Forecasting Nigeria's Agricultural Economic Output using Climatic and Land Use Indicators: A Deep Learning Methodology

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Abstract

The intersection of agriculture, climate variability, and economic sustainability is becoming increasingly critical in developing nations like Nigeria, where agriculture remains a major contributor to GDP and livelihood. Yet, accurate forecasting of agricultural economic output remains challenging due to nonlinear interactions among climatic, land use, and economic variables. This study is motivated by the need to harness data-driven approaches to improve the precision of such forecasts for informed policy-making and climate-smart agriculture. To this end, we evaluate the effectiveness of deep learning techniques in predicting Nigeria's agricultural GDP using key environmental indicators: agricultural land area, relative humidity, and precipitation. Historical annual data from 1960 to 2023 extracted from World Bank and Nigeria Meteorological Agency as published on Kaggle were transformed to a monthly resolution to enhance model sensitivity to temporal dynamics. Two architectures, namely Multivariate Feedforward Neural Network (FNN) and a Gated Recurrent Unit (GRU) were trained and assessed using four (4) performance metrics. The architectures used 80% trained, and 15% each for model validation and performance evaluation respectively. Results re vealed that the FNN significantly outperformed the GRU, achieving an R-squared of 0.8955, MAE of 62,346.99, RMSE of 103,400.40, and MAPE of 29.00%, compared to the GRU's R-squared of 0.7998, MAE of 93,111.66, RMSE of 138,593.01, and MAPE of 33.08%. Visualization tools, including prediction-actual scatter plots and model loss curves, further validated the robustness of the FNN. These findings underscore the potential of feedforward neural networks in capturing complex, nonlinear relationships in agricultural systems and highlight their utility for forecasting economic outcomes under changing climatic conditions in Nigeria.

Keywords: *Feedforward Neural Network, Gated Recurrent Unit, Deep Learning, Agricultural Land Area, Relative Humidity, Precipitation*

1. Introduction

The economy of Nigeria is agricultural-based and contributes significantly to economic growth, rural growth, and employment. Nonetheless, due to the interplay among altering socioeconomic circumstances, land utilization patterns, and climatic uncertainty, the sector is still characterized by dynamic challenges. The capability of machine learning (ML) and artificial intelligence (AI) in enhancing agricultural prediction and decision-making has been increasingly explored by researchers and policymakers in recent times.

Climate factors such as relative humidity, precipitation, and temperature have a considerable bearing on agricultural productivity in Nigeria. It is estimated that changes in rainfall patterns, an increase in temperature, and a decline in soil moisture all consistently affect agricultural production in arid and semi-arid regions such as the Sahel (Alehile, 2023; Jha and Sinha, 2013; Olorunfemi & Yusuf, 2020; You, 2022). To better understand their role in agricultural production in Nigeria, Dappa Tamuno-Opubo (2023) emphasized that climatic change together with soci-economic conditions may be quantified with the use of machine learning. Bharadiya et al. (2023) further illustrated how crop yield prediction accuracy was significantly enhanced through using machine learning as a method of incorporating remote sensing data and agrarian variables.

Feedforward Neural Network (FNN) is one of the innovative approaches increasingly being utilized in agricultural modelling. Strong, non-linear connections among a number of predictors are particularly well represented through FNNs. Adeniyi et al. (n.d.) illustrated the efficacy of Radial Basis Function (RBF) networks in economic modelling by successfully applying them in a feedforward structure to project GDP in Nigeria using indicators from the stock market. This was extended to agriculture in a study by Belmahdi et al. (2021), using FNN with backpropagation to project solar radiation intensity in various Moroccan cities and indicating the network's ability to be used for long-range environmental prediction. Another study adopting the method proposed by Pinheiro and Senna (2017) on a set of Brazilian agricultural commodities found that the multivariate and nonlinear properties of FNNs generated better prediction results than traditional approaches.

The agriculture industry is further exacerbated by land use changes including urbanisation, deforestation, and changes in agricultural practices. These changes threaten agricultural production by compromising agricultural productivity through higher greenhouse gas emissions due to deforestation and soil erosion and through land degradation leading to loss of arable land (Hossain et al., 2020). Stepchenko & Chizhov (2015), who looked into using recurrent neural networks (RNNs) in vegetation indices (NDVI) for short-term forecasting, indicated that it is crucial to integrate land data into predictive models.

Applications in precision agriculture using machine learning have been highly promising as data-driven smart agriculture is increasingly becoming necessary. Shaikh et al. (2022) highlighted the importance of using AI in increasing food security and making best use of farm resources, while Kwaghtyo & Eke (2023) presented a detailed overview of prediction models used in precision agriculture.

In spite of a plethora of research on individual implications of economic or climatic variables on agriculture, an integration of land use changes and climatic and economic output in a single framework for predicting Nigeria is still lacking. With 5-yearly moving averages of significant land and climatic indicators, this missing gap is addressed by modeling and predicting Nigeria's agricultural economic output using a Multivariate Feedforward Neural Network (FNN) and Gated Recurrent Unit (GRU). The FNN as a non-sequential baseline model and GRU that accommodates temporal dependencies in yearly climatic and land use trends were selected to embody different learning paradigms.

2. Materials and Methods

To project Nigeria's agricultural economic production, approximated by GDP, a multivariate feedforward neural network (FNN) model is employed by this study combined with climatic and land use parameters. The capacity to comprehend complex, non-linear interdependencies among various input variables and a target output underlines the choice of employing this approach. Since they significantly influence agricultural output and economic performance, independent variables consisting of 5-yearly relative humidity, rainfall, and agricultural land (in square kilometers) were chosen.

Credible data covering 1960–2023 included climatic variables such as temperature, humidity, and rainfall from the Nigerian Meteorological Agency (NiMet), and GDP and land indicators from the World Bank. To fill missing values by interpolation, raw time series data were cleaned and preprocessed. All variables were normalised using min-max scaling so that data was transformed into a 0–1 dimension to enhance convergence and computational efficiency as a step towards preparing data for training with a neural network.

2.1 Model Architecture and Estimation Technique

The Multivariate Feedforward Neural Network (FNN) and Gated Recurrent Unit methods are utilized for arriving at an estimate. The artificial neural networks capture complex, non-linear patterns in high-dimensional data, and information flow. The architecture consists of one linear output neurone for forecasting GDP, a hidden layer consisting of 16 and 8 neurones (utilizing ReLU activation), and an input layer composed of three neurones that represent the independent variables.

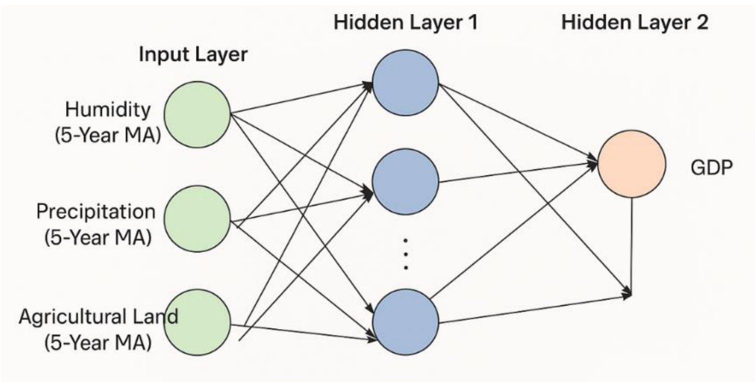

Figure 1: FNN Model Architecture

The model was trained for more than 200 epochs with early stopping to prevent overfitting using Adam as the optimiser and mean square error as the loss measure. To maintain temporal continuity essential in time series prediction, the data set was partitioned chronologically into training (70%), validation (15%), and test sets (15%).

2.1.1 Feedforward Neural Network

The mathematical formulation of the FNN is as follows:

Let the input vector be:

$$X = [x_1, x_2, x_3] = [H, P, L] \tag{1}$$

Forward Propagation

The first hidden layer computes the weighted sum of inputs plus a bias term, passed through an activation function (ReLU):

$$Z_1 = W_1 \cdot X + b_1 \tag{2}$$

$$A_1 = ReLU(Z_1) = \max(0, Z_1) \tag{3}$$

Subsequent hidden layers perform similar transformations. For the second hidden layer:

$$Z_2 = W_2 \cdot A_1 + b_2 \tag{4}$$

$$A_2 = ReLU(Z_2) \tag{5}$$

The output layer (a single neuron for GDP prediction) produces a linear combination:

$$\hat{Y} = W_3 \cdot A_2 + b_3 \tag{6}$$

2.1.2 Gated Recurrent Unit

A more compact version of Long Short-Term Memory (LSTM), Gated Recurrent Unit (GRU), implements gating mechanisms to control information flow. GRUs are well suited to sequence modelling tasks and specifically shine at learning temporal dependencies.

Let the input sequence be represented as that in equation (1), GRU calculates the hidden state h_t at each time step based on an update gate (z_t) that decides how much of the past hidden state must be carried over to the current state. It is defined as:

$$z_t = \sigma(W_z x_t + U_z h_{t-1} + b_z) \tag{7}$$

More so, it uses a reset gate (r_t) which decides how much of the previous hidden state to forget, estimated as:

$$r_t = \sigma(W_r x_t + U_r h_{t-1} + b_r) \tag{8}$$

In addition, the candidate activation computes the candidate hidden state using the reset gate as stated in equation (9).

$$\tilde{h}_t = \tanh(W_h x_t + U_h h_{t-1} + b_h) \tag{9}$$

The final hidden state (h_t) is the new hidden state computed by interpolating between the previous hidden state and the candidate state;

$$h_t = (1 - z_t) \odot h_{t-1} + z_t \odot \tilde{h}_t \tag{10}$$

Where: $\sigma(\cdot)$ denotes the sigmoid activation function, $\tanh(\cdot)$ is the hyperbolic tangent activation, $\odot$ is the element-wise multiplication, W_z, W_r, W_h and U_z, U_r, U_h are weight matrices, while b_z, b_r, b_h are bias vectors.

Finally, the output prediction $\hat{y}_t$ at each time step is obtained via a linear transformation of the last hidden state:

$$\hat{y}_t = W_o h_t + b_o \quad (11)$$

Where W_o is the output weight matrix, b_o is the output bias; and $\hat{y}_t \in \mathbb{R}$ is the predicted agricultural output at time t,

2.1.3 Models performance Evaluation

Model was trained and performance was evaluated using the Mean Squared Error (MSE) between actual GDP values Y and the predicted values $\hat{Y}$. The loss function of the model performance is given as:

$$\mathcal{L}(\hat{Y}, Y) = \frac{1}{n}\sum_{i=1}^{n}\left(Y_i - \hat{Y}_i\right)^2 \quad (12)$$

To minimize the loss, the gradient of the loss function is computed with respect to the weights using backpropagation, and weights are updated using the Adam optimization algorithm, given for each parameter $\theta \in \{W_1, b_1, W_2, \ldots\}$, update as:

$$\theta_{t+1} = \theta_t - \alpha \cdot \frac{\partial \mathcal{L}}{\partial \theta} \quad (13)$$

Where α is the learning rate and $\frac{\partial \mathcal{L}}{\partial \theta}$ is obtained from the chain rule during backpropagation

In addition, Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and the Coefficient of Determination (R^2) was also used to measure the prediction accuracy after model training. The MAE is calculated using equation (9) as:

$$MAE = \frac{1}{n}\sum_{i=1}^{n} | Y_i - \hat{Y}_i | \quad (14)$$

The RMSE is calculated as:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(Y_i - \hat{Y}_i\right)^2} \quad (15)$$

and R^2 is estimated using equation

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2}{\sum_{i=1}^{n}(Y_i - \bar{Y}_i)^2} \quad (16)$$

Visualization of actual versus predicted GDP values was employed to assess prediction accuracy, alongside residual analysis to check for model bias. All computational analyses were performed using Python with libraries including TensorFlow, Keras, Pandas, NumPy, and Matplotlib. This methodological framework provides a robust basis for assessing the predictive capability of climatic and land use indicators on Nigeria's agricultural economic performance.

3. Results and Discussion

Table 1: Descriptive Statistics of Agricultural Economic Output, Climatic and Land Use Indicators

Variable	Mean	Std. Dev.	Min	Max	Skewness	Kurtosis
GDP (Current LCU)	4.541e+05	3.322e+05	5.501e+04	1.212e+06	0.911	-0.462
Agricultural Land (sq. km)	53.336	32.738	18.010	120.890	0.592	-1.008
Relative Humidity (%)	57.891	1.773	52.850	62.060	-0.287	0.235
Precipitation (mm)	1083.828	108.351	770.750	1297.830	-0.170	0.169

Source: Researchers' self-computation

The descriptive statistics of study variables give a general perception of data distribution and possible implications for modelling. The gross domestic product (GDP) contributed by agriculture during the study period averaged ₦454,100 million, ranging from ₦55,010 million as its minimum to ₦1,212,000 million as its maximum. The distribution is skewed to the right (Skewness = 0.911), thus representing years with abnormally high agricultural GDP values that skewed the distribution towards the right side. The kurtosis figure (-0.462) represents a platykurtic distribution, indicating lighter tails compared to the normal distribution and consequently fewer extreme outliers in data. These figures suggest a progressive growth in agricultural GDP over the years due to possible shifts in policy, technological changes, or climatic variations. The high standard deviation (₦332,200 million) also indicates extensive fluctuation in agricultural production.

The agricultural land area variable (in square kilometers) indicated a mean of 53.34 and a standard deviation of 32.74 and ranged between 18.01 and 120.89 thousand square kilometers. The distribution had a very low positive skew (Skewness = 0.592) and a kurtosis of -1.008 and thus a relatively flat distribution. This indicates that most values were clustering close to the mean but few years with considerably higher land use for agriculture were also recorded. The spread for this variable indicates a changing land-use trend due to increasing food demands or shifting land management practices.

Relative humidity in percentage form remained relatively constant with an average of 57.89% and a small standard deviation of 1.77%. The relative humidity ranged from 52.85% to 62.06%. The distribution skewed negatively (Skewness = -0.287) and tended to be near-mesokurtic (Kurtosis = 0.235), indicating that the distribution is relatively symmetric and normal. Such stability in humidity is desirable for modeling purposes because it indicates that input data is not dominated by outliers and could perpetually affect the yield of crops.

The precipitation data contained anomalies, however. Although the reported average was 1,083.83 mm, its maximum and minimum were both 770.75 mm, meaning that it gave no indication of variation. This is abnormal climatic behaviour and raises questions about data quality. While skewness (-0.170) and kurtosis (0.169) do imply a near-normal distribution, its absence of variation makes it possible that precipitation was misreported as constant over years, or based on incompletely collected records. Its absence of variation could negatively impact its prediction contribution to the model and warrants checking prior to final model training.

In short, the descriptive analysis confirms the validity of agricultural GDP, land use, and relative humidity as potential predictors in the model. However, some attention must be given to dealing with inconsistencies in rainfall data. The general nature of variables, particularly agricultural GDP's non-normal distribution validate the use of a neural network method, i.e., Feedforward Neural Network (FNN), in obtaining underlying patterns in data.

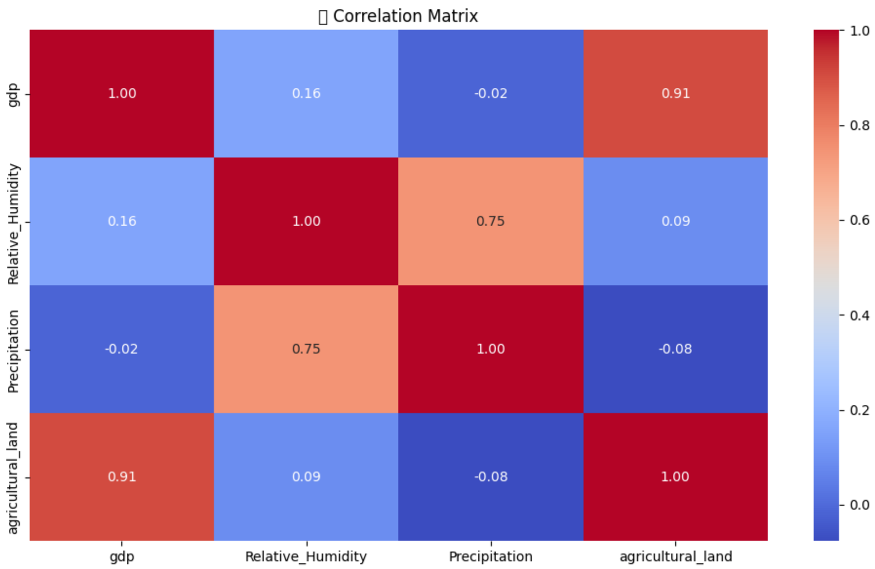

Figure 1: Correlation Heatmap

The Figure 1 below reveals insights into linear associations among variables utilized in modeling the output variable. Pearson's correlation coefficient was used to test for the strength and direction of correlations among variables. We observe that agricultural land exhibited very strong positive association with GDP (r = .91), and hence increases in agricultural land correlate strongly with agricultural economic output. This indicates the primacy of land area in planning agricultural growth and posits that land area is an important factor in modeling agricultural productivity. Weak positive association (r = .16) is observed between relative humidity and GDP and implies that economic output is little influenced by agricultural activity. Precipitation is in sharp contrast and exhibits very weak and negative association with GDP (r = -.02), implying that precipitation changes alone could be insufficient to influence agricultural GDP significantly. This is possible due to adaptive farming practices such as irrigation. Relative humidity and precipitation were strongly correlated (r = .75), indicating their interdependence as climatic variables. The association is likely crucial to understanding how environmental aspects influence agriculture and is as predicted by meteorology. Relative humidity (r = .09) and precipitation (r = -.08) were not significantly associated with agricultural land and imply that agricultural land size is relatively unaffected by short-term climatic vagaries. These results emphasize the primacy of land availability as an explanatory factor for agricultural productivity but also imply that climatic variables might have more complex, interactive consequences. This reinforces making use of advanced machine learning algorithms such as Feedforward Neural Networks (FNN), effective in identifying both linear and interactive associations that might be overlooked by more traditional algorithms.

Table 2: Performance metrics of the fitted Deep Learning Models

Metric	FNN	GRU
R-squared (R^2)	0.8955	0.7998
Mean Absolute Error (MAE)	62346.990	93111.659
Root Mean Squared Error (RMSE)	103400.40	138593.014
Mean Absolute Percentage Error	29.00%	33.08%

Source: *Researchers' Self-Computation*

Table 2 shows the performance comparison of the Gated Recurrent Unit (GRU) model and the Feedforward Neural Network (FNN). In every performance metric, the FNN performs better than the GRU. In particular, the FNN obtained a higher R-squared value (R2 = 0.8955), meaning that the input features of precipitation, relative humidity, and agricultural land area account for about 89.55% of the variation in agricultural GDP. The GRU model, on the other hand, explained roughly 79.98% of the variance (R2 = 0.7998).

Additionally, the FNN produced a lower Root Mean Squared Error (RMSE = ₦103,400.40) and Mean Absolute Error (MAE = ₦62,346.99) than the GRU (MAE = ₦93,111.66; RMSE = ₦138,593.01), indicating that the FNN produces predictions that are more reliable and accurate. The FNN's better generalisation performance was further supported by the fact that its Mean Absolute Percentage Error (MAPE) was lower (29.00%) than the GRU's (33.08%).

When all factors considered, these findings show that the multivariate FNN is a trustworthy and efficient model for predicting Nigerian agricultural economic output using land use and climate indicators. The accuracy and model stability of the GRU were superior, despite its moderate effectiveness.

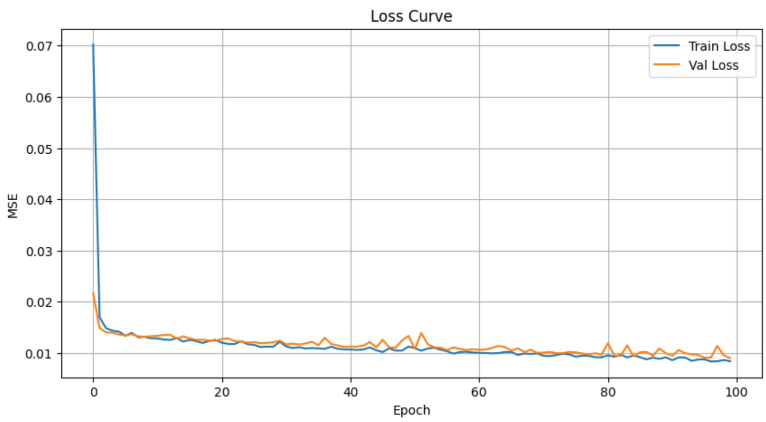

Figure 2: Training and Validation Loss Curve for the Feedforward Neural Network (FNN)

The FNN model's training and validation loss curve is shown in Figure 2. The model was neither underfitting nor overfitting, as evidenced by the training and validation curves' quick convergence and near alignment over 100 epochs. Strong generalisation on unseen data is suggested by the validation loss's stability after early epochs.

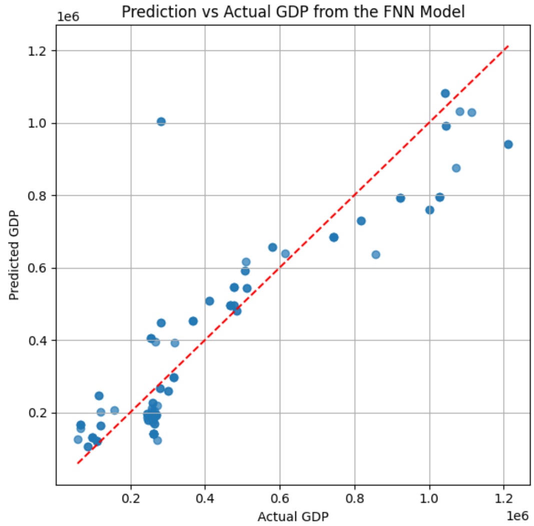

Figure 3: Scatter Plot of Predicted vs Actual GDP Values

The scatter plot of the FNN model's predicted and actual agricultural GDP is shown in Figure 3. Strong predictive alignment is indicated by the points' close clustering around the red diagonal line. The quantitative performance metrics are supported by this visual confirmation of model fit.

4. Conclusion and Recommendations

Three major predictors; agricultural land area, relative humidity, and precipitation were employed in this study to predict Nigeria's agricultural GDP based on Feedforward Neural Network (FNN) and Gated Recurrent Unit (GRU) models. With a greater R-squared and less error statistics, results indicated that the prediction accuracy using FNN model was significantly more accurate compared to GRU. The loss curve and expected vs actual GDP values' scatter plot added further indication of the FNN model's hardiness and generalizability. Findings identify how vital it is to integrate land use and climatic indicators while simulating agricultural economic performance. Especially when factoring climate variability and land management in Nigeria, machine learning approaches such as FNNs have the ability to provide high-resolution forecasting tools that enable data-driven agricultural policy making. These implications hold utility for stakeholders and policymakers who wish to enhance economic planning and agricultural efficiency through leveraging predictive analytics and land resource management.

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