. In this regard, when a shock is applied to $LNCO_2$, the random shock that will occur positive effect on itself. While this shock has a significant effect, it later reduces (Figure 4).

The variance decomposition function for the VAR (1) model is valid. Variance decomposition analyses explore the source of variations in the variance of a variable, revealing the endogenous states of the variables. The following table shows the variance decomposition results of the Cholesky decomposition, based on the LNAGR and $LNCO_2$ ranking (Table 7). In Table 7, firstly LNAGR variance decomposition results are provided. In the first period, change in standard deviations of LNAGR, 100% depends on itself. In the second period, around 99.81% of the total change comes from itself, and 0.19% is derived from $LNCO_2$. After ten periods, 96.71% is derived from itself, and 3.29% from $LNCO_2$.

Table 7 also presents the results of the variance decomposition of $LNCO_2$. In the first period, 92.06% of the change in the standard deviations of $LNCO_2$ come from itself, while 7.94% is stemmed from LNAGR. However, after 10 periods, 88.05% of the change in the standard deviations of $LNCO_2$ is derived from itself, and 11.95% is derived from LNAGR.

In Table 8, the results of the variance decomposition are presented by Cholesky decomposition based on $LNCO_2$ and LNAGR ordering (Table 8). Table 8 shows firstly the LNAGR variance decomposition results. In the first period, 92.06% of the change in the standard deviations of LNAGR came from itself, and 7.94% from $LNCO_2$. In the second period, 90.46% of the change in standard deviations of LNAGR came from itself, and 9.54% from $LNCO_2$. After 10 periods, 84.07% of the change in standard deviations of LNAGR came from itself, and 15.93% from $LNCO_2$. Table 8 provides also the $LNCO_2$ variance decomposition results. In the first period, 100% of the change in standard deviations of $LNCO_2$ derive from itself. However, ten periods later, 79.01% of the change in the standard deviations of $LNCO_2$ came from itself, and 20.99% from LNAGR.

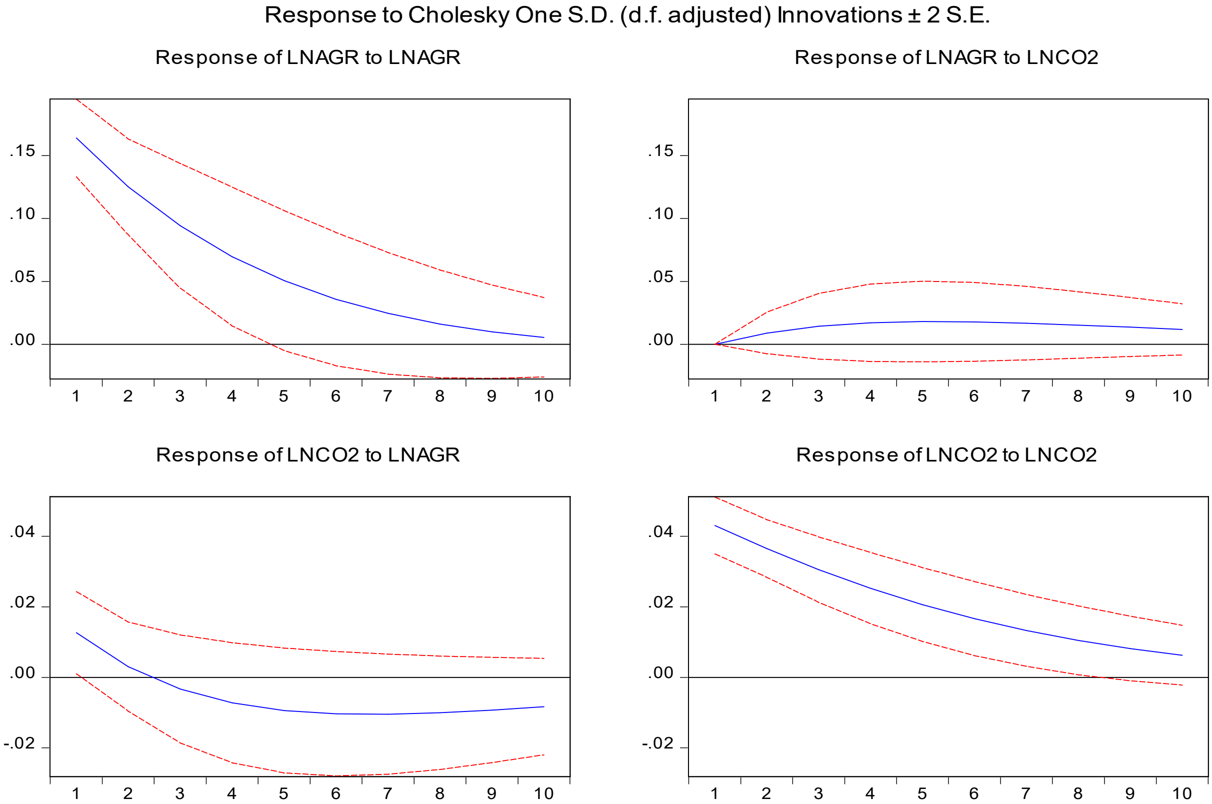

Figure 4. Response to Cholesky One S.D. (d.f. adjusted) Innovations ±2 S.E. Panels: a, b, c, d left to right, respectively

Table 7. Variance decomposition of LNAGR and $LNCO_2$

Variance decomposition of LNAGR			
Period	S.E.	LNAGR	$LNCO_2$
1	0.163974	100.0000	0.000000
2	0.206500	99.80935	0.190646
3	0.227426	99.44262	0.557381
4	0.238486	98.97583	1.024167
5	0.244462	98.47663	1.523316
6	0.247717	97.99727	2.002734
7	0.249504	97.57118	2.428821
8	0.250500	97.21479	2.785209
9	0.251072	96.93113	3.068871
10	0.251416	96.71459	3.285411
Variance decomposition of $LNCO_2$			
Period	S.E.	LNAGR	$LNCO_2$
1	0.044907	7.944435	92.05556
2	0.057981	5.038544	94.96146
3	0.065636	4.186893	95.81311
4	0.070704	4.656992	95.34301
5	0.074252	5.831832	94.16817
6	0.076799	7.274136	92.72586
7	0.078641	8.713322	91.28668
8	0.079970	10.004690	89.99531
9	0.080921	11.087590	88.91241
10	0.081593	11.952250	88.04775
Cholesky Ordering: LNAGR $LNCO_2$			

Table 8. Variance decomposition of $LNCO_2$ and LNAGR

Variance Decomposition of LNAGR			
Period	S.E.	LNAGR	$LNCO_2$
1	0.16397	92.05556	7.94444
2	0.20650	90.46347	9.53653
3	0.22743	88.98917	11.01083
4	0.23849	87.69491	12.30509
5	0.24446	86.61522	13.38478
6	0.24772	85.75690	14.24310
7	0.24950	85.10470	14.89530
8	0.25050	84.62955	15.37045
9	0.25107	84.29680	15.70320
10	0.25142	84.07238	15.92762
Variance decomposition of $LNCO_2$			
Period	S.E.	LNAGR	$LNCO_2$
1	0.044907	0.000000	100.00000
2	0.057981	1.627061	98.37294
3	0.065636	4.502425	95.49757
4	0.070704	7.839884	92.16012
5	0.074252	11.109520	88.89048
6	0.076799	14.019250	85.98075
7	0.078641	16.449470	83.55053
8	0.079970	18.387400	81.61260
9	0.080921	19.877340	80.12266
10	0.081593	20.988200	79.01180
Cholesky Ordering: $LNCO_2$ LNAGR			

3.2. ARDL results

The logarithms of both the CO_2 emission and agriculture value added series are taken, and the time path graphs of both series are presented in Figures 1 and 2. It can be stated that both series ($LNCO_2$ and LNAGR) are integrated from the first order, i.e. I (1) (Table 3). Since both series ($LNCO_2$ and LNAGR) are integrated in the first order, that is, I (1), an ARDL matching analysis is initiated. The number of lags included in the estimated model during the implementation of the ADF unit root test and Phillips-Perron (PP) test are determined based on the Akaike Information Criteria (AIC). The relevant values are presented in Table 3. According to these values, when both evaluation criteria are considered, it can be seen that no serial correlation exists in the residuals if the model is lagged by 1 (one) (Table 3). The ARDL model estimate results are presented in Table 9.

The calculation of long-term parameters using the results of the ARDL model estimation is given below.

$$\alpha^* = \frac{\alpha}{1-\sum_{j=1}^{k}\alpha_i} = \frac{4.987641}{1-(0.779500)} = 22.61969$$

$$\beta^* = \frac{\sum_{j=1}^{k}\beta_i}{1-\sum_{j=1}^{k}\alpha_i} = \frac{(0.935522-0.636049)}{1-(0.779500)} = 1.358154$$

In this case, the co-integration model showing the long-term relationship can be defined as:

$$\widehat{AGR}_T = 22.61969 + 1.358154(CO2_T)$$

The deviation can be calculated from the equilibrium:

$$\hat{\varepsilon}^*_t = \widehat{AGR}_T - 22.61969 - 1.358154(CO2_T)$$

A stationary test for deviations from the equilibrium is carried out:

$$\widehat{\Delta\varepsilon}^*_t = -0.385\hat{\varepsilon}^*_{t-1} + 0.306(\Delta\hat{\varepsilon}^*_{t-1}) + 0.290(\Delta\hat{\varepsilon}^*_{t-2}) + 0.131(\Delta\hat{\varepsilon}^*_{t-3}) - 0.017(\Delta\hat{\varepsilon}^*_{t-4}) + 0.315(\Delta\hat{\varepsilon}^*_{t-5})$$

t-stats (respectively); (-3.212), (2.014), (2.013), (0.908), (-0.115), (2.214).

The calculated value of -3.212 is less than the critical values at the three significance levels, and the basic hypothesis is thus rejected. This means that both variables are counteracted. Later, based on these results, an Error Correction Model can be estimated (Table 10). The main conclusion from this study is that the impact of CO_2 emissions on agricultural value added are valid and relatively large.

4. Conclusion

The main aim of this empirical study is to assess the impact of climate change on agricultural output in Turkey within the 1961–2018 period. The study employed unit root tests, such as ADF and PP, to check the stationarity of variables. The ARDL approach is used to check the causality between these variables through long- and short-run analysis. Unit root test estimations confirm that the variables are stationary at the I (1). Moreover, the results of the ARDL approach indicate a long-run association between LNAGR and $LNCO_2$ emissions at 1%, 5% and 10% significance levels. Autoregressive Distributed Lag and Vector Autoregressive models are used to determine the relationship between them, and the numerical results indicate a robust relationship between the variables. The indicators of the variables are consistent with the expectations.

The findings of the study reveal that CO_2 emissions and agriculture value added are co-integrated in the long-run. In the ARDL model, it

Table 9. ARDL model estimation results

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	4.987641	1.955752	2.550242	0.0137
$LNCO_2$	0.935522	0.431370	2.168724	0.0346
$LNCO_2$ (-1)	-0.636049	0.443656	-1.433654	0.1575
LNAGR (-1)	0.779500	0.086566	9.004681	0.0000
R-squared	0.960970			
Adj. R-squared	0.958761			
F-statistic	434.9808			

Table 10. Unit root tests for residuals

		t-statistic	Prob.
Augmented Dickey-Fuller test statistic		-3.212054	0.0018
	Test critical values: 1% level	-2.610192	
	5% level	-1.947248	
	10% level	-1.612797	

is seen that the obtained -3.212 value is less than the critical values at 1%, 5% and 10% significance levels, and so the null hypothesis is rejected. This means that variables are counteracted. Impulse response functions provide clues to causality, although interpretations must be made considering random shocks, not on the basis of causality. Thus, as Turkey's population increases, food sufficiency and security will emerge as more important issues over the next decade, it is vital to take adaptive measures to cope with climate change and its impact on agriculture. There is, however, a need for further studies of CO_2 emissions and agriculture value added at provincial levels in Turkey. In future studies, the link between CO_2 emissions and the yields of any crops could be analysed using other econometrics models for the sake of precision.

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