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Grain Production in Turkey and Its Environmental Drivers Using ARDL in the Age of Climate Change

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Abstract: This study aims to evaluate the long-run and causality relationships between the annual grain production (kg per hectare) in Turkey, fertilizer used in agriculture, the number of tractors, agricultural greenhouse gas emissions, and grain production area from 1988 to 2018. The study's data for the years 1988–2018 were taken from the World Bank and Turkish Statistical Institute (Turkstat) databases. The autoregressive distributed lag bounds (ARDL) test was applied to estimate the cointegration between the variables. The cointegration test results confirmed a long-run relationship between the variables. The short-run estimation revealed that the error correction coefficient was negative and statistically significant. The result obtained for the error correction term estimated that the deviations from the short-run equilibrium would be corrected, and the system would converge to the long-run equilibrium within 1.05 years. Further, the long-run estimation showed that all variables included in the model had a statistically significant effect on the dependent variable. While this relationship was negative for grain production amount and carbon emission, it was positive for fertilizer use and the number of tractors. The grain areas estimated as the dependent variable in the ARDL model were in a feedback relationship with the current production and number of tractors variables, while the fertilizer and carbon emission variables were in a unidirectional causality relationship towards the grain production area. There is a negative relationship between grain production (kg per hectare) and grain production areas (hectares). A 1% increase in grain production leads to a decrease of approximately 0.30% in grain production areas. Agricultural greenhouse gas emissions, another variable that stands out with its negative impact in ARDL long-run estimation results, indicate that product groups produced as an alternative to grain have a higher emission-generating power. The other long-run estimation results reveal that the tractor variable positively affects grain production areas.

Keywords: sustainability; grain production; fertilizer usage; greenhouse gas emissions; Toda–Yamamoto causality test

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1. Introduction

Agriculture provides food and nutrition security; it also significantly affects poverty in the long term [1,2]. Agricultural production in Turkey is significant in meeting sustainable food needs and being a livelihood source for the rural population [3,4]. Meeting sustainable food needs [5] is possible with the balanced and consistent production of the industry's agricultural products [6]. Currently, 17.2% of those employed in Turkey [7] work in the agricultural sector, which carries out 5.5% of Turkey's Gross Domestic Product (GDP). An average of 3–4% of the goods produced in the agricultural industry are exported [8]. Especially with products obtained from grains, the foreign trade of finished goods provides vital income to the country's economy [9–11].

One of the most critical issues of the 21st century, alongside the greenhouse gas effect and global warming, is an atmospheric event that occurs with the destructive interaction of soil, human, and climate elements [12–14]. Many existing studies state that 25% of

global warming is caused by agricultural activities [15]. This 25% share proves that many factors, such as the greenhouse effect and global warming, the cultivation of the land in livestock activities and agricultural production, the exhaust gases of the machinery used during production, and the number of fertilizers, should be analyzed from a broader perspective [16,17]. According to the Statista Report, the top three countries that pollute the world most by emitting carbon into the atmosphere are industrialized countries such as China (11,472 million tons), the USA (5007 million tons), and India (2710 million tons) [18]. Turkey ranked 13th, with 446 million tons released into the atmosphere in 2021 [19]. Turkey recorded an increase of 70.8% between 2010 and 2020 and is one of the countries with the fastest growth in atmospheric pollution in the world [20,21]

The use of machinery, or mechanization in agriculture, is vital in providing agricultural productivity in developed countries. It includes the application of advanced technologies, as well as soil, water, fertilizer, pesticides, etc. [22]. It is an important production tool that provides efficiency in agriculture by enabling the effective use of inputs [23]. Mechanization in agricultural production constitutes approximately 40–50% of total farm production inputs from soil preparation to harvest [24,25]. This effect increases the importance of mechanization in agricultural enterprises. Two critical indicators of the farm mechanization level of a country are "Tractor Park" and "Agricultural Machinery Park" and their changes over the years [26]. Some indicators are widely used to evaluate the Agricultural Mechanization situation in the "Tractor + Machine" integrity, especially in international comparisons: the number of tractors is 1000 ha^{-1}, ha tractor^{-1}, kW ha^{-1}, and the number of machines is tractor^{-1} [23]. The kW ha^{-1} value throughout Turkey has increased by an average of 3.22% in the last ten years (2010–2019) and has reached 2.22 kW ha^{-1}. The increase in tractor power per cultivated area (kW ha^{-1}) over the years in the entire country and agricultural regions is due to the rise in the number of tractors and power values. In the same period, the tractor 1000 ha^{-1} value increased by 3.01% and became 58.66. In contrast, the ha tractor^{-1} value decreased by 2.91% and became 17.05. The decline in ha tractor^{-1} value results from the increase in mechanization. Lastly, the number of tools/machines per tractor (machine tractor^{-1}) in 2010–2019 decreased by 0.89% and became 4.78. When compared with EU countries, based on 2010 data, the tractor power per 1 ha production area is 6 kW, the production area per tractor is 11.30 ha, the number of tractors per 1000 ha agricultural area is 89, and the number of machines per tractor is 10 [27].

Chemical fertilizers are indispensable inputs of plant production and significantly affect yield and quality [28]. Compared to the increasing world population and destroyed agricultural lands, the size of agricultural land per capita has decreased. Nevertheless, fertilizer use is increasing worldwide [29]. The increase rates were 26% in nitrogen fertilizer, 27% in phosphorus fertilizer, and 43% in potassium fertilizer, respectively [30]. The amount of fertilizer used in Turkey was 5,198,779 tons in 2005 and increased by 72% in 2020 to 7,143,144 tons. Fertilizer use in Turkey is 149.6 kg ha^{-1}, in Greece 150 kg ha^{-1}, in the Netherlands 278 kg ha^{-1}, in Germany 163 kg ha^{-1}, and in France 169 kg ha^{-1}. While chemical fertilizers have decreased in European countries in recent years, their rate is increasing in Turkey [31]. Excessive and unconscious use of fertilizers leads to the accumulation of various chemicals in groundwater and surface waters, and severe losses occur [32]. High costs arise if these losses cannot be controlled [33].

According to 2022 Turkstat data, arable land in Turkey is 38 million hectares, economically gross irrigable agricultural land is around 8.5 million hectares, and the number of tractors is 1.481.461. Cereals are the most produced product group in agricultural areas in Turkey. Grain production is carried out on an area of 11.1 million hectares. Wheat is grown in 60.55% of this area, barley in 28.45%, and corn in 6.81%. These products are followed by rye (0.9%), paddy (1.16%), oats (1.23%), and triticale (0.84%) [8].

This study investigates the determinants of grain production areas in Turkey during 1988–2018. For this purpose, we developed a model that contains grain production amount, CO_2 emission, and essential inputs that affected grain productivity, including the number of trucks and fertilizer consumption. We used cointegration analysis to understand

these variables' short- and long-run impact on grain production areas. Moreover, the Toda–Yamamoto causality test was used to determine the causal relationships between the variables. This study contributes significantly to the literature on the sustainability of grain production in Turkey by analyzing the course of grain production and its relationship with the environment over thirty years.

Many studies exist regarding grain production efficiency, agricultural inputs, climate change, and economic and environmental indicators. These research results are presented in Table 1.

Table 1. Results for literature research.

Author(s)	Method	Variables and Their Descriptions	The Dependent Variable	Relationship −/+ (Long Term)	Country, Period
Abate and Kuang [34]	ARDL	OGC = Output of Grain Crops TNREL = Total Number of Employed Rural Labor, AGC = Total Sown Area of Grain Crops, TPAM = Total Power of Agricultural Machinery	OGC	TNREL (+), AGC (+), PAM (+)	China, 1978–2012
Ahsan et al. [35]	Johansen cointegration test, ARDL, Granger	CP = Cereal Crops Production, CO_2 = Carbon Dioxide Emissions, EN = Energy Consumption, CA = Cultivated Area, LF = Labor Force	CP	CO_2 (+), CA (+), EN (+), LF (+)	Pakistan, 1971–2014
Ali et al. [36]	Johansen cointegration test, ARDL	CO_2 = Carbon Dioxide Emissions, GDP = Gross Domestic Product, LCC = Land Under Cereal Crop, AVA = Agriculture Value Added	CO_2	LCC (+), GDP (+), AVA (−)	Pakistan, 1961–2014
Chandio et al. [37]	ARDL, ECM	WP = Wheat Production, AR = Area Under Cultivation, SP = Support Price, FC = Fertilizer Consumption	WP	AR (+), SP(+), FC (+)	Pakistan, 1971–2016
Chandio et al. [38]	ARDL	YC = Yield of Cereal Crop, CO_2 = CO_2 Emissions Per Capita, AT = Average Temperature, AR = Average Rainfall, LCP = Land Under Cereal Production, EC = Energy Consumption, LAB = Labor Force	YC	CO_2 (−)	Turkey, 1968–2014
Chopra [39]	ARDL, ECM, FMOLS, DOLS	TP = Total Crop Production, LU = Cultivable Land Use, AWU = Agricultural Water Use, GIA = Gross Irrigated Area, AR = Annual Rainfall, Tmax = Maximum Temperature and Tmin = Minimum Temperature.	TP	LU (+), GIA (+)	India, 1960–2015
Koondhar et al. [40]	ARDL, VECM, Granger	CFP = Cereal Food Production, AS = Area Sown, ACO_2 = Agricultural CO_2 Emissions, FPI = Food Production Index	CFP	AS (+), ACO_2 (−)	China, 1985–2018
Kumar et al. [41]	FMOLS, DOLS	CP = Cereal Production, AATD = Average Annual Temperature, AAR = Average Annual Rainfall, CO_2 = Carbon Dioxide Emissions, LCP = Land Under Cereal Production, RPOP = Rural Population	CP	FGLS RESULT; CO_2 (+), LCP (+), FMOLS RESULT; CO_2 (+), LCP (+)	1971–2016 Bangladesh, Ghana, India, Kenya, Myanmar, Nigeria, Phillippines, Sri Lanka, Vietnam, Indonesia, and Pakistan
Ramzan et al. [42]	ARDL, WTC, Toda–Yamamoto	TFP = Total Agricultural Productivity (Index Value), ALB = Agricultural Labor, ALD = Agricultural Land, FD = Agricultural Feed, FT = Fertilizer, CO_2 = Carbon Dioxide Emissions	TFP	ALB (+), ALD (+), FD (+), FD (+), FT (+), CO_2 (+)	Pakistan, 1961–2018
Rehman et al. [33]	ARDL, Granger	CO_2 = Carbon Dioxide Emissions, MCP = Maize Crop Production, AMC = Area Under Maize Crop, WA = Water Availability, RF = Rainfall and TM = Temperature	CO_2	MCP (+), WA (+), RF (+), TM (+), AMC (−)	Pakistan, 1988–2017
Yurtkuran [43]	Gregory Hansen cointegration test, ARDL	CO_2 = Carbon Dioxide Emissions, REN = Renewable Energy Production, AGR = Agriculture (% of GDP); and KOFE, KOFS, and KOFP represent the economic, social, and political KOF globalization indices, respectively	CO_2	AGR (+), REN (+), KOFE (+)	Türkiye, 1970–2017

Many studies have examined the relationship between carbon emissions and agricultural production. Among them, Ahsan et al. [35] analyzed the factors affecting grain production in Pakistan with the Vector Error Correction Model (VECM), ARDL, and Granger causality test. Authors estimated that carbon emissions, energy consumption, harvest area, and labor force positively affected production. On the other hand, in the study by Ali et al. [36], the relationship between carbon emissions, gross national product (GNP), grain-planted land, and agricultural value added was analyzed using the Johansen cointegration test, ARDL model, and Granger causality tests. Although ARDL long-run estimation results revealed a statistical insignificance between agricultural value added, grain-planted land, and carbon emissions, the Granger causality test results showed that agricultural value added, GNP, and grain-cultivated land were the Granger cause. Amponsah et al. [44] investigated the effect of carbon emissions on grain yield in Ghana using the ARDL model. The long-run estimation revealed a negative relationship between carbon emissions and grain yield. A positive relationship was found between GDP and grain yield. Chandio et al. [38] researched the relationship between grain yield and climate change factors (carbon emissions, temperature, precipitation) in Turkey with the ARDL model and Granger causality test. According to the long-run estimation results, no statistically significant relationship was found between climate change factors and productivity. However, statistically significant and positive results were obtained for energy use and labor force variables. Statistically significant and negative results were obtained for grain-planted land. Koondhar et al. [40] discovered that the relationship between grain production (mt), agricultural carbon emissions, grain-cultivated area (square km), and food production index could be estimated using ARDL and VECM models. ARDL long-run estimation showed that grain-cultivated land and food production index variables had a statistically significant and positive relationship with the amount of grain production (mt).

In contrast, carbon emissions negatively and statistically significantly affected grain production area (square km). The results of the VECM Granger causality test conducted within the scope of the study are essential since these results emphasize that the agricultural carbon emissions and grain production variables are the Granger cause of the grain-cultivated area variable. Kumar et al. [41] empirically examined the effect of climate change on grain production in low and middle-income countries with a balanced panel dataset. The results showed that the increase in temperature affected cultivated land under grain production (hectares) negatively, whereas the increase in carbon emissions and precipitation positively affected the production area. Using four independent estimation methods, Zhao et al. [45] investigated how the changes in temperature affected wheat yield, paddy, corn, and soybean. Analyzing this change is vital because they constitute two-thirds of the calorie intake of humanity. The research results reveal that the global yield would decrease significantly for each product examined.

The study aimed to evaluate the determinants of grain production in Turkey by analyzing the long-run and causality relationships between the amount of grain produced in Turkey, the amount of fertilizer used in agriculture, the number of tractors and agricultural greenhouse gas emissions, and the area where grain is produced between 1988 and 2018.

2. Materials and Methods

The primary material of this study is based on the statistical data of the Turkish Statistical Institute (Turkstat) and the World Bank between 1988 and 2018. The dataset consists of the area of grain production as the independent variable, and the annual grain production amount, the amount of fertilizer, the number of tractors, and the agricultural greenhouse gas emissions variables as the dependent variables. Descriptions for variables are shown in Table 2. Variables in this study were used by taking their natural logarithms, and the graphs of variables are given in Figure 1.

This study considered previous studies and Turkey's unique conditions while determining the factors that are assumed to affect grain production areas.

Table 2. Description of the variables.

Abbreviations	Variable	Measurement	Sources
DKR	Area Under Cultivation of Grain Crops	Million hectares	TURKSTAT
TON	Amount of Grain Production	Kg per hectare	TURKSTAT
GBR	Fertilizer Consumption	Kg per hectare of arable land	WorldBank
TRK	Number of Trucks	Unit	TURKSTAT
CO_2	Agricultural Greenhouse Gas Emissions	Gigagrams	WorldBank

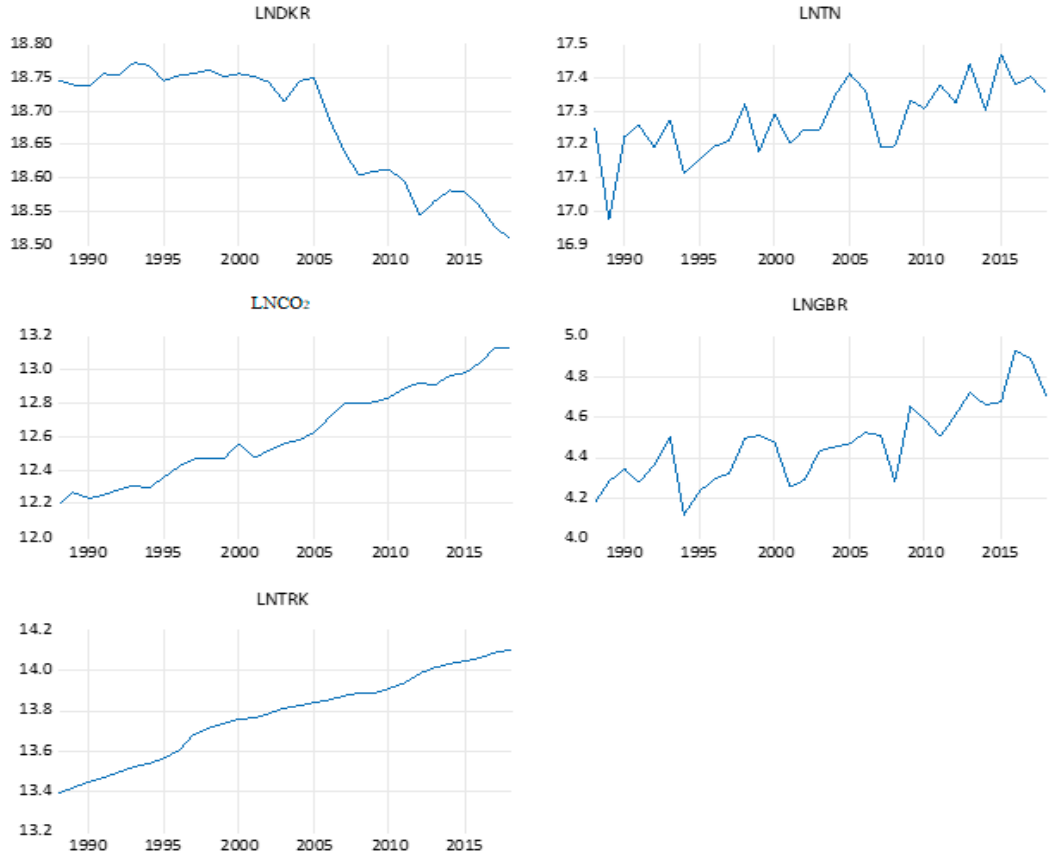


Figure 1. Graphical representation of the series in the model (DKR: grain production area by years (in decares), TON: total amount of grain produced annually (in tons), GBR: amount of fertilizer used annually (tons), TRK: number of tractors per year (in pieces), CO_2: annual agricultural greenhouse gas emissions (gigagrams)).

Based on the results obtained in the study by Koondhar et al. [40], it was thought that there might be a causal relationship between the grain production area and greenhouse gas emissions originating from agriculture, and related variables were added to the model as independent variables. In addition, using tractor and fertilizer inputs was considered necessary and these were added to the model as independent variables. This model can be formulated in Equation (1) as follows:

$$LnDKR = \beta_0 + \beta_1 lnTONt + \beta_2 lnGBRt + \beta_3 lnTRKt + LnCO_2t + \varepsilon t \quad (1)$$

In Equation (1), DKR: grain production area by years (in decares), TON: total amount of grain produced annually (in tons), GBR: amount of fertilizer used annually (tons), TRK: number of tractors per year (in pieces), CO_2: annual agricultural greenhouse gas emissions (gigagrams), and εt: error terms. It has been taken into account that the increase in the amount of tractor and fertilizer used, which are the inputs used extensively in grain production, will also increase the production capacity. It is expected that these inputs will

affect the production areas positively. On the other hand, a negative relationship between the production amount and decares is expected when the increase in the production amount and the demand remains constant. Similarly, the CO_2 variable is expected to have a negative coefficient.

2.1. Augmented Dickey and Fuller (ADF) and Phillips and Perron (PP) Tests

In time series analysis, it is necessary to determine whether the variables subjected to analysis contain a unit root. If these variables have the unit root, deciding on the order in which they become stationary is crucial.

The main reason for this requirement is that each cointegration analysis has certain constraints. For this reason, the series to be used in the study were tested with the commonly used unit root tests, Augmented Dickey and Fuller (ADF) [46] and Phillips and Perron (PP) [47] unit root tests. The H_0 hypothesis states that the series contains a unit root and is not stationary for both unit root tests used in the study. On the other hand, hypothesis H_1 shows that the series does not contain a unit root and is stationary. The Akaike Information Criteria (AIC) was used to determine the optimal lag length for the ADF unit root test. Newey–West bandwidth was preferred as the bandwidth for the PP test.

2.2. Cointegration Analysis: ARDL Bounds Test Approach

There are several cointegration tests in the literature to reveal long-run relationships between time series. The first was developed by Engle and Granger [48]. Later, alternative cointegration tests emerged, especially the multi-equation approach introduced by Johansen [49] and Johansen and Juselius [50]. This analysis was suitable for cointegration analysis for time series and possible economic situations. However, due to their constraints on stationarity, they are not eligible for cointegration testing for equations with the "I(0)" series at the stationary level. This constraint was eliminated by the ARDL bounds test developed by Pesaran et al. [51]. The ARDL bounds test approach allows cointegration testing to be performed regardless of whether the series' stationarity levels are "I(0)" or "I(1)" [52].

Nevertheless, it should be noted that the method can only be applied for the I(0) and I(1) series, that is, the relevant test cannot be applied for series that become stationary at I(2) or higher levels. Another advantage of the ARDL bounds test is that it can achieve successful results even in small samples. Studies by Narayan and Narayan [53] show that the results obtained with the ARDL bounds test are more effective and unbiased than other cointegration tests and give more consistent results in small samples. The ARDL approach was used in the study in light of these advantages. The Unrestricted Error Correction Model (UECM) created for the ARDL bounds test can be expressed as in Equation (2):

$$\begin{aligned}\Delta lnDKR_t = \beta_0 + \sum_{i=1}^{k} \beta_{1i}\Delta lnDKR_{t-i} + \sum_{i=0}^{k} \beta_{2i}\Delta lnTON_{t-i} + \sum_{i=0}^{k} \beta_{4i}\Delta lnTRK_{t-i}\sum_{i=0}^{k} \beta_{5i}\Delta lnCO_{2t-i} + \\ \beta_6 lnDKR_{t-1} + \beta_7 lnTON_{t-1} + \beta_8 lnGBR_{t-1} + \beta_9 lnTRK_{t-1} + \beta_{10} lnCO_{2t-1} + \varepsilon_t\end{aligned} \quad (2)$$

Here, Δ represents the first difference operator of the variables, ε_t represents the error term, and k represents the optimal lag length. In the model, short-run relations between variables are represented by coefficients β_1, β_2, β_3, β_4, and β_5, while the β_6, β_7, β_8, β_9, and β_{10} coefficients show the long-run relationship between the variables.

The ARDL bound test allows testing the long-run relationship between variables by using the alternative hypotheses below (Equation (3)). The null hypothesis (H_0) shows the equivalence relation between the variables.

$$\begin{aligned}H_0 &= \beta_6 = \beta_7 = \beta_8 = \beta_9 = \beta_{10} \\ H_1 &= \beta_6 \neq \beta_7 \neq \beta_8 \neq \beta_9 \neq \beta_{10}\end{aligned} \quad (3)$$

Firstly, the lag length shown as *k* in Equation (2) must be determined to undertake the bound test. Akaike information criterion (AIC) was used to determine the lag length.

This test selection is made according to the value at which the optimal lag length AIC is the smallest.

The cointegration test compares the F value obtained with the ARDL model with the critical bound values. The F value is above the critical values for I(0), and I(1) means a cointegration relationship between the variables included in the model. Although Pesaran et al. [51] calculated these critical values, nowadays, the critical values calculated by Narayan [54] are widely used since their relevant critical values are suitable for large samples. In the study of Narayan [54], critical value calculations were made in sample sizes for 30–80 observations in all conditional error correction models introduced by Pesaran et al. [51]. Since the number of observations in this study was within the observation range calculated by Narayan [54], critical values of the authors were used.

After confirming the cointegration relationship between the variables is confirmed by the bounds test, the estimation results for the long-run and short-run can be interpreted. The ARDL model (Equation (4)) is created to estimate the long-run coefficients.

$$lnDKR_t = \beta_0 + \Sigma_{i=1}^{k} \beta_{1i} lnDKR_{t-i} + \Sigma_{i=0}^{k} \beta_{2i} lnTON_{t-i} + \Sigma_{i=0}^{k} \beta_{3i} lnGBR_{t-i} \Sigma_{i=0}^{k} \beta_{4i} lnTRK_{t-i} + \Sigma_{i=0}^{k} \beta_{5i} lnCO_{2t-i} + \varepsilon t. \quad (4)$$

Following the establishment of the coefficients of the long-run relationship, the model's suitability is confirmed by undertaking diagnostic tests. An ARDL-based error correction model determines short-run relationships between variables (Equation (5)).

$$\Delta lnDKR_t = \beta_0 + \Sigma_{i=1}^{k} \beta_{1i} \Delta lnDKR_{t-i} + \Sigma_{i=0}^{k} \beta_{2i} \Delta lnTON_{t-i} + \Sigma_{i=0}^{k} \beta_{4i} \Delta lnTRK_{t-i} \Sigma_{i=0}^{k} \beta_{5i} \Delta lnCO_{2t-i} + \beta_6 ECT_{t-1} + \varepsilon_t \quad (5)$$

ECT_{t-1} in Equation (5) refers to the error correction term in the model. This variable is expected to have a negative and statistically significant coefficient since the error correction term indicates how much of the effect of a short-run shock will disappear in the long run. CUSUM and CUSUM square (CUSUMSQ) tests, commonly suggested by Brown et al. [55], are used to understand whether the ARDL model provides the condition for stability. If the values calculated in both tests are within the critical values specified for the 5% significance level, it is accepted that the model created meets the stability requirement.

2.3. The Causality Test

Determining the causal relationships between the variables is essential. It shows the direction of the relationship and, thus, the existence of feedback. Therefore, in addition to the cointegration analysis, the study includes the causality test. It is possible to encounter many studies in this field, including the test developed by Granger [56], who introduced causality in econometric analysis. The causality test developed by Toda and Yamamoto (1995) comes to the fore as it can be applied to series that become stationary at different degrees. This approach, which is based on Vector Autoregression (VAR), first determines the maximum degree of stationarity (d_{max}) for the variables and then determines the optimal lag length (k) for the VAR model. The variables included in the model, afterward, are added to the VAR model as exogenous variables for a lag length equal to the sum of the k and d_{max} values. Then,

the results of the causality test are obtained with the Wald test. The Toda Yamamoto [57] test for the variables used in the study is presented in Equation (6).

$$\begin{bmatrix} lnDKR \\ \text{lnTON} \\ lnCO_2 \\ \text{lnGBR} \\ lnTRAK \end{bmatrix} = \begin{bmatrix} \alpha \\ \beta \\ \delta \\ \varphi \\ \sigma \end{bmatrix} + \sum_{i=1}^{k} \begin{bmatrix} b_{11i} & b_{12i} & b_{13i} & b_{14i} & b_{15i} \\ b_{21i} & b_{22i} & b_{23i} & b_{24i} & b_{25i} \\ b_{31i} & b_{32i} & b_{33i} & b_{34i} & b_{35i} \\ b_{41i} & b_{42i} & b_{43i} & b_{44i} & b_{45i} \\ b_{51i} & b_{52i} & b_{53i} & b_{54i} & b_{55i} \end{bmatrix} \times \begin{bmatrix} \text{lnDKR}_{t-i} \\ \text{lnTON}_{t-i} \\ lnCO_{2t-i} \\ \text{lnGBR}_{t-i} \\ \text{lnTRAK}_{t-i} \end{bmatrix} + \sum_{j=k+1}^{d_{max}} \begin{bmatrix} b_{11j} & b_{12j} & b_{13j} & b_{14j} & b_{15j} \\ b_{21j} & b_{22j} & b_{23j} & b_{24j} & b_{25j} \\ b_{31j} & b_{32j} & b_{33j} & b_{34j} & b_{35j} \\ b_{41j} & b_{42j} & b_{43j} & b_{44j} & b_{45j} \\ b_{51j} & b_{52j} & b_{53j} & b_{54j} & b_{55j} \end{bmatrix} \times \begin{bmatrix} \text{lnDKR}_{t-j} \\ \text{lnTON}_{t-j} \\ \text{lnCO}_{2t-j} \\ \text{lnGBR}_{t-j} \\ lnTRAK_{t-j} \end{bmatrix} + \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \\ \varepsilon_{3t} \\ \varepsilon_{4t} \\ \varepsilon_{5t} \end{bmatrix} \quad (6)$$

3. Results

The first step in determining the method in the econometric analysis is to test whether the series contains a unit root. The unit root test results of the variables used in the study are given in Table 3.

Table 3. Augmented Dickey and Fuller (ADF) and Phillips and Perron (PP) unit root tests.

Variables	ADF		PP	
	Level	1st Difference	Level	1st Difference
lnDKR		−3.850819 (0.0004) ***		−3.903828 (0.0003) ***
lnTON	−4.334403 (0.0098) ***		−14.76907 (0.0000) ***	
$lnCO_2$		−6.391589 (0.0000) ***		−6.550400 (0.0000) ***
lnGBR	−4.337709 (0.0091) ***		−4.337709 (0.0091) ***	
lnTRAK		−3.553848 (0.0135) **		−3.429667 (0.0180) **

The ADF test determined the appropriate lag length according to the Schwarz (SIC) information criterion, and the maximum lag number was chosen as 9. In the PP test, the kernel method was determined by the "Barlett–Kernel" and "Newey–West Bandwidth" methods. The *p* value is presented in parentheses. ***, ** denote statistical significance at the 1%, 5% levels, respectively.

ADF and PP tests were used under the Unit Root test. According to the test results, the grain production area (DKR) data (the dependent variable), the annual number of tractors (TRK), and annual agricultural greenhouse gas emissions (CO_2) data were stationary at the first difference, and the other variables were stationary at the level. These results indicate that using the ARDL model to investigate the short and long-run relationships between the series is appropriate.

3.1. ARDL Bounds Test

While determining the appropriate lag length for the model estimation of the study, the model with the lowest AIC value was preferred among the models with normal distribution, no variance problems, no autocorrelation, and no stability condition. Boundary test results for ARDL (2,3,3,1,1), which is the model that meets the relevant criteria, are given in Table 4.

Examination of the F-test results in Table 4 indicates that the calculated F-statistics value is above the critical values stated at the 1% significance level. Therefore, the null hypothesis, meaning "no cointegration", is rejected. The t-bounds test results in Table 4 confirm a cointegration relationship between the variables, similar to the F-bounds test results. The short-run and long-run estimation results for the ARDL (2,3,3,1,1) model are given in Table 5.

Table 4. ARDL bounds test.

Test	F-Stat	Probability	Result
Breusch–Godfrey serial correlation LM test	2.087005	0.1705	No problem with serial correlations
Breusch–Pagan–Godfrey heteroscedasticity test	1.7011	0.173	No problem of heteroscedasticity
Jarque–Bera test	1.026939	0.598416	The estimated residual is normal
Ramsey test	0.100048	0.7572	The model is specified correctly

Critical values calculated by Narayan [54] were used.

Table 5. Long-run and short-run estimation results for the ARDL (2,3,3,1,1) model.

Long-Run			
Variable	Coefficient	t statistic	Prob.
lnTON	−0.299075 **	−2.852220	0.0136
$lnCO_2$	−0.776908 ***	−15.38627	0.0000
lnGBR	0.106338 **	2.584972	0.0226
lnTRK	0.638938 ***	10.56377	0.0000
Short-Run			
Variable	Coefficient	t statistic	Prob.
C	23.19385 ***	7.943460	0.0000
D(lnDKR(−1))	0.452619 ***	3.434853	0.0044
D(lnTON)	−0.003477	−0.106257	0.9170
D(lnTON(−1))	0.130862 ***	4.149396	0.0011
D(lnTON(−2))	0.049165 *	2.060700	0.0599
$D(lnCO_2)$	−0.10276 *	−1.921108	0.0769
$D(lnCO_2(-1))$	0.441496 ***	4.422994	0.0007
$D(lnCO_2(-2))$	0.2710509 ***	4.099552	0.0013
D(lnGBR)	0.034123 *	2.000659	0.0668
D(lnTRK)	−0.118232	−0.843892	0.4140
CointEq(−1)	−0.952379 ***	−7.943820	0.0000
Sensitivity Analysis			
R^2	0.901617		
Adjusted R^2	0.843744		
F statistic	15.57936		
Prob (F statistic)	0.000001		
Durbin-Watson stat	2.354542		

***, ** and * denote 1%, 5%, and 10% significance level, respectively.

Analysis of the short-run estimation results in Table 5 reveals that the error correction coefficient (CointEq(−1)) is negative and statistically significant. The result obtained for the error correction variable predicts that the deviations from the short-run equilibrium will be corrected, and the system will converge to the long-run equilibrium within 1.05 years. The long-run estimation results in Table 5 confirm that all variables included in the analysis have a statistically significant effect on the dependent variable in the long run. While this relationship is negative for grain production amount and carbon emission, it is positive for fertilizer use and the number of tractors.

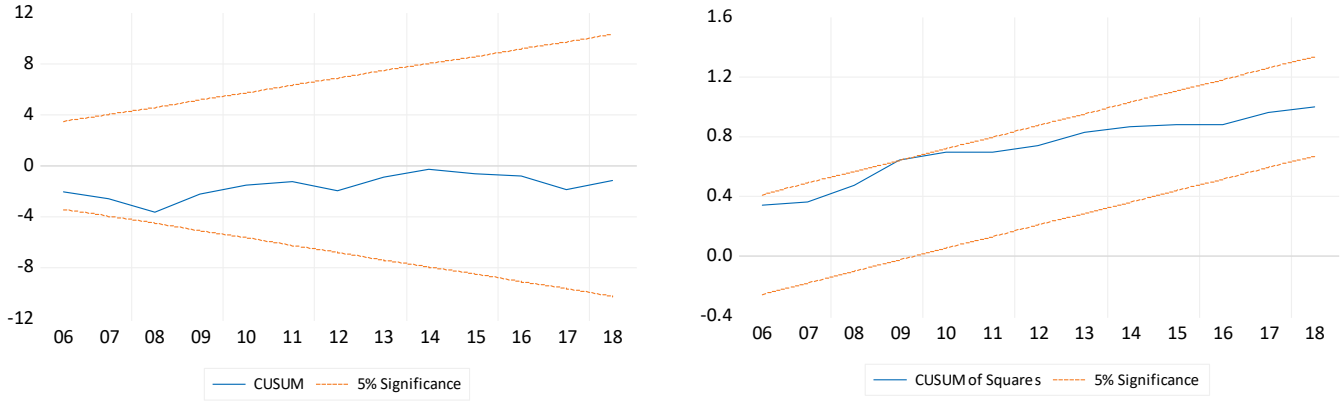
3.2. Diagnostic Tests

Diagnostic tests are performed to determine whether the model is functional. The diagnostic test results in Table 6 show that automatic association, normality, varying variance, and modeling error test statistics are acceptable in the predicted model.

Table 6. ARDL diagnostic test results.

Test	F-Stat	Probability	Result
Breusch–Godfrey serial correlation LM test	2.087005	0.1705	No problem with serial correlations
Breusch–Pagan–Godfrey heteroscedasticity test	1.701100	0.1730	No problem of heteroscedasticity
Jarque–Bera test	1.026939	0.598416	The estimated residual is normal
Ramsey test	0.100048	0.7572	The model is specified correctly

CUSUM and CUSUMSQ stability tests were also performed to test the structural stability in the estimated long-run model. Figure 2a,b shows plots of the CUSUM and CUSUMSQ tests for the ARDL model. The fact that the CUSUM and CUSUMQ test statistics are in the 5% critical value range indicates that the coefficients are stable in the long run, and there is no break in the model in the long run.



(**a**) (**b**)

Figure 2. (**a**) CUSUM stability tests. (**b**) CUSUMSQ stability tests.

3.3. Toda–Yamamoto Causality Test

The Toda–Yamamoto test was used to determine whether the variables have a statistically significant effect on each other. This test is regarded as the most appropriate causality test for the dataset used in the study. Test results are presented in Table 7.

Table 7. Toda and Yamamoto Granger causality analysis.

Variable	lnDKR	lnTON	$lnCO_2$	lnGBR	lnTRK
lnDKR	-	6.493 *** (0.010)	-	-	2.692 * (0.100)
lnTN	16.200 *** (0.000)	-	8.156 *** (0.004)	4.040 ** (0.044)	-
$lnCO_2$	28.436 *** (0.000)	-	-	-	4.636 ** (0.031)
lnGBR	8.487 *** (0.003)	-	2.709 * (0.099)	-	6.849 *** (0.008)
lnTRK	28.031 *** (0.000)	6.461 ** (0.011)	-	-	-
lnTON ⟷ lnDKR		lnTRK → lnTN		lnTON → lnGBR	
$lnCO_2$ → lnDKR		lnTON → $lnCO_2$		$lnCO_2$ → lnTRK	
lnGBR → lnDKR		lnGBR → $lnCO_2$		lnGBR → lnTRK	
lnTRK ⟷ lnDKR					

*, **, and *** indicate the null hypothesis rejected at the 1%, 5%, and 10% significance level, respectively. Values in parentheses are *p* values. The optimal lag length was chosen using the Akaike information criterion (AIC).

According to the test results in Table 7, the grain production areas estimated as the dependent variable in the ARDL model are in a feedback relationship with the grain production amount and tractor number variables. However, the fertilizer and carbon emission variables have a unidirectional causality relationship towards the grain production area. Other variables for which the amount of grain production is the cause of Toda–Yamamoto were determined as carbon emissions and fertilizer use. Moreover, variables that were

caused by Toda–Yamamoto were estimated as carbon emissions and the number of tractors. It was determined that the tractor variable was the cause of only grain production, except for grain production areas.

4. Discussion

The study used the ARDL model to determine the factors affecting grain production areas in the long run. The Toda–Yamamoto causality test was also used to examine the causality relationships. The estimation results obtained for the long run are primarily compatible with the literature and the economic theory. Agricultural mechanization equipment is extensively used in crop production. The tractor is the most widely used of them. For this reason, it is logical that among the variables included in the model, the variable with the highest impact on the production area is the number of tractors. The positive long-run coefficient of the tractor variable shows that it has a long-run positive impact on the production area, which is the dependent variable and this impact is statistically significant. This points out that there will be an increase in the long run in the area under grain production if the number of tractors increases. On the other hand, the negative short-run coefficient shows that tractor numbers (independent variable) have a short-run negative effect on the grain production area (dependent variable). This indicates that momentary changes in tractor numbers cause an increase or a decrease in grain production area in the short run. Even though the short-run effect is negative, this effect is not statistically significant. In this case, the short-run effect can be said to be random. In conclusion, positive long-run and negative short-run coefficients show that the relationship between these two variables is complex and prone to change over time.

These findings obtained from the research are supported by current studies showing that agricultural mechanization [34] and energy use in agriculture [58,59] positively affect grain production and grain yield in the long run. Similarly, the fertilizer used in grain production also positively affects the cultivated area. Many studies support this finding [42,58,60]. Although many studies examine the effects of fertilizer and tractor variables on grain production, there needs to be research examining the impact of both variables on production areas. In this respect, the present study is the first to reveal the effects of commonly used inputs in agricultural production on production areas.

The amount of output is another factor affecting the change in grain production areas. The estimation results show that this variable negatively affects grain production areas. Koondhar et al. [40] revealed that grain production (mt) significantly affects grain production areas (square km). However, research in the literature needs to examine the direction and coefficient of this relationship, including the researchers mentioned earlier. On the other hand, there are many studies on the effect of grain production areas on grain production [34,35,38–41]. Chandio et al. [38] found the effect of land under grain production (hectares) on grain yield (kg per hectare) to be negative. However, this relationship is positive in the studies of Ahsan [35], Abate [34], Koondhar et al. [40], Kumar et al. [41], and Chopra [39]. Resultingly, the findings obtained within the scope of the current research coincide with those commonly acquired in the literature. Comparing the study's results with the literature leads to the conclusion that the two variables affect each other in the opposite direction. Likewise, in their research in Turkey, Chandio et al. [38] concluded that the variables affect each other in the same direction in a negative way.

This result contrasts with economic growth and can be associated with the production pattern that has transformed Turkey in recent years. This transformation led to decreased grain production in highly productive basins in Turkey. Those consequences can be summarized under several headings. First, the significant increase in grain imports in recent years has reduced the producer prices for these products compared to alternative products. Trademap's [61] data on firms' grain imports increased approximately eight times in 2021 compared to 2002. In addition, while government subsidies for the production of forage crops increased to meet the high amount of feed needed by the livestock sector, there was an increase in the diversity and production areas of forage crops [62,63]. It has led to

increased production of forage crops such as alfalfa in wet and fertile lands where grain is produced under normal conditions. The decrease in grain production in moist and fertile areas decreased the yield per unit area. It turned the relationship between the increase in production areas and the amount of output negative. It is a common phenomenon that when the grain production area decreases, the total production will also decrease. However, especially in the last ten years, the increase in agricultural input costs in Turkey, the drought due to climate change, and the increase in imports pushed the producers to seek more efficiency.

Carbon emissions are another variable that negatively affects grain production areas according to the long-run estimation results of the ARDL model. These estimation results contradict certain aspects of research that predicted a negative relationship between grain production [35,60,64], grain yield [44,45], and carbon emissions for various regions of the world.

Studies [65] have shown that food insecurity has increased. Research highlights that in 2021, 29.3% of the world's population (2.3 billion people) will face moderate or severe food insecurity. Further, according to estimates made by FAO, food production should increase by 60% by 2050 due to population growth and dietary changes [66]. The need for grain is constantly growing. Therefore, carbon emissions, which are negatively related to production amount and efficiency, are positively related to production areas. However, suppose the reduction in grain yield does not reach a satisfactory price level for the farmers. In that case, the carbon emission grain production areas mechanism may operate negatively, as in the case of Turkey.

Analysis of the Toda–Yamamoto causality test reveals that the results are generally compatible with the literature. The feedback relationship determined between the grain production areas and the grain production amount is in line with the results obtained in the studies conducted by Ahsan et al. [35] for Pakistan, Koondhar et al. [64] for China, and Kumar et al. [41] for low- and middle-income countries. Further, no study found a unidirectional causality relationship between grain production areas to production amount [67] and grain production and production areas [68]

Causality analyses are the primary tools that reveal the direction of the relationships. Therefore, it is usual to encounter a widespread feedback relationship for variables expected to theoretically affect each other, such as grain production areas and grain production, except for special situations that countries may have (economic crisis, natural disasters, etc.). On the other hand, unlike the results obtained in this study, a feedback relationship was found between carbon emissions and grain production areas in the studies conducted by Koondhar et al. [64] and Kumar et al. [41]. The study's results indicate a unidirectional causality from carbon emissions to grain production areas, similar to the findings of the study by Warsame et al. [67], rather than a feedback relationship. This discrepancy observed between other studies and the results of this study might be explained by technical factors such as the difference between the time intervals considered by other studies and the time intervals considered in this study. Therefore, further studies examining the relationship between agricultural production areas and carbon emissions in Turkey are needed. Moreover, studies have yet to be performed on the causal relationship between the tractor numbers and the use of fertilizers and grain production areas.

5. Conclusions

The first noticeable result of the ARDL long-run estimation results is the negative relationship between grain production and grain production areas. This outcome is closely related to the market conditions in the relevant period. As long as the need for different crops like forage crops and grain imports continues in Turkey, it can be concluded that the amount of production increases will continue to reduce grain production areas. However, changes in the demand side of Turkey's grain products and developments affecting international grain prices may alter the negative relationship between grain production and grain production areas. Decreased grain production areas provide a field for producing

alternative products such as pulses and forage crops. The point to be considered here is to ensure that alternative products can be produced without giving up the production of products with a high level of specialization.

Agricultural greenhouse gas emissions, another variable with its negative impact in ARDL long-run estimation results, indicate that product groups produced as an alternative to grain have a higher emission-generating power. For instance, increases in forage crop production areas indirectly contribute to the rise in enteric fermentation, which constitutes the majority of agricultural emission sources. However, considering this study is the first observed study of the long-run relationship between grain production areas and carbon emissions, this hypothesis needs further testing.

The other long-run estimation results reveal that the tractor variable positively affects grain production areas. When the agricultural production structure of Turkey is reviewed, it is seen that the use of mechanization in the production of many other agricultural product groups, such as fruits and vegetables, is lower than grain production. Due to its critical importance in grain production areas, agricultural mechanization should be given priority by decision makers who will develop policy on this issue. In addition, considering the significant effect of the number of tractors on grain production areas, the necessity of studies on the impact of the quality and efficiency of agricultural mechanization on grain production and grain production areas emerges.

This study significantly explains the main factors affecting grain production areas. However, due to data limitations and low sample size, which are the main limitations of the study, many potential factors and analysis methods were not included in the study. These potential factors include changing grain prices, water availability, drought, and input prices, and we believe that their use in future studies will make significant contributions to the literature if the data constraint is eliminated. In addition, our causality test results, which reveal that grain production and tractor use are the cause of carbon emissions, indicate that we can obtain important information with a cointegration analysis in which carbon emissions are also considered as a dependent variable. In this way, not only the effect of emissions on grain production but also the effect of grain production on emissions can be explained. However, the stationarity level of our data and sample length are not sufficient to apply multiple cointegration approaches such as the Johansen approach.

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