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Research Article

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Advanced Predictive Modeling for Sweet Potato Production Estimation in Mozambique: A Comparative Analysis of ARIMA and LSTM Models for Supporting Food Security

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ABSTRACT
This study evaluated the application of two predictive models, ARIMA and LSTM neural networks, to estimate sweet potato production in Mozambique, aiming to provide accurate forecasts to support agricultural planning and food security. Sweet potato is a crucial crop in Mozambique, significantly contributing to the food subsistence of much of the rural population. Given the vulnerability of agricultural production to climate conditions and other external factors, accurate food production forecasting is vital for mitigating food insecurity in the country. The methodology included the use of the ARIMA model to capture linear patterns and historical trends from 1961 to 2009, with validation conducted between 2010 and 2020. The LSTM model, on the other hand, was trained with data from 1961 to 2013 and validated between 2014 and 2022. This model was chosen for its ability to identify complex and nonlinear patterns, offering greater accuracy in agricultural contexts with high variability. Forecasts for the period from 2023 to 2030 were generated using both models, focusing on providing insights that could support strategic decision-making in the agricultural sector. The results demonstrated that the LSTM model outperformed ARIMA in terms of accuracy, presenting a significantly lower Mean Absolute Percentage Error (MAPE), indicating greater effectiveness in predicting sweet potato production. Projections for the 2023–2030 period indicate stable production, with slight annual variations but no significant growth. This reflects resilient agriculture, but also highlights the need for strategic interventions to increase production and meet growing food demand. In conclusion, the LSTM model proved to be a more effective tool for forecasting agricultural production in scenarios of high uncertainty and variability, such as in Mozambique. The stable forecasts provided by this study underscore the importance of improving agricultural practices and investing in infrastructure and technologies to ensure that sweet potato production contributes sustainably to the country's food and nutritional security.

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

Introduction

Food insecurity is a persistent global challenge affecting millions of people, particularly in developing regions such as Sub-Saharan Africa and South Asia. Agriculture plays a vital role in mitigating this issue, especially through the production of staple crops like sweet potatoes, which are an important source of food and nutrition for many rural populations. However, agricultural production, including sweet potatoes, is influenced by various factors such as climate variability, resource limitations, and traditional farming practices, making production forecasting a continuous challenge [1,2].

Given the growing impact of climate change and the volatility of agricultural systems, traditional production forecasting models like ARIMA have been widely used to predict agricultural time series. These models have the ability to capture linear trends in historical data and have been useful in forecasting the production of staple crops like sweet potatoes in contexts of limited variability [3,4]. However, ARIMA presents significant limitations when dealing with nonlinear and complex data, such as those associated with climate change and socioeconomic impacts in vulnerable regions.

To address these limitations, the use of Artificial Neural Networks (ANNs), particularly Long Short-Term Memory (LSTM) models, has shown promise. LSTM has the ability to

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learn and model complex, nonlinear patterns over time, making it particularly effective in predicting agricultural production variations influenced by multiple interconnected factors, such as climate, land use, and agricultural management practices [5,6]. Recent studies demonstrate that LSTM outperforms traditional time series models like ARIMA, especially in contexts of high variability [7].

In Sub-Saharan Africa, where food insecurity is particularly severe, sweet potatoes are a key crop. They not only provide an affordable source of calories but are also rich in essential nutrients like vitamin A, which are crucial for combating malnutrition [8,9]. However, sweet potato production in countries like Mozambique remains vulnerable to climate fluctuations, with drought and heavy rains frequently negatively impacting agricultural yields [10].

Accurately forecasting sweet potato production is essential for ensuring food and nutritional security in Mozambique, where subsistence farming is the primary source of livelihood for over 80% of the rural population [11]. The introduction of advanced predictive methods, such as LSTM models, offers a new perspective on improving the accuracy of production forecasts, thereby enabling policymakers and farmers to make more informed and effective decisions [12,13].

LSTM models are particularly well-suited to handling the complexity of agricultural systems in tropical regions. Their ability to capture long-term patterns, even in noisy time series data, allows for more accurate forecasts, taking into account factors that ARIMA models may not be able to capture. The flexibility of LSTM in integrating multiple variables, such as temperature, precipitation, and farming practices, offers a significant advantage over traditional linear models [14,15].

Furthermore, the integration of climate and socioeconomic variables into LSTM forecasting models is crucial for reflecting the dynamic realities faced by farmers in Mozambique. Agriculture in Mozambique is highly dependent on climatic factors, with droughts, floods, and frequent cyclones often disrupting agricultural production [16]. Thus, incorporating historical climate data and future forecasts into LSTM models can help provide a more accurate view of expected sweet potato production and other staple crops.

The application of these advanced predictive models is not limited to forecasting agricultural production but can also help in planning food security policies. More accurate production forecasts allow for the implementation of effective strategies for resource allocation, such as improved seeds, fertilizers, and access to irrigation, helping to mitigate the impacts of adverse climatic conditions [17,18].

Moreover, the ability of LSTM models to learn from real-time data makes them a valuable tool for adapting forecasts as new information becomes available. This is particularly relevant in regions like Mozambique, where the impacts of climate change are unpredictable, and agricultural policies need to be constantly adjusted to respond to variable conditions [19,20]. The flexibility of LSTM models can thus provide a competitive edge over static models like ARIMA in highly uncertain contexts.

By integrating LSTM with traditional time series models such as ARIMA, a balance can be achieved between capturing long-term trends and seasonal patterns while responding to nonlinear variations in the data. Research suggests that combining both approaches offers improved predictive accuracy, allowing agricultural policies to be adjusted more effectively [4,21]. This hybrid approach is especially relevant for the production of staple crops like sweet potatoes, which are critical for food and nutritional security in Mozambique.

The present research aims to explore the applicability and effectiveness of LSTM and ARIMA models in forecasting sweet potato production in Mozambique. Through a comparative analysis, the study seeks to identify which models provide the most accurate forecasts and how these predictions can be used to develop agricultural strategies that ensure food and nutritional security in the country. The application of these advanced models not only contributes to the academic literature but also provides a solid foundation for the formulation of public agricultural policies in Mozambique.

Literature Review

Global Context of Sweet Potato Production

Sweet potato (Ipomoea batatas (L.) Lam., Convolvulaceae) holds a significant position in global agriculture, especially in developing countries where it contributes to food security, nutrition, and income generation. With its origin believed to be in Central and South America, sweet potato has spread across the globe, becoming a staple crop in many regions due to its adaptability to diverse climates and soil types [22]. This crop thrives in tropical and subtropical climates, with production concentrated in regions such as Africa, Asia, and parts of Latin America. It plays a vital role in addressing food security challenges, particularly in areas prone to food shortages and malnutrition [23].

The global production of sweet potatoes reached 86 million metric tons in 2022, with Africa and Asia contributing the largest shares [24]. Africa, particularly Sub-Saharan Africa, accounts for approximately 34% of global production, with countries like Nigeria, Uganda, and Tanzania being major producers. In these regions, sweet potato is a critical food source, providing essential calories and micronutrients to millions of people. The crop is often regarded as a “food security crop” due to its resilience to drought and its ability to grow in poor soils, making it an invaluable asset in areas with unpredictable rainfall and challenging growing conditions [25].

Sweet potato’s nutritional value further enhances its importance. It is rich in carbohydrates, providing a significant source of dietary energy, especially in regions where other staple crops such as maize or wheat may not thrive. The orange-fleshed varieties of sweet potatoes are particularly valued for their high beta-carotene content, a precursor to vitamin A, which is essential for preventing deficiencies that can lead to blindness and immune system deficiencies, especially in children [26]. This nutritional advantage has led to increased promotion of orange-fleshed sweet potatoes in regions like Sub-Saharan Africa, where vitamin A deficiency is prevalent [27].

In addition to its food security role, sweet potato has significant potential in the industrial sector. The starch extracted from sweet potatoes is used in various food products, as well as in non-food industries such as textiles, adhesives, and biofuels [28]. The versatility of sweet potato starch makes it a valuable commodity, particularly in Asia, where it is processed into products like noodles and desserts. The use of sweet potato in bioethanol production is also gaining traction, particularly in China, where the demand for alternative energy sources is growing [29].

Globally, sweet potato cultivation is expanding, driven by its adaptability to different agricultural systems and its potential to improve food security in regions facing climate challenges. The crop's ability to grow in a wide range of soil types, including sandy, loamy, and clay soils, combined with its tolerance to drought, makes it suitable for areas with limited resources [30]. Furthermore, its relatively short growing cycle—typically 3 to 4 months—allows for multiple harvests in a year, increasing its productivity and profitability for smallholder farmers [31].

However, despite its many advantages, sweet potato production faces significant challenges. Pests and diseases, such as the sweet potato virus disease (SPVD), caused by the interaction between the sweet potato feathery mottle virus (SPFMV) and the sweet potato chlorotic stunt virus (SPCSV), pose major threats to yield [32]. These diseases can cause substantial crop losses, particularly in Sub-Saharan Africa, where limited access to improved varieties and disease-resistant cultivars exacerbates the problem. Additionally, post-harvest losses due to poor storage conditions, mechanical damage, and pest infestations further reduce the amount of sweet potatoes available for consumption or sale [33].

Efforts to address these challenges include the development of disease-resistant sweet potato varieties and improved post-harvest management techniques. Researchers are working on breeding programs to enhance the resistance of sweet potato to SPVD and other diseases, while also improving yields and nutritional content [34]. These advancements are critical for ensuring the sustainability of sweet potato production, especially in regions heavily reliant on the crop for food security and income generation [35].

Another key area of focus is improving the value chain for sweet potato products. In many developing countries, sweet potatoes are consumed primarily in their fresh form, limiting their market potential. Expanding the processing and value addition of sweet potatoes—such as producing sweet potato flour, chips, and other processed products—can increase the shelf life of the crop and open up new markets, both domestically and internationally [36]. This, in turn, can provide smallholder farmers with higher returns and reduce post-harvest losses, which are a significant issue in the sweet potato sector [37].

Despite these challenges, the future of sweet potato production looks promising. With growing recognition of its nutritional benefits and its role in sustainable agriculture, governments and international organizations are investing in sweet potato research and development. Programs promoting the cultivation and consumption of orange-fleshed sweet potatoes have been particularly successful in addressing vitamin A deficiency in vulnerable populations, leading to improvements in public health outcomes [23].

As global populations continue to rise and climate change impacts agricultural systems, the importance of resilient crops like sweet potato will only increase. It is essential that research and development efforts continue to focus on improving sweet potato productivity, pest and disease resistance, and post-harvest management to ensure that this vital crop can meet the growing demand for food and nutrition in the years to come [38].

Sweet Potato Production in Mozambique

Sweet potato holds a vital place in Mozambique's agriculture and diet, serving as both a staple food and a source of income for many rural households. The crop's adaptability to diverse climatic conditions and its nutritional value make it indispensable in both urban and rural settings [39]. In Mozambique, sweet potatoes are cultivated across various provinces, reflecting the crop's resilience and significance in the country's food security strategy [40].

Mozambique ranks 16th globally and 13th in Africa in sweet potato production, with an area harvested of approximately 83,646 hectares and a total production of 510,238 tons in 2022 [24]. The provinces of Zambezia and Nampula are among the leading producers, benefiting from favorable climatic conditions and fertile soils that support sweet potato cultivation [41]. The crop's ability to grow in both sandy and clay soils, coupled with its tolerance to periods of drought, makes it an ideal choice for smallholder farmers who often face unpredictable weather patterns [26].

Sweet potato roots are consumed in various forms in Mozambique, including boiled, roasted, fried, or processed into flour for making porridges, which are a staple in many households [42]. The versatility of sweet potatoes in local cuisine not only enhances dietary diversity but also provides essential nutrients, contributing to improved health outcomes [43]. Despite this, the consumption of sweet potato leaves remains underutilized in some regions, although they are rich in vitamins A and C, iron, and calcium [44]. Promoting the use of sweet potato leaves could significantly enhance the nutritional intake of communities, particularly in areas with high rates of malnutrition [45].

The commercialization of sweet potatoes in Mozambique varies significantly across provinces. According to the Integrated Agricultural Survey of 2020 conducted by the Ministry of Agriculture and Rural Development (MADER), there is a notable difference in the marketing of orange-fleshed sweet potatoes (OFSP) compared to non-orange-fleshed varieties [41]. Provinces like Nampula and Tete show higher percentages of producers selling OFSP, with 58.6% and 39.4%, respectively, which is considerably above the national average of 18.2%. This indicates a growing awareness and demand for OFSP, likely due to its high beta-carotene content, which is essential for combating vitamin A deficiency [27].

Conversely, provinces such as Gaza and Maputo have lower commercialization rates for OFSP, at 2.9% and 6.6%, respectively [41]. These disparities highlight the need for targeted interventions to promote the cultivation and marketing of sweet potatoes, especially OFSP, in regions where commercialization is low. Enhancing market access and providing education on the nutritional benefits of OFSP can stimulate demand and improve the livelihoods of smallholder farmers [46].

Despite its importance, sweet potato production in Mozambique faces several challenges, particularly post-harvest losses, which can range from 20% to 40% of the total production [37]. Factors contributing to these losses include mechanical damage during harvesting, inadequate post-harvest handling, poor storage facilities, and infestation by pests and diseases [47]. The high moisture content of sweet potatoes makes them susceptible to rapid deterioration, especially under the hot and humid conditions prevalent in Mozambique [26].

To address these challenges, implementing improved post-harvest management practices is crucial. Training farmers on proper harvesting techniques can reduce mechanical damage to the roots, thereby extending their shelf life [33]. Additionally, investing in better storage facilities, such as ventilated warehouses and temperature-controlled environments, can significantly reduce spoilage and losses due to pests and diseases [48]. The adoption of curing techniques, where freshly harvested roots are held under specific conditions to heal wounds, can also enhance storability [49].

The role of women in sweet potato production and marketing in Mozambique is significant but often underrecognized. Women are predominantly involved in the cultivation and processing of sweet potatoes, yet they face barriers in accessing markets and resources [50]. Empowering women through training programs and facilitating their access to credit and markets can enhance the overall efficiency of the sweet potato value chain and contribute to gender equity in the agricultural sector [26].

Sweet potato cultivation also offers opportunities for income diversification and poverty reduction among smallholder farmers. By expanding into value-added products such as sweet potato flour, chips, and snacks, farmers can access new markets and increase their earnings [36]. Such diversification requires support in terms of training in processing techniques, quality control, and marketing strategies to meet consumer demands both locally and internationally [51].

The nutritional benefits of sweet potatoes, especially OFSP, are particularly relevant in Mozambique, where vitamin A deficiency remains a public health concern [39]. Programs promoting the cultivation and consumption of OFSP have the potential to improve nutritional outcomes, especially among children and pregnant women [27]. Integrating nutrition education into agricultural extension services can raise awareness about the health benefits of OFSP and encourage its adoption among farmers and consumers [44].

Research and development efforts are essential to address the agronomic challenges facing sweet potato production in Mozambique. Developing and disseminating improved varieties that are resistant to local pests and diseases, have higher yields, and possess desirable market traits can enhance productivity [34]. Collaboration between national research institutions, international organizations, and farmers can facilitate the breeding and adoption of such varieties [35].

Climate change poses an additional challenge to sweet potato production, with increased incidences of droughts and floods affecting crop yields [38]. Implementing climate-smart agricultural practices, such as conservation agriculture and the use of drought-tolerant varieties, can help mitigate these impacts and build resilience among farming communities [30].

Furthermore, strengthening the sweet potato value chain requires improving market infrastructure and access. Enhancing rural roads and transportation networks can reduce post-harvest losses by facilitating quicker movement of produce from farms to markets [40]. Establishing cooperatives and farmer groups can also empower producers by providing better bargaining power and access to market information [43].

Sweet potato production in Mozambique is a critical component of the country's agricultural sector and food security framework. Addressing the challenges of post-harvest losses, market access, and gender disparities can significantly enhance the benefits derived from this crop [37]. With strategic interventions and support from government and development partners, sweet potato has the potential to contribute even more substantially to nutrition, income generation, and sustainable agricultural development in Mozambique [39].

Previous Studies on Agricultural Production Modeling and Sweet Potato Forecasting

The use of Long Short-Term Memory (LSTM) and AutoRegressive Integrated Moving Average (ARIMA) models for forecasting agricultural yields has garnered significant attention due to their capacity to manage temporal variability and the inherent complexities of agriculture. ARIMA is particularly renowned for its efficiency in analyzing linear and stationary time series data, making it a preferred tool for predicting agricultural production in crops like rice, maize, and wheat [52]. The model remains a robust approach for managing time series data that exhibit seasonal patterns and predictable trends [53]. Furthermore, ARIMA has been confirmed as useful in forecasting agricultural series under stable conditions [54].

However, ARIMA faces limitations when it comes to dealing with highly dynamic and nonlinear data. Agriculture, being dependent on unpredictable climate factors, requires more sophisticated methods to capture complex interactions between variables like temperature, precipitation, and soil conditions. In this context, LSTM models have emerged as a superior alternative. As a type of recurrent neural network (RNN), LSTM excels in processing long-term dependencies, which is crucial for predicting agricultural production cycles that are influenced by climate variations [55].

LSTM's capability to retain information over extended periods allows it to outperform ARIMA by capturing nonlinear dependencies in agricultural data. Studies have demonstrated the successful application of LSTM in forecasting agricultural yields, offering a more flexible approach to managing seasonal and climate fluctuations [12]. This is particularly relevant in regions where climate variability significantly impacts crop yields [56].

Although LSTM is gaining traction, ARIMA remains a valuable tool for more predictable and linear time series data. For instance, ARIMA was applied to forecast soybean meal production, demonstrating its strength in capturing historical trends in agricultural time series [4]. Similarly, ARIMA was successfully used for maize yield forecasting in Tanzania, showing positive results in seasonal series with clear cyclical patterns [57].

When data complexity increases, LSTM provides more robust results. LSTM networks are particularly effective for predicting yields affected by non-stationary variables and irregular climate events. Research by Zareef et al. shows that LSTM outperforms traditional methods in predicting yields for crops such as rice and soybeans, where the interdependence of climate factors and agricultural practices creates dynamics that ARIMA fails to fully capture [14].

LSTM also holds an advantage in long-term agricultural yield forecasting by integrating historical climate data and environmental variables. This is especially useful in scenarios involving climate change, where agricultural forecasting requires a detailed analysis of interactions between climate and production. Research by Weng et al. highlights the importance of LSTM in predicting the impacts of climate variations on agricultural productivity [58].

Additionally, LSTM's adaptability to new conditions sets it apart from ARIMA. Unlike ARIMA, which relies on stationary data and predefined structures, LSTM can learn from new data and emerging patterns, making it ideal for agricultural systems facing continuous challenges like drought, floods, and pests [59]. LSTM's ability to predict these variables with greater precision supports more effective policy-making in agricultural management.

Recent studies suggest that combining ARIMA and LSTM could offer a more robust approach to agricultural forecasting. According to Parvin, integrating ARIMA's strengths in analyzing seasonal patterns with LSTM's capacity to handle nonlinear and complex dependencies can result in more accurate and comprehensive predictions [21]. This hybrid model has been explored in several crops, including maize and soybeans, with promising results.

The use of hybrid models that combine ARIMA and LSTM shows great potential for time series modeling in agriculture. Mamadou-Diéne Diop & Kamdem observe that integrating both approaches allows for a better capture of seasonal components and long-term dynamics, providing more reliable forecasts in complex agricultural systems [60]. This is particularly relevant in agricultural regions vulnerable to extreme climatic conditions.

The application of LSTM and ARIMA in agricultural forecasting has proven to be a powerful tool for addressing challenges related to food security. Research indicates that improving the accuracy of production forecasts significantly contributes to strategic planning and mitigating the effects of climate change on agriculture [4]. Accurate crop yield predictions provide a critical advantage in reducing farmers' vulnerability to climate shocks and market fluctuations.

As technological advancements continue, the use of LSTM and ARIMA in agricultural forecasting reflects the growing need for solutions that can manage the complexity and variability of agricultural systems. With the integration of new machine learning techniques and large datasets, these models are expected to play an increasingly central role in agricultural forecasting and food security planning [12,14].

Materials and Methods

Materials

This study focused on analyzing sweet potato 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 sweet potato 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 sweet potato 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 sweet potato 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

The ARIMA was conducted using sweet potato production data from Mozambique for the period from 1961 to 2009. The identification of the appropriate model began with the analysis of the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) of the differenced time series. Differentiation was applied to make the series stationary by removing long-term trends. Based on the observed patterns in the ACF and PACF, potential ARIMA models were identified by considering different combinations of autoregressive (AR), integration (I), and moving average (MA) terms.

Parameter Estimation

The parameters of the identified ARIMA models were estimated using the maximum likelihood method, adjusting the AR and MA terms to best represent the time series. Model selection criteria such as the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) were employed to balance model accuracy with complexity, ensuring that the chosen model offered a good fit without overfitting.

Validation and Evaluation

To validate the accuracy of the ARIMA models, the production data from 2010 to 2020 were used for model evaluation. Predictive performance was assessed through metrics such as the Mean Absolute Percentage Error (MAPE) and the Root Mean Square Error (RMSE), which compared the predicted values to actual production data, helping to identify the model that best captured the time series dynamics.

LSTM Neural Networks

Data Preparation

LSTM (Long Short-Term Memory) modeling was conducted using sweet potato production data from 1961 to 2013. Prior to training, the data were normalized using the MinMaxScaler technique to scale all values between 0 and 1. This normalization process was crucial to ensure that the LSTM model could learn patterns without being influenced by differences in data scale. Time windows of five consecutive years were created to allow the model to capture the temporal dependencies within the series.

Model Architecture and Training

The LSTM model was designed with two hidden layers, each containing 50 units, followed by a dense layer responsible for generating predictions. The Adam optimizer was used with a learning rate of 0.01, and the model was trained over 100 epochs. During training, the model adjusted its weights to minimize the error between predictions and actual values, using the Mean Squared Error (MSE) as the loss function.

Evaluation and Validation

The performance of the LSTM model was evaluated using data from 2014 to 2022. The model's accuracy was assessed through metrics such as MAPE and RMSE to measure how closely the model's predictions aligned with actual production data. This validation process ensured that the model was capable of generalizing and accurately forecasting sweet potato production.

Forecasting for 2023 to 2030

After training and validation, the LSTM model was used to forecast sweet potato production for the period from 2023 to 2030. These forecasts were generated using the Bootstrapping technique to estimate confidence intervals, providing a range of likely future production outcomes while accounting for the uncertainty inherent in agricultural production data.

Selection of the Best Model for Estimating Agricultural Production

To identify the most suitable model for forecasting sweet potato 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 Sweet Potato Time Series

The statistical analysis of sweet potato production in Mozambique over 62 years provides valuable insights into the characteristics and variability of this agricultural crop (Table 1). The average annual production is 279,355.07 tons, but the median is significantly lower at 55,000 tons. This stark difference between the mean and median suggests a highly skewed distribution.

A skewness of 1.39 indicates a strong rightward skew, suggesting that production in some years was exceptionally high, pulling the mean above the more commonly observed values. The mode, at 40,000 tons, reflects the most frequent production value, highlighting years when output was relatively low compared to the mean. The standard deviation of 339,804.05 tons and a variance of 115,466,789,235.38 demonstrate a high level of variability in annual sweet potato production. This is further emphasized by the coefficient of variation of 1.22 (or 122%), which indicates substantial fluctuations in production relative to the mean, reflecting significant inconsistency over the years.

Extreme production values range from a maximum of 1,468,575 tons (in 2013) to a minimum of 21,000 tons (in 1966), resulting in a range of 1,447,575 tons. This wide range underscores the influence of external factors, such as climatic conditions, farming practices, and agricultural policies, which greatly impact annual production. The kurtosis of 1.55 suggests a leptokurtic distribution, characterized by longer tails and a sharper peak than a normal distribution. This indicates the presence of outliers, with years of exceptionally high production contributing to the observed variability.

Table 1: Descriptive Measures of the Annual Sweet Potato Production Series

Descriptive Statistics	Value
Mean	279355.07
Median	55000.00
Mode	40000.00
Variance	115466789235.38
Standard Deviation	339804.05
Coefficient of variation	1.22
Maximum	1468575
Minimum	21000
Skewness	1.39
Kurtosis	1.55
Range	1447575.00
n	62.00

Stationarity Test or Unit Root Test of the Sweet Potato 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 Sweet Potato Production in Mozambique

The time series graph of sweet potato production in Mozambique, from 1961 to 2022, reveals a sharp increase in production in recent years, particularly from the late 1990s onwards (Figure 1). This growth can be attributed to improvements in agricultural practices, greater investment in sweet potato cultivation, or a rising demand for this crop. Despite the overall increase, the series displays significant fluctuations, alternating between periods of steady production and sudden growth spurts, which may reflect the influence of external factors such as variable climatic conditions or changes in agricultural policies.

The differentiated series for sweet potato highlights the annual changes in production from 1961 to 2022. This transformation was applied to remove long-term trends, allowing for a more focused analysis of short-term variations. By eliminating the growth trend, differentiation helps in identifying inter-annual fluctuations, which may be caused by specific events or temporary changes in cultivation conditions. This provides a clearer view of the dynamics affecting sweet potato production on a year-to-year basis.

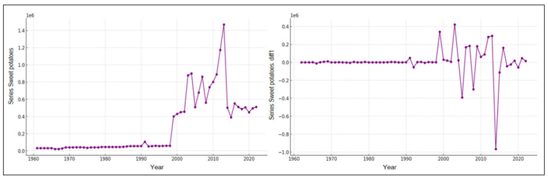

Figure 1: Time Series Analysis of Sweet Potato Production in Mozambique (1961-2022)

Decomposition of the Time Series of Sweet Potato Production in Mozambique

The time series decomposition highlights the trend, seasonality, and residual components (Figure 2). The overall trend shows a noticeable growth, particularly pronounced in the last two decades, which may be linked to technological advancements, improvements in agricultural techniques, or incentive policies promoting sweet potato cultivation. The analysis does not reveal a clear seasonal pattern, suggesting that sweet potato production does not follow consistent seasonal cycles during the analyzed period. The residuals exhibit variability not explained by the trend, indicating the presence of random fluctuations or the influence of external factors that were not modeled.

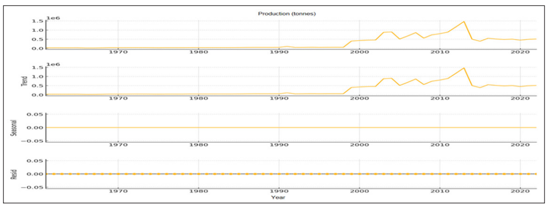

Figure 2: Decomposition of the Time Series of Sweet Potato Production in Mozambique

Autocorrelation Function (ACF) of Sweet Potato Production in Mozambique

The ACF (Autocorrelation Function) plot of the original sweet potato production series does not exhibit significant peaks at specific lags, indicating the absence of strong seasonality in the data (Figure 3). The rapid decline in autocorrelation values suggests that the annual sweet potato production does not have a strong long-term dependence on past values, reflecting a lack of cyclical or repetitive patterns over time.

After differentiation, the ACF plot shows that autocorrelations decrease rapidly after the first few lags, indicating that the differentiated series does not possess significant long-term correlation structures. This suggests that the differentiated series is closer to being stationary, which is ideal for predictive models that require stationarity. Stationarity implies that the statistical properties of the series, such as the mean and variance, remain constant over time, facilitating the analysis and prediction of short-term variations in sweet potato production.

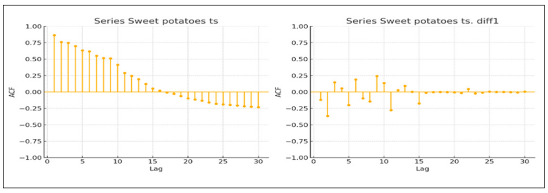

Figure 3: Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) of Sweet Potato Production in Mozambique

Partial Autocorrelation Function (PACF) of Sweet Potato Production in Mozambique

The PACF plot of the original series reveals several peaks in the first lags, indicating the presence of low-order autoregressive components (Figure 4). This suggests that past values moderately influence future values, implying that recent observations have a significant, yet limited, impact on subsequent sweet potato production values. Such influence is typical of time series with short-term dependency patterns.

In the differenced series, the PACF plot still shows peaks in the first lags, confirming the persistence of low-order autoregressive components even after removing long-term trends. This means that past values continue to moderately affect future values, allowing low-order autoregressive models to effectively capture the underlying dynamics of the time series. This structure facilitates the application of models like ARIMA, which can leverage this autocorrelation to provide accurate forecasts based on historical sweet potato production data.

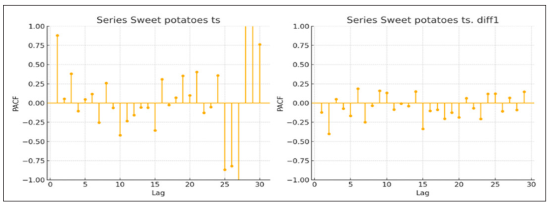

Figure 4: Partial Autocorrelation Function (PACF) of Sweet Potato Production in Mozambique

Augmented Dickey-Fuller (ADF) Test for the Sweet Potato Series

As shown in Table 2, the ADF test statistic of -0.8791 for the original time series indicates that the series is not stationary, as the null hypothesis of a unit root cannot be rejected. This confirms the presence of a trend in the series, suggesting that its statistical properties, such as mean and variance, change over time. To make the series stationary and suitable for predictive modeling, a differencing transformation would be necessary to remove this long-term trend.

After differencing, the p-value of 0.000 in the ADF test indicates that the null hypothesis of a unit root is rejected, confirming that the differenced series is stationary. This means the series now has constant statistical properties over time, making it more appropriate for applying forecasting models that require stationarity. The stationarity of the differenced series allows for more accurate analysis of short-term variations, improving the reliability of forecasts and inferences based on the data.

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

Test Statistic	p-Value	Lags	n	Critical Value		
				(1%)	(5%)	(10%)
Orginal Series						
-0.8791	0.0478	10	51	-3.5656	-2.9201	-2.5980
Differenced Series						
-8.545	0.000	0	61	-3.544	-2.911	-2.593

Estimation with Time Series Models (ARIMA) for Sweet Potato Production

Model Identification

Based on the analysis of the ACF and PACF plots of the differenced time series of sweet potato production in Mozambique, it is possible to identify the most suitable ARIMA models for forecasting this series. The ACF plot reveals a gradual decay after the initial lags, suggesting the need to include moving average (MA) components in the model. Meanwhile, the PACF plot shows a sharper cut-off after the first few lags, indicating that autoregressive (AR) terms are also relevant for capturing the series' dynamics.

Considering these observations, the ARIMA(1,1,1), ARIMA(2,1,1), and ARIMA(1,1,2) models are the most appropriate for estimating sweet potato production. The ARIMA(1,1,1) model combines one autoregressive term and one moving average term, offering a balanced approach to capturing both temporal dependencies and random fluctuations. The ARIMA(2,1,1) and ARIMA(1,1,2) models introduce additional complexity by including more AR or MA terms, potentially capturing more intricate variations in the series.

These models are robust and suitable for forecasting sweet potato production, providing a solid foundation for estimating future trends and supporting decision-making in Mozambique's agricultural sector. When choosing among these models, it is important to consider the balance between accuracy and complexity to ensure that the selected model effectively captures the underlying dynamics of the time series.

Parameter Estimation

Table 3 presents the parameter estimates for the ARIMA(1,1,1), ARIMA(2,1,1), and ARIMA(1,1,2) models fitted to the time series of sweet potato production in Mozambique. The analysis of these parameters, considering the t-Stat values and p-values, allows for an evaluation of the significance and adequacy of each model in capturing the underlying dynamics of the time series.

In the ARIMA(1,1,1) model, the moving average parameter MA(1) is highly significant, with a p-value of 0.001, while the autoregressive parameter AR(1) is not statistically significant (p-value = 0.1231). This result suggests that the moving average component plays a crucial role in this model, but the lack of significance of the AR component indicates that the model may not fully capture all the temporal dependencies present in the series.

On the other hand, the ARIMA(2,1,1) model stands out due to the statistical significance of both parameters. The second autoregressive term AR(2) shows a p-value of 0.0000, and the moving average term MA(1) has a p-value of 0.0025. This suggests that this model is more robust, effectively combining autoregressive and moving average components that capture the variations in sweet potato production. However, the first autoregressive term AR(1) is not significant (p-value = 0.4947), which does not compromise the model's overall effectiveness.

The ARIMA(1,1,2) model, despite effectively capturing random fluctuations through the moving average terms MA(1) and MA(2), shows that the autoregressive term AR(1) is not significant (p-value = 0.3630). This lack of significance may indicate that the model has limitations in capturing long-term temporal dependencies. Based on this analysis, the ARIMA(2,1,1) model is suggested as the most suitable for forecasting sweet potato production in Mozambique, followed by the ARIMA(1,1,1) as a viable alternative, though slightly less robust.

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

Model	Parameter	Estimates	t-Stat	P-value
ARIMA (1,1,1)	AR (1)	4.241322e-1	1.541634	0.1231
ARIMA (1,1,1)	MA (1)	-6.927773e-1	-3.270290	0.0010
ARIMA (1,1,1)	ϕ_2	3.099608e+10	3.289735e+22	0.0000
ARIMA (2,1,1)	AR (1)	-2.889120e-1	-6.827485e-1	0.4947
ARIMA (2,1,1)	AR (2)	3.925510e-1	-3.904858	0.0000
ARIMA (2,1,1)	MA (1)	-5.865350e-1	-3.904858	0.0025
ARIMA (2,1,1)	ϕ_2	3.040932e+10	-3.015761	0.0000
ARIMA (1,1,2)	AR (1)	2.484389e-1	3.318517e+22	0.3630
ARIMA (1,1,2)	MA (1)	-1.140022e-1	-1.049951e-1	0.0000
ARIMA (1,1,2)	MA (2)	-3.553270e-1	-3.765093	0.0001
ARIMA (1,1,2)	ϕ_2	3.021758e+10	3.296811e+22	0.0000

Diagnostic Test of Residuals for Sweet Potato Production Models

The diagnostic test analysis of residuals for the ARIMA(2,1,1) and ARIMA(1,1,1) models applied to the time series of sweet potato production in Mozambique provides crucial insights into the adequacy of these models (Table 4). The Box-Pierce test, which assesses the presence of autocorrelation in the residuals, indicates that neither model exhibits significant autocorrelation. This is evidenced by p-values of 0.6243 for ARIMA(2,1,1) and 0.1502 for ARIMA(1,1,1), suggesting that the residuals of both models are independent, and that these models effectively capture the temporal structure of the data.

Regarding the ARCH test, which checks for heteroscedasticity (the variation in residuals over time), both models display relatively high p-values (0.6317 for ARIMA(2,1,1) and 0.2548 for ARIMA(1,1,1)), indicating no significant heteroscedasticity in the residuals. This implies that the variability in the residuals remains constant over time, which is desirable for model stability. However, both models fail the normality test of the residuals, as evidenced by the very low p-values (0.0000) in the Shapiro-Wilk and Jarque-Bera tests. The violation of the normality assumption is not uncommon in time series data, particularly in agricultural production, where external factors often influence the data. Therefore, despite the violation of the normality assumption, the ARIMA(2,1,1) model performs slightly better in capturing the temporal structure and ensuring residual stability, making it the preferred option for forecasting sweet potato production in Mozambique.

Table 4: Diagnostic Test of Residuals for Sweet Potato Production Models

Model	Box-Pierce		ARCH		Shapiro-WilK		Jarque-Bera	
	Q	p-value	TR2	p-value	W	p-value	JB	p-value
ARIMA (2,1,1)	8.04632	0.6243	7.9707	0.6317	0.6604	0.0000	445.974	0.0000
ARIMA (1,1,1)	14.5299	0.1502	12.4700	0.2548	0.6985	0.0000	296.305	0.0000

Comparison of Model Performance

Table 5 compares the performance of the ARIMA(2,1,1) and ARIMA(1,1,1) models in forecasting sweet potato production in Mozambique. The ARIMA(2,1,1) model presents lower values for AIC, BIC, and HQIC, indicating a better balance between model complexity and fit to the data, which is crucial for predictive performance. The lower RMSE (155,901.9497) of the ARIMA(2,1,1) model suggests a smaller mean squared error, leading to more accurate predictions. Additionally, the MAPE of 19.9597% for ARIMA(2,1,1) is lower than that of ARIMA(1,1,1), further reinforcing its superiority in terms of percentage accuracy. Based on these metrics, the ARIMA(2,1,1) model is the most suitable for forecasting sweet potato production in Mozambique, offering overall better performance compared to ARIMA(1,1,1).

Table 5: Comparison of Model Performance for Sweet Potato Production

Model	AIC	BIC	HQIC	RMSE	MAPE
ARIMA (2,1,1)	1641.1144	1649.5579	1644.4235	155901.9497	19.9597%
ARIMA (1,1,1)	1644.9732	1651.3058	1647.4550	163141.4836	20.4113%

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

Table 6 presents a comparative analysis of the ARIMA(2,1,1) and ARIMA(1,1,1) models applied to the forecast of sweet potato production in Mozambique for the period from 2010 to 2020. The results show that both models generate estimates that generally align with actual data, although significant discrepancies occur in certain years. One notable instance is in 2014, when both models overestimated sweet potato production, with ARIMA(2,1,1) predicting 1,326,787 tons and ARIMA(1,1,1) estimating 1,314,294 tons, while the actual production was only 502,611 tons.

When analyzing the error metrics, RMSE and MAPE provide insight into the models' accuracy. The ARIMA(2,1,1) model had an RMSE of 304,531.5 and a MAPE of 31.08%, whereas the ARIMA(1,1,1) had a slightly higher RMSE of 307,900 and a MAPE of 33.42%. These figures suggest that, while both models perform relatively similarly, ARIMA(2,1,1) is marginally better in terms of overall precision. Based on the data presented, the ARIMA(2,1,1) model is the most suitable for forecasting sweet potato production in Mozambique, due to its lower RMSE and MAPE, indicating a better forecasting ability and lower percentage error compared to ARIMA(1,1,1).

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

Year	Actual Dada	Predicted Data	
		ARIMA (1,1,0)	ARIMA (2,1,1)
2010	801706	835115.5	716797.7
2011	890226	708536.7	769015.5
2012	1173404	867589.9	843798.3
2013	1468575	1102497	1065166
2014	502611	1326787	1314294
2015	390407	542777.8	655229.9
2016	552184	779266.7	526281
2017	510054	515589.1	602853.8
2018	487246	457893.8	556474.9
2019	504815	514755.7	525532.6
2020	448633	507208.4	526619.3
RMSE		304531.5	307900
MAPE		31.08%	33.42%

Forecasted Sweet Potato Production in Mozambique from 2023 to 2030

Table 7 presents the forecasted values for sweet potato production in Mozambique for the period from 2023 to 2030. The predicted values show relatively stable production over the years, with slight variation ranging between approximately 487,000 and 496,000 tons. The 95% confidence intervals reflect the uncertainty associated with these forecasts. In 2023, the confidence interval ranges from 368,866.73 to 606,150.61 tons, indicating moderate uncertainty in the predictions. In subsequent years, the confidence intervals vary, with the lower limit dropping significantly in 2024 (267,893.71 tons) and the upper limit rising in 2026 (691,918.82 tons), suggesting increased uncertainty in the production forecasts. Throughout the period, the confidence intervals continue to exhibit some variation, remaining particularly wide in the more distant years, such as in 2030, when the confidence interval ranges from 313,932.80 to 659,958.31 tons. This indicates that, although the central forecasts suggest stability in sweet potato production, there remains considerable uncertainty regarding the actual values that may be achieved.

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

Year	Forecasted Value	Confidence Intervals (95%)	
		Lower Bound	Upper Bound
2023	487508.67	368866.73	606150.61
2024	488241.74	267893.71	608589.78
2025	496952.37	246495.33	647409.41
2026	494148.00	313622.83	691918.82
2027	491538.85	361702.48	644780.18
2028	493393.52	299544.55	686331.60
2029	493881.91	335079.63	622843.45
2030	493012.76	313932.80	659958.31

Estimation with the LSTM Model for Sweet Potato Production

Model Training with LSTM

The training of the LSTM model for the time series of sweet potato production in Mozambique was conducted using historical data from 1961 to 2013. To enhance model performance, the data was initially normalized using the MinMaxScaler, which scaled the values to a range between 0 and 1. This normalization process is crucial to ensure that the LSTM model can learn the patterns in the data without being influenced by large disparities in scale. Subsequently, temporal sequences were created using blocks of five consecutive years, allowing the model to capture the temporal dependencies within the series over time.

The architecture of the LSTM model consisted of two layers with 50 units each, followed by a dense layer responsible for producing the final predictions. This configuration is particularly effective for handling the complexity of time series data, capturing patterns that simpler models might overlook. The model was trained over 100 epochs, using the Adam optimizer with a learning rate of 0.01. During this process, the model's weights were adjusted to minimize the mean squared error between the predicted and actual values. Careful monitoring of the training process ensured model convergence, resulting in a robust tool for forecasting sweet potato production in Mozambique over the years.

Model Evaluation

The evaluation of the LSTM model for sweet potato production in Mozambique, between 2014 and 2022, demonstrates highly satisfactory performance, with an average MAPE of 2.06% (Table 8). This figure indicates that the model was able to predict production with relatively low percentage error, showcasing its ability to capture the trends and variations in production over time.

The average RMSE of 9,784 tons further reinforces the accuracy of the predictions, indicating that the average absolute deviation between the predicted and actual values is quite low, particularly in relation to the scale of the analyzed productions. Results for specific years, such as 2014 and 2022, with MAPE values of 0.93% and 0.75%, respectively, confirm the model's high precision. Although in years like 2015 and 2020 the errors were slightly higher, they still remained within acceptable limits. Given the consistent performance of the model over the evaluated years, the LSTM model proves to be suitable for forecasting sweet potato production from 2023 to 2030, providing reliable estimates that can be utilized for decision-making in Mozambique's agricultural sector.

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

Year	Actual Dada	LSTM Model		
		Predicted Data	RMSE	MAPE
2014	502611	497944.74	4666.26	0.93%
2015	390407	403428.19	13021.19	3.34%
2016	552184	561663.65	9479.87	1.72%
2017	510054	513777.77	3723.77	0.73%
2018	487246	474843.34	12402.66	2.55%
2019	504815	491964.22	12850.78	2.55%
2020	448633	433961.89	14671.11	3.27%
2021	495377	508800.25	13423.25	2.71%
2022	510238	514055.86	3817.86	0.75%
Mean	489062.7533	488937.7678	9784.083	2.06%

Forecasts for 2023 to 2030

The forecast for sweet potato production in Mozambique for the period from 2023 to 2030, as estimated by the LSTM model combined with the Bootstrapping technique, reveals a trend of stability with slight fluctuations over the years (Table 74). The predicted values indicate production levels ranging from 490,000 to 510,000 tons annually, with variations that can be attributed to natural fluctuations in agricultural production. The 95% confidence intervals suggest a relatively narrow margin of uncertainty, indicating that while variations are expected, production is likely to remain consistently within this range throughout the forecast period.

The average annual percentage growth during this period is practically negligible (-0.52%), suggesting that sweet potato production in Mozambique will remain stable without significant variation or substantial growth trends. This behavior aligns with the values observed in recent years, where production has remained relatively constant. This stability reflects the resilience of sweet potato production in the country but also signals the need for strategic interventions if there is a goal to increase production levels.

Table 9: Forecasted Sweet Potato 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	511476.12	443447.55	579504.70
2024	516222.50	462276.16	570168.84
2025	509119.66	474879.88	545359.44
2026	500120.13	435473.08	564767.18
2027	502142.92	443820.01	560465.82
2028	492513.51	423717.12	561309.91
2029	499062.81	460569.25	537556.38
2030	492711.24	455375.06	530047.42

Discussion

The exploratory analysis of sweet potato production in Mozambique over 62 years reveals several characteristics that highlight the volatility and variability of this crop in the country. The average annual production of 279,355.07 tons, in contrast to the median of 55,000 tons, suggests a highly skewed distribution, with production in a few years being exceptionally high. This pattern is evidenced by the high skewness of 1.39, indicating that a few years of elevated production raised the average, while most years had significantly lower outputs.

The high variability in production is further underscored by the coefficient of variation of 122%, indicating that annual production is extremely inconsistent. This behavior is common in regions where agriculture is heavily influenced by unpredictable external variables such as climate changes and market volatility, as discussed by authors like Kar [61]. The range of 1,447,575 tons, with a maximum of 1,468,575 tons in 2013 and a minimum of 21,000 tons in 1966, highlights the impact of specific events that may have caused abrupt increases or decreases in production. The kurtosis of 1.55, indicating a leptokurtic distribution, confirms the presence of outliers, or years of exceptionally high production, likely due to favorable climatic conditions or successful agricultural interventions.

The time series analysis of sweet potato production in Mozambique from 1961 to 2022 reveals an upward trend in production, especially from the late 1990s onwards. This growth can be attributed to several factors, including improvements in agricultural practices, increased investments in the sector, and policies promoting food crop production, as pointed out by studies from Sekaran et al. and Pawlak and Kołodziejczak [62-63]. However, the series also shows significant fluctuations, suggesting the influence of external factors such as adverse climatic conditions and changes in government policies. Differentiating the time series, which removes long-term trends, highlights these year-to-year fluctuations and allows for a more focused analysis of short-term variations, as recommended by Mahaluça [64].

The decomposition of the time series did not reveal a clear seasonal pattern, suggesting that sweet potato production in Mozambique does not follow consistent seasonal cycles, a result similar to those observed in studies conducted in other sub-Saharan African regions Keyser [65]. The residuals from the decomposition indicate the presence of variability unexplained by the trend, which may be associated with random factors or external events such as pests or economic crises, as highlighted by authors like Kaphaika [66].

The ACF and PACF plots, which show a rapid drop in autocorrelation after the first lags, confirm the absence of significant long-term correlation structure. These patterns suggest that the differenced series is close to stationarity, which is ideal for the application of predictive models such as ARIMA. The ADF test also confirms that, after differentiation, the series becomes stationary, making it suitable for modeling and forecasting, as suggested by Kaur [67].

The analysis of ARIMA models applied to forecasting sweet potato production in Mozambique reveals that the ARIMA (2,1,1) is the most suitable model, showing better performance in terms of predictive accuracy and data fit. The initial identification of models, based on the analysis of ACF and PACF plots of the differenced time series, indicated that both autoregressive and moving average terms are relevant to capturing the dynamics of the series.

The ARIMA (2,1,1) stood out due to the statistical significance of its parameters and its ability to capture more complex variations in sweet potato production. This result is consistent with the literature, where more complex ARIMA models are often used for agricultural time series [68]. Diagnostic tests confirmed that the ARIMA (2,1,1) does not present significant issues of autocorrelation or heteroscedasticity in the residuals, suggesting that the model captures the temporal structure of the data well. However, the violation of normality in the residuals is a common limitation in agricultural production data due to outliers and external variability [69].

In terms of performance, the ARIMA (2,1,1) had the lowest RMSE and MAPE, indicating superior accuracy compared to the ARIMA (1,1,1), making it the preferred choice for forecasting sweet potato production. These results align with studies that highlight the effectiveness of ARIMA models in predicting time series with significant variability, such as agricultural production in regions vulnerable to external factors [70].

The comparison between the LSTM model and the ARIMA (2,1,1) in forecasting sweet potato production in Mozambique shows the clear superiority of the LSTM in terms of predictive accuracy. The LSTM achieved an average MAPE of 2.06%, while the ARIMA (2,1,1) had a significantly higher MAPE of 31.08%. This stark difference suggests that the LSTM is more effective in capturing the complex dynamics of the time series, especially in agricultural contexts characterized by high variability. Studies like those by Poongadan & Lineesh confirm the superiority of LSTM networks over linear models like ARIMA in non-linear and complex time series [71].

The LSTM architecture, consisting of two layers of 50 units and data normalization via the MinMaxScaler, was crucial for achieving this high accuracy. Using five-year temporal sequences allowed the model to capture temporal dependencies that linear models like ARIMA cannot replicate. Additionally, the learning rate of 0.01 and the Adam optimizer ensured efficient model convergence, resulting in an RMSE of 9,784 tons, significantly lower than the RMSE of the ARIMA (2,1,1). These technical elements were critical to the success of the LSTM in forecasting sweet potato production.

The performance of the LSTM in specific years, such as 2014 and 2022, with MAPEs of 0.93% and 0.75%, respectively, demonstrates the robustness of the model, despite slightly larger errors in years like 2015 and 2020. Studies also highlight the effectiveness of LSTM networks in forecasting time series with long-term trends and seasonal fluctuations [72,73], making LSTM a valuable tool for agricultural forecasts in Mozambique. Given its consistent performance, LSTM is highly recommended for future sweet potato production forecasts, providing a solid foundation for strategic decision-making in the agricultural sector.

The projections for sweet potato production in Mozambique from 2023 to 2030 indicate a trend of stability, with minimal variations between 490,000 and 510,000 tons annually, as forecasted by the LSTM model combined with Bootstrapping. This scenario of stability, with an average annual percentage growth of -0.52%, reflects an agricultural sector that, although resilient, faces challenges in terms of productive expansion.

This projection aligns with studies such as Malec et al., which point to limitations in agricultural productivity growth in sub-Saharan Africa due to structural factors such as a lack of investment in technology and agricultural infrastructure [74]. The absence of significant growth in sweet potato production, a crucial crop in Mozambique, suggests that without strategic interventions, the country may continue to struggle to increase food production sustainably.

In the context of food and nutritional security in Mozambique, particularly in rural areas, the stabilization of sweet potato production presents both opportunities and challenges. While stability may suggest some resilience, it also indicates that production may not keep pace with population growth, exacerbating food security challenges. FAO highlights that population growth without a corresponding increase in agricultural production could result in greater food insecurity, particularly in regions where agriculture is the main means of subsistence [40].

Sweet potato, as a vital subsistence crop, plays a crucial role in the diet of rural communities. If production does not increase as projected, the SDG 2 goals of eradicating hunger and ensuring food security may become unattainable in more vulnerable regions. Studies such as Karoliina et al. also emphasize the need for agricultural diversification and improved farming practices to increase the resilience of food systems in contexts of high vulnerability [75].

In Mozambique, this means that, in addition to increasing sweet potato production, it is crucial to invest in other crops and strengthen the agricultural value chain. Lufeyo et al. argue that strengthening distribution and storage infrastructure, coupled with farmer training programs, is essential to improving food and nutritional security. Without these measures, forecasts of stable production may not be sufficient to meet growing food needs, especially in rural areas, compromising the country's progress toward the SDGs and poverty reduction [76].

Conclusions

The analysis of sweet potato production in Mozambique using both ARIMA time series models and Long Short-Term Memory (LSTM) neural networks provides valuable insights into the dynamics of agricultural production and the suitability of different predictive approaches. From a methodological standpoint, the LSTM model demonstrated superior performance in forecasting production, as it is better equipped to capture nonlinear and complex patterns. The significantly lower MAPE achieved by LSTM compared to ARIMA underscores the advantage of neural networks in contexts marked by high agricultural variability.

However, the stable production projections for 2023 to 2030, generated by both LSTM and ARIMA models, highlight the absence of significant growth in sweet potato output. This finding likely reflects structural limitations in Mozambique's agricultural sector, such as a lack of investment in technology and modern farming practices. While the models provide stable forecasts, the lack of growth suggests that strategic interventions are needed to overcome productivity challenges and ensure sustainable agricultural expansion.

From a food security perspective, the stabilization of sweet potato production presents both opportunities and challenges. On the one hand, production resilience is positive, ensuring a consistent supply; on the other hand, the absence of growth may not be sufficient to meet the demands of a growing population, potentially exacerbating food insecurity in rural areas. This highlights the need for robust agricultural policies focused on improving both productivity and crop diversification.

In conclusion, while the stable forecasts provided by the models are encouraging, they should serve as a call to action for transforming Mozambique's agricultural sector. Focusing on innovation, infrastructure, and supportive policies for farmers will be essential to ensure that sweet potato production, along with other key crops, not only stabilizes but also grows to meet rising demand and contribute to the country's sustainable development goals.

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