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MACHINE LEARNING-BASED APPROACHES TO IMPROVE CROP YIELD PREDICTION IN AGRICULTURE IN ADAMAWA STATE, NIGERIA

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Abstract

Accurate yield forecasting is critical for sustainable agriculture in developing countries like Nigeria. This study evaluates three machine learning models: **Artificial Neural Network (ANN), Decision Tree (DT),** and **Support Vector Machine (SVM)** for predicting crop yields across five agriculturally diverse Local Government Areas in Adamawa State, Nigeria. Using environmental data from 2019 to 2023, including rainfall, temperature, and soil moisture, we trained models to forecast yields (kg/ha) for staple crops like maize, sorghum, and groundnuts. Results showed that **ANN and DT outperformed SVM,** achieving high accuracy (R^2: 0.93–0.98) and low errors (RMSE: 5.5–10.9). While the ANN excelled in Madagali (R^2=0.97, RMSE=6.7), the DT performed best in Mubi North (R^2=0.98, RMSE=5.5), whereas the SVM consistently underperformed (R^2: 0.42–0.46; RMSE: 29.8–36.6) in all study areas. The result also showed rainfall and soil moisture were stronger yield predictors than temperature. These results demonstrate ANN and DT's suitability for yield prediction in diverse environments. We recommend that models which prioritize rainfall and soil moisture over temperature be employed in crop yield prediction in the study areas and ANN or DT tools are to be adopted to aid smallholder farmers in farm resource planning. These will reduce prediction errors by 76 to 82% compared to traditional methods, enabling proactive resource allocation and enhancing food security in Northern Nigeria.

Keywords: Crop Yield, Agriculture, Prediction, Machine Learning, Nigeria.

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Introduction

According to the report of World Bank, Agriculture contributes 4% and 25% growth of global and developing countries' GDP respectively, including Nigeria, hence plays a significant role in the national development. However, the agricultural enterprise is replete with risks and uncertainty necessitating decision making processes that require a significant measure of precision to avert or decrease failures. Crop yield can be described as the measurement of a farm product grown per unit area (Paudel et al., 2021). Crop yield prediction is one of most challenging problems in Agriculture es[ecially in developing nations as it depends on factors such as climate, weather, soil, fertilizer application and seed variety, management and their complex interactions (Klompenburg, et al., 2020; Ansarifar, et al., 2021). For instance, what to grow, how to grow it and what to do during the growing season of crops is a major factor in determining the output and the overall outcome of crop production enterprise. Underscoring the importance of accurate crop yield prediction in Agriculture Ali et al. (2022) observed that pre-harvest forecasting of crop yields can help decision makers, including farmers to use reliable and accurate precautionary strategies to safeguard their harvests thereby reducing yield damage and wastages. Traditionally, crop performance and yield outcomes relied heavily on observations by farmers with errors leading to sub optimal outcomes like food shortages. Such methods are not accurate in determining the exact yields of crops because they rarely address the various factors influencing crop yield prediction, such as type and content of fertilizers and pesticides, available soil water, available resources for crop growth, total cultivable land, temperature, humidity, and rainfall, seasonal changes and the stress caused by biotic and abiotic agents. In addition, the accuracy of crop yield prediction is primarily dependent on the type and form of the data selected for prediction and the method applied to extract the data and the sources of the data. Therefore, there is need to deploy tools that can enhance the decision making process of farmers with greater precision, promoting efficient resource management and enhancing reasonable yield estimates, thereby mitigating food scarcity (Cedric, et al., 2022; Jabed & Murad, 2024). Different technologies are available for crop monitoring and yield prediction including Machine Learning (ML). ML takes a data-driven or empirical modeling approach to learn useful patterns and relationships from input data and offers a promising opportunity for improving crop yield predictions (Willcock et al., 2018; Paudel et al., 2021). ML models are mathematical algorithms or computational systems that are designed to learn patterns and make predictions or decisions based on input data. These models are trained on large datasets to recognize and generalize patterns, enabling them to perform tasks such as classification, regression, clustering, or anomaly detection (Zhao, 2020). Nowadays, ML can even to do future prediction using a set of collected

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present data. Although ML has been adopted to design models for crop yield prediction in Agriculture for several years, it is yet still desirable (Klompenburg, et al., 2020; Thomas et al., 2021). This research focuses on assessing the suitability of models developed using ML in predicting crop yields across different geographical locations in Adamawa State Nigeria, with a view to decreasing errors in yield prediction and enhancing accuracy of prediction by farmers.

Aim and Objectives of the study

Aim

To evaluate ML algorithms for accurate crop yield prediction for enhanced crop production in Adamawa State.

Objectives

The objectives of the study are:

I. To evaluate the performance of ANN, DTs, and SVM models in crop yield prediction in the study areas.
II. To describe the evaluation metrics for crop yield prediction models for the study areas.

Research Questions

I. What is the performance of ANN, DTS and SVM in crop yield prediction in the study areas?
II. What are the evaluation metrics for assessing the accuracy of crop yield prediction models in the study areas?

Significance of the study

Results from the study will successfully leverage ML to bridge the gap between manual prediction techniques and automated techniques, thereby addressing the problems encountered using the traditional method of predicting seasonal crop yields. The results will provide smallholder farmers with data driven tool to plan their farming systems, thereby decreasing the risks associated with haphazard planning based on previous farmers' knowledge independent of data. Government agencies and other stakeholders in the farming business can also use the data to plan intervention measures appropriately, based on the results of the model.

Literature Review

ML has demonstrated significant capabilities for crop yield prediction across diverse agricultural systems. Accordingly, Ghosh et al., (2023) noted that integrating

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environmental covariates particularly temperature and precipitation into ML frameworks enhanced prediction accuracy of crop yield outputs. A systematic analysis of 50 studies revealed that covariates like soil type, rainfall, and temperature were the most dominant variable in yield prediction models, with Artificial Neural Networks (ANN) becoming the dominant algorithmic approach. In the application domain of ML to agriculture notable specializations have been reported evidenced not only by the development of state-of-the-art ML algorithms but also extended to Remote Sensing applications, disease detection, and growth monitoring (Mamunur et al. 2021). Studies show ML models predict crop yields with varying accuracy, as results depend on the specific crop, input variables, and environmental conditions highlighting the multidimensional utility of ML in precision agriculture. Thus, Ranjan and Parida (2019) employed Random Forest (RF) classification for paddy acreage mapping and linear regression for yield prediction and showed how near-real-time crop monitoring could enhance decision-making for agricultural stakeholders. Furthermore, Agarwal and Tarar (2021) introduced a deep learning framework incorporating Support Vector Machines (SVM), Long Short-Term Memory (LSTM) networks, and Recurrent Neural Networks (RNN) to predict optimal crop selection based on soil composition, climatic variables, and input costs and demonstrated the potential of multivariate analysis in enabling data-driven farming decisions. Further innovations in interpretable yield forecasting were demonstrated by Paudel et al. (2021), who developed supervised regression models using physiological metrics derived from crop growth principles. Ahmed et al. (2023) observed that Random Forest (RF) algorithms could significantly improve prediction accuracy over traditional manual methods, while simultaneously reducing estimation errors in large-scale agricultural monitoring. Reports by Asamoah et al., (2024) demonstrate good prediction performance of Random Forest for yield of Maize while showing moderate performance for agronomic efficiency with climatic variables being less important predictors than soil variables, except for temperature. Accordingly, Jiya, et. al., (2023) utilized a dataset of Rice yield from 1970 to 2017, and tested Logistic Regression (LR), Artificial Neural Networks (ANN), Random Forest (RF), Random Trees (RT), and Naïve Bayes (NB) models to predict yield; The RF and RT outperformed the other models, achieving the highest accuracy in yield prediction over this period. Burdette and Wellen (2022) tested Artificial Neural Networks (ANN), Random Forests (RF), Decision Trees (DTs), and Multiple Linear Regression (MLR) models for yield prediction of corn and soybean; Random Forests (RF) demonstrated superior predictive power as it outperformed all the other methods, achieving high accuracy (R^2 = 0.85 for corn, 0.94 for soybeans), while Multiple Linear Regression (MLR) was least effective (R^2 = 0.40 for corn, 0.45 for soybeans). However, for Maize yield prediction, Olanrewaju, et al., (2024) reported that the Random Tree model (RT) outperformed

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Random Forest (RF) and Neural Networks (NN) in yield prediction giving the lowest errors (e.g., 19.7% average error) and nearly 80% accuracy, although the Artificial Neural Networks (ANN) helped detect relationships between yields, soil, and terrain. Furthermore, Cvjic, et al., (2023) evaluated Artificial Neural Network (ANN), Support Vector Regression (SVR), K-Nearest Neighbour (KNN), and Random Forest Regressor (RFR) models for sunflower oil yield prediction, the results showed that the Random Forest Regression (RFR) demonstrated superior performance, achieving the highest R^2 (0.92 in 2019), while the ANN recorded the lowest MAE indicating strong predictive accuracy in minimizing error. Conversely, Ajith, et al., (2024) highlighted the superior performance of Artificial Neural Network (ANN) and Support Vector Regression (SVR) in predicting crop yields as both offer optimization options, allowing them to adapt to complex relationships between weather conditions and crop yields. While the ANN can be fine-tuned using different activation functions, learning rates, and hidden layer neurons, the SVR allows for customization through various kernel functions and hyper parameter combinations. Shankrapa et al., (2024) evaluated the accuracy of SMLR yield forecasting models in addition to ANN, RF, SVM, and showed that the Artificial Neural Network (ANN) outperformed other models, demonstrating the capability to predict cotton yield four months prior to harvest. However, in forecasting organic potato yield, Abrougui, et al., (2019) revealed that the Multiple Linear Regression (MLR) model estimated crop yield more accurately than the Artificial Neural Network (ANN). Despite slightly lower accuracy, the ANN demonstrated stronger potential for analyzing relationships between potato yield, tillage practices, and soil properties. However, Hara, et al., (2023) compared a linear model (MLR) and a non-linear Artificial Neural Network (ANN) to predict pea seed yield using weather, farming practices, and crop-related data from 2016 to 2020; the Artificial Neural Network (ANN) showed a high accuracy making it a reliable tool for pea yield forecasting, outperforming traditional linear methods. Karongo et al. (2025) evaluated five ML models (RF, DTs, SVM, ANN) to forecast end-of-season sorghum yield in conflict-affected South Sudan. Among these, DTs and RF demonstrated the highest predictive accuracy, outperforming other models in the 2021 yield assessment suggesting a strong capability for crop yield prediction in unstable agricultural regions. In conclusion, the literature has shown that the performance of ML models in yield prediction is dependent on environmental factors and the input variables used.

Research Design

This study employed already existing crop yield prediction models to examine how rainfall, temperature, and humidity vary across different farming areas over time. Using

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detailed weather data, we tracked these key climate factors to characterize location-specific microclimate patterns, crop growing conditions and their effects on crop yield.

Study Area

This research was conducted in the Northern Senatorial Zone of Adamawa State, Nigeria, encompassing five key Local Government Areas (LGAs) with Agriculture as their main human activity: Madagali, Maiha, Michika, Mubi North, and Mubi South. These study sites were strategically selected to represent the diverse agro-ecological conditions of the region, ranging from Sudan Savanna to Montane vegetation zones. As detailed in Table 1, the selected LGAs vary significantly in their geographical characteristics.

Table 1. Climate and Environmental characteristics of the study areas

LGAs	Rainfall (mm)	Latitude	Longitude	Altitude	Vegetation Type	Key crops cultivated
Mubi North	87.75	10.26°N	13.26°E	~ 600	Northern Guinea Savannah	Cotton, Maize, Groundnuts
Mubi South	92.48	10.26°N	13.26°E	~ 600	Northern Guinea Savannah	Cowpea, Sorghum, Tomato
Madagali	89.78	10.89°N	13.63°E	~700	Sub-sudan zone	Millet, Sorghum, Onion
Michika	91.75	10.62°N	13.63°E	~800	Northern Guinea Savannah	Groundnuts, Sorghum, Maize. Cowpea.

The study areas showed the following key features based on (2019 to 2023) data:

1. **Rainfall**: Data reflects averages from 2019 to 2023, with Mubi South being the wettest (92.48 mm) and Mubi North the driest (87.75 mm).
2. **Elevation**: Approximated based on Adamawa Plateau topography; Michika and Madagali are higher-altitude areas.
3. **Vegetation**: Northern Guinea Savannah dominates, except Madagali, which transitions to Sub-Sudan vegetation with thicker forests.
4. **Climate**: All LGAs experience tropical wet/dry seasons, with temperatures ranging from 20.06°C (Michika/Madagali) to 33.42°C (Maiha).

Research Instruments

This study employed secondary datasets obtained from two governmental sources: the Adamawa State Ministry of Agriculture, Yola Adamawa State and the Nigerian Meteorological Agency (NiMet), Abuja which provides quality-controlled records. These datasets included temperature, rainfall, wind speed and soil moisture content which were used as primary inputs for model development.

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Models Adopted

This study tested and implemented three already existing distinct ML algorithms strategically selected based on their demonstrated complementary capabilities in modeling using agricultural data. These three ML approaches were: **Artificial Neural Network (ANN)** that excels at capturing complex nonlinear relationships, well suited to complex crop-environment interactions typical in agriculture; **Decision Tree (DTs)** which identifies critical decision boundaries, while being robust to missing data, and **Support Vector Machine (SVM)** that optimize generalization across spatial domains and mitigate the difficulties in analyzing datasets with many correlated environmental variables.

Data Preparation

Description of Datasets: Secondary meteorological and agricultural datasets were obtained from authoritative Government sources: the Nigerian Meteorological Agency (NiMet), Abuja, and the Adamawa State Ministry of Agriculture covering the period from 2019 to 2023. The data encompassed key climatic variables including temperature, rainfall patterns, and soil moisture measurements collected across five representative LGAs (Maiha, Madagali, Mubi South, Mubi North, and Michika) in Adamawa State.

Data Cleaning and Preprocessing: Missing values and duplicate entries were removed, and date formats were standardized to a monthly level, ensuring consistent alignment across all variables.

Feature Engineering: Daily maximum and minimum temperatures were aggregated into a single average temperature variable, while evapotranspiration values were interpreted as proxies for soil moisture. Additionally, dates were standardized into a Year-Month format to ensure temporal consistency across the dataset.

Data features and target variable

The prediction models used three key monthly environmental features:

1. Maximum temperature (°C)
2. Rainfall (mm)
3. Soil moisture (mm, measured as actual evapotranspiration).

In addition, the target variable was **crop yield (kg/ha)** representing actual field measurements from all five study areas. We aligned monthly yield records with their corresponding environmental data to create our training dataset. This approach ensures our predictions reflect real-world farming results rather than theoretical estimates.

Training and Testing model

The dataset for each LGA was split into: i) Training Set: 80% and Testing set: 20%. This split ensures the model is evaluated on unseen data, enhancing generalizability. Data

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normalization was not explicitly required due to the scale of inputs, though internal preprocessing was used where necessary (especially in ANN and SVM).

Model evaluation metrics

The R^2 Score that measures proportion of variance explained by the model and the Root Mean Squared Error (RMSE) that Measures average model error were used as metrics to evaluate the model.

Results and Discussion

Environmental variability across Study Areas

The study area exhibited significant spatial variability in key environmental parameters during the 2019 to 2023 observation periods. Rainfall distribution showed a gradient across locations, with Mubi South (92.48 mm) and Michika (91.75 mm) receiving the highest precipitation, followed by Madagali (89.78 mm), Maiha (88.20 mm), and Mubi North (87.75 mm). Temperature patterns revealed distinct thermal regimes, with Maiha (33.42 °C) and Mubi North (33.35 °C) experiencing the highest temperatures, while Michika and Madagali maintained notably cooler conditions (20.06 °C). Soil moisture content demonstrated considerable variation, ranging from 72.56% in Maiha to 51.89% in Mubi South, with intermediate values recorded in Madagali (67.65%), Mubi North (65.98%), and Michika (69.01%) (Fig.1).

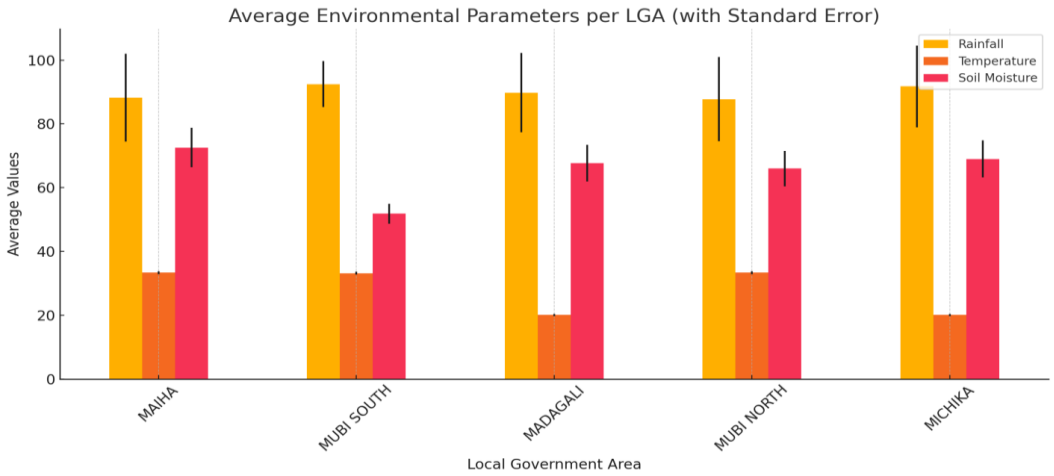

Fig.1. Average values of Rainfall, Temperature, and Soil Moisture across Maiha, Mubi South, Madagali, Mubi North, and Michika LGAs of Adamawa State from 2019 to 2023. Each bar shows the mean value while the error bars represent the standard error of the mean. Error bars show variability or uncertainty in the data. Smaller error bars indicate more stable conditions, while larger bars show variability.

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Research Question I. What is the performance of ANN, DTS and SVM models in crop yield prediction in the study areas?

Model Performance of ANN, DTS and SVM in the study areas

A summary of model performance for the three ML models is shown on Table 2. The three ML models, Decision Trees (DTs), Support Vector Machine (SVM), and Artificial Neural Network (ANN) revealed significant performance differences across the four LGAs: The DTs model had a consistently high accuracy (R^2: 0.93 - 0.98), with low prediction errors (RMSE: 5.5 – 10.9) and the best performance in Mubi North (R^2=0.98, RMSE=5.5). On the other hand, The SVM displayed poor predictive capability (R^2: 0.42 - 0.46) with highest errors (RMSE: 29.8 - 36.6) and consistently underperformed across all LGAs. However, the ANN had excellent accuracy (R^2: 0.96 - 0.97), low errors (RMSE: 6.7 - 9.7) and achieved the best results of all in Madagali (R^2 = 0.97, RMSE=6.7) and also slightly outperformed DTs in Madagali (lower RMSE: 6.7 vs 10.9). Whereas the SVM showed limited capability for yield prediction in all LGAs, there was a < 5% variation in model performance for DTs and ANN across different LGAs.

Table 2. Summary of R^2 and RMSE Values

LGAS	DT (R^2 / RMSE)	SVM (R^2 / RMSE)	ANN (R^2 / RMSE)
Maiha	0.96 / 8.1	0.45 / 29.8	0.96 / 8.2
Madagali	0.93 / 10.9	0.42 / 31.4	0.97 / 6.7
Mubi North	0.98 / 5.5	0.42 / 33.6	0.96 / 8.8
Michika	0.97 / 8.7	0.46 / 36.6	0.96 / 9.7

Research Question 2. What are the evaluation metrics for assessing the accuracy of crop yield model predictions in the study areas?

To assess the comparative accuracy of Artificial Neural Network (ANN), Decision Tree (DTSs), and Support Vector Machine (SVM) for yield prediction in the study areas, two key evaluation metrics: **Coefficient of Determination (R^2) and Root Mean Square Error (RMSE**) was employed (Table 3). These metrics were calculated for each model across the four LGAs to provide a comprehensive assessment of predictive capability of the models being tested under varying environmental conditions.

1. **Coefficient of determination (R^2)**: Quantifies the proportion of variance in observed yield values explained by each model, with values ranging from 0 (no explanatory power) to 1 (perfect prediction).
2. **Root Mean Square Error (RMSE)**: Measures prediction accuracy in actual yield units (kg/ha), where lower values indicate better model performance.

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Table 3. Evaluation metrics for crop yield prediction in the study areas

Metric	Purpose	Interpretation
R^2	Measures the proportion of variance in yield explained by the model.	- **Closer to 1** = Better fit (perfect prediction) - **Closer to 0** = Poor fit
RMSE	Quantifies prediction error in actual yield units (e.g., kg/ha).	- **Lower RMSE** = More accurate predictions - **Higher RMSE** = Larger errors

The results showed that the DTs slightly outperforms ANN in most (three out of four) LGAs yielding higher R^2, and lower RMSE, whereas the **ANN** excels in Madagali with the best R^2 and RMSE. The **SVM** is consistently the weakest model.

Discussion

The current study demonstrates that **Artificial Neural Networks (ANN)** and **Decision Trees (DTS)** consistently outperform **Support Vector Machines (SVM)** in crop yield prediction, particularly in regions like Madagali and Mubi North. This highlights ANN's and DTS's superiority in handling nonlinear agricultural data due to its ability to capture complex relationships between input variables (e.g., soil moisture, rainfall) and yield outputs. This performance is anchored on ANN's multilayer architecture that enables it to approximate intricate, nonlinear processes, such as soil-plant-atmosphere interactions, that SVM often overlook especially under variable environmental conditions (Jabed, 2024). This aligns with similar results depicting ANN's high ability to model nonlinear and complex relationships compared with MLR models (Abdpour, et al., 2018; Ahmed et al., 2023; Mamunur et al., 2021). Furthermore, ANN achieved the **highest R^2 and lowest RMSE**, corroborating findings by Adeyemi et al. (2018) on ANN's robustness in yield prediction. However, the results reveal model performance disparities across the LGAs (e.g., Madagali vs. Mubi North) perhaps due to the temperature differences of about 10 °C between Madagali and Mubi North that may affect crop yield differently (Fig. 1). Hence, model performance variability can be explained by variations in temperature across locations explained by geographical differences in data collection areas and the complexity of data patterns in different LGAs. The results show that rainfall and soil moisture affect yield prediction more than temperature; this is supported by the low variability of the data. Thus, for better accuracy when using an ANN model for yield prediction, rainfall and soil moisture data should be prioritized over temperature data. The environmental heterogeneity observed across regions, especially in rainfall (87.75 to 92.48 mm), temperature (20.06 °C to 33.42 °C), and soil moisture (51.89 % to 72.56%),

underscores the need for adaptable yield prediction models with their ability to handle non-linear relationships and complex environmental interactions. This makes the ANN and DTs models particularly suited for such heterogeneous agricultural conditions and explain the superior performance of Artificial Neural Network (ANN) and Decision Tree (DTs) over the Support Vector Machine (SVM) models in the current study.

Conclusion

This study tested ML models to predict crop yields using data from Five LGAs in Adamawa State, Nigeria. The Artificial Neural Network (ANN) and Decision Tree (DTs) models achieved the highest accuracy, while the Support Vector Machine (SVM) performed poorly. These results highlight the potential of Artificial Neural Network (ANN) and Decision Tree (DTs) models to support data-driven farming decisions and Agricultural planning in the Adamawa State, Nigeria.

Recommendations based on findings

The following are recommended to support data-driven agriculture in the study areas.

1. Priority should be given to ANN and Decision Tree models over SVM, given their superior performance in developing yield forecasting models in the study areas.
2. User friendly tools like mobile apps, web platforms can be developed integrating ANN/DT models to assist smallholder farmers in yield forecasting, while emphasizing rainfall and soil moisture over temperature as the major determinants for the success of such tools.
3. The traditional forecasting methods should be replaced with ML-based approaches, which reduced errors by 76 – 82%.
4. There is need for training agricultural extension workers on interpreting ML-based forecasts to aid farmers in decision-making in the study areas.

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