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Uncovering time-varying drivers of agricultural output in Türkiye: A panel ARDL and Kalman Filter Analysis

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Abstract

Purpose: This study analyzes the factors affecting Türkiye's agricultural production performance between 1991 and 2022. By examining the role of key production inputs, it seeks to provide insights into the determinants of agricultural output and contributes to policy discussions on improving agricultural efficiency and sustainability.

Design/Methodology/Approach: The study employs the agricultural output index as the dependent variable, while independent variables include agricultural labor, capital, land, and material indices, along with the import and export rates of agricultural raw materials. Panel ARDL and Kalman filter methods assess short- and long-run dynamics.

Findings: The results indicate that capital and exports positively impact agricultural output, while land use contributes significantly. In contrast, labor's impact diminishes due to mechanization and the adoption of modern technology. Material use has a limited effect, highlighting the importance of cost management. Additionally, agricultural imports negatively influence productivity by increasing external dependence and costs.

Research Limitations/Implications: Potential limitations include data constraints and unobserved structural changes in the agricultural sector that may affect the robustness of the results. Future research could incorporate additional variables related to climate change and technological advancements.

Originality/Value: This study is among the rare analyses examining agricultural inputs' time-varying effects using advanced econometric techniques. It offers valuable insights into the evolving dynamics of Türkiye's agricultural sector.

Keywords: Agricultural output, agricultural input, agricultural TFP

Türkiye'de tarımsal üretimin zamanla değişen belirleyicileri: Panel ARDL ve Kalman Filtresi bulguları

Özet

Amaç: Bu çalışma, 1991-2022 yılları arasında Türkiye'nin tarımsal üretim performansını etkileyen faktörleri analiz etmeyi amaçlamaktadır. Çalışma, temel üretim girdilerinin rolünü inceleyerek, tarımsal çıktının belirleyicileri hakkında içgörü sağlamayı ve tarımsal verimliliği ve sürdürülebilirliği artırmaya yönelik politika tartışmalarına katkıda bulunmayı amaçlamaktadır.

Tasarım/Metodoloji/Yaklaşım: Çalışmada bağımlı değişken olarak tarımsal hasıla endeksi kullanılırken, bağımsız değişkenler arasında tarımsal işgücü, sermaye, arazi ve malzeme endeksleri ile tarımsal hammadde ithalat ve ihracat oranları yer almaktadır. Kısa ve uzun dönem dinamiklerini değerlendirmek için panel ARDL ve Kalman filtresi yöntemleri kullanılmıştır.

Bulgular: Sonuçlar, sermaye ve ihracatın tarımsal çıktı üzerinde en güçlü pozitif etkiye sahip olduğunu, arazi kullanımının da önemli katkı sağladığını göstermektedir. Buna karşılık, makineleşme ve modern teknolojinin benimsenmesi nedeniyle emeğin etkisi azalmaktadır. Malzeme kullanımı sınırlı bir etkiye sahiptir ve maliyet yönetiminin önemini vurgulamaktadır. Ayrıca, tarımsal ithalat dışa bağımlılığı ve maliyetleri artırarak verimliliği olumsuz etkilemektedir.

Araştırma Sınırlamaları/Etkileri: Potansiyel kısıtlamalar arasında veri kısıtlamaları ve sonuçların sağlamlığını etkileyebilecek tarım sektöründeki gözlenemeyen yapısal değişiklikler yer almaktadır. Gelecekteki araştırmalar iklim değişikliği ve teknolojik ilerlemelerle ilgili ek değişkenler içerebilir.

Özgünlük/Değer: Bu çalışma, tarımsal girdilerin zamanla değişen etkilerini ileri ekonometrik teknikler kullanarak inceleyen nadir analizler arasında yer almakta ve Türkiye'nin tarım sektörünün değişen dinamiklerine ilişkin değerli bilgiler sunmaktadır.

Anahtar Kelimeler: Tarımsal çıktı, tarımsal girdi, tarımsal TFV

INTRODUCTION

Agricultural production has been one of the cornerstones of economic and social development. However, challenges such as the rapidly growing world population, dwindling natural resources, and climate change bring the concepts of sustainability and efficiency in agricultural production to the forefront. Sustainability in the farming sector means maintaining current production levels and ensuring future food security through efficient use of resources. Studies such as Barton and Cooper (1948) and Barton and Durost (1960) have extensively addressed how agricultural production can be made more efficient through improvements in technology and resource utilization.

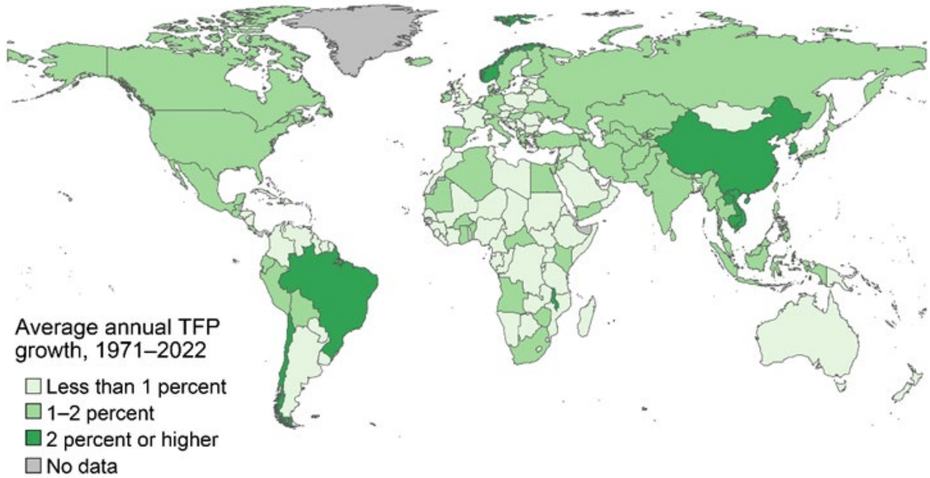

Figure 1. Agricultural total factor productivity growth by country, average annual percentage change, 1971-2022.

Source: USDA, Economic Research Service, International Agricultural Productivity data product. The data is from October 2024.

Agricultural total factor productivity (TFP) is a fundamental measure that emphasizes the importance of the quantity of inputs and the efficient use of resources in increasing output in the agricultural sector. Agricultural TFP is a significant indicator of economic development and global food security. The global map (Figure 1) showing the average annual percentage change in agricultural TFP reveals that agricultural productivity growth in different countries is not homogeneous. For example, regions such as Asia and Latin America have been at the forefront of productivity growth, while in some African countries, this growth has been relatively limited. Türkiye stands out as an important starting point on this map (Muraya, 2017; Peplinski, 2012).

Figure 2, analyzing the factors driving agricultural output growth worldwide, highlights that the share of TFP growth in total output growth has gradually increased. Especially in the 1960s, a large part of agricultural growth was driven by introducing new agricultural land and developing irrigation infrastructure. In contrast, today, TFP growth has become the primary determinant. Technology, irrigation practices, and innovations in land management are among the factors accelerating this process (Sharma, 2023; Barton & Cooper, 1948).

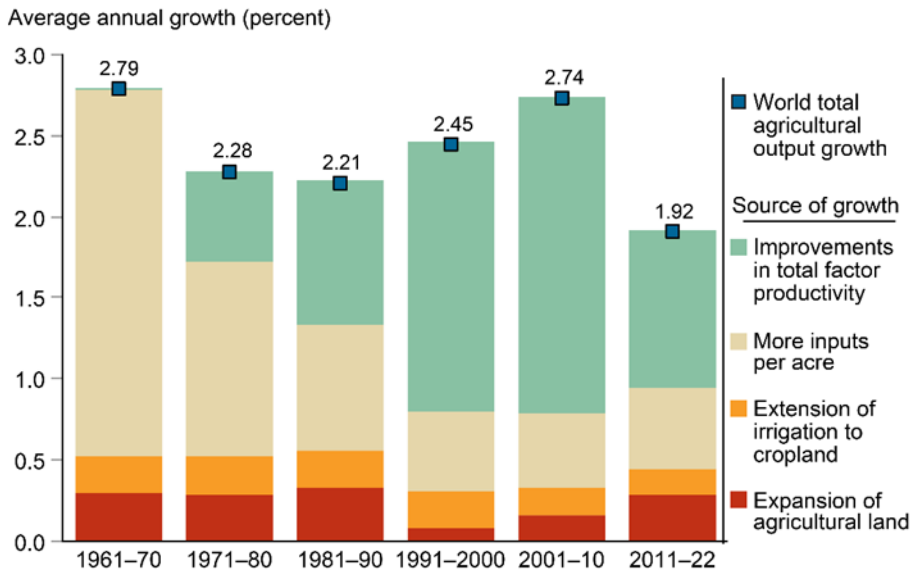

Figure 2. Sources of growth in global agricultural output, 1961-2022.

Source: USDA, Economic Research Service, International Agricultural Productivity data product. The data is from October 2024.

Studies on the factors affecting agricultural output and productivity provide various results with different countries and methods. Warsi and Mubarik (2015), with a sensitivity analysis covering 81 countries, found that land, physical capital, human capital, and fertilizer use have a positive and statistically significant effect on agricultural output. Raza and Siddiqui (2014) showed that agricultural output depends on inputs such as labor, modern machinery, fertilizer use, and water supply in Pakistan using a Johansen cointegration approach covering 1972-2012. Coca et al. (2023) examined the determinants of agricultural performance in European Union member countries and found that differences across countries are generally related to technical and economic efficiency. Odhiambo et al. (2004) emphasized that growth in Kenyan agriculture relies heavily on labor and land inputs, while total factor productivity contributes only about 10%. Suh and Moss (2021) argue that the demand for inputs in US agriculture has low price sensitivity and that inputs exhibit substitutable relationships. Their study showed that substitution effects between inputs are important but limited in reducing production costs.

The reviewed literature broadly supports the neoclassical production theory, where a combination of capital, labor, land, and technological efficiency determines output. In line with the total factor productivity (TFP) approach, this study builds upon existing empirical research by incorporating time-varying effects, thus allowing for structural shifts in input-output relationships over time. While earlier studies focused on static determinants, this research addresses a gap by adopting a dynamic methodology that reflects the evolving nature of agricultural systems.

In addition to these country-specific analyses, recent global studies provide further evidence of the evolving nature of agricultural productivity. According to the Global Agricultural Productivity Report, the global annual growth rate of total factor productivity has declined to 1.14% between 2011 and 2021, underscoring the need for technology-driven solutions and policy reform, particularly in middle-income economies such as Türkiye (USDA, 2023). Xu et al. (2023), examining G20 countries, found that agricultural exports significantly improve TFP, while the productivity effects of imports depend on institutional strength and cost structures. These results are consistent with the findings of this study, where export performance supports productivity while import dependency creates cost-driven inefficiencies. Furthermore, He et al. (2025) emphasize the role of digital transformation in enhancing input efficiency and output growth in Chinese agriculture, suggesting that integrating digital technologies into production systems is increasingly critical. Although the current study does not include digital variables directly, the rising productivity impact of capital and land may partially reflect the influence of modern technologies and mechanized systems.

Agricultural productivity on a global scale has shown significant changes over the last century. Based on USDA data, figure 3, the Agricultural TFP shows that between 1961 and 2022, total factor productivity worldwide exhibited a clear upward trend. While developed countries recorded higher productivity gains thanks to technological innovations and mechanization, this increase was more uneven in developing countries (Coppola et al., 2018; Ketema, 2020). This graph allows for an analysis of Türkiye's agricultural performance in a regional and global context. The first graph shows the agricultural TFP development of Türkiye, West Asia, and the world between 1961 and 2022. This graph reveals the steady increase in Türkiye's agricultural TFP over time and allows for a comparison with the global TFP growth. The fact that West Asia and Türkiye exhibit very close curves emphasizes Türkiye's influence in this region.

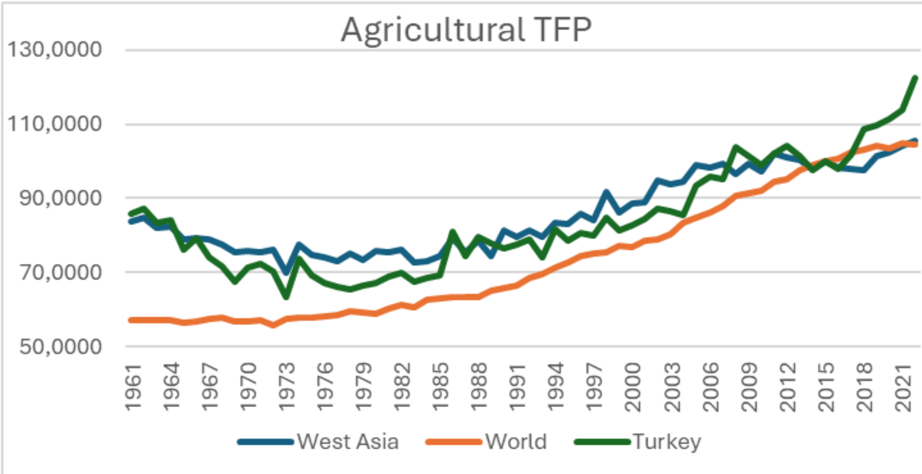

Figure 3. Agricultural TFP for Türkiye, West Asia and World, 1961-2021.

Source: USDA

In the Turkish context, agricultural output and productivity changes align with global trends. However, Türkiye exhibits differences with its unique socioeconomic structure and policies. Figure 4, Agricultural Employment, shows that since the 1990s, agricultural employment has been on a steady downward trend, which is attributed to the increase in agricultural mechanization and technology use (Peplinski, 2012; Ketema, 2020). This has contributed to increased labor productivity and higher per-unit production.

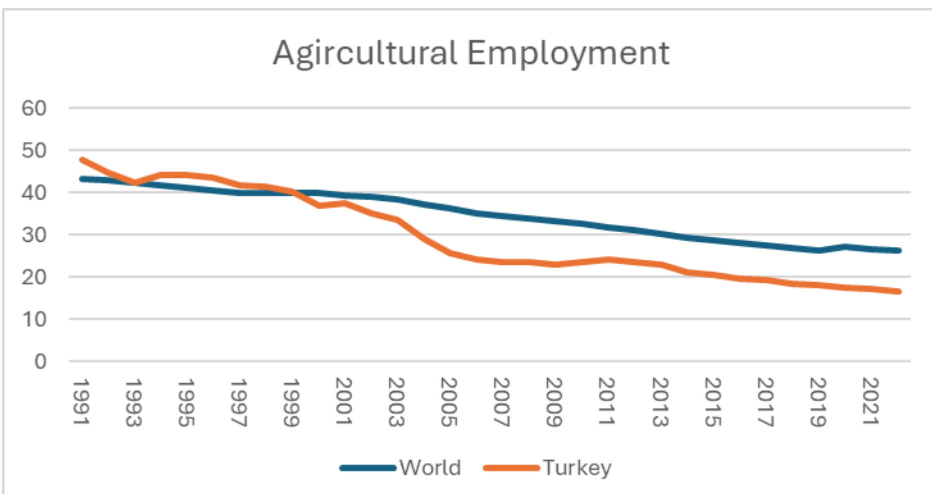

Figure 4. Agricultural employment for Türkiye and World, 1991 – 2021.

By adopting modern approaches and traditional practices in the agricultural sector, Türkiye has significantly increased its agricultural TFP. However, global literature has frequently emphasized that technology, education, and infrastructure development play a critical role in increasing agricultural productivity (Coppola et al., 2018; Ketema, 2020). Moreover, findings from literature reviews show that agricultural productivity increases at higher rates, mainly when supported by human capital, innovative technology use, and social capital (Muraya, 2017; Peplinski, 2012). In Türkiye's agricultural development policies in recent years, emphasizing technological innovations and increasing agricultural infrastructure investments have been the main factors supporting TFP growth.

This study analyzes Türkiye's agricultural production performance between 1991 and 2022 through the factors affecting agricultural output. The agricultural output index is taken as the dependent variable in the study. In contrast, the independent variables include agricultural labor, capital, land and material indices, and agricultural raw materials import and export rates. The panel ARDL and Kalman filter methodologies provide the opportunity to evaluate short- and long-term effects from a dynamic perspective. In this context, the study aims to contribute to the literature by providing new findings on the dynamics of agricultural production in Türkiye. Overall, the existing and emerging literature supports the relevance of total factor productivity frameworks, and the present study contributes to this field by combining panel ARDL and Kalman filter approaches to reveal both stable and dynamic input-output relationships in the case of Türkiye.

MATERIALS AND METHODS

The data set used in this study consists of various agricultural indicators obtained from the United States Department of Agriculture (USDA) and the World Bank to analyze agricultural production and the impact of production factors. The agricultural output index, which is used as the dependent variable, is a measure designed to show the agricultural sector's production in a given period. Independent variables include labor, capital, land, material indices, and export and import rates of agricultural raw materials.

The selection of input indices—labor, capital, land, and material—is based on the total factor productivity (TFP) framework, which conceptualizes output as a function of multi-factor inputs. These indices are directly sourced from the USDA's international productivity database and are consistent with the TFP decomposition models used in global agricultural productivity studies (e.g., Warsi & Mubarik, 2015; Coppola et al., 2018). The export and import ratios of agricultural raw materials reflect the open-economy dimension of Türkiye's agricultural sector. It aims to capture the external trade-related effects on domestic production, a growing concern in the agricultural economics literature.

The agricultural output index (Output) is a measure used to assess the overall performance of agricultural production. It expresses a standardized value of the output achieved in a given period. This index measures the volume of agricultural production in real terms, utilizing constant global average farm prices to account for inflation and price variability over time. The labor index (Labor) quantifies the human resources used in the agricultural sector, while the capital index (Capital) measures the value of fixed assets used in agriculture. The Land Index (Land) reflects the amount and efficiency of agricultural land. The agricultural land index reflects the physical area of land employed in agricultural activities, measured in hectares. It captures the extent of land use without incorporating monetary valuations, focusing solely on the quantity of land utilized. The Material Index (Material) represents the agricultural sector's overall use of inputs (such as seeds, fertilizers, and energy). The export and import rates of agricultural raw materials are used to assess the foreign trade performance of the agricultural sector and its impact on the economy. The trade variables used in the model—agricultural raw materials exports and imports—are expressed as the percentage share of agricultural raw materials in total merchandise exports and imports, respectively. These indicators, sourced from the World Bank, capture the sector's relative importance and integration in Türkiye's international trade rather than its direct quantitative contribution to agricultural output.

While input variables such as labor, capital, land, and materials are represented through index values obtained from USDA to ensure consistency and comparability over time, agricultural raw material imports and exports are incorporated as ratios of total merchandise trade rather than as indexed series. This modeling choice reflects the structural role of trade in affecting input cost and market integration rather than functioning as a direct production factor. Unlike physical inputs, trade flows are not used directly in production functions but act as external economic determinants that influence productivity indirectly. Therefore, their expression as ratios allows the model to capture the relative exposure of the agricultural sector to global trade, highlighting the weight of imports and exports in the broader economic structure. Additionally, reliable time-consistent input-output trade indexes disaggregated at the raw material level are limited or unavailable, which justifies using normalized trade ratios for empirical clarity.

The data set covers the period between 1991 and 2022. It is obtained from the detailed international agricultural productivity database provided by the USDA and economic indicators provided by the World Bank. The main objective of the study is to analyze these data to determine the extent to which agricultural output is affected by which factors and to assess short-run, long-run, and dynamic effects.

Table 1. Descriptive Statistics

	Output	Capital	Labor	Land	Material	Imports	Exports
Mean	84.225	79.545	120.878	102.742	72.003	3.309	0.868
Maximum	126.89	118.709	170.48	108.157	123.36	5.587	2.751
Minimum	60.985	53.309	86.634	97.451	41.733	2.245	0.369
Std. Dev.	19.085	21.451	31.069	3.477	25.563	0.991	0.559
Observations	32	32	32	32	32	32	32

The descriptive statistics in Table 1 summarize the general characteristics and distributions of the variables used in the study. The table presents the mean, maximum, minimum, and standard deviation values for agricultural output and related independent variables. When the general structure of the data is analyzed, it is seen that there are significant differences between agricultural output and independent variables. In particular, capital, labor, land, and material use variables have a wide distribution, indicating that the resources used in the agricultural sector are distributed differently over time. In addition, import and export values exhibit a lower standard deviation, suggesting relatively little change in these indicators. These statistics provide a basic framework for understanding the range of variables to be used in the modeling process and their possible relationships.

In the empirical analysis, after employing unit root tests (Augmented Dickey-Fuller and NG Perron), the Bound test, developed by Pesaran et al. (2001) for the cointegration analysis, is implemented. For the Bound Test analysis, Equation (1) represents the Unrestricted Error Correction Model (UECM) specification model for this study.

$$\Delta Output_t = \beta_0 + \beta_{1t} + \sum_{i=1}^{m} \beta_{2i} \Delta Output_{t-i} + \sum_{i=0}^{m} \beta_{3i}\, \Delta Capital_{t-i} + \sum_{i=0}^{m} \beta_{4i}\, \Delta Labor_{t-i} + \sum_{i=0}^{m} \beta_{5i}\, \Delta Land_{t-i} + \sum_{i=0}^{m} \beta_{6i}\, \Delta Material_{t-i} + \sum_{i=0}^{m} \beta_{7i}\, \Delta Imports_{t-i} + \sum_{i=0}^{m} \beta_{8i}\, \Delta Exports_{t-i} + \beta_9 Output_{t-1} + \beta_{10} Capital_{t-1} + \beta_{11} Labor_{t-1} + \beta_{12} Land_{t-1} + \beta_{13} Material_{t-1} + \beta_{14} Imports_{t-1} + \beta_{15} Exports_{t-1} + \varepsilon_t \quad (1)$$

In the UECM model specified in Equation (1), the terms "m" and "t" denote the lag and trend variables, respectively. For this analysis, the null hypothesis for the Bound test is defined as Ho: $\beta_9 = \beta_{10} = \beta_{11} = \beta_{12} = \beta_{13} = \beta_{14} = \beta_{15} = 0$, indicating an absence of a cointegration relationship among the variables. The null hypothesis is evaluated by comparing the calculated F-statistic to the critical values provided by Pesaran et al. (2001). The null hypothesis is rejected if the estimated F-statistic surpasses the upper bound of the critical values. Conversely, if the F-statistic falls below the lower bound of the critical values, the null hypothesis cannot be rejected (Pesaran et al., 2001; Narayan & Narayan, 2005).

Upon confirming a cointegration relationship, the ARDL (Autoregressive Distributed Lag) model is employed to investigate long-term and short-term relationships among the variables. The ARDL model is favored for its distinct advantages over conventional approaches. Specifically, it does not necessitate pre-testing for the integration order of the variables. Additionally, the ARDL method allows for simultaneous analysis of short-run and long-run effects of the independent variables on the dependent variable. It is particularly advantageous in studies with small sample sizes, often outperforming alternative techniques (Seker et al., 2015). Equations (2) and (3) in the study outline the ARDL model specifications.

$$Output_t = \beta_0 + \sum_{i=1}^{p} \beta_{1i} Output_{t-i} + \sum_{i=0}^{q} \beta_{2i}\, Capital_{t-i} + \sum_{i=0}^{q} \beta_{3i}\, Labor_{t-i} + \sum_{i=0}^{q} \beta_{4i}\, Land_{t-i} + \sum_{i=0}^{q} \beta_{5i}\, Material_{t-i} + \sum_{i=0}^{q} \beta_{6i}\, Imports_{t-i} + \sum_{i=0}^{q} \beta_{7i}\, Exports_{t-i} + \varepsilon_t \quad (2)$$

$$\Delta Output_t = \beta_0 + \beta_1 ECT_{t-1} + \sum_{i=1}^{m} \beta_{2i} \Delta Output_{t-i} + \sum_{i=0}^{n} \beta_{3i}\, \Delta Capital_{t-i} + \sum_{i=0}^{n} \beta_{4i}\, \Delta Labor_{t-i} + \sum_{i=0}^{n} \beta_{5i}\, \Delta Land_{t-i} + \sum_{i=0}^{n} \beta_{6i}\, \Delta Material_{t-i} + \sum_{i=0}^{n} \beta_{7i}\, \Delta Imports_{t-i} + \sum_{i=0}^{n} \beta_{8i}\, \Delta Exports_{t-i} + \varepsilon_t \tag{3}$$

Equations (3) and (4) outline the ARDL model specifications for the long-run and short-run relationships, respectively. The error correction term (ECT) represents the speed at which the model adjusts to equilibrium, with an expectation that it will be negative and statistically significant.

This study lastly applies The Kalman filter, an algorithm for accurately estimating the state of time-varying systems with noisy and incomplete observations. In particular, this method is used to estimate dynamical systems with observed data and continuously update the estimated data with new observations to reach the most accurate state. In economics and finance, the Kalman filter is often applied to time series analysis where structural breaks, regime changes, and uncertainties are present (Harvey, 1990). Based on its mathematical foundations and assumptions, the Kalman filter incorporates the optimal estimation approach of the Gauss-Markov theorem. It minimizes the estimation error in linear systems and provides the closest estimate to the actual state of the system.

The basic equations of the Kalman filter consist of two main components: the system state equation and the observation equation. The state equation predicts the current state based on the system's previous state. The observation equation describes the current state through observations. Mathematically, the state of the Kalman filter is expressed as follows:

$$x_t = A_{t-1}x_{t-1} + B_{t-1}u_{t-1} + w_{t-1} \tag{4}$$

In this equation, x_t represents the system state at time *t*. Here A_t is the state transition matrix and determines how the system transitions from the previous state to the next state. B_t is the control matrix, and u_t represents an external input. w_t is the white noise term with zero mean and represents the system noise. The observation equation is written as follows:

$$y_t = H_t x_t + v_t \tag{5}$$

In this equation, y_t describes the observations at time *t*. H_t is the observation matrix and determines the relationship between the state of the system and the observations. v_t is the observation noise defined as a white noise with zero mean. The goal of the Kalman filter is to optimally estimate the unknown state of the system using these two equations, considering the observation noise and the system noise.

The Kalman filter has two basic stages: prediction and update. In the first stage, the current state of the system and the error covariance are estimated. The estimation step is represented by the following equations:

$$\hat{x}_{t|t-1} = A_{t-1}\hat{x}_{t-1|t-1} + B_{t-1}u_{t-1} \tag{6}$$

$$P_{t|t-1} = A_{t-1}P_{t-1|t-1}A'_{t-1} + Q_{t-1} \tag{7}$$

In these equations, $\hat{x}_{t|t-1}$ is the estimate of the state at time *t* and $P_{t|t-1}$ is the error covariance matrix. The system noise Q_t is a component that updates the error covariance and reflects the uncertainties of the system. The update step is performed to correct the state of the system as new observations arrive and is described by the following equations:

$$K_t = P_{t|t-1}H'_t\left(H_t P_{t|t-1}H'_t + R_t\right)^{-1} \tag{8}$$

$$\hat{x}_{t|t} = \hat{x}_{t|t-1} + K_t\left(y_t - H_t\hat{x}_{t|t-1}\right) \tag{9}$$

$$P_{t|t} = (I - K_t H_t)P_{t|t-1} \tag{10}$$

These equations calculate the Kalman gain (K_t) and minimize the difference between observations and prediction. The predicted state $\hat{x}_{t|t}$ is updated each time a new observation arrives and corrected together with the error covariance $P_{t|t}$. R_t represents the observation error covariance matrix and is defined as the covariance of the observation error vector, v_t. The applicability of the Kalman filter in econometric models arises primarily in the estimation of time-varying parameters and latent states. For example, unobservable variables such as latent technological progress on the growth rate of an economy can be estimated using this filter (Hamilton, 1994). Moreover, the Kalman filter is also used to estimate time-varying regression coefficients. In the dynamic analysis of macroeconomic variables such as economic growth, inflation, and unemployment, tracking parameters change over time provides a significant advantage (Stock & Watson, 1999).

The success of the Kalman filter relies on certain assumptions. In particular, the system must be linear; the state and observation errors must have zero mean and constant covariances. Under the white noise assumption, system and observation errors are independently distributed. If these assumptions are unmet, nonlinear models such as the extended Kalman filter or particle filter should be used. Furthermore, accurate observability of the observations is critical to the success of the Kalman filter. Deviations in the model can cause errors to grow and reduce the accuracy of the prediction (Durbin & Koopman, 2012).

In conclusion, the Kalman filter is a powerful tool in econometric modeling. It is a highly effective method for estimating latent variables or time-varying parameters, especially in the presence of structural breaks and uncertainties in time series. In its use in economic analysis, the Kalman filter not only predicts the future state of the system by making optimal estimations when working with noisy data but also continuously updates these predictions as new observations come in. In this respect, the Kalman filter is an indispensable tool for understanding the dynamic nature of time series in economics and finance.

The choice of the panel ARDL model is grounded in its flexibility to accommodate variables integrated at different orders (i.e., I(0) and I(1)) without requiring pre-testing for unit root homogeneity across units. This makes it particularly suitable for agricultural data characterized by heterogeneous dynamics across time. Additionally, panel ARDL is advantageous in small sample contexts, providing robust long-run and short-run estimates, as emphasized by Pesaran et al. (2001) and Seker et al. (2015).

The Kalman filter, on the other hand, captures the time-varying nature of parameter relationships, which static models fail to address. In the context of agricultural production—where structural shifts, technological change, and input price volatility are prevalent—the Kalman filter provides a framework for dynamically updating model coefficients in response to new information. This dual-method approach enables both stable long-run estimations and dynamic short-run insights.

While panel ARDL offers a robust framework for modeling dynamic heterogeneous panels, it assumes homogeneity in long-run relationships when using the PMG estimator, which might not fully capture country-specific dynamics. Additionally, its dependence on lag length selection can influence parameter stability. Although powerful in capturing evolving dynamics, the Kalman filter assumes linearity and requires reliable initial conditions and noise assumptions, which may not always hold in macroeconomic or sectoral data. However, combining these methods mitigates individual weaknesses and enhances the reliability and depth of the findings.

RESULTS AND DISCUSSION

This section presents a detailed analysis of the findings obtained from the econometric methods used in the study. The analysis reveals results better to understand the relationships between dependent and independent variables and improve the model's accuracy. The results obtained will be discussed in comparison with existing studies in literature and will form the basis for policy recommendations.

Table 2. Unit Root Test Results

	ADF Test	Ng-Perron Test			
		MZa	MZt	MSB	MPT
Output	3.223	2.962	2.756	0.931	83.977
Capital	-3.077	-4.284	-1.361	0.318	20.289
Labor	-1.249	-0.154	-0.103	0.671	27.920
Land	-0.939	-1.184	-0.634	0.535	16.216
Material	-0.240	0.414	0.255	0.615	27.461
Import	-1.012	-1.952	-0.903	0.463	11.603
Export	-2.603	-1.993	-0.899	0.451	11.253
ΔOutput	-7.521	-12.008	-2.178	0.181	3.035
ΔCapital	-3.607	-12.833	-2.469	0.192	7.444
ΔLabor	--4.979	-14.840	-2.722	0.183	6.152
ΔLand	-4.529	-14.720	-2.654	0.180	1.884
ΔMaterial	-6.086	-14.774	-2.715	0.184	1.669
ΔImport	-5.710	0.089	0.221	2.467	312.49
ΔExport	-6.297	0.489	1.060	2.171	268.79

ADF Critical Values at 5% = -2.964
Ng-Peron critical values at %5 significance for MZa, MZt, MSB, and MPT: -8.10, -1.98, 0.23, 3.17, respectively.

In time series analyses, determining the stationarity properties of variables is critical for the model to produce reliable results. This study prefers ADF (Augmented Dickey-Fuller) and Ng-Perron tests. The ADF test is a traditional and widely used method with many applications. On the other hand, the Ng-Perron test is used because it provides stronger results, especially in small samples, and provides an alternative perspective to the stationarity analysis. Both tests are applied to assess the validity of the model's basic assumptions and to determine whether the series contains unit roots.

Table 2 demonstrates the results of the ADF and Ng-Perron tests, which were used to analyze the stationarity of the variables in the study. Each variable was evaluated at the level and first difference. The test results show that most variables are not stationary at the level but become stationary when the first differences are taken. This implies that the series contains unit roots and should be made stationary by taking their first differences in the modeling process. Thus, possible wrong results in time series analysis are prevented.

Table 3. Bound Test Results[1]

k	F statistics	Significance level	Critical Values	
			Lower Bound	Upper Bound
6	6.016	1%	3.976	5.691
		5%	2.794	4.148

k is the number of independent variables in Equation (1).
Critical values are obtained from Table CI(iv) by Pesaran et al. (2001).
[1] The optimal lag length for the ARDL bounds test was selected using the Akaike Information Criterion (AIC) derived from unrestricted VAR models. Given the annual structure of the dataset and the number of observations, the maximum lag was limited to three.

Bound test results shown in Table 3 provide important information about the long-run relationship of the model. In the analysis, the existence of a long-run relationship between the dependent variable and the independent variables was tested. The results support a long-run relationship by comparing the model with the critical values. This indicates a balanced long-run relationship between the variables and that the model provides an appropriate basis for long-run forecasts. The analysis strengthens the assumptions of the study and confirms the validity of the methodology used.

In Table 4, the long and short-run effects of the factors affecting agricultural production performance are analyzed in detail. The analysis conducted within the framework of the ARDL model allows us to understand the fundamental dynamics in Türkiye's agricultural sector and to comprehensively evaluate the inputs affecting the agricultural output index, which is treated as the dependent variable.

Table 4. ARDL (3, 1, 1, 0, 2, 0, 2) model results

Long-run Estimation		
Variables	**Coefficient**	**T-statistics**
Material	-0.286***	-4.411
Land	1.261***	5.561
Labor	0.058*	1.804
Capital	1.562***	10.672
Imports	-2.533***	-3.373
Exports	12.678***	4.707
C	-160.489***	-4.796
Short-run Estimation		
Variables	**Coefficient**	**T-statistics**
D(Output(-1))	0.724***	3.912
D(Output (-2))	0.285**	2.565
D(Material)	-0.237***	-4.985
D(Capital)	0.754***	3.915
D(Capital(-1))	3.899***	9.244
D(Exports)	-1.984***	-4.537
D(Exports(-1))	-4.354***	-2.111
ECT (-1)	-0.4637***	-6.937
Diagnostic Tests		
Serial Correlation LM test (Breusch-Godfrey)	0.908	[0.431]
Heteroscedasticity test (Breusch-Pagan-Godfrey)	2.558	[0.219]
Jargue-Bera Normality test	0.567	[0.753]
Ramsey Reset Test	2.690	[0.103]

***, **, and * denotes 1%, 5%, and 10% significant level, respectively. p values in parentheses.

The results of the long-run analysis reveal the most important inputs affecting the agricultural output index. The findings show that capital and exports have a positive and significant effect on agricultural output. This suggests that capital investments and external market linkages play a critical role in increasing the productivity of the agricultural sector. Similar studies in the literature also support these findings. For example, Warsi and Mubarik (2015) emphasize the contribution of capital and exports to agricultural production and find that the efficient use of these inputs increases productivity. On the other hand, the fact that the imports variable has a negative effect suggests that external dependence has a negative impact on productivity by increasing costs in agricultural output. Similarly, Coca et al. (2023) draw attention to the restrictive effects of import dependence on economic efficiency.

Land and labor variables also have positive effects, but these effects are relatively smaller and partially significant. This suggests that the effect of labor and land use decreases with the increase in modern technology and mechanization in Türkiye's agricultural sector. In the literature, studies such as Suh and Moss (2021) state that mechanization reduces the dependence on labor and brings the use of capital and technology to the fore.

Short-run results reveal that the positive effects of capital and exports on agricultural output persist, and the effect of capital changes is more substantial in short-run dynamics. However, material and import variables show adverse effects in the short run. This reflects the pressures of external input costs and material utilization on production in the short run. Raza and Siddiqui (2014) highlighted similar short-run effects on agricultural production in Pakistan and emphasized the importance of efficient use of material inputs. The error correction term (ECT) is negative and statistically significant, indicating that the model quickly reaches long-run equilibrium. This finding is consistent with the Bound test results and confirms that the model has a strong theoretical foundation.

The Breusch-Godfrey, Breusch-Pagan-Godfrey, and Ramsey RESET tests show that the model is free from problems such as autocorrelation, changing variance, and model misspecification. These results increase the model's reliability and the validity of the estimation results.

These findings support the soundness of the study's methodological approach and provide an important contribution to understanding the dynamic effects of inputs in Türkiye's agricultural sector. In the literature, studies such as Ketema (2020) and Coppola et al. (2018) have also emphasized the central role of capital and technology in agricultural production. However, the negative effects of import dependence have been underlined and the importance of measures for policymakers to reduce imports and promote local production has been emphasized. The negative impact of agricultural raw material imports on domestic output reflects increased external dependency and exposure to currency volatility. In the Turkish context, where agricultural inputs like fertilizers and chemicals are largely imported, fluctuations in exchange rates directly inflate input costs. These rising costs can suppress domestic production by narrowing farmers' profit margins. Moreover, trade liberalization policies, while aiming to enhance supply security, may inadvertently undermine local producers who cannot compete with subsidized or cheaper imported goods. Coca et al. (2023) also emphasize that import dependency in agricultural systems can lead to economic inefficiencies and reduced sectoral resilience, especially in developing countries.

This analysis provides an important reference point for determining a more sustainable growth strategy for Türkiye's agricultural sector. The findings suggest that especially capital investments and exports should be encouraged, while import dependency should be minimized.

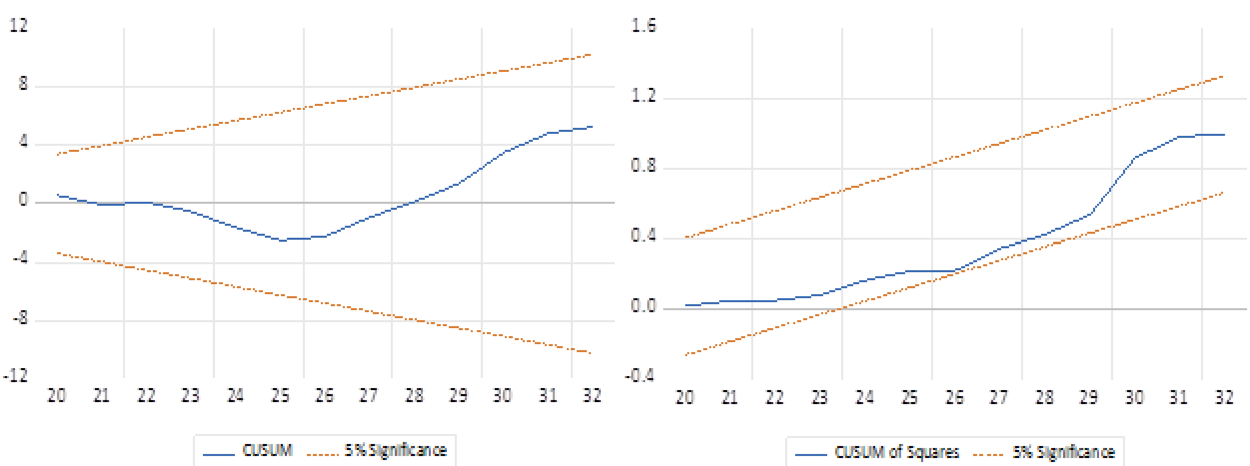

Figure 5. CUSUM and CUSUM of Squares

The analysis of the CUSUM and CUSUM of Squares graphs in Figure 5 is important to assess the stability of the model over time. The results show that the blue lines in the graphs remain within the 5% significance limits. This suggests that the model is stable without structural breaks and the forecasting results are reliable. While the CUSUM test evaluates the overall stability of the model, the CUSUM of Squares test examines whether the variance changes over time. Both graphs remain within the bounds, confirming that the model is stable in terms of both mean and variance. This finding supports the methodological rigor of the study and increases the robustness of the forecasts.

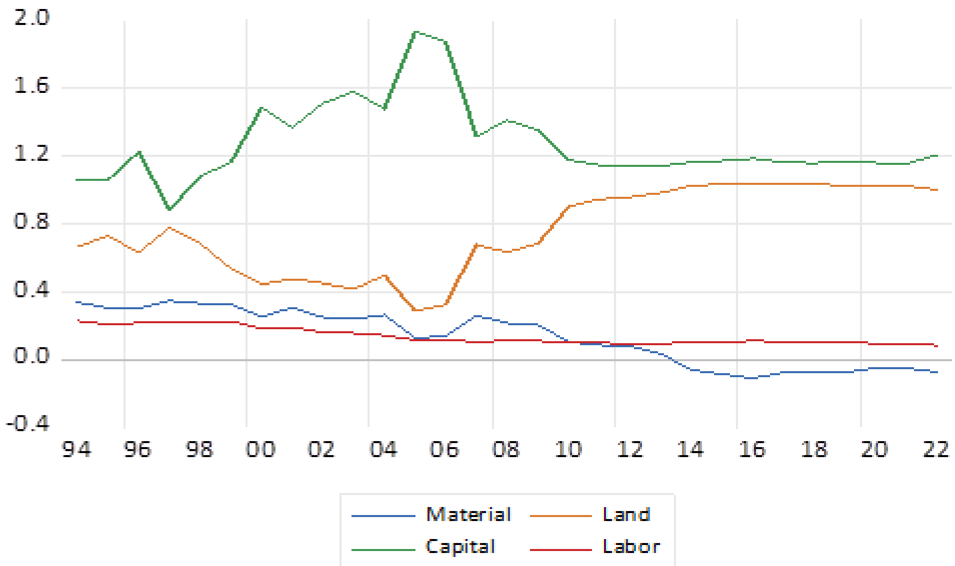

Figure 6. Time varying parameter estimates

The Time Varying Parameter Estimates in Figure 6 reveal the dynamic effects of inputs on Türkiye's agricultural output index. This analysis is an important tool to visualize the contributions of inputs used in agricultural output over time and to reveal changing effects. Capital and land indices have a strong and positive effect. The increasing effect of the capital index over time emphasizes the importance of mechanization, modern technologies and infrastructure investments in Türkiye's agricultural sector. Studies such as Ketema (2020) and Coppola et al. (2018) also support the determinant role of capital investments and technological innovations on agricultural productivity. In Türkiye, the increasing use of tractors and modern equipment in the agricultural sector is consistent with these findings.

The steady increase in the impact of the land index in the 2000s can be attributed to Türkiye's adoption of modern management practices in agricultural land use. Improvements in irrigation infrastructure and effective planning for land use can be considered as the main reasons behind this positive contribution. Similarly, Muraya (2017) and Peplinski (2012) emphasize the impact of land management and irrigation investments on agricultural productivity.

The graph shows that the contribution of the material index is relatively lower over time but shows a slight recovery from negative to positive. This indicates that the efficiency of material use has increased over time but is still not as decisive as basic inputs such as capital and land. The limited effect of material input on agricultural output can be attributed to the cost sensitivity and suboptimal use of inputs such as fertilizers, pesticides, and energy in Turkey. Unlike capital or land investments, which tend to yield more consistent productivity gains, material inputs are more vulnerable to fluctuations in global commodity prices and are often used inefficiently due to lack of technical knowledge or inadequate extension services. Additionally, fragmented land structure in Turkey may reduce economies of scale, thereby lowering the marginal return of material inputs. This finding aligns with Warsi and Mubarik (2015), who note that the productivity effect of agricultural inputs heavily depends on cost efficiency and optimal usage.

The effect of the labor index is quite low and stable in the graph. With the expansion of agricultural mechanization in Türkiye, the dependence on labor has decreased, leading to a relatively limited contribution of labor. This finding is in line with studies such as Suh and Moss (2021), who find that mechanization increases productivity by emphasizing the use of capital over labor. However, despite the low impact of labor, the positive contributions of skilled labor and education on agricultural production should not be ignored.

In conclusion, this graph is an important tool that visualizes Türkiye's agricultural production dynamics with changing effects over time. While capital and land indices stand out as the strongest determinants of output, the impact of material and labor indices remains relatively low. These findings suggest that agricultural production policies in Türkiye should focus on increasing capital investments and improving land management. Moreover, increasing the efficiency of material utilization and strengthening policies for a skilled labor force is critical for the sustainability of agricultural production. This study adds a new perspective to the literature and provides an important basis for understanding the changing dynamics of inputs in Türkiye's agricultural production over time.

These findings are consistent with Coppola et al. (2018), who highlight the dominant role of capital and technological innovation in enhancing agricultural productivity in the Italian context. Similarly, Raza and Siddiqui (2014) found that increased reliance on imported inputs in Pakistan led to volatility and inefficiency in the agricultural sector. In contrast, Odhiambo et al. (2004) emphasize labor and land as the primary growth factors in Kenyan agriculture, suggesting that the structure and input-intensity of agricultural systems can significantly shape productivity patterns across countries. Compared to these studies, the Turkish case illustrates a transition phase where mechanization and capital accumulation are becoming more influential, while input costs and external shocks increasingly challenge material and import-based productivity.

CONCLUSION

This study was conducted to analyze the factors affecting Türkiye's agricultural production performance in the period 1991–2022. In the analysis, the agricultural output index was used as the dependent variable, while the independent variables included indices for agricultural labor, capital, land, materials, and the import and export ratios of agricultural raw materials. The main objective of the study was to assess both short- and long-run dynamics by employing the panel ARDL and Kalman filter methods and to develop policy recommendations tailored to the structural characteristics of Türkiye's agricultural sector.

The empirical findings indicate that capital investments and export performance have the strongest positive effects on agricultural output. Enhancing capital accumulation through mechanization, infrastructure improvements, and innovative farming practices plays a vital role in boosting productivity. Land use also shows a significant and positive impact, while the role of labor appears to be diminishing, which is consistent with the increasing adoption of mechanized and technology-driven practices in agriculture. The material input index, although positive, exhibits a relatively limited effect, underscoring the importance of improving input-use efficiency and managing production costs effectively. On the other hand, the import variable demonstrates a negative relationship with agricultural output, suggesting that dependence on foreign-sourced inputs increases production costs and reduces sectoral productivity.

In light of these findings, several policy implications can be drawn. First, the positive impact of capital investments highlights the need for targeted financial instruments such as subsidized credit lines and tax incentives for farm machinery and infrastructure development. In particular, financial access mechanisms tailored to small and medium-sized farms would enhance inclusivity in capital-driven productivity gains. Moreover, support for the widespread adoption of precision agriculture technologies, sensor-based irrigation, and renewable energy-based farming systems could reinforce technological diffusion and long-term sustainability.

Improving land productivity remains essential. Therefore, prioritizing modern irrigation systems and promoting climate-resilient land use planning at the regional level would strengthen the adaptive capacity of agriculture. These measures should be complemented by investment in land consolidation programs and improved cadastral services to address fragmented land ownership structures.

With regard to material input use, reducing Türkiye's dependency on imported agricultural chemicals and fertilizers can be achieved through support for domestic production and localization of input supply chains. Public investment in fertilizer plants and the integration of renewable energy into input production could reduce vulnerability to global price shocks. Furthermore, expanding farmer training programs on cost-efficient input management would help optimize resource use and reduce unnecessary expenditure.

To mitigate the negative impact of imports, policy reforms should encourage import substitution where feasible and provide incentives for locally sourced inputs. Establishing price stabilization mechanisms or import tariffs for critical agricultural inputs may shield domestic producers from exchange rate fluctuations and external market volatility, thus enhancing economic resilience.

Finally, the findings underline the need to invest in human capital. Strengthening vocational agricultural training programs, expanding rural extension services, and incorporating digital literacy into farmer education will contribute to forming a workforce capable of implementing modern techniques and responding effectively to environmental and market-based challenges. Türkiye's demographic advantage, particularly its youthful population, presents a strategic opportunity to build an agile and innovation-oriented agricultural workforce.

This study contributes to existing literature by offering one of the few empirical assessments of agricultural production using time-varying econometric techniques. The application of the Kalman filter not only enriches the methodological framework but also enables a nuanced understanding of how input effects evolve over time in response to technological, structural, and economic changes.

Nonetheless, the study has certain limitations. The explanatory power of the import and export variables could be enhanced with more disaggregated trade data. Additionally, the exclusion of environmental indicators and agricultural policy variables may limit the broader scope of interpretation. Future research could benefit from incorporating climate-related variables, subsidy mechanisms, and institutional factors to further refine the understanding of agricultural productivity dynamics in Türkiye.

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