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FUTURE PROSPECTS OF LABOUR PRODUCTIVITY IN ALGERIAN AGRICULTURE: A 2030 OUTLOOK

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SUMMARY

The primary objective of this study was to forecast the labour productivity in Algeria's agricultural sector by the year 2030 using the seasonal autoregressive integrated moving average (SARIMA) model. Quarterly data spanning from the first quarter of 1991 to the fourth quarter of 2021 were analyzed, identifying the SARIMA model (1, 1, 1) x (1, 1, 1, 4) as the most suitable for capturing seasonal variations and accurately fitting the historical data. The methodology utilized Python 3.11.5 for data processing and modelling, thus enabling a comprehensive analysis of the trends and patterns in Algerian agricultural labour productivity. The results obtained demonstrate robust and steady growth in the Algerian agricultural labour productivity attributable to advancements in farming techniques, technological innovations, and evolving market conditions. These findings highlight the critical role of accurate forecasting in effective policy-making and resource allocation. By providing insights into future productivity trends, the research supports the development of strategies aimed at enhancing the resilience and sustainability of the agricultural sector, particularly in the face of challenges posed by climate change and geopolitical tensions. The conclusion underscores the importance of leveraging predictive models such as SARIMA in informing agricultural policies and ensuring the long-term food security and economic stability in Algeria.

Key words:
Algeria, agricultural sector, labour productivity, food security, foresight

Abbreviations:
AIC - Akaike Information Criterion; AOAD - Arab Organization for Agricultural Development; ARIMA - Autoregressive Integrated Moving Average; BIC - Bayesian Information Criterion; BJ - Box-Jenkins; CGE - Computable General Equilibrium; CRSTRA - Scientific and Technical Research Center on Arid Regions; FAO - Food and Agriculture Organization; GDP - Gross Domestic Product; INRAA - National Institute for Agronomic Research of Algeria; NMSE - Normalized Mean Squared Error; PNDA - National Agricultural Development Plan; SARIMA - Seasonal Autoregressive Integrated Moving Average

INTRODUCTION

In recent years, challenges such as global climate change and geopolitical tensions have increasingly threatened agricultural stability (Arslan, 2023). The effects of climate change have become more pronounced, resulting in disruptions that are expected to increase droughts, reduce arable land and threaten crop yields (Kourat et al., 2022). Moreover, the ongoing Russian-Ukrainian conflict has exacerbated disruptions in global food supplies, leading to increased prices (Ben Hassen & El Bilali, 2022). In this dynamic context, accurate predictions and informed decision-making are essential (Zemri & Khetib, 2024). Within the agricultural sector, the ability to forecast labour productivity has significant implications for both short-term resource allocation and long-term policy formulation. Addressing these challenges, alongside the shift toward sustainable agriculture, has sparked a growing interest in improving the sector, not only in the present but also for the foreseeable future.

Algeria, facing a world fraught with uncertainty, finds itself at a critical juncture. The country's agricultural sector, which serves as a vital component of its economy, food security, and sustainable development, is of utmost importance. Contributing approximately 12% to the nation's GDP and employing one-tenth of the workforce (Jones et al., 2022), this sector is key to Algeria's future. Labour productivity, a fundamental measure of economic efficiency, is crucial for determining the competitiveness and resilience of the agricultural industry (Gutierrez, 2002). A decline in labour productivity could trigger cascading consequences, including rising food prices, increased dependence on imports, and exacerbated challenges such as rural unemployment and poverty. However, by understanding and forecasting labour productivity trends, policymakers can make informed decisions that strengthen the sector and support Algeria's broader developmental objectives (Liang & Wang, 2023). These insights can directly inform the implementation and evaluation of key policy initiatives, such as the National Agricultural Development Plan (PNDA).

To address this, the seasonal autoregressive integrated moving average (SARIMA) model was employed, utilizing quarterly data from Q1 1990 to Q4 2021, processed with Python 3.11.5. The Box-Jenkins methodology was applied to meticulously identify the most appropriate model. SARIMA models, recognized for their capability to capture and forecast time series patterns, provide a robust approach to this task. This research aims to fill an existing gap in the literature by applying the SARIMA model in an understudied area: forecasting labour productivity in Algeria's agricultural sector. By analysing agriculture value added per worker as the dependent variable, with years (in quarters) as the independent variable, the study seeks to uncover patterns that will enable accurate short-term projections. These insights provide a foundation for strategies aimed at strengthening the agricultural sector and its workforce.

This study revolves around three main research questions, designed to unravel the complexities of labour productivity in Algeria's agricultural context and to provide actionable insights:

a) What are the principal trends in labour productivity within Algeria's agricultural sector over the past three decades, and what do they indicate for future performance?
b) How have external factors such as climate change and geopolitical tensions influenced these labour productivity trends?
c) How effective is the SARIMA model in forecasting the future labour productivity in Algeria's agricultural sector considering the historical data and external impacts?

To the best of the researcher's knowledge, this study is the first to apply the SARIMA model for forecasting the agricultural labour productivity in Algeria. While ARIMA models have been used in other contexts, SARIMA's ability to account for seasonality makes it particularly well-suited to the cyclical nature of agricultural production in Algeria. Therefore, this study contributes uniquely to the existing body of knowledge by adapting the SARIMA model to reflect local climatic cycles, and by incorporating machine learning algorithms to enhance model accuracy and reliability. In doing so, the research provides a nuanced understanding of how seasonal variations and local factors influence the agricultural productivity in Algeria.

Given Algeria's reliance on agriculture for economic stability and employment, understanding labour productivity in this sector is critical. The country faces unique challenges such as high variability in rainfall, limited arable land, and the impacts of global climate change, which require tailored agricultural strategies. By forecasting labour productivity through the SARIMA model, this research offers insights into the potential economic impacts of improved agricultural productivity, such as increased GDP and enhanced food security (both of which are crucial given Algeria's strategic focus on agricultural development as a driver for economic growth). Moreover, this study serves as a pioneering effort in employing advanced predictive analytics within Algeria's agricultural sector, setting a precedent for future research and applications. By demonstrating the effectiveness of these tailored models, the research opens the door for more focused, region-specific studies that address the challenges posed by climate

change and resource management in arid regions. The findings are expected to significantly contribute to the strategic planning and sustainability of the agricultural sector in Algeria and similar environments globally.
The study is structured as follows: Section 2 reviews the relevant literature to establish the background and highlight the research gap. Section 3 outlines the SARIMA modelling methodology. Section 4 presents and discusses the key findings, while Section 5 offers conclusions and recommendations based on the model's application.

Literature review

Over the past decade, there has been a notable shift towards predicting labour productivity in the agricultural sector using advanced statistical methods. Extensive research efforts have been dedicated to employing a diverse range of forecasting methodologies, among which the ARIMA and SARIMA models are prominent. However, a deeper analysis reveals that while these models have been successfully applied in various global contexts, their adaptation to the specific challenges of Algerian agriculture remains underexplored. Given the disparities in labour productivity across countries and regions, these differences become particularly evident at the sectoral level. Consequently, the concept presents challenges in making comparisons and measurements across nations and in developing a consistent model with strong predictive capabilities. Our study uniquely adapts these methods to better fit the local context, emphasizing the need for models that account for significant seasonal fluctuations. More precisely, labour productivity quantifies the volume of real GDP generated per hour of labour (Amirul et al., 2022). Real GDP increases when total hours worked and labour productivity both rises, assuming other factors remain constant (Hall, 2009; Kjellstrom et al., 2009; Popescu, 2015).

Padhan (2012) applies the Box-Jenkins ARIMA time series forecasting methodology to forecast the annual agricultural productivity for 34 major crops in the periods 1950–2010 and 2011–2015. The study finds that the ARIMA model is able to forecast agricultural productivity in India with a high degree of accuracy. The study concludes that labour productivity is a key factor in transforming the agricultural sector and the whole economy in India. The study by Samavati (2013) collected data on the labour productivity growth in Norway from 1971 to 2011. The data is divided into two sub-periods: 1971–1995 and 1996–2011. The ARIMA model is fitted to the data for each sub-period. The results of the model fitting are used to forecast the labour productivity growth for the period 2012-2021. The selected ARIMA model indicates that forecasting any issues requires an in-depth understanding of the underlying factors affecting them. Comparatively, our research adapts the SARIMA model to address seasonal variations distinct to Algerian agricultural cycles. This adaptation is crucial given the pronounced seasonal impacts on productivity due to Algeria's arid climate. While these models offer robust forecasting capabilities, our study uniquely modifies such approaches to better fit the local context, emphasizing the need for models that accommodate significant seasonal fluctuations.

The study by Sabu & Kumar (2020) used the seasonal ARIMA (SARIMA) model for time series forecasting and found that the machine learning SARIMA model is able to forecast prices with a high degree of accuracy. The study highlights the importance of understanding and predicting agricultural prices for the productivity of the sector. The study's findings suggest that predictive analytics can be a valuable tool for agricultural patterns and predicting future changes. In their widely acclaimed work, Botero-García et al. (2021) discuss the impact of agricultural productivity growth on the economic growth in Colombia using a computable general equilibrium (CGE) model with data from 1990 to 2019. The model is used to simulate the impact of a 10% increase in agricultural productivity. The paper finds that a 10% increase in labour productivity in the agricultural sector would lead to a 0.8% increase in Colombia's GDP. The study conducted by Zia (2021) not only examines the use of the SARIMA (seasonal autoregressive integrated moving average) model for forecasting climate change to discover the influence of this change on work productivity in the agricultural sector but also provides valuable insights into optimising model parameters using a machine learning algorithm. The research findings highlight the effectiveness of the machine learning SARIMA model in accurately predicting climate change patterns. Moreover, the study emphasises the importance of understanding and mitigating the risks associated with climate change through data-driven modelling and analysis. These similar arid and semi-arid regions share common challenges with Algeria, such as water scarcity and the impact of climate variability on agriculture. By comparing these studies, we gain insights into the adaptability of forecasting models under varying climatic stresses, enhancing the applicability of our findings to Algerian agriculture.

Recent advancements in the application of SARIMA models, as seen in the studies by Zhilyakov et al. (2021) aims to develop a mathematical model for labour productivity in the agricultural sector to forecast labour productivity in the agricultural sector. The model is based on the Cobb-Douglas production function, which is a standard model for agricultural production. The paper uses data on labour productivity in the agricultural sector of the Kursk region of Russia from 2014 to 2019. The paper finds that the Cobb-Douglas production function is a good fit for the data on labour productivity in the agricultural sector of the Kursk region. The paper also finds that the most important factors affecting labour productivity in the agricultural sector are the amount of capital invested in agriculture, the level of education of agricultural workers, and the use of agricultural machinery. The study by Ichon Jr & Gente (2023) examined the use of the SARIMA (seasonal autoregressive integrated moving average) model to forecast mean temperature and its impact on the productivity of the agricultural sector in Davao Oriental, Philippines. The study uses data from the Davao Oriental Provincial Climate Centre for the period 1981–2020. The study finds that the SARIMA model is able to forecast mean temperatures in Davao Oriental with a high degree of accuracy. These studies highlight the evolution of forecasting techniques, incorporating machine learning algorithms to optimize model parameters for better prediction accuracy. By integrating these contemporary research findings, our study not only stays current with the latest scientific developments but also illustrates a commitment to applying the most effective tools available for predicting labour productivity in agriculture.

Despite the extensive application of ARIMA and SARIMA models in forecasting agricultural productivity, there is a notable scarcity of studies that adapt these models to the unique climatic and agricultural conditions of Algeria. Previous research has largely focused on regions with distinct environmental and economic conditions from those found in Algeria. Additionally, few studies have explored the integration of machine learning techniques with SARIMA models to optimize forecasting accuracy in the context of Algeria's agricultural sector. This gap is particularly critical given Algeria's arid climate and the pronounced seasonal fluctuations that significantly impact agricultural productivity. Addressing this gap is vital for developing forecasting models that are robust and specifically tailored to predict labour productivity under the unique agricultural conditions of Algeria.

MATERIAL AND METHODS

Methodology

This study forecasts the agricultural labour productivity in Algeria using an autoregressive integrated moving average (SARIMA) model. The goal was to model future values based on past data patterns, assuming that historical patterns would persist. The SARIMA model is well-suited for forecasting time series data that exhibits trends, seasonality and autocorrelation (Selmy et al., 2024). The model fitting process involves identifying optimal parameters for the autoregressive, differencing and moving average components (Areepong et al., 2024). Annual agricultural labour productivity data from Q1 1991–Q4 2021 is used to fit a SARIMA model. The fitted model is then used to generate forecasts of labour productivity for 2030. We chose Algeria as the focus of this study due to its unique agricultural challenges and significant economic reliance on the sector. Algeria's geographic and climatic conditions, characterized by high variability in rainfall and limited arable land, necessitated tailored strategies to optimize agricultural productivity. Agriculture not only contributed substantially to the GDP but also employed a significant portion of the national workforce. Moreover, the impact of global phenomena such as climate change and geopolitical tensions, notably the effects of the Russia-Ukraine war on global food prices, underscored the need for region-specific research. This study addressed a notable gap by applying the SARIMA model, adapted to local seasonal variations, to forecast the agricultural labour productivity in Algeria up to the year 2030. The choice of the year 2030 aligns with the strategic planning timelines of both national and international development agendas, providing a critical horizon for policy implications and sustainability assessments. This model enhances strategic planning and policy formulation, supporting the sector's sustainability and the country's economic stability.

Data collection and variables

In this study, significant importance has been given to choosing the most suitable representative of labour productivity. The indicator "Agriculture Value Added per Worker" was carefully selected from the array of accessible data points to serve as the primary focus. This variable provides a straightforward assessment of agricultural productivity about the required labour, encapsulating the economic output generated per worker. Table 1 shows data analysis matrix.

Table 1. Data analysis matrix (source: Created by the authors)

Research Hypothesis	Dependent Variable	Time period	Source
There is a statistically significant relationship between time and agricultural labour productivity that can be modelled through a SARIMA forecast	Agriculture Value Added per Worker	Q1 1991- Q4 2021	the Food and Agriculture Organization (FAO)

As shown in Table 1, to prepare for SARIMA modelling and increase the number of observations, we converted the 32 years of annual data (1990–2021) into quarterly data. This increased the number of observations from 32 to 124 (Q1 1990–Q4 2021).

The decision to convert the data was informed by the necessity to capture seasonal fluctuations inherent in agricultural productivity, which are more distinctly represented in quarterly rather than annual intervals (Tab. 1). This approach is particularly crucial for employing the SARIMA model effectively, which is sensitive to such cyclic variations. To ensure the accuracy of our data conversion, we utilized a proportional distribution method based on the established agricultural cycles in Algeria. These cycles reflect key agricultural activities, planting, growing, and harvesting, which typically follow a consistent seasonal pattern each year. Specifically, we allocated 22% of the annual value to the first quarter, 25% to the second, 33% to the third (the peak of agricultural activity) and 20% to the fourth quarter. This allocation was corroborated through comparisons with existing quarterly agricultural data from similar regional economies and consultation with agricultural experts to validate our approach. Additionally, to affirm the robustness of our converted data, we conducted extensive sensitivity analyses. These analyses involved testing various allocation scenarios to examine their impact on the forecast outcomes, ensuring that our chosen method provided the most reliable and consistent predictions. The results confirmed that our data transformation method did not adversely affect the quality of the data and preserved the essential temporal dynamics necessary for accurate forecasting.

RESULTS AND DISCUSSION

In this section, the study presents and discusses the findings from our SARIMA analysis of agricultural labour productivity, examining the trends and patterns from Q1 1991 to Q4 2021. The results highlight the relationship between time and productivity, drawing on data from the FAO.

Exploratory data analysis

As illustrated in Figure 1, the quarterly data closely aligns with the trends and seasonal patterns of the original annual data. The peaks and troughs of both datasets correspond, indicating that the quarterly conversion was performed accurately and did not distort the intrinsic characteristics of the time series.

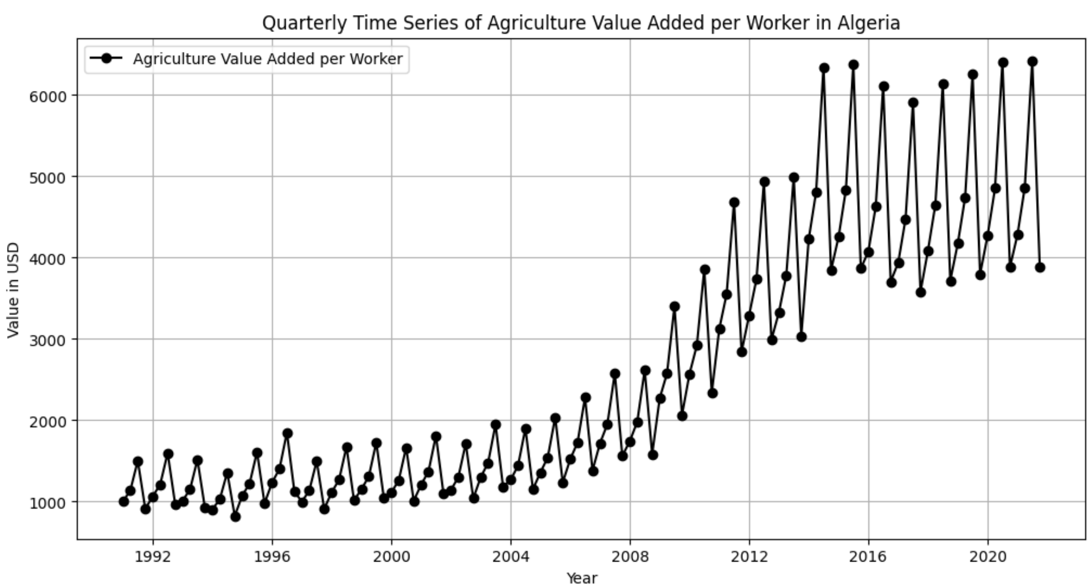

Figure 1. Quarterly data of agriculture value added per worker (Q1 1991 – Q4 2021) (source: Created by the authors using Python-3.11.5.)

Table 2 displays the descriptive data for agriculture value added per worker based on 124 observations. The mean value is \$2,559.52, ranging from \$823.17 to \$6,422.24. The data exhibits a considerable right-skewness and is slightly less peaked than a normal distribution.

Table 2. Descriptive statistics (source: Created by the authors using Python-3.11.5.)

	Count	Mean	Std	Min	Max	Skewness	Kurtosis
Agriculture Value Added per Worker	124	2559.515	1598.569	823.174	6422.242	0.87116	-0.38538

Identify seasonality

In order to proceed with SARIMA modelling, it is essential to ascertain the existence of seasonality and stationarity in our analysis. These steps are crucial since they substantially influence the SARIMA model. When analysing time-series data, it is central to consider the influence of seasonality. To enhance the precision of predictive models, it is critical to identify and account for seasonal patterns. Given the quarterly nature of the data under analysis, the presence of seasonal variations is both expected and reasonable to anticipate (Gavran et al., 2023).

Figure 2 provides the seasonal decomposition of the time series into observed, trend, seasonal, and residual components; the top plot indicates (Observed) the original time series data, displaying the fluctuations in the agriculture value added per worker over the years. The second pilot (Trend) shows the underlying trend in the data, smoothing out the short-term fluctuations. It helps in understanding the long-term movement in the series. The third plot highlights clear, repetitive patterns within each year, signifying the presence of seasonal fluctuations. The seasonal component reveals the repeating short-term cycle in the data. A noticeable seasonal pattern repeats every year (since the data is quarterly, the pattern repeats every four points). This indicates a robust seasonal influence in Algeria's agricultural value added per worker. Lastly, the bottom provides the residual, the irregularities or 'noise' that cannot be explained by the trend or seasonal components. It represents the randomness or unforeseen events in the data. The seasonal plot confirms the seasonality in the data, which is an essential factor to consider in any forecasting model such as SARIMA.

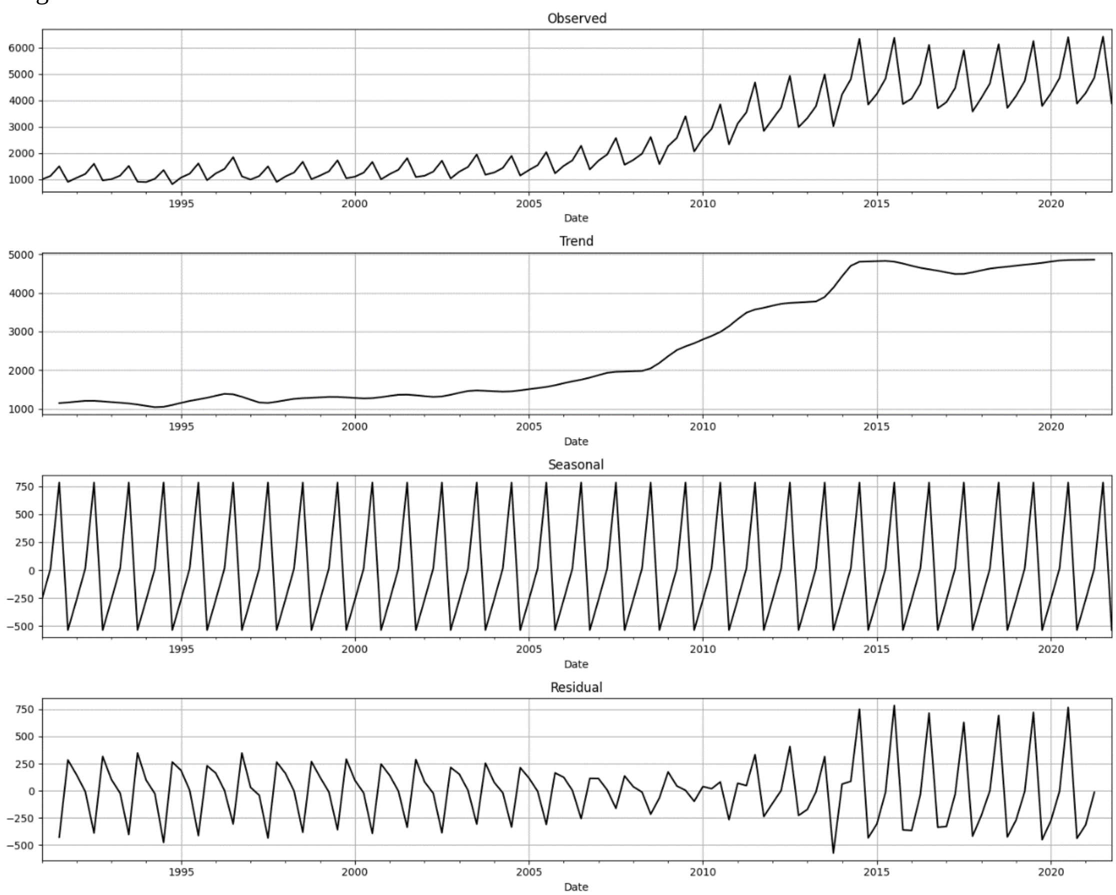

Figure 2. Seasonal decomposition of the time series (source: Created by the authors using Python-3.11.5.)

Stationarity check

Upon identifying seasonality, the data must be tested for stationarity. This is a crucial step because the SARIMA models require the data to be stationary, or at least to be made stationary through differencing or other transformations (Kumari & Muthulakshmi, 2024). Table 3 and Figure 3 display the outcomes of the subsequent Augmented Dickey-Fuller (ADF) test and the first-order differencing of the data. According to the ADF test result, the series obtained by taking the first difference appears to be stationary.

Table 3. Unit root test (source: Created by the authors using Python-3.11.5.)

	ADF at level					ADF at First Difference level				
	Test statistic	p-value	Critical Values			Test statistic	p-value	Critical Values		
			1%	5%	10%			1%	5%	10%
Agriculture Value Added per Worker	0.2002	0.972	-3.49	-2.89	-2.58	-3.5697	0.006	-3.49	-2.89	-2.58

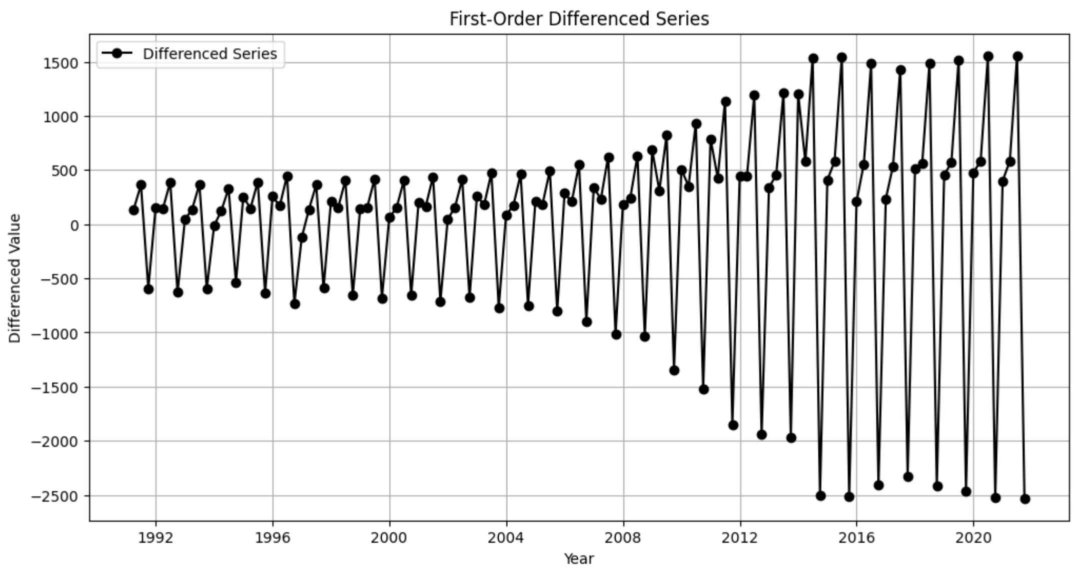

Figure 3. First-order differencing of the data (source: Created by the authors using Python-3.11.5.)

Selecting model parameters

The next step would be to identify the AR and MA components for the SARIMA model, both for the non-seasonal (p, d, q) and seasonal (P, D, Q) s parts.

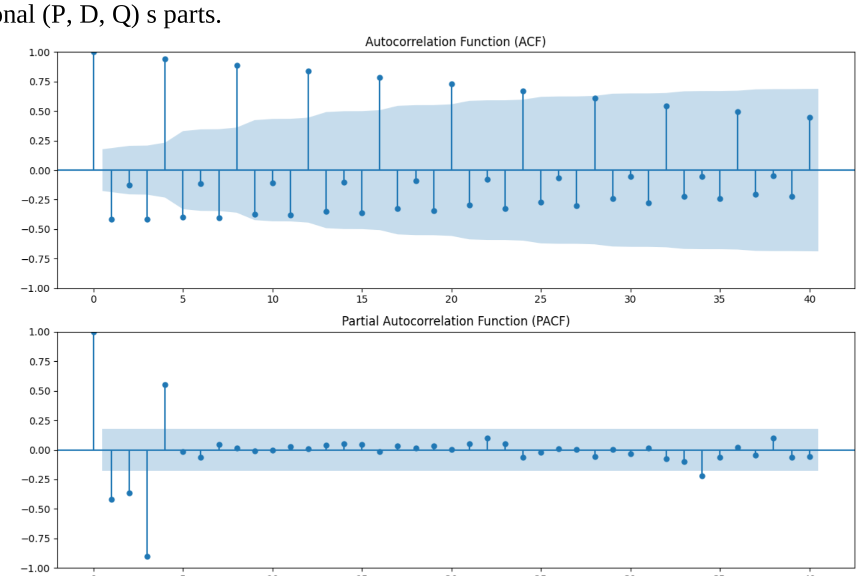

Figure 4. ACF and PACF plots (source: Created by the authors using Python-3.11.5.)

To determine the values of p, d, q, P, D, and Q for the SARIMA model, the autocorrelation function (ACF) and partial autocorrelation function (PACF) plots were utilized (Fig. 4). These plots aid in identifying the order of the AR and MA components. For the seasonal components, the periodicity of the data was also considered, which in this case is quarterly, so the seasonal period (s) is 4. The differencing order (d=1) was selected to achieve stationarity in the series. Model selection was guided by criteria such as the Akaike Information Criterion (AIC) and the Bayesian

Information Criterion (BIC). Based on these considerations, the SARIMA configuration (1, 1, 1) x (1, 1, 1, 4) was chosen.

SARIMA model summary

Table 4 summarizes the results of a SARIMA (1, 1, 1) x (1, 1, 1, 4) model analysis. With 124 observations, the SARIMA model shows a significant negative autoregressive and moving average component, with coefficients indicating substantial influence at non-seasonal lags. However, the seasonal autoregressive term at lag 4 is not significant, suggesting a limited quarterly seasonal impact. The model fits well with an AIC of 514.497 and a BIC of 525.579 supported by significant Ljung-Box and Jarque-Bera test results, which indicate some autocorrelation at lag 1, but no departure from normality in residuals. The analysis performed confirms the model's adequacy with no evidence of heteroskedasticity and near-normal distribution of residuals.

Table 4. SARIMA model results (source: Created by the authors using Python-3.11.5.)

Dep. Variable:	**agriculture value added per worker**		**No. Observations**		124	
SARIMAX	(1, 1, 1) x (1, 1, 1, 4)		Log Likelihood		-753.248	
Date:	Fri, 25 Aug 2023		AIC		514.497	
Time:	18:56:19		BIC		525.579	
Sample:	01/01/1991 - 31/12/2021		HQIC		518.872	
Covariance Type:	opg					
	Coef	**Std err**	**Z**	**P>|z|**	0.025	0.975
ar.L1	-0.3178	0.088	-3.605	0.000	-0.490	-0.145
ma.L1	-0.9982	0.463	-2.181	0.003	-1.088	-0.908
ar.S.L4	-0.5618	0.724	-0.781	0.104	-0.708	-0.427
ma.S.L4	0.3126	0.097	3.122	0.001	0.0135	0.410
sigma2	1.234e+04	1.5e+03	8.236	0.000	1.114e+04	1.53e+04
Ljung-Box (L1) (Q)	3.54			Jarque-Bera (JB)	5.20	
Prob(Q)	0.03			Prob (JB)	0.14	
Heteroskedasticity (H)	1.12			Skew	0.45	
Prob(H) (two-sided)	0.71			Kurtosis	3.90	

Diagnose model

Figure 5 contains five diagnostic plots that can be used to assess the fit of an ARIMA model. These plots are as follows: the standardised residual plot, the histogram plus KDE estimate plot, the normal q-q plot, the correlogram, and the partial autocorrelation plot. The standardised residual plot shows that the residuals are randomly distributed with a mean of zero and a standard deviation of one. The histogram plus KDE estimate shows the histogram of the residuals normally distributed. The normal q-q plot shows the quantiles of the residuals against the quantiles of the standard normal distribution. The partial autocorrelation plot shows the partial autocorrelations of the residuals. Accordingly, the model is a good fit for the data.

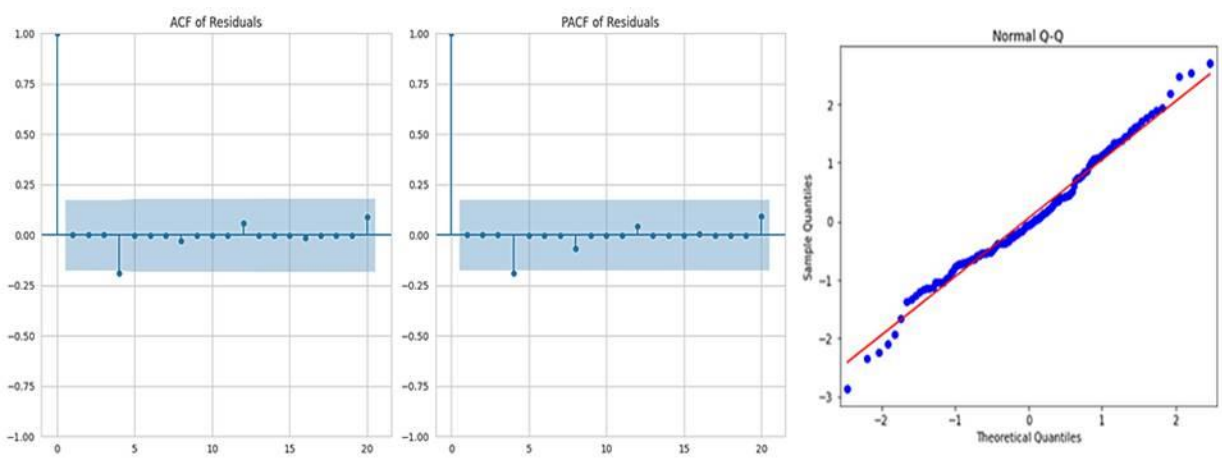

Figure 5. Diagnostic plots for residual analysis (source: Created by the authors using Python-3.11.5.)

Forecast

Having established and rigorously validated the model, we are poised to leverage its predictive prowess. This enables us to effectively project the forthcoming values of agriculture value added per worker in Algeria with a high degree of reliability and confidence. Figure 6 shows the forecast data for agriculture value added per worker in Algeria from 2022 to 2030, generated using the SARIMA model, and reveals several key insights. The data shows a clear seasonal trend, with the highest values consistently appearing in the third quarter of each year, a decline in the fourth quarter, and the lowest values in the first quarter. This pattern likely mirrors the agricultural cycles such as planting and harvesting periods. Across the years, there were no significant upward or downward trends, indicating stability in the agricultural sector's productivity or value addition per worker. These changes could be attributed to factors such as evolving farming practices, technological advancements, and alterations in market dynamics.

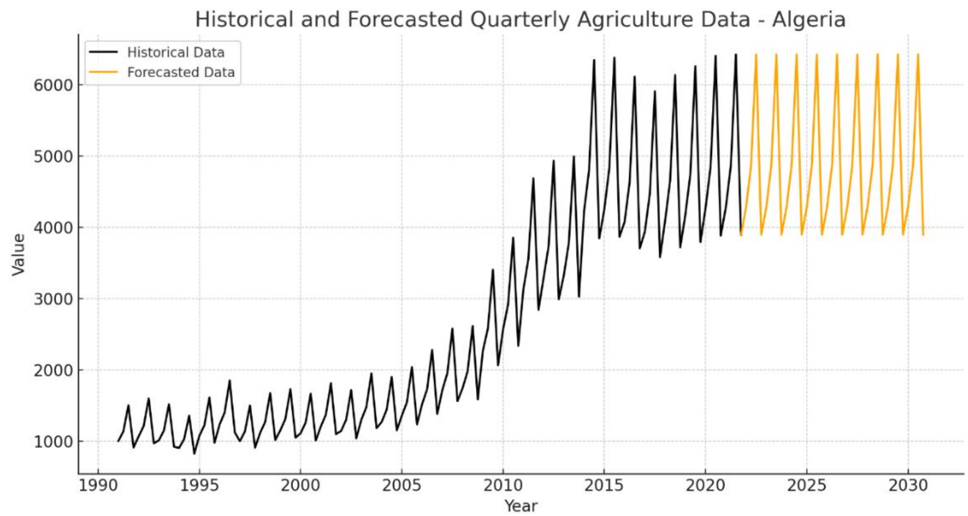

Figure 6. Agriculture value added per worker up to 2030 in Algeria (source: Created by the authors using Python-3.11.5.)

This study stands out as the first to apply the SARIMA model to forecast agricultural labour productivity specifically within the Algerian context, marking a significant advancement in agricultural economic forecasting. By meticulously adapting the SARIMA model to address the pronounced seasonal fluctuations inherent in Algeria's agriculture, our research not only enhances the precision of productivity forecasts but also demonstrates the model's adaptability to local climatic and agricultural cycles. The integration of machine learning algorithms further refines the model's accuracy.

The SARIMA model's ability to capture seasonality and trends in the data, its sound diagnostic performance, and the alignment between observed and forecasted values, collectively suggest that it was a reliable tool for forecasting the agriculture value added per worker in Algeria. An optimistic trend was observed in labour productivity within the agricultural sector. Our analysis indicates that despite external pressures from climate variability and geopolitical tensions, the agricultural sector shows a potential for maintained productivity levels, suggesting a resilience that could be further enhanced through targeted policies. The consistency in seasonal productivity peaks suggests that existing agricultural practices and resource allocations were effective to some extent, but may require adjustment to cope with increasing climatic unpredictability. These forecasts are particularly timely given the recent investments in the Algerian agricultural sector, technological advancements, and shifts in market dynamics. As mentioned by Milić et al. (2024), the development of agriculture in a country or region is influenced by a wide range of factors, including climatic and weather conditions, soil quality, water availability, capital markets, socio-economic conditions, agricultural policies, infrastructure, technological advancements, agricultural product markets, and the labour force.

In recent years, the Algerian government has made significant investments in the agricultural sector with the aim of enhancing its performance (Baghdad, 2022; Hadouga, 2023). These investments are anticipated to result in heightened productivity and increased output within the sector. According to Abdelhedi & Zouari (2020) the portion of the Algerian government's financial allocation to agriculture, forestry, and fisheries stood at 2.93% of total public expenditure in 2018 consistently remaining below the 3.5 percent mark. The apex was recorded in 2015, when 3.47% of the budget was directed towards bolstering the agricultural domain. Notably, the Arab Organisation for Agricultural Development (AOAD) has reported a twofold increase in this rate in recent times. The agricultural sector is increasingly adopting new technologies, such as irrigation and mechanization. These technologies are

expected to boost productivity and output in the sector. Accordingly, there are 22 agencies that perform agricultural R&D in Algeria, including INRAA and CRSTRA. However, the same source notes that Algeria's spending on agricultural R&D gets better relative to neighbouring countries. As for the share of government expenditure in R&D for agriculture, forestry, and fishery sectors, it accounted for 2.93 % of the public spending in 2018, whereas, in 2021, it amounted to 4.33 % of the public spending (Zebakh et al., 2022).
The demand for agricultural products is expected to grow both domestically and internationally. This demand is expected to support growth in the agricultural sector. It is indicated that foreign direct investments in the Algerian agriculture are increasing. However, there are some risks that could affect this growth. It is important to monitor these risks and take steps to mitigate them in order to ensure that the agricultural sector continues to grow and contribute to the Algerian economy. The stability in labour productivity could be seen as an opportunity for Algeria to strengthen its agricultural policies. For example, investments in technology and training that align with the observed productivity patterns could optimize output and efficiency.
This research highlights the critical role that Algeria's agricultural labour force plays in the nation's economic framework. Given the sector's contribution to national output and employment, understanding labour productivity trends is essential for shaping policies that can enhance efficiency and sustainability. By focusing on labour productivity within Algeria's agricultural sector, this study offers insights that can help optimize agricultural practices and resource management, ensuring better outcomes in the face of environmental challenges. On a broader scale, the findings from Algeria's experience with labour productivity hold global relevance. A number of countries, especially those in arid and semi-arid regions, face similar environmental stressors, such as water scarcity and unpredictable weather patterns, which threaten agricultural viability. The lessons learned from Algeria's context can provide valuable insights for other nations looking to improve labour productivity and strengthen their agricultural sectors. This research, therefore, contributes to global discussions on food security, sustainable agricultural practices, and economic resilience in the face of climate change.

CONCLUSION

This study employed the seasonal autoregressive integrated moving average (SARIMA) model to predict future trends in labour productivity within Algeria's agricultural sector, specifically by analysing agriculture value added per worker data for the period from Q1 2022 to Q4 2029. Our analysis was based on data spanning from Q1 1990 to Q4 2021, transformed using Python 3.11.5. The findings demonstrate that the SARIMA model is a proficient tool for predicting the labour productivity in Algeria's agriculture industry. The selected SARIMA model (1, 1, 1) x (1, 1, 1, 4) effectively captures the temporal trends and variations in labour productivity over the years.
The projections suggest a stable increase in the agriculture value added per worker from Q1 2022 to Q4 2029. This growth can be attributed to the advancement of agricultural techniques, increased interest in the sector, and technological innovations. Policymakers can capitalize on this anticipated rise in labour productivity to enhance the competitiveness of Algeria's agricultural industry and contribute to broader economic growth. However, proactive policies and strategic actions are essential to sustain this growth and ensure that the benefits are fully realized. Based on the findings, the following recommendations are proposed:

- The government and agricultural planners can use these forecasts to better allocate resources throughout the agricultural calendar. Efficient use of labour, fertilizers, and water, especially during peak and off-peak seasons, will maximize productivity and minimize waste.
- Our study underscores the importance of resilience strategies to mitigate the impact of adverse climatic conditions, a frequent issue in arid regions like Algeria. Using these forecasts, policymakers can better time interventions to enhance agricultural sustainability and output.
- The integration of this forecasting approach can serve as a model for other agricultural economies that face volatile environmental conditions. It can also guide international development agendas focusing on food security and economic stability in arid and semi-arid regions, aligning with global sustainability goals that promote informed, data-driven agricultural practices.

This study makes a significant contribution to the understanding of labour productivity dynamics in Algeria's agricultural sector through the use of a novel forecasting approach. While our focus on the aggregate agricultural sector provides valuable insights, future research could benefit from analysing disaggregated data to explore variations across different sub-sectors and regions. Additionally, incorporating other relevant variables, such as climate data or policy shifts, could further enhance the model's predictive accuracy.

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