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Review Article

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Forecasting Rice Production in Mozambique Using Time Series Models and Artificial Neural Networks: Implications for Food and Nutritional Security in the Context of SDG 2

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Abstract

The study presented a comparative analysis between ARIMA models and LSTM neural networks for forecasting rice production in Mozambique, covering the period from 2023 to 2030. Initially, the ARIMA(1,1,0) model was identified and fitted based on ACF and PACF plot analysis, followed by parameter estimation using the maximum likelihood method. Validation was conducted through diagnostic tests applied to the residuals, such as the Box-Pierce and ARCH tests, and model performance was evaluated using metrics like AIC, BIC, HQIC, RMSE, and MAPE. Concurrently, the LSTM neural network was configured with two LSTM layers of 50 units, trained with normalized historical data from 1961 to 2013, and validated with data from 2014 to 2022. To enhance the robustness of the forecasts, the Bootstrapping technique was applied, generating multiple data samples to calculate 95% confidence intervals. The results showed that the LSTM model outperformed the ARIMA(1,1,0) in terms of accuracy, with an average MAPE of 5.58%, compared to ARIMA's MAPE of 7.99%. Both models indicated a trend of stabilization in rice production over the years, suggesting a possible maturity stage in the country's agriculture. However, the LSTM model's superiority in capturing nonlinear patterns and long-term dependencies makes it the more suitable model for future projections. These forecasts are crucial in the context of Mozambique's food and nutritional security, as they underscore the urgent need for strategic interventions and investments in agricultural technology to stimulate production growth. Addressing these challenges is vital for achieving Sustainable Development Goal 2 (SDG 2), which aims to end hunger and ensure food security by 2030. The findings provide a solid foundation for agricultural planning and the formulation of effective public policies to support food and nutritional security in Mozambique.

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

1. Introduction

Food insecurity is a persistent global concern, affecting millions of people worldwide. Food security is defined as the access by all people, at all times, to sufficient, safe, and nutritious food to meet their dietary needs and food preferences for an active and healthy life [1]. However, food insecurity remains a significant challenge, particularly in regions such as Sub-Saharan Africa and South Asia, where hunger and child malnutrition rates are alarmingly high. The COVID-19 pandemic and the conflict in Ukraine have exacerbated the global food crisis, impacting the food security of approximately 735 million people in 2023, representing about 9% of the world's population [2].

Globally, the number of undernourished people has increased by more than 150 million since 2019, and projections indicate that the world is not on track to achieve Sustainable Development

Goal 2 (SDG 2), which aims to end hunger by 2030 [3]. Hunger, defined as the pain or discomfort due to insufficient nutrient intake, is one of the most visible consequences of food insecurity and predominantly affects vulnerable populations in developing regions [4]. Sub-Saharan Africa remains one of the most affected regions, with 21% of the population facing hunger [5]. Furthermore, factors such as climate change, conflicts, socio-economic inequalities, and corruption exacerbate the situation, making the fight against hunger even more challenging [6].

Mozambique, located in Sub-Saharan Africa, faces significant challenges related to food insecurity and malnutrition. The country, with a population of approximately 32.4 million people in 2023, is characterized by high poverty rates, low income, and an economy heavily dependent on agriculture [7]. Agriculture, which accounts for about 25% of the country's GDP and employs between 70% to 80% of the workforce, is predominantly subsistence-based and vulnerable to climatic shocks such as droughts and floods [8]. These conditions have negatively impacted agricultural production, exacerbating food and nutritional insecurity in the country.

Between 2021 and 2022, approximately 2 million people in Mozambique faced high levels of acute food insecurity [9]. The situation is worsened by factors such as armed conflict in northern regions, endemic corruption, and poor management of public resources, which negatively affect food distribution and access to essential services [10]. Additionally, the country's dependence on food imports, particularly rice, increases its vulnerability to food insecurity, especially during global crises [11]. Rice production in Mozambique is crucial for food security, being the third most cultivated cereal in the country [12]. However, rice productivity has historically been low, with average yields of only 1.3 tons per hectare, significantly below the African average [13]. This low yield, combined with challenges such as inadequate infrastructure, post-harvest losses, and reliance on traditional agricultural practices, contributes to the insufficient national production to meet domestic demand [14].

Mozambique also faces significant climatic challenges that directly impact agriculture and food security. The country is highly vulnerable to extreme weather events such as cyclones, droughts, and floods, which frequently destroy crops and displace entire communities [15]. These conditions, coupled with population growth and urbanization, increase pressure on food resources, exacerbating food insecurity across the country.To address these challenges, it is crucial to adopt advanced agricultural production forecasting techniques that can help plan and mitigate risks associated with food insecurity. Traditionally, models such as ARIMA (Autoregressive Integrated Moving Average) have been used to forecast time series, including agricultural production. However, these models have limitations in capturing the complexity of variables involved in agriculture, especially in contexts like Mozambique, where climatic and socio-economic interactions are highly dynamic [16].

In this context, Artificial Neural Networks (ANNs), particularly Long Short-Term Memory (LSTM) models, emerge as a promising alternative. ANNs can capture non-linear and complex patterns in temporal data, offering greater accuracy in agricultural production forecasts [17]. This study aims to compare the effectiveness of ARIMA and LSTM models in forecasting rice production in Mozambique, contributing to the development of more robust agricultural strategies aligned with SDG 2 objectives.

Thus, the research problem this study addresses is the need to improve the accuracy of rice production forecasts in Mozambique by using Time Series Models and Artificial Neural Networks to provide inputs for effective policymaking in combating food and nutritional insecurity in the country. The research seeks to answer the following question: how can the use of advanced forecasting models contribute to food security in Mozambique, particularly in a context of climate change and socio-economic challenges?

2. Literature Review

2.1. Global Context of Rice Production

Rice (Oryza sativa) has a long and rich history, with its origins traced back to the ancient civilizations of East and Southeast Asia, where archaeological evidence suggests its domestication around 7,000 to 5,000 BCE in China [18]. As one of the earliest cultivated grains, rice has played a crucial role in the development of human societies, particularly in Asia, where it became a staple food and a key element in cultural and religious practices [19]. Over time, rice spread to other parts of the world, including Africa and the Americas, through trade routes and colonial expansion, cementing its status as a global staple [20]. Today, rice is the third most important cereal crop globally, following maize and wheat, and it feeds more than half of the world's population, making it indispensable for food security [21].

The global importance of rice is not only due to its historical significance but also because it is a major source of calories and nutrients for billions of people. Rice is particularly critical in regions where food insecurity is prevalent, as it provides a substantial portion of daily caloric intake [22]. The nutritional profile of rice, rich in starch, protein, and essential vitamins and minerals, makes it a key food item in many developing countries, where diets may lack diversity [23]. However, the reliance on rice also poses challenges, especially in areas prone to environmental stressors and socio-political instability, which can disrupt rice production and exacerbate food insecurity [24]. The vulnerability of rice production to climate change and other external factors underscores the need for sustainable agricultural practices and resilient food systems [25]. In terms of agricultural practices, rice cultivation requires specific environmental conditions, including high temperatures and sufficient water availability. These requirements have historically confined rice farming to regions with favorable climates, primarily in Asia, which accounts for over 90% of global rice production [26]. Countries like China, India, Indonesia, and Vietnam are the largest producers of rice, with their economies heavily reliant on this crop [27]. In these regions, rice is not just a food item but a cultural and economic cornerstone, supporting millions of livelihoods [28].

The Green Revolution of the mid-20th century significantly boosted rice production through the introduction of high-yielding varieties, improved irrigation systems, and the widespread use of fertilizers and pesticides [29]. However, while these advancements have led to increased productivity, they have also contributed to environmental degradation, such as soil erosion, water pollution, and loss of biodiversity [30]. Moreover, the benefits of the Green Revolution have not been uniformly distributed, with many regions in Africa and South Asia still struggling with low productivity and food insecurity [31].In Sub-Saharan Africa, rice has become increasingly important due to rapid population growth and urbanization, which have driven up demand for this staple [32]. Despite efforts to boost local production, many African countries remain dependent on rice imports, particularly from Asia, to meet their needs [33]. This reliance on imports makes these countries vulnerable to global market fluctuations and trade disruptions, further threatening food security [24]. In recent years, efforts to increase rice production in Africa have focused on improving water management, adopting high-yield varieties, and enhancing agricultural infrastructure [34].

The environmental and health impacts of rice cultivation are also critical considerations. While rice is a vital source of nutrition, it is also associated with the accumulation of toxic elements like arsenic in the grains, especially in regions with contaminated water sources[35]. This presents a significant public health risk, particularly in countries where rice is a dietary staple and food safety regulations may be insufficient [36]. Addressing these risks requires not only agricultural innovation but also stricter monitoring and regulation to ensure food safety [37]. Looking forward, the challenges of climate change, population growth, and limited natural resources will continue to shape the future of rice production [38]. The development of climate-resilient rice varieties, along with sustainable farming practices, will be essential to ensure that rice can continue to play its role in global food security [39]. Moreover, as the world seeks to meet the Sustainable Development Goals (SDGs), particularly SDG 2, which aims to end hunger and achieve food security by 2030, the focus on rice production will need to balance productivity with environmental sustainability [40].

Therefore, rice remains a cornerstone of global agriculture and food security, with its production and consumption deeply embedded in the socioeconomic fabric of many nations. However, the future of rice production will depend on how environmental, health, and sociopolitical challenges that threaten its sustainability are addressed. Through ongoing research, innovation, and international cooperation, it is possible to build a more resilient and sustainable rice production system capable of meeting the needs of a growing global population [41].

2.2. Rice Production in Mozambique

Mozambique has approximately 900,000 hectares of potential land suitable for rice cultivation, predominantly located in the central and northern provinces, as well as in the irrigated regions of the southern part of the country. Despite this significant potential, only 25.6% of the land is currently utilized for rice farming, leaving much room for expansion and development [42]. Rice is the third most cultivated cereal in Mozambique, following maize and sorghum. It plays a crucial role in providing carbohydrates and contributes significantly to the local economy. In recent years, rice has also shown potential as an export commodity, further enhancing its economic importance [12].

An analysis of the temporal trends in per capita rice yield reveals a slight decline from 12.3 kg in 1961 to 11.1 kg in 2022, representing a decrease of approximately 10% [43]. This decline can be attributed to various factors, including the impacts of climate change, inadequate agricultural policies, and socio-economic challenges. The stagnation or modest decline in rice production per capita over the decades highlights the need for strategic interventions to reverse this trend and improve rice productivity in Mozambique. Comparing Mozambique's rice production with the African and global averages reveals a significant gap. While the per capita rice yield in Africa increased from 13.4 kg in 1961 to 28.7 kg in 2022, Mozambique's production remained below this average. The disparity is even more pronounced on a global scale, where the per capita yield increased from 70.3 kg to 97.4 kg over the same period [44].These figures emphasize the critical need for Mozambique to invest in innovative agricultural practices and sustainable farming techniques to boost rice productivity and enhance food security.

Regionally, the provinces of Zambezia, Sofala, Nampula, and Gaza are the most significant contributors to rice production in Mozambique. Zambezia leads with 31% of the national production, followed closely by Sofala with 30%. Nampula and Gaza contribute 16% and 13%, respectively. These provinces also dominate in terms of cultivated area, with Sofala and Zambezia having the largest rice cultivation areas [45]. Despite these substantial contributions, the national average rice yield remains low at approximately 1.3 tons per hectare, which is significantly lower than the African average.The low productivity of rice in Mozambique is further highlighted by the country's dependence on imports to meet domestic demand. Despite being a major rice producer in the region, Mozambique imports a significant portion of its rice from Asian countries such as Thailand, Pakistan, and Vietnam. In 2021, Mozambique imported $352 million worth of rice, making it the 27th largest global importer [11]. This reliance on imports underscores the need for substantial investments in agricultural infrastructure, production technologies, and improved farming practices to increase domestic production and reduce dependency on foreign rice.

One of the key challenges facing rice production in Mozambique is the relatively low productivity compared to neighboring countries. For example, Mozambique's rice yield is only 50% of Zambia's yield, 39% of Malawi's yield, and less than 25% of other countries such as Tanzania, Zimbabwe, and South Africa [46]. The yields in Mozambique range from 1.0 to 1.2 tons per hectare in rainfed areas and 2.8 to 3.5 tons per hectare in irrigated areas, with most of the production concentrated in coastal regions and wetland areas in the northern part of the country [47].Another significant issue is the post-harvest losses of rice, which can reach up to 25% of the total production in some vulnerable regions. These losses are attributed to factors such as inadequate management, adverse weather conditions, and insufficient drying and storage techniques [14]. Strategies to mitigate these losses include improving storage practices, such as using hermetic silos, and implementing advanced post-harvest technologies [48].

To address these challenges, the Mozambican government, through the National Rice Development Program (NRDP-2016-2027), has set ambitious goals to increase rice productivity over the coming years. The program aims to raise yields from 1.15 tons per hectare to 1.8 tons per hectare by 2027, focusing on improving yields in both rainfed and irrigated systems [49]. This plan also seeks to increase the total rice production from 371,000 tons in 2016 to nearly 1 million tons by 2027.Despite these efforts, the current performance of Mozambique's rice sector remains disappointing. In 2022, rice production totaled 365,000 tons, down from 390,000 tons in 2021, despite a slight increase in yield [13]. This decline is particularly concerning given the investments and initiatives implemented under the Sustainable Development Goals (SDGs) and the National Rice Development Program. The continued challenges in the sector suggest that further analysis is needed to identify and address the barriers preventing Mozambique from fully realizing its rice production potential.

While rice remains a strategic crop for Mozambique, there are significant challenges that need to be addressed to improve productivity and achieve food security. By focusing on reducing post-harvest losses, improving agricultural practices, and investing in infrastructure, Mozambique can enhance its rice production, reduce its dependence on imports, and strengthen its position in the regional and global markets.

3. Materials and Methods

3.1. Materials

This study examines rice production in Mozambique using annual data from 1961 to 2022, encompassing 61 observations. The selection of 1961 as the starting point is driven by its historical and methodological importance, marking the launch of the FAOSTAT statistical series. This starting year ensures a consistent and thorough analysis of agricultural production trends in Mozambique, offering a detailed perspective on the evolution of rice production over 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 rice 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 rice production data was sourced from FAOSTAT, maintained by the Food and Agriculture Organization of the United Nations (FAO). This secondary database provides extensive statistical information on agriculture and food security, serving as a crucial resource for academic research and public policy.

3.3. Methods

3.3.1. ARIMA Modeling

i. Model Identification

For the ARIMA modeling, the process began with verifying the stationarity of the time series using the augmented Dickey-Fuller (ADF) test. After confirming the need for differencing to achieve stationarity, the appropriate model was identified by analyzing the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots of the differenced rice production time series. These analyses allowed for determining the orders of the autoregressive (AR) and moving average (MA) components.

ii. Parameter Estimation

After identifying the model, the next step was the estimation of the parameters for the selected models using the maximum likelihood method. The estimates for the autoregressive and moving average parameters were obtained, and the statistical significance of these parameters was assessed through p-values.

iii. Validation and Evaluation

The ARIMA models were validated using diagnostic tests applied to the model residuals, such as the Box-Pierce, ARCH, Shapiro-Wilk, and Jarque-Bera tests. These tests were used to verify the absence of autocorrelation, heteroscedasticity, and to check the normality of the residuals, ensuring the adequacy of the selected model. The model's performance was evaluated using metrics like AIC, BIC, HQIC, RMSE, and MAPE. Additionally, the models were trained and evaluated with real data from 2010 to 2020, to further validate their predictive accuracy. The best-performing model was then used to forecast rice production from 2023 to 2030.

3.3.2. LSTM Neural Networks

i. Data Preparation

The data preparation for the LSTM neural network involved collecting and normalizing historical rice production data in Mozambique, covering the period from 1961 to 2013. Normalization was performed to ensure that the data was within a range that facilitated the training process of the network. Following normalization, the data was structured into 5-year time sequences, where each input sequence fed the model with data from the previous 5 years, enabling the LSTM to capture temporal patterns and long-term dependencies.

ii. Model Architecture and Training

The LSTM model architecture was configured with two LSTM layers, each containing 50 units, followed by a dense layer responsible for generating the predictions. The configuration of the LSTM layers was chosen due to their ability to capture complex patterns and long-term temporal dependencies. The model was compiled using the Adam optimizer, known for its efficiency in convergence, and was trained over 100 epochs, allowing the network to adjust its parameters to minimize prediction error.

During training, the model learned from historical patterns, refining its internal connections to enhance predictive accuracy.

iii. Evaluation and Validation

The evaluation of the LSTM model was conducted using actual rice production data from the period 2014 to 2022, which were not included in the training phase. The predictions generated by the model were compared with the real values to calculate performance metrics, such as the Mean Absolute Percentage Error (MAPE) and the Root Mean Squared Error (RMSE).

iv. Forecasting for 2023 to 2030

After validation, the LSTM model was applied to forecast rice production in Mozambique for the period from 2023 to 2030. To enhance the robustness of the forecasts, the Bootstrapping technique was employed, allowing for the generation of multiple data samples to estimate the distribution of the forecasts and calculate 95% confidence intervals.

3.3.3. Selection of the Best Model for Estimating Agricultural Production

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

4. Results

4.1. Exploratory Analysis of the RiceTime Series

The statistical analysis of rice production in Mozambique from 1961 to 2022 (n=62) reveals several key characteristics essential for understanding the dynamics of this agricultural activity over the years (Table 1). The average production recorded was 152,485.94 tons, while the median was 99,378.5 tons. The difference between the mean and median indicates a right-skewed distribution, further confirmed by a skewness of 1.29. This skewness suggests that although most years have production levels below the average, there are some years with exceptionally high production that raise the overall mean. The mode, at 85,000 tons, represents the production level most frequently achieved over the years.

The standard deviation of 110,198.40 tons and the variance of 12,143,686,621 highlight significant annual variability in rice production. This variability is further emphasized by the coefficient of variation of 72.27%, indicating substantial inconsistency in annual production relative to the mean. The kurtosis of 0.18 suggests a slightly leptokurtic distribution, implying the presence of some extreme values, though not in sufficient numbers to significantly impact the overall distribution.The extreme production values, with a maximum of 413,000 tons (2018) and a minimum of 32,618 tons (1992), result in a range of 380,382 tons, demonstrating the considerable variation in production performance over the years. This wide range reflects the influence of significant external factors, such as adverse climatic conditions, fluctuating agricultural policies, and limited access to modern agricultural technologies.

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 Rice Production Series

4.2. Stationarity Test or Unit Root Test of the Rice 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 Rice Production in Mozambique

The time series graph of rice production in Mozambique from 1961 to 2022 (Figure 1) reveals a general upward trajectory over time, punctuated by several annual fluctuations. A significant increase in production is observed starting in 2009, possibly reflecting improvements in agricultural practices or the implementation of government policies favorable to rice cultivation.The differenced rice series highlights the annual variations in production, with differencing applied to remove long-term trends and focus the analysis on short-term changes. This approach allows for a more detailed observation of interannual variations, making it easier to identify patterns or anomalies that might be obscured by the overall growth trend. Analyzing these short-term fluctuations can provide valuable insights into immediate and temporary influences on production, such as climatic events, temporary policies, or market shifts that impact rice production on a year-to-year basis.

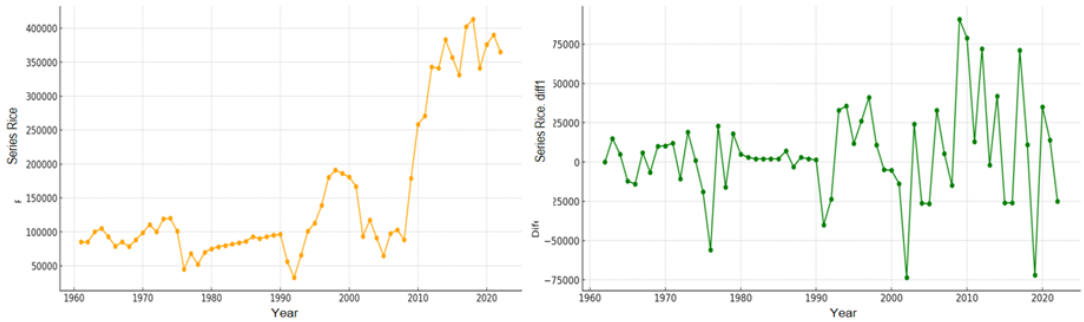

Figure 1: Analysis of the Time Series (Original and Differenced) of Rice Production in Mozambique (1961-2022)

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

The time series decomposition provides a clear view of the trend, seasonality, and residual components (Figure 2). The trend component indicates a general increase in rice production over the years. Seasonality is virtually nonexistent, suggesting that rice production does not follow a consistent seasonal pattern, as corroborated by the graphical analysis. The residuals display random variations that are not accounted for by the trend or seasonality, indicating that other unmodeled factors may be influencing rice production.

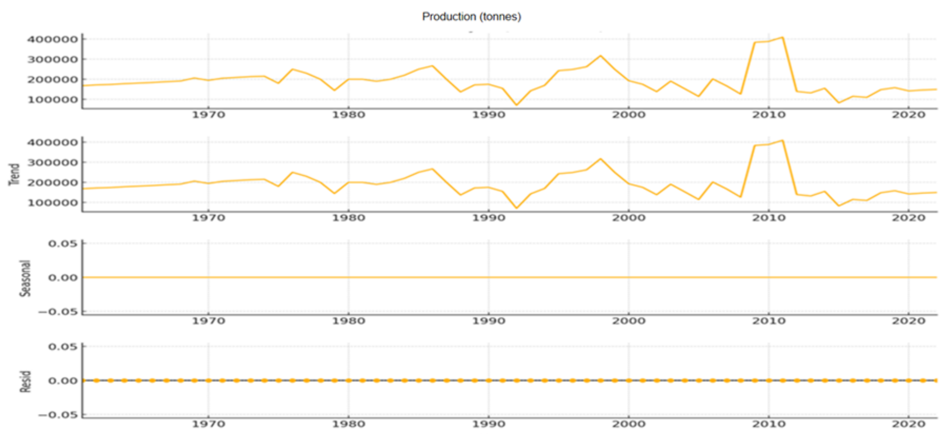

Figure 2: Decomposition of the Time Series of Rice Production in Mozambique

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

The ACF plot of rice production (Figure 3) does not display significant peaks at specific lags, indicating the absence of pronounced seasonality. The rapid decline in autocorrelation values after the initial lags suggests that successive observations are not strongly correlated in the long term, apart from the underlying trend. This characteristic reflects that the original series is primarily influenced by a long-term trend rather than consistent seasonal patterns.After differencing, the ACF plot shows a quick drop in autocorrelation after the first few lags, indicating that the differenced series lacks significant long-term correlation structure. This is indicative of stationarity, suggesting that the differenced series has more consistent statistical properties over time, which is crucial for the application of many forecasting models that require stationarity to provide accurate and reliable results.

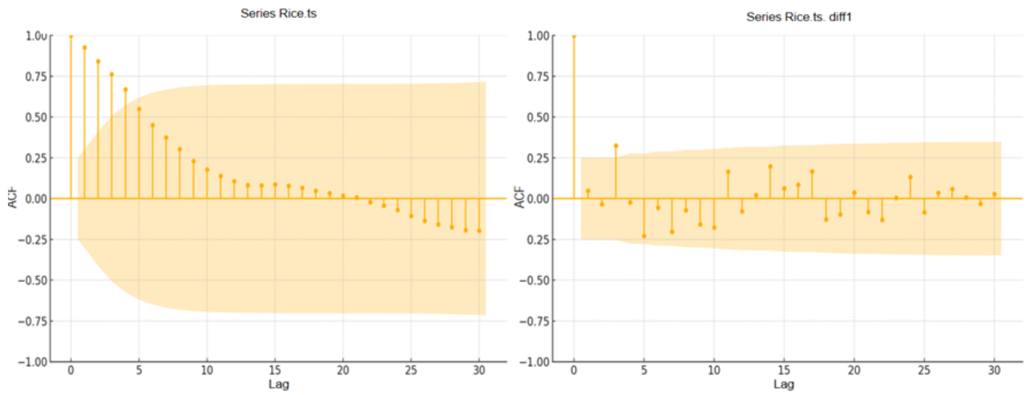

Figure 3: Function (ACF) of Rice Production in Mozambique

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

The PACF plot (Figure 4) shows significant peaks only in the first few lags, suggesting that the series can be modeled with a low-order autoregressive component. This behavior indicates that past observations have a moderate influence on future values, reflecting that correlations are stronger between values that are close in time.In the differenced series, the PACF plot continues to display some peaks in the initial lags, confirming the presence of low-order autoregressive components. This implies that while past values exert a limited but still relevant influence on future values, the identification of low-order autoregressive components is useful for simplifying the predictive model. This ensures that the model effectively captures the essential dynamics of the time series without adding unnecessary complexity.

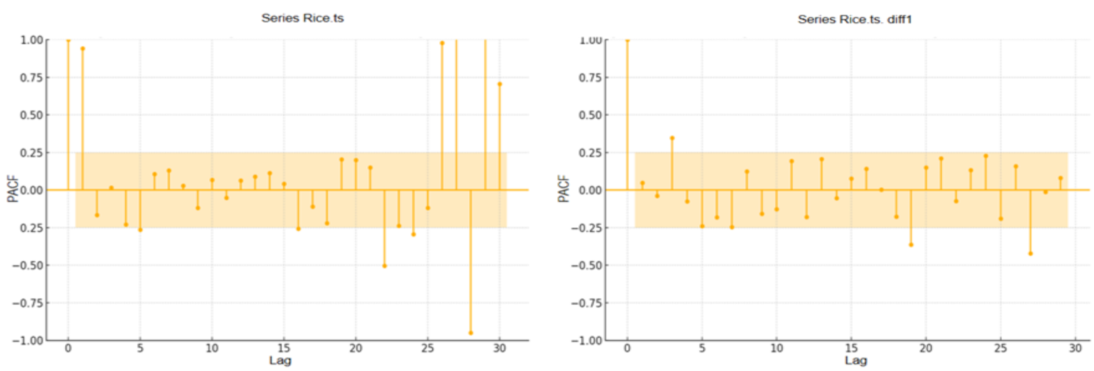

Figure 4: Partial Autocorrelation Function (PACF) of Rice Production in Mozambique

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

The high p-value of 0.731 from the ADF test (Table 22) indicates insufficient evidence to reject the null hypothesis of a unit root, meaning that the time series is not stationary. This implies that the series contains a trend that must be removed for the application of models that assume stationarity. The presence of this trend can distort analyses and forecasts, making it essential to transform the series to achieve stationarity.After differencing, the p-value drops to 0.000, indicating that the null hypothesis of a unit root is rejected, confirming that the differenced series is stationary. This suggests that the series now exhibits constant statistical properties over time, making it suitable for analysis with models that require stationarity, such as ARIMA models, which are used for forecasting and time series analysis.

Test Statistic		Lags	n	**Critical Value**		
	p-Value			(1%)	(5%)	(10%)
Orginal Series						
-1.0603	0.7306	3	58	-3.5485	-2.9128	-2.5941
Differenced Series						
-8.234	0.000	1	60	-3.544	-2.911	-2.593

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

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

4.3.1. Model Identification

Based on the analysis of the ACF and PACF plots for the differenced rice production series, the following ARIMA models are suggested to capture the underlying dynamics of the data: ARIMA(1,1,0), ARIMA(0,1,1), and ARIMA(1,1,1). The ARIMA(1,1,0) model is recommended because the PACF plot shows a clear cutoff after the first lag, indicating that an autoregressive (AR) component of order 1 can adequately describe the time series. This suggests that significant correlation is only evident at the first lag, characteristic of an AR(1) process.

On the other hand, the ARIMA(0,1,1) model is suggested by the ACF plot, which exhibits a clear cutoff after the first lag, indicating the presence of a negative correlation that can be captured by a moving average (MA) component of order 1.Finally, the ARIMA(1,1,1) model is also a viable option, considering the patterns observed in both the ACF and PACF plots, with cutoffs after the first lag in each, suggesting that a combination of AR(1) and MA(1) components might provide a robust model for the differenced time series. These suggestions are based on the sharp cutoffs in the ACF and PACF plots, which are classical indicators for selecting the AR and MA orders in ARIMA models.

4.3.2. Parameter Estimation

Table 3 presents the parameter estimates for three ARIMA models fitted to rice production in Mozambique: ARIMA(1,1,0), ARIMA(0,1,1), and ARIMA(1,1,1). All models show that the parameters are highly significant, as indicated by the very low p-values (0.0000). This suggests that the autoregressive (AR) and moving average (MA) terms are crucial for modeling the time series of rice production.The ARIMA(1,1,0) model has an AR(1) parameter estimate of 0.064, indicating a positive, albeit modest, influence of the first lag on future values. The ARIMA(0,1,1) model stands out with an MA(1) parameter estimate of 0.068, suggesting that the first-order moving average also plays a role in explaining the variations in production. Both models exhibit high variance terms (Ø_2), which is expected due to the scale of the data.

The ARIMA(1,1,1) model is more complex, incorporating both an AR(1) term and an MA(1) term. The AR(1) parameter has a negative estimate (-0.551), indicating that past values have an inverse influence on future values. The MA(1) parameter, on the other hand, has a positive estimate (0.662), suggesting that past fluctuations contribute positively to the forecast. This model can capture more nuances in the time series due to the combination of both AR and MA components.Given its complexity and ability to capture the underlying dynamics of the time series, the ARIMA(1,1,1) model is the most suitable for estimating rice production in Mozambique. This model not only considers short-term dependence through the AR component but also incorporates the effects of past fluctuations via the MA component, providing a more robust and accurate modeling of the time series.

Model	Parameter	Estimates	t-Stat	P-value
ARIMA(1,1,0)	AR(1)	0.064359969	10.59171748	0.0000
ARIMA(1,1,0)	$Ø_2$	956758276.3	8.33e+19	0.0000
ARIMA(0,1,1)	MA(1)	0.067851679	10.59592998	0.0000
ARIMA(0,1,1)	$Ø_2$	999172070.5	8.06e+19	0.0000
ARIMA(1,1,1)	AR(1)	-0.550819484	-12.7950165	0.0000
ARIMA(1,1,1)	MA(1)	0.661721605	11.03803508	0.0000
ARIMA(1,1,1)	$Ø_2$	991182649.9	6.10e+18	0.0000

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

4.3.3. Diagnostic Test of Residuals for Rice Production Models

To estimate rice production in Mozambique, it is crucial to assess the diagnostic test results of the residuals from the ARIMA models presented in Table 4. These tests help determine the adequacy of the models by ensuring that the residuals do not exhibit autocorrelation, heteroscedasticity, and that they follow a normal distribution. The ARCH test examines the presence of heteroscedasticity in the residuals, where p-values greater than 0.05 indicate the absence of significant heteroscedasticity. Among the evaluated models, only the ARIMA(1,1,1) model has a p-value greater than 0.05 (0.074), suggesting the absence of heteroscedasticity, while the other two models (ARIMA(1,1,0) and ARIMA(0,1,1)) indicate some degree of heteroscedasticity.

The Shapiro-Wilk test assesses the normality of the residuals, with p-values greater than 0.05 indicating normally distributed residuals. However, all models have p-values less than 0.05, indicating that the residuals do not follow a normal distribution. The Jarque-Bera test provides another check for the normality of residuals. All models have p-values greater than 0.05, particularly the ARIMA(1,1,1) model, with a p-value of 0.133, suggesting that this model's residuals are the closest to being normally distributed. While normality of residuals is desirable in ARIMA models, its absence does not invalidate the model, as these models are robust in forecasting complex time series. They can be evaluated using metrics such as AIC, BIC, RMSE, and MAPE, which allow for adjustments and transformations to improve model fit without compromising predictive capacity.

Model	Box-Pierce		ARCH		Shapiro-WilK		Jarque-Bera	
	Q	p-value	TR2	p-value	W	p-value	JB	p-value
ARIMA(1,1,0)	15.38	0.119	19.08	0.039	1.34	0.0016	4.73	0.094
ARIMA(0,1,1)	15.35	0.120	19.06	0.040	1.34	0.0016	4.71	0.095
ARIMA(1,1,1)	13.87	0.179	17.03	0.074	1.17	0.0044	4.04	0.133

Table 4: Diagnostic Test of Residuals for Rice Production Models

Based on the residual diagnostic tests, the ARIMA(1,1,1) model appears to be the most suitable. Although none of the models pass the Shapiro-Wilk normality test, the ARIMA(1,1,1) model performs best in the other tests: the Box-Pierce test indicates no autocorrelation in the residuals (p-value = 0.179), the ARCH test suggests the absence of heteroscedasticity (p-value = 0.074), and the Jarque-Bera test shows that the residuals are closest to normality (p-value = 0.133) compared to the other models. Therefore, the ARIMA(1,1,1) model is the most appropriate for estimating rice production in Mozambique, as it demonstrates a more robust performance in terms of the absence of autocorrelation, heteroscedasticity, and proximity to normality of the residuals compared to the other models evaluated.

4.3.4. Comparison of Model Performance

Table 25 presents a performance comparison of the ARIMA models fitted to rice production, based on several evaluation metrics. The ARIMA(1,1,0) model stands out with the lowest AIC value (1113.33), indicating that it is the most efficient model in terms of fit, considering the penalty for complexity. This model also exhibits the lowest BIC (1117.08), further reinforcing its efficiency when applying a stronger penalty for model complexity. Additionally, the HQIC (1114.75) for ARIMA(1,1,0) is the lowest among the compared models, suggesting that this model is preferable when considering the quality of fit with a complexity penalty.

However, when analyzing the RMSE, which measures the absolute accuracy of the forecasts, the ARIMA(0,1,1) model shows the lowest value (174,513), indicating a slight advantage in predictive accuracy. This model also has the lowest MAPE (47.46%), suggesting it provides slightly more accurate percentage forecasts. Although the ARIMA(0,1,1) model has advantages in terms of predictive accuracy, the AIC, BIC, and HQIC values indicate that the ARIMA(1,1,0) model is more efficient in terms of fit and complexity penalty. Therefore, considering the balance between fit quality and model complexity, the ARIMA(1,1,0) model is suggested as the best model for predicting rice production in Mozambique.

When combining the results from Tables 3 and 4, although the ARIMA(0,1,1) model shows a slight advantage in RMSE and MAPE, the fit efficiency of the ARIMA(1,1,0) and ARIMA(0,1,1) models is very similar. However, ARIMA(1,1,0) stands out in the AIC, BIC, and HQIC criteria, suggesting it is a slightly more efficient model when considering the balance between fit and complexity.

Therefore, considering both the residual diagnostics and performance metrics, the ARIMA(1,1,0) model is recommended as the best model for forecasting rice production. This model offers a good balance between fit quality and complexity, providing relatively accurate forecasts.

Model	AIC	BIC	HQIC	RMSE	MAPE
ARIMA(1,1,0)	1113.33	1117.08	1114.75	174549	47.47%
ARIMA(0,1,1)	1113.45	1117.19	1114.87	174513	47.46%
ARIMA(1,1,1)	1115.36	1120.97	1117.48	174824	47.55%

Table 5: Comparison of Model Performance for Rice Production

When combining the results from Tables 15 and 16, although the ARIMA(0,1,1) model shows a slight advantage in RMSE and MAPE, the fit efficiency of the ARIMA(1,1,0) and ARIMA(0,1,1) models is very similar. However, ARIMA(1,1,0) stands out in the AIC, BIC, and HQIC criteria, suggesting it is a slightly more efficient model when considering the balance between fit and complexity. Therefore, considering both the residual diagnostics and performance metrics, the ARIMA(1,1,0) model is recommended as the best model for forecasting rice production. This model offers a good balance between fit quality and complexity, providing relatively accurate forecasts.

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

The analysis of ARIMA models for forecasting rice production, based on training data from 2010 to 2020, reveals significant differences in performance metrics, MAPE and RMSE, between the ARIMA(1,1,0) and ARIMA(0,1,1) models (Table 6). The ARIMA(1,1,0) model exhibits the lowest RMSE (28,151.75) and the lowest MAPE (7.99%), indicating that this model has the best forecasting capability in terms of absolute and percentage error.The ARIMA(1,1,1) model, although more complex, performs worse than the ARIMA(1,1,0), with an RMSE of 47,579.13 and a MAPE of 11.91%. Despite capturing more dynamics in the time series, its overall accuracy is lower compared to the ARIMA(1,1,0). On the other hand, the ARIMA(0,1,1) model shows the poorest results, with an RMSE of 74,157.49 and a MAPE of 20.09%, suggesting that this model is not suitable for forecasting rice production.

Year	Actual Dada	Predicted Data		
		ARIMA(1,1,0)	ARIMA(0,1,1)	ARIMA(1,1,1)
2010	258000	261542.23	260535.43	189800.3
2011	271000	264526.79	263070.86	259614.5
2012	343000	294654.48	265606.29	271373.4
2013	341000	304569.17	268141.72	350737.9
2014	383000	321465.10	270677.16	335657.9
2015	357000	334785.04	273212.59	391192.9
2016	331000	354189.31	275748.02	348695.1
2017	402000	394587.58	278283.45	333612.1
2018	413000	401526.79	280818.88	408145.6
2019	341000	404526.42	283354.31	410153.2
2020	376000	401526.29	285889.74	334898.8
RMSE		28151.75	74157.49	47579.13
MAPE		7.99%	20.09%	11.91%

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

Given that the ARIMA(1,1,0) provides the most accurate forecasts with the lowest absolute and percentage error, it is the most recommended model for estimating rice production in Mozambique. The model's simplicity, combined with its effectiveness, makes it the best option among the models evaluated. This superiority demonstrated by the ARIMA(1,1,0) not only validates its effectiveness for the analyzed period but also positions it as the best choice for projecting rice production from 2023 to 2030.

4.3.6. Forecasted Rice Production in Mozambique from 2023 to 2030

Table 7 presents the forecasted values for rice production in Mozambique for the period 2023 to 2030, based on the ARIMA model. The predicted values indicate relatively stable production over the years, consistently around 364,000 tons. In addition to the forecasted values, the table provides 95% confidence intervals, which allow for an assessment of the uncertainty associated with the predictions.

It is observed that, although the central forecast values remain nearly constant, the confidence intervals widen over time. In 2023, the confidence interval ranges from 302,961.9 to 426,373.2 tons, indicating lower uncertainty for nearer-term predictions. However, by 2030, the confidence interval expands from 178,701.5 to 550,873.3 tons, reflecting increased uncertainty in long-term forecasts. This pattern suggests that while the ARIMA model predicts a steady rice production, there is greater uncertainty associated with the forecasts as time progresses, which is typical in time series models.

Year	Forecasted Value	Confidence Intervals (95%)	
		Lower Bound	Upper Bound
2023	364667.5	302961.9	426373.2
2024	364850.7	272619.7	457081.6
2025	364749.8	252042.5	477457.1
2026	364805.3	233761	495849.7
2027	364774.7	218177.6	511371.8
2028	364791.6	203881.7	525701.5
2029	364782.3	190864.7	538699.9
2030	364787.4	178701.5	550873.3

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

4.4. Estimation with the LSTM Modelfor Rice Production

4.4.1. Model Training with LSTM

To analyze rice production in Mozambique and forecast its future trends, a LSTM artificial neural network, specifically designed for time series analysis, was employed. LSTM is particularly effective for complex time series due to its ability to capture long-term patterns and dependencies. Historical data from 1961 to 2013 were used to train the model, with the dataset normalized and transformed into 5-year time sequences, allowing each prediction to be based on the data from the preceding five years.

The LSTM network was configured with two LSTM layers, each containing 50 units, followed by a dense layer to generate the predictions. The model was compiled using the Adam optimizer and trained over 100 epochs (cycles). This training process enabled the network to internally adjust its parameters, minimizing prediction errors and effectively capturing the nuances of the time series for rice production in Mozambique.

4.4.2. Model Evaluation

After training, the model was tested using data from 2014 to 2022, a period that includes both increasing and decreasing production years, reflecting the typical variability of agriculture in Mozambique. The evaluation of the LSTM model, as presented in Table 8, shows that the model consistently captured the general trends in rice production, with an average MAPE of 5.58%, indicating a moderate percentage error.This value reflects that, on average, the model's predictions deviated from the actual values by approximately 5.58%, demonstrating the model's reasonable accuracy in forecasting despite the inherent variations in agricultural production over the years. The average RMSE was 20,349.95 tons, suggesting that while the model was able to predict values close to the actual ones, there were still significant deviations in certain years.

Notably, the model exhibited higher accuracy in years like 2014 and 2015, with MAPE values of 1.09% and 0.97%, respectively, indicating a low margin of error. However, in years such as 2021, the MAPE reached 14.14%, revealing that the model struggled to accurately predict production for that specific year, possibly due to fluctuations or atypical events not fully captured by the model. These results suggest that while the LSTM model is effective in predicting rice production in most years, it may benefit from additional adjustments or the inclusion of external variables to improve accuracy in years with more extreme behaviors.

Year	Actual Dada	LSTM Model		
		Predicted Data	RMSE	MAPE
2014	343000	339250.30	3749.7	1.09%
2015	341000	344317.28	3317.28	0.97%
2016	383000	354532.49	28467.51	7.43%
2017	357000	367030.87	10030.87	2.81%
2018	331000	360951.52	29951.52	9.05%
2019	402000	378990.73	23009.27	5.72%
2020	413000	384391.78	28608.22	6.93%
2021	341000	389212.94	48212.94	14.14%
2022	376000	383802.22	7802.22	2.08%
Mean	365222.22	366942.24	20349.95	5.58%

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

4.4.3. Forecasts for 2023 to 2030

The forecast for rice production in Mozambique for the period from 2023 to 2030, utilizing an LSTM neural network combined with the Bootstrapping technique, indicates a general trend of stabilization in production (Table 9). The predicted values show slight variation over the years, with production oscillating between 360,580.84 tons in 2029 and 369,507.14 tons in 2024. This stability is also reflected in the 95% confidence intervals, which, although showing some variability, remain relatively close to the predicted values, indicating moderate confidence in the estimates.The average annual absolute growth in rice production in Mozambique for the period from 2023 to 2030 is approximately 273.77 tons per year, with an average annual percentage growth of about 0.08%, indicating modest growth. These results suggest that rice production in Mozambique may be entering a maturity phase, where expansion appears limited, highlighting the need for potential strategic interventions to drive more robust growth.

Year	Forecasted Value	Confidence Intervals (95%)	
		Lower Bound	Upper Bound
2023	363745.40	321723.10	399830.24
2024	369507.14	325345.69	410002.27
2025	367319.94	336908.25	405958.84
2026	365986.58	316588.38	401811.16
2027	361560.19	314911.34	403797.25
2028	361559.95	327313.17	394349.83
2029	360580.84	326944.34	396423.73
2030	365661.76	334993.67	405989.00

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

5. Discussion

The statistical analysis of rice production in Mozambique reveals a time series characterized by high variability and asymmetric distribution, which are common in regions where agriculture is highly vulnerable to external factors. Studies indicate that the variability in rice production, especially in developing countries, is often influenced by climatic factors such as drought and floods, as well as technological and infrastructural limitations, as corroborated by the high coefficient of variation [50].

In contrast, countries like Vietnam, which have consistently invested in irrigation and more resilient rice varieties, show lower variability [51], suggesting that Mozambique could benefit from similar investments to stabilize and increase its rice production. The study by Saito et al. points out that inconsistent agricultural policies and limited access to modern technologies also contribute to the inconsistency in cereal production in Sub-Saharan Africa, reflected in the wide range between the maximum and minimum values of rice production [52].

The positive skewness, evidenced by production peaks in specific years, can be attributed to temporary government initiatives or sporadic improvements in agricultural infrastructure, as discussed by Jellason et al. [53]. However, without sustainable long-term interventions, rice production in Mozambique remains susceptible to extreme fluctuations, hindering the country's food security.

The time series analysis of rice production in Mozambique underscores the need for transformation to achieve stationarity, which is essential for accurate predictive modeling, as indicated by the ADF test results and the ACF and PACF charts. The presence of a long-term trend, as evidenced by the high ADF test value before differencing, suggests that structural factors and production policies have significantly influenced rice production over the years, as corroborated by studies like Zhang et al., which emphasize the importance of removing trends to improve the accuracy of agricultural forecasts [54].

Differencing the series allowed for the elimination of these trends, resulting in a stationary series, which is crucial for applying ARIMA models, as suggested by Dimri et al., who highlight the need for stationarity in time series to avoid distortions in analyses [55]. Furthermore, the absence of significant seasonality, as shown in the ACF and PACF charts, reinforces the idea that short-term factors, such as climatic events and temporary agricultural policies, have a more immediate impact and should be considered in predictive modeling, aligning with the findings of Guido et al. on the importance of considering external shocks in agricultural forecasts [56].

The selection of ARIMA models for estimating rice production in Mozambique reflects a careful analysis of the underlying dynamics of the time series, utilizing ACF and PACF charts. Among the models tested, the ARIMA(1,1,1) model appeared promising due to its ability to capture both autoregressive and moving average components. However, performance analysis and diagnostic tests revealed that the ARIMA(1,1,0) model is more efficient in terms of fit and simplicity, despite limitations in the normality of residuals. Comparative studies, such as those by Anderson et al., indicate that parsimony in ARIMA models, favoring simpler and well-fitted models, can be equally or more effective in agricultural scenarios with high variability [57]. The superiority of this model over the others tested is consistent with the findings of Elsaraiti and Merabet, who emphasize the importance of models that minimize predictive error without unnecessary complications [58]. Therefore, the ARIMA(1,1,0) model not only adequately captures the variations in rice production but also provides more reliable future forecasts, which is crucial for agricultural planning in Mozambique.

The comparison between ARIMA and LSTM models for forecasting rice production in Mozambique reveals significant differences in performance, reflecting the complexity of the agricultural time series. The LSTM model demonstrated an average MAPE of 5.58%, indicating higher accuracy compared to ARIMA, whose best model (ARIMA 1,1,0) had a MAPE of 7.99%. This result suggests that LSTM, with its ability to capture nonlinear patterns and long-term dependencies, is more effective in handling the variability of rice production in Mozambique.

Recent studies show that neural network-based models, like LSTM, have outperformed traditional time series models, especially in contexts with high variability and external influences, as observed in Mozambique [59]. The superior performance of LSTM in the present study is consistent with this global trend, where neural networks are increasingly being adopted for agricultural forecasts due to their flexibility and ability to learn complex patterns [60].

On the other hand, the ARIMA model, despite its simplicity and ease of interpretation, showed limitations in capturing the nonlinear dynamics present in the rice production series. Although it performed reasonably well, especially in the short term, as evidenced by the lower RMSE, ARIMA failed to capture the more complex fluctuations, resulting in lower accuracy compared to LSTM. This is corroborated by studies indicating that for highly volatile time series, such as agricultural ones, models like LSTM tend to outperform ARIMA in long-term forecasting [61], [62].

Therefore, when considering forecasts for the period from 2023 to 2030, LSTM offers a more robust and accurate solution for rice production in Mozambique. However, the use of hybrid models, combining the strengths of ARIMA in capturing short-term trends with the ability of LSTM to handle complex patterns, could be a promising approach to further improve forecast accuracy [63].

The combination of the LSTM model with the Bootstrapping technique in forecasting rice production in Mozambique, as pointed out by studies, allows for capturing the complexity and uncertainties inherent in agricultural time series, offering more robust forecasts with more realistic confidence intervals [64], [65]. This approach is particularly effective in high-variability contexts like agriculture, where factors such as climate change and technological limitations significantly influence production. However, as highlighted by Herrera-Casanova et al., this methodology requires large volumes of data and advanced computational capabilities, underscoring the need for continuous investment in agricultural data technology and infrastructure in Mozambique to maximize the benefits of these forecasts [66].

The results of the forecast for rice production in Mozambique for the period from 2023 to 2030, indicating stabilization in production, reflect a trend observed in other studies on agriculture in developing countries. For example, studies like those by Carrilho et al. and Abbas suggest that the stabilization of agricultural production in countries like Mozambique is often the result of structural limitations, such as limited access to modern technologies, reliance on traditional agricultural practices, and vulnerability to climate change [67], [68]. These barriers hinder significant production increases, even with efforts to improve agricultural efficiency.

Furthermore, the literature points out that the stabilization of agricultural production can have negative impacts on food security. As highlighted by Owasa & Fall, stagnation in the production of staple foods, such as rice, in countries with high rates of food insecurity can exacerbate hunger and malnutrition [69]. The lack of substantial growth in rice production in Mozambique may hinder the achievement of the goals set by SDG 2, which aims to eradicate hunger by 2030.

Studies on agricultural interventions in vulnerable regions, such as the one by Raji et al., suggest that without significant investments in agricultural innovation and infrastructure, food production will continue to face challenges [70]. Therefore, the forecast indicates that without significant interventions, the growth of rice production in Mozambique will remain limited, highlighting the urgency of robust agricultural policies and investments in technology and infrastructure to address food insecurity and meet the growing nutritional needs of the population.

6. Conclusions

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 aimthe analysis of forecasting models applied to rice production in Mozambique revealed that while the ARIMA(1,1,0) model offers simplicity and good alignment with historical data, the LSTM model stands out for its greater accuracy, particularly in capturing nonlinear patterns and long-term dependencies. Both models suggest a stabilization trend in production between 2023 and 2030, indicating a potential maturity phase in the country's agriculture. The robustness of the LSTM model, demonstrated by an average MAPE of 5.58%, underscores its effectiveness in forecasting during this period. However, this stabilization highlights the urgent need for strategic interventions and investments in agricultural technology and infrastructure, which are crucial to driving growth and supporting efforts to achieve SDG 2, aimed at eradicating hunger by 2030. Strengthening agricultural policies and exploring hybrid predictive modeling approaches, combining the simplicity of ARIMA with the LSTM's capacity to capture complexities, is essential for ensuring more accurate forecasts and enhancing food security in Mozambique.ed at improving maize production and ensuring food security in Mozambique.

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