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Original Article

Forecasting Patent Trends in the Agricultural Sector Using the ARIMA Model: A Case Study of IPC A01 Class

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ABSTRACT

Patents play an important role in stimulating growth and innovation across various sectors, including agriculture. This study focuses on tracking technological progress in the agricultural domain by examining patent data as a proxy for innovation activity. Patents categorized under IPC A01, obtained from the European Patent Office (EPO) database, were analyzed to generate strategic insights that can inform future research and development initiatives. Applying the ARIMA time series model, patent application trends within the agricultural sector were examined, and forecasts were generated for the period ahead. The study showed that the best model for forecasting agricultural patents was the ARIMA(1,1,0) model. The MAPE value of the model was calculated as 7,88, and the RMSE value of the model was calculated as 7328,31. According to the model, the number of applications is expected to reach approximately 150.778 in 2023 and rise to 161.220 by 2028. This upward trajectory reflects a sustained momentum in agricultural innovation. The findings not only demonstrate the sector's increasing engagement with technological advancement but also offer valuable foresight regarding future innovation patterns. The global rise in agricultural patenting, along with these projections, serves as a useful indicator of the sector's growing emphasis on inventive activity and its commitment to long-term technological development.

Key words: Agricultural patents, forecasting, ARIMA.

Tarım Sektöründe Patent Eğiliminin ARIMA Modeli ile Tahmini: IPC A01 Sınıfı Örneği

ÖZ

Patentler, tarım da dahil olmak üzere çeşitli sektörlerde büyümeyi ve inovasyonu teşvik etmede önemli bir rol oynamaktadır. Bu çalışma, tarım sektöründe teknolojik ilerlemeyi izlemek ve gelecekteki inovasyon eğilimlerini değerlendirebilmek amacıyla patent verilerini analiz etmeyi amaçlamaktadır. Avrupa Patent Ofisi (EPO) veri tabanından alınan IPC A01 sınıflandırması altındaki patent başvuruları incelenerek, elde edilen verilerin araştırma ve geliştirme faaliyetlerine stratejik katkı sağlaması hedeflenmiştir. Çalışmada ARIMA zaman serisi modeli kullanılarak tarımsal patent başvurularının yıllar içindeki seyri değerlendirilmiş ve gelecek dönemlere yönelik tahminler yapılmıştır. Çalışmada tarımsal patentlerin tahmini için en iyi modelin ARIMA(1,1,0) modeli olduğu belirlenmiştir. Modelin MAPE değeri 7,88 ve RMSE değeri 7328,71 olarak hesaplanmıştır. Model sonuçlarına göre, 2023 yılı için başvuru sayısı yaklaşık 150.778 olarak öngörülürken, bu rakamın 2028 yılına kadar 161.220'ye ulaşacağı tahmin edilmektedir. Bu artış, tarımsal inovasyonda süreklilik gösteren bir ivmeye işaret etmektedir. Elde edilen bulgular, sektördeki teknolojik ilerlemenin giderek hızlandığını ortaya koymakta ve geleceğe yönelik patent eğilimlerine dair önemli ipuçları sunmaktadır. Dünya genelinde tarım alanında artan patent başvuruları ve bu çalışmada sunulan öngörüler, sektörde yenilikçi faaliyetlerin güç kazandığını ve uzun vadeli teknolojik gelişmelerin sürdürülebilir şekilde ilerlediğini göstermektedir.

Anahtar kelimeler: Tarım patentleri, tahmin, ARIMA

INTRODUCTION

Patents are a significant instrument that shapes investment planning, scientific research, and commercial enterprise development decision-making processes (Fischer et al., 2020). Beyond their legal function, patents play an important role in fostering economic growth, stimulating innovation, and securing competitive advantage within national and global markets (Dereli, 2019). Accordingly, the utilisation of these dynamic instruments extends beyond the analysis of current market conditions, contributing to strategic decision-making by enabling the anticipation of future developments. In this regard, patents and other forms of intellectual property rights are of critical importance in safeguarding and commercializing innovative ideas (Özdemir and Yavuz, 2021). Furthermore, public policy and governmental incentives have a significant influence on the rise in agricultural patent applications. State-supported research and development (R&D) initiatives, tax incentives, and subsidies for agricultural technologies serve as key drivers of innovation. Driven by policy-induced incentives, countries including China, the United States, and South Korea have reported notable surges in patent applications, contributing to rapid advancements in agricultural technologies. These policy measures have created a sustained drive toward innovation and the exploration of environmentally sustainable approaches within the agricultural sector. This global upward trend in agricultural patenting activity is also increasingly evident in developing economies such as Türkiye.

A patent, regarded as a mechanism for converting inventions or existing knowledge into commercially viable solutions, serves to motivate inventors to disclose and realise their innovations (Dahlborg et al., 2017). Beyond securing intellectual property rights, patents grant legal control over the commercial exploitation of inventions. They function as dynamic repositories of technological information, offering not only insights into specific technologies but also into their potential areas of application. As such, patents are valuable tools for tracking innovation patterns and emerging technological trends (Griliches, 1998; Castells et al., 2000; Ma and Porter, 2015). Patents function as a driving force for innovation within the agricultural sector by offering valuable insights into prevailing technological trends and potential future directions. The systematic analysis of patent data facilitates the identification of priority areas for research and development, including agricultural machinery, data automation, irrigation systems, and greenhouse technologies (Sozzi et al., 2018). Agricultural patents often embody intricate and application-oriented advancements in agricultural science and technology, and may be filed by a wide range of entities, including individuals, private enterprises, research institutions, and universities (Li et al., 2018). Moreover, patents serve as a lens through which the integration of cross-sectoral knowledge into agricultural innovation can be observed. Technological inputs derived from non-agricultural sectors significantly contribute to the emergence of innovative advancements in agriculture (Clancy et al., 2020).

Patent applications related to agricultural innovations have shown a significant upward trend over the past two decades, paralleling the increasing integration of science-based technologies in agricultural practices in Türkiye. The number of agricultural patent applications increased approximately fivefold between 2000 and 2020. According to Türkiye's 12th Development Plan, the number of international patent applications, which was 1.771 in 2022, is targeted to triple and reach 5.000 applications in 2028 (PSBRT, 2023). This rise coincides with the growing global population, which continues to drive demand for agricultural products and, consequently, compels the sector to develop innovative and sustainable solutions. The adoption of advanced tools and machinery in agricultural processes plays a critical role in enhancing operational efficiency and reducing labor intensity (Tian et al., 2020). In this context, creative ideas and novel inventions stand as fundamental components in the transition toward a more modernized and productive agricultural sector.

Patent data are used to identify innovation trends, predict technological developments, describe technological gaps and potential competitors. Analysing patent data gains importance in assessing innovative activities and technological progress in various fields (Dechezleprêtre et al., 2017; Yang et al., 2015). The European Patent Office (EPO) and the World Patent Statistics Database (PATSTAT) have facilitated the accessibility and analytical examination of patent data, thus increasing the efficiency of research and decision-making processes in related fields (Leusin et al., 2020; Baumann et al., 2021). The study of patent information is recognised as a systematic and logical approach that is useful in understanding technological progress (Sandal and Kumar, 2015). It also serves as a valuable tool for determining the stage of development of specific technologies, distinguishing current technological trends and assessing the competitive capabilities of enterprises or nations in the global technological landscape (Yang et al., 2021; Shokouhyar et al., 2024).

The international patent classification (IPC) consists of eight main headings: human needs, processes, chemistry, textiles, fixed structures, mechanical engineering, physics and electricity. The agricultural sector (IPC A01) is included under the main heading of human needs. The agriculture sector is further subdivided into subclasses. Topics such as tillage, sowing, harvesting, animal husbandry, and gardening constitute the subheadings of the agricultural sector. IPC A01 class covers patents related to agriculture, forestry, animal husbandry, hunting, trapping and fishing and represents a critical area of technological innovations and developments in the agricultural sector. Given the ever-changing nature of agriculture and the increase in global food demand, analysing this class allows one to understand the direction of innovation in agriculture and can guide future research and development activities. In this respect, the IPC A01 class provides an important perspective for understanding the transformation and growth in the agricultural sector and is the main focus of this study.

The number of patent applications related to IPC A01, which includes the agriculture sector, between 1960-2022 is shown in Figure 1. The number of applications, which was 5.350 in 1960, reached 163.273 in the A01 category by 2022. Figure 1 displays a consistent upward trend over the decades. After 2010, there has been a significant increase in the number of applications. This is an indication that technological developments and innovative studies have intensified in recent years. However, as of 2020, there has been a decline in the number of applications. This decline may be due to the possible effects of the pandemic.

The A01 class, central to this study, encompasses a wide range of agricultural innovations. To understand the specific technological domains within this broad classification, it is essential to refer to its subclasses as defined by the International Patent Classification (IPC) system, maintained by the World Intellectual Property Organization (WIPO, 2025). According to this scheme, key subclasses include: A01B (soil working in agriculture or forestry; parts of agricultural machines), A01C (planting; sowing; fertilising), A01D (harvesting; mowing), A01F (threshing; baling; storing agricultural produce), A01G (horticulture; cultivation of various crops; forestry), A01H (new plants or processes for obtaining them; plant reproduction by tissue culture), A01J (manufacture of dairy products), A01K (animal husbandry; fishing; new breeds of animals), A01L (shoeing of animals), A01M (catching, trapping or scaring of animals; apparatus for destruction of noxious organisms), A01N (preservation of organisms; biocides; pest repellants or attractants; plant growth regulators), and A01P (biocidal, pest repellant, or plant growth regulatory activity of chemical compounds). The distribution and trends of patent applications across these distinct technological areas, as categorized for this study, are illustrated in Figure 1.

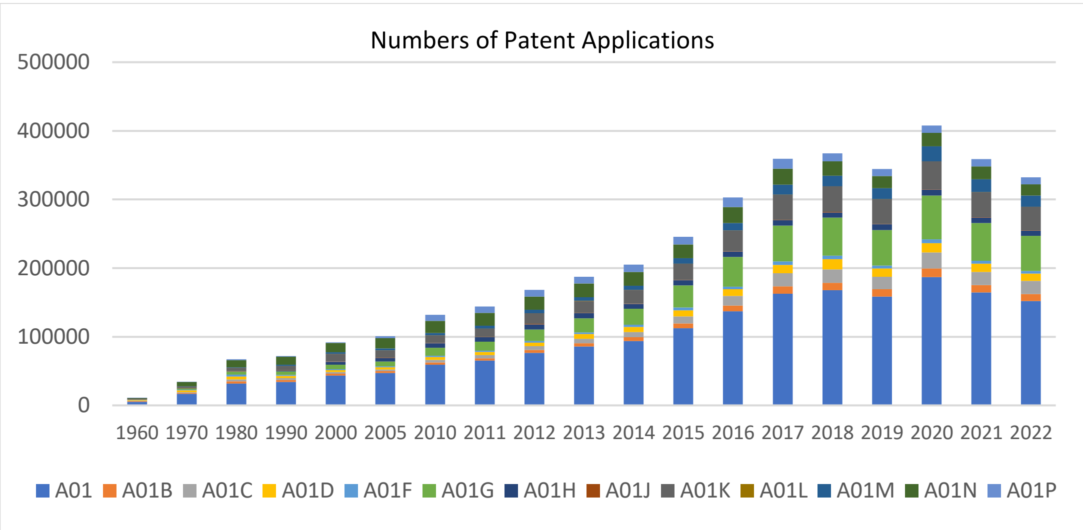

Figure 1. Distribution of patent applications in patent group A01 (EPO, 2025)

Figure 2 presents the proportional distribution of patent applications filed under the A01 classification in 2022. The A01G subclass, which pertains to horticulture and floriculture, holds the largest share at 28%, indicating a significant level of innovation activity in this domain. This is followed by A01K (animal husbandry) at 19% and A01C (planting, sowing, fertilizing) at 11%, highlighting strong interest in biological production practices. Subclasses A01M and A01N, associated with pest control and agricultural chemicals, each account for 9% of the total. A01B, A01D, and A01P—focusing respectively on soil working, harvesting, and plant growth regulation—each represent 6% of the applications. A01H (new plants or processes for modifying genotypes) has a share of 4%, whereas A01F (threshing) accounts for only 2%. No patent applications were recorded in A01L and A01J subclasses. These findings reveal that patenting activity under A01 is primarily concentrated in areas related to horticulture, animal breeding, and crop management technologies (EPO, 2025).

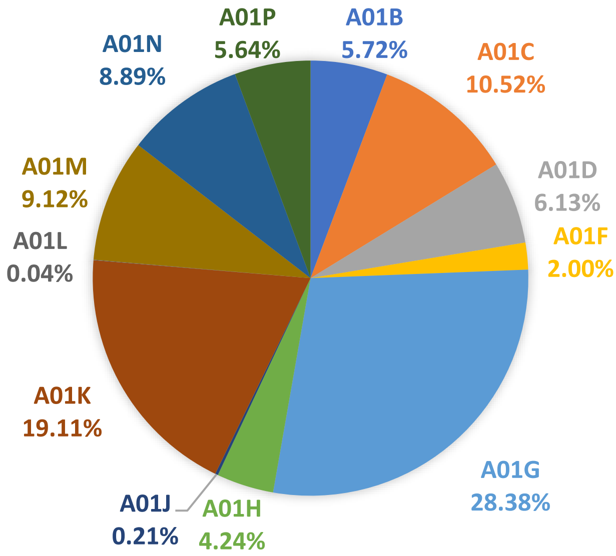

Figure 2. Distribution of patents in the A01 patent group in 2022 (EPO, 2025)

An analysis of patent applications within the A01 classification over the past five decades reveals that China, Japan, the United States, and South Korea consistently rank among the top countries in terms of application number. Collectively, these four countries account for approximately 67% of all A01-related patent filings during this period. In the last two decades, their dominance has become even more pronounced, with their combined share rising to 77%, indicating a significant acceleration in patent activity. This trend suggests a continuous and increasing focus on innovation in agriculture by these countries. In contrast, Türkiye's share in A01 patent applications has remained relatively limited, fluctuating between 0.1% and 0.2% in both time frames (Table 1). In terms of global rankings, Türkiye holds the 35th position for the last 50 years and the 30th position for the last 20 years within the A01 patent applications.

The remarkable increase in China's patent activity is largely attributed to the implementation of intellectual property policies that gained momentum in the post-1990s period, characterised by liberalisation, privatisation, and integration into the global economy (Dang and Motohashi, 2015). The growth in patent applications is widely recognised as a key indicator of a country's scientific and technological advancement, reflecting its rising innovative capacity (Furman et al., 2002; Blind, 2012). In addition to supporting innovation, patenting activities play a critical role in enhancing a nation's global competitiveness by facilitating the commercialisation of technological inventions (Griliches, 1990). Furthermore, patent data provide a valuable basis for analysing countries' sectoral specialisation and for tracking the dynamics of technological development (Archibugi and Pianta, 1996; Jaffe and Trajtenberg, 2002).

Table 1. Number of patent applications by country (EPO, 2025)

Number	Country	The last 50 years	Number	Country	The last 20 years
1	China	1.294.628	1	China	1.254.909
2	Japan	410.986	2	The United States	175.144
3	The United States	273.990	3	Japan	111.568
4	South Korea	106.671	4	South Korea	78.673
-	Total	2.086.275	-	Total	1.620.294

Previous studies on patent-related topics have extensively explored the relationship between R&D expenditures and patent applications in the context of high-tech product exports (Kırankabeş and Erçakar, 2012; Koçakoğlu and Bayraktar, 2019), the determinants of regional patent activity (Karaca, 2021), and the contribution of patenting and R&D investments to economic growth (Dam and Yıldız, 2016; Özcan and Özer, 2017; Akarsu et al., 2020; Tekin and Demirel, 2022; Özkurt, 2024; Yağış, 2024). In addition, recent research has highlighted patent network analyses in sustainable and precision agriculture practices (Ferrari et al., 2021; Tey et al., 2024) as well as examined the general trends and innovation potential in agricultural patents (Liu et al., 2014; Anwer et al., 2023; Li et al., 2024). These studies collectively enhance our understanding of how patent systems influence technological advancement and broader economic development across diverse sectors.

Despite the growing interest in patent statistics and the application of time series models across various fields, there remains a noticeable gap in the literature concerning trend forecasting in agricultural patents, particularly within the IPC A01 classification. Although ARIMA models have been widely used in contexts such as industrial data prediction and regulatory impact assessments on patent activity, their specific application to forecasting patent trends in agricultural machinery and related technologies has received limited attention. This study addresses this gap by employing ARIMA models to examine time-dependent patterns in A01 class patent applications. This study aims to clarify agricultural innovation's development over time and generate empirically grounded forecasts to inform evidence-based policy-making and guide future investments in agricultural research and development.

MATERIALS AND METHODS

This study utilizes the ARIMA model to forecast global patent application trends over 62 years, with a specific focus on patent data classified under IPC A01, which pertains to agricultural machinery and forms the core dataset of the analysis. The data were collected from a specialised patent database and subsequently compiled and structured using Microsoft Excel to ensure accuracy and consistency throughout the research process.

For the analytical phase, advanced statistical software EViews and Minitab were used to conduct time series modelling and generate forecasts for the period 2023–2028. These tools facilitated econometric analysis, allowing for the identification of temporal patterns and the projection of future developments in patent activity within the agricultural sector.

The ARIMA model is a widely utilized time series forecasting method that incorporates autoregressive (AR), moving average (MA), and differencing components (Hosking, 1984). The representation of the ARIMA model is denoted as ARIMA (p, d, q), where p signifies the order of the autoregressive component, d represents the degree of differencing, and q indicates the order of the moving average component (Sharma and Nigam, 2020). The ARIMA model can be expressed as follows:

$$Z_t=\delta+a_t-\theta_{1at-1}--\theta_{2at-2}-...--\theta_{qat-q} \quad (1)$$

This equation represents the moving average (MA) component of a time series model. In the equation, *Zt* represents the variable being predicted, while *δ* is a constant term. The term at*at* denotes the random error term, which is associated with a linear combination of the model's previous error terms (*at*−1,*at*−2,…,*at*−*q*). The coefficients (*ϑ1,ϑ2,…,ϑq*) indicate the influence of the previous error terms on the current period's variable.

$$Z_t=\delta+\varnothing_1 Z_{t-1}+\varnothing_2 Z_{t-2}+...+\varnothing_p Z_{t-p}+a_t \quad (2)$$

This equation represents the autoregressive (AR) model. In the equation, *Zt* represents the variable to be predicted, while *δ* is a constant term. The terms *Zt*−1, *Zt*−2,…, *Zt*−*p* represent the observations or values from previous periods. The coefficients *ϕ*1,*ϕ*2,…,*ϕp* indicate the influence of these past observations on the current period's variable. Finally, *at* is the random error term. This structure is known as the AR(p) model, which relies solely on past observations to make predictions.

$$Z_t=\delta+\varnothing_1 Z_{t-1}+\varnothing_2 Z_{t-2}+...+\varnothing_p Z_{t-p}+a_t-\theta_1 a_{t-1}--\theta_2 a_{t-2}-...--\theta_q a_{t-q} \quad (3)$$

This equation represents the ARIMA(p, q) model, which incorporates both past observations and error terms to make predictions. In the equation, *Zt* represents the variable to be predicted, while *δ* is a constant term. The terms *Zt*−1, *Zt*−2,…, *Zt*−*p* represent the observations from previous periods, and the coefficients *ϕ*1, *ϕ*2,…,*ϕp* quantify the influence of these past observations on the current period's variable. Additionally, *at* is the random error term, and the model operates in conjunction with previous error terms *at*−1,*at*−2,…,*at*−*q*. The impact of these error terms is determined by the coefficients *ϑ*1,*ϑ*2,…,*ϑq*.

The ARIMA model consists of three main components, each capturing a distinct aspect of the time series dynamics. The autoregressive (AR) component models the linear relationship between a current observation and its previous values, thereby capturing the persistence or memory in the data. The moving average (MA) component reflects the linear relationship between the current observation and past error terms, allowing the model to account for shocks or irregular fluctuations. Lastly, the differencing component (I) is employed to transform a non-stationary time series into a stationary one by calculating the differences between consecutive observations. This process ensures the statistical stability required for reliable forecasting (Sharma and Nigam, 2020).

The ARIMA model, denoted as p, d, q, is a widely used and versatile method for analyzing and forecasting time series data. It combines the autoregressive (AR), moving average (MA), and differencing (I) components, where “p”, “d”, and “q” represent the respective degrees of these components. The differencing degree (d) enables the model to account for long-term dependencies in the data, transforming a non-stationary time series into a stationary one. This approach has proven effective in both predicting patterns over time and in data analysis across various fields. Autocorrelation (ACF) and partial autocorrelation (PACF) plots were examined to assess patent application trends. Additionally, the Generalized Dickey-Fuller (ADF) test was applied to determine whether the patent application series exhibits a unit root, indicating a non-stationary series that would require differencing to achieve stationarity.

RESULTS AND DISCUSSION

The autocorrelation function (ACF) and the partial autocorrelation function (PACF) are used as diagnostic tools in time series analysis, particularly for identifying the optimal lag structure of autoregressive (AR) and moving average (MA) components (Wiśniewski, 2011). Figure 3 illustrates that the series exhibits a strong autocorrelation structure, with particularly high correlations at the first two lags. These gradually diminish toward zero, suggesting the presence of a clear trend in the data and indicating that the series is not stationary in its original form.

The PACF plot, on the other hand, shows a significant spike at lag one, followed by rapidly decreasing values that remain within the confidence bounds from the second lag onward. This pattern is characteristic of a time series influenced by an autoregressive component. The ACF and PACF plots imply that an AR(p) model may effectively capture the underlying structure of the data. However, the visible trend suggests that differencing is necessary to achieve stationarity before proceeding with model estimation.

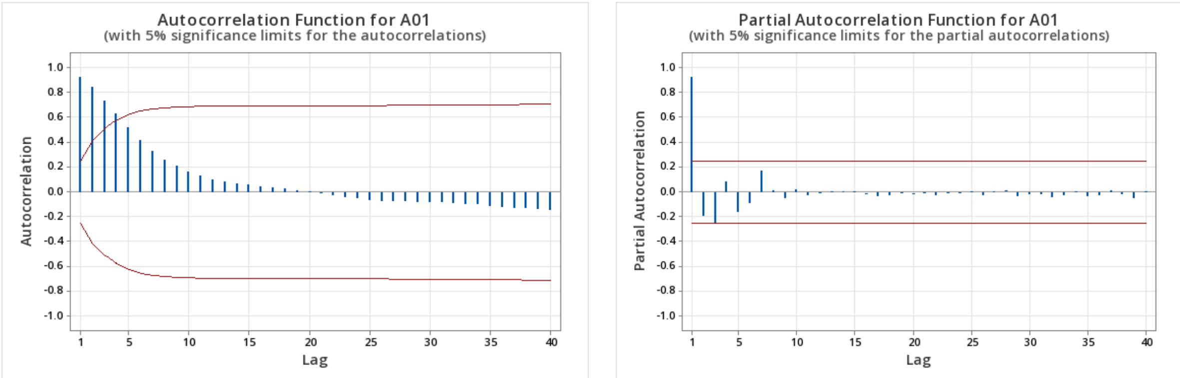

Figure 3. Level ACF and Level PACF

A critical prerequisite for applying ARIMA models is the stationarity of the time series, as non-stationary data can lead to spurious regression results. Therefore, the Augmented Dickey-Fuller (ADF) test, a standard method for detecting unit roots (Dickey and Fuller, 1979; Said and Dickey, 1984), was used to assess the stationarity of the patent application series. The results indicated that the series was non-stationary at its level form ($p > 0.005$). Consequently, first-order differencing was applied to the series in order to achieve stationarity. Following this transformation, the ADF test results showed a statistically significant p-value ($p < 0.005$), confirming that the differenced series is stationary. Furthermore, the t-statistic was found to be lower than the critical value, providing additional evidence that the series became stationary after first differencing and is thus suitable for analysis using the ARIMA model.

Table 2. Dickey-Fuller test result

		Level		First Difference	
		t-test	P value*	t-test	P value*
Augmented Dickey-Fuller test statistic		0,412	0,6435	-4,333	0,0010
Test critical values	1% level	-3,552		-3,552	
	5% level	-2,914		-2,914	
	10% level	-2,595		-2,595	

*MacKinnon (1996) p-values.

The autocorrelation function (ACF) and the partial autocorrelation function (PACF) are essential tools in time series modelling, particularly for identifying the appropriate orders of autoregressive (AR) and moving average (MA) terms (Wiśniewski, 2011). An examination of the ACF and PACF plots presented in Figure 3 reveals that the ACF plot indicates a strong autocorrelation structure within the time series. High autocorrelation values are observed at the first two lags, gradually declining toward zero in subsequent lags. This pattern suggests the presence of a prominent trend in the series, implying that it is non-stationary and requires differencing to achieve stationarity.

In contrast, the PACF plot displays a strong autocorrelation at the first lag, followed by a sharp decline in autocorrelation values, which fall within the confidence bounds from the second lag onward. This indicates the presence of an autoregressive component in the series. The structure of the ACF and PACF plots suggests that an AR(p) model may effectively capture the dynamics of the series, while also highlighting the necessity of differencing the data to render it stationary.

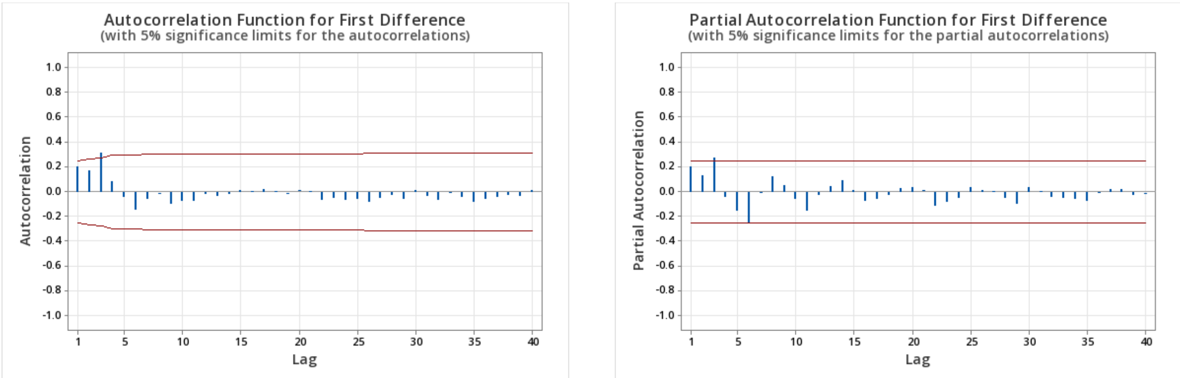

Figure 4. The first difference between ACF and PACF

The model selection table presented in Table 3 compares the performance of ARIMA (d = 1) models based on the Log-Likelihood, AICc, AIC, and BIC criteria. These criteria evaluate both the goodness of fit of the model to the dataset and its complexity, thereby assisting in identifying the most appropriate model. The model with parameters p = 1 and q = 0 stands out as the best-fitting model, as it exhibits the lowest AICc (1283.96) and AIC (1283.54) values. When multiple models are available to represent a particular time series, the model with the minimum AIC value should be selected (Akaike, 1974). The BIC value of the model (1260.46) is also relatively low compared to those of the other models, indicating that it fits the data well without overfitting through excessive parameterization. Since the other models exhibit higher AICc and BIC values, the model with p = 1 and q = 0 is considered the most suitable for the dataset.

Table 3. ARIMA model selection

Model (d = 1)	LogLikelihood	AICc	AIC	BIC
p = 1, q = 0 *	-638,771	1283,96	1283,54	1289,92
p = 0, q = 1	-639,076	1284,56	1284,15	1290,53
p = 0, q = 0	-640,204	1284,61	1284,41	1288,66
p = 0, q = 2	-638,754	1286,21	1285,51	1294,02
p = 1, q = 2	-641,160	1291,02	1290,32	1298,83

* Best model with minimum AIC.

The model's performance was evaluated using several metrics. The R^2 value was calculated as 97,4%, indicating a strong fit to the data. The Mean Absolute Percentage Error (MAPE) was found to be 7,88%, suggesting an acceptable level of forecast accuracy. Furthermore, the Root Mean Square Error (RMSE) was 7328,71 patent applications, providing another measure of the average magnitude of the forecast errors. These results show that the model makes predictions with high accuracy, and the error rate is at an acceptable level. The autoregressive (AR) coefficient was found to be 0,220, with a standard error (SE) of 0,131. The t-statistic for this coefficient is calculated as 1,682, indicating statistical significance at the 10% level (p<0,10).

Table 4 presents the forecast results for the years 2023 to 2028 obtained using the ARIMA model. The estimated values are accompanied by confidence intervals, represented by the Upper Confidence Limit (UCL) and Lower Confidence Limit (LCL). For the year 2023, the forecasted number of patent applications is 150.778, with a UCL of 165.143 and an LCL of 136.412. The forecasted values exhibit a degree of fluctuation across the years, reflecting the inherent variability in the time series. By 2028, the model predicts that the average number of patent applications will reach 161.220. This projection indicates a moderate upward trend in patent activity over the forecast period. The inclusion of confidence intervals enhances the interpretability of the results by providing a range within which the actual values are expected to fall with a specified level of confidence, thereby accounting for the uncertainty associated with future estimates.

Table 4. Estimated number of patent applications for the years 2023-2028

Year	Forecast	Upper Confidence Limit	Lower Confidence Limit
2023	150.778	165.143	136.412
2024	152.309	175.010	129.609
2025	154.423	183.578	125.269
2026	156.667	191.172	122.163
2027	158.940	198.087	119.793
2028	161.220	204.517	117.922

The forecast results indicate a gradual increase in the projected number of patent applications over time; however, this upward trend is accompanied by a widening confidence interval, reflecting increasing uncertainty in long-term estimations. For instance, while the projected number of applications for 2024 is 152.309, this figure is expected to rise to 161.220 by 2028. Concurrently, the forecast interval broadens significantly, with the upper confidence limit (UCL) reaching 204.517 and the lower confidence limit (LCL) declining to 117.922 in 2028. This suggests a reduction in the precision of forecasts as the projection horizon extends, emphasizing the necessity of interpreting long-term forecasts with caution. Although the ARIMA model provides valuable insights into general trends, it simultaneously highlights the inherent limitations in forecasting due to increasing uncertainty over time (Figure 5). Time series analyses represent a critical methodological approach for understanding innovation dynamics and technological trajectories within the agricultural sector. In particular, ARIMA models offer a robust framework for forecasting future patenting activity based on historical data. Such analyses enable policymakers and stakeholders to better anticipate sectoral developments and allocate research and development (R&D) resources more effectively. Recent studies have utilized patent data to classify technological fields into categories such as "emerging," "mature," or "declining," thereby identifying priority areas for investment and development within agricultural innovation systems (Wei et al., 2023).

The increase in patents related to agricultural technologies reflects a growing interest in sustainable agricultural practices (Hu and Xu, 2022). Time series analyses contribute strategically to agricultural research and development processes by identifying innovation cycles and the diffusion patterns of technological advancements (Kim et al., 2019). The rising number of patents in agricultural machinery and smart farming technologies indicates heightened interest in automation and precision agriculture applications within the sector (Chun et al., 2021).

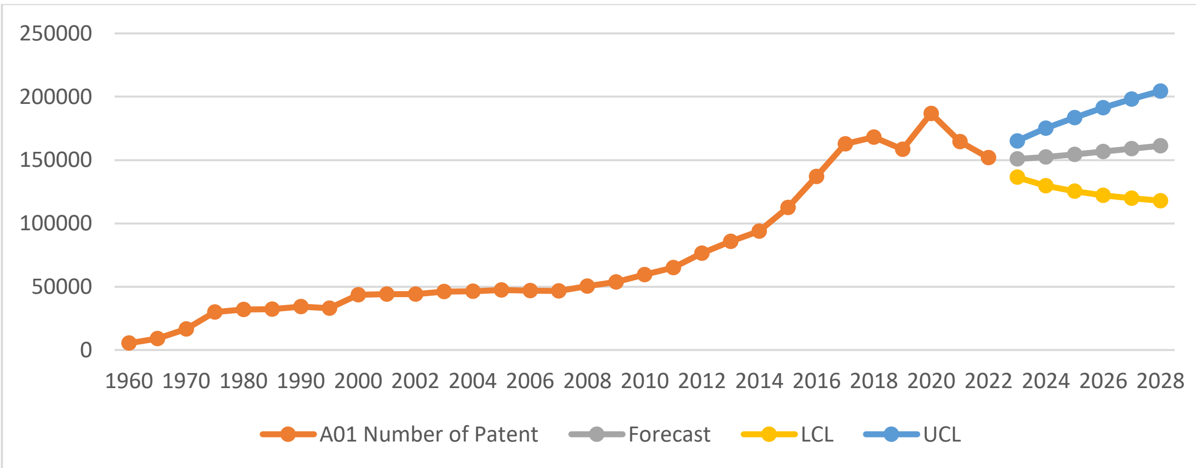

Figure 5. ARIMA model forecast

CONCLUSION

Given the accelerating emphasis on innovation within the agricultural sector, this study applies the ARIMA model to examine patent activity classified under IPC A01 and to project future trends in agricultural patenting. The ARIMA approach was selected due to its robustness in modeling temporal dependencies and trend components inherent in time series data, thereby facilitating reliable and interpretable forecasts. The results highlight the dynamics of agricultural innovation and emphasize the critical role of IPC A01 patent statistics in understanding technological advancement and guiding research and development strategies in the agricultural sector.

This study emphasises the significance of patent applications as indicators of sustainable innovation within the agricultural sector and highlights their strategic value in guiding decision-making processes. The observed increase in patent filings indicates that agricultural innovations not only contribute to sectoral development but also hold considerable potential for addressing future global food demands. Analysis of data spanning from 1960 onward reveals a steady rise in patent applications, with a particularly sharp increase after 2010, peaking at 186.839 applications in 2020. This trend reflects the rapid pace of technological progress and the intensification of innovation-oriented activities in the sector. Subclass-level analysis within the A01 category further indicates that patents related to horticulture and the cultivation of vegetables, flowers, rice, fruits, vines, hops, or seaweed (A01G) constitute the largest share, followed by patents concerning animal husbandry (A01K) and crop production (A01C).

China, Japan, the USA, and South Korea are leading countries in patent applications related to agricultural technologies, collectively accounting for a significant share of global submissions. These countries have strong research and development efforts, supportive innovation policies, and good infrastructure that help drive technological progress and protect intellectual property. Compared to these leading countries, Türkiye's contribution to agricultural patent activity remains modest, ranking 30th in patent applications over the past 20 years. This relative underperformance may be linked to a combination of factors, including limited allocation of resources to research and development, challenges in the protection and commercialization of novel technologies, and a prevailing dependence on externally developed innovations. These observations point to the critical need for a more robust national strategy that prioritizes investment in agricultural R&D, enhances the mechanisms for safeguarding intellectual property, and encourages closer cooperation between governmental institutions and private enterprises to cultivate a more innovation-oriented ecosystem within the sector.

The ARIMA (1,1,0) model, which provided the best fit after standard tests, suggests a steady increase in agricultural patent applications through 2028. The model choice reflects the data's need for differencing to ensure stationarity and the presence of a significant autoregressive pattern. These results indicate a continuing trend of innovation, though uncertainty in longer-term forecasts may be influenced by factors such as economic variability, changes in innovation policies, climate-related challenges, and shifts in global intellectual property frameworks, which can lead to variation in application numbers over time. For instance, the estimated number of patents for 2023 is 150.778, with a projected increase to 161.220 by 2028. Nonetheless, this growth is accompanied by uncertainty, with the upper confidence limit (UCL) reaching 204.517 and the lower confidence limit (LCL) narrowing down to 117.922 by 2028.

A growing global population and limited natural resources make agricultural innovation essential for efficient and sustainable production. Modern farming techniques, precision agriculture, and biotechnological advances have increased productivity while reducing environmental impact. These technologies help meet rising food demand and promote smarter use of land, water, and energy. Smart farming tools such as sensor-based irrigation, data-driven crop monitoring, and renewable energy integration are central to building resilient agricultural systems. By optimizing resources and minimizing environmental harm, they support adaptation to climate change and food security challenges. Strategic development and adoption of these innovations are key to securing long-term agricultural productivity and a future-ready food system.

Future research could explore subcategories of agricultural patents. Additionally, comparing machine learning methods such as Artificial Neural Networks (ANN) and Long Short-Term Memory (LSTM) models with traditional approaches like ARIMA could help clarify their relative effectiveness. Investigating the impact of global agricultural policies on patent activity may also reveal how institutional frameworks influence innovation across countries.

Declaration of interests

The authors of this article declare that there are no conflicts of interest.

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