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Advanced Predictive Modeling for Peanut Production Estimation in Mozambique: Addressing Food Security Challenges through ARIMA and LSTM Approaches Aligned with SDG 2

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ABSTRACT
This study investigates the application of advanced predictive modeling techniques, specifically ARIMA models and LSTM neural networks, to estimate peanut production in Mozambique from 1961 to 2022, with projections extending to 2030. The research aims to provide accurate forecasts that are essential for addressing food security challenges, in alignment with Sustainable Development Goal 2 (SDG 2). The ARIMA models were calibrated using data from 1961 to 2009 and validated with actual production data from 2010 to 2020. Meanwhile, the LSTM model was trained on data from 1961 to 2013 and evaluated with data from 2014 to 2020. The analysis highlighted the relative stability of peanut production in Mozambique, alongside moderate variability, indicating the sector's susceptibility to external factors such as climate change and agricultural practices. The ARIMA (1,1,1) model was identified as the most robust among the ARIMA models, effectively capturing temporal dependencies and smoothing abrupt fluctuations. However, the LSTM model's ability to model nonlinear sequences and long-term dependencies resulted in significantly more accurate forecasts, with a mean absolute percentage error (MAPE) much lower than that of the ARIMA models. This study underscores the superiority of LSTM neural networks over ARIMA models for forecasting peanut production in Mozambique, demonstrating their effectiveness in capturing complex temporal patterns and generating more precise predictions. The projections indicate relatively stable production, albeit with a slight declining trend by 2030. These findings highlight the importance of investing in advanced agricultural technologies and climate change mitigation strategies to ensure the resilience of agricultural production in the country. In summary, the adoption of more sophisticated modeling approaches, such as LSTM, is crucial for addressing food security challenges in Mozambique, directly contributing to the achievement of SDG 2.

Keywords: Agricultural Forecasting, ARIMA Models, LSTM Neural Networks, Peanut, Food Security

Introduction

Peanut (*Arachis hypogaea*) play a crucial role in global food security, particularly in regions vulnerable to food insecurity, such as many parts of Sub-Saharan Africa. With a unique combination of high nutritional value and adaptability to various agro-ecological conditions, peanut are vital for the livelihoods of millions of small-scale farmers and for feeding populations facing significant challenges in accessing nutritious and safe food [1]. In the context of the Sustainable Development Goals (SDGs), particularly SDG 2, which aims to end hunger and promote sustainable agriculture, increasing the production and efficiency of peanut cultivation emerges as a key strategy to enhance food and nutritional security in countries like Mozambique.

Mozambican agriculture, characterized by subsistence practices and significant reliance on crops such as peanut, has been impacted by a range of challenges, including climate variability, low productivity, and market access difficulties [2]. Peanut production, as a critical source of protein and unsaturated fats, becomes essential in regions where malnutrition and food insecurity are prevalent [3]. Moreover, peanut contribute to the rural economy, particularly among women farmers, who play a central role in its production and commercialization [4].

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However, peanut production in Mozambique faces several challenges that compromise its sustainability and ability to meet growing demand. Among these challenges are post-harvest losses, aflatoxin contamination, and low productivity due to traditional agricultural practices [5]. These limitations not only affect the availability of peanut in the domestic market but also hinder Mozambique from fully capitalizing on the opportunities offered by the international peanut trade [6].

Given the strategic importance of peanut for food security and the local economy, it becomes imperative to explore advanced production estimation methods that can provide more accurate and informed forecasts. Time series models, such as ARIMA (Autoregressive Integrated Moving Average), and artificial neural networks, like LSTM (Long Short-Term Memory), have been widely used in agricultural forecasting due to their ability to capture complex and dynamic patterns in temporal data [7-10]. The ARIMA model is traditionally used for time series forecasting because of its simplicity and effectiveness in capturing linear correlations, while LSTM is particularly effective in modeling nonlinear sequences and long temporal dependencies [11].

Applying these methodologies to forecast peanut production can provide valuable tools for agricultural planning and policy formulation. The combination of ARIMA and LSTM allows for a robust assessment of production trends and offers a comprehensive understanding of the variability and risks associated with agricultural production in Mozambique [12,13]. These forecasts are particularly relevant in the context of the SDGs, where the ability to predict and respond to fluctuations in agricultural production can directly contribute to reducing food insecurity and promoting sustainable agricultural practices.

Furthermore, the use of advanced predictive models can help identify priority areas for intervention, enabling policies and resources to be directed more effectively. By integrating these technologies into agricultural planning, policymakers in Mozambique can enhance the resilience of the agricultural system to climate change and other risk factors, aligning with global sustainable development goals. Therefore, the objective of this research is to develop and evaluate predictive models using ARIMA and LSTM for estimating peanut production in Mozambique. The study aims to provide accurate forecasts that can be used to inform agricultural planning and public policy formulation, focusing on improving food security and meeting the objectives established by SDG 2, particularly in vulnerable regions of the country. By applying these advanced modeling techniques, this research seeks to deepen the understanding of peanut production patterns and promote more effective interventions to strengthen the resilience of Mozambique's agricultural sector.

Literature Review

Global Context of Peanut Production

Peanut is a globally significant crop, whose origin and evolution are closely linked to processes of all polyploidization and domestication. The genetic origin of modern peanut is associated with the natural hybridization between the wild species Arachis duranensis and Arachis ipaënsis, resulting in the allopolyploid genome (AABB) that characterizes cultivated peanut today [14,15]. Archaeological evidence indicates that peanut were domesticated around 8,500 years ago in the region that now comprises southern Bolivia and northern Argentina, highlighting their relevance in the agricultural history of the Americas [16,17].

During the domestication process, human selection favored traits such as increased seed size and productivity, leading to two main subspecies: Arachis hypogaea subsp. hypogaea and Arachis hypogaea subsp. fastigiata, each with distinct plant and seed morphologies [18,19]. Despite limited genetic variation, peanut exhibit remarkable morphological diversity, reflecting the rich biological and cultural diversity associated with this crop [20].

Nutritionally, peanut are highly valued, especially in tropical and subtropical regions, playing a vital role as a source of protein, oil, and essential micronutrients [21,22]. Peanut proteins, particularly the arachin and non-arachin globulins, are crucial in maintaining muscle mass, especially in vegetarian and vegan diets, providing an important source of essential amino acids [23,24].

In addition to their protein content, peanut are an excellent source of B-complex vitamins, including niacin, folate, riboflavin, and thiamine, which are essential for energy metabolism and nervous system health [25]. Niacin, in particular, is known for its ability to lower cholesterol levels, contributing to the prevention of cardiovascular diseases [26]. The vitamin E present in peanut, with its antioxidant properties, protects cells from oxidative stress, reducing the risk of chronic diseases such as cancer and heart problems [27].

Peanut stand out for their versatility, being consumed in various forms, such as raw, roasted, boiled, and baked. Furthermore, they are widely used in the production of peanut butter, oil, and flour, making them an essential ingredient in numerous culinary and industrial products [28]. Their applications extend beyond food, as peanut by-products, such as shells, are used in the manufacture of plastics, abrasives, and other industrial products, highlighting their economic and ecological importance [29].

However, peanut consumption is not without risks. Peanut allergy is one of the most common and can be fatal, accounting for a significant portion of food allergy-related deaths [30]. Additionally, peanut are susceptible to contamination by aflatoxins, toxins produced by fungi that are highly carcinogenic, making proper management during cultivation and storage essential [4].

In the context of sustainable development, peanut play an important role due to their ability to fix nitrogen in the soil, improving fertility and reducing the need for chemical fertilizers [31]. However, peanut cultivation faces challenges such as intensive water use and vulnerability to diseases and pests, requiring more sustainable agricultural practices and ongoing research to improve plant resilience [32].

In terms of food security, peanut is a strategic crop as they provide a dense source of energy and essential nutrients in regions where malnutrition is prevalent. Their ability to be stored for long periods without losing quality makes them a valuable resource for food emergencies and a key element in the diet of many cultures [33]. However, their consumption should be moderated due to the high-fat content, though most fats are unsaturated and beneficial for heart health.

Peanut cultivation is influenced by climatic factors and soil characteristics, being a typical crop of tropical and subtropical regions. Peanut prefer temperatures between 20°C and 30°C for optimal growth and are sensitive to extreme temperatures, which can significantly affect production [34,35]. Additionally, water management is crucial, as the crop requires an even distribution of rainfall throughout its growing cycle [36].

Peanut production faces constant challenges from pests and diseases, which can drastically reduce yields. Strategies such as the use of resistant cultivars and biocontrol practices are essential to mitigate these impacts and ensure sustainable production [37,38].

Globally, peanut production is dominated by a few countries that play crucial roles in both the quantity produced and the quality of derived products. China and India are the largest peanut producers, accounting for more than.

Peanut Production in Mozambique

Peanut is a crop of great importance in Mozambique, playing a crucial role in both the country's food security and economy. As one of the main legumes cultivated, peanut is vital for the subsistence of rural populations, particularly due to their ability to grow in less fertile soils and under adverse climatic conditions. Their versatility and nutritional value make them a vital source of protein, vitamins, and minerals, significantly contributing to food security in regions where access to other protein sources is limited [1,2].

Peanut production in Mozambique is primarily carried out by smallholder farmers who rely on traditional farming practices. Most of the production is concentrated in the northern provinces, such as Nampula, Zambézia, and Cabo Delgado, which together account for a significant portion of the total cultivated area and national peanut production. Nampula, for instance, stands out as the leading producer, contributing around 44.7% of the country's total peanut production [5].

Despite the importance of peanut in the Mozambican diet and economy, production faces several challenges. The lack of access to modern inputs, such as improved seeds and fertilizers, as well as the absence of adequate technical assistance, limits the productivity and efficiency of farmers [39]. Additionally, post-harvest management practices, which are often inadequate, result in significant production losses, affecting both the quality and quantity of peanut available for consumption and commercialization [40].

Post-harvest losses of peanut in Mozambique vary significantly across provinces. Studies indicate that loss rates can reach up to 25% of the total production, with large peanut being the most affected [41]. These losses are attributed to various factors, including improper harvesting, storage, and handling practices, as well as the lack of adequate infrastructure for processing and preserving peanut [42].

Aflatoxin contamination is another critical issue affecting peanut production in Mozambique. Aflatoxins are toxins produced by fungi that can develop during the improper storage of peanut, especially under high humidity and temperature conditions [4]. The presence of aflatoxins not only poses a serious public health risk but also limits Mozambican farmers' access to international markets, where aflatoxin levels are strictly regulated [6].

To mitigate these challenges, it is essential to improve post-harvest management and storage practices, as well as to promote the use of technologies that can reduce losses and aflatoxin contamination [43]. Investments in storage infrastructure, farmer training, and the development of public policies that encourage sustainable agricultural practices are crucial to ensuring the quality and safety of peanut produced in Mozambique [44].

In addition to production and post-harvest challenges, the peanut market in Mozambique also faces limitations. The commercialization of peanut is predominantly informal, with much of the production being consumed locally or sold in informal markets [5]. This results in low incomes for farmers and limits the potential for growth in peanut production as a sustainable source of income [39].

The promotion of urban and peri-urban agriculture in Mozambique has been identified as an effective strategy to increase peanut production and improve food security in urban areas. These practices not only help meet the food demand of urban populations but also provide an additional source of income for urban farmers [45]. Urban agriculture also contributes to the resilience of urban food systems by supporting local production and reducing dependence on food imports [46].

The genetic diversity of peanut varieties cultivated in Mozambique is vast, with different genotypes being selected to maximize productivity and adaptability to local conditions. However, the genotype-environment interaction remains a challenge, with variability in climatic and soil conditions affecting peanut production in different regions of the country [47].

Initiatives such as the SUSTENTA program, implemented nationwide, have shown promising results in increasing peanut productivity in Mozambique. Between 2020 and 2022, the average productivity increased significantly, reaching 0.5 tons per hectare [5]. This growth can be attributed to the support provided to farmers in terms of inputs, technical training, and market access, reflecting the importance of agricultural policies oriented towards sustainability.

Despite the advances in productivity, total peanut production in Mozambique has decreased compared to 2014 and 2016 levels, prior to the implementation of the Sustainable Development Goals (SDGs) [48]. This decline raises concerns about the country's ability to achieve SDG 2, which aims to eradicate hunger and malnutrition by 2030. Maintaining peanut production and other food crops is crucial to ensuring the food security of the Mozambican population.

An analysis of the distribution of peanut production by province in Mozambique reveals significant disparities. While provinces such as Nampula and Zambézia stand out for their high production and commercialization, other regions like Maputo and Gaza face considerable challenges in the commercialization chain, resulting in low sales rates [5]. Improving logistics and market access is essential to increasing the commercialization of peanut in Mozambique and ensuring that farmers can fully benefit from their labor.

Finally, technical training of farmers in efficient harvesting and storage practices, along with investment in technologies that minimize post-harvest losses, is crucial to reducing losses and ensuring better food security in Mozambique. Addressing these issues in an integrated and sustainable manner will allow the country to improve its peanut production, contributing to the economic development and social well-being of rural communities.

Previous Studies on Agricultural Production Modeling and Peanut Forecasting

The Auto-Regressive Integrated Moving Average (ARIMA) models have been widely utilized for the analysis and forecasting of non-stationary time series, offering a robust approach to capturing and predicting the dynamics of data over time [49]. The inclusion of a differencing component in ARIMA transforms a non-stationary series into a stationary one, enabling the application of the model to forecast future trends and patterns [50]. The versatility of the ARIMA model, expressed in its general formula ARIMA (p, d, q)—where p, d, and q represent the order of the autoregressive component, the number of differences needed, and the order of the moving average component, respectively—allows its application in various agricultural contexts [51].

Scientific literature highlights the extensive use of ARIMA models in forecasting various agricultural parameters, such as oilseed production and crop productivity in different regions of the world. For instance, studies in India have applied ARIMA to predict oilseed production, demonstrating its effectiveness in capturing complex temporal patterns and providing reliable forecasts for strategic decision-making [52]. The application of ARIMA in agricultural production forecasting has proven valuable, particularly in scenarios where accuracy is crucial for ensuring food security and optimizing resource use [53].

Using ARIMA models to forecast agricultural yields has been particularly effective for crops like wheat, rice, and maize, where the ability to accurately predict future yields allows for better resource allocation planning and risk mitigation associated with climatic variability [54]. Studies in India have shown that ARIMA forecasts have helped optimize resource use and plan mitigation strategies, which is essential for ensuring food security in vulnerable regions [55].

Additionally, the application of ARIMA models has been fundamental in analyzing the dynamic relationships between cultivated areas and production in different regions, aiding in understanding past trends and formulating future forecasts that support agricultural policy formulation [56]. The ability to predict fluctuations in agricultural production allows for the implementation of strategies that minimize losses and improve operational efficiency, promoting stability in agricultural markets [57].

In agricultural management, using ARIMA models to predict crop prices based on historical data has proven to be a valuable tool for farmers. By providing insights into price trends, these models assist in strategic decision-making, such as crop selection and optimal harvest timing, reducing financial risks and improving farmers' resilience [58]. The accuracy of ARIMA forecasts is crucial for negotiating contracts and managing inventories, contributing to the stability and sustainability of the agricultural sector [59].

Integrating ARIMA models into decision support systems enhances farmers' ability to manage price fluctuations and market uncertainties, improving agricultural operations' efficiency and optimizing economic outcomes [60]. The application of these models has a significant impact on mitigating food insecurity by providing reliable forecasts on crop production and prices, helping stabilize markets and ensuring a continuous food supply [61].

On the other hand, Artificial Neural Networks (ANNs) have emerged as a transformative tool in modern agriculture, offering advanced solutions for modeling and forecasting agricultural production [62]. Inspired by the structure of the human brain, ANNs can learn complex patterns from large volumes of data, making them ideal for dealing with the variability and complexity of agricultural systems [63]. Recent research shows that ANNs can accurately predict the production of crops such as wheat, rice, maize, and soybeans based on variables like climatic conditions, soil properties, and agricultural management practices [64].

ANNs have proven particularly effective in forecasting agricultural time series, outperforming traditional methods by providing more precise and detailed predictions. Studies like those of Sadenova et al. demonstrate that ANNs can accurately predict yields for cereals, legumes, oilseeds, and other crops using historical production data and environmental conditions, offering advanced tools for risk management and resource optimization [65]. Beyond yield forecasting, ANNs are used for early detection of diseases and pests in crops, processing satellite images and drones equipped with sensors to identify stress signals in plants. This application allows for rapid and effective interventions, protecting crops and minimizing losses, which is crucial for ensuring food security, particularly in vulnerable regions [66].

Applying ANNs in demand forecasting and inventory management in agricultural supply chains has also shown promising results. By accurately predicting product demand, ANNs enable more efficient inventory management, reducing operational costs and ensuring that food reaches consumers in a timely manner [67]. Therefore, both ARIMA models and ANNs play critical roles in forecasting agricultural production and managing associated risks, contributing to global food security. By providing accurate forecasts and enabling more efficient resource management, these technologies emerge as indispensable tools in promoting agricultural sustainability and mitigating the effects of food insecurity.

Materials and Methods

Materials

This study focused on analyzing peanut 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 peanut 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.

Data Source

The peanut 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.

Methods

ARIMA Modeling

Model Identification

For ARIMA modeling, model identification was conducted by analyzing the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots of the peanut production time series in Mozambique. The analysis of these plots allowed for determining the orders of the autoregressive (AR), differencing (I), and moving average (MA) components, establishing the initial structure of the ARIMA models for subsequent parameter estimation.

Parameter Estimation

The parameters of the ARIMA models were estimated using peanut production data from 1961 to 2009. The estimation process was conducted using maximum likelihood methods, which adjusted the AR and MA component parameters to adequately capture the temporal dependencies of the differenced time series. Each model was adjusted and refined to ensure the accuracy and adequacy of the modeling.

Validation and Evaluation

The validation of the ARIMA models was performed using actual peanut production data from 2010 to 2020. Diagnostic tests, such as the Box-Pierce test, were applied to verify the absence of autocorrelation in the residuals of the fitted models, while the ARCH test was used to assess the presence of heteroscedasticity. The models were evaluated by comparing the forecasts with observed data using metrics such as RMSE and MAPE.

LSTM Neural Networks

Data Preparation

For LSTM neural network modeling, peanut production data was normalized using the MinMaxScaler, scaling them to a range between 0 and 1. The data were then organized into time sequences of five consecutive years, creating input (X) and output (y) datasets for the model to predict the subsequent value based on the previous five years. Data preparation was conducted using production data from 1961 to 2013.

Model Architecture and Training

The LSTM model was structured with two layers, each containing 50 LSTM units, followed by a dense layer responsible for generating the final predictions. The model was trained over 100 epochs using the Adam optimizer with a learning rate of 0.01. During training, the model adjusted its weights to minimize the mean squared error between predictions and actual values, ensuring model convergence without displaying output during execution.

Evaluation and Validation

The evaluation and validation of the LSTM model were conducted using actual peanut production data from 2014 to 2022. The model's accuracy was assessed based on metrics such as RMSE and MAPE, and cross-validation was employed to ensure the model maintained its predictive capability across different data subsets, ensuring the robustness and generalization of the predictions.

Forecasting for 2023 to 2030

The LSTM model, combined with the Bootstrapping technique, was used to generate peanut production forecasts in Mozambique for the period from 2023 to 2030. The Bootstrapping technique was employed to calculate 95% confidence intervals, providing an estimate of the uncertainty associated with the forecasts, which were subsequently used to support strategic planning and decision-making in the agricultural sector.

Selection of the Best Model for Estimating Agricultural Production

To identify the most suitable model for forecasting peanut 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.

Results

Exploratory Analysis of the Peanut Time Series

The statistical analysis of peanut production in Mozambique (1961-2022), based on annual data, provides a detailed understanding of the characteristics and variability of this crop over time (Table 1). The average annual peanut production is 115,434.68 tons, with a median of 114,081 tons. The close proximity between the mean and median indicates a relatively symmetrical distribution, although the skewness of 0.93 suggests a slight rightward tilt. This skewness points to the presence of years with slightly higher productions, raising the mean above the median.

The mode of 140,000 tons indicates that this production level was the most frequently observed over the years, suggesting that conditions were favorable for achieving this level of production in multiple years. The standard deviation of 26,544.78 tons and the variance of 704,625,435.6 reveal moderate variability in annual production. The coefficient of variation of 22.99% indicates that, relative to the mean, peanut production has a relatively controlled variation, demonstrating a certain consistency in production over the years.

An analysis of the extreme production values shows a maximum of 225,824 tons and a minimum of 60,000 tons, resulting in a range of 165,824 tons. This range reflects annual fluctuations, possibly influenced by external variables such as climatic conditions, agricultural practices, and economic policies.

The kurtosis measure of 3.70 indicates a leptokurtic distribution, characterized by longer tails and a more pronounced peak compared to a normal distribution. This suggests the presence of some outliers, with years of significantly different production from the average, both higher and lower, contributing to the observed variability.

Table 1: Descriptive Measures of the Annual Peanut Production Series

Descriptive Statistics	Value
Mean	115434.6774
Median	114081
Mode	140000
Variance	704625435.6
Standard Deviation	26544.7817
Coefficient of variation	0.229955004
Maximum	225824
Minimum	60000
Skewness	0.928587985
Kurtosis	3.702622871
Range	165824
n	62

Stationarity Test or Unit Root Test of the Peanut 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.

Analysis of the Time Series for Peanut Production in Mozambique

The time series graph of peanut production in Mozambique from 1961 to 2022 reveals significant variation in production over the years (Figure 1). During the 1960s and 1970s, there was an increase in production, followed by fluctuations in the subsequent decades. In recent years, peanut production appears to have stabilized at higher levels, although some variations still occur.

The differenced series of peanut production highlights the annual variation, with differentiation applied to remove long-term trends and focus on short-term changes. This approach allows for a more precise analysis of interannual fluctuations, facilitating the identification of temporary factors or specific events that influence peanut production from one year to the next.

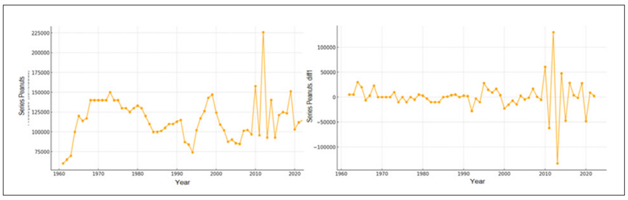

Figure 1: Time Series Analysis of Peanut Production in Mozambique (1961-2022)

Decomposition of the Time Series of Peanut Production in Mozambique

The decomposition of the time series reveals insights into the trend, seasonality, and residual components (Figure 2). The trend shows fluctuations over the decades, without a clear direction, but it does indicate stabilization at higher levels in more recent years. The graphical analysis does not reveal an evident seasonal pattern, suggesting that peanut production does not follow consistent seasonal cycles during the analyzed period. The residuals display variability that is not explained by the trend or seasonality, indicating the presence of external or random factors that influence production.

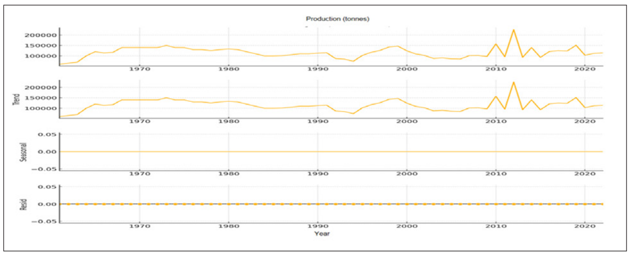

Figure 2: Decomposition of the Time Series of Peanut Production in Mozambique

Autocorrelation Function (ACF) of Peanut Production in Mozambique

The Autocorrelation Function (ACF) of the original peanut production series in Mozambique reveals significant correlations at multiple lags, suggesting a strong trend or seasonal component (Figure 3). This indicates that past values have a persistent influence on future values, characterizing a dependent temporal structure that reflects consistent patterns over the years.

After differentiating the series, the ACF shows a drastic reduction in autocorrelations, signaling the elimination of trends or seasonality present in the original series. This process transforms the series into something closer to white noise, which is essential to meet the stationarity requirements necessary for predictive models like ARIMA, ensuring the validity and accuracy of subsequent analyses.

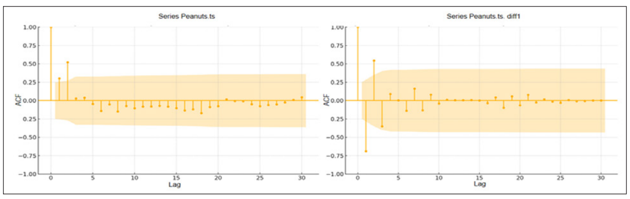

Figure 3: Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) of Peanut Production in Mozambique

Partial Autocorrelation Function (PACF) of Peanut Production in Mozambique

The PACF (Partial Autocorrelation Function) graph of the original series shows some peaks at the initial lags, suggesting the presence of low-order autoregressive components (Figure 4). This indicates that past values moderately influence future values, reflecting significant correlations between observations that are close in time.

The presence of peaks at the initial lags in the PACF graph confirms the existence of low-order autoregressive components, meaning that past values have a moderate influence on future values. This pattern suggests that the series can be effectively modeled with a low-order autoregressive component, capturing the essential dynamics of the temporal relationships between observations.

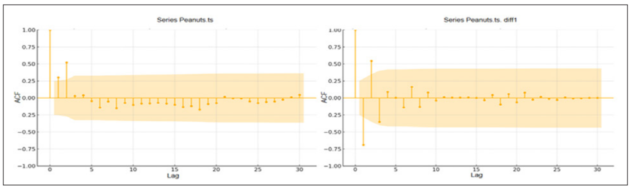

Figure 4: Partial Autocorrelation Function (PACF) of Peanut Production in Mozambique

Augmented Dickey-Fuller (ADF) Test for the Peanut Series

The ADF test statistic value of -2.8918 for the original series suggests that the null hypothesis of a unit root cannot be rejected at the 5% significance level (Table 2), indicating that the series is non-stationary. This implies that the original series exhibits statistical properties, such as mean and variance, that change over time, making it challenging to apply models that require stationarity.

After differencing, the p-value of 0.000 indicates that the null hypothesis of a unit root is rejected, confirming that the differenced series is stationary. This means that the statistical properties of the series remain constant over time, making it suitable for applying forecasting models that assume stationarity, such as ARIMA models, allowing for more accurate and reliable analysis of short-term variations.

Table 2: Augmented Dickey-Fuller (ADF) Test for the Peanut Series

Test Statistic	p-Value	Lags	n	Critical Value		
				(1%)	(5%)	(10%)
Orginal Series						
-2.8918	0.0463	4	57	-3.5507	-2.9138	-2.5946
Differenced Series						
-6.240	0.000	1	59	-3.546	-2.912	-2.594

Estimation with Time Series Models (ARIMA) for Peanut Production

Model Identification

Based on the analysis of the ACF and PACF plots for the differenced peanut production series in Mozambique, it is possible to identify the most appropriate temporal structure for modeling. The ACF plot, which shows a gradual decay after the first lag, suggests the presence of a significant autoregressive component in the time series. On the other hand, the PACF plot exhibits an abrupt cutoff after the first lag, indicating that an ARIMA (1,1,0) model would be suitable to capture the underlying dynamics of the series, as it considers the influence of the previous value in predicting the current value.

However, the significance observed up to the second lag in the PACF also suggests the viability of an ARIMA (2,1,0) model. This model may be able to capture more complex relationships in the time series by considering not just the immediate lag but also the second lag, which can be important in series with more persistent patterns over time.

Additionally, the inclusion of a moving average (MA) component could help smooth out temporary fluctuations and capture abrupt shocks in the series. Therefore, the ARIMA (1,1,1) model is proposed as a robust alternative, combining autoregressive effects with the ability to model temporary shocks. This model could provide more accurate forecasts in time series characterized by volatility or variations that are not predicted solely by past values.

Parameter Estimation

The analysis of the estimated parameters for the ARIMA models fitted to peanut production in Mozambique reveals significant differences in the significance and magnitude of the autoregressive (AR) and moving average (MA) parameters (Table 3). In the ARIMA (1,1,0) model, the AR(1) parameter is highly significant (p-value = 0.0000) with an estimate of -0.643128, indicating a strong influence of past values on the future production forecast. This model effectively captures the short-term temporal dependence in the series.

In the ARIMA (2,1,0) model, both AR(1) and AR(2) parameters are significant, with AR(1) showing a high t-statistic (-7.970266), suggesting that this model can capture more complex relationships in the time series, including the influence of two past periods. The AR(2) parameter is also significant (p-value = 0.0000), reinforcing the suitability of this model for capturing longer-term dynamics in the series.

The ARIMA (1,1,1) model combines an autoregressive component AR(1) and a moving average component MA(1), both of which are highly significant. This model may be more robust, as it combines the ability to capture temporal dependencies with the smoothing of abrupt fluctuations.

Based on these results, all the presented ARIMA models demonstrate statistically significant parameters, but the ARIMA(1,1,1) model stands out by effectively combining autoregressive and moving average components. This makes it the most suitable choice for forecasting peanut production in Mozambique, as it captures temporal dependencies and smooths out temporary shocks, offering more accurate and stable predictions.

Table 3: Parameter Estimates for the ARIMA (p,d,q) Model Fitted to Peanut Production

Model	Parameter	Estimates	t-Stat	P-value
ARIMA(1,1,0)	AR(1)	-0.643128	-13.781429	3.30e-43
ARIMA(2,1,0)	AR(1)	-0.540914	-7.970266	6.69e-07
ARIMA(1,1,1)	AR(2)	0.141328	11.004652	3.15e-10
ARIMA(1,1,1)	AR(1)	-0.713721	-5.2282247	1.71e-07
ARIMA(1,1,1)	MA(1)	0.129644	10.5418300	5.78e-8

Diagnostic Test of Residuals for Peanut Production Models

The analysis of Table 4, which presents the diagnostic tests of the residuals from the ARIMA models applied to peanut production, reveals that all models have high p-values in the Box-Pierce test, indicating the absence of significant autocorrelation in the residuals. This suggests that the models fit the time series well, capturing temporal dependencies without leaving unexplained patterns in the residuals.

Regarding the ARCH test, the high p-values across all models indicate no significant heteroscedasticity in the residuals. This implies that the residual variance is constant over time, which is desirable as it suggests the model is stable and consistent in its predictive capacity.

However, all models fail the normality test of the residuals, as indicated by the low p-values in the Shapiro-Wilk and Jarque-Bera tests. This violation of normality is a common concern in time series analysis but does not invalidate the use of the models for forecasting. In practical contexts, as long as the residuals do not exhibit autocorrelation and heteroscedasticity, the model can still be considered adequate. The violation of normality may be attributed to the presence of outliers or non-normal data distributions, which are frequently observed in agricultural production time series due to external variability factors such as climate and agricultural policies.

Given that all models show good results in the autocorrelation and heteroscedasticity tests, but the ARIMA (1,1,1) model efficiently combines autoregressive and moving average components, this model remains the most robust for estimating peanut production. It offers a balanced combination of accuracy and the ability to smooth out temporary shocks, despite the violation of the normality assumption.

Table 4: Diagnostic Test of Residuals for Peanut 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)	7.04142	0.72152	12.61422	0.24604	0.94479	0.0075	21.250	0.0000
ARIMA(2,1,1)	6.30452	0.78906	15.66523	0.10962	0.93807	0.0037	20.521	0.0000
ARIMA(1,1,1)	6.4711	0.77424	14.23508	0.16253	0.94120	0.0051	21.526	0.0000

Comparison of Model Performance

The analysis of Table 5, which compares the performance of ARIMA models fitted to peanut production, reveals some important differences in terms of predictive accuracy and data fit. The ARIMA (1,1,1) model shows the lowest RMSE (31,856.41) and the lowest MAPE (22.97%), suggesting that it provides more accurate predictions with a lower mean absolute percentage error compared to the other models. This model also has intermediate values in the information criteria (AIC, BIC, HQIC), indicating a good balance between complexity and data fit.

The ARIMA (1,1,0) model performs slightly below the ARIMA (1,1,1), with an RMSE of 31,981.82 and a MAPE of 23.45%. Although its information criteria (AIC and BIC) are slightly better than those of the ARIMA (1,1,1), the difference is marginal, and the slightly higher RMSE and MAPE suggest that it may not capture the nuances of the time series as effectively as the ARIMA (1,1,1).

On the other hand, the ARIMA (2,1,1) model has the highest RMSE (32,123.74) and the highest MAPE (24.12%), indicating that this model is the least accurate among the three in forecasting peanut production. Although this model has a more complex structure, its greater complexity does not translate into better predictive performance, as evidenced by its slightly higher values in the information criteria.

Given the results presented, the ARIMA (1,1,1) model stands out as the best option for estimating peanut production in Mozambique. It combines predictive accuracy with a sufficiently complex structure to capture the underlying dynamics of the time series, while maintaining an acceptable balance between fit and complexity penalty, as indicated by the information criteria.

Table 5: Comparison of Model Performance for Peanut Production

Model	AIC	BIC	HQIC	RMSE	MAPE
ARIMA(1,1,0)	855.13	861.74	857.76	31981.82	23.45%
ARIMA(2,1,1)	857.91	866.17	861.61	32123.74	24.12%
ARIMA(1,1,1)	856.04	863.65	859.67	31856.41	22.97%

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

The analysis of Table 6, which compares peanut production forecasts in Mozambique from 2010 to 2020 with actual values, shows that all three ARIMA models exhibit similar performance, with some differences that are important to consider when selecting the most appropriate model. The RMSE (Root Mean Square Error) and MAPE (Mean Absolute Percentage Error) values indicate the accuracy of the models relative to the observed data.

The ARIMA (1,1,0) model has the lowest RMSE (32,502.69), suggesting that it has a slight edge in terms of absolute accuracy. The MAPE of 24.23% also reflects that this model offers reasonably accurate forecasts, with a lower mean absolute percentage error compared to the other two models. However, the model seems to have underestimated production in certain years, particularly in 2010 and 2011.

On the other hand, the ARIMA (2,1,1) model has the highest RMSE (33,343.45) and the highest MAPE (24.87%), indicating that, despite its additional complexity, it does not significantly improve accuracy compared to the other models. This performance may be due to an overestimation of production in years like 2014 and 2020, where the predicted values were considerably higher than the actual values.

The ARIMA (1,1,1) model strikes a good balance between the other two, with an RMSE of 33,090.43 and a MAPE of 24.65%. Although it does not have the lowest absolute error, its performance is consistent, and it avoids large deviations in forecasts for any specific year. Given that it combines autoregressive and moving average components, this model offers robustness that can be advantageous for capturing different dynamics in the time series.

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

Year	Actual Dada	Predicted Data		
		ARIMA (1,1,0)	ARIMA (2,1,1)	ARIMA (1,1,1)
2010	157685	100341.69	99935.38	99937.40
2011	95700	118656.81	124125.31	121859.50
2012	225824	135564.26	137805.06	136548.55
2013	92740	142137.68	146677.90	144525.85
2014	140124	178329.98	183117.19	181011.07
2015	92797	109650.05	95684.79	101004.30
2016	121000	123234.30	125093.53	125511.23
2017	125000	102861.88	99055.96	100286.08
2018	123438	122427.49	126822.23	125349.13
2019	151220	124442.57	124848.22	124305.07
2020	103000	133352.63	135971.58	134880.77
RMSE		32502.69	33343.45	33090.43
MAPE		24.23%	24.87%	24.65%

Therefore, the ARIMA (1,1,1) model is the most suitable for estimating peanut production in Mozambique, as it combines higher predictive accuracy with a sufficiently robust structure to capture the complexity of the time series, maintaining a balance between fit and complexity penalty. Additionally, it offers more consistent forecasts and avoids large deviations in specific years, making it the ideal choice for this context.

Forecasted Peanut Production in Mozambique from 2023 to 2030

Table 7 presents the forecasted peanut production values in Mozambique for the period from 2023 to 2030, based on the ARIMA model. The predicted values indicate relatively stable production over the years, consistently hovering around 114,000 tons.

However, the 95% confidence intervals reveal increasing uncertainty in the forecasts as time progresses. In 2023, the confidence interval ranges between 71,430.55 and 156,648.56 tons, indicating moderate uncertainty. From 2025 onwards, there is a noticeable widening of the confidence intervals, with the lower limit gradually decreasing and the upper limit increasing, reaching a considerable range by 2030, where the interval spans from 29,343.65 to 198,847.07 tons.

This growing uncertainty in the confidence intervals suggests that while the ARIMA model predicts stable peanut production, there is significant uncertainty regarding the actual values that may be achieved, particularly in the more distant years. This scenario underscores the importance of considering external and unforeseen factors that could impact peanut production in Mozambique in the coming years.

Table 7: Forecasted Peanut Production in Mozambique from 2023 to 2030 by the ARIMA Model

Year	Forecasted Value	Confidence Intervals (95%)	
		Lower Bound	Upper Bound
2023	114039.55	71430.55	156648.56
2024	114126.95	67979.36	160274.54
2025	114064.57	55851.67	172277.48
2026	114109.09	51587.86	176630.32
2027	114077.32	43908.56	184246.07
2028	114099.99	39476.41	188723.58
2029	114083.81	33653.32	194514.30
2030	114095.36	29343.65	198847.07

Estimation with the LSTM Model for Peanut Production

Model Training with LSTM

The training of the LSTM model for the peanut production time series in Mozambique utilized historical data from 1961 to 2013. Initially, the data were normalized using the MinMaxScaler, scaling them to a range between 0 and 1, thereby optimizing the model's performance. The time sequence was structured in five-year blocks, enabling the model to capture the temporal dependencies within the series. This process generated input (X) and output (y) datasets, with the model trained to predict the subsequent value in the series based on the previous five years.

The LSTM model was built with two layers, each containing 50 LSTM units, followed by a dense layer to produce the final predictions. This architecture is effective for handling complex temporal dependencies, capturing patterns that simpler models might miss. The training process spanned 100 epochs, employing the Adam optimizer with a learning rate of 0.01, which adjusted the model's weights to minimize the mean squared error between predictions and actual values. Although the model was trained without displaying output during execution, it was carefully monitored to ensure convergence, resulting in a model that accurately captures the trends in peanut production over time and is ready to be evaluated and applied to future forecasts.

Model Evaluation

Table 8 presents the evaluation of the LSTM model based on the actual peanut production data in Mozambique from 2014 to 2022. The model demonstrated high accuracy in its predictions, with an average RMSE of 2,216.14 tons and an average MAPE of 1.78%, indicating that, on average, the model's predictions deviated only 1.78% from the actual values. This performance suggests that the LSTM model effectively captured the trends in the peanut production time series, with relatively small errors over the years analyzed. The consistency of the low RMSE and MAPE values, especially in recent years, further reinforces the robustness of the model.

Based on these results, the LSTM model proves to be highly suitable for estimating peanut production in Mozambique for the period from 2023 to 2030. The observed accuracy in the evaluation of previous years indicates that the model is capable of reliably predicting future values, making it a valuable tool for agricultural planning and strategic decision-making. The model's stability, as evidenced by the low forecast errors, suggests that it will continue to provide accurate estimates for future production, even with potential annual fluctuations.

Table 8: LSTM Model Evaluation with Real Peanut Production Data from 2017 to 2022

Year	Actual Dada	LSTM Model		
		Predicted Data	RMSE	MAPE
2014	140124	144039.67	3915.67	2.79%
2015	92797	94131.76	1334.76	1.44%
2016	121000	121740.14	740.14	0.61%
2017	125000	122334.14	2665.86	2.13%
2018	123438	120805.27	2632.73	2.13%
2019	151220	147076.75	4143.25	2.74%
2020	103000	105338.40	2338.4	2.27%
2021	111924	112625.67	701.67	0.63%
2022	114162	115634.75	1472.75	1.29%
Mean	120296.1	120414.06	2216.14	1.78%

Forecasts for 2023 to 2030

Table 9 presents the peanut production estimates in Mozambique for the period from 2023 to 2030, using the LSTM model combined with the Bootstrapping technique. The predictions indicate relatively stable production over the years, with values ranging between approximately 110,000 and 116,000 tons. The production behavior does not show significant fluctuations, suggesting stability in annual peanut production, with minor variations that can be attributed to natural variability and external conditions.

The average annual growth rate of peanut production in Mozambique between 2023 and 2030 is approximately -0.52%, reflecting a slight declining trend, particularly noticeable in 2026 and 2028. However, the variations are minimal, and the confidence intervals show that although there is some uncertainty in the forecasts, peanut production is expected to remain within a predictable range.

This behavior suggests that, barring significant external disruptions, peanut production in Mozambique is likely to remain relatively constant until 2030, with a slight downward trend that could be monitored and, if necessary, adjusted through appropriate agricultural interventions and policies.

Table 9: Forecasted Peanut 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	115054.45	110251.59	119857.31
2024	116122.13	112727.49	119516.76
2025	114524.37	112900.39	116148.35
2026	112499.96	108035.26	116964.67
2027	112954.98	109122.69	116787.27
2028	110788.89	105909.25	115668.53
2029	112262.13	110412.77	114111.48
2030	110833.37	109099.75	112566.98

Discussion

The analysis of peanut production in Mozambique between 1961 and 2022 reveals relatively stable production, with an average of 115,434.68 tons annually. However, moderate variability in production, indicated by a coefficient of variation of 23%, points to fluctuations influenced by factors such as climate change, agricultural policies, and variations in farming practices. The presence of outliers, evidenced by a kurtosis of 3.70, suggests that there were years with extremely high or low production, reflecting the crop's susceptibility to extreme events like droughts or floods, which is consistent with observations made by Baez et al. regarding the vulnerability of Mozambican agriculture to external variables [68].

Studies like Shitikova and Povarnitsyna reinforce that the slight rightward skewness, with a value of 0.93, indicates that in some years, production exceeded the average, possibly due to favorable agricultural conditions or effective policy interventions [69]. However, to mitigate fluctuations and ensure more stable production, it is necessary to implement resilient agricultural technologies and improve storage and distribution infrastructure, as suggested by Richard et al. [70]. These efforts can help ensure more predictable production, which is crucial for sustainable agricultural development in Mozambique.

The time series analysis of peanut production in Mozambique from 1961 to 2022 reveals a complex behavior characterized by significant fluctuations over the decades, stabilization in certain periods, and marked variability. The decomposition of the time series, which separates trend, seasonality, and residual components, indicates that peanut production does not follow a clear seasonal pattern.

This lack of seasonality is corroborated by studies by Kephe et al, which suggest that food crops in tropical regions like Mozambique face challenges related to climatic unpredictability, making it difficult to form consistent seasonal patterns [71]. Additionally, Grigorieva et al. point out that the lack of infrastructure and reliance on traditional farming practices contribute to the absence of seasonality, reflecting an unstable agricultural scenario [72].

The ACF and PACF plots reveal significant peaks at the first lags, suggesting the presence of low-order autoregressive components. These patterns indicate that peanut production is influenced by past events, aligning with the findings of Guo et al. and Oktoviany et al, which demonstrate that agricultural time series often exhibit correlations with previous values due to dependence on factors such as climate and policy decisions [73,74].

The ADF test confirms that the original series is not stationary, which is consistent with the literature, as highlighted by Ray et al. who emphasize the importance of differencing in volatile time series [8]. After differencing, the series becomes stationary, allowing the application of ARIMA models, facilitating more accurate predictions in contexts of high variability, as observed by Guo in his study on agricultural economics and yield forecasting [75].

The identification of ARIMA models for peanut production in Mozambique, based on the ACF and PACF plots, suggests that the ARIMA (1,1,0) model is suitable due to its ability to capture the short-term dependence observed in the time series. The gradual decay in the ACF and the abrupt cut-off in the PACF after the first lag indicate that peanut production has a strong dependence on past values, a common behavior in agricultural time series, as highlighted by Bhimavarapu et al. [76].

However, the inclusion of additional components, such as ARIMA (2,1,0) and ARIMA (1,1,1), allows capturing more complex patterns, considering the influence of multiple previous periods and temporary shocks. Studies like those of Khadka and Chi and Zelingher and Makowski reinforce the effectiveness of these models in scenarios of high variability, common in regions like Mozambique [77,78].

The parameter estimation for the ARIMA models shows that the ARIMA (1,1,1) model stands out by combining autoregressive and moving average components, capturing both temporal dependencies and smoothing abrupt fluctuations. This balance is crucial in agricultural series, where factors like climate and policies can introduce significant shocks in production, as observed by Emediegwu and Ubabukoh [79].

The statistical significance of the AR and MA parameters in ARIMA (1,1,1) suggests that this model is more robust in predicting peanut production, which is corroborated by its better performance in information criteria and diagnostic tests. Despite the violation of normality in the residuals, the absence of significant autocorrelation and heteroscedasticity in the residuals validates the use of the model for forecasting [80].

The performance comparison between the ARIMA models confirms the superiority of the ARIMA (1,1,1), with the lowest RMSE and MAPE, indicating greater accuracy in predictions. Although the ARIMA (2,1,1) model has a more complex structure, its inferior performance suggests that adding additional components does not necessarily translate into better forecasting, a phenomenon discussed by Albeladi et al. [81]. The training and evaluation analysis with real data also reflects the consistency of ARIMA (1,1,1) in capturing the dynamics of peanut production, making it the best choice for future projections in Mozambique, especially in an agricultural context marked by volatility and uncertainties.

The comparison between the LSTM model and ARIMA (1,1,1) based on MAPE reveals that the LSTM model significantly outperforms ARIMA in terms of predictive accuracy. The LSTM exhibited a mean MAPE of 1.78%, while the ARIMA (1,1,1) had a MAPE of 24.65%. This notable difference can be attributed to the LSTM's ability to capture more complex and nonlinear temporal patterns, which is a limitation of ARIMA models, especially in agricultural time series that are influenced by multiple external factors, such as climate and agricultural policies.

Studies highlight that recurrent neural network, like LSTM, are particularly effective for modeling time series with high volatility and complex temporal dependencies, common characteristics in agricultural production in regions like Mozambique [82]. The LSTM's superiority can also be explained by its architecture, which includes two LSTM layers with 50 units, capable of retaining information over several periods and identifying patterns that a linear ARIMA model may not capture.

Additionally, the LSTM's training with a normalized dataset and the use of a five-year window allowed the model to better learn the temporal dependencies, resulting in more accurate predictions. The LSTM's ability to handle the complexity and volatility of peanut production is corroborated by studies such as Hopfe et al, which emphasize the advantage of neural networks in predicting nonlinear and noisy time series [83]. Thus, for forecasting peanut production in Mozambique, the LSTM model emerges as a more effective and reliable tool, particularly in a dynamic agricultural environment subject to substantial variability.

The forecast of peanut production in Mozambique for the period 2023 to 2030, using the LSTM model combined with the Bootstrapping technique, offers a perspective of stability with a slight declining trend. The relatively stable production behavior, ranging between 110,000 and 116,000 tons, reflects a common reality in sub-Saharan African countries, where the agricultural sector faces persistent challenges.

Studies such as those by Medellín-Azuara et al. and Paudel et al. indicate that in regions vulnerable to climate change and global market variability, stability in agricultural production may mask the underlying lack of resilience in the sector [84,85]. This is particularly true in Mozambique, where agriculture still relies heavily on traditional methods and low investment in agricultural infrastructure.

The slight declining trend of -0.52% per year in peanut production reflects the vulnerability that the forecasts capture. This behavior may be related to various factors, such as the impact of climate change on agricultural productivity, soil depletion, and the lack of access to advanced agricultural technologies. Studies emphasize that crops like peanuts are particularly sensitive to climatic variations, which may explain the small fluctuations predicted, especially in years like 2026 and 2028 [86]. The Bootstrapping technique, by providing confidence intervals, reinforces this uncertainty, highlighting the need to consider the impact of extreme events and future climate variability.

The relationship between peanut production and food security in Mozambique is critical, especially in rural areas, where peanuts are not only a subsistence crop but also an important source of protein. Studies such as FAO emphasize that any decline in agricultural production can have direct impacts on food availability, exacerbating food insecurity [87]. The projected decline in peanut production could, therefore, intensify nutritional challenges in Mozambique, where chronic malnutrition rates are already high. Moreover, the reduction in peanut production could decrease the income of small farmers, further aggravating rural poverty.

The projected decline in peanut production in Mozambique by 2030 jeopardizes the achievement of SDG 2, which aims to end hunger and ensure food security. Although peanut production is relatively stable, the downward trend suggests that, without significant interventions, the country may struggle to meet the established targets. SDG 2 not only demands increased agricultural production but also requires that this production be sustainable and resilient, ensuring that everyone has access to nutritious and sufficient food.

To mitigate the risk of not achieving SDG 2, Mozambique will need to adopt a multifaceted approach. This includes strengthening agricultural practices, such as introducing more advanced technologies and access to quality inputs, like pest-resistant seeds and climate-resilient varieties. Additionally, improving infrastructure, such as irrigation systems and storage facilities, can help stabilize production and reduce post-harvest losses.

Studies like those by Johnson and Sithole et al. emphasize that investment in agricultural education and strengthening value chains are crucial to ensuring that small farmers can adapt to changes and contribute to the country's food security. If effectively implemented, these measures can increase peanut productivity and ensure that Mozambique is better prepared to meet the SDG 2 targets [88-90].

Conclusions

The statistical analysis of peanut production in Mozambique between 1961 and 2022 reveals a time series characterized by relatively stable production, though marked by moderate variations that highlight the influence of external factors such as climate change, agricultural policies, and farming practices. The presence of outliers within the series suggests significant vulnerability to extreme events, such as droughts and floods, underscoring the need for adaptive strategies to mitigate these impacts.

The confirmation of the non-stationarity of the original series through stationarity tests reinforces the importance of differentiation to enable effective predictive modeling. Among the models tested, the ARIMA (1,1,1) model emerged as the most robust, efficiently integrating autoregressive and moving average components, capturing both temporal dependencies and abrupt fluctuations in production.

In contrast, the application of the LSTM model demonstrated significantly superior predictive accuracy, outperforming the ARIMA models. This result underscores the effectiveness of artificial neural networks in handling complex and nonlinear temporal patterns, which are common in agricultural time series influenced by multiple external variables. The forecast of peanut production through 2030, using LSTM combined with Bootstrapping, indicates a trend of stability in production, albeit with a slight downward trend.

These findings highlight the necessity of adopting more advanced modeling approaches, such as LSTM, particularly in agricultural contexts characterized by high variability and uncertainty. The forecasted declining trend in production, coupled with increasing uncertainty, points to the urgency of strategic interventions aimed at mitigating the adverse effects of climate change and ensuring the resilience of agricultural production in Mozambique.

Therefore, this research not only validates the superiority of LSTM models over ARIMA in complex scenarios but also emphasizes the importance of investments in agricultural technology and infrastructure. These investments are crucial to ensuring stable and predictable agricultural production, capable of contributing to the sustainable socioeconomic development of Mozambique and achieving the targets set by the Sustainable Development Goals, particularly SDG 2, which aims to eradicate hunger and ensure food security.

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