Turkish Journal of Agricultural and Natural Sciences 13 (4): 805–818, 2026

https://doi.org/10.30910/turkjans.2011183

TÜRK TARIM ve DOĞA BİLİMLERİ DERGİSİ

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TURKISH JOURNAL of AGRICULTURAL and NATURAL SCIENCES

www.dergipark.gov.tr/turkjans

Original Article

Effects of Digitalization on Agricultural Value Added in Türkiye: An ARDL Approach

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ABSTRACT

Agricultural digitalization has become an important part of productivity growth and sustainable development of agriculture. However, empirical evidence remains mixed about how different dimensions of digitalization affect agricultural value added. This study looks at the short-run and long-run effects of digitalization on agricultural value added in Türkiye, by using annual data for the period 2001–2023**.** Agricultural value added is used as the dependent variable, while Internet use and fixed broadband subscriptions stand for two indicators of digitalization. Fertilizer consumption and rural population are added as control variables. The Autoregressive Distributed Lag (ARDL) bounds-testing approach is used to estimate both the long-run relationship and the short-run dynamics among the variables. The bounds test provides evidence of a long-run relationship at the 10% significance level, although the result is inconclusive at the 5% level. In the long-run estimates, Internet use has a positive but statistically insignificant coefficient, while fixed broadband subscriptions have a positive and statistically significant coefficient. Fertilizer consumption has a negative but statistically insignificant coefficient, whereas rural population has a negative and statistically significant coefficient. The Error Correction Model (ECM) shows that short-run deviations from the long-run relationship are corrected over time, with a negative and statistically significant error-correction coefficient**.** The diagnostic tests indicate no evidence of serial correlation or heteroskedasticity, while the CUSUM tests support parameter stability. An additional analysis using mobile cellular subscriptions extends the sample period and shows that the results are sensitive to the digitalization indicator used. In this alternative specification, the bounds test does not provide evidence of a long-run relationship. The findings therefore do not support a uniform relationship between digitalization and agricultural value added. Instead, the results vary across digitalization indicators and model specifications**.** Rather than combining digitalization measures into a single ICT indicator, the study examines alternative digitalization measures separately to assess whether the results depend on the indicator used.

Key words: Agricultural value added , Digitalization, Fixed broadband subscriptions, Internet use, Türkiye

Dijitalleşmenin Türkiye'de Tarımsal Katma Değer Üzerindeki Etkileri: ARDL Yaklaşımı

ÖZ

Tarımsal dijitalleşme, verimlilik artışı ve tarımsal sürdürülebilir kalkınmanın önemli bir parçası haline gelmiştir. Bununla birlikte, dijitalleşmenin farklı boyutlarının tarımsal katma değeri nasıl etkilediğine dair ampirik kanıtlar hala çelişkilidir. Bu çalışma, 2001-2023 dönemini kapsayan yıllık verileri kullanarak, Türkiye'de dijitalleşmenin tarımsal katma değer üzerindeki kısa ve uzun vadeli etkilerini incelemektedir. Tarımsal katma değer bağımlı değişken olarak kullanılırken, internet kullanımı ve sabit geniş bant abonelikleri dijitalleşmenin iki göstergesi olarak ele alınmıştır. Gübre tüketimi ve kırsal nüfus kontrol değişkenleri olarak eklenmiştir. Değişkenler arasındaki hem uzun vadeli ilişkiyi hem de kısa vadeli dinamikleri tahmin etmek için Otoregresif Dağıtılmış Gecikme (ARDL) sınır testi yaklaşımı kullanılmıştır. Sınır testi, %10 anlamlılık düzeyinde uzun dönemli bir ilişkiye ilişkin kanıt sunarken, %5 düzeyinde sonuç kesin değildir. Uzun dönem tahminlerinde internet kullanımının

katsayısı pozitif ancak istatistiksel olarak anlamsızdır. Sabit geniş bant aboneliklerinin katsayısı ise pozitif ve istatistiksel olarak anlamlıdır. Gübre tüketiminin katsayısı negatif ancak istatistiksel olarak anlamsızken, kırsal nüfusun katsayısı negatif ve istatistiksel olarak anlamlıdır. Hata Düzeltme Modeli (ECM), uzun vadeli ilişkiden kısa vadeli sapmaların negatif ve istatistiksel olarak anlamlı hata düzeltme katsayısı ile zaman içinde düzeltildiğini göstermektedir. Tanısal testler seri korelasyon veya değişen varyans sorununa ilişkin bir kanıt göstermezken, CUSUM testleri parametre istikrarını desteklemektedir. Daha uzun bir dönemin incelenmesine olanak sağlayan mobil hücresel aboneliklerin alternatif dijitalleşme göstergesi olarak kullanıldığı ek analiz, sonuçların kullanılan dijitalleşme göstergesine duyarlı olduğunu göstermektedir. Bu alternatif modelde sınır testi uzun dönemli bir ilişkiye ilişkin kanıt sunmamaktadır. Sonuçlar bu nedenle dijitalleşme ile tarımsal katma değer arasında tek tip bir ilişkiyi desteklememektedir. Bunun yerine, bulgular kullanılan dijitalleşme göstergesine ve model spesifikasyonuna göre farklılık göstermektedir. Tek bir bileşik BİT göstergesine dayanan birçok önceki çalışmanın aksine, bu çalışma farklı dijitalleşme göstergelerini ayrı ayrı ele alarak sonuçların kullanılan göstergeye bağlı olup olmadığını değerlendirmektedir.

Anahtar kelimeler: Tarımsal katma değer, Dijitalleşme, Sabit genişbant abonelikleri, İnternet kullanımı, Türkiye

INTRODUCTION

Agriculture is closely linked to food security, rural livelihoods, employment, trade and the management of natural resources. In many developing countries, the sector is also associated with poverty reduction and regional development. Yet agricultural production is increasingly affected by rising input costs, labour shortages, structural changes and pressure on limited water resources. Under these conditions, digital technologies have become more widely used in agricultural production, particularly in relation to productivity, efficiency, market access and resilience.

Digitalization has also altered how agricultural information is produced, exchanged and accessed. Internet-based services, broadband infrastructure, mobile technologies, artificial intelligence, remote sensing, the Internet of Things (IoT) and precision agriculture provide farmers with information on weather, market prices, production practices, pests and agricultural policies. They also facilitate communication between farmers and other actors, including extension services and financial institutions. Such communication can reduce transaction costs and improve the allocation of resources within the agricultural value chain (Abiri et al., 2023; Gebresenbet et al., 2023).

The relationship between digital technologies and agricultural performance operates through several channels. Production planning, input management, irrigation, mechanization and farm monitoring can be managed with digital tools, while farmers can also use these technologies to reach markets, financial services and agricultural knowledge. Büyüközkan and Uztürk (2024) relate data-based decision-making to more efficient and sustainable agricultural systems. Zhang et al. (2025), meanwhile, report that digital infrastructure is associated with higher agricultural export value added through labour productivity, technological innovation and the business environment. These studies link digitalization with changes in both agricultural production and marketing.

The presence of digital infrastructure, however, does not necessarily mean that these benefits will be realized in agricultural production. Its effective use may be constrained by limited digital skills, high investment costs, fragmented farm structures, weak extension services and restricted access to finance. The FAO report on digital agriculture in Türkiye notes progress in the country's digital environment but also identifies continuing problems, including fragmented farmland, differences in technological capacity and the limited use of digital solutions (Höllinger and Şener, 2025).

Among digital technologies, internet utilization is one of the most important measures of agricultural digitalization. According to the literature, internet use improves agricultural productivity by facilitating farmers' access to information, markets, mechanization, agricultural extension services, and social networks (Nguyen et al., 2023; Deng et al., 2024; Eyike Mbongo and Djoumessi, 2024). Matsvai and Hosu (2024) showed that internet use increased agricultural output and total factor productivity in South Africa, while Hasan et al. (2023) found a positive long-term relationship between internet use and agricultural production in Bangladesh. However, the results are not always the same. Evans (2018), Abdullahi et al. (2024) and Benghalem and Fettane (2025) report nonlinear, insignificant or negative effects, so this suggests that the economic benefits of Internet use depend on institutional conditions, complementary investments and the level of digital adoption.

Fixed broadband subscriptions represent another important dimension of digitalization. Unlike Internet-use indicators, broadband subscriptions measure the availability of stable and high-speed connectivity that can support precision agriculture, cloud-based farm management, remote sensing, digital extension services and online agricultural markets. Existing studies generally report positive effects of broadband expansion on

agricultural productivity and rural development (LoPiccalo, 2021; Kim and Paudel, 2025; Li, 2024). However, these benefits depend largely on complementary investments in digital skills, finance and institutional capacity. As Mack et al. (2024) point out, broadband availability should not be considered the same as productive broadband use in agriculture because expanding infrastructure does not automatically lead to technology adoption at the farm level.

Conventional agricultural inputs and demographic conditions also need to be considered when examining agricultural performance. Fertilizer use, when applied appropriately, is associated with higher agricultural productivity through its effects on crop yields and nutrient management (Hasan et al., 2023; Gürbüz and Kadıoğlu, 2024). The relationship between rural population and agricultural performance is less straightforward, as production increasingly relies on mechanization, technological progress and capital investment rather than labour availability alone.

Although agricultural digitalization has received increasing attention, the available empirical evidence leaves some issues less explored. Internet use and broadband infrastructure have often been examined separately or represented through a combined ICT indicator, even though they capture different aspects of digital transformation. Much of the empirical literature is also based on cross-country panels or household-level surveys, with fewer country-specific time-series studies. For Türkiye, evidence that considers Internet use and fixed broadband subscriptions together with fertilizer consumption and rural population in relation to agricultural value added remains limited.

The present study examines the short-run and long-run relationships between these variables in Türkiye using annual data for 2001–2023. The dependent variable is agriculture, forestry and fishing value added measured in constant 2015 US$, while Internet use and fixed broadband subscriptions represent digitalization. Fertilizer consumption and rural population are included as control variables. Since the variables are stationary either at level or after first differencing, the analysis uses the Autoregressive Distributed Lag (ARDL) bounds-testing approach to estimate the short-run dynamics and long-run relationship.

The study differs from much of the existing empirical work by considering Internet use and fixed broadband subscriptions within the same framework without combining them into a single ICT measure. This distinction makes it possible to examine the two digital indicators separately using recent annual data for Türkiye. Their relationships with agricultural value added are estimated alongside fertilizer consumption and rural population within the same ARDL specification. In addition, mobile cellular subscriptions are used as an alternative digitalization indicator in a longer sample to examine whether the results are sensitive to the choice of digitalization measure and sample period.

The baseline estimates provide evidence of a long-run relationship at the 10% significance level, although the bounds-test result is inconclusive at the 5% level. In the long-run estimates, Internet use has a positive but statistically insignificant coefficient, while fixed broadband subscriptions have a positive and statistically significant coefficient. Fertilizer consumption has a negative but statistically insignificant coefficient, whereas rural population has a negative and statistically significant coefficient. The additional analysis based on mobile cellular subscriptions does not provide evidence of a long-run relationship. These results indicate that the relationship between digitalization and agricultural value added is sensitive to the digitalization indicator and model specification.

The remainder of the paper is organized as follows. Section 2 reviews the relevant literature. Section 3 presents the data, variables and econometric methodology. Section 4 reports and discusses the empirical findings. The final section presents the policy implications and suggestions for future research.

LITERATURE REVIEW

Digitalization has increasingly changed agricultural production, marketing, extension services, financial inclusion and resource management. Digital agriculture includes Internet-based platforms, broadband infrastructure, mobile communication, artificial intelligence, the IoT, cloud computing, automation, remote sensing and precision farming technologies. These technologies improve farmers' access to information, reduce transaction costs, strengthen market participation and improve the efficiency of agricultural production (Abiri et al., 2023; Gebresenbet et al., 2023). However, empirical evidence shows that the effects of digitalization are not the same in every case and depend on the type of technology, farmers' digital skills, institutional quality and complementary infrastructure.

Accordingly, the literature can be grouped into three main strands. The first examines the relationship between digitalization and agricultural development. The second focuses on the effects of Internet use on agricultural productivity. The third examines the contribution of broadband infrastructure to agricultural performance. Together, these strands provide the basis for examining the long-run relationship between Internet

use, fixed broadband subscriptions, fertilizer consumption, rural population and agricultural value added in Türkiye.

Digitalization and Agriculture

Digitalization has become an important part of modern agriculture. It has helped agriculture move from traditional production methods to more knowledge-based and data-driven farming. Technologies such as the Internet, broadband infrastructure, artificial intelligence, the IoT, remote sensing, cloud computing and precision agriculture help farmers manage their farms better, use inputs more efficiently, improve market access and make better production decisions (Abiri et al., 2023; Gebresenbet et al., 2023).

Previous studies describe several ways in which digitalization supports agricultural development. Digital technologies reduce information gaps, lower transaction costs, improve communication among people in the agricultural value chain and make it easier for farmers to access extension services, financial services and agricultural information (Büyüközkan and Uztürk, 2024; Höllinger and Şener, 2025). Smart farming technologies also help improve production efficiency by using data to support better decisions while also helping environmental sustainability (Büyüközkan and Uztürk, 2024).

Most studies report a positive relationship between digitalization and agricultural performance. Research from China, South Africa and other developing countries shows that digital technologies improve agricultural productivity by giving farmers better access to information, encouraging the use of new technologies and improving production efficiency (He et al., 2011; Matsvai and Hosu, 2024; Sethi et al., 2025). However, many studies have discovered lesser or even negative impacts, particularly during the early phases of technological adoption. High investment costs, low digital skills, and inadequate supporting infrastructure are listed as the primary reasons for these disparities (Adamson et al., 2026). Digitalization, therefore, does not necessarily translate into better agricultural performance. What matters is how digital technologies are actually used in agricultural production. In Türkiye, digital infrastructure has expanded considerably in recent years, but differences in digital skills and high technology costs continue to restrict the use of these technologies in agriculture (Höllinger and Şener, 2025). Therefore, the benefits of digitalization depend not only on having digital infrastructure but also on how well these technologies are adopted and used in agricultural production.

Internet and Agricultural Productivity

The internet plays a crucial role in facilitating commerce, education, transportation, and communication. For a long time, the internet has been regarded as a valuable resource. According to Nguyen et al. (2023), Vietnam's internet usage has led to significant improvements in education and employment opportunities. According to Deng et al. (2024), internet access, advanced technology, language learning, and a wide range of business services can lead to increased linguistic proficiency. Studies from Bangladesh and South Africa have also shown that internet access has a positive long-term impact on agricultural output and productivity (Hasan et al., 2023; Matsvai and Hosu, 2024). Eyike Mbongo and Djoumessi (2024) also show that Internet and mobile technologies improve agricultural productivity by improving education and making agricultural inputs more accessible.

However, not all studies report the same results. Evans (2018) finds a nonlinear relationship between Internet use and agricultural performance, while Abdullahi et al. (2024) report negative effects on agricultural production but positive effects on agricultural trade. These different results suggest that the benefits of Internet use depend on factors such as digital skills, institutional quality, infrastructure and farmers' ability to use digital technologies.

Broadband and Agricultural Performance

Broadband infrastructure is another important part of digitalization because it provides stable and high-speed Internet connections. These connections support precision agriculture, cloud-based farm management, remote sensing and real-time data sharing.

Many studies report that broadband expansion has a positive effect on agricultural performance. Studies from the United States show that broadband helps increase crop yields, reduce production costs and raise farmland values (LoPiccalo, 2021; Kim and Paudel, 2025; Qu et al., 2026). Li (2024) also reports that rural broadband development improves agricultural total factor productivity in China, especially when it is supported by agricultural credit and financial development.

However, broadband access alone does not always improve agricultural productivity. Mack et al. (2024) show that broadband supports rural development only when farmers have the skills to use digital technologies and receive institutional support. McKinion et al. (2004) and Kostelnick et al. (2024) also argue that broadband

creates greater economic benefits when it is used together with precision agriculture technologies and digital farm management systems.

Broadband subscriptions have increased considerably in Türkiye in recent years, yet structural constraints continue to limit the wider adoption of advanced digital technologies in agriculture (Höllinger and Şener, 2025). This suggests that greater broadband access by itself may not be sufficient to improve agricultural performance.

Research Gap

Despite increasing interest in agricultural digitalization, some areas remain less examined. Previous studies have generally considered Internet use, broadband infrastructure or ICT adoption separately, although Internet use and fixed broadband subscriptions capture different aspects of digital transformation and may be related to agricultural performance in different ways (Li, 2024; Matsvai and Hosu, 2024; Sethi et al., 2025). Existing evidence also comes largely from cross-country panel analyses and household surveys, while country-specific time-series studies are less common. This is relevant for Türkiye, where digital infrastructure has expanded alongside continuing structural changes in agriculture (Höllinger and Şener, 2025). In addition, conventional agricultural factors such as fertilizer use and rural population have received less attention in studies centered on digital technologies, although both are associated with agricultural production (Hasan et al., 2023; Gürbüz and Kadıoğlu, 2024).

This study addresses these issues by examining Internet use and fixed broadband subscriptions as separate indicators within the same empirical model rather than combining them into a single measure of digitalization. Using annual data for Türkiye, the ARDL approach is applied to estimate their short-run and long-run relationships with agricultural value added. Fertilizer consumption and rural population are included in the same specification, allowing the relationships of the digitalization indicators with agricultural value added to be examined while accounting for these control variables.

MATERIALS AND METHODS

Data and Variables

Annual time-series data for Türkiye covering 2001–2023 are used to examine the relationship between digitalization and agricultural value added. All data were obtained from the World Bank's World Development Indicators (WDI) database (World Bank, 2026). The sample period is determined by the joint availability of the variables included in the baseline model. Although some variables are available for earlier years, the coverage of the digitalization indicators, particularly fixed broadband subscriptions, limits the common sample period.

The dependent variable is agricultural value added. Internet use and fixed broadband subscriptions are considered separately as indicators of digitalization, reflecting different aspects of digital transformation. The model also includes fertilizer consumption and rural population as controls for agricultural inputs and demographic conditions. Mobile cellular subscriptions are additionally used as an alternative digitalization indicator. This indicator provides a longer data series and is used to examine the sensitivity of the results to the digitalization measure and sample period. The definitions, units of measurement and data sources for all variables are reported in Table 1.

Table 1. Definitions, Measurement Units, and Data Sources of the Variables

Variable	Definition	Unit
Ava	Agriculture, forestry and fishing, value added	Constant 2015 US$
Internet	Individuals using the Internet	% of population
Broadband	Fixed broadband subscriptions	Per 100 people
Fert	Fertilizer consumption	Kilograms per hectare of arable land
Rural	Rural population	% of total population
Mobile	Mobile cellular subscriptions	Per 100 people

Source: World Bank (WDI), 2026.

Agricultural Value Added (Ava), Internet use (Internet), fixed broadband subscriptions (Broadband), fertilizer consumption (Fert), rural population (Rural) and mobile cellular subscriptions (Mobile) were transformed into their natural logarithms. The logarithmic transformation was applied consistently to the continuous variables to reduce scale differences and allow the estimated long-run coefficients to be interpreted

as elasticities. In particular, Internet use and rural population are both expressed as population shares, and applying the same transformation avoids inconsistent coefficient interpretation between these two variables.

Model Specification

Following the selection of the study variables, the empirical relationship can be expressed in its functional form as follows:

$$lnAva = f(lnInternet, lnBroadband, lnFert, \ln Rural) \quad (1)$$

The corresponding estimable benchmark model is specified as:

$$lnAva_t = \beta_0 + \beta_1 lnInternet_t + \beta_2 lnBroadband_t + \beta_3 lnFert_t + \beta_4 lnRural_t + \varepsilon_t \quad (2)$$

where:
lnAva denotes the natural logarithm of agricultural value added;
lnInternet denotes the natural logarithm of Internet use;
lnBroadband denotes the natural logarithm of fixed broadband subscriptions;
lnFert denotes the natural logarithm of fertilizer consumption;
lnRural denotes the natural logarithm of rural population; and
ε is the random error term.

Equation (2) represents the baseline specification. As a sensitivity check, the model is also estimated using the Akaike Information Criterion (AIC) for lag selection, while the baseline specification uses the Bayesian Information Criterion (BIC). In addition, mobile cellular subscriptions are used as an alternative digitalization indicator. The longer availability of this series allows the analysis to examine whether the results are sensitive to the digitalization measure and sample period. The alternative specification is expressed as follows:
Alternative Model (Mobile Cellular Subscriptions)

$$lnAva_t = \beta_0 + \beta_1 lnMobile_t + \beta_2 lnFert_t + \beta_3 lnRural_t + \varepsilon_t \quad (3)$$

where lnMobile denotes the natural logarithm of mobile cellular subscriptions.

Based on previous studies, Internet use and fertilizer consumption are expected to have positive relationships with agricultural value added because they may improve access to information, support production practices and contribute to agricultural productivity. The expected relationship for fixed broadband subscriptions is less clear because its contribution depends on how digital technologies are adopted and used in agriculture. The expected relationship for rural population is also uncertain. A larger rural population may increase agricultural labour availability, but it may also reflect structural conditions associated with lower productivity. The relationship between mobile cellular subscriptions and agricultural value added is examined as an alternative measure of digitalization rather than imposing a predetermined direction.

ARDL Methodology

To examine the long-run and short-run relationships between digitalization and agricultural value added, this study employs the ARDL bounds testing approach developed by Pesaran et al. (2001). The ARDL approach can be used whether the variables are integrated of order zero, I(0), order one, I(1), or a mix of both, as long as none of the variables are integrated of order two, I(2). The approach is also applicable in relatively small samples, although the limited number of annual observations may reduce the precision of the estimates and the power of time-series tests.

Compared with conventional cointegration techniques such as Engle–Granger (Engle & Granger, 1987) and Johansen (1988, 1991) approaches, the ARDL framework offers several advantages. First, it permits the estimation of both long-run equilibrium relationships and short-run dynamic adjustments within a single reduced-form equation. Second, the ARDL model accommodates different lag lengths for each explanatory variable, thereby allowing greater flexibility in capturing the dynamic interactions among variables.

The ARDL procedure begins with testing the order of integration of the variables using unit root tests. After confirming that none of the variables is integrated of order two, the existence of a long-run relationship is examined using the bounds testing procedure proposed by Pesaran et al. (2001). Given the limited sample size, the bounds-test statistics are evaluated using finite-sample critical values. Both the F-statistic for the joint

significance of the level variables and the t-statistic for the lagged dependent variable are considered when assessing evidence of a level relationship.

Once evidence of a long-run relationship is obtained, the analysis proceeds with the estimation of the long-run coefficients and the error correction model (ECM). The ECM captures the short-run dynamics and measures the speed at which deviations from the long-run equilibrium are corrected after a short-run shock. A negative and statistically significant error correction coefficient indicates adjustment toward the estimated long-run equilibrium and shows the proportion of disequilibrium corrected in each period. To examine the adequacy of the estimated ARDL model, post-estimation tests for serial correlation and heteroskedasticity are carried out. In addition, recursive CUSUM and OLS-CUSUM tests are used to evaluate parameter stability over the sample period.

$$\Delta lnAva_t = \alpha_0 + \sum_{i=1}^{p} \alpha_1 \Delta lnAva_{t-i} + \sum_{i=0}^{q_1} \alpha_2 \Delta lnInternet_{t-i} + \sum_{i=0}^{q_2} \alpha_3 \Delta lnBroadband_{t-i} + \sum_{i=0}^{q_3} \alpha_4 \Delta lnFert_{t-i} + \sum_{i=0}^{q_4} \alpha_5 \Delta \ln Rural_{t-i} + \lambda_1 lnAva_{t-1} + \lambda_2 lnInternet_{t-1} + \lambda_3 lnBroadband_{t-1} + \lambda_4 lnFert_{t-1} + \lambda_5 lnRural_{t-1} + \varepsilon_t \quad (4)$$

where Δ denotes the first-difference operator, $\boldsymbol{\alpha}$ represents the short-run dynamic coefficients, $\boldsymbol{\lambda}$ captures the long-run relationship among the variables, and $\boldsymbol{\varepsilon_t}$ is the white-noise error term. The optimal lag lengths (p and q) are selected using the Bayesian Information Criterion (BIC). Evidence of a long-run level relationship is assessed using the F- and t-statistics together with the corresponding finite-sample bounds-test critical values.

Estimation Procedure

The empirical analysis begins with descriptive statistics and pairwise correlations to examine the main characteristics of the variables and possible multicollinearity. Stationarity is then tested using the Augmented Dickey–Fuller (ADF; Dickey and Fuller, 1981) and Phillips–Perron (PP; Phillips and Perron, 1988) unit root tests. After examining the integration properties of the variables and considering the sensitivity of the unit root results to the test specification, the ARDL bounds test is used to examine the presence of a long-run level relationship.

The bounds-test decision is based on the F- and t-statistics and the corresponding finite-sample critical values. When the bounds test provides evidence of a level relationship, the long-run coefficients are estimated from the selected ARDL specification. The corresponding ECM is then used to examine short-run dynamics and the adjustment of deviations from the long-run equilibrium following temporary shocks. Model adequacy is assessed through post-estimation tests for serial correlation and heteroskedasticity, while parameter stability is examined using the recursive CUSUM and OLS-CUSUM tests. The optimal lag length in the baseline model is selected according to the BIC. As a sensitivity check, the model is also estimated using the AIC. An additional ARDL specification using mobile cellular subscriptions as an alternative digitalization indicator is estimated over the longer available sample period. All estimations are performed in Stata/IC 15.0.

RESULTS AND DISCUSSION

The results are based on annual data for Türkiye covering 2001–2023 and examine agricultural value added in relation to Internet use, fixed broadband subscriptions, fertilizer consumption and rural population. The ARDL analysis first tests for a long-run relationship among these variables. The long-run coefficients and the ECM are then estimated to examine the long-run estimates and short-run dynamics, respectively.

Table 2. Descriptive Statistics

Variable	Mean	Median	Maximum	Minimum	Standard Deviation	Skewness	Kurtosis
lnAva	24.6847	24.6903	24.9713	24.3388	0.2039	−0.0366	1.6792
lnInternet	3.6017	3.8095	4.4539	1.6466	0.7682	−0.9232	2.9665
lnFert	4.6294	4.6498	5.0082	4.2512	0.2182	−0.0478	2.1045
lnBroadband	1.5969	2.3480	3.1117	−4.1058	1.9949	−1.8826	5.4272
lnRural	3.0541	3.2666	3.6921	2.3817	0.5393	−0.1620	1.2270

Table 2 reports the descriptive statistics for the variables over the 2001–2023 baseline sample. All variables are expressed in natural logarithms. lnAva has a mean of 24.6847 and shows relatively limited variation, with a standard deviation of 0.2039. Among the digitalization indicators, lnBroadband shows greater variation than lnInternet, with standard deviations of 1.9949 and 0.7682, respectively. The descriptive statistics also show

differences in the distributions of the variables, particularly for lnBroadband, which has the largest absolute skewness and kurtosis values.

Table 3. ADF Unit Root Test Results

Variable	ADF Level	ADF First Difference	PP Level	PP First Difference	Assessment
lnAva	−3.770**	—	−4.665***	—	I(0)
lnInternet	−3.201*	−3.872**	−3.464**	—	Mixed
lnBroadband	−20.245***	—	−4.643***	—	I(0)
lnFert	−6.745***	—	−5.792***	—	I(0)
lnRural†	−1.308	−3.209**	−0.379	−1.934	Mixed
lnMobile	−3.176	−9.859***	−2.851	−7.943***	I(1)

Notes: ADF and PP tests for lnAva, lnInternet, lnBroadband, lnFert and lnMobile include an intercept and deterministic trend. †The reported tests for lnRural include an intercept without a deterministic trend. ***, ** and * indicate rejection of the unit-root null hypothesis at the 1%, 5% and 10% significance levels, respectively. A dash indicates that first-difference results are not reported where stationarity is already supported at level.

Table 3 reports the ADF and PP unit root test results. The results support level stationarity for lnAva, lnBroadband and lnFert. For lnInternet, the evidence differs across the tests and significance levels. The ADF test does not reject the unit-root null at the 5% level in levels but rejects it after first differencing, whereas the PP test rejects the null in levels at the 5% level. The results for lnRural are also sensitive to the test specification. Under the intercept-only specification, the ADF test rejects the unit-root null after first differencing, while the PP test does not. For lnMobile, neither the ADF nor the PP test rejects the unit-root null at level, whereas both tests reject the null after first differencing at the 1% significance level, indicating that lnMobile is I(1). Overall, the unit root results are sensitive for some variables and should therefore be interpreted cautiously. The tests do not provide a uniform classification across all variables.

The lag structure of the baseline ARDL model was selected using the BIC. With a maximum lag length of two, the BIC selected an ARDL(1,2,1,0,1) specification. The resulting estimation sample covers 2003–2023 and contains 21 observations.

Table 4. ARDL Bounds Test Results

Significance	F: I(0)	F: I(1)	t: I(0)	t: I(1)
10%	3.010	4.531	−2.524	−3.662
5%	3.871	5.703	−2.966	−4.205
1%	6.275	8.924	−3.935	−5.403

Test statistics: F = 6.332; t = −4.170; k = 4; N = 21.

Note: Finite-sample critical values are based on Kripfganz and Schneider (2020). The selected baseline specification is ARDL(1,2,1,0,1).

Table 4 presents the finite-sample ARDL bounds-test results for the baseline specification. The F-statistic is 6.332 and the t-statistic is −4.170. At the 10% significance level, both statistics exceed the corresponding upper-bound critical values in the direction required for rejection of the null hypothesis of no level relationship. At the 5% level, however, the F-statistic exceeds its upper-bound critical value, while the t-statistic does not exceed the corresponding upper-bound critical value in absolute terms. The bounds-test decision is therefore inconclusive at the 5% level. The evidence of a long-run level relationship should consequently be interpreted with caution.

Given the bounds-test evidence, the long-run coefficients and the corresponding ECM are reported for the baseline ARDL specification, while their interpretation takes the finite-sample bounds-test result into account.

Table 5 reports the error-correction representation of the selected ARDL(1,2,1,0,1) model. The error-correction coefficient is negative and statistically significant (−0.7853, p = 0.002), indicating adjustment following deviations from the estimated long-run relationship. Approximately 78.5% of the previous period's disequilibrium is corrected within one year. The coefficient lies between −1 and 0, indicating convergence toward equilibrium without the oscillatory adjustment implied by an error-correction coefficient below −1.

Table 5. ARDL Error-Correction Model Estimates

Component	Variable	Coefficient	Std. Error
Adjustment	ECT(-1)	−0.7853	0.1883
Long run	lnInternet	0.1026	0.0700
	lnBroadband	0.0795	0.0355
	lnFert	−0.1337	0.0826
	lnRural	−0.1817	0.0467
Short run	ΔlnInternet	−0.3378	0.0674
	ΔlnInternet(-1)	−0.1945	0.0829
	ΔlnBroadband	0.1274	0.0726
	ΔlnRural	0.1288	0.0750
	Constant	19.9229	4.5850

Notes: ECT denotes the error-correction term. Δ denotes the first-difference operator. The estimates are based on the BIC-selected ARDL(1,2,1,0,1) specification.

In the long run, Internet use has a positive but statistically insignificant coefficient (β = 0.1026, p = 0.171). Fixed broadband subscriptions have a positive and statistically significant coefficient (β = 0.0795, p = 0.047), while fertilizer consumption has a negative but statistically insignificant coefficient (β = −0.1337, p = 0.134). Rural population has a negative and statistically significant coefficient (β = −0.1817, p = 0.003). Since all variables are expressed in natural logarithms, the coefficients can be interpreted as long-run elasticities. However, these estimates should be interpreted cautiously because the bounds-test decision is inconclusive at the 5% significance level.

Regarding the short-run dynamics, the contemporaneous change in Internet use has a negative and statistically significant coefficient (β = −0.3378, p < 0.001), and its first lag is also negative and statistically significant (β = −0.1945, p = 0.039). In contrast, the short-run coefficients of fixed broadband subscriptions (β = 0.1274, p = 0.107) and rural population (β = 0.1288, p = 0.114) are not statistically significant.

Table 6. Long-Run Estimates of the ARDL Models

Variable	BIC Model Coefficient	p-value	AIC Model Coefficient	p-value
lnInternet	0.1026	0.171	0.0714	0.356
lnBroadband	0.0795	0.047	0.0711	0.064
lnFert	−0.1337	0.134	−0.0915	0.302
lnRural	−0.1817	0.003	−0.2082	0.002
ECT(-1)	−0.7853	0.002	−0.8276	0.001

Notes: The BIC selects ARDL(1,2,1,0,1), while the AIC selects ARDL(1,2,1,0,2). The finite-sample bounds test could not be computed for the AIC specification because of the number of parameters relative to the available observations. The AIC model is therefore reported only as a lag-selection sensitivity check.

Table 6 compares the long-run estimates from the baseline BIC specification with those obtained when the AIC is used for lag selection. The signs of all four long-run coefficients remain unchanged across the two specifications. Internet use remains positive and statistically insignificant, while fertilizer consumption remains negative and statistically insignificant. The coefficient of rural population remains negative and statistically significant. Fixed broadband subscriptions remain positive in both specifications, although its statistical significance changes from the 5% level under the BIC specification (β = 0.0795, p = 0.047) to the 10% level under the AIC specification (β = 0.0711, p = 0.064).

In the baseline BIC specification, Internet use has a positive but statistically insignificant long-run coefficient. Therefore, the results do not provide sufficient evidence of a long-run association between Internet use and agricultural value added over the sample period. Although the positive sign is consistent with the view that Internet access may facilitate access to production, market and advisory information, the estimated coefficient does not allow a statistically supported long-run effect to be established.

Fixed broadband subscriptions have a positive and statistically significant long-run coefficient in the BIC specification (β = 0.0795, p = 0.047). Since the variables are expressed in logarithms, a 1% increase in fixed broadband subscriptions is associated with an approximately 0.08% increase in agricultural value added, holding the other variables constant. However, this result is sensitive to lag selection, as the coefficient is significant only at the 10% level in the AIC specification. The broadband result should therefore be interpreted as suggestive rather than as strong evidence of a stable relationship across specifications.

Fertilizer consumption has a negative but statistically insignificant long-run coefficient in the baseline model (β = −0.1337, p = 0.134). The coefficient remains negative and statistically insignificant under the AIC specification. The revised estimates therefore do not provide statistical evidence of a long-run relationship between fertilizer consumption and agricultural value added.

Rural population has a negative and statistically significant long-run coefficient in both specifications. In the BIC model, the estimated elasticity is −0.1817 (p = 0.003), implying that a 1% increase in rural population is associated with an approximately 0.18% decrease in agricultural value added, holding the other variables constant. The coefficient remains negative and statistically significant in the AIC specification (β = −0.2082, p = 0.002). This negative association may reflect structural characteristics of agriculture in which a larger rural population does not necessarily correspond to higher agricultural productivity.

Overall, the comparison between the BIC and AIC specifications shows that the signs of the estimated long-run coefficients are relatively stable, but their statistical significance is not uniform. In particular, the evidence for fixed broadband subscriptions weakens under the AIC specification. Together with the finite-sample bounds-test result, these findings support a cautious interpretation of the estimated long-run relationships.

Table 7. Alternative ARDL Specification Using Mobile Cellular Subscriptions

Component	Variable	Coefficient	Std. Error	p-value
Adjustment	ECT(-1)	−0.3209	0.1537	0.045
Long run	lnMobile	0.0146	0.0095	0.134
	lnFert	0.2945	0.2258	0.202
	lnRural	−0.2769	0.0834	0.002
Short run	ΔlnAva(-1)	−0.4474	0.1622	0.010
	Constant	7.7602	3.8982	0.056

Notes: Mobile cellular subscriptions allow the common data sample to be extended to 1986–2023. The BIC selects an ARDL(2,0,0,0) specification, resulting in an estimation sample of 1988–2023 (N = 36).

As an additional robustness exercise, mobile cellular subscriptions are used as an alternative measure of digitalization. This indicator allows the common data sample to be extended to 1986–2023, compared with 2001–2023 in the baseline specification. After accounting for the selected lag structure, the ARDL(2,0,0,0) model is estimated over 1988–2023 with 36 observations. This specification therefore addresses the limited time coverage of the baseline digitalization indicators while also examining whether the results depend on the measure of digitalization used.

The coefficient of mobile cellular subscriptions is positive but statistically insignificant (β = 0.0146, p = 0.134). Fertilizer consumption also has a statistically insignificant coefficient (β = 0.2945, p = 0.202), while rural population has a negative and statistically significant coefficient (β = −0.2769, p = 0.002). The error-correction coefficient is negative and statistically significant (−0.3209, p = 0.045). However, the bounds test does not reject the null hypothesis of no level relationship (F = 1.820; t = −2.088), even at the 10% significance level. The long-run coefficients from this alternative specification should therefore not be interpreted as evidence of established long-run effects.

The alternative specification therefore does not confirm the long-run evidence obtained from the baseline model. Instead, it indicates that the results are sensitive to the digitalization indicator and sample period. This finding supports a cautious interpretation of the relationship between digitalization and agricultural value added rather than suggesting a uniform effect across alternative measures. Since the alternative specification also covers a longer sample period, differences between the baseline and mobile models cannot be attributed solely to the choice of digitalization indicator.

Diagnostic tests were conducted for the baseline ARDL(1,2,1,0,1) specification. The Breusch–Godfrey LM test does not reject the null hypothesis of no serial correlation (χ^2 = 1.840, p = 0.175). Similarly, the Breusch–Pagan/Cook–Weisberg test does not indicate heteroskedasticity (χ^2 = 0.000, p = 0.980). These results provide no evidence of serial correlation or heteroskedasticity in the baseline specification.

Parameter stability was examined using the recursive CUSUM and OLS-CUSUM tests. The recursive CUSUM statistic is 0.2756, which is below the 5% critical value of 0.9479. The OLS-CUSUM statistic is 0.3311 and is also below its corresponding 5% critical value of 1.3581. The null hypothesis of parameter stability is therefore not rejected by either test.

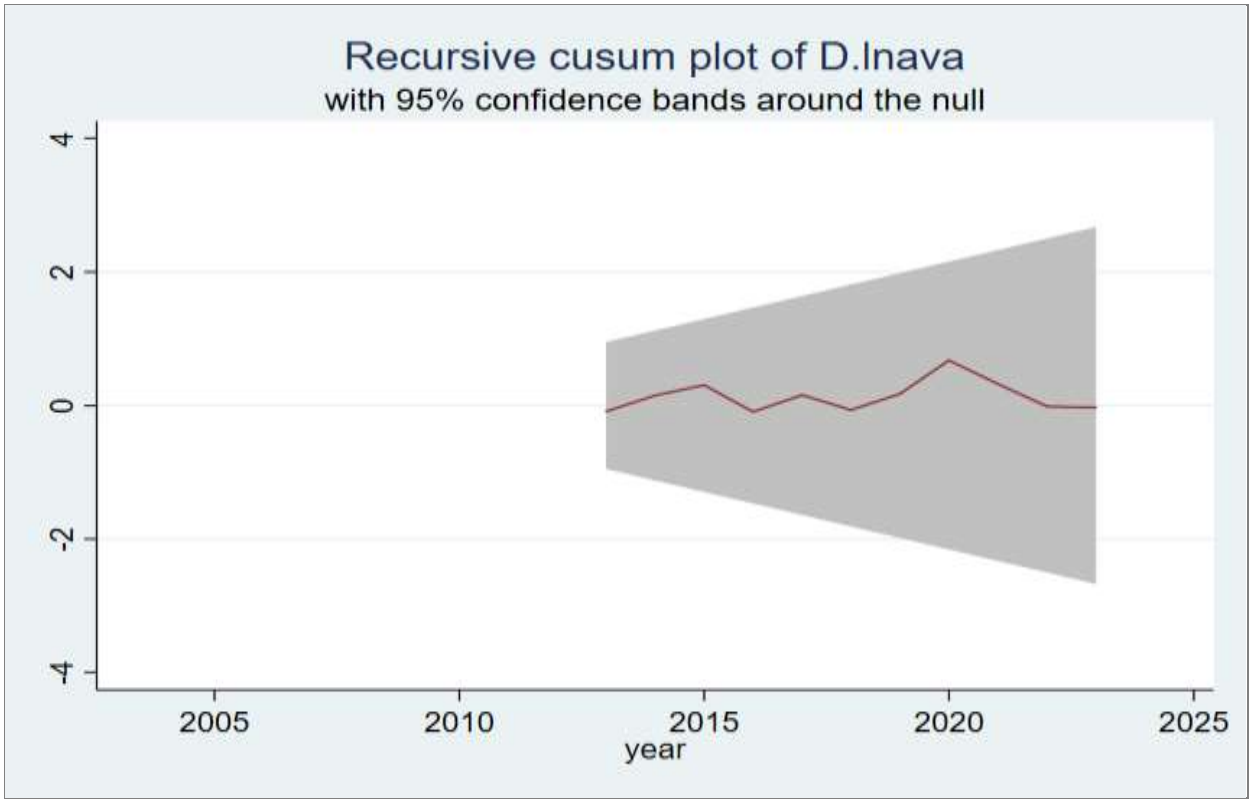


Figure 1. Recursive CUSUM Stability Test

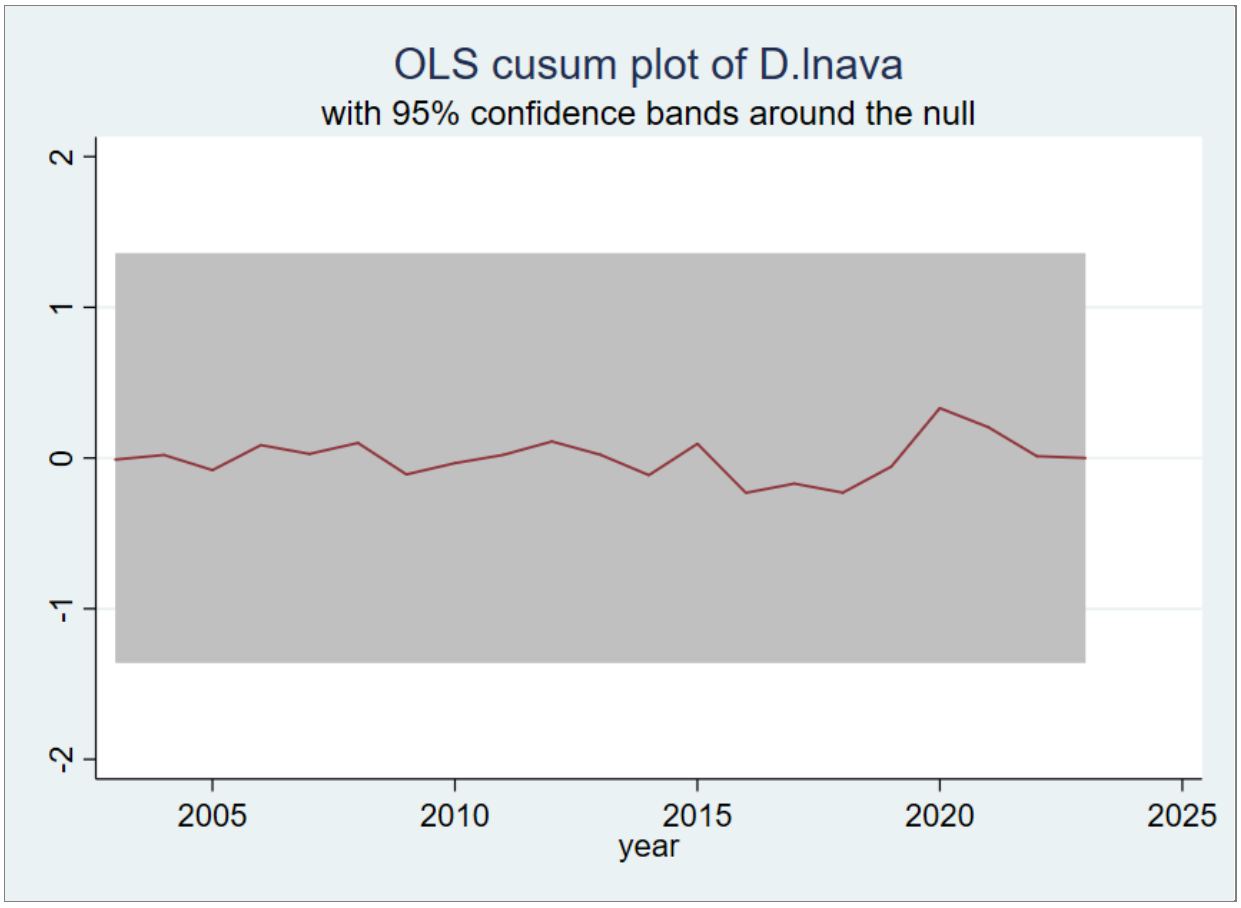


Figure 2. OLS-CUSUM Stability Test

Figures 1 and 2 present the recursive CUSUM and OLS-CUSUM stability tests for the baseline ARDL specification. Both test statistics remain below their respective 5% critical values, indicating that the null hypothesis of parameter stability cannot be rejected. The stability tests therefore do not provide evidence of parameter instability over the estimation period.

CONCLUSION

This study examined the short-run and long-run relationships between digitalization and agricultural value added in Türkiye using the ARDL approach. Internet use and fixed broadband subscriptions were considered as separate indicators of digitalization, while fertilizer consumption and rural population were included in the model. The finite-sample bounds test provides evidence of a long-run level relationship at the 10% significance level, although the result is inconclusive at the 5% level. The ECM coefficient is negative and statistically significant, indicating adjustment following short-run deviations from the estimated long-run relationship.

The long-run estimates differ across the variables. Internet use has a positive but statistically insignificant coefficient, while fixed broadband subscriptions have a positive and statistically significant coefficient in the baseline BIC specification. The broadband coefficient remains positive when the AIC is used for lag selection, although its statistical significance weakens to the 10% level. Fertilizer consumption has a negative but statistically insignificant coefficient, whereas rural population has a negative and statistically significant coefficient in both the BIC and AIC specifications. These results indicate that the estimated relationships differ across variables and are partly sensitive to lag selection.

As an additional analysis, mobile cellular subscriptions were used as an alternative digitalization indicator, allowing the common data sample to be extended from 2001–2023 to 1986–2023. In this specification, the coefficient of mobile cellular subscriptions is positive but statistically insignificant, and the bounds test does not provide evidence of a long-run level relationship. The alternative specification therefore does not confirm the long-run evidence obtained from the baseline model. Overall, the findings indicate that the relationship between digitalization and agricultural value added is sensitive to the digitalization indicator and sample period.

Taken together, the results do not support a uniform relationship between digitalization and agricultural value added. The positive coefficient of fixed broadband subscriptions in the baseline model provides some evidence of a positive association, but this result weakens under alternative lag selection and is not reproduced when mobile cellular subscriptions are used as the digitalization indicator. The findings should therefore be interpreted as evidence of indicator- and specification-sensitive associations rather than as general effects of digitalization on agricultural value added.

Policy Implications

The findings suggest that policies concerning agricultural digitalization should distinguish between different forms of digital access rather than treating digitalization as a single dimension. The positive broadband coefficient in the baseline specification suggests that digital infrastructure may be relevant for agricultural value added, although its statistical significance is sensitive to lag selection. At the same time, the insignificant coefficients obtained for Internet use and mobile cellular subscriptions show that wider access to digital technologies does not necessarily translate into measurable increases in agricultural value added.

Policies may therefore consider digital infrastructure together with the conditions that determine how digital technologies are used in agricultural production. Digital extension services, advisory platforms and digital-skills programs can support farmers' ability to use available technologies (Klerkx et al., 2019). However, the present results do not establish the causal effects of such interventions, and policy recommendations should therefore be interpreted cautiously.

The negative association between rural population and agricultural value added also suggests that changes in the size of the rural population alone should not be interpreted as an indicator of improved agricultural performance. Policies concerning agricultural development may instead consider productivity, human capital, technological capacity and the effective use of available digital infrastructure together.

An important limitation of the study is the relatively short baseline sample. Although agricultural value added and some control variables are available for earlier years, the availability of the baseline digitalization indicators restricts the common sample to 2001–2023. The limited number of annual observations may reduce the precision of the estimates and the power of time-series tests. The alternative mobile specification provides a longer sample, but its results also show that the findings are sensitive to the digitalization indicator and sample period. Future research could use longer time series as additional digitalization indicators become available and examine whether the relationships identified here remain stable across alternative measures and periods.

Acknowledgements

Not applicable.

Declaration of interests

The author declares that there are no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Author Contributions

Tuğçe Kaya **:**Conceptualization; data curation; formal analysis; funding acquisition; investigation; methodology; project administration; software; writing— original draft; writing—review and editing.

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Article History	
Submission received:	04.08.2026
Revised:	28.09.2026
Accepted:	01.10.2026

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