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Article

Statistical analysis of wheat production in Nigeria

Muhammad Aliyu Auwal[1*], Garba Abubakar Abdullahi[1], and Muhammad Sadiq Nasir[1]

1 Department of Mathematics, SR University, Warangal-506371, Telangana State, India

* Correspondence: amauwal97@gmail.com

Abstract: Wheat is a major cereal crop and a fundamental component of global food security. In Nigeria, however, domestic production has never matched rising demand, making the country extremely import-reliant. This study analyzes trends in wheat production in Borno, Jigawa, and Katsina, the three major wheat-producing states in Nigeria using annual data for the years 2015–2024. Three time series models, namely linear, exponential, and polynomial, were employed in identifying production trends and forecasting future production. The models' performance was compared using the coefficient of determination (R^2), root mean square error (RMSE) and mean absolute error (MAE). The findings exhibit an overall upward trend in production, although significant fluctuations were recorded, particularly in 2020, reflecting climatic change and policy disruption. Among the models considered, the polynomial specification was the most appropriate fit, and it described the nonlinear dynamics of production more so than the linear and exponential specifications. The findings underscore the effects of climate, seed quality, mechanization, and government policy interventions on wheat production. To promote self-sufficiency, the study recommends investment in irrigation facilities, adoption of climate-resilient agriculture, integration of advanced forecasting methods, and farmers' capacity development. These measures are to be taken in order to reduce the dependency on wheat import and strengthen Nigeria's food security system.

Keywords: wheat production; agricultural policy; time series analysis; food security; statistical modelling.

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1. Introduction

Wheat is one of the most widely cultivated of the world's cereal grains and a pillar of world food security. It is consumed directly as food and indirectly as bakery, pasta, and stock for livestock industries. In Nigeria, however, indigenous wheat production has always lagged behind demand growth, and therefore there is heavy dependence on importation. This reliance not only erodes the government's agricultural reformation agenda, but it also subjects the economy to the volatility of the global wheat market prices [1], [2].

North Nigeria, particularly Borno, Jigawa, and Katsina States, has the most conducive conditions for wheat production due to availability of irrigation during the dry season. Despite this promise, production there is retarded by climatic uncertainty, low coverage of improved seed varieties, low levels of mechanization, lack of infrastructure, and inconsistencies in policy [3], [4] . As a result, the problem of wheat self-sufficiency remains.

There have been several research on trends in wheat yields and forecasting methods in different settings. [5] demonstrated quadratic time series models to be efficient when describing spring wheat yields in Canada. [6] highlighted the variability of cereal production in India due to climatic uncertainty. Later research made use of machine learning techniques, i.e., neural networks and hybrid ARIMA-based models, to improve the forecast of wheat and other cereals yields in the face of uncertainty [7], [8], [9]. These research papers emphasize the necessity to combine conventional statistical techniques with advanced forecasting techniques to improve agricultural planning.

Drawing on this literature, the present study employs and compares linear, exponential, and polynomial time series models over Nigerian top producing states' wheat production data from 2015 to 2024. By testing predictive performance between these models, the study speaks to the dynamics of wheat production and identifies implications for food security policy. The findings contribute methodologically by showing the applicability of polynomial trend models and practically, by furnishing evidence-based recommendations for reducing Nigeria's dependence on wheat imports.

2. Related Work

2.1. Trends and Determinants of Wheat Production

Wheat production in the Northern regions of Nigeria has faced tremendous change over the past few years owing to a number of factors ranging from technological advancements, environmental factors, and government policies. [10] identified key determinants of farm size, fertilizer availability, credit, and adoption of better wheat varieties as crucial factors in improving the commercialization of wheat. The presence of low output prices, low land availability, and low input in spite of such developments still hinders production capacity. [1] state that climatic and government policy factors highly impact wheat production trends. Government policy interventions in the form of subsidies, access to credit, and investment in research and development have the potential to enhance productivity, whereas adverse weather conditions can have catastrophic implications for yield outcomes. Both refer to the necessity of policy interventions in terms of specific and adaptive interventions to cushion the impacts of climatic uncertainty on wheat production. In addition, the study of [6] revealed significant differences in growth and instability in the area, production, and productivity of various crops, including wheat. They noted that positive growth rates were achieved in some areas, but others experienced high instability in productivity. This disparity underscores the necessity for region-specific approaches in addressing the unique issues of wheat farmers in various regions of Northern Nigeria.

2.2. Statistical and Machine Learning Models for Wheat Yield Forecasting

Accurate estimation of wheat production is vital to effective agricultural planning and policymaking. Statistical as well as machine learning techniques have been employed with varying degrees of success in estimating wheat production. An extremely robust study by [7] proposed a hybrid model that comprised ARIMA and WNN models. The authors demonstrated that the hybrid model had higher forecasting accuracy than individual ARIMA as well as existing hybrid ARIMA-ANN models. A second study by [9] demonstrated the application of a random forest ranking approach using UAV-based vegetation spectral indices to predict maize yield effectively. Reference [8] contrasted ARIMA and Artificial Neural Network (ANN) models for forecast of wheat yield in Iran. They found that the ANN model, i.e., five hidden layers of Multilayer Perceptron

Neural Network (MLP-NN), was better than the ARIMA model. This finding represents the promise of ANN models to be applied in agricultural forecasting. In addition, Boken, (2000) utilized time series analysis techniques and discovered that the quadratic model gave the best forecasts of spring wheat yield in the Canadian Prairies. The research underscored the importance of selecting appropriate models based on the specific nature of the time series data. These studies collectively highlight the efficacy of combining conventional statistical methods with advanced machine learning techniques in optimizing the accuracy of wheat yield prediction. Policymakers and farmers can make informed decisions about optimizing resource use and enhancing wheat production through these models.

2.3. Impact of Climatic Factors on Wheat Production

Climate factors, particularly rainfall and temperature, significantly impact wheat production in Northern Nigeria and elsewhere. Madhukar et al., (2022) revealed that rising February season temperatures cause the highest negative effect on wheat yield and account for up to 78% of the variability in yields. This illustrates that the production of wheat is sensitive to climate change and necessitates immediate adaptation to tolerant farming practices and improved crop varieties.

Furthermore, [11] emphasized the necessity of including machine learning models for predicting crop yields in conditions of climatic uncertainty. By their study, they demonstrated that ensemble models integrating SARIMAX and LSTM strategies were able to plot high accuracy for rice crop yield in Nigeria. This renders the use of such methodologies viable for wheat yield prediction and could provide valuable information for better planning and resource management.

Reference [12] Research also puts into perspective the economic impacts of climatic variability on crop production. Their economic modeling of Indian sugarcane cultivation identified significant technical and cost efficiency differences between large sugarcane-producing states and suggested that climatic conditions are the basis for these differences. Applying the same analysis to wheat cultivation would be useful in determining the most affected areas and guiding targeted interventions to mitigate their impacts.

Lastly, climatic factors have a great impact on wheat production and need the use of climate-resilient agriculture practices and the application of advanced forecasting models. Through the application of these measures, farmers and policymakers can enhance wheat production and attain food security despite climate change.

2.4. Government Policies and Interventions

Government policies and intervention are at the core of shaping the agriculture landscape, particularly in the production of staple crops like wheat. In Nigeria, policies have been designed to improve wheat production and address counter-related issues. According to (Garba et al., 2020), government support in terms of subsidies, credit access, and the provision of improved seed varieties has significantly contributed to improving wheat output. These interventions not only raised productivity but also enhanced farmers' livelihoods since they have made them able to adopt improved practices of farming.

However, these policies have varying degrees of effectiveness in varying areas and for varying farmers. (Joshi, 2020) highlighted that some policies have been effective in bridging yield gaps, others have failed because they have not been effectively implemented and there has been no follow-up support. Furthermore, policy-based price controls and market regulations have sometimes produced undesirable outcomes, such as market distortions and reducing farmers' incentives.

In addition, (Sharma et al., 2013) examined the evolution and trends in pulse production in India, and the positive influence of the Technology Mission on Pulses (TMOP). The study emphasized the necessity of continuous support and policy revision to meet evolving agricultural concerns. The same policies would be beneficial for wheat production in Northern Nigeria, as targeted policies and continuous support are necessary for the long-term improvement of productivity.

Briefly, the government's policies and interventions can significantly influence wheat production in Northern Nigeria. Effective policy execution, continuous assistance, and local-oriented approaches are imperative in an attempt to address the unique challenges facing the wheat farmers as well as ensure sustainable agriculture practices.

2.5. Technological Innovations and Advances in Wheat Cultivation

Wheat farming has been highly affected by technological advancements, leading to productivity and efficiency enhancement. Among the key fields of innovation is precision agriculture application. Precision agriculture refers to the application of technologies such as GPS, remote sensing, and data analysis for optimal resource use and crop management techniques. With the provision of instant information regarding weather, crop health, and soil, the technologies enable farmers to make informed decisions and intervene in a timely manner.

Reference [15] indicated the utility of combining linear regression models with ARIMA errors in forecasting wheat production. Drawing on their research, they established that the combined model provided superior accuracy to traditional methods and illustrated the possibility of combining statistical techniques for the improvement of forecasting outcomes.

The Nigeria wheat report recognizes higher policy maker interest in being independent and utilization of advanced techniques such as satellite imaging and artificial intelligence models to estimate land area for wheat with greater precision [16].

Technologies like satellite imagery and drones have revolutionized crop monitoring and management. A regression-based model with MODIS data was designed by Becker-Reshef et al., (2010) to forecast wheat yields, which was very accurate where ground data were lacking. These technologies supply valuable information regarding crop health and development and allow for targeted intervention for specific problems.

The use of genetically modified (GM) crops and improved seed varieties has also been critical in enhancing wheat resistance to pests, diseases, and environmental factors. Joshi, (2020) indicated significant variation in combining ability among wheat genotypes, indicating specific crosses for commercial use to increase levels of yield. Such advancements in crop breeding have led to the development of wheat varieties that are more suited to survive adverse conditions and increase overall production.

Furthermore, the application of machine learning models in crop forecasting has also been proven to be promising. Marina Minh Nguyen, Nastaran Khodaei, (2021) demonstrated the ability of ensemble models, combining SARIMAX and LSTM approaches, to achieve high precision in crop yield forecasting. These advanced models are able to recognize complex, non-linear patterns in farm data, which can be beneficial for enhanced planning and resource management.

In short, technological innovations have witnessed dramatic changes in wheat cultivation, making it more efficient and productive. Some of the technologies whose application has the potential to transform the landscape of wheat cultivation to bring in sustainable cultivation methods and improved returns on yield include precision agriculture, remote sensing technology, genetically modified organisms, and machine learning algorithms.

2.6. Challenges and Constraints in Wheat Production

Wheat farming in Northern Nigeria is faced with various challenges and constraints that impact productivity as well as sustainability. A primary challenge is access to quality inputs such as improved seeds and fertilizers. Falola et al., (2017), affirm that poor access to such essential inputs inhibits farmers' ability to provide maximum output. The use of improved agricultural practices is usually discouraged by poor access to the inputs, thus resulting in underexploited levels of production.

Reference [4] in their study revealed that small-scale in wheat production in Jigawa State, Nigeria is profitable but faces significant challenges such as high cost, inadequate finance, and infrastructural issues. Weak infrastructure further exacerbates wheat farmers' issues. Ineffective irrigation equipment and storage mechanisms drastically limit farmers' ability to manage their crops. For instance, [6] indicated that development and instability in the region, production, and productivity of wheat are fixed by the availability of irrigation facilities. Without effective irrigation, farmers are more susceptible to the adverse effects of irregular rainfall and prolonged dry spells.

Climatic uncertainty poses a significant threat to wheat production. Unpredictable weather patterns, such as erratic rainfall and harsh temperatures, lead to crop losses and reduced production. [3] emphasized the adverse effects of higher seasonal temperatures on wheat yield and indicated the significance of climate-resilient agricultural practices. The growing threat of climate change requires adaptation strategies to mitigate its effect on wheat farming.

Socio-economic determinants also have a critical function in shaping wheat production dynamics. Market volatility, low prices, and limited access to credit may discourage farmers from engaging in wheat farming. [2] highlighted the importance of state intervention in reducing these challenges. Good policy interventions, such as subsidies and credit facilities, help enhance farmers' resilience and productivity, which will enable them to adopt better farming practices and invest in inputs.

In summary, wheat production in Northern Nigeria is faced with a plethora of challenges and constraints, from poor infrastructure and climatic uncertainty to socio-economic impediments. These need to be addressed through an integrated approach that brings together technological innovation, policy intervention, and capacity development to facilitate sustainable wheat production.

3. Methodology

3.1. Data Source

Secondary data from 2015–2024 were obtained from the United States Department of Agriculture (USDA). The data set includes wheat production (1,000 tons), area under cultivation (100 ha), and yield (tons/ha) of Borno, Jigawa, and Katsina States.

3.2. Data Preparation and Analysis

The collected data were systematically organized and processed to prepare them for time series analysis. The study focused on analyzing the trends in annual wheat production (in 1000 tons) for Borno, Jigawa, and Katsina states over the 10-year period. All the analysis of this study was performed using python programming language.

3.3. Time Series Models

To capture and forecast production trends, three time series models were applied, namely:

1. *Linear Model:* Assumes a constant annual change in production over time.

$$y_t = a + bt \tag{1}$$

where y_t is the wheat production at time t, a is the intercept and b is the trend coefficient. The values of a

and b are obtained using the least square methods by solving the following equations.

2. *Exponential Model:* Suitable for modeling constant percentage growth or decay.

$$y_t = ae^{bt} \quad (2)$$

By taking log to both sides

$$\Sigma Y_t = nA + b\Sigma t \quad (3)$$

$$log\, y_t = log\, a + bt\, log\, \mathrm{e} \quad (4)$$

Let $log\, y_t = Y_t$ and $= log\, a$ t then we have:

$$Y_t = A + bt \quad (5)$$

The equations for estimating A and b are as follows:

$$\Sigma Y_t = nA + b\Sigma t \quad (6)$$

$$\Sigma tY_t = A\Sigma t + b\Sigma t^2 \quad (7)$$

where $a = antilog(A)$

3. *Polynomial Model:* Designed to capture nonlinear trends and fluctuations.

$$\boldsymbol{y_t = a + bt + ct^2} \quad (8)$$

The choice of models reflects the need to test whether wheat production trends follow a linear path, grow exponentially, or exhibit complex nonlinear patterns shaped by climatic, economic, and policy factors.

3.4. Model Evaluation Metric

To assess the performance and predictive accuracy of the models, three standard evaluation metrics were used:

1. Coefficient of Determination (R^2)**:** Indicates the proportion of variance in the observed data explained by the model.

$$R^2 = 1 - \frac{\Sigma(y_t - \hat{y}_t)^2}{\Sigma(y_t - \bar{y})^2} \quad (9)$$

2. Root Mean Square Error (RMSE): Measures the average magnitude of prediction errors, giving higher weight to larger errors.

$$RMSE = \sqrt{\frac{1}{n}\Sigma(y_t - \hat{y}_t)^2} \quad (10)$$

3. Mean Absolute Percentage Error (MAE): Measures the average absolute percentage deviation between predicted and actual values.

$$MAE = \frac{1}{n}\sum_{t=1}^{n} |y_t - \hat{y}_t| \quad (11)$$

where $\boldsymbol{y_t}$ is the actual production at time t, $\boldsymbol{\hat{y}_t}$ is the predicted production at time t$\boldsymbol{t}$, and $\boldsymbol{n}$ is the number of observations (years). These metrics assessed the model accuracy.

4. Results and Discussion

The results depict that wheat production in Nigeria's best-performing states has been increasing from 2015 to 2024, but with high volatility. The drop that was witnessed in 2020 reveals how vulnerable the production systems are to climatic variability and socio-economic shocks such as unpredictable rains, rising input prices, and reductions in farm support programs. The return in the following years depicts the strength of rural communities when times improve.

The comparative model analysis in Table (2) confirms that polynomial descriptions are more suitable than linear and exponential trends. This is in line with existing evidence that crop yields would follow nonlinear dynamics rather than homogeneous or exponential growth patterns [5], [6], [15]. Particularly, the quadratic term in the polynomial specification can capture changes in the slope of the trend over time, reflecting the fact in the agricultural setting that the levels of production respond to climatic conditions, technology adoption, and government interventions.

These results are also found in overseas studies. Quadratic specifications predicted wheat yields in Canada better according to [5]. [15] also found the same for India. [8] demonstrated subsequently that artificial neural networks are superior to traditional ARIMA models in wheat yield forecasting in Iran.
Subsequently, [19] demonstrated the ability of advanced machine learning algorithms in forecasting agricultural harvests amidst uncertain climatic conditions. All these findings collectively emphasize that blending nonlinear models and computational intelligence approaches can substantially improve agricultural forecasting.

Policy, therefore, highlights the importance of targeted interventions. Expansion of irrigation facilities is critical to achieving normal output under rain unpredictability. Mechanization and the application of climate-resilient wheat varieties can also boost productivity. Official assistance in terms of subsidies, credit, and extension remains important, as reported by findings in [2] and [4]. Furthermore, investment in data-driven forecast systems that bring together statistical and machine learning approaches can provide better estimates for planning and policy.

Overall, the foregoing analysis underscores two points of note. Firstly, wheat production in Northern Nigeria is increasing but remains highly sensitive to external shock. Secondly, polynomial and other nonlinear models more accurately portray patterns of production than less advanced trend models and are hence useful for planning purposes. Overall, these points taken together can guide policymakers towards evidence-based alternatives to reduce Nigeria's dependence on wheat imports and promote national food security.

Table 1. Time series data of wheat production (in 1000 tones) in selected states in Nigeria

Year	Borno	Jigawa	Katsina
2015	40.20	10.2	4.2
2016	40.20	10.2	4.2
2017	55.61	14.11	5.81
2018	58.96	14.96	6.16
2019	58.29	14.79	6.09
2020	36.85	9.35	3.85
2021	60.30	15.3	6.3
2022	73.70	18.7	7.7
2023	80.40	20.4	8.4
2024	80.40	20.4	8.4

Figures 1-9 illustrate how each model (linear, exponential, and polynomial) predicts wheat production in Borno, Jigawa, and Katsina states. The polynomial model closely follows the observed data points, confirming its greater predictive ability.

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(a) Linear Model Prediction

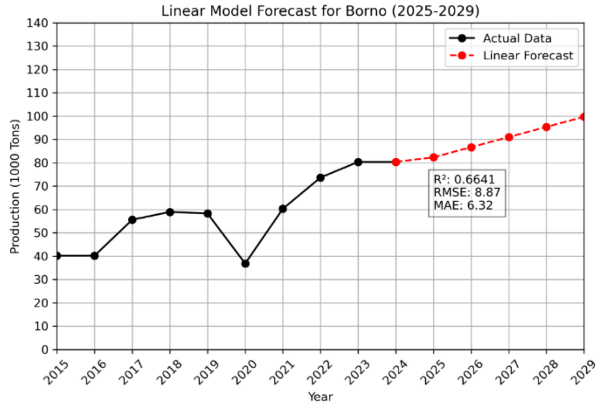

Figure 1. Linear prediction for Borno

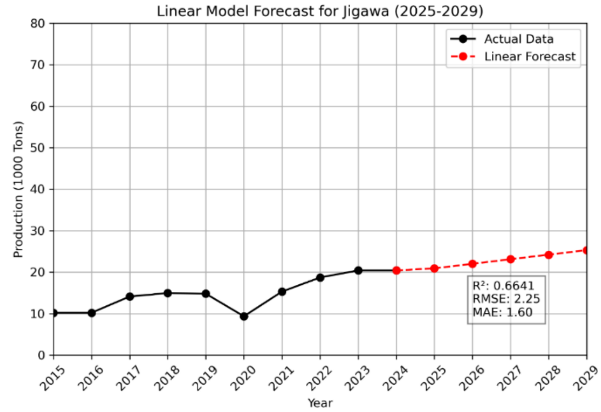

Figure 2. Linear prediction for Jigawa

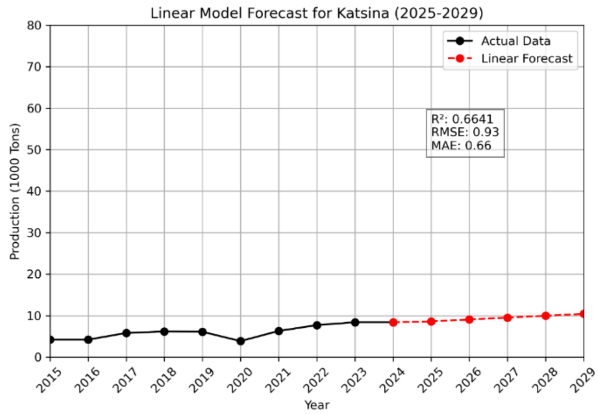

Figure 3. Linear prediction for Katsina

(b) *Exponential Model Prediction*

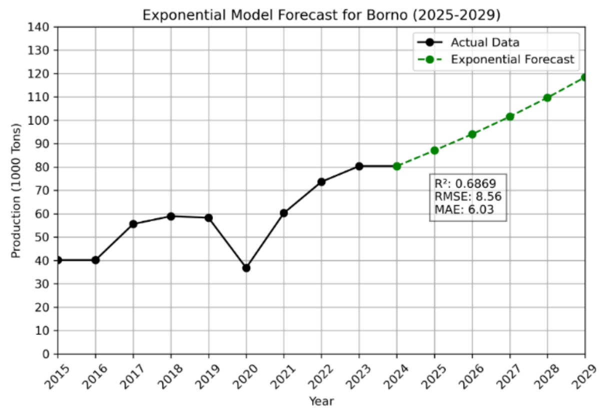

Figure 4. Exponential predictionl for Borno

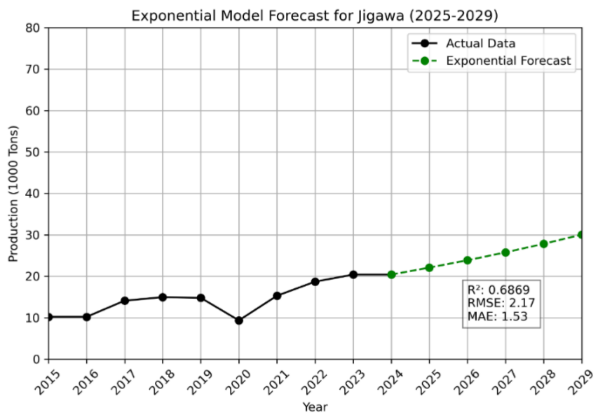

Figure 5. Exponential prediction for Jigawa

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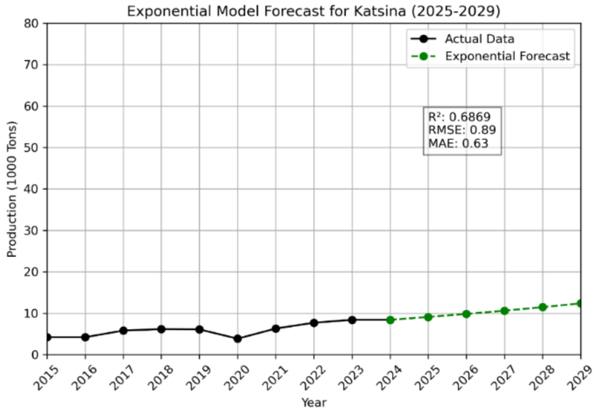

Figure 6. Exponential Model prediction for Katsina

(c) Polynomial Model

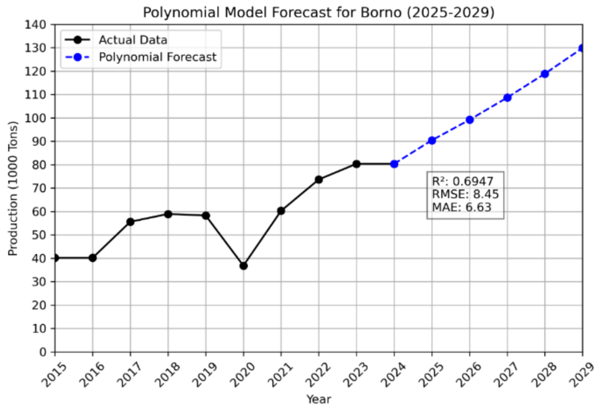

Figure 7. Polynomial model prediction for Borno

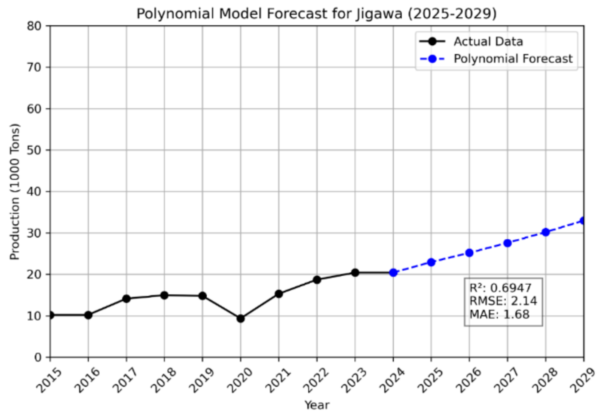

Figure 8. Polynomial model prediction for Jigawa

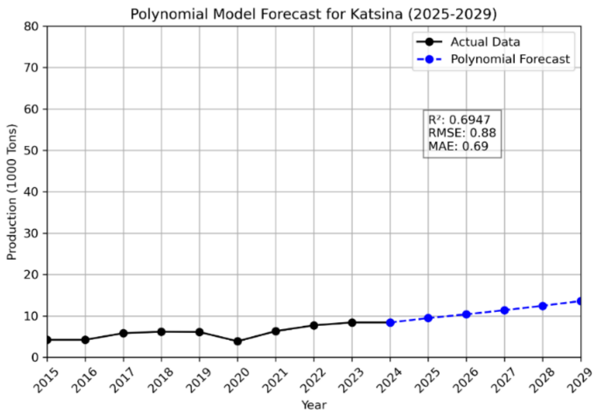

Figure 9. Polynomial model prediction for Katsina

Table 2 illustrates the model fit statistics for each state. Polynomial models always yielded the highest R-squared (R^2) values and therefore are better fits than linear and exponential models.

1. Borno State: The polynomial model provided the highest R^2 (0.6947) and the lowest RMSE (8.45) and is hence the most appropriate to forecast trends in wheat production.
2. Jigawa State: The polynomial model also did better than other models, with an R^2 of 0.6947 and a smaller RMSE (2.14), indicating high predictive power.
3. Katsina State: Similarly, the polynomial model had the best fit with $R^2 = 0.6947$ and RMSE = 0.88.

These observations suggest that wheat trends occur in nonlinear growth patterns and thus the optimal model for predicting trends in the future must be polynomial

Table 2. Model evaluation metrics

State	Model	R^2	RMSE	MAE
Borno	Linear	0.6641	8.87	6.32
	Exponential	0.6869	8.56	6.03
	Polynomial	0.6947	8.45	6.63
Jigawa	Linear	0.6641	2.35	1.60
	Exponential	0.6869	2.17	1.53
	Polynomial	0.6947	2.14	1.68
Katsina	Linear	0.6641	0.93	0.66
	Exponential	0.6869	0.89	0.63
	Polynomial	0.6947	0.88	0.69

4.1. Model Selection

The selection of the most effective predictive model is crucial in policy and future planning. The better performance of the polynomial model demonstrates that wheat production does not follow a linear or exponential path but is controlled by a number of interacting variables. The better performance of this model implies that:

- Wheat growth goes through phases of decelerated and accelerated growth but not a uniform rate of growth.
- Climate change, regulation by governments, and market demand influence production levels in a nonlinear manner.

The linear model (Equation 1) assumes a constant rate of change in wheat production, which is rarely true in agriculture. While useful in identifying long-term upward or downward trends, it cannot identify cyclical patterns or abrupt changes brought about by exogenous shocks. The exponential model (Equation 2) also assumes a constant percentage rate of growth, which is restrictive in view of the fact that agricultural systems are constrained by land, climate, and resources. Eventually, these limits hinder indefinite exponential growth. The polynomial model (Equation 8), however, has a quadratic term that allows for curvature in the trend. This enables the model to observe periods of deceleration or acceleration in production, modeling the real dynamics of crop output. For example, output rises in years of favorable weather and benevolent policies but declines during droughts or policy shocks. Mathematically, the quadratic term ct^2 introduces flexibility by permitting the slope of the trend $(dy/dt = b + 2ct)$ to change over time, instead of remaining constant.

5. Conclusions

This study employed linear, exponential, and polynomial time series models to forecast trends in the production of wheat in Borno, Jigawa, and Katsina States (2015–2024). Overall growth in wheat production with occasional shocks was indicated by the findings, and the most precise forecasts were provided by the polynomial model. These observations highlight the non-linear nature of agricultural processes of production. Enhancing Nigeria's wheat self-sufficiency requires irrigation development, climate-resilient practice uptake, and advanced forecasting tool integration. The study shows how statistical modeling can be employed to inform food security planning and agricultural policy.

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