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Forecasting Maize Production in Mozambique: A Comparative Analysis of Arima And Lstm Models

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Abstract

This study investigates the prediction of maize production in Mozambique, a crucial component for the country's food security, using two predictive models: ARIMA and LSTM. The research encompasses historical data from 1961 to 2022, allowing for a detailed analysis of trends and variations in production over the decades. The methodology involved ARIMA modeling, known for its effectiveness in capturing linear patterns in time series, and the LSTM model, which excels in forecasting nonlinear and complex patterns in temporal data. For the ARIMA model, the first step was to conduct an exploratory analysis of the time series, identifying the need for transformation to achieve stationarity. The Dickey-Fuller test confirmed the necessity of differencing, removing long-term trends. After this transformation, the ARIMA model was fitted, and its parameters were estimated using the maximum likelihood method. Three ARIMA models were tested (ARIMA (1,1,0), ARIMA (0,1,1), and ARIMA (1,1,1)), and their performance was compared using metrics such as AIC, BIC, RMSE, and MAPE. The ARIMA (1,1,1) model emerged as the most robust, offering the best balance between simplicity and accuracy in capturing the dynamics of maize production.

Concurrently, the LSTM model was trained using feedback neural networks, with normalized data to enhance training efficiency. The model architecture consisted of two LSTM layers with 50 units each, followed by a dense layer to generate predictions. The model was trained for 100 epochs using the Adam optimizer and mean squared error (MSE) loss function. LSTM evaluation was conducted using data from 2014 to 2022, which were not used in training, and prediction accuracy was measured using RMSE and MAPE. The results indicate that while the ARIMA (1,1,1) model showed solid performance, with an RMSE of 390,016.3 and a MAPE of 16.39%, the LSTM model outperformed it in predictive accuracy, achieving a significantly lower MAPE of 2.64%. LSTM proved more effective in capturing the complexities of the maize production time series, particularly in years of greater variability. These findings corroborate previous studies that highlight the superiority of LSTM neural networks in scenarios where time series exhibit nonlinear patterns and complex external influences.

Maize production forecasts for the period 2023 to 2030 were generated using the LSTM model combined with the Bootstrapping technique, which allowed the creation of 95% confidence intervals, quantifying the uncertainty of the predictions. The forecasts indicate stabilization in maize production, with small annual variations but no significant growth. While the stabilization is positive, it raises concerns in the context of food security, particularly considering Sustainable Development Goal 2 (SDG 2), which aims to eradicate hunger by 2030. The lack of substantial growth may hinder Mozambique's ability to meet the growing food needs of its population.

The conclusions of this study demonstrate that the LSTM model is a powerful and more accurate tool than ARIMA for predicting maize production in Mozambique, underscoring the need for proactive agricultural policies and continued investments in technologies to increase productivity and mitigate food insecurity risks. The uncertainties in the confidence intervals of the forecasts highlight the importance of strategic planning and political interventions to ensure the resilience of Mozambique's agricultural sector in the face of climate change and economic fluctuations. In addition to advancing scientific knowledge in agricultural production forecasting, the study provides valuable insights for public policy formulation aimed at food security and sustainable development in Mozambique.

Keywords: Agricultural Forecasting, Arima Models, Lstm Neural Networks, Maize, Food Security

1. Introduction

Food insecurity and malnutrition remain critical public health challenges in several regions worldwide, particularly in Sub-Saharan Africa and South Asia, where hunger and child malnutrition rates are alarmingly high [1]. The unequal distribution of global food production, coupled with the stagnation in agricultural sector growth, has exacerbated these issues, creating heightened vulnerability among the most disadvantaged populations. Food security, which is defined as the consistent access to safe and nutritious food necessary for a healthy life, remains an elusive goal for millions of people globally, including those in Mozambique [2]. Mozambique is among the countries most vulnerable to climate-related disasters such as droughts, floods, and cyclones, which severely impact food security and the national economy. The 2021 Global Climate Risk Index ranked Mozambique as the country most affected by extreme weather events, underscoring its vulnerability and lack of preparedness to address climate change [3]. This climate vulnerability not only jeopardizes Mozambique's economy but also threatens its food systems, adding further challenges to achieving food security [4].

Between 2021 and 2022, approximately 2 million people in Mozambique faced severe levels of acute food insecurity [5]. The Mozambican government has acknowledged food and nutritional security as one of its top priorities, which is reflected in strategic documents such as the Government's Five-Year Plan (PQG) and the Economic and Social Plan and State Budget (PESOE). These plans aim to improve access to food, strengthen human capital, and ensure better living conditions for the population. Despite significant economic growth over the past two decades, with an average annual rate of 7.9% between 1993 and 2015, Mozambique continues to grapple with challenges such as high unemployment and persistent poverty [6]. The unemployment rate, which reached 18.4% in 2022, coupled with the growing difficulty for households to access adequate food, has exacerbated food insecurity in the country [7]. Moreover, endemic corruption in Mozambique exacerbates these issues by diverting resources intended for food programs and perpetuating socioeconomic inequalities [8,9].

In Mozambique, food insecurity is exacerbated by various factors, including poverty, social inequality, conflicts, lack of access to healthcare, poor food distribution, and climate change [5]. The direct impact of this insecurity is evident in hunger, a condition that arises from insufficient consumption of essential nutrients, leading to discomfort and compromised health [10]. Hunger, while often associated with economic and social issues, is also intrinsically linked to natural and political factors, making it one of the most pressing global challenges [11]. The recent COVID-19 pandemic and the conflict in Ukraine have further intensified the global hunger crisis, affecting nearly one billion people [12]. Between 2021 and 2022, the number of people experiencing hunger increased by 20%, reflecting a troubling rise of 196 million individuals since 2019 [13]. The persistence of economic and climate shocks, combined with ongoing conflicts, has kept food vulnerability at elevated levels, particularly in countries like Mozambique, which rely on food imports to meet their basic needs [14].

In Mozambique, approximately 80% of rural households rely on subsistence farming, making the agricultural sector crucial for the population's survival [15]. However, this sector faces significant challenges, including low productivity and dependence on imports. Despite an increase in agricultural production from 2021 to 2022, particularly in cereals and legumes, the country continues to struggle with efficient resource management and adapting to climate change [16]. The production of maize, one of the key staple crops in Mozambique, plays a crucial role in the country's food security. Increasing agricultural production and productivity, including maize, is essential to reduce food insecurity and lessen the dependence on imports [17]. However, the growth in production has primarily been driven by the expansion of cultivated areas rather than improvements in productivity, underscoring the need for more effective strategies to optimize the use of agricultural resources [18].

Accurate forecasting of maize production is therefore a critical tool for planning strategic interventions that can enhance food security in the country. Forecasting models, such as ARIMA and LSTM, have been employed to estimate agricultural crop production, each with its distinct features. The ARIMA model is well-known for its ability to capture linear and short-term patterns in time series data, while the LSTM model excels in identifying nonlinear patterns and complex dynamics [19]. Studies have shown that LSTM models, in particular, outperform traditional time series models like ARIMA in scenarios where variability is high and relationships between variables are nonlinear [20]. In the Mozambican context, where agriculture is highly vulnerable to climatic and economic shocks, the application of LSTM models can provide more robust and accurate forecasts, aiding in the formulation of more resilient agricultural policies [21].

Furthermore, the combination of traditional time series models with artificial neural networks, such as LSTM, emerges as a promising approach to improve the accuracy of agricultural forecasts. This hybrid approach can be especially beneficial in Mozambique, where climatic variability and reliance on traditional farming practices increase the complexity of predicting maize and other crop production [22].

Therefore, the primary objective of this research is to accurately estimate maize production in Mozambique using a comparative approach between ARIMA and LSTM models. The significance of this research lies in its potential to contribute to effective strategies that mitigate food insecurity in Mozambique. By comparing the performance of ARIMA and LSTM models, this study provides an in-depth analysis of the best practices for forecasting maize production in the country. This not only expands the scientific knowledge base but also offers practical guidelines for policymakers with the aim of strengthening the agricultural sector and, consequently, improving food security in Mozambique [23]. Through the application of advanced forecasting models like ARIMA and LSTM, the study hopes to contribute to a more resilient agricultural sector capable of addressing the challenges posed by climate and economic changes.

2. Literature Review

2.1. Global Context of Maize Production

Maize (Zea mays L.) is one of the most significant agricultural crops globally, with its cultivation spanning over 160 million hectares across diverse regions. The United States, China, and Brazil contribute to over 60% of the world's maize production, highlighting their dominance in this sector [24,25]. Originating in the highlands of Mexico, maize has become a staple food for numerous societies, playing a crucial role in global food security and economic stability [26]. In 2022, global maize production reached approximately 1.2 billion tons, solidifying its position as the most produced cereal crop [24]. The versatility of maize is a key factor driving its global demand. Serving as food for humans, animal feed, and a raw material for biofuels, maize's applications are diverse. Notably, around 60% of the world's maize production is allocated for animal feed, with the United States leading in production and export [27]. Additionally, maize's role in biofuel production, particularly ethanol, is expanding, with Brazil and the U.S. being at the forefront of this industry [28,29].

This multifunctionality underlines the crop's economic importance and its contribution to sustainable energy solutions. Historically, maize's domestication can be traced back to the Balsas River Valley of Mexico around 2,000 to 2,500 BC, where it played a pivotal role in the development of Mesoamerican civilizations [26]. Theories about its evolutionary origins vary, with some suggesting it resulted from the crossing of teosinte and tripsacum, while others propose it evolved from a small-eared teosinte [30,31]. Regardless of the theory, maize's evolution highlights its adaptability and significance throughout history. Maize's remarkable photosynthetic efficiency, particularly under high irradiance conditions, distinguishes it from other crops [32]. However, its production is closely tied to climatic and hydric variables. For optimal yields, maize requires specific planting conditions, often determined by the number of consecutive days without precipitation, and a total water requirement of 350 to 500 mm during its growth cycle [33]. Despite these challenges, maize remains a crucial food source for over a billion people globally, even as the majority of its production is directed towards animal feed [25].

Beyond its role in food and feed, maize also contributes to renewable energy production. Maize cobs and husks possess a high calorific value, making them valuable resources for energy generation [34]. Additionally, the residual biomass from maize, including leaves and husks, can be utilized for energy cogeneration, though the efficiency of this process is influenced by factors such as stacking density and airflow [35]. This energy potential further underscores maize's versatility and its contribution to sustainable agriculture. In the context of sustainable agriculture, maize plays a significant role in promoting soil health and biodiversity. For example, specific maize cultivars with unique root traits are more tolerant to poor soil conditions, contributing to enhanced agricultural resilience [36]. Moreover, when maize is cultivated alongside cover legumes, it promotes soil nutrient accumulation and biodiversity, further demonstrating its environmental benefits [37]. However, the environmental sensitivity of maize also highlights the need for sustainable practices to mitigate potential negative impacts.

Nutritionally, maize is rich in essential vitamins, including vitamin A and vitamin E, with variations across different varieties [26].The presence of pro-vitamin A carotenoids and tocopherols enhances its potential in preventing conditions such as blindness and macular degeneration [38]. However, challenges related to air pollution, mycotoxin contamination, and heavy metal exposure in maize production pose significant public health concerns [39], highlighting the need for improved safety and quality control measures in maize cultivation. The debate surrounding maize's use in biofuel production, particularly ethanol, has intensified over the years. Corn ethanol has emerged as a viable alternative to fossil fuels, reducing greenhouse gas emissions and enhancing energy security in key regions like the U.S. and Brazil [28,40]. However, despite the rapid growth in maize-based biofuel production between 2007 and 2020, recent projections suggest a slight decline in consumption due to market saturation and international biofuel policies [29], underscoring the complex dynamics of this sector.

Maize cultivation, however, faces growing challenges from climate change, which poses significant risks to agricultural productivity worldwide. Extreme temperatures and precipitation fluctuations are expected to reduce maize yields, particularly in vulnerable regions such as Sub-Saharan Africa and Southeast Asia [41,42]. To address these challenges, there has been a surge in research focused on developing maize varieties that are more resilient to adverse climatic conditions, emphasizing the need for innovation in maize breeding and agricultural practices [43].

Maize production is deeply intertwined with global trade dynamics, as evidenced by recent disruptions caused by geopolitical conflicts. For example, the war between Ukraine and Russia has significantly impacted global grain supply chains, leading to price volatility and raising concerns about food security [29,44]. These challenges underscore the importance of diversifying supply sources and implementing effective trade policies to ensure the continued growth and sustainability of global maize production [45,46]. Looking forward, while global maize production is projected to continue increasing, the pace of growth may slow, highlighting the need for sustainable practices and technological advancements in the sector [34,47].

2.2. Maize Production in Mozambique

In Mozambique, maize is the primary food crop and plays a crucial role in the country's food security, being cultivated by over 70% of farming households, mainly on smallholder farms [48,49]. Maize production in Mozambique is heavily reliant on rainfall, with yields significantly affected by climatic variability, such as droughts and floods, which are frequent in the country [50,51]. From 1961 to 2022, maize production in Mozambique increased from 641.8 thousand tons to 2.51 million tons, a growth attributed to improvements in agricultural practices and the expansion of cultivated areas [24]. However, maize productivity in the country remains low, with an average yield of only 1.1 tons per hectare in 2022, which is lower than in many other countries in the region, such as South Africa and Zambia [52]. This highlights the need for greater investments in agricultural technologies, such as improved seeds and irrigation systems [41,51].

In 2022, the area harvested for maize in Mozambique expanded to

1.8 million hectares, a 10.6% increase compared to 2019. Yields reached 1.1 tonnes per hectare, reflecting a 21.7% improvement over 2019 levels. As a result, total maize production in the country increased to approximately 2 million tonnes in 2022, a significant 34.6% rise from the previous year. This growth can largely be attributed to the SUSTENTA programme, which introduced initiatives to enhance agricultural productivity, expand cultivated areas, and promote sustainable farming practices. Comparing maize production from 2022 to 2014, Mozambique experienced a 43.9% increase, with a 60.5% rise since the implementation of the Sustainable Development Goals (SDGs) in 2016, indicating consistent growth and significant progress in the agricultural sector [24]. Despite these gains, Mozambique continues to face challenges in meeting domestic maize demand due to limited agricultural practices and external dependencies.

The provinces of Tete, Zambézia, and Manica are the leading maize-producing regions in Mozambique, accounting for more than 48% of the national production [53]. These provinces benefit from favorable agroecological conditions, such as fertile soils and regular rainfall, although they also face challenges related to limited access to agricultural inputs and inadequate infrastructure [49]. Maize commercialization is limited, with most of the production being destined for local consumption, and only 17.7% being marketed [53]. The government of Mozambique has implemented programs like SUSTENTA, which aim to improve agricultural productivity and promote sustainable farming practices, [54]. This program has contributed to increasing maize production in the country, especially in irrigated areas, where yields can be significantly higher than in rainfed areas. However, the dependence on maize imports, mainly from South Africa, remains a challenge for the country's food security [52].

Post-harvest losses are another significant challenge for Mozambican farmers. On average, about 13.5% of the maize produced is lost after harvest due to inadequate storage and transportation conditions [53,55]. Reducing these losses is essential to improving food security and increasing farmers' incomes, particularly in rural areas [56]. Looking ahead, Mozambique is expected to continue investing in the modernization of its agricultural sector, with a focus on increasing maize productivity and reducing reliance on imports. Promoting sustainable farming practices, enhancing farmer training, and improving rural infrastructure will be essential to ensure the country can meet the growing food demands of its population and contribute to food security in the Southern African region [50].

3. Materials and Methods

3.1. Materials

This study focused on analyzing maize production in Mozambique, using annual data from 1961 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 maize production, advanced models such as LSTM feedback neural networks and ARIMA were employed. Python's widespread use in scientific research ensured the precision and reliability of the results obtained.

3.2. Data Source

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

3.3. Methods

3.3.1. Arima Modeling

i. Model Identification

To model maize production in Mozambique, the time series properties were first analyzed, including autocorrelation (ACF) and partial autocorrelation (PACF) plots, to identify the appropriate order of the ARIMA model. The original series was tested for stationarity using the Augmented Dickey-Fuller (ADF) test, and if non-stationary, differencing was applied to remove long-term trends.

ii. Parameter Estimation

With the time series stationary, the ARIMA models were fitted, and their parameters were estimated using the maximum likelihood method. The models were then compared using metrics such as AIC, BIC, RMSE, and MAPE to identify the model with the best fit and highest predictive accuracy.

iii. Validation and Evaluation

The ARIMA models were validated using real data from 2010 to 2020, which were not included in the training phase. The predictive performance of each model was assessed by comparing the forecasts with actual data, using RMSE and MAPE to quantify accuracy. The best-performing model was then used to forecast maize production from 2023 to 2030.

3.3.2. Lstm Neural Networks

i. Data Preparation

For the LSTM (Long Short-Term Memory) neural network modeling, historical maize production data from 1961 to 2013 were normalized to enhance training efficiency. The time series was split into input and output sequences, enabling the model to capture temporal dependencies effectively.

ii. Model Architecture and Training

The LSTM model architecture consisted of two LSTM layers, each with 50 units, followed by a dense layer for generating predictions. The model was trained over 100 epochs using the Adam optimizer and mean squared error (MSE) loss function. During training, the model adjusted its parameters to capture underlying patterns in the time series.

iii. Evaluation and Validation

After training, the LSTM model was evaluated using data from 2014 to 2022, which were not used in training. Prediction accuracy was measured using RMSE and MAPE, allowing for the assessment of the model's ability to generalize to new data. The model's predictions were compared with actual production values to validate its performance.

iv. Forecasting for 2023 to 2030

To forecast maize production from 2023 to 2030, the LSTM model was combined with the Bootstrapping technique, generating multiple samples to quantify forecast uncertainty. Predictions were accompanied by 95% confidence intervals, providing robust estimates for the future evolution of maize production in Mozambique.

3.3.3. Selection of the Best Model for Estimating Agricultural Production

To determine the most suitable model for forecasting maize production in Mozambique, the performance of the ARIMA and LSTM models was compared using the MAPE metric. The model with the lowest MAPE was selected as the most accurate and thus the most appropriate for future projections. This approach ensured greater reliability in the estimates, providing solid support for decision-making in agricultural and food security policies.

4. Results

4.1. Exploratory Analysis of the Maize Time Series

The analysis of maize production data in Mozambique from 1961 to 2022 (n=62) reveals important statistical characteristics (Table 1). The mean maize production over this period is 829,501.85 tons, reflecting the average annual volume. The median, at 494,743 tons, indicates that in more than half of the years, production was lower than the average, highlighting an asymmetric distribution, further confirmed by the positive skewness of 0.92. This skewness suggests that there are years with exceptionally high production that pull the average upwards, indicating the presence of outliers that boost production. The mode, or most frequent value, is 330,000 tons, which may indicate a common production level under certain historical conditions. The standard deviation of 561,189.75 tons, along with the high variance of 314,933,932,830.95, demonstrates considerable variability in the data. This high variability is also reflected in the coefficient of variation of 67.65%, indicating that the variation relative to the mean is significant, pointing to considerable instability in maize production.

The production range of 2,222,731 tons, resulting from the difference between the maximum of 2,354,778 tons (in 2012) and the minimum of 132,047 tons (in 1992), highlights the significant fluctuations in maize production over the decades. The kurtosis measure of -0.07 indicates a slightly platykurtic distribution, suggesting that the data has fewer outliers than a normal distribution, although this difference is small and may not be statistically significant. However, along with the skewness, it helps characterize the distribution as right-skewed but without significant extremes.

Descriptive Statistics	Value
Mean	152485.9355
Median	99378.5
Mode	85000
Variance	12143686621
Standard Deviation	110198.3966
Coeficient of variation	0.722679087
Maximum	413000
Minimum	32618
Skewness	1.294974685
Kurtosis	0.180718385
Range	380382
n	62

Table 1: Descriptive Measures of the Annual Maize Production Series

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

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

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

The original time series plot of maize production in Mozambique from 1961 to 2022 (Figure 1) reveals a significant upward trend over the years, particularly from the 1990s onwards. However, the series also exhibits notable fluctuations in certain years, likely reflecting the influence of external factors such as extreme weather conditions or changes in agricultural policies. The absence of clear repetitive patterns in the graph further supports the notion that the series is non-stationary, as evidenced by the upward trend over time. The differenced series, on the other hand, represents the annual changes in maize production, effectively removing long-term trends and enabling a more focused analysis of short-term fluctuations. Differencing helps highlight interannual variations that might be obscured by the overall upward trend in the original series.

This approach facilitates the identification of abrupt changes and anomalies that could be driven by external factors, providing a clearer understanding of the underlying dynamics of maize production in Mozambique. By removing the trend, the differenced series approximates stationary behavior, which is essential for the application of analytical methods that assume constant statistical properties over time.

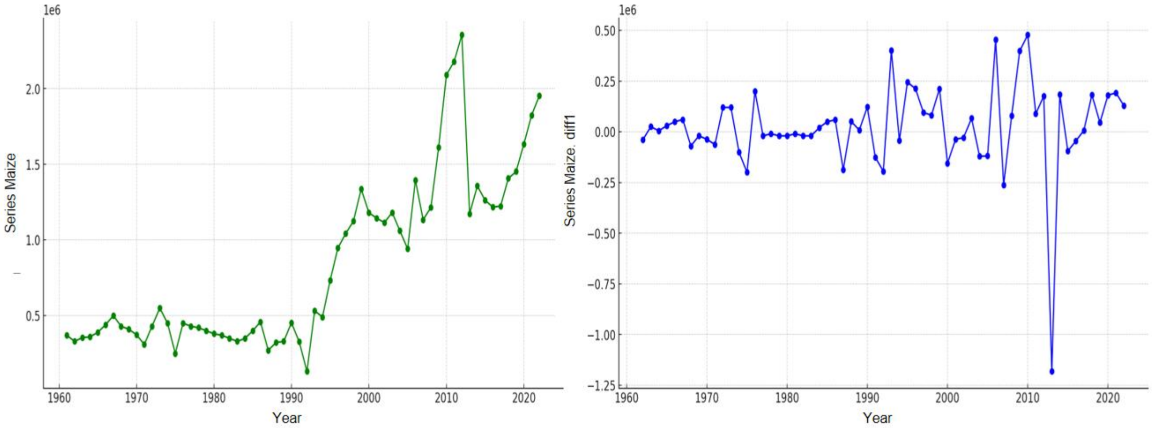

Figure 1: Analysis of the Time Series (Original and Differenced) of Maize Production in Mozambique (1961-2022)

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

The decomposition of the time series allows for the identification of three main components: trend, seasonality, and residuals (Figure 2). The trend component reveals a sharp increase in production over the decades. Seasonality is virtually absent, indicating a lack of consistent seasonal patterns, suggesting that maize production is not significantly influenced by annual seasonal factors but rather by long-term trends. The residuals, on the other hand, reflect the remaining random variations after removing the trend and seasonality components, indicating that other unmodeled variables may influence maize production, though they do not follow a clear structure.

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

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

The ACF plot for maize production in the original series (Figure 3) does not show significant peaks at specific lags, indicating the absence of seasonality. The rapid decline in autocorrelation values after a few initial lags suggests that successive observations are not strongly correlated in the long term, except for the presence of a trend. This implies that the original series is dominated by a trend component that obscures any potential seasonal patterns or regular cycles over time. After differencing the series, the ACF plot reveals that autocorrelation values drop quickly after the initial lags, indicating that the series does not have a significant long-term correlation structure. This rapid decline strongly suggests that the differenced series approaches more stationary behavior.

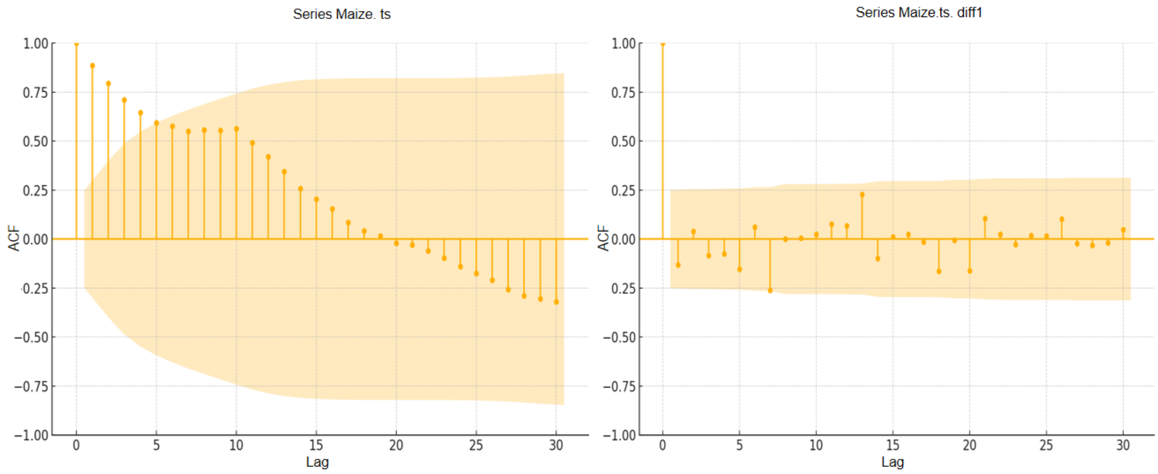

Figure 3: Function (ACF) of Maize Production in Mozambique

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

The PACF plot for the original series (Figure 4) shows significant peaks at the first few lags, suggesting a possible low-order autoregressive structure. This indicates that past values have a limited but discernible influence on predicting future values, implying that the series could be effectively modeled with a low-order autoregressive component. This structure suggests that values close in time exert some influence on subsequent values, which can be useful in predictive modeling. After differencing, the PACF plot still shows some peaks at the initial lags, indicating the presence of low-order autoregressive components in the differenced series. This suggests that even after removing long-term trends, past values still have a moderate influence on future values. This persistent autocorrelation in the first few lags implies that a simple autoregressive model could capture the essential dynamics of the differenced series, enabling more accurate short-term predictions of maize production variations.

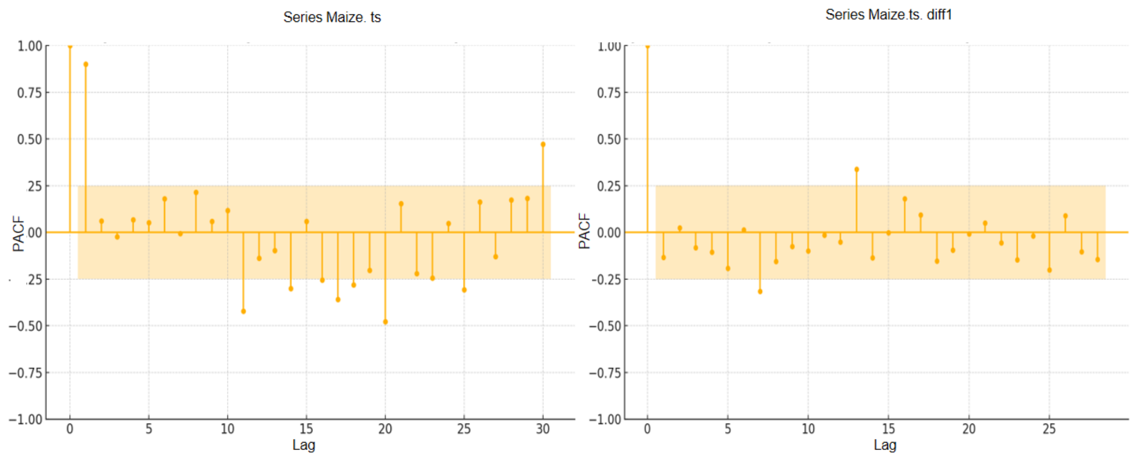

Figure 4: Partial Autocorrelation Function (PACF) of Maize Production in Mozambique

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

The ADF test yields a p-value of 0.762 for the original time series (Table 2), indicating that the series is non-stationary. The null hypothesis of a unit root cannot be rejected, confirming the presence of a trend in the series. To achieve stationarity, it is necessary to apply a differencing transformation, which removes this long-term trend, allowing for a more accurate analysis of the data. After differencing, the ADF test returns a p-value of 0.000, suggesting that the null hypothesis of a unit root is rejected, and the differenced series is stationary. This implies that the statistical properties of the series, such as the mean and variance, remain constant over time, making it suitable for the application of forecasting models that assume stationarity, such as ARIMA.

After differencing, the maize production series became stationary, as confirmed by the Augmented Dickey-Fuller test and the analysis of the ACF and PACF plots. This indicates that differencing was effective in removing long-term trends and stabilizing the series, making it suitable for modeling with the ARIMA framework.

Test Statistic	**p-Value**	**Lags**	**n**	**Critical Value**		
				(1%)	**(5%)**	**(10%)**
Orginal Series						
-0.973	0.762	0	61	-3.542	-2.910	-2.593
Differenced Series						
-7.217	0.0000	1	60	-3.544	-2.911	-2.593

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

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

4.3.1. Model Identification

After differencing the time series of maize production in Mozambique, three ARIMA models were suggested and evaluated based on the analysis of the Autocorrelation (ACF) and Partial Autocorrelation (PACF) plots. The ARIMA (1, 1, 0) model was considered due to the presence of a significant peak at the first lag in the PACF plot, indicating a first-order autoregressive component.

The ARIMA (0, 1, 1) model was suggested based on the observation of a peak at the first lag in the ACF plot, indicating the presence of a first-order moving average component. Finally, the ARIMA (1, 1, 1) model was proposed to capture both autoregressive and moving average characteristics, potentially enhancing the model's predictive capability by considering more complex interactions between past values of the series.

4.3.2. Parameter Estimation

Table 3 presents the parameter estimates for the three ARIMA models fitted to maize production in Mozambique: ARIMA (1,1,0), ARIMA (0,1,1), and ARIMA (1,1,1). All estimated parameters in each model are highly significant, as indicated by very low p-values (0.0000), suggesting that both autoregressive (AR) and moving average (MA) components are important for capturing the dynamics of the time series. In the ARIMA (1,1,0) model, the AR(1) parameter has an estimate of -0.1155, indicating a negative influence of past lags on future production, although this effect is relatively small. In the ARIMA (0,1,1) model, the MA(1) parameter has an estimate of 0.6718, suggesting that past random fluctuations have a moderate and positive influence on production. The ARIMA (1,1,1) model combines both components, with the AR(1) parameter estimated at -0.8272 and the MA(1) parameter at 0.7465, indicating that this model captures both the effects of past lags and random fluctuations.

Given that the ARIMA (1,1,1) model incorporates both the autoregressive and moving average components, with both parameters being highly significant, it is the most suitable model for forecasting maize production. This model is capable of more comprehensively capturing the underlying dynamics of the time series, which may result in more accurate and robust forecasts compared to the simpler ARIMA (1,1,0) and ARIMA (0,1,1) models.

Model	**Parameter**	**Estimates**	**t-Stat**	**P-value**
ARIMA (1,1,0)	AR (1)	-0.1155	-10.849	0.0000
ARIMA (1,1,0)	$\emptyset_2$	4.783e+10	7.18e+13	0.0000
ARIMA (0,1,1)	MA (1)	0.6718	11.211	0.0000
ARIMA (0,1,1)	$\emptyset_2$	4.795e+10	13.05e+07	0.0000
ARIMA (1,1,1)	AR (1)	-0.8272	-11.671	0.0000
ARIMA (1,1,1)	MA (1)	0.7465	11.256	0.0000
ARIMA (1,1,1)	$\emptyset_2$	5.017e+10	4.05e+23	0.0000

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

4.3.3. Diagnostic Test of Residuals for Maize Production Models

Table 4 presents the results of diagnostic tests applied to the residuals of the ARIMA (1,1,0), ARIMA (0,1,1), and ARIMA (1,1,1) models used to forecast maize production. The p-values from the Box-Pierce test indicate that there is no significant autocorrelation in the residuals of any of the models, with all p-values above 0.75. This suggests that all models adequately capture the time series structure, leaving no unmodeled patterns in the residuals. The ARCH test assesses the presence of heteroscedasticity in the residuals, and the high p-values (all above 0.76) indicate no significant heteroscedasticity in any of the models. Therefore, the residual variance is constant over time, which is desirable for ensuring model stability.

However, all models fail the residual normality test, as evidenced by very low p-values (0.0000) in the Shapiro-Wilk and Jarque-Bera tests. This violation of residual normality is common in time series, but the ARIMA (1,1,1) model shows the lowest Jarque-Bera value, suggesting that its residuals are slightly closer to normal distribution compared to the other models.

Model	Box-Pierce		ARCH		Shapiro-WilK		Jarque-Bera	
	Q	p-value	TR2	p-value	W	p-value	JB	p-value
ARIMA (1,1,0)	0.01557	0.9006	6.5238	0.7695	2.4864	0.0000	479.033	0.0000
ARIMA (0,1,1)	0.03701	0.8474	6.5434	0.7677	2.4311	0.0000	475.417	0.0000
ARIMA (1,1,1)	0.09830	0.7538	6.3387	0.7860	2.5881	0.0000	454.534	0.0000

Table 4: Diagnostic Test of Residuals for Maize Production Models

Although residual normality is desirable in ARIMA models, its absence does not invalidate the model, as these models are robust and effective in forecasting complex time series often influenced by external factors that introduce deviations. They can be evaluated using metrics such as AIC, BIC, RMSE, and MAPE, which are more relevant for measuring predictive performance. These metrics allow for adjustments and transformations to improve model fit without compromising forecasting capability, especially when the primary focus is on prediction rather than statistical inference. Therefore, considering all diagnostics, the ARIMA (1,1,1) model is the most robust among the three analyzed and is the most suitable for forecasting maize production.

4.3.4. Comparison of Model Performance

Table 5 provides a comparison of the performance of three ARIMA models (ARIMA (1,1,0), ARIMA (0,1,1), and ARIMA (1,1,1)) applied to maize production forecasting, using metrics such as AIC, BIC, HQIC, RMSE, and MAPE. The ARIMA (1,1,0) model shows the lowest AIC, BIC, and HQIC values, suggesting a good balance between fit and complexity. However, its relatively high RMSE and MAPE values indicate that, while parsimonious, its predictive accuracy is limited. The ARIMA (0,1,1) model also has low AIC, BIC, and HQIC values, and it significantly improves accuracy compared to ARIMA (1,1,0), with a lower RMSE of 543,375.9 and a MAPE of 36.24%. This indicates that the ARIMA (0,1,1) model offers a reasonable trade-off between simplicity and accuracy, capturing the time series dynamics more effectively than ARIMA (1,1,0).

The ARIMA (1,1,1) model, although having slightly higher AIC, BIC, and HQIC values, stands out with the lowest RMSE and MAPE values, at 390,016.3 and 16.39%, respectively. These results indicate that ARIMA (1,1,1) is the most accurate and robust model among the three, better capturing the variations in maize production.

Model	AIC	BIC	HQIC	RMSE	MAPE
ARIMA (1,1,0)	1676.157	1680.379	1677.811	641974.5	43.39%
ARIMA (0,1,1)	1676.345	1680.567	1678	543375.9	36.24%
ARIMA (1,1,1)	1677.804	1684.136	1680.285	390016.3	16.39%

Table 5: Comparison of Model Performance for Maize Production

Therefore, despite being slightly more complex, the ARIMA (1,1,1) model offers the best predictive performance, making it the optimal choice for estimating maize production.

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

Table 6 presents a comparison of three ARIMA models (ARIMA (1,1,0), ARIMA (0,1,1), and ARIMA (1,1,1)) applied to forecast maize production in Mozambique between 2010 and 2020. The RMSE and MAPE values provide a measure of each model's accuracy. The ARIMA (1,1,1) model stands out with the lowest RMSE (390,016.30) and MAPE (16.39%), indicating that it offers the most accurate predictions in both absolute and relative terms. The ARIMA (0,1,1) model, while showing a lower RMSE (535,915.2) and MAPE (36.24%) compared to ARIMA (1,1,0), still does not achieve the same level of precision as ARIMA (1,1,1). On the other hand, ARIMA (1,1,0) has the highest RMSE (634,241.40) and MAPE (43.39%), suggesting that this model is the least effective at capturing the dynamics of maize production during the analyzed period.

Year	Actual Dada	Predicted Data		
		ARIMA (1,1,0)	ARIMA (0,1,1)	ARIMA (1,1,1)
2010	2089890	1586757.36	1613384.30	1609372
2011	2178842	1650922.98	1654076.68	2053309
2012	2354778	1715088.61	1694220.17	2198976
2013	1173709	1779254.24	1734008.37	2325558
2014	1357220	1843420.11	1773404.80	1290778
2015	1262038	1907585.99	1812439.18	1255025
2016	1217000	1971752.16	1851161.63	1346005
2017	1224000	2035918.12	1889613.97	1157950
2018	1406794	2100084.47	1927838.13	1267517
2019	1451686	2164250.67	1965856.34	1359565
2020	1632321	2228416.68	2003684.43	1483323
RMSE		634241.40	535915.2	390016.30
MAPE		43.39%	36.24%	16.39%

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

Considering the results, the ARIMA (1,1,1) model is clearly the most suitable for estimating maize production in Mozambique. Its superior accuracy compared to the other models makes it the best choice for future forecasts, as it more robustly captures the variations in maize production over the years.

4.3.6. Forecasted Maize Production in Mozambique from 2023 to 2030

Table 7 presents the forecasted maize production in Mozambique from 2023 to 2030, as estimated by the ARIMA model, along with 95% confidence intervals. The forecast values indicate relative stability in maize production over the years, with small annual variations, maintaining levels around 1.93 to 1.94 million tons. However, the confidence intervals widen over time, reflecting increasing uncertainty in the forecasts. The lower bound of the confidence intervals shows a gradual decline, from around 1.49 million tons in 2023 to approximately 753 thousand tons by 2030, while the upper bound increases, reaching over 3.13 million tons by 2030. These results suggest that although the ARIMA model predicts stable production, there is growing uncertainty regarding the impact of external factors as the forecast horizon extends, which is captured by the broader confidence intervals.

Year	Forecasted Value	Confidence Intervals (95%)	
		Lower Bound	Upper Bound
2023	1931958.86	1492953.58	2370964.14
2024	1948520.54	1352183.90	2544857.17
2025	1934821.25	1197930.78	2671711.71
2026	1946152.86	1103531.49	2788774.24
2027	1936779.71	991373.16	2882186.26
2028	1944532.88	913203.93	2975861.83
2029	1938119.71	822335.61	3053903.80
2030	1943424.48	753139.32	3133709.64

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

4.4. Estimation with the LSTM Model for Maize Production

4.4.1. Model Training with LSTM

To analyze maize production in Mozambique and forecast its future trajectory, a feedback neural network of the LSTM type was utilized. This model was trained using historical data from 1961 to 2013 over 100 epochs. The model architecture consisted of two LSTM layers with 50 units each, followed by a dense layer that generated the predictions. During training, the model adjusted its parameters to capture temporal dependencies present in the historical series, preparing it to forecast future production based on identified patterns.

4.4.2. Model Evaluation

After training, the model was evaluated using data from 2014 to 2022, which were not included in the training (Table 8). This evaluation was crucial to verify the model's ability to accurately predict maize production outside the training period, ensuring its generalization capability. The predictions were compared with actual values using RMSE and MAPE metrics to confirm the model's precision and reliability for future forecasts. The LSTM model evaluation, as presented in Table 8, demonstrates robust performance in forecasting maize production in Mozambique from 2014 to 2022, with an average RMSE of 39.2 thousand tons and a MAPE of 2.64%. These values indicate that the model was able to predict annual production with reasonable accuracy, maintaining relatively low percentage deviations, especially in years like 2014, 2017, and 2022, where percentage errors were below 1%.

Year	Actual Dada	LSTM Model		
		Predicted Data	RMSE	MAPE
2014	1357220	1341043.72	16176.28	1.19%
2015	1262038	1316075.77	54037.77	4.28%
2016	1217000	1243821.98	26821.98	2.20%
2017	1224000	1235472.01	11472.01	0.94%
2018	1406794	1360822.46	45971.54	3.27%
2019	1451686	1404244.15	47441.85	3.27%
2020	1632321	1563792.81	68528.19	4.20%
2021	1824281	1887741.78	63460.78	3.48%
2022	1951981	1970731.59	18750.59	0.96%
Mean	1480813.44	1480416.25	39184.55	2.64%

Table 8: LSTM Model Evaluation with Real Maize Production Data from 2014 to 2022

Although years like 2015 and 2020 showed larger discrepancies, indicating that the model may struggle to capture more abrupt production variations, it proved effective in most cases. These results indicate that the model is accurate and reliable for agricultural production forecasting, adequately capturing trends and variations in historical data, justifying its suitability for future forecasts.

4.4.3. Forecasts for 2023 to 2030

To forecast maize production in Mozambique from 2023 to 2030, a combination of the LSTM neural network and Bootstrapping technique was employed. The trained LSTM model generated forecasts, while Bootstrapping quantified the uncertainty associated with these predictions by generating multiple data samples. This combination resulted in forecasts accompanied by 95% confidence intervals, providing a robust and reliable estimate of the future evolution of maize production in the country. The maize production forecast for Mozambique from 2023 to 2030, as presented in Table 20, indicates a modest average annual growth of 0.12%, with annual variations reflecting both slight growth and decline periods. The LSTM model, combined with the Bootstrapping technique, suggests that production does not follow a constant growth pattern; instead, there are predicted years with reductions in production, such as in 2026, 2028, and 2030. The 95% confidence interval for each year reflects the uncertainty associated with these predictions, with ranges suggesting considerable variability in future production.

Year	Forecasted Value	Confidence Intervals (95%)	
		Lower Bound	Upper Bound
2023	1960841.68	1871827.39	2049855.97
2024	1979037.82	1897064.65	2061010.99
2025	1951807.73	1878687.84	2024927.62
2026	1917306.30	1829982.78	2004629.82
2027	1925061.04	1840899.58	2009222.49
2028	1888144.87	1798746.67	1977543.07
2029	1913252.87	1839006.08	1987499.65
2030	1888902.89	1815234.80	1962570.98

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

Overall, the forecast points to a stabilization in maize production, with small fluctuations over the years, without significant growth or decline trends.

5. Discussion

The exploratory analysis of maize production in Mozambique reveals an asymmetrical distribution, with a mean of 829,501.85 tonnes and a median of 494,743 tonnes. This positive skewness, reflected by a value of 0.92, indicates that maize production has been marked by years of high output, influenced by exceptional events. Studies suggest that such asymmetries in agricultural time series may be linked to exogenous shocks, such as favorable agricultural policies or technological innovations that significantly boost productivity in certain years [57]. Additionally, the high variability, evidenced by a coefficient of variation of 67.65%, also reflects the dependence of maize production on external factors, such as climate change and market fluctuations, as discussed by [58]. The time series analysis and decomposition revealed an upward trend starting in the 1990s, with no clear seasonal patterns. This aligns with studies indicating that agricultural liberalisation policies and increased investment in agricultural technology have driven maize production in Mozambique in recent decades [59]. The absence of seasonality suggests that maize production is more influenced by long-term factors, such as structural changes in the agricultural economy, rather than seasonal cycles. This corroborates the analysis of, who point to increased resilience of maize crops in response to seasonal variations in Sub-Saharan Africa [60].

The Augmented Dickey-Fuller test confirms that the maize production series is non-stationary, which is expected given the observed growth over time. Various findings suggest that maize production series exhibit non-stationary characteristics, influenced by both environmental factors and modelling approaches [61,62]. Studies such as highlight the importance of transforming non-stationary series for forecasting models like ARIMA to achieve more accurate estimates. Differencing the time series proved effective in achieving stationarity, enabling the application of predictive models, as discussed by, who advocates differencing as a key technique for modelling non-stationary time series [63,64].

The estimation of ARIMA models revealed that ARIMA (1,1,1) is the most suitable for capturing the dynamics of maize production in Mozambique, combining both autoregressive and moving average components. This result is consistent with studies demonstrating the effectiveness of ARIMA (1,1,1) in modelling agricultural time series with long-term trends and random fluctuations [65]. Furthermore, model diagnostics indicate that although the residuals do not follow a normal distribution, the ARIMA (1,1,1) model still offers robust predictive capabilities, as evidenced by its lower RMSE and MAPE values compared to other models.

The performance evaluation of ARIMA models using real data from 2010 to 2020 reinforces the superiority of ARIMA (1,1,1) in terms of predictive accuracy. With a MAPE of 16.39% and RMSE of 390,016.3 tonnes, the model stands out in predicting maize production in Mozambique, offering a reliable tool for future projections. This aligns with the conclusions, who assert that ARIMA is one of the most effective models for forecasting complex agricultural time series [66]. Comparing the performance of the ARIMA (1,1,1) model with the LSTM model for forecasting maize production in Mozambique shows that LSTM offers superior performance in terms of MAPE. While ARIMA (1,1,1) recorded a MAPE of 16.39%, the LSTM model achieved a significantly lower MAPE of 2.64%. This result highlights LSTM's ability to capture the complexities of the maize production time series more accurately, which is consistent with studies such as that demonstrate the efficacy of neural networks, particularly LSTM, in predicting time series with nonlinear patterns and complex dynamics [67].

The evaluation of the LSTM model for the period 2014 to 2022 shows that, despite some discrepancies in years like 2015 and 2020, the model successfully predicted maize production in most years. These results corroborate studies that identify LSTM as a robust tool for forecasting in agricultural scenarios where time series are often influenced by external factors such as climate conditions and agricultural policies [68,69]. Moreover, LSTM's ability to handle long-term temporal dependencies makes it particularly well-suited for forecasting crops with complex production cycles, such as maize. Regarding forecasts for 2023 to 2030, combining the LSTM model with the Bootstrapping technique provides an interesting approach, enabling not only future production predictions but also quantifying the uncertainty associated with these forecasts.

Studies advocate the use of Bootstrapping alongside neural network models to improve forecast robustness, especially in scenarios of high variability and uncertainty [70,71]. The forecasts indicate a stabilization of maize production, with limited annual variations but no signs of significant growth. This scenario is concerning in the context of food insecurity in Mozambique, particularly in light of the Sustainable Development Goals (SDGs), especially SDG 2, which aims to end hunger and achieve food security by 2030. Stagnant maize production, a crucial staple food, may hinder the achievement of these goals, highlighting the need for policy interventions and investments in sustainable agriculture.

Moreover, the wide confidence intervals suggest considerable uncertainties, emphasising the urgency of actions to mitigate food insecurity risks. The forecasted stabilisation is consistent with trends observed in other agricultural regions facing similar challenges due to structural and environmental limitations, as noted by [72]. The small predicted fluctuations over the years reinforce the importance of proactive agricultural policies to boost growth and ensure food security in the country.

6. Conclusions

The analysis of maize production in Mozambique from 1961 to 2022 revealed an asymmetrical distribution and the influence of external factors, such as climate and agricultural policies, on production variability. Since the 1990s, production growth has been driven by structural changes, with no significant seasonal influence. The Dickey-Fuller test confirmed the need for differencing to achieve precise modeling, with the ARIMA (1,1,1) model standing out for its superior predictive accuracy, validated with real data from 2010 to 2020. When comparing the ARIMA model with the LSTM model, LSTM demonstrated superiority in terms of accuracy, particularly in handling the nonlinear patterns and complex dynamics of maize production. The LSTM model achieved a significantly lower MAPE, highlighting its capability to forecast maize production with greater precision. This superiority aligns with recent studies emphasizing the effectiveness of LSTM networks in time series forecasting, especially in scenarios with long-term dependencies and external influences.

The forecasts for 2023 to 2030, generated using the LSTM model combined with the Bootstrapping technique, suggest a stabilization in maize production with modest annual variations. However, the wide confidence intervals highlight significant uncertainties, underscoring the need for continued investment in agricultural innovation and political support. The lack of substantial growth in maize production, a staple food in Mozambique, raises concerns about the country's ability to achieve the Sustainable Development Goals, particularly SDG 2, which aims to end hunger and achieve food security by 2030. In conclusion, while the LSTM model offers a powerful tool for forecasting maize production in Mozambique, the results underscore the importance of proactive agricultural policies to address food insecurity challenges and promote sustainable growth in the agricultural sector. The findings of this study provide a foundation for future research and policy interventions aimed at improving maize production and ensuring food security in Mozambique.

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