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Determining the Dynamics Affecting Forest Areas in Türkiye with the ARDL Model

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ABSTRACT

This study investigates how industrialization, population growth, cultivated agricultural land, and greenhouse gas emissions affect forest area in Türkiye using annual data for 1990-2022 and an ARDL bounds testing approach. The estimates indicate a positive long run association between industrialization and forest area ($\beta = 6.627589$, $p < .01$) and negative association with cultivated agricultural land ($\beta = -6.969850$, $p < .01$), population growth ($\beta = -2.293148$, $p < .01$), and greenhouse gas emissions ($\beta = -0.660565$, $p < .01$). The positive industrialization effect likely reflects the integration of forestry policy with industrial development and the diffusion of sustainable industrial practices and carbon balancing mechanisms. By contrast, agricultural expansion and demographic pressure systematically reduce forest assets. Policy implications include shifting from land extensive growth to productivity oriented production; managing forest, agriculture and settlement interfaces through forest prioritized spatial planning, tightening satellite based MRV (measurement, reporting and verification) and land use conversion permits, prioritizing compact urban form and fire risk management at the wildland and aligning greenhouse gas emission, mitigation policy with these instruments to protect and expand forests sustainability.

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Türkiye'de Orman Alanlarını Etkileyen Dinamiklerin ARDL Modeli ile Belirlenmesi

ÖZET

Bu çalışma; sanayileşme, nüfus artışı, işlenebilir tarım alanı ve sera gazı emisyonlarının 1990-2022 dönemi yıllık verileri kullanılarak Türkiye'deki orman alanları üzerindeki etkilerini ARDL sınır testi yaklaşımıyla incelemektedir. Tahmin sonuçları, sanayileşme ile orman alanı arasında uzun vadede pozitif bir ilişki ($\beta = 6.627589$, $p < .01$), işlenebilir tarım alanı ($\beta = -6.969850$, $p < .01$), nüfus artışı ($\beta = -2.293148$, $p < .01$) ve sera gazı emisyonları ($\beta = -0.660565$, $p < .01$) ile negatif bir ilişki olduğunu göstermektedir. Sanayileşmenin olumlu etkisi, ormancılık politikalarının sanayi gelişimiyle bütünleşmesi ve sürdürülebilir sanayi uygulamaları ile karbon dengeleme mekanizmalarının yaygınlaşmasıyla açıklanabilir. Buna karşılık, tarımsal genişleme ve demografik baskı, orman varlıklarını sistematik olarak azaltmaktadır. Politika önerileri arasında; arazilerin artırılması yerine verimlilik odaklı üretime geçilmesi, orman, tarım ve yerleşim alanları arasındaki sınırların orman öncelikli mekânsal planlama ile yönetilmesi, uydu tabanlı MRV (ölçüm, raporlama ve doğrulama) ve arazi kullanım değişikliği izinlerinin sıkılaştırılması, kompakt kent formunun ve orman arayüzünde yangın riski yönetiminin öncelenmesi ile sera gazı emisyon azaltımı politikalarının bu araçlarla uyumlu hale getirilmesi yer almaktadır.

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INTRODUCTION

Problems such as deteriorations in natural ecosystems, loss of biodiversity, air, water, and soil pollution, desertification, and climate change have long been defined as an "ecological crisis". Increasing human activities and unsustainable use of natural resources disrupt the functioning of ecosystems, further deepening global environmental problems. The ecological crisis can be explained in its most basic sense as damage to ecosystem processes such as photosynthesis, water and substance cycles, energy flow, and the food chain. Although natural events such as ice ages, meteor impacts and volcanic activities have historically led to such crises, especially with the spread of agriculture, the colonial movements in the 15th century, the Industrial Revolution in the 19th century, and the rapid industrialization process after World War II, the extent of human-induced environmental destruction has become a serious problem on a global scale (Tolunay, 2021). In recent years, environmental sustainability has become an even more important area of research, along with interconnected dynamics such as economic growth, deforestation, urbanization, and climate change (Adedoyin et al., 2019; Nasreen et al., 2020; Abdul et al., 2021; Tanveer et al., 2021). In this context, it has become critical to examine the effects of factors such as rapid population growth, urbanization, expansion of agricultural lands, and industrialization, especially in developing countries, on environmental resources and forest areas.

Population growth, land use, and urbanization dynamics

Population growth and urbanization transform land use patterns due to basic needs such as housing, nutrition, and energy that they bring with them. At the Glasgow Climate Summit, deforestation was defined as "the permanent conversion of forests to a different land use due to agricultural use, grazing, urban development, or industrial activities" (Chakravarty et al., 2012; WRI, 2021). Especially in developing countries, opening forest areas to agricultural production in order to expand agricultural lands has become a widespread practice (Kissinger et al., 2012). This situation leads not only to the shrinking of forest areas, but also to the decrease of biodiversity and the weakening of ecosystem services (Göl, 2007; Mather, 2007). The effects of increasing population on urbanization cause fragmentation of forest habitats, loss of natural sink areas, and an increase in greenhouse gas emissions (Stuart-Smith et al., 2021). In Türkiye, the urbanization process has led to the rapid opening of agricultural, pasture, and forest areas to construction, especially in metropolitan cities. Especially in metropolises such as Istanbul, Ankara, and Izmir, serious losses were experienced in forest areas in the post-1980 period, and these losses were mostly associated with unplanned urbanization, transportation investments, and the expansion of industrial areas. In addition, 2B applications and constructions on coastal strips and water basins damage the integrity of forest ecosystems (Erdönmez, 2013; Yıldırım & Ayanoğlu, 2014).

Agricultural expansion and deforestation

Deforestation can occur not only as a result of human-induced activities but also due to natural factors such as fires, natural disasters, and insect infestations (Cesareo et al., 2021). Since 1990, approximately 420 million hectares of forest area have been lost on a global scale. In particular, between 2000 and 2010, 40% of tropical forests were destroyed by being converted for agricultural activities (FAO, 2020). Deforestation triggers an increase in regional temperatures by causing the soil surface to absorb more sunlight. According to FAO (2020) data, approximately 420 million hectares of forest area have been lost worldwide since 1990. Opening land for agricultural activities, especially in tropical regions, is the main cause of these losses. The destruction of forest cover causes the soil surface to absorb more sunlight and disrupts the local climate balance. This situation also brings with it the effects of adverse local climatic events such as microclimate changes, shifts in precipitation regimes, and increased drought cycles (Stuart-Smith et al., 2021). Similar trends are observed in the context of Türkiye. In some regions, it has lost its forest status and turned into agricultural areas such as fields, vineyards, and gardens; It has caused the forest and agricultural boundary to become blurred by turning into areas used in animal husbandry such as pastures, meadows, and wintering areas, which has accelerated deforestation processes (Yıldırım & Ayanoğlu, 2014). In particular, 2/B practices, that is, the sale of areas that have lost their forest status, have led to an increase in both construction and agricultural activities in the coastal strip and plain regions.

Carbon emissions, greenhouse gases, and climate change

Deforestation and land-use changes are among the processes that directly affect the carbon cycle and greenhouse gas emissions (CO_2, CH_4, N_2O, CO, and F-gases), adversely affecting environmental sustainability as a result of human activities such as transportation, industrial production, deforestation, urbanization, and the expansion of agricultural lands (Olale et al., 2018; Sarkodie & Strezov, 2019). In particular, the increase in CO_2 emissions is considered one of the main causes of global warming and ozone layer depletion (Zhu & Shan, 2020; Yorucu & Varoglu, 2020). Forests play a critical role in combating climate change by storing a large portion of the carbon in the atmosphere within them. Trees absorb CO_2 during photosynthesis and store it in their branches, leaves, roots, and soil (Pan et al., 2011). However, deforestation and forest degradation cause this stored carbon to be released back into the atmosphere, increasing greenhouse gas emissions and accelerating climate change (Houghton, 2005). According to the Environmental Protection Agency's (EPA, 2020) report, it was stated that a large portion of global greenhouse gas emissions is CO_2-related. CO_2 emissions from industry and fossil fuel use account for 65% of total emissions, while CO_2 release from deforestation and land-use changes accounts for 11%. In addition, methane (CH_4) contributes 16%, nitrous oxide (N_2O) 6%, and F-gases 2% to greenhouse gas emissions. Adopting sustainable land management policies and controlling deforestation is critical to preventing global warming (Lin & Ahmad, 2017). In Türkiye, the removal of forest areas for different purposes directly reflects on the greenhouse gas inventory and contributes to the increase in CO_2 emissions in particular. Therefore, protecting the carbon sequestration capacity at the country level and spreading integrated land planning practices are of great importance both for ecosystem health and for combating climate change (Demir, 2025).

Industrialization, energy consumption, and sustainable forestry policies

The acceleration of industrialization increases energy demand, accelerating fossil fuel consumption and therefore greenhouse gas emissions. The main factors causing the increase in carbon emissions worldwide are: population growth and urbanization, the decrease in forest areas and the loss of natural sinks, and the uncontrolled and unfiltered release of greenhouse gases into nature with the effect of industrialization (Kahraman, 2019). In particular, emissions consisting of carbon-based compounds have become one of the main triggers of global warming.

In Türkiye, increasing industrialization and energy consumption have made the management of greenhouse gas emissions a priority issue on the environmental and political agenda. In this context, the country officially adopted the goal of net-zero carbon emissions by 2053, ratifying the Paris Climate Agreement in 2021. This goal is not only an environmental commitment but also entails a multi-dimensional transformation process, such as the restructuring of Türkiye's energy policies, the reduction of fossil fuel use, and the widespread adoption of renewable energy sources (MFA, 2025).

Literature review

As stated in the paragraphs above, it is seen in the literature that population increase and agricultural land use stand out in the studies conducted to determine the factors affecting forest areas. Imai et al. (2018) examined the factors affecting forest area change in eight countries in Southeast Asia using data from 1980-2010. A negative correlation was determined between forest area and population density, and forest land suitable for agricultural use in lowland areas. The influence of environmental, agricultural, and social variables on forest area dynamics has been revealed, and it has been stated that it will have important implications for predicting future tropical forest change. Mon et al. (2012) examined the factors affecting deforestation and forest degradation in the Bago Mountains region of Myanmar, using forest cover density maps obtained from satellite images from 1989-2006, environmental factors, location characteristics, and logging records. In the research, as a result of the analyses made with logistic regression models, it was determined that altitude and distance to the nearest town had a strong effect on both deforestation and forest degradation probability. It has been stated that these findings play a critical role in protecting forest ecosystems with the implementation of sustainable forestry policies. Ahmed et al. (2015) examined the effects of variables such as economic growth, energy consumption, commercial openness, and population on deforestation with the ARDL boundary test method, using data from 1980-2013 in Pakistan. The findings of the study determined that economic growth and energy consumption increased deforestation. In the study conducted by Ibrahim et al. (2022), the effect of the forestry sector on the economy in Nigeria and the factors determining this contribution were analyzed. In the study, it was emphasized that rapid population growth and the expansion of agricultural production areas increased net forest loss, and this reduced the economic contribution of the forestry sector. Özbek & Oğul (2023) examined the interaction between agricultural production, forest assets, and environmental pressure in Türkiye between 1990 and 2019 with the ARDL boundary test. The findings showed that agricultural added value and energy consumption increased the ecological footprint, while the increase in forest areas decreased the ecological footprint. In the study carried out by Ahlat & Yurtkuran (2025), the relationship between forest areas and economic growth, energy consumption, and industrial production in Türkiye was analyzed within the framework of the Environmental Kuznets Curve (EKC) and Load Capacity Curve (YKE). ARDL and FMOLS methods were used in the study. According to the findings, while economic growth negatively affects forest areas in the short term, a positive relationship emerges in the long term. Energy consumption, on the other hand, has a reducing effect on forest areas in both the short and long term.

As a result, human-induced pressures such as urbanization, agricultural expansion, and industrialization lead to the decrease of forest areas, the weakening of carbon sinks, and consequently the increase of greenhouse gas emissions. These dynamics threaten not only environmental sustainability but also social welfare. In this context, sustainable land management and integrated forestry policies stand out as the cornerstones of the fight against climate change.

In this context, the main objective of the study is to analyze the extent to which determining factors such as industrialization, population growth, arable agricultural land, and greenhouse gas emissions are effective on forest areas in Türkiye with the ARDL boundary test and to develop recommendations for sustainable environmental policies in line with the findings. In addition, although many studies in the literature generally focus on the relationship between greenhouse gas emissions and economic activities, it is noteworthy that the number of studies in which the reduction of forest areas and factors such as population, industry, and agriculture are discussed is limited. In this aspect, the study makes an important contribution to the literature in terms of evaluating the multivariate structure affecting forest areas in the context of Türkiye with an econometric approach.

MATERIAL and METHOD

The main material of the research consists of the data obtained from the questionnaire study applied to the third and fourth-grade students studying at Tokat Gaziosmanpaşa University Faculty of Agriculture. The questionnaire application was carried out in March of the 2024-2025 academic year, and was carried out meticulously with the necessary ethical approval in line with the decision numbered 01-68 of the Tokat Gaziosmanpaşa University Ethics Committee.

Method Used in Obtaining Data

Data

Detailed information on the variables and data sources used in the study is shown in Table 1. The data set covers the years 1990-2022 and was obtained from the General Directorate of Forestry (GDF, 2025), the Turkish Statistical Institute (TURKSTAT, 2025), and the World Development Indicators (WDI, 2025) databases. The Eviews 10 package program was used in the analyses. Within the scope of the analysis, forest areas (ha) in Türkiye were taken as the dependent variable. Forest area data includes areas with forest cover at a certain density, and treeless forest areas were excluded and not taken into consideration (GDF, 2020). In the study, the dependent variable is forest area (ha), and the independent variables are population growth rate (%), industrialization rate (%), greenhouse gas emission (metric tons/person), and the amount of cultivated agricultural land (ha).

Table 1. Definition of variables
Çizelge 1. Değişkenlerin tanımı

Variables	Definition of Variables	Data Source
FA	Forest Area (ha)	GDF-TURKSTAT
PG	Population Growth Rate (% annual)	TURKSTAT
AL	Cultivated Agricultural Land (ha)	TURKSTAT
IND_GDP	Industrialization Rate (% GDP)	WDI
GHG	Greenhouse Gas Emissions (% change from 1990)	WDI

Unit root test

In the study, since all variables have positive values, logarithmic transformation was applied first, and in order to determine the trend structure, i.e., the stationarity status of the series, the Augmented Dickey-Fuller (ADF) test (Dickey & Fuller, 1981) and the Phillips-Perron (PP) test (Phillips & Perron, 1988) were used to determine whether the series were stationary at level (I(0)) or at first difference (I(1)). It was investigated whether it is.

The ARDL (Autoregressive Distributed Lag) model developed by Pesaran & Shin (1995) was used to test the long-term relationship between the variables. This method allows cointegration analysis for series with different stationarity levels and is also known as the Bounds Test. The ARDL model was developed to examine the long-term equilibrium relationship in models that include both level stationary (I(0)) and first difference stationary (I(1)) variables. While traditional cointegration tests can only be applied if all series are at the same stationarity level, the ARDL method eliminates this restriction and enables the analysis of short and long-term relationships together. In particular, it stands out as an effective method in data sets with a limited number of observations (Nkoro & Uko, 2016). However, cointegration analysis cannot be performed if all of the series are level stationary (I(0)). The ARDL model offers a flexible and reliable approach in evaluating long-term relationships by ignoring differences in stationarity levels.

Autoregressive distributed lag (ARDL) model

The ARDL model consists of two basic steps. First, the existence of a long-term relationship between the series is analyzed using the boundary test method. In the second stage, the dynamic structure of the model is revealed by estimating the short and long-term parameters (Narayan & Smyth, 2006). One of the most important advantages of the ARDL model is that the variables are stationary only at the level (I(0)) or at the first difference (I(1)), which does not constitute a restriction in terms of the applicability of the model. However, a critical point to be considered when applying the ARDL approach is that the series should not be stationary in the second difference (I(2)) (Brown et al., 1975; Pesaran et al., 2001). In this aspect, the ARDL model stands out as a flexible and reliable method in analyzing the cointegration relationship between series with different stationarity levels. In addition, the ARDL method gives statistically more reliable results in the error correction model compared to cointegration tests. This model is widely used in time series analyses by providing detailed information on both short and long-term relationships between series (Akel & Gazel, 2014; Belen & Karamelikli, 2016). In the study, a linear estimation equation for the model is given in equation (1).

$$LFA = \beta_0 + \beta_1\,LPG + \beta_2\,LIND_{GDP} + \beta_3\,LGHG + \beta_4\,LAL + \epsilon_i \qquad (1)$$

Calculations were made by taking the natural logarithms of the variables in the linear estimation equation. The prefix 'L' used in the equation indicates the natural logarithm (ln) of the relevant variable. In addition, the error correction model created to estimate the short-term coefficients is given in equation (2).

$$\begin{aligned}\Delta LFA = \alpha_0 &+ \sum_{i=1}^{p}\beta_{1i}\,\Delta LFA_{t-i} + \sum_{i=0}^{q1}\beta_{2i}\,\Delta LPG_{t-i} + \sum_{i=0}^{q2}\beta_{3i}\,\Delta LGDP_{t-i} + \sum_{i=0}^{q3}\beta_{4i}\,\Delta LGHG_{t-i} + \sum_{i=0}^{q4}\beta_{5i}\,\Delta LAL_{t-i} + \delta_1\,LFA_{t-1} \\ &+ \delta_2\,LPG_{t-1} + \delta_3\,LIND\_GDP_{t-1} + \delta_4\,LGHG_{t-1} + \delta_5\,LAL_{t-1} + \epsilon_i \qquad (2)\end{aligned}$$

In the above equation $\alpha, \Delta, \epsilon_i$ denote the intercept, the differencing operator, and the error term, respectively. After estimating equation (2), the existence of a long-run relationship is evaluated using the Wald (F) test (Pesaran et al., 2001). The hypotheses for this test are as follows;

H0: $\delta_1 = \delta_2 = \delta_3 = \delta_4 = \delta_5 = 0$ (No cointegration)

H1: $\delta_1 \neq \delta_2 \neq \delta_3 \neq \delta_4 \neq \delta_5 \neq 0$ (Cointegration exists)

The calculated F-statistic is compared with the significance levels derived asymptotically in the studies of Pesaran et al. (2001). In this study, lower and upper values are given according to the situations where the variables are completely I(0) and I(1). If the computed F-statistic lies below the lower bound, the null of no cointegration cannot be rejected, implying the absence of cointegration. Conversely, if the statistic exceeds the upper bound of the critical values, the null hypothesis that no long-run relationship exists is rejected. When the F-statistic falls between the lower and upper bounds (the inconclusive region), no definitive conclusion about cointegration can be drawn (Nkoro & Uko, 2016). In such a case, the use of error terms for cointegration and the application of different cointegration tests according to the stationarity levels of the variables are recommended. If it is determined that there is a long-term relationship between the variables as a result of the boundary test, long-term coefficients need to be estimated in the next stage.

After the lag lengths for the dependent and independent variables are determined using information criteria, the most appropriate ARDL model is selected, and long-term coefficients are obtained from the estimated model. Considering equation (1) for this study, the ARDL (p, q1, q2, q3, q4) model given in equation (3) was created using the variables (LFA, LAL, LPG, LIND_GDP, LGHG) whose natural logarithms were taken in order to estimate the long-term coefficients.

$$LFA = \alpha_0 + \sum_{i=1}^{p}\alpha_{1i}\,LFA_{t-i} + \sum_{i=0}^{q1}\alpha_{2i}\,LPG_{t-i} + \sum_{i=0}^{q2}\alpha_{3i}\,LIND\_GDP_{t-i} + \sum_{i=0}^{q3}\alpha_{4i}\,LGHG_{t-i} + \sum_{i=0}^{q4}\alpha_{5i}\,LAL_{t-i} + \epsilon_i \qquad (3)$$

In equation (3), while α represents the regression coefficients, p represents the optimal lag lengths of the dependent variable, and q1, q2, q3, and q4 represent the explanatory variables. If the existence of a long-term relationship between the variables is determined in the boundary test results, long-term and short-term coefficients are estimated using the ARDL (p, q1, q2, q3, q4) model.

After the long-term coefficients are determined, the validity of the model is evaluated by applying the diagnostic tests of the model, and it is decided whether the model is appropriate. To test the validity of the model, the Breusch-Godfrey test for autocorrelation, the Breusch-Pagan test for varying variance, and the Jarque-Bera test to determine whether the error terms conform to the normal distribution were applied. In addition, CUSUM and CUSUMSQ tests can be used for the stability of the variables in the ARDL model. An error correction model based on ARDL, such as the one below, can be used to determine the short-term relationships between the variables.

$$\Delta LFA = \alpha_0 + \sum_{i=1}^{p} \lambda_{1i}\,\Delta LFA_{t-i} + \sum_{i=0}^{q1} \lambda_{2i}\,\Delta LPG_{t-i} + \sum_{i=0}^{q2} \lambda_{3i}\,\Delta LIND_{GDP\,t-i} + \sum_{i=0}^{q3} \lambda_{4i}\,\Delta LGHG_{t-i} + \sum_{i=0}^{q4} \lambda_{5i}\,\Delta LAL_{t-i} + \lambda_6 ECM_{t-1} + \epsilon_i \tag{4}$$

In equation (4), the variable shown as ECMt-1 expresses the error correction term. This term represents the lagged error terms of the model with a long-term relationship between the variables. The ECM coefficient shows the extent to which imbalances that occur in the short term will be eliminated in the long term. The error correction term being negative and significant indicates that the model is heading towards its long-term equilibrium and that deviations disappear over time.

RESULTS and DISCUSSION

Unit root test

In the study, firstly, the stationarity levels of the time series data set regarding forest areas and independent variables were determined. As a matter of fact, in time series models, the first stage is to determine the stationarity levels of the variables, and for this purpose, Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) unit root tests are applied. ADF and PP test results are presented in Table 2, revealing that the series show stationarity at different levels and that the variables have cointegration properties at different levels. These tests were applied to determine whether the series are stationary and to determine whether the variables become stationary at level (I(0)) or at first difference (I(1)).

Table 2. Unit root test result

Çizelge 2. Birim kök testi sonuçları

		Variables	ADF	PP		*Variables*	ADF	PP
Level	Constant	FA	-4.371445***	-3.955100***	*First Differences*	FA	-6.806106***	-10.14916***
		AL	-0.616638	-0.645622		AL	-4.432902***	-4.389183***
		GHG	-3.057108	-5.194539***		GHG	-5.968514***	-5.945960***
		IND_GDP	-1.732842	-1.505558		IND_GDP	-4.791266***	-4.791266***
		PG	-4.321688***	-4.297122***		PG	-8.734259***	-22.15282***
	Constant +Trend	FA	-4.011358***	-3.905306**		FA	-7.099807***	-11.94187***
		AL	-1.671582	-1.841272		AL	-4.341560***	-4.296298***
		GHG	-1.462588	-5.065779***		GHG	-7.462732***	-6.992195***
		IND_GDP	-0.931137	-0.931137		IND_GDP	-5.167853***	-5.142305***
		PG	-4.489759***	-4.479939***		PG	-8.584627***	-23.23284***

Notes: *, **, and *** indicate significance at 10%, 5%, and 1% levels, respectively.

According to the results obtained, FA (Forest Area) and PG (Population Growth Rate) variables were found to be stationary at the 1% significance level in the tests performed at the level. However, the GHG (Greenhouse Gas Emission) variable did not show a significant stationarity in the ADF test, although it was stationary at the level according to the PP test. On the other hand, the AL (Cultivated Agricultural Land) and IND_GDP (Industrialization Rate) variables were not stationary at the level, but became stationary when their first differences were taken. When the constant and trend model was used, it was determined that the PG variable was stationary at the 1% significance level. The FA variable was found to be stationary at the 1% significance level in the ADF test and at the 5% significance level in the PP test. Since the ARDL model can be applied with both level stationary (I(0)) and first difference stationary (I(1)) variables, the data obtained are suitable for the ARDL model. In addition, the fact that all variables are stationary at the second difference (I(2)) supports the applicability of the ARDL model. As a result, it has been determined that the ARDL boundary test method is an appropriate approach for examining the long and short-term relationships between variables.

ARDL model

The first step in applying the ARDL model is to determine the optimal lag length. In this process, variables are tested with different lag combinations and evaluated by considering the Akaike Information Criterion (AIC), Schwarz Information Criterion (SIC), and Hannan-Quinn (HQ) criteria. The model with the lowest information criterion value is accepted as the most suitable model (Pesaran & Shin, 1995). In this study, the optimal lag length was determined as 2 according to the minimum AIC value. The next step for the ARDL model to be applied is to calculate the F-statistic value within the scope of the Bounds Test. This test is a critical step to determine whether there is a long-term relationship between variables (Pesaran et al., 2001). In this context, whether the hypothesis

"H_0: There is no cointegration relationship between the variables" is accepted is determined by comparing the F-statistic value with critical limits. If the F-statistic value is greater than the specified upper critical limit, H_0 is rejected, and it is accepted that there is a cointegration relationship between the variables. When the F-statistic value remains below the lower critical limit, the H_0 hypothesis is accepted, that is, it is concluded that there is no long-term relationship between the variables. The ARDL boundary test results carried out in the study are presented in Table 3.

Table 3. Cointegration boundary test result

Çizelge 3. Eşbütünleşme sınır testi sonucu

Test Statistic	Value	K
F-statistic	8.198006	4
Critical Values	Lower Bound I(0)	Upper Bound I(1)
10%	2.45	3.52
5%	2.86	4.01
2.5%	3.25	4.49
1%	3.74	5.06

Since the F-statistic value calculated according to the cointegration boundary test results is greater than the lower (3.74) and upper (5.06) values, the H_0 hypothesis has been rejected. When the calculated F-statistic is compared with the critical values in the table, it is at the 1% significance level, and it has been determined that there is a cointegration relationship between the variables. Accordingly, it proves that there may be a long-term relationship between FA and AL, GHG, IND_GDP, and PG variables.

Diagnostic tests applied to evaluate the reliability of the model play a critical role in determining whether model assumptions are met. In addition, diagnostic tests such as Breusch-Godfrey LM Autocorrelation, Heteroskedasticity Test: ARCH Varying Variance Test, Jarque-Bera normality test, and Ramsey reset were applied to ensure that the model does not have autocorrelation and constant variance problems and to test other assumptions. The results of the diagnostic tests are given in Table 4.

Table 4. The validity of the model result

Çizelge 4. Model sonucunun geçerliği

Diagnostic Tests	Statistic Value	Probability Value
Autocorrelation Test: Breusch-Godfrey (LM)	0.594536	0.5613
Heteroskedasticity Test: ARCH Heteroskedasticity Test	1.099975	0.3032
Normality Test: Jarque-Bera	1.882282	0.390182
Functional Form Test: Ramsey RESET Test	5.658299	0.1131

According to the test results, the Breusch-Godfrey (LM) test was applied to determine whether there is autocorrelation in the model. As a result of the test, the F-statistic value was obtained as 0.594536, and the probability value was obtained as 0.5613. The probability value being greater than 0.05 indicates that there is no autocorrelation between the error terms. This shows that there is no sequential dependency problem in the model and the estimated coefficients are reliable (Breusch & Godfrey, 1981). The ARCH varying variance test was applied to determine whether the variance in the error terms is constant (homoscedasticity). The F-statistic was 1.099975, and the probability value was calculated as 0.3032. The probability value being greater than 0.05 indicates that the error terms have constant variance and there is no heteroscedasticity problem in the model (Engle, 1982). The Jarque-Bera test was applied to evaluate whether the error terms of the model have a normal distribution. The Jarque-Bera test statistic was obtained as 1.882282, and the probability value was obtained as 0.390182. The probability value being greater than 0.05 indicates that the error terms are normally distributed. This indicates that the estimation results of the model are reliable and were created in accordance with classical regression assumptions (Jarque & Bera, 1987). The Ramsey RESET test was applied to determine whether the model was established correctly and whether it contains missing variables. The Ramsey RESET test statistic was calculated as 5.658299, and the probability value was calculated as 0.1131. The probability value being greater than 0.05 indicates that there is no functional form error in the model and the model has an appropriate structure (Ramsey, 1969). When the diagnostic test results are evaluated in general, it has been determined that there is no autocorrelation in the model, there is no varying variance problem, and the error terms are normally distributed. These findings show that the model is statistically valid and suitable for analysis.

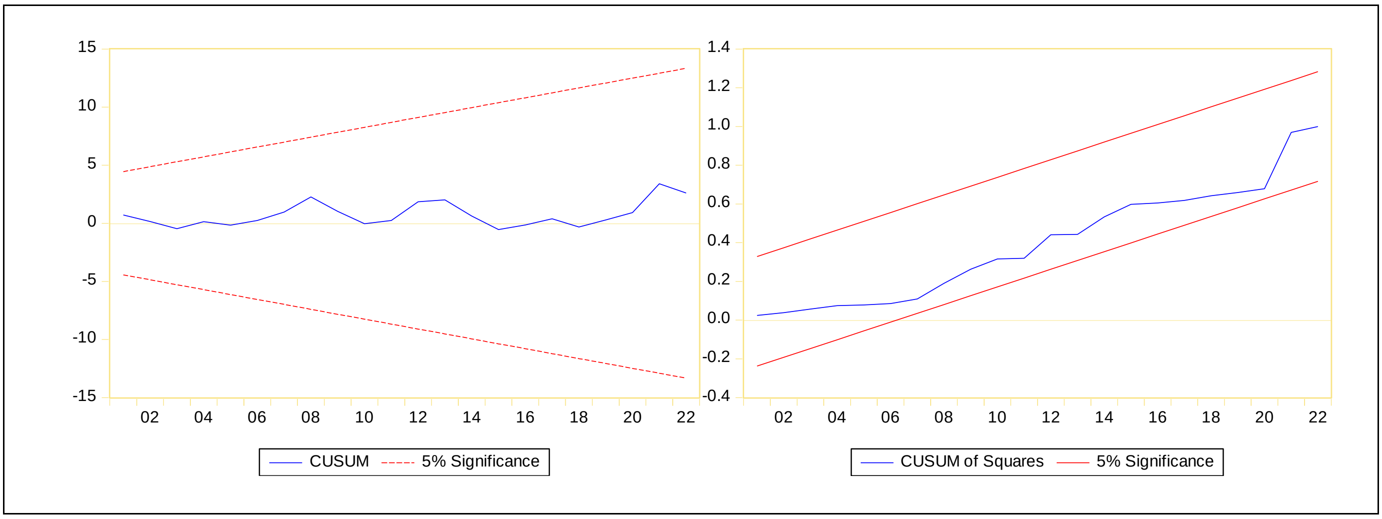

Figure 1. Plot of the CUSUM and CUSUMSQ tests
Şekil 1. CUSUM ve CUSUMSQ testlerinin grafiği

Upon examining the CUSUM and CUSUMSQ test statistics presented in Figure 1, it was observed that the CUSUM and CUSUMSQ curves, shown in blue, remained within the critical bounds indicated by the red dashed lines. This situation indicates that the curve remains within the critical limits, which indicates a significance level of 5%, and that there is no structural break problem in the model. In addition, it was concluded that the variables are stable in the long term and the estimated coefficients maintain their reliability. According to the results of the long-term coefficients estimated by the ARDL (1,0,0,2,1) model, it has been determined that there is a negative relationship between forest areas and cultivated agricultural areas (AL), population growth rate (PG), and greenhouse gas emissions (GHG) in Türkiye. In contrast, a positive relationship was found between forest area and industrialization rate (IND_GDP).

Table 5. ARDL (1,0,0,2,1) long-term coefficients
Çizelge 5. ARDL (1,0,0,2,1) uzun dönem katsayıları

Variables	Coefficient	Std. Error	t-statistic	P-Value
AL	-6.969850	2.414547	-2.886608	0.0086
GHG	-0.660565	0.208759	-3.164246	0.0045
IND_GDP	6.627589	2.281789	2.904558	0.0082
PG	-2.293148	0.704296	-3.255945	0.0036
EC = LFA -(-6.9698*LAL-0.6606*LGHG + 6.6276*LIND_GDP-2.2931*PG)				

According to the results of the ARDL model used in the study, it was determined that the expansion of cultivated agricultural areas negatively affects forest areas (β = -6.969850, p <.01). This finding reveals that agricultural expansion is one of the main determinants of forest loss. Similar results have been reported in the international literature. Kissinger et al. (2012) stated that agricultural activities are one of the most important causes of deforestation, especially in tropical and temperate regions. In a global study conducted by Gibbs et al. (2010), it was emphasized that the expansion of agricultural areas leads to the reduction of forest areas and that this process can only be controlled with sustainable forest management policies. It supports the FAO's assessments in the State of the World's Forests Report (2024) that agricultural expansion is the main driving force of global forest loss and the IPCC AR6 Synthesis Report (2023)'s findings on the climate risk-increasing effects of land use changes. In this context, the conversion of natural ecosystems for agricultural production and the intensification of agricultural activities can be considered as a significant pressure factor on forest areas in Türkiye.

It has been determined that there is a negative relationship between forest assets and population growth rate (β =-2.293148, p< .01). The expansion of residential areas, the increase in the use of natural resources and the increase in the need for agricultural production are among the main factors that accelerate forest loss (Mather, 2007; Demirbaş & Aydın, 2020). With the increase of the population in Türkiye from 13.6 million (year 1927) to 85.7 million (year 2024) during the republican period, there has been an intense migration from rural areas to urban centers, which has led to an increase in urbanization and industrialization. This process has led to significant changes in land use, accelerating deforestation and increasing pressure on natural ecosystems. The expansion of agricultural lands and the decrease of pasture areas create serious pressures on forest ecosystems (Özgür, 2017; Çalışkan & Göl, 2022; TURKSTAT, 2025). The decrease in forest areas leads to deterioration in ecosystem services and accelerates the loss of biodiversity. This situation reduces the carbon sequestration capacity of forests and increases greenhouse gas emissions. Population dynamics, increased consumption, and urban structuring play an important role in the increase of greenhouse gas emissions in cities. Increased energy consumption, transportation activities, and industrialization in the urbanization process cause an increase in greenhouse gas emissions, creating negative effects on forest ecosystems. As a matter of fact, it has been determined that greenhouse gas emissions hurt forest ecosystems ($\beta = -0.660565$, $p < .01$). Climate change, such as temperature increase and extreme weather events, directly threatens forest health (IPCC, 2019). The decrease of forests creates a positive feedback mechanism for climate change; as the climate changes, forest ecosystems deteriorate, and as they deteriorate, their capacity to hold greenhouse gases in the atmosphere decreases, and this further accelerates climate change.

On the other hand, it has been determined that the industrialization rate (IND_GDP) has a positive effect on forest areas ($\beta = 6.627589$, $p < .01$). This finding can be explained by supporting forestry policies with industrialization and spreading sustainable industrial practices. The support of industrialization to forestry policies, the introduction of incentive mechanisms such as carbon credits, and the promotion of sustainable afforestation projects are among the factors explaining this situation (Lambin & Meyfroidt, 2011). However, considering the long-term environmental effects of carbon dioxide emissions, this relationship should be carefully evaluated within the framework of sustainable forestry policies (IPCC, 2019). The impact of industrialization on forest areas may vary depending on regional and political factors. Some studies suggest that industrialization may have an effect of increasing forest areas. According to a study by the Food and Agriculture Organization of the United Nations (FAO), between 1990 and 1995, forest areas in industrialized countries (excluding the Russian Federation) increased by 1.75 million hectares, while in developing countries, a total of 13 million hectares of forest area were lost in the same period (FAO, 1997; Lanly, 1997). This situation can be explained by the increase in environmental awareness, the increase in economic welfare in industrialized countries, and the implementation of policies to expand forest areas. However, the impact of industrialization on forest areas may not always be positive; In some regions, industrialization can also lead to deforestation and environmental degradation (Oladipo, 2015). Especially in developing countries, the increasing pressure of land use and the consumption of natural resources due to industrial activities cause the decrease of forest areas (Shahbaz et al, 2016). In regions where government policies and environmental regulations are lacking, industrialization can create great pressure on forest ecosystems (Houghton, 2005). Industrial expansions, infrastructure projects, and uncontrolled industrialization processes can cause the destruction of forests in many regions (Oladipo, 2015).

The error correction model results based on the ARDL model are given in Table 6, and ECT_{t-1} is negative and significant at the 1% level. The error correction model is a model widely used in time series analyses. The obtained error correction term (ECT) coefficient indicates the rate at which short-term imbalances will be eliminated in the long term and the speed at which the system will return to equilibrium (Engle & Granger, 1987; Banerjee et al., 1993; Nkoro & Uko, 2016). The R^2 value of the model was calculated as 0.695177, and the adjusted R^2 value was calculated as 0.648281. These values indicate that the explanatory power of the model's dependent variable is high. In other words, the independent variables in the model can explain 69.52% of the change in forest areas.

Table 6. ARDL (1,0,0,2,1) error correction model

Çizelge 6. ARDL (1,0,0,2,1) hata düzeltme modeli

Variable	Coefficient	Std. Error	t-statistic	P-Value
C	61.63953	8.854536	6.961351	0.0000
D(LIND_GDP)	6.715908	2.343600	2.865638	0.0090
D(LIND_GDP(-1))	-7.578863	2.335792	-3.244665	0.0037
D(PG)	-0.885586	0.401020	-2.208336	0.0379
CointEq(-1)*	-0.985737	0.141627	-6.960084	0.0000
R2				0.695177
Adjusted R^2				0.648281

ECT_{t-1} in the equation is a parameter that represents the one-period lagged value of the error terms obtained within the long-term model and is called the error correction variable. The error correction coefficient determines the rate at which the system returns to its long-term equilibrium, and this coefficient is expected to be negative and statistically significant (Pazarlıoğlu, 2007; Koçak, 2014). According to the model results, the fact that the error correction term is negative and significant at the 1% level is also consistent with other studies in the literature.

Alam & Quazi (2003) revealed in their study that if the error correction coefficient is between -1 and 0, the system tends to equilibrium in the long run. Narayan & Smyth (2006) similarly stated that if the error correction coefficient is close to -1, it indicates that the system reaches equilibrium more quickly.

CONCLUSION

This study has demonstrated that the ARDL (1,0,0,2,1) model established with data from the 1990-2022 period successfully passed diagnostic tests, providing a reliable framework: autocorrelation and varying variance problems were not detected, the functional form was found to be appropriate, error terms were normally distributed, and the fact that the CUSUM/CUSUMSQ curves remained within the 5% critical limits confirmed that the coefficients were structurally stable throughout the period. According to the long-term results obtained, there is a positive relationship between forest areas and the rate of industrialization, and a negative relationship with cultivated agricultural areas, population growth rate, and greenhouse gas emissions. The rapid elimination of short-term imbalances indicates that the system returns to equilibrium in the long term and that the findings have predictive power in terms of policy design.

The findings clearly indicate that the strongest pressure on forests stems from agricultural land expansion. The literature also emphasizes that agricultural expansion is one of the main causes of deforestation (Gibbs et al., 2010; Kissinger et al., 2012). The widespread agricultural production in rural areas of Türkiye accelerates the conversion of natural habitats into agricultural land, creating pressure on forest ecosystems. While the demand for food and housing triggered by population growth expands agricultural activities, urbanization and infrastructure investments enlarge settlement areas, narrowing forest areas; this process weakens the integrity of ecosystems, increases habitat fragmentation, and biodiversity loss. The negative relationship detected with greenhouse gas emissions confirms the pressure of climate change on forest ecosystems: increasing temperatures, extreme weather events, and drought directly threaten forest health and can disrupt the ecological balance (IPCC, 2019).

Within this framework, the focus of the growth strategy should be shifted from opening new areas to increasing productivity in the same area. The widespread adoption of precision and smart agriculture practices (irrigation modernization, variable rate fertilization and spraying, sensor and remote sensing-based decision support), climate-resilient and improved varieties, soil health-enhancing practices (organic matter increase, crop rotation, erosion control), cold chain and storage investments that reduce post-harvest losses; Strengthening on-farm to market efficiency and cooperativism capacity will make it possible to meet food demand without creating expansion pressure on forest and agricultural boundaries. In parallel, spatial planning that prioritizes ecological integrity, forest-priority zoning, forest and agricultural buffer zones, and the continuity of ecological corridors, fast and transparent cadastre processes, effective operation of satellite and ground observation-based measurement, reporting, and verification (MRV) infrastructure, and the use of economic instruments that deter transformation or encourage protection are essential.

The positive correlation between industrialization and forest areas suggests that growth and conservation targets can be reconciled in a policy framework where environmental regulations are effectively implemented, carbon balancing and credit mechanisms are in place, and sustainable forestry principles are adopted. Indeed, there is evidence that forest areas can expand while industrialization increases in developed countries (FAO, 1997; Lambin & Meyfroidt, 2011); however, it should not be forgotten that rapid industrialization can trigger deforestation without protective frameworks (Shahbaz et al., 2016). In terms of climate, increasing sink capacity through reforestation and restoration of degraded forests, fire risk management (fuel load reduction, early warning, climate and smart silviculture) and widespread adoption of techniques that reduce emission intensity in agriculture (drip and pressurized irrigation, fertilizer efficiency, methane, nitrous oxide reduction) should be addressed together; clean production in industry and forest-based bioeconomy incentives will complete this transformation.

In conclusion, it reveals that protecting and increasing forest areas in Türkiye is possible if production strategies that increase agricultural productivity without expanding land, land use planning that considers ecological integrity, practices sensitive to regional differences, and integration with climate policies are carried out simultaneously.

Contribution Rate Statement Summary of Researchers

The authors declare that they have contributed equally to the article.

Conflict of Interest

The authors of the articles declare that they have no conflicts of interest.

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