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RESEARCH ARTICLE

MACHINE LEARNING-BASED CROP YIELD PREDICTION UNDER CLIMATIC VARIABILITY: A COMPARATIVE STUDY TO SUPPORT AGRICULTURAL EXTENSION SERVICES IN KANO STATE, NIGERIA

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ABSTRACT

Machine learning algorithms like artificial neural networks (ANN) and Multiple Linear Regression (MLR) are capable of providing accurate predictions of crop yields based on climatic variables. Meteorological data from 1993 to 2023 and crop yield from 2009 to 2023 were obtained from the National Aeronautics and Space Administration (NASA) and the Kano Agricultural and Rural Development Agency (KNARDA) respectively. The ANN and MLR algorithm were compared in predicting Sorghum, Millet, Groundnut and Soya beans yield based on the dataset of the climatic variables. Seven climatic variables (Rainfall, Maximum, temperature, Minimum temperature Relative humidity, Sunshine hours, Wind speed and direction) were used as input neurons for the ANN algorithm. ANN performed better than MLR in predicting Sorghum yield with R^2 0.945 (94%) and RMSE of 26, while MLR showed 0.745 (74%) and high RMSE of 816.531. For Millet yield revealed R^2 value of 0.99 (99%) and a corresponding low RMSE of 3.16 for ANN. While MLR present R^2 value of 0.40 (40%) and with a very high of 0.925.Equally for prediction of Soya beans A very high R^2 of 0.99 (99%) was obtained by using ANN model, indicating a more accurate prediction when compared to MLR with R^2 of 0.67 (67). For Groundnut ANN gave R^2 0.803(80%) and a low RMSE of 3.05, and MLR showed R^2 of 0.532 (53%) and a corresponding high RMSE of 159.387 Therefore comparing both models developed in the study indicated that ANN model has high prediction capacity of Sorghum, Millet , Groundnut and Soya beans yield more than the MLR model. It is recommended that ANN-based models be adopted in extension services, researches, and agro-meteorologist for accurate and better prediction of crop yields produce through rain-fed system.

Keywords: Machine learning, crop yield, rain-fed, predictive models, agro-extension services.

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1.0. INTRODUCTION

Climatic variability describes short- to medium-term fluctuations in atmospheric conditions within a specific location over time. These fluctuations are reflected in changes in average rainfall, maximum and minimum temperatures, and relative humidity, duration of sunshine, as well as wind speed and direction. In recent years, climatic variability has gained global attention due to its increasing influence on agricultural systems, particularly its adverse effects on crop productivity when combined with long-term shifts in weather patterns (Haakana et al., 2024).

Across the world, agricultural production has already experienced the consequences of climate-related fluctuations. Variations in temperature and rainfall have produced uneven outcomes, enhancing crop performance in some regions while reducing yields in others. This uneven response highlights the strong sensitivity of crop production to changes in mean climatic conditions and associated variability (Sjulgård et al., 2023). In many developing countries, livelihoods are closely tied to rainfed agriculture, which serves as a major source of household food supply and income. Studies indicate that climate variability significantly disrupts rainfed farming systems in West Africa, leading to unstable production of staple crops such as millet, sorghum, and rice. These disruptions increase food insecurity and expose large segments of the population to heightened vulnerability (Osei et al., 2024).

Rainfed agriculture, which is largely subsistence-oriented and characterized by low productivity, remains particularly susceptible to climatic fluctuations despite its critical role in employment generation and regional food security. (Thornton et al 2014, 2014) emphasized that the impacts of climatic variability on agricultural output are complex and multifaceted. In Nigeria, changes in rainfall distribution and temperature regimes pose serious threats to rainfed farming systems, undermining crop performance and farm stability (Doe et al., 2021).

Irregular and unpredictable rainfall patterns disproportionately affect smallholder farmers, who are highly exposed to rainfall anomalies that may result in drought conditions in certain areas (Ndamani & Watanabe, 2015), (Gaveta, 2024). Conversely, excessive rainfall can accelerate soil erosion, wash away essential nutrients, and ultimately reduce crop yields under rainfed production systems (Abdisa et al., 2022), (Zike, 2019). Future projections suggest that cereal yields in several parts of Africa may decline due to increasing climatic variability, including potential reductions in maize output, thereby threatening food security on a continent where agriculture largely depends on rainfall (Stuch et al., 2020).

Climatic variability is particularly evident in Nigeria, including the present study area, where a large proportion of the population depends on rainfed agriculture for both food and income. In Kano State, approximately 75% of the working population is engaged either directly or indirectly in agricultural activities, and the state contributes more than 20% of Nigeria's non-oil export earnings (KRPP, 2014). In many rural communities, sociocultural values strongly shape perceptions of environmental change. These beliefs influence how farmers interpret and respond to climate-related challenges. As a result, climate variability and change are sometimes viewed as natural phenomena with limited perceived implications for livelihoods and environmental sustainability.

The persistent challenges confronting agricultural production underscore the importance of reliable crop yield prediction as a strategy for enhancing food security and accommodating rapid population growth (Jabed et al., 2024). Climatic conditions play a decisive role in agricultural success by determining crop suitability, productivity, and the overall viability of rainfed farming systems. Climate factors largely dictate which crops can be cultivated successfully in a given location and season. Recent studies have shown that crop yield prediction based on climatic variables is becoming a critical research area within agricultural science, given its potential to inform development strategies, strengthen socioeconomic resilience, and support national food security initiatives (Matopote, 2025). Accurate yield forecasting is therefore essential for farmers, agricultural agencies, and policymakers in guiding effective planning, policy formulation, and implementation.

Previous studies have demonstrated that machine learning approaches, including Artificial Neural Networks (ANN) and Multiple Linear Regression (MLR), can improve the accuracy of crop yield prediction when climatic variables are considered. For example, (Nirmitha .A.S and G.S Rashek, 2024) applied ANN to predict rice yields in India and reported that climatic variables exerted significant influence on crop performance, emphasizing the advantages of advanced modeling techniques. Similarly, (Karongo et al., 2025) evaluated five machine learning models for sorghum yield prediction and found that ANN produced superior accuracy with higher coefficients of determination compared to MLR.

(Prado et al., 2024) further confirmed the effectiveness of ANN in estimating soybean yields, where the model outperformed conventional statistical methods. Other studies have also highlighted the importance of integrating multiple modeling approaches to enhance prediction accuracy in climate-agriculture research. In Maharashtra, India, ANN was employed using climatic data from 1998 to 2002 to forecast crop yields, demonstrating the model's potential to support extension services and farmers' decision-making through improved yield forecasts.

Crop production systems are influenced by numerous interrelated factors, making it difficult to adequately capture their interactions using traditional statistical techniques alone (Islam et al., 2016). ANN is particularly suitable for modeling such complex and non-linear relationships between climatic variables and crop yields. Several studies have successfully applied ANN to agricultural yield prediction like Braga et al., 2007, as cited in (Santos et al., 2015)

In contrast, MLR has also been widely used to estimate crop yields based on climatic parameters such as rainfall, temperature, relative humidity, and sunshine duration. (Jabed et al., 2024) and (Hara et al, 2021) reported strong predictive performance using MLR, achieving an R^2 value of 85%. Despite the widespread application of both methods, relatively few studies have simultaneously applied and compared ANN and MLR in predicting the yields of cereal and legume crops specifically Sorghum, Millet, Groundnut and Soya beans under rainfed farming conditions in Kano State. This study therefore seeks to develop ANN and MLR models and to evaluate their comparative effectiveness in predicting Sorghum, Millet, Groundnut and Soya beans yield during the rainy season. Previous research has suggested that hybrid modeling approaches combining ANN and MLR may further enhance prediction accuracy (Sharma et al., 2024). The outcomes of this study are expected to guide stakeholders in agro-meteorology and agricultural planning toward selecting the most efficient

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modeling tools, thereby supporting informed decision-making and improving rainfed crop production in Kano state and Nigeria at large.

1.1. Scope of the Study

This research is confined to Kano State, Nigeria, and focuses on comparing and predicting yield of Cereal and Legume crops produce through rainfed system in relation to climatic variability using ANN and MLR models. The aim of making comparison is to suggests the most simplest crop yield prediction model that can be used by the researchers in agro-meteorology and equally extension workers to ensure optimization of resources and to support designing of informed decision for agricultural practices The climatic variables examined include rainfall, maximum and minimum temperatures, relative humidity, sunshine duration, wind speed, and wind direction for the period 1993–2023. The crop yields analyzed include Sorghum, Millet, Groundnut and Soya beans, with records covering the period 2009–2023.

2.0. DESCRIPTION OF THE STUDY AREA

Kano State lies between Latitudes 10° 05″ and 12°45″ North of the Equator and Longitudes 7°45″ and 9°75″ East of Greenwich Meridian. It is bordered by Katsina State to the northwest, Jigawa State to the northeast, Bauchi State to the southeast, and Kaduna State to the southwest. The state covers an estimated land area of approximately 20,131 km².

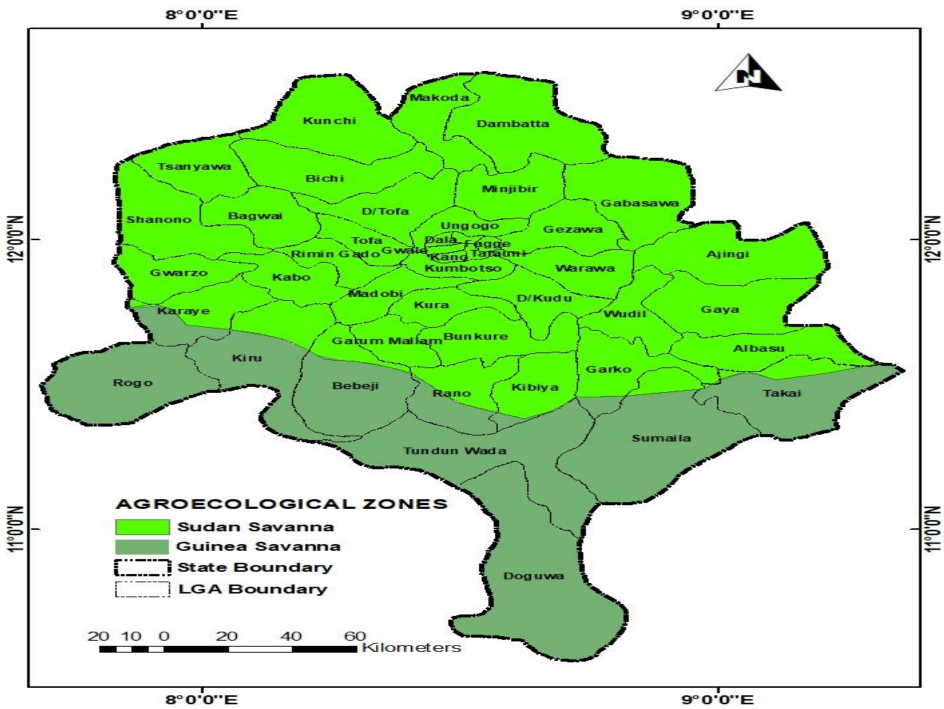

Figure 1: Kano State Showing Agroecological Zones
Source: Adopted from IITA Agroecological Map of Nigeria (2004) as used in (Hassan et al., 2021)

The climate of Kano State is classified as tropical wet-and-dry (Aw) according to the Köppen classification system. Seasonal climatic conditions are governed by the alternating influence of two dominant air masses: the dry tropical continental air mass and the moist tropical maritime air mass. These air masses give rise to distinct wet and dry seasons. The rainy season generally occurs between June and September, with occasional humidity in May, while the dry season extends from mid-October to mid-May. Average annual rainfall ranges from 800 mm to 900 mm, with deviations of up to ±30% from the mean (Olofin, 2016, as cited in (Hassan et al., 2021). August typically records the highest rainfall, often exceeding 300 mm

3.0. MATERIALS AND METHODS

3.1. Data Type, Sources, and Variables

Historical climatic data covering a 30-year period (1993–2023) were obtained from the NASA POWER database. These data include rainfall, maximum and minimum temperatures, relative humidity, sunshine hours, wind speed, and wind direction. Crop yield data for Sorghum, Millet, Groundnut and Soya beans spanning 14 years were sourced from the Kano Agricultural and Rural Development Agency (KNARDA). Similar datasets have been widely used in climate and agricultural studies to analyze trends and support yield prediction (Ishaku et al., 2024); (Hassan et al., 2021) and (Udeh et al., 2024). In this study, climatic variables were treated as independent variables, while the yields of crops served as dependent variables.

3.2. Methods of Data Collection

Daily climatic data were accessed through the NASA POWER Data Access Viewer, from which annual mean values were computed. Annual crop yield data (measured in tons) were obtained from KNARDA. All datasets were organized and processed using Microsoft Excel.

3.3. Data Analysis

Artificial Neural Network modeling was applied by dividing the dataset into training (70%) and validation (30%) subsets. The training phase enabled the model to learn underlying data patterns, while validation assessed its predictive accuracy. Multiple Linear Regression analysis was also conducted using the same dataset to ensure comparability. Separate regression models were developed for Sorghum, Millet, Groundnut and Soya beans using seven meteorological variables: rainfall, maximum and minimum temperature, relative humidity, solar radiation, wind speed, and wind direction. Model performance was evaluated using statistical criteria including the coefficient of determination (R^2), adjusted R^2, root mean square error (RMSE), and mean absolute error (MAE), following the approach of (Peter & Precious, 2018).

4.0. PRESENTATION OF RESULTS AND DISCUSSION

4.1. Comparison between ANN and MLR in Predicting Sorghum Yield

ANN and MLRA were compared in order to ascertain the most efficient and significant model to be adopted for prediction. The models performances were determined using the goodness of fit R^2, R^2 adjusted and RMSE as used by other scholars as criteria for comparing model performance, studies

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like that of (Grossi et al., 2015), (Kaul et al., 2005), (Kumar et al., 2024). Thus, the result are presented in the tables and figures below.

The table indicates that the ANN has a coefficient of determinant of R^2 0.94 (94%), R^2 and RMSE of 26. In comparison with MLR indicating 0.745 (74%) R^2 and a corresponding high RMSE. The results shows that ANN has a very high prediction accuracy, and this supports the finding of (Kaul et al., 2005) that revealed how ANN gives more accurate crop yield prediction when compared to linear regression in studying Corn yield in Maryland, where R^2 of 0.77 (77%) and 0.42 (42%) for ANN and MLR respectively was reported. In the same study ANN present 1036 RMSE while 1356 was obtained as RMSE for MLR. Because ANN is an artificial intelligence model and it can be trained to learn the pattern of the data set, it also does not deteriorate by complex variables. Therefore, ANN are suitable in handling issues related to Agriculture and other disciplines, and has become a known tool in various human endeavor (Isaac et al., 2018).

Also Pachepsky *et al.*,(1996) as reported by (Kaul et al., 2005) ANN can be applied in different disciplines, like estimation of soil water was carried out using ANN model and a good R^2 was obtained 0.98 (98%) indicating higher performance when compared to regression model with R^2 0.78. But (Abyaneh, 2014) reported that MLR model is best suited to model linear relationship that exist between dependent and few independent variables. Therefore, it cannot handle large complex dataset with non-linear pattern. Equally the figure 3.1 displayed how the scatter plot of ANN revealed a better prediction than MLR model, because the points are clustered and arrange along a diagonal line of x-y, indicating a high predicting accuracy. While some points in MLR are scattered along the diagonal line, indicating a low predictive accuracy.

Table 1: Comparative Model of Sorghum Yield Prediction using ANN and MLR

Sorghum	ANN	MLR
R^2	0.945 (94%)	0.745 (74%)
R^2 Adjusted	0.814	0.448
RMSE	26	816.531

Source: Authors; Analysis (2025).

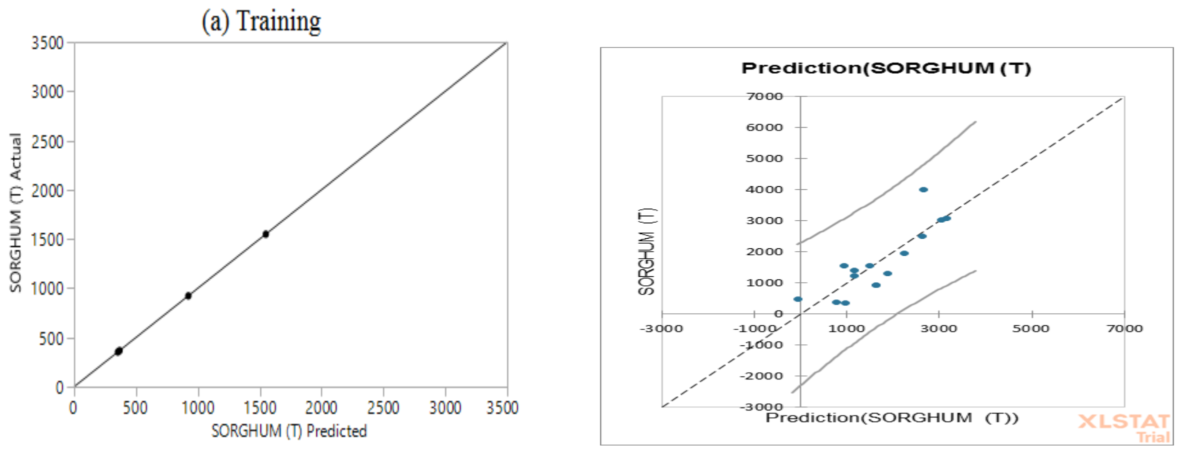

Figure 2: Graphical Model of Sorghum Yield Prediction between ANN and MLR

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4.2. Comparison between ANN and MLR in Predicting Millet Yield

Model evaluation results indicate that ANN significantly outperformed MLR in predicting millet yield. The ANN model achieved a very high R^2 value of 0.99 with a low RMSE of 3.16, while the MLR model recorded an R^2 of 0.40 accompanied by a much higher RMSE. These findings are consistent with previous studies that reported superior performance of ANN compared to regression-based models (Hara et al, 2021) ; (Asif et al., 2023). Similar results were also reported in South American studies where ANN demonstrated higher predictive accuracy than MLR in rainfall estimation (Santos et al., 2015). Scatter plot analysis further confirmed the stronger predictive capability of ANN, as predicted values closely aligned with observed values along the diagonal line.

Table 2 Comparative Model of Millet Yield Prediction between ANN and MLR

Millet	ANN	MLR
R^2	0.999 (99%)	0.402 (40%)
R^2 Adjusted	0.765	0.925
RMSE	3.16	504.925

Source: Authors' Analysis (2025).

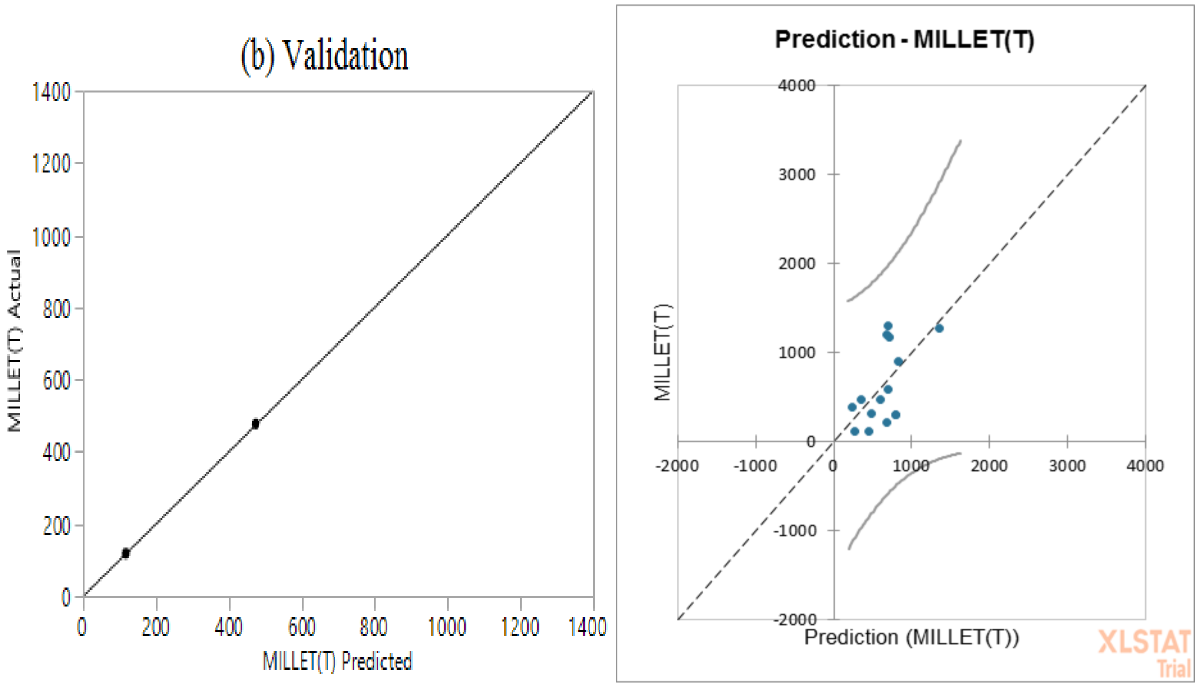

Figure 3: Graphical Models of Millet Yield Prediction between ANN and MLR

4.3. Comparison between ANN and MLR in Predicting Groundnut Yield

The table presented below shows the goodness of fit of both ANN and MLR model in predicting Groundnut yield. The results shows that MLR has low accuracy level with R^2 value of 0.53 (53 percent) when compared to ANN with higher R^2 value of 0.80 (80 percent). ANN also revealed a very low RMSE (3.05) when compared to MLR with a very high RMSE value of 159.387. (Mishra & Thakur, 2020) compared ANN and MLR in predicting Broccoli yield, and the result revealed that the ANN

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performance using 10 hidden neurons present a more accurate prediction with a very high R^2 value of **0.99 (99%)** and corresponding low value of mean square error and RMSE than MLR prediction. The study also concluded that researches often use MLR in prediction studies, but it might not o give the exact predictions while dealing with complex datasets. Thus, ANN is essential tool in handling strong non-linearity between datasets like crop yield estimation. Another study also conducted by (Norouzian et al., 2021) compared ANN and MLR to predict dairy Cow and the findings shows that ANN offered a higher coefficient of determination (R^2) value than MLR, where the MLR present R^2 value of **0.53** (**53%)** and RMSE of **0.36**, and with the same dataset ANN gave R^2 value of **0.80 (80%)** and RMSE of **0.16**.

Table 3 Showing Groundnut Yield Prediction between ANN and MLR

Groundnut	ANN	MLR
R^2	0.803(80%)	0.532 (53%)
R^2 Adjusted	0.531	0.295
RMSE	3.05	159.387

Source: Authors' Analysis (2025).

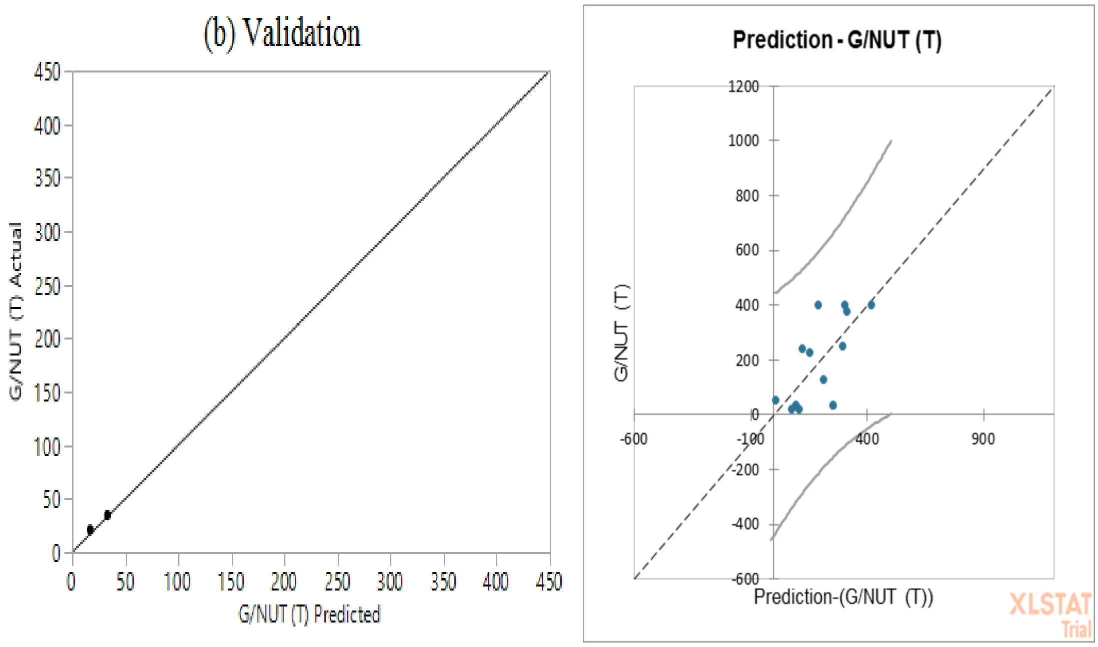

Figure 4: Graphical Model of Groundnut Yield Prediction between ANN and MLR

4.4. Comparison of ANN and MLR in Predicting Soya Bean Yield

The ANN model also demonstrated superior performance in predicting soya bean yield, achieving an R^2 value of 0.99 compared to 0.67 for MLR. This result aligns with the findings of Kaul et al. (2005), who reported higher predictive accuracy for ANN than MLR in soybean yield estimation. Additional studies have shown that ANN performs well in modeling complex, non-linear relationships in agricultural datasets (Mishra & Thakur, 2020); (Jabed et al., 2024). Scatter plot results further revealed that ANN predictions closely matched observed yields, whereas MLR predictions showed greater dispersion.

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Table 4: Showing Soya beans Yield Prediction between ANN and MLR

Soya beans	ANN	MLR
R^2	0.99 (99 percent)	0.675 (67 percent)
R^2 Adjusted	0.832	0.295
RMSE	0.028	113.111

Source: Authors' Analysis (2025).

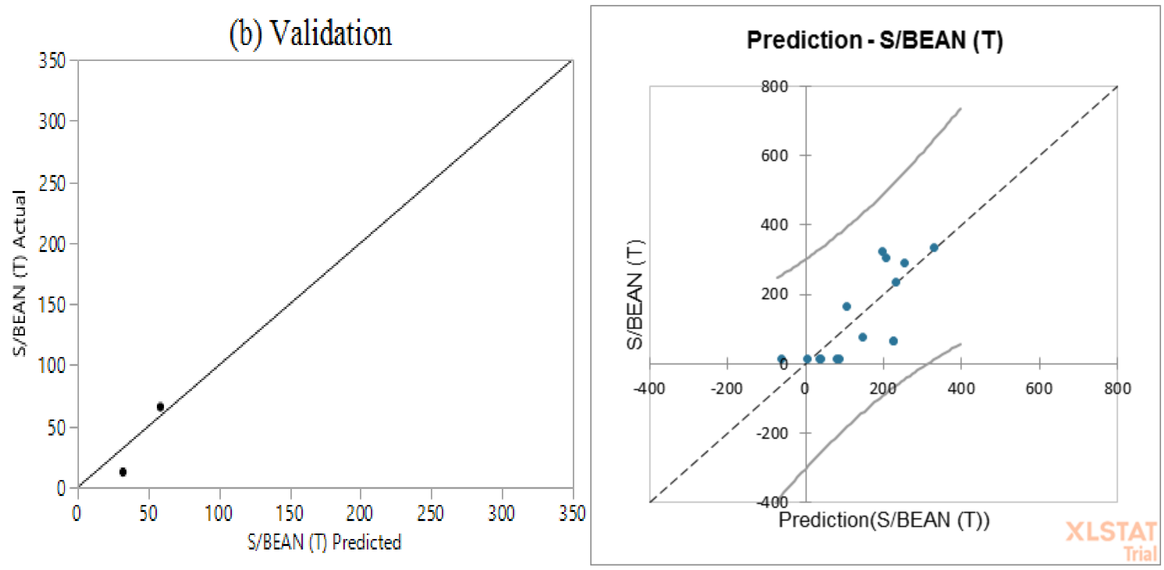

Figure 5: Graphical Model of Soya beans Yield Prediction between ANN and MLR

5.0. CONCLUSION AND RECOMMENDATIONS

The Artificial Neural Network model developed in this study demonstrated excellent predictive accuracy, characterized by very high coefficients of determination and low prediction errors. In contrast, the Multiple Linear Regression model showed lower to moderate accuracy. Overall, ANN proved to be more effective than MLR in predicting the yields of Cereals (Sorghum and Millet) and Legumes (Groundnut and Soya beans) under rain-fed farming conditions.

Given the superior performance of the ANN model, it is recommended that ANN-based approaches be adopted by researchers, agricultural extension services, and agro-meteorological institutions for improved prediction of rain-fed crop yields. Such adoption would support more informed agricultural planning, policy formulation, and food security strategies

Conflict of Interest

The authors declare no conflict of interest in this manuscript.

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