International Journal of Agricultural Economics
2025, Vol. 10, No. 2, pp. 67-85
https://doi.org/10.11648/j.ijae.20251002.13

Research Article

Modeling and Forecasting Bean Production in Mozambique: Challenges and Implications for Food Security and SDG 2

Filipe Mahaluca[1, 2, *], Faizal Carsane[2], Alfeu Vilanculos[1, 3]

[1]Higher Institute of Accounting and Auditing of Mozambique (ISCAM), Maputo, Mozambique
[2]Department of Economics, University Saint Thomas of Mozambique (USTM), Maputo, Mozambique
[3]Faculty of Economics, Eduardo Mondlane University (UEM), Maputo, Mozambique

Abstract

This study examines the effectiveness of ARIMA and LSTM models in forecasting bean production in Mozambique, using data from 2002 to 2022. The analysis reveals that the limited sample size, comprising only 21 years of data, significantly impacts the accuracy of both models, as reflected in high MAPE values. The ARIMA(1,1,1) model demonstrates robustness with the lowest RMSE among the ARIMA models, but the LSTM model, despite its challenges, shows superior capability in capturing nonlinear patterns, resulting in a lower average MAPE. Forecasts for the period from 2023 to 2030 suggest stable bean production with slight annual variations, although the wide confidence intervals highlight the inherent uncertainty in these predictions. This study underscores the importance of improving forecasting models to better guide agricultural planning and policy-making, particularly in the context of Mozambique's food insecurity challenges and the global objectives of SDG 2. The results emphasize the need for more extensive data collection and the inclusion of additional variables to enhance the accuracy of future forecasts, contributing to the reduction of food insecurity and the achievement of sustainable development goals in Mozambique.

Keywords

Agricultural Forecasting, ARIMA Models, LSTM Neural Networks, Beans, Food Security

1. Introduction

Food insecurity remains a critical global issue, affecting millions of people and challenging progress toward the Sustainable Development Goals (SDGs). In 2023, approximately 735 million people worldwide faced hunger, accounting for about 9% of the global population [1]. While this marks a slight decrease from the 842 million who faced hunger in 2022, it still represents a significant increase compared to the 828 million in 2021. If current trends continue, projections indicate that the number of people affected by hunger could exceed 850 million in 2024 [2]. In Mozambique, one of the countries most affected by food insecurity, agriculture, particularly the production of common beans (*Phaseolus vulgaris*), is essential for the livelihood of rural populations and national food security [3, 4].

Beans, one of the most consumed legumes globally, play a crucial role in the diet of both rural and urban populations in Mozambique. As a vital source of plant-based proteins, fibers, vitamins, and minerals, beans are particularly important in

*Corresponding author: mahaluca@gmail.com (Filipe Mahaluça)

Received: 1 September 2024; **Accepted:** 18 September 2024; **Published:** 29 April 2025

Copyright: © The Author(s), 2025. Published by Science Publishing Group. This is an **Open Access** article, distributed under the terms of the Creative Commons Attribution 4.0 License (http://creativecommons.org/licenses/by/4.0/), which permits unrestricted use, distribution and reproduction in any medium, provided the original work is properly cited.

regions where access to animal protein is limited [4]. However, bean production in the country faces numerous challenges, including climate variability, low soil fertility, and restricted access to quality agricultural inputs, resulting in yields that are often below potential [5].

Adverse climatic conditions, exacerbated by global climate change, are becoming more frequent and unpredictable, negatively impacting agricultural production in Mozambique [6]. The irregularity of rainfall and the occurrence of prolonged droughts present ongoing challenges for farmers who rely on traditional farming practices. These factors, combined with management techniques that do not maximize resource efficiency, contribute to the instability of bean production, further aggravating food insecurity in vulnerable communities [7].

For the development of resilient food systems, sustainable agricultural production is fundamental, and beans, with their high nutritional value, play an essential role in this context. Improving bean productivity in Mozambique can significantly impact food security by increasing food availability and promoting sustainable farming practices that preserve soil fertility [8, 9]. However, achieving these goals requires a detailed understanding of the factors affecting bean production, including the complex interactions between climate, soil, and agricultural management practices [10].

Agricultural production modeling emerges as a crucial tool for predicting trends and guiding interventions that can mitigate negative impacts and optimize available resources [11]. Predictive models for bean production are particularly relevant in a context like Mozambique, where agricultural conditions are challenging, and the need for food security is critical [12]. The application of modeling techniques, such as time series analysis and artificial neural networks, can provide more accurate forecasts, enabling farmers and policymakers to make more informed and effective decisions.

Several studies have explored the application of predictive models in agriculture, focusing on widely cultivated crops such as maize and rice [13]. However, modeling bean production, particularly in vulnerable regions like Sub-Saharan Africa, has been less explored in the scientific literature, representing a significant opportunity for advancements in this area [14]. The use of local and regional data, combined with advanced modeling techniques, can offer solutions more adapted to the specific realities of Mozambique, contributing to the maximization of agricultural production and sustainable food security.

This study aims to develop robust predictive models for estimating bean production in Mozambique through the application of advanced modeling techniques, including the ARIMA model and Long Short-Term Memory (LSTM) neural networks. The relevance of this research lies in its contribution to mitigating food insecurity, aligning with the goals of SDG 2, and supporting the development of more effective public policies and agricultural management strategies. With an integrated and scientifically grounded approach, this study seeks to offer solutions that not only increase bean productivity but also strengthen the resilience of agricultural systems in Mozambique.

2. Literature Review

2.1. Global Context of Beans Production

Beans, scientifically known as *Phaseolus vulgaris*, are one of the most important legumes globally, valued both for their nutritional content and their critical role in food security. Originating from the Americas, beans were domesticated over 7,000 years ago, particularly in regions that now correspond to Mexico and Central America, becoming a staple crop in pre-Columbian civilizations [15, 16]. Today, beans are widely cultivated in various regions around the world, adapting to different climatic conditions and cultivation methods.

Rich in nutrients, beans are an excellent source of plant-based proteins, fibers, vitamins such as B1 (thiamine) and folic acid, and essential minerals like iron, zinc, magnesium, and calcium. These nutrients make beans a vital food for promoting health and well-being, especially in regions where access to animal proteins is limited [3]. Additionally, beans contain bioactive compounds, such as antioxidants, that contribute to the prevention of chronic diseases, including cardiovascular diseases and diabetes [17].

The sustainability of bean cultivation is another aspect worth highlighting. As a legume, beans have the ability to fix atmospheric nitrogen in symbiosis with soil bacteria, reducing the need for nitrogen fertilizers. This trait not only improves soil fertility but also contributes to the sustainability of agricultural systems, making beans an ideal crop for sustainable farming practices [8, 9]. Furthermore, beans can be grown in crop rotation systems, helping to maintain soil health and reduce the incidence of pests and diseases [18].

The primary global producers of beans include India, Brazil, Myanmar, Tanzania, and Uganda. India leads global production, accounting for approximately 23.3% of the world's bean production, followed by Brazil, which accounts for 10% of the global total. These countries not only lead in terms of production volume but also play a crucial role in stabilizing the global bean market [19, 20]. The production of beans in these countries is essential to meet the growing demand for plant-based proteins, particularly in developed countries where there is a rising trend toward plant-based diets [21].

In Africa, beans are a vital crop, especially in Sub-Saharan Africa, where they are one of the main sources of protein for millions of people. Countries like Tanzania, Uganda, Ethiopia, Kenya, and Burundi are the continent's largest producers, collectively contributing to over 50% of Africa's bean production. Tanzania stands out as the largest producer in Africa, with production representing about 17.2% of the continent's total. These countries not only grow beans for domestic consumption but also serve as important regional exporters [22, 23].

Bean production in Africa is predominantly carried out by smallholder farmers who heavily rely on this crop for food security and income generation. In many areas, beans are grown in intercropping systems with other crops such as maize, which helps improve soil fertility and the overall productivity of farms. However, these smallholder farmers face significant challenges, such as low soil fertility, lack of access to high-quality seeds, and adverse climatic conditions, which limit productivity [7, 24, 25].

Climate change poses a significant threat to bean production in Africa. Variations in climatic conditions, such as prolonged droughts and extreme temperatures, directly impact crop yields. Studies show that to mitigate these impacts, it is necessary to develop bean varieties that are more resistant to water and heat stress, as well as to adopt more sustainable farming practices that can help farmers adapt to changing climate conditions [4, 5].

Despite these challenges, the potential to increase bean production in Africa is significant. With adequate support in terms of research, agricultural extension, and infrastructure, African farmers can substantially increase their yields. Breeding programs aimed at developing varieties with greater resistance to pests and diseases, as well as a higher nitrogen-fixing capacity, are essential for advancing productivity in the region [8, 9].

The global bean market is expanding, driven by the growing demand for plant-based proteins, especially in developed countries where there is a rising trend toward plant-based diets. The commercialization of beans in international markets, particularly among the largest producers in Africa and Latin America, has the potential to increase farmers' incomes and improve the trade balance of these countries. However, challenges such as price volatility and trade barriers must be addressed to maximize economic benefits [21, 26].

Post-harvest management practices are crucial for reducing losses and ensuring the quality of beans destined for the market. It is estimated that post-harvest losses in Africa can vary significantly depending on storage conditions and handling practices. Investments in infrastructure, such as hermetic silos and advanced drying techniques, are essential for minimizing these losses and improving the efficiency of the supply chain [27, 28].

Research and technological development play a vital role in promoting bean production. Initiatives involving genetic editing, the use of artificial intelligence for crop monitoring, and yield forecasting are gaining traction, especially in regions where resources are limited. These technologies can help optimize production, improve crop resilience, and ultimately ensure food security [10, 11].

Beans are not only a food crop but also a strategically important commercial crop. In countries like Brazil and India, large volumes of beans are produced both for domestic consumption and for export, contributing significantly to these countries' economies. Competing in international markets requires not only high production volumes but also quality assurance and the ability to meet the specific demands of different markets [29, 30].

In Africa, beans play a fundamental role in food security, especially in rural communities where access to other protein sources is limited. The per capita consumption of beans in East African countries, such as Tanzania and Uganda, is among the highest in the world, reflecting the cultural and nutritional importance of this legume in the diet of these populations. Promoting beans as a resilient and nutrient-rich crop is essential to improving food security and public health in the region [14, 31].

Developing value chains for beans is essential for maximizing the economic benefits of this crop. This includes strengthening farmers' cooperatives, improving access to credit and international markets, and implementing policies that encourage sustainable production and bean exports. Such measures can significantly contribute to the economic development of producing countries [32, 33].

Finally, beans continue to play a central role in the global food security agenda. As the world faces increasing challenges related to climate change and the need for more sustainable diets, beans emerge as a key crop, with the potential to contribute to both nutrition and agricultural resilience. Global and regional initiatives should continue to support the research, development, and expansion of bean production, ensuring that this essential grain continues to feed millions of people worldwide [13, 34].

2.2. Beans Production in Mozambique

Beans production in Mozambique plays a crucial role in food security and the livelihoods of rural populations, particularly in arid and semi-arid regions. As the second most cultivated cereal in the country after maize, beans is highly valued for its drought resistance and ability to grow in less fertile soils, making it a vital crop for Mozambican agriculture [35]. Despite its potential, beans productivity in Mozambique faces significant challenges, including irregular rainfall, limited use of certified seeds, and lack of access to quality agricultural inputs [36, 37].

In Mozambique, beans (Phaseolus vulgaris) are one of the most important legumes, playing a vital role in food security and the agricultural economy of the country. Originally from the Americas, beans were introduced to Mozambique during the colonial period and have since become a key crop for many rural communities. The diversity of varieties cultivated in the country reflects the different agro-ecological conditions and regional food preferences, with Boer, Nhemba, Manteiga, Jugo, and Oloko beans being the most common varieties [38].

Bean production in Mozambique is largely carried out by smallholder farmers who rely on the crop for subsistence and income generation. Agricultural practices in Mozambique are characterized by traditional farming techniques and family labor, making beans an essential crop for the sustainability of small farms. This reliance on beans is evident in many regions where beans are intercropped with other crops like maize and cassava, helping to diversify production and increase household food security [39].

The diversity of bean varieties grown in Mozambique reflects their adaptation to the country's varied climate and soil conditions. For example, Boer beans are prevalent in drier areas, such as the southern provinces, while Manteiga beans are more common in regions with greater water availability, like Zambezia. This variety in production allows farmers to select the species best suited to local conditions, maximizing productivity and crop resilience [38].

However, bean production in Mozambique faces significant challenges, including low soil fertility, climate variability, and limited access to quality agricultural inputs. Soil fertility is a critical issue, especially in regions where the use of fertilizers is limited due to high costs. Additionally, bean crops are often affected by pests and diseases, which can drastically reduce yields. These challenges highlight the need for research and development interventions, as well as policies supporting access to appropriate agricultural technologies [5, 40]

Mozambique has significant potential to increase bean production, particularly with the adoption of improved agricultural practices and higher-yielding varieties. Programs like Sustenta, aimed at increasing agricultural productivity through technical and financial support for farmers, have shown promising results. For instance, despite a reduction in the area cultivated with beans in 2021, there was a substantial increase in productivity, indicating that improvements in agricultural management can compensate for limited land area.

Sustainability is a central concern in Mozambique's bean production. Beans' ability to fix nitrogen in the soil helps improve fertility and reduce the need for chemical fertilizers, which are expensive and often inaccessible to smallholder farmers, [41]. This characteristic makes beans particularly important in low-input farming systems, as found in many parts of Mozambique, contributing to the long-term sustainability of agriculture in the country [24].

The bean market in Mozambique is dominated by domestic consumption, with a large portion of the production intended for home use. However, Boer beans have emerged as an export product, particularly to markets in India. Bean exports are an important source of income for farmers and contribute to the country's trade balance. Nevertheless, reliance on a volatile external market poses risks, and legal and logistical issues have occasionally hampered exports, as recently seen with temporary restrictions imposed at the port of Nacala [42].

Post-harvest losses in Mozambique's bean production also pose significant challenges. These losses are estimated to range from 10% to 30%, depending on the variety and storage conditions. Improving post-harvest practices, including the adoption of hermetic silos and better drying techniques, is essential to reduce these losses and ensure a greater proportion of production is available for consumption or sale [43, 44].

The climatic context in Mozambique is a critical factor influencing bean production. Irregular rainfall and prolonged droughts pose constant challenges for farmers. Moreover, climate change is increasing the frequency and severity of these events, requiring more resilient agricultural practices and the development of bean varieties more resistant to water stress [4, 25].

Agricultural research in Mozambique has focused on improving bean varieties to increase productivity and resistance to pests and diseases. The development of cultivars adapted to local conditions, with greater nitrogen-fixing capacity and better resistance to adverse climatic conditions, is a priority for agricultural research institutions in the country. These innovations are essential to ensure the long-term viability of bean production [9, 40]

Promoting bean production in Mozambique extends beyond technical aspects and involves empowering farmers with sustainable agricultural practices and post-harvest management skills. Ongoing training and technical support are crucial to ensuring that farmers adopt best practices and maximize their crop yields. Additionally, improving access to finance and markets is vital for farmers to invest in inputs and technologies that enhance productivity [32, 33].

Beans, as both a subsistence and commercial crop, are fundamental to food security in Mozambique. In many regions of the country, beans are the primary source of protein and essential nutrients, especially in rural communities where access to other protein sources is limited. The role of beans in the diet of these populations cannot be underestimated, and promoting them as a strategic food is crucial for public health and nutrition [14, 45].

In terms of sustainability, beans play a critical role in mitigating the effects of climate change and promoting agricultural practices that preserve natural resources. Beans' ability to improve soil health and reduce the need for chemical fertilizers significantly contributes to environmental sustainability. Additionally, intercropping beans with other crops helps diversify agricultural production, increasing the resilience of farming systems and improving food security [13, 34].

Finally, the future of bean production in Mozambique depends on an integrated approach that combines technological innovation, government support, and farmer empowerment. With continued investment in research and development, strengthening value chains, and improving market access, beans have the potential to remain a vital crop for food security and sustainable economic development in Mozambique.

2.3. Previous Studies on Agricultural Production Modeling and Bean Forecasting

The modeling and forecasting of agricultural production have been the focus of numerous studies over the years, underscoring their importance for food security and efficient resource management. In the context of beans (Phaseolus vulgaris), a wide range of methodological approaches have been explored, from traditional statistical models like ARIMA (Auto-Regressive Integrated Moving Average) to more advanced machine learning techniques, including Artificial Neural Networks (ANN) and Support Vector Regression (SVR) [46]. These models have been extensively used to predict bean production, aiming to support strategic agricultural decisions, especially in regions where this crop plays a crucial role in food security [47].

Traditional statistical models like ARIMA have been popular due to their ability to capture temporal patterns in historical production data [48]. These models are particularly useful in situations where a significant amount of historical data is available, allowing for a robust analysis of trends and seasonality in agricultural production. Studies have shown that despite the relative simplicity of ARIMA, it can provide reliable forecasts in contexts where external variables are minimally influential or where cultivation conditions remain relatively stable over time [49, 50].

On the other hand, machine learning techniques such as ANN have gained prominence in agricultural production modeling due to their ability to handle large volumes of data and capture complex nonlinear patterns. These techniques are particularly effective in scenarios where agricultural production is influenced by a wide range of factors, including climatic variables, management practices, and soil characteristics. Recent studies have demonstrated that ANNs, especially when combined with other techniques such as Principal Component Analysis (PCA) for dimensionality reduction, can outperform traditional statistical models in terms of prediction accuracy [51, 52].

Furthermore, hybrid approaches that combine statistical models and machine learning techniques have shown promise in bean production forecasting. These hybrid models leverage the strengths of traditional methods like ARIMA to capture temporal patterns while using machine learning techniques to incorporate external and nonlinear variables. Studies indicate that these approaches can significantly improve forecast accuracy, particularly in scenarios with high variability in cultivation conditions [49].

Finally, the literature review highlights the growing importance of integrating climate data into predictive modeling. With climate change increasingly affecting agricultural production, models that incorporate real-time climate data have the potential to provide more accurate short-term forecasts, helping farmers make informed decisions about crop management. In the context of beans, this integration is essential for developing mitigation and adaptation strategies, ensuring the resilience of agricultural practices in the face of future climate variability.

3. Materials and Methods

3.1. Materials

This study focused on analyzing beans production in Mozambique, using annual data from 2002 to 2022, covering 61 observations. The choice of 1961 as the starting point is based on its historical and methodological significance, marking the beginning of the FAOSTAT statistical series. This starting point ensures a consistent and comprehensive analysis of agricultural production trends in Mozambique over time, providing valuable insights into the evolution of maize production across six decades.

The data analysis was conducted using Python 3.12.5, chosen for its robustness and the wide range of specialized libraries available, such as Pandas, Numpy, TensorFlow, and Scikit-learn. These tools are essential for data manipulation and predictive modelling, particularly in the context of time series. To capture trends and patterns in beans production, advanced models such as LSTM feedback neural networks and ARIMA were employed. Python’s widespread use in scientific research ensured the precision and reliability of the results obtained.

3.2. Data Source

The beans production data was sourced from FAOSTAT, maintained by the Food and Agriculture Organization of the United Nations (FAO). This secondary database provides extensive statistical information on agriculture and food security, serving as a crucial resource for academic research and public policy.

3.3. Methods

3.3.1. ARIMA Modeling

(i). Model Identification

For modeling bean production in Mozambique, the ARIMA approach was utilized. The first step involved analyzing the ACF (Autocorrelation Function) and PACF (Partial Autocorrelation Function) plots of the differenced time series. These analyses are essential for identifying the order of the autoregressive (AR), differencing (I), and moving average (MA) components that best fit the time series. Based on the observed patterns, several ARIMA models were proposed for subsequent parameter estimation and validation.

(ii). Parameter Estimation

The parameters of the identified ARIMA models were estimated using the maximum likelihood method, which seeks to optimize the values of the AR and MA components. This method allows for determining the most suitable configuration of the model parameters, ensuring that the fitted model accurately represents the historical data. The training period for the ARIMA model included data from 2002 to 2009.

(iii). Validation and Evaluation

The validation of the ARIMA models was performed using actual data from the period 2010 to 2020. Diagnostic tests were applied to the residuals of the fitted models, including the Box-Pierce test to check for autocorrelation in the residuals and the ARCH test to evaluate heteroscedasticity. Additionally, normality tests, such as the Shapiro-Wilk and Jarque-Bera tests, were conducted to ensure the residuals of the model conformed to a normal distribution. These procedures were crucial in ensuring that the selected model was robust and reliable for forecasting.

3.3.2. LSTM Neural Networks

(i). Data Preparation

For building the LSTM model, the historical bean production data was initially normalized using the MinMaxScaler technique, which scales the values between 0 and 1. This step is crucial for improving the efficiency and effectiveness of the neural network training process. The data was then split into training and testing sets. The training period comprised the years 2002 to 2016, while the data from 2017 to 2022 was reserved for model evaluation. Time sequences of 3 years were created to capture temporal dependencies present in the data.

(ii). Model Architecture and Training

The architecture of the LSTM neural network was defined with two LSTM layers, each containing 50 units. Following the LSTM layers, a dense layer was added to generate the predictions. The model was trained over 100 epochs, using the mean squared error (MSE) loss function and the Adam optimizer. During training, which used data from 2002 to 2016, the model iteratively adjusted its weights to minimize prediction errors, refining its ability to capture complex temporal patterns.

(iii). Evaluation and Validation

The LSTM model was evaluated using the test data from 2017 to 2022. The model's performance was assessed through metrics such as RMSE and MAPE, providing a quantitative evaluation of prediction accuracy. These metrics were crucial in validating the effectiveness of the LSTM model in forecasting bean production.

Forecasting for 2023 to 2030

After validation, the LSTM model was used to forecast bean production for the period 2023 to 2030. Additionally, the Bootstrapping technique was applied to calculate confidence intervals for the forecasts, providing a measure of the uncertainty associated with the predictions. These confidence intervals help contextualize the robustness of the forecasts made by the model.

3.3.3. Selection of the Best Model for Estimating Agricultural Production

To identify the most suitable model for forecasting beans production in Mozambique, a comparative analysis of the ARIMA and LSTM models was conducted using the MAPE metric. The model that demonstrated the lowest MAPE was selected as the most accurate, making it the preferred choice for future projections. This rigorous approach enhances the reliability of the forecasts, providing a robust foundation for informed decision-making in agricultural planning and food security policy development.

4. Results

4.1. Exploratory Analysis of the Beans Time Series

The statistical analysis of bean production in Mozambique (2002-2022), based on the annual data series, provides a detailed understanding of the variability and characteristics of this crop over the years (Table 1). The average production is 217,641.75 tons, while the median is slightly lower at 203,582.41 tons. The modest difference between the mean and median suggests a relatively symmetrical distribution, which is further supported by a skewness of 0.46. This skewness value indicates a slight rightward tilt, but not significantly so, implying that the data distribution is fairly balanced.

The absence of a mode implies that there is no most frequently observed value in the data series, reflecting a distribution without a clear dominant pattern of production over the years. The standard deviation of 129,407.66 tons and the variance of 16,746,341,530 indicate considerable variability in the annual bean production. The coefficient of variation of 59.46% points to high variability relative to the mean, suggesting that while there is a defined average production, the annual fluctuations are quite significant.

The range, which is the difference between the maximum of 469,886 tons (2022) and the minimum of 47,725 tons (2015), is 422,161 tons. This wide variation reflects the influence of variable external factors, such as climatic conditions, cultivation practices, and agricultural policies, which affect the annual bean production in Mozambique.

Table 1. Descriptive Measures of the Annual Beans Production Series.

Descriptive Statistics	Value
Mean	217641.7524
Median	203582.41
Mode	#N/A
Variance	16746341530
Standard Deviation	129407.6564
Coeficient of variation	0.594590215
Maximum	469886

Descriptive Statistics	Value
Minimum	47725
Skewness	0.456081156
Kurtosis	-1.064378315
Range	422161
n	21

4.2. Stationarity Test or Unit Root Test of the Beans Series

Stationarity is crucial for the application of many time series models, as it suggests that the statistical properties of the series are consistent over time, allowing for more accurate modeling and forecasting.

4.2.1. Analysis of the Time Series for Beans Production in Mozambique

The time series plot of bean production in Mozambique from 2002 to 2022 reveals an overall increasing trend, marked by significant annual fluctuations (Figure 1). A sharp increase is observed after 2015, possibly indicating improvements in agricultural practices, government support policies, or favorable climatic conditions. However, the abrupt declines in 2014 and 2015 suggest the influence of unfavorable external factors during that period.

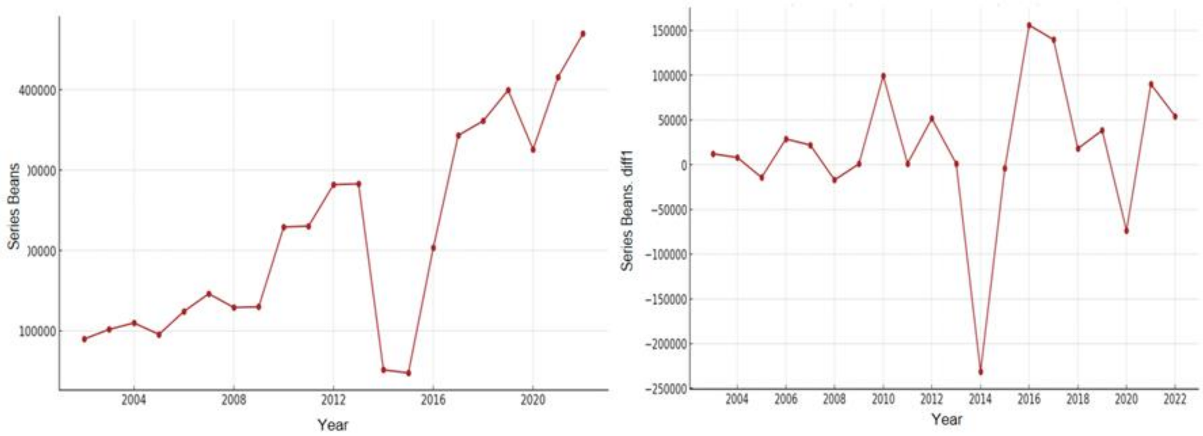

Figure 1. Time Series Analysis of Beans Production in Mozambique (1961-2022).

The differenced series of bean production highlights the annual changes from 2002 to 2022. This transformation was applied to remove long-term trends, allowing for a more precise analysis of short-term variations. Focusing on interannual variations helps to identify fluctuations that may be related to specific events or temporary factors, providing a clearer understanding of the underlying dynamics in bean production.

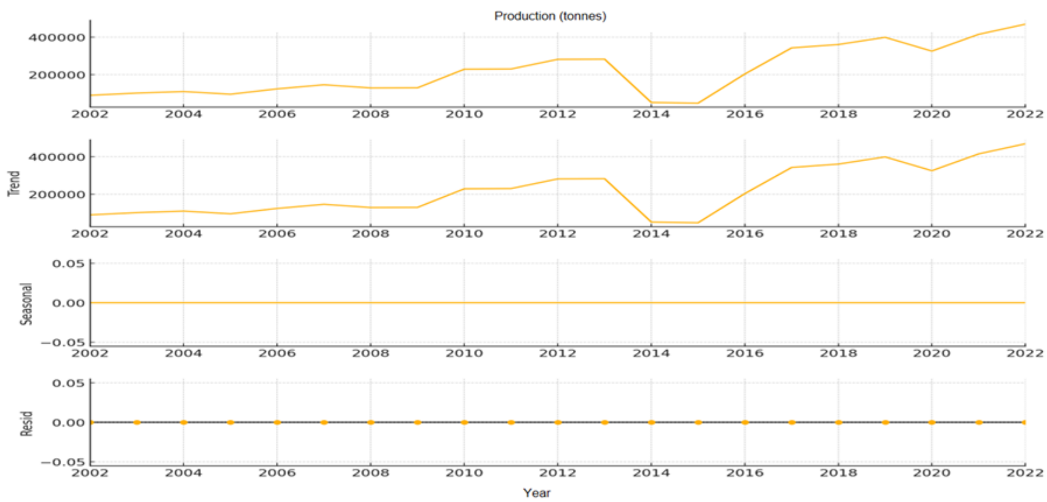

Figure 2. Decomposition of the Time Series of Beans Production in Mozambique.

4.2.2. Decomposition of the Time Series of Beans Production in Mozambique

The time series decomposition provides a detailed view of the trend, seasonality, and residual components (Figure 2). The trend indicates a sharp increase in recent years, possibly linked to improvements in agricultural infrastructure or a rise in demand for beans. The graphical analysis does not reveal a clear seasonal pattern, suggesting that bean production does not follow defined seasonal cycles during the analyzed period. The residuals show fluctuations that are not explained by the trend, indicating the presence of random variability or the influence of unmodeled factors.

4.2.3. Autocorrelation Function (ACF) of Beans Production in Mozambique

The ACF (Autocorrelation Function) plot of the original series does not show significant peaks at specific lags, indicating the absence of consistent seasonality (Figure 3). The autocorrelation values decrease rapidly, suggesting that annual production does not strongly depend on previous values over long intervals. This rapid decline in autocorrelations reflects the predominance of a short-term trend, with little influence from cycles or regular long-term patterns.

After differentiation, the ACF plot shows that autocorrelations continue to drop quickly after the initial lags, indicating that the series lacks significant long-term correlation structure. This suggests that the differenced series is closer to being stationary, which is crucial for analyses requiring statistical consistency over time, enabling a more effective approach to modeling and forecasting variations in production.

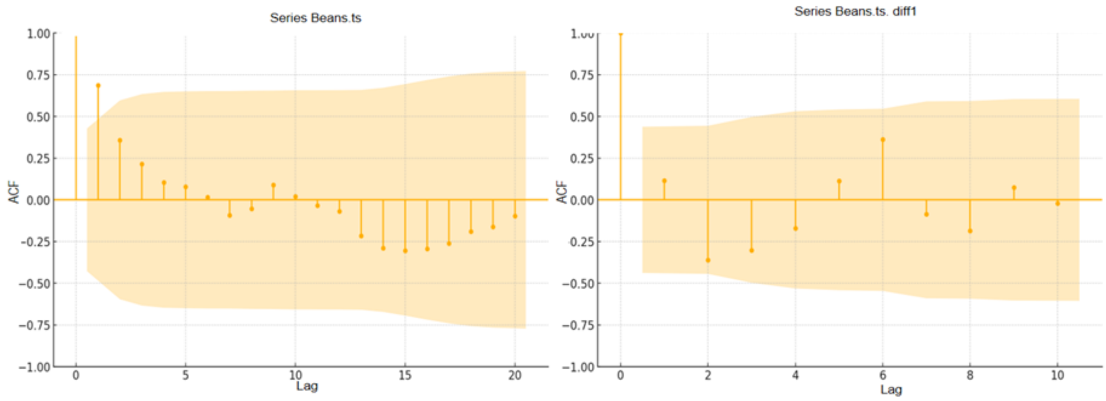

Figure 3. *Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) of Beans Production in Mozambique.*

4.2.4. Partial Autocorrelation Function (PACF) of Beans Production in Mozambique

The PACF (Partial Autocorrelation Function) plot shows some peaks in the initial lags, suggesting the presence of low-order autoregressive components (Figure 4). This indicates that past values have a moderate influence on future values, reflecting that recent observations directly affect the subsequent values in the series.

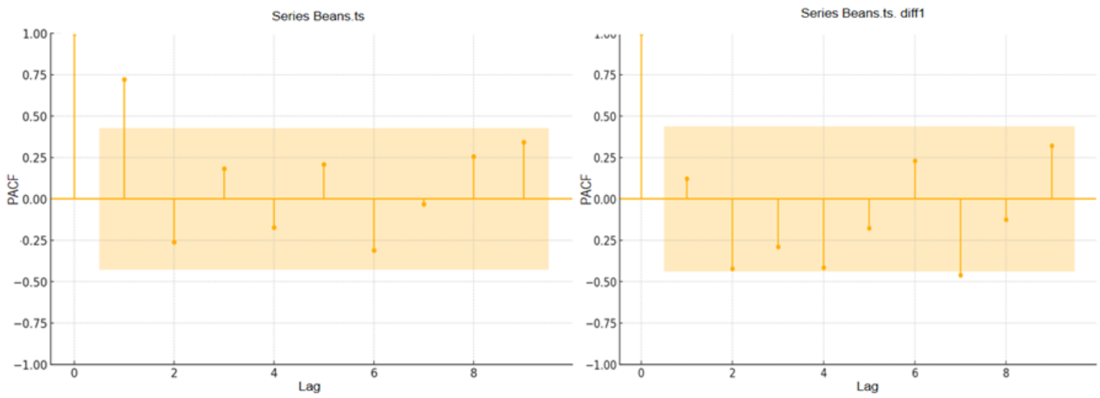

Figure 4. *Partial Autocorrelation Function (PACF) of Beans Production in Mozambique.*

The presence of peaks in the early lags in the PACF plot confirms the existence of low-order autoregressive components, meaning that past values moderately influence future values. This behavior is typical in time series where adjacent observations are correlated, allowing low-order autoregressive models to effectively capture the underlying dynamics of the series.

4.2.5. Augmented Dickey-Fuller (ADF) Test for the Beans Series

The p-value of 0.354 from the ADF (Augmented Dickey-Fuller) test for the original series suggests that there is not enough evidence to reject the null hypothesis of a unit root (Table 2). This indicates that the series is non-stationary and may require a transformation, such as differencing, for short-term modeling. The non-stationarity of the series implies that its statistical properties, such as mean and variance, change over time, which can complicate the application of certain forecasting models.

After differencing, the p-value of 0.0001 indicates that the null hypothesis of a unit root is rejected, confirming that the differenced series is stationary. This means that the series now has constant statistical properties over time, making it suitable for applying time series models that assume stationarity, such as the ARIMA model, thereby facilitating more accurate analyses and forecasts.

Table 2. Augmented Dickey-Fuller (ADF) Test for the Beans Series.

Test Statistic	p-Value	Lags	n	Critical Value		
				(1%)	(5%)	(10%)
Orginal Series						
-1.859	0.354	3	17	-3.920	-3.065	-2.673
Differenced Series						
-4.652	0.0001	1	19	-3.831	-3.030	-2.655

4.3. Estimation with Time Series Models (ARIMA) for Beans Production

4.3.1. Model Identification

The analysis of the ACF and PACF plots for the differenced time series of bean production suggests specific characteristics indicative of temporal dependencies. The ACF plot shows a gradual decay after the first lag, which is suggestive of a potential autoregressive structure in the series. This pattern indicates that production in a given year is influenced by production levels in previous years, justifying the consideration of an ARIMA model with an autoregressive component. Moreover, the PACF plot exhibits a sharp cut-off after the first lag, indicating that the influence of lags beyond the first is not significant. This behavior supports the suitability of a first-order autoregressive term (AR(1)), which captures the direct relationship between the current value and the immediately preceding value in the time series.

Based on these observations, the ARIMA(1,1,0) and ARIMA(0,1,1) models emerge as strong candidates for modeling the series, with the former capturing the autoregressive dependency and the latter accounting for the possibility of temporary shocks. For a more robust modeling approach that captures both the autoregressive effects and short-term shocks, the ARIMA(1,1,1) model can also be considered, as it incorporates both AR and MA components, providing greater flexibility in capturing the underlying dynamics of the data. On the other hand, the ARIMA(0,1,1) model is suggested by the ACF plot, which shows a clear cut-off after the first lag, indicating the presence of a negative correlation that can be captured by a first-order moving average (MA) component.

Finally, the ARIMA(1,1,1) model remains a viable option, considering the patterns observed in both the ACF and PACF plots, with cut-offs after the first lag in each, suggesting that a combination of AR(1) and MA(1) components may provide a robust model for the differenced time series. These recommendations are based on the sharp cut-offs in the ACF and PACF plots, which are classic indicators for selecting the AR and MA orders in ARIMA models.

4.3.2. Parameter Estimation

Table 3 presents the diagnostic test results for the residuals of the ARIMA models fitted to bean production. These tests are crucial for evaluating the adequacy of the models by examining residual autocorrelation (Box-Pierce), heteroscedasticity (ARCH), and residual normality (Shapiro-Wilk and Jarque-Bera). In the Box-Pierce test, all models show relatively high p-values (above 0.4), indicating no significant evidence of autocorrelation in the residuals. This suggests that the ARIMA(1,1,0), ARIMA(0,1,1), and ARIMA(1,1,1) models are appropriate in terms of residual independence, which is an essential assumption for the validity of ARIMA models.

Regarding the ARCH test, all models exhibit high p-values (above 0.8), indicating no significant heteroscedasticity in the residuals. This implies that the residual variances are constant over time, a positive sign that the models are stable and consistent in their predictive capabilities. However, the normality tests, such as Shapiro-Wilk and Jarque-Bera, reveal low p-values for all models, indicating a violation of the normality assumption in the residuals. Although normality is a desirable assumption, especially for statistical inference, its violation is not uncommon in time series data. As long as the residuals are approximately symmetric and free from significant autocorrelation, the models can still be considered valid for forecasting purposes. The violation of normality, however, suggests that the forecasts may have uncertainties not fully captured by the confidence intervals.

Considering all the diagnostic tests, the ARIMA(1,1,1) model appears to be the most robust, balancing residual independence and the absence of heteroscedasticity, despite the violation of the normality assumption. This model effectively captures the dynamics of the time series and provides a solid foundation for forecasting bean production in Mozambique.

Table 3. *Parameter Estimates for the ARIMA (p, d, q) Model Fitted to Beans Production.*

Model	**Parameter**	**Estimates**	**t-Stat**	**P-value**
ARIMA(1,1,0)	AR(1)	0.1600351	5.9156461	0.0003
ARIMA(1,1,0)	$\emptyset_2$	6.665689e+9	1.206511e+21	0.0000
ARIMA(0,1,1)	MA(1)	-0.2853856	-7.039339	0.0000
ARIMA(0,1,1)	$\emptyset_2$	7.870594e+9	5.882748e+20	0.0000
ARIMA(1,1,1)	AR(1)	-0.2897991	-6.313837	0.0001
ARIMA(1,1,1)	MA(1)	0.5418300	8.716570	0.000
ARIMA(1,1,1)	$\emptyset_2$	7.837963e+9	4.413375e+19	0.0000

4.3.3. Diagnostic Test of Residuals for Beans Production Models

Table 4 presents the diagnostic test results for the residuals of the ARIMA models fitted to bean production. These tests are crucial for evaluating the adequacy of the models by examining residual autocorrelation (Box-Pierce), heteroscedasticity (ARCH), and residual normality (Shapiro-Wilk and Jarque-Bera). In the Box-Pierce test, all models show relatively high p-values (above 0.4), indicating no significant evidence of autocorrelation in the residuals. This suggests that the ARIMA(1,1,0), ARIMA(0,1,1), and ARIMA(1,1,1) models are appropriate in terms of residual independence, which is an essential assumption for the validity of ARIMA models.

Regarding the ARCH test, all models exhibit high p-values (above 0.8), indicating no significant heteroscedasticity in the residuals. This implies that the residual variances are constant over time, a positive sign that the models are stable and consistent in their predictive capabilities. However, the normality tests, such as Shapiro-Wilk and Jarque-Bera, reveal low p-values for all models, indicating a violation of the normality assumption in the residuals. Although normality is a desirable assumption, especially for statistical inference, its violation is not uncommon in time series data. As long as the residuals are approximately symmetric and free from significant autocorrelation, the models can still be considered valid for forecasting purposes. The violation of normality, however, suggests that the forecasts may have uncertainties not fully captured by the confidence intervals.

Considering all the diagnostic tests, the ARIMA(1,1,1) model appears to be the most robust, balancing residual independence and the absence of heteroscedasticity, despite the violation of the normality assumption. This model effectively captures the dynamics of the time series and provides a solid foundation for forecasting bean production in Mozambique.

Table 4. Diagnostic Test of Residuals for Beans Production Models.

Model	Box-Pierce		ARCH		Shapiro-WilK		Jarque-Bera	
	Q	p-value	TR^2	p-value	W	p-value	JB	p-value
ARIMA(1,1,0)	9.993	0.4411	1.2123	0.8761	0.8825	0.0163	13.0579	0.0015
ARIMA(0,1,1)	8.596	0.5708	0.8005	0.9384	0.8949	0.0279	10.9280	0.0042
ARIMA(1,1,1)	8.283	0.6012	0.8732	0.9284	0.8905	0.0230	9.99704	0.0068

4.3.4. Comparison of Model Performance

Table 5 presents a performance comparison between three ARIMA models applied to the time series of bean production, utilizing metrics such as AIC (Akaike Information Criterion), BIC (Bayesian Information Criterion), HQIC (Hannan-Quinn Information Criterion), RMSE (Root Mean Square Error), and MAPE (Mean Absolute Percentage Error). These metrics are essential for evaluating the adequacy and accuracy of the models.

The ARIMA(1,1,0) model shows an AIC of 512.1632, a BIC of 514.1547, and an HQIC of 512.5520. These values are slightly lower than those of the ARIMA(1,1,1) model but very close to those of the ARIMA(0,1,1) model. In terms of RMSE and MAPE, the ARIMA(1,1,0) model has an RMSE of 80,099.9815 and a MAPE of 45.06%, indicating that while the model has reasonable accuracy, it is not the most precise among the three.

The ARIMA(0,1,1) model is slightly superior to the ARIMA(1,1,0) in terms of AIC, BIC, and HQIC, with values of 512.1592, 514.1507, and 512.5480, respectively. The RMSE for this model is 79,099.6801, which is lower than that of the ARIMA(1,1,0), suggesting a smaller root mean square error. However, the MAPE of 48.27% indicates that the model is less accurate in terms of mean absolute percentage error.

On the other hand, the ARIMA(1,1,1) model exhibits competitive performance with an RMSE of 78,451.9424, the lowest among the three models, suggesting better overall accuracy. Despite having slightly higher AIC, BIC, and HQIC values (513.8875, 516.8747, and 514.4707, respectively), the lower RMSE and a MAPE of 46.43% indicate that this model may better capture the data's variation, albeit with a slight penalty in terms of complexity.

Based on these results, the ARIMA(1,1,1) model, despite being slightly more complex, appears to be the most suitable for estimating bean production in Mozambique due to its lower RMSE, indicating higher forecast accuracy, and an acceptable MAPE, showing good performance in terms of percentage error.

Table 5. Comparison of Model Performance for Beans Production.

Model	AIC	BIC	HQIC	RMSE	MAPE
ARIMA(1,1,0)	512.1632	514.1547	512.5520	80099.9815	45.06%
ARIMA(0,1,1)	512.1592	514.1507	512.5480	79099.6801	48.27%
ARIMA(1,1,1)	513.8875	516.8747	514.4707	78451.9424	46.43%

4.3.5. Training and Evaluation of ARIMA Models with Real Data from 2010 to 2020

The analysis of the training results for the ARIMA models applied to bean production in Mozambique from 2010 to 2020 reveals significant discrepancies between the models (Table 6). The ARIMA(1,1,1) model exhibits the lowest RMSE (74,293.80) and the lowest MAPE (59%), suggesting that it fits the historical data better and provides more accurate forecasts compared to the other two models. However, the relatively high MAPE still indicates that, despite being the most accurate among the three, this model presents a considerable margin of error.

The high MAPE values in the ARIMA(1,1,0) and ARIMA(0,1,1) models, particularly in the ARIMA(0,1,1) model with a MAPE of 103%, indicate significant lack of precision. This inaccuracy may be attributed to various factors, including extreme variations in production during 2014 and 2015 when the actual values were substantially lower than in previous and subsequent years. These fluctuations may have made modeling more challenging, especially for models that rely on more stable patterns over time.

Another factor that may have contributed to the high MAPE values is the limited size of the time series, composed of only 21 observations. In time series with few observations, forecasts tend to be less accurate due to the lack of sufficient data to capture the underlying complexity. This can result in models that do not generalize well, consequently producing forecasts with large margins of error, particularly during periods of high volatility, as observed in the years of low production.

Table 6. Training and Evaluation of ARIMA Models with Real Beans Production Data from 2010 to 2020.

Year	Actual Dada	Predicted Data		
		ARIMA(1,1,0)	ARIMA(0,1,1)	ARIMA(1,1,1)
2010	229232	259164.77	2614913.61	247692.73
2011	230461	262791.16	285394.07	274329.38
2012	282000	230640.94	216141.12	193059.63
2013	283000	289545.87	299238.45	327124.26
2014	51583	283146.41	278748.42	243728.60
2015	47725	177014.04	278942.97	20946.35
2016	203582	47160.15	62287.81	74187.48
2017	343290	226401.16	240576.81	226774.40
2018	361207	363744.77	370183.14	365430.01
2019	399511	363830.24	358856.80	346440.25
2020	325872	405119.12	410155.37	425581.95
RMSE		79254.24	91417.68	74293.80
MAPE		83%	103%	59%

The ARIMA(1,1,1) model is the most suitable for estimating bean production in Mozambique due to its efficient combination of autoregressive and moving average components, which demonstrate statistical significance. This model maintains the independence and stability of the residuals, despite the violation of the normality assumption, and it presents the lowest RMSE and an acceptable MAPE, reflecting a good predictive capability even in the face of extreme production fluctuations and a limited time series.

4.3.6. Forecasted Beans Production in Mozambique from 2023 to 2030

Table 7 presents the forecasted values for bean production in Mozambique for the period from 2023 to 2030, using the ARIMA model. The forecasted values indicate stable production over the years, with figures consistently hovering around 465,000 tons for all the years analyzed.

The 95% confidence intervals illustrate the uncertainty associated with these forecasts. For 2023, the confidence interval ranges from 290,082.74 to 637,122.92 tons, indicating a significant spread, which reflects a moderate level of uncertainty in the predictions. Over the years, the confidence intervals remain broad, but with slight variations, suggesting that while the central forecast remains stable, the uncertainty about the actual outcomes is relatively constant.

This stability in the forecasted values suggests that, according to the ARIMA model, no major fluctuations in bean production in Mozambique are expected during this period. However, the width of the confidence intervals indicates that considerable uncertainty factors still exist, which should be taken into account in agricultural planning and in the formulation of policies related to bean production in the country.

Table 7. Forecasted Beans Production in Mozambique from 2023 to 2030 by the ARIMA Model.

Year	Forecasted Value	Confidence Intervals (95%)	
		Lower Bound	Upper Bound
2023	463602.80	290082.74	637122.92
2024	465423.66	287539.18	636429.76
2025	464895.98	287003.46	630046.29
2026	465048.90	287049.29	628417.71
2027	465004.59	283479.07	630184.48
2028	465017.43	285462.71	629990.03
2029	465013.71	284381.22	628611.47
2030	465014.79	284762.97	629560.66

4.4. Estimation with the LSTM Model for Beans Production

4.4.1. Model Training with LSTM

For training the LSTM model aimed at forecasting bean production in Mozambique, the historical production data was organized and normalized using the MinMaxScaler, which scales the values between 0 and 1, facilitating the model's learning process. The data was divided into training and testing sets, with the training data comprising the years prior to 2017. Time sequences of 3 years were created, allowing the model to capture dependencies over time. The LSTM model was then trained over 100 epochs, featuring two LSTM layers with 50 units each, followed by a dense layer that generated the predictions.

4.4.2. Model Evaluation

Table 8 presents the evaluation of the LSTM model using actual bean production data in Mozambique from 2017 to 2022. Overall, the model was able to capture the production trend, but it exhibited significant variations in specific years. For instance, in 2018 and 2022, the model showed considerable deviations, with a MAPE of 19.47% and 14.86%, respectively, indicating that the model's predictions for these years either underestimated or overestimated the actual production. The RMSE was also relatively high in these years, reflecting a greater discrepancy between the predicted and actual values.

The average errors over the evaluated years reveal a MAPE of 11.48%, suggesting that, on average, the model's predictions deviated from the actual values by approximately 11.48%. While the model was reasonably accurate in some years, such as 2017 and 2020, where the MAPE was 5.42% and 4.26% respectively, the larger variations in other years indicate that the model may struggle to capture more abrupt fluctuations in bean production. This variability suggests the need for further refinement of the model, possibly by incorporating additional variables or adjusting the model architecture to improve its ability to handle such fluctuations.

The larger variations in certain years indicate that the LSTM model may not fully capture all the dynamics influencing bean production, suggesting the need for further adjustments. These adjustments could include incorporating external variables such as climatic conditions, agricultural practices, or market policies that may impact production fluctuations. However, despite these limitations, the model demonstrated a reasonable ability to predict general trends, making it a useful tool for estimating bean production from 2023 to 2030.

Table 8. LSTM Model Evaluation with Real Beans Production Data from 2017 to 2022.

Year	Actual Dada	LSTM Model		
		Predicted Data	RMSE	MAPE
2017	343290	324684.14	18605.86	5.42%
2018	361207	431537.10	70330.1	19.47%
2019	399511	439550.54	40039.54	10.02%
2020	325872	339760.82	13888.82	4.26%
2021	415828	354035.98	61792.02	14.86%
2022	469886	400056.07	69829.93	14.86%
Mean	385932.33	381604.11	45747.71	11.48%

4.4.3. Forecasts for 2023 to 2030

The analysis of the bean production forecasts in Mozambique for the period from 2023 to 2030, utilizing an LSTM model combined with the Bootstrapping technique, reveals a relatively stable trend over the years (Table 9). The forecasts indicate a production range between 383,000 and 401,000 tons, with no significant annual variations. The average annual growth rate during this period is modest, approximately 0.5% per year. This stability suggests that, in the absence of significant external factors, bean production could remain relatively constant, with only slight fluctuations resulting from natural variations in cultivation conditions.

Additionally, the 95% confidence intervals for each year, ranging between approximately 27,000 to 55,000 tons, highlight considerable uncertainty in the predictions, which is common in agricultural contexts due to the variability of factors such as climate, pests, and agricultural management practices. This uncertainty is particularly noticeable in years like 2026 and 2028, where the forecasts suggest a potentially wider fluctuation.

However, the LSTM model, reinforced by the Bootstrapping technique, provides a robust and reliable estimate of future bean production, making it a valuable tool for agricultural forecasting and strategic planning in Mozambique.

Table 9. *Forecasted Beans Production in Mozambique from 2023 to 2030 by the LSTM Model and Bootstrapping Technique.*

Year	Forecasted Value	Confidence Intervals (95%)	
		Lower Bound	Upper Bound
2023	398048.43	369034.14	427062.72
2024	401742.22	379769.05	423715.39
2025	396214.55	383094.66	409334.44
2026	389210.80	361887.28	416534.32
2027	390785.00	366623.55	414946.46
2028	383291.07	353892.87	412689.27
2029	388387.96	374141.18	402634.74
2030	383444.95	369776.86	397113.04

5. Discussion

The analysis of descriptive statistics for bean production in Mozambique from 2002 to 2022 reveals considerable variability, with a standard deviation of 129,407 tons and a coefficient of variation of 59.46%, indicating significant annual fluctuations. The slightly positive skewness of 0.46 suggests that production has generally been moderately above the average in some years, while the negative kurtosis of -1.06 indicates a lower frequency of extreme values, reflecting production that is relatively concentrated around the mean. These characteristics are consistent with studies such as those by Loo et al. and Kumari et al., which highlight the impact of climatic factors and agricultural policies on the variability of legume production in tropical regions [53, 54]. The wide range of 422,161 tons between the maximum and minimum values underscores the vulnerability of bean production to external shocks, reinforcing the need for interventions to ensure greater stability and resilience in production.

The time series analysis of bean production in Mozambique from 2002 to 2022 reveals an upward trend, especially after 2015, possibly due to improvements in agricultural practices or government support policies, as suggested by studies by Odeku et al. and Sileshi et al., which emphasize the positive impact of agricultural interventions in tropical regions [55, 56]. However, the significant fluctuations observed in the series, such as the sharp declines in 2014 and 2015, indicate the vulnerability of production to external factors, such as adverse climatic events, corroborating the findings of Oyebanji et al. on the sensitivity of legume crops to climatic variations [57].

The decomposition of the series does not reveal consistent seasonal patterns, aligning with research by Jha et al., which shows that bean production in tropical climates does not follow predictable seasonal cycles [58]. The absence of seasonality in the ACF graph and the initial spikes in the PACF suggest that the series can be modeled with low-order autoregressive components, as recommended by Amato et al. in their recommendations for time series modeling [59].

The ADF test confirms that the series is non-stationary, a common conclusion in agricultural time series, as observed by Lu et al. [60]. After differencing, the series becomes stationary, making it suitable for modeling with the ARIMA model, as recommended by Dimri et al. [61]. This transformation is essential for enabling more accurate and robust forecasts, particularly in an agricultural context as volatile as Mozambique.

The analysis of ARIMA models applied to forecasting bean production in Mozambique highlights the ARIMA(1,1,1) model as the most effective, balancing accuracy and robustness compared to other configurations. This model proves superior to ARIMA(1,1,0) and ARIMA(0,1,1), especially during periods of high volatility, such as 2014 and 2015, efficiently capturing the fluctuations in production over the years. With the lowest RMSE (74,293.80) and a MAPE of 59%, the ARIMA(1,1,1) model establishes itself as the best option for modeling bean production, despite the limitations associated with the sample size.

The high MAPE value, even in the ARIMA(1,1,1) model, can be attributed to the limited sample size, comprising only 21 observations. Short time series tend to complicate precise modeling, particularly in contexts like agriculture in Mozambique, where large annual fluctuations are common. The lack of sufficient data limits the ability of models to capture the full complexity of the underlying dynamics, resulting in forecasts with large margins of error. Studies suggest that small and volatile time series often result in high MAPE values due to greater sensitivity to outliers and extreme events [62].

Despite these limitations, the ARIMA(1,1,1) model remains the most suitable choice for forecasting bean production, given its ability to capture both temporal dependence and abrupt fluctuations. This performance underscores the importance of using flexible models in agricultural contexts, as highlighted by Dong et al., who point to the effectiveness of ARIMA models in high-volatility scenarios, even when the sample size is smaller [63]. Therefore, although the high MAPE suggests caution in interpreting forecasts, the ARIMA(1,1,1) model remains the best available option for modeling bean production in Mozambique.

Additional studies suggest that, despite the violation of the normality assumption of the residuals, the ARIMA(1,1,1) model can be considered valid for forecasting as long as the residuals are free of significant autocorrelation [64]. The model's ability to handle variability and the short duration of the series is crucial in regions like Mozambique, where agriculture is highly vulnerable to climatic and policy changes, as highlighted by Komara & Sirodj [65]. Thus, ARIMA(1,1,1) not only offers more accurate forecasts but also becomes a valuable tool for informing agricultural policies and production strategies in an environment of high uncertainty.

The analysis of LSTM models applied to forecasting bean production in Mozambique reveals that it outperforms the ARIMA(1,1,1) model when compared based on MAPE. While ARIMA(1,1,1) achieved a MAPE of 59%, the LSTM model recorded an average MAPE of 11.48%. This result suggests that LSTM, with its ability to capture nonlinear and complex patterns in time series, offers more accurate and robust forecasts for bean production in Mozambique.

Although the LSTM model demonstrated a reasonable ability to predict general trends in bean production in Mozambique, significant variations observed in specific years, such as 2018 and 2022, suggest that the model still faces challenges in forecasting abrupt fluctuations. The high MAPE in those years, reaching 19.47% and 14.86%, respectively, indicates that the LSTM either underestimated or overestimated the actual production considerably. These deviations may be partially attributed to the limited sample size, which includes only 21 observations. Short time series, as noted by Liu et al., tend to hinder the effective training of complex models like LSTM, which depend on large volumes of data to capture nonlinear and complex patterns [66]. The lack of sufficient data can limit the model's ability to learn underlying dynamics, resulting in forecasts with larger error margins. Despite these limitations, the LSTM model still outperforms ARIMA(1,1,1), standing out in its ability to capture the variability of bean production in Mozambique.

Studies such as those by Alzakari et al. reinforce that LSTM models, when properly adjusted, can surpass traditional models in high-volatility scenarios like agriculture [67]. The inclusion of exogenous variables, such as climatic data, agricultural practices, government policies, and market indicators, can significantly improve LSTM performance, reducing MAPE and increasing forecast accuracy. Expanding the training sample or using data enrichment techniques may also be effective strategies to improve the predictive capacity of LSTM models, as suggested by Tang et al., making it an even more robust tool for agricultural production forecasting in challenging contexts like Mozambique [68]. This is crucial for effective planning and mitigating the risks associated with bean production, thus contributing to food and nutritional security in the country.

The analysis of bean production forecasts in Mozambique for the period 2023 to 2030, using the LSTM model combined with the Bootstrapping technique, suggests stability in production, with values oscillating between 383,000 and 401,000 tons. This forecast, although showing a modest average annual growth rate of about 0.5%, reflects the possibility of agricultural production that, in the absence of significant external shocks, remains relatively constant. The apparent stability in agricultural forecasts may mask underlying vulnerabilities, especially in contexts like Mozambique, where unpredictable climatic factors and reliance on traditional farming practices can introduce unexpected variations in production.

The wide confidence intervals, ranging from 27,000 to 55,000 tons, reinforce this inherent uncertainty in forecasts, suggesting that despite the robustness of the LSTM model, there is a considerable margin of error. Studies like those by Bouri et al. and Gvozdenac et al. emphasize that in agricultural contexts, forecasts should always be interpreted with caution, given that climatic variability, the presence of pests, and agricultural management practices play crucial roles [69, 70]. In Mozambique, this uncertainty is exacerbated by the lack of adequate infrastructure and vulnerability to climate change, as mentioned by Manuel et al. [71].

In the context of food and nutritional insecurity in Mozambique, this projected stability in bean production may offer some assurance of continuity in supply, but it does not necessarily mean an improvement in food security. Beans are an important source of protein and nutrients, especially in rural areas, and any disruption in production can have significant impacts on the population's diet. The modest projected growth rate does not keep pace with population growth, which may exacerbate food insecurity unless additional interventions are implemented. SDG 2, which aims to end hunger, achieve food security, and improve nutrition, depends not only on stability in production but also on significant increases to meet growing demand.

Moreover, the SDG 2 targets in Mozambique, which include improving agricultural productivity and ensuring sustainable food production systems, require a continued focus on policies that encourage agricultural innovation and climate resilience. The projection of stable but slightly fluctuating production suggests that Mozambique needs policies that not only maintain this stability but also increase production to reduce food insecurity. Investments in agricultural technology, infrastructure, and sustainable management practices are crucial to ensuring that stability projections translate into long-term food security.

6. Conclusions

The analysis of the ARIMA and LSTM models applied to the forecasting of bean production in Mozambique from 2002 to 2022 reveals significant challenges due to the limited sample size, which spans only 21 years. This limitation contributes to the high MAPE values observed, reflecting the difficulty these models face in capturing the full complexity of the underlying dynamics of bean production in a highly volatile context. This issue is particularly relevant in the context of food insecurity, where accurate forecasts are crucial for agricultural planning and ensuring food supply.

The ARIMA(1,1,1) model demonstrated robustness among the evaluated options, with the lowest RMSE and a lower MAPE compared to other ARIMA models. However, the LSTM model, despite its limitations, showed a superior ability to capture nonlinear patterns, resulting in a lower average MAPE than ARIMA. This suggests that, with additional adjustments, such as incorporating exogenous variables like climatic data and agricultural practices, the LSTM model could provide more accurate forecasts, contributing more effectively to food security.

Forecasts for the period from 2023 to 2030 indicate a trend of stability in bean production, with slight annual variations. However, the wide confidence intervals suggest considerable uncertainty that must be factored into agricultural planning and policy formulation. This projected stability, while encouraging, may not be sufficient to keep pace with population growth and mitigate food insecurity, underscoring the urgent need for interventions that increase productivity and agricultural resilience in Mozambique, aligning with SDG 2 goals to end hunger and ensure food and nutritional security.

In conclusion, while the ARIMA and LSTM models offer valuable guidance for forecasting bean production, the results should be interpreted cautiously, given the impact of the limited sample size on the accuracy of the forecasts. To improve future estimates and support the achievement of SDG 2 targets, it would be beneficial to expand the analyzed time series and incorporate additional variables that can better explain fluctuations in production, contributing to more effective agricultural planning and the reduction of food insecurity in Mozambique.

Abbreviations

SDG	Sustainable Development Goal
ARIMA	Autoregressive Integrated Moving Average
ANN	Artificial Neural Network
LSTM	Long Short-Term Memory
RMSE	Root Mean Square Error
MAPE	Mean Absolute Percentage Error
ACF	Autocorrelation Function
PACF	Partial Autocorrelation Function
ADF	Augmented Dickey-Fuller
AIC	Akaike Information Criterion
BIC	Bayesian Information Criterion
HQIC	Hannan-Quinn Information Criterion
FAO	Food and Agriculture Organization

Author Contributions

Filipe Mahaluca: Conceptualization, Data curation, Formal Analysis, Methodology, Software, Writing – original draft, Writing – review & editing

Faizal Carsane: Formal Analysis, Investigation, Methodology, Supervision, Validation

Alfeu Vilanculos: Investigation, Methodology, Supervision, Validation

Conflicts of Interest

The authors declare no conflicts of interest.

References

[1] FAO, IFAD, UNICEF, WFP, and WHO, 'The State of Food Security and Nutrition in the World 2023', 2023. [Online]. Available: https://www.fao.org/3/cc3017en/cc3017en.pdf

[2] FAO, IFAD, UNICEF, WFP, and WHO, 'The Stat of Food Security and Nutrition in the World', 2024. [Online]. Available: https://openknowledge.fao.org/server/api/core/bitstreams/31af4e18-aaeb-4164-991e-2431fe9d41ca/content

[3] M. Rezaey, 'Popping Efficiencies of Popping Beans, and Physicochemical Characteristics and Functional Properties of Their Flour, Protein, and Starch Fractionates', Washington State University, 2023.

[4] N. Gogoi, K. K. Baruah, and R. S. Meena, 'Grain legumes: impact on soil health and agroecosystem', in *Legumes for Soil Health and Sustainable Management,* Springer, 2018, pp. 511-539.

[5] E. Kebede, 'Contribution, Utilization, and Improvement of Legumes-Driven Biological Nitrogen Fixation in Agricultural Systems', *Front. Sustain. Food Syst.*, vol. 5, no. November, pp. 1-18, 2021, https://doi.org/10.3389/fsufs.2021.767998

[6] World Bank, 'Climate-Smart Agriculture in Mozambique', 2017. [Online]. Available: https://climateknowledgeportal.worldbank.org/sites/default/files/2019-06/CSA-in-Mozambique.pdf

[7] Ambika *et al.*, 'Unraveling Origin, History, Genetics, and Strategies for Accelerated Domestication and Diversification of Food Legumes', *Front. Genet.*, vol. 13, no. July, pp. 1-21, 2022, https://doi.org/10.3389/fgene.2022.932430

[8] A. E. Yanni, S. Iakovidi, E. Vasilikopoulou, and V. T. Karathanos, 'Legumes: A Vehicle for Transition to Sustainability', *Nutrients*, vol. 16, no. 1, p. 98, 2023, https://doi.org/10.3390/nu16010098

[9] B. Vanlauwe, M. Hungria, F. Kanampiu, and K. E. Giller, 'The role of legumes in the sustainable intensification of African smallholder agriculture: Lessons learnt and challenges for the future', *Agric. Ecosyst. Environ.*, vol. 284, no. March, p. 106583, 2019, https://doi.org/10.1016/j.agee.2019.106583

[10] S. M. T. Gharibzahedi and B. Smith, 'The functional modification of legume proteins by ultrasonication: A review', *Trends Food Sci. Technol.*, vol. 98, no. 10, pp. 107-116, 2020, https://doi.org/10.1016/j.tifs.2020.02.002

[11] R. Elahi and T. Mu, 'High Hydrostatic Pressure (HHP)-Induced Structural Modification of Patatin and Its Antioxidant Activities', *Molecules*, vol. 22, no. 438, pp. 1-20, 2017, https://doi.org/10.3390/molecules22030438

[12] FAO, 'Mozambique Country Brief', 2023. [Online]. Available: https://www.fao.org/mozambique

[13] F. Sparvoli *et al.*, 'Sensory characteristics and nutritional quality of food products made with a biofortified and lectin free common bean (Phaseolus vulgaris l.) flour', *Nutrients*, vol. 13, no. 12, pp. 1-28, 2021, https://doi.org/10.3390/nu13124517

[14] M. Philipo, P. A. Ndakidemi, and E. R. Mbega, 'Importance of common bean genetic zinc biofortification in alleviating human zinc deficiency in sub-Saharan Africa', *Cogent Food Agric.*, vol. 7, no. 1, 2021, https://doi.org/10.1080/23311932.2021.1907954

[15] A. Pathania, S. K. Sharma, and P. N. Sharma, *Cammon Bean*. 2014.

[16] P. Smýkal *et al.*, 'Legume Crops Phylogeny and Genetic Diversity for Science and Breeding', *CRC. Crit. Rev. Plant Sci.*, vol. 34, pp. 43-104, 2015, https://doi.org/10.1080/07352689.2014.897904

[17] C. Chávez-Mendoza and E. Sánchez, 'Bioactive compounds from mexican varieties of the common bean (Phaseolus vulgaris): Implications for health', *Molecules*, vol. 22, no. 8, pp. 1-32, 2017, https://doi.org/10.3390/molecules22081360

[18] K. Rani *et al.*, *Legumes for Sustainable Soil and Crop Management*. 2019.

[19] FAOSTAT, 'Crops and livestock products (Production)', *27.12.2023*, 2023. https://www.fao.org/faostat/en/#data/QCL (accessed Jan. 03, 2024).

[20] M. K. Pandey *et al.*, 'Emerging genomic tools for legume breeding: Current status and future prospects', *Front. Plant Sci.*, vol. 7, no. MAY2016, pp. 1-18, 2016, https://doi.org/10.3389/fpls.2016.00455

[21] N. S. Affrifah, M. A. Uebersax, and S. Amin, 'Nutritional significance, value-added applications, and consumer perceptions of food legumes: A review', *Legum. Sci.*, vol. 5, no. 4, pp. 1-16, 2023, https://doi.org/10.1002/leg3.192

[22] C. Mukankusi *et al.*, 'Genomics, genetics and breeding of common bean in Africa: A review of tropical legume project', *Plant Breed.*, vol. 138, no. 4, pp. 401-414, 2019, https://doi.org/10.1111/pbr.12573

[23] C. Ojiewo *et al.*, 'The Role of Vegetables and Legumes in Assuring Food, Nutrition, and Income Security for Vulnerable Groups in Sub-Saharan Africa', *World Med. Heal. Policy*, vol. 7, no. 3, pp. 187-210, 2015, https://doi.org/10.1002/wmh3.148

[24] M. A. Uebersax *et al.*, 'Dry beans (Phaseolus vulgaris L.) as a vital component of sustainable agriculture and food security—A review', *Legum. Sci.*, vol. 5, no. 1, p. e155, 2023, https://doi.org/10.1002/leg3.155

[25] S. S. Snapp, C. M. Cox, and B. G. Peter, 'Multipurpose legumes for smallholders in sub-Saharan Africa: Identification of promising 'scale out' options', *Glob. Food Sec.*, vol. 23, no. February, pp. 22-32, 2019, https://doi.org/10.1016/j.gfs.2019.03.002

[26] A. Mookerjee and T. Tanaka, 'Influence of enzymatic treatments on legume proteins for improved functional and nutritional properties: expansion of legume protein utilization as food ingredients', *Curr. Opin. Food Sci.*, vol. 49, p. 100974, 2023, https://doi.org/10.1016/j.cofs.2022.100974

[27] S. Debebe, 'Post ‑ harvest losses of crops and its determinants in Ethiopia : tobit model analysis', *Agric. Food Secur.*, vol. 11, no. 13, pp. 1-8, 2022, https://doi.org/10.1186/s40066-022-00357-6

[28] E. Ellis, E. M. Kwo, and M. Ngadi, 'Economic and nutritional implications of losses and contributing factors along the bean value chain', *J. Stored Prod. Res.*, vol. 87, pp. 1-13, 2020, https://doi.org/10.1016/j.jspr.2020.101582

[29] FAOSTAT, 'Value of food imports in total merchandise exports (percent) (3-year average)', *Food and Agriculture Organization of the United Nations*, 2023. Value of food imports in total merchandise exports percent 3-year average (accessed Jul. 31, 2023). https://www.fao.org/faostat/en/#search/

[30] A. R. M. Al-Tawaha *et al.*, 'Legume Production and Climate Change', in *Improvement of Plant Production in the Era of Climate Change*, CRC Press, 2022, pp. 221-248.

[31] E. B. Nchanji and C. K. Lutomia, 'Regional impact of COVID-19 on the production and food security of common bean smallholder farmers in Sub-Saharan Africa: Implication for SDG's', *Glob. Food Sec.*, vol. 29, no. January, p. 100524, 2021, https://doi.org/10.1016/j.gfs.2021.100524

[32] K. C. Kaizzi *et al.*, 'Bean yield and economic response to fertilizer in eastern and southern Africa', *Nutr. Cycl. Agroecosystems*, vol. 111, no. 1, pp. 47-60, 2018, https://doi.org/10.1007/s10705-018-9915-9

[33] D. S. MacCarthy, J. Kihara, P. Masikati, and S. G. K. Adiku, 'Decision support tools for site-specific fertilizer recommendations and agricultural planning in selected countries in sub-Sahara Africa', *Nutr. Cycl. Agroecosystems*, vol. 110, no. 3, pp. 343-359, 2018, https://doi.org/10.1007/s10705-017-9877-3

[34] A. Reuzé *et al.*, 'Stages of Change toward Meat Reduction: Associations with Motives and Longitudinal Dietary Data on Animal-Based and Plant-Based Food Intakes in French Adults', *Nutr. Epidemiol.*, vol. 153, no. 11, pp. 3295-3307, 2023, https://doi.org/10.1016/j.tjnut.2023.09.017

[35] R. F. Nanelo and A. E. José, 'Modelos de produção agroecológica familiar: o caso dos distritos de Metuge e Gondola, Moçambique', *Rev. Verde Agroecol. e Desenvolv. Sustentável*, vol. 17, no. 2, pp. 118-126, 2022, https://doi.org/10.18378/rvads.v17i2.9302

[36] T. F. Khumalo, *Social issues related to climate change and food production (crops)*. Elsevier Inc., 2021.

[37] G. Munkombwe, C. Nthewa, and J. A. Mutaliano, 'Strengthening seed delivery system for enhanced adoption of improved sorghum varieties among smallholder farmers in Malawi, Mozambique and Zambia', in *IOP Conference Series: Earth and Environmental Science*, 2020, vol. 482, no. 012008, pp. 1-6, https://doi.org/10.1088/1755-1315/482/1/012008

[38] MADER, 'Inquérito Integrado Agrário', 2020. [Online]. Available: https://www.agricultura.gov.mz/wp-content/uploads/2021/06/MADER_Inquerito_Agrario_2020.pdf

[39] E. Maereka *et al.*, 'Estimation and Characterization of Bean Seed Demand in Angonia District of Mozambique', 2015. [Online]. Available: https://cgspace.cgiar.org/server/api/core/bitstreams/1295ee00-901f-4eeb-8c46-2921997fcaff/content

[40] M. Farid, 'Symbiotic Nitrogen Fixation in Common Bean', University of Guelph, 2015.

[41] I. Karavidas *et al.*, 'Agronomic Practices to Increase the Yield and Quality of Common Bean (Phaseolus vulgaris L.): A Systematic Review', *Agronomy*, vol. 12, no. 2, pp. 1-39, 2022, https://doi.org/10.3390/agronomy12020271

[42] Diário Económico, 'Tribunal Moçambicano Volta a Suspender Exportação de Feijão Bóer Para a Índia', *19/12/2023*, 2023. https://www.diarioeconomico.co.mz/2023/12/19/negocios/comercio/tribunal-mocambicano-volta-a-suspender-exportacao-de-feijao-boer-para-a-india/ (accessed Apr. 04, 2024).

[43] O. A. Outlook, 'Chapter 3. Cereals', pp. 125-141, 2019.

[44] M. Y. Chidege, P. B. Venkataramana, and P. A. Ndakidemi, 'Enhancing Food Grains Storage Systems through Insect Pest Detection and Control Measures for Maize and Beans: Ensuring Food Security Post-COVID-19 Tanzania', *Sustainability*, vol. 16, no. 1767, pp. 1-22, 2024, https://doi.org/10.3390/su16051767

[45] E. Santos, G. Marques, and T. Lino-Neto, *Phaseolus vulgaris L. as a functional food for aging protection*, 2nd ed. Elsevier Inc., 2020.

[46] E. R. Abraham *et al.*, 'Time series prediction with artificial neural networks: An analysis using Brazilian soybean production', *Agric.*, vol. 10, no. 10, pp. 1-18, 2020, https://doi.org/10.3390/agriculture10100475

[47] P. Hara, M. Piekutowska, and G. Niedbała, 'Selection of Independent Variables for Crop Yield Prediction Sensing Data', *Land*, vol. 10, no. 609, pp. 1-21, 2021, https://doi.org/10.3390/land10060609

[48] F. Mahaluça *et al.*, 'Mozambique Consumer Price Index Estimation through Time Series Models', *J. Econ. Res. Rev.*, vol. 2, no. 2, 2022, https://doi.org/10.33140/jerr.02.02.01

[49] A. S. Ahmar, P. K. Singh, R. Ruliana, and A. K. Pandey, 'NNAR Models to Predict Food Grain in India', *Forecasting*, vol. 5, no. 138-152, pp. 138-152, 2023, https://doi.org/10.3390/forecast5010006

[50] Y. Guo *et al.*, 'Agricultural Price Prediction Based on Combined Forecasting Model under Spatial-Temporal Influencing Factors', *Sustain.*, vol. 14, no. 17, pp. 1-18, 2022, https://doi.org/10.3390/su141710483

[51] F. B. Tchimeutcheu, J. Marie, and A. Ngono, 'Keys Determinants of Food Insecurity in Sub-Saharan Africa', *J. Humanit. Soc. Sci.*, vol. 7, no. 3, pp. 01-10, 2024, https://doi.org/10.33140/jhss.07.03.02

[52] S. Devra, P. DV, S. MS, and R. SR, 'Time series forecasting of price for oilseed crops by combining ARIMA and ANN', *Int. J. Stat. Appl. Math.*, vol. 8, no. 4, pp. 40-54, 2023, https://doi.org/10.22271/maths.2023.v8.i4a.1098

[53] W. T. Loo, K. Chua, P. Mazumdar, A. Cheng, and N. Osman, 'Arbuscular Mycorrhizal Symbiosis : A Strategy for Mitigating the Impacts of Climate Change on Tropical Legume Crops', *Plants*, vol. 11, no. 2875, pp. 1-33, 2022, https://doi.org/10.3390/plants11212875

[54] V. V. Kumari *et al.*, 'Drought and Heat Stress in Cool-Season Food Legumes in Sub-Tropical Regions: Consequences, Adaptation, and Mitigation Strategies', *Plants*, vol. 10, no. 1038, pp. 1-21, 2021, https://doi.org/10.3390/plants10061038

[55] O. A. Odeku, Q. A. Ogunniyi, O. O. Ogbole, and J. Fettke, 'Forgotten Gems : Exploring the Untapped Benefits of Underutilized Legumes in Agriculture, Nutrition, and Environmental Sustainability', *Plants*, vol. 13, no. 1208, pp. 1-27, 2024, https://doi.org/10.3390/plants13091208

[56] G. W. Sileshi, J. C. Dagar, A. J. Nath, and E. Kuntashula, *Agroforestry as a Climate-Smart Agriculture: Strategic Interventions, Current Practices and Policies*. Springer, 2023.

[57] O. O. Oyebanji *et al.*, 'Impact of climate change on the spatial distribution of endemic legume species of the Guineo-Congolian forest, Africa', *Ecol. Indic.*, vol. 122, pp. 1-8, 2021, https://doi.org/10.1016/j.ecolind.2020.107282

[58] P. K. Jha, S. Beebe, P. Alvarez-Toro, C. Mukankusi, and J. Ramirez-Villegas, 'Characterizing patterns of seasonal drought stress for use in common bean breeding in East Africa under present and future climates', *Agric. For. Meteorol.*, vol. 342, no. 10, p. 109735, 2023, https://doi.org/10.1016/j.agrformet.2023.109735

[59] U. Amato, A. Antoniadis, I. De Feis, Y. Goude, and A. Lagache, 'Forecasting high resolution electricity demand data with additive models including smooth and jagged components', *Int. J. Forecast.*, vol. 37, no. 1, pp. 171-185, 2021, https://doi.org/10.1016/j.ijforecast.2020.04.001

[60] J. Lu, G. J. Carbone, X. Huang, K. Lackstrom, and P. Gao, 'Mapping the sensitivity of agriculture to drought and estimating the effect of irrigation in the United States, 1950-2016', *Agric. For. Meteorol.*, vol. 292-293, no. 7, p. 108124, 2020, https://doi.org/10.1016/j.agrformet.2020.108124

[61] T. Dimri, S. Ahmad, and M. Sharif, 'Time series analysis of climate variables using seasonal ARIMA approach', *J. Earth Syst. Sci.*, vol. 129, no. 1, pp. 1-16, 2020, https://doi.org/10.1007/s12040-020-01408-x

[62] H. Teichgraeber *et al.*, 'Extreme events in time series aggregation: A case study for optimal residential energy supply systems', *Appl. Energy*, vol. 275, pp. 1-6, 2020, https://doi.org/10.1016/j.apenergy.2020.115223

[63] H. Dong, X. Guo, H. Reichgelt, and R. Hu, 'Predictive power of ARIMA models in forecasting equity returns: a sliding window method', *J. Asset Manag.*, vol. 21, no. 6, pp. 549-566, 2020, https://doi.org/10.1057/s41260-020-00184-z

[64] E. B. Sinu, M. A. Kleden, and A. Atti, 'Application of Arima Model for Forecasting National Economic Growth: a Focus on Gross Domestic Product Data', *J. Math. Its Appl.*, vol. 18, no. 2, pp. 1261-1272, 2024, https://doi.org/10.30598/barekengvol18iss2pp1261-1272

[65] L. Komara and D. Sirodj, 'Metode Autoregressive Integrated Moving Average (ARIMA) untuk Meramalkan Produksi Padi di Provinsi Jawa Tengah', *Bandung Conf. Ser. Stat.*, vol. 3, no. 2, pp. 496-504, 2023, https://doi.org/10.29313/bcss.v3i2.8442

[66] Z. Liu, Z. Zhu, J. Gao, and C. Xu, 'Forecast Methods for Time Series Data: A Survey', *IEEE Access*, vol. 9, pp. 91896-91912, 2021, https://doi.org/10.1109/ACCESS.2021.3091162

[67] S. A. Alzakari, A. A. Alhussan, A. T. Qenawy, A. M. Elshewey, and M. Eed, 'An Enhanced Long Short - Term Memory Recurrent Neural Network Deep Learning Model for Potato Price Prediction', *Potato Res.*, pp. 1-19, 2024, https://doi.org/10.1007/s11540-024-09744-x

[68] T. Tang, D. Jiao, T. Chen, G. Gui, and S. Member, 'Medium- and Long-Term Precipitation Forecasting Method Based on Data Augmentation and Machine Learning Algorithms', *IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens.*, vol. 15, no. Ml, pp. 1000-1011, 2022, https://doi.org/10.1109/JSTARS.2022.3140442

[69] M. Bouri, K. S. Arslan, and F. Sahin, 'Climate-Smart Pest Management in Sustainable Agriculture: Promises and Challenges', *Sustainability*, vol. 15, no. 4592, pp. 1-17, 2023, https://doi.org/10.3390/su15054592

[70] S. Gvozdenac, B. Dedić, S. Mikić, J. Ovuka, and D. Miladinović, 'Impact of Climate Change on Integrated Pest Management Strategies', in *Climate Change and Agriculture: Perspectives, Sustainability and Resilience*, 2022, pp. 311-372.

[71] L. Manuel, O. Chiziane, G. Mandhlate, F. Hartley, and E. Tostão, 'Impact of climate change on the agriculture sector and household welfare in Mozambique : an analysis based on a dynamic computable general equilibrium model', *Clim. Change*, vol. 167, no. 6, pp. 1-18, 2021, https://doi.org/10.1007/s10584-021-03139-4