Integrating GeoAI and Deep Learning for Sustainable Agriculture: Sentinel-2 Based Crop Mapping and Yield Prediction for Selected Crops in Sokoto, Nigeria

Abstract

Sustainable agriculture, particularly in semi-arid areas, depends on precise crop mapping and yield forecasting. In this study, Random Forest (RF) classification and regression implemented in Google Earth Engine (GEE) are combined with GeoAI and machine learning techniques. It evaluates crop distribution and predicts yields in Sokoto State, Nigeria, using Sentinel-2 surface reflectance imagery. 3,167.57 hectares of cropland were analysed using 690 cloud-filtered Sentinel-2 scenes that were gathered between January and December of 2023. Crop classification demonstrated good reliability in identifying rice, pepper, and onion crops with an overall accuracy of 99.7% and a Kappa coefficient of 0.82. With a coefficient of determination (R^2) of 0.84 and a Pearson correlation of 0.92, the Random Forest yield model predicted crop yields, demonstrating a very significant positive link between observed and anticipated yields. With a little positive bias of +9,244 kg/ha, the model's root mean squared error (RMSE) and mean absolute error (MAE) were 10,870 kg/ha and 9,244 kg/ha, respectively. According to yield figures, the average yield was 20,971 kg/ha, with a range of 7,000 to 40,000 kg/ha. These findings show how precise crop mapping and yield estimation can be achieved by combining GeoAI, multispectral satellite data, and machine-learning approaches. The results assist better decision-making, sustainable farming methods, and increased food security in semi-arid regions by providing agricultural scientists and policymakers with practical insights.

Keywords: Random Forest Classifier, Sentinel-2 Imagery, GeoAI, Machine Learning, Crop Mapping, Yield Prediction, Remote Sensing, Precision Agriculture

Introduction

For crop mapping and yield prediction, remote sensing and GIS are vital technologies that offer thorough, data-driven insights that facilitate accurate agricultural management and food security planning(Gebeyehu, 2019a; Nandeha et al., 2025). The importance is derived from several crucial skills: According to Joshi et al., (2023), these technologies provide comprehensive spectral information and global coverage for mapping crop extent and yield prediction prior to harvest. By offering real-time data on crop health, soil conditions, and water status, Sangeetha et al.,(2024) demonstrate their capacity to maximise crop yield. Crop discrimination and growth monitoring, soil moisture estimation, yield projection, environmental event damage assessment, and site-specific precision agriculture management are all made possible by these technologies. According to Hisar, India, et al., (2020); Gebeyehu, (2019b); Mother Teresa Women's University, India et al., (2025), these methods give producers, managers, and policymakers fast, accurate information that helps them make important decisions about economic planning and food security.

Crop production prediction and agricultural monitoring have been transformed by the combination of artificial intelligence and remote sensing technologies. With its high-resolution multispectral capabilities, Sentinel-2 satellite imagery offers vital information on soil moisture, plant health, and growth patterns that facilitates precise crop monitoring (Aslan et al., 2024).

By capturing nonlinear relationships between variables, deep learning techniques such as Convolutional Neural Networks (CNNs) and ensemble methods have shown impressive success in processing complex agricultural datasets for crop mapping and yield prediction (Joshi et al., 2023). Despite obstacles from cloud cover, small farm sizes, and varied cropping systems, Sentinel-2 data has been successful in mapping smallholder farming systems in African environments, especially in Nigeria (Ibrahim et al., 2021). However, the absence of standardised procedures, the scarcity of training data, and the requirement for more generalisable models across various locales and crops are some of the issues facing current research (Aslan et al., 2024; Joshi et al., 2023).

The substantial potential of integrating satellite imagery with machine learning techniques for precision agriculture applications is demonstrated by recent research. In order to estimate crop yield in coastal regions using Sentinel-2 data and NDVI analysis, Mahalakshmi et al., (2025) devised a deep learning strategy that improved food productivity by 20% while attaining 98.7% accuracy compared to standard methods' 85–90%. For crop mapping in Senegal's groundnut basin, Panwar & Singh, (2024) used Random Forest models using Sentinel-2 multispectral data. They achieved 93.57% accuracy after resolving class imbalance through SMOTE, compared to 57.43% before to augmentation. Baidar (2020) demonstrated recommendable performance with excellent accuracy using 2D and 3D Convolutional Neural Networks with multi-temporal Sentinel-2 data for rice crop categorisation and yield estimation in Nepal's Terai districts. Together, these studies demonstrate how satellite remote sensing combined with cutting-edge machine learning algorithms can offer precise, affordable solutions for crop monitoring, yield prediction, and precision agriculture deployment in underdeveloped nations.

Methodology

Study Area

The Sokoto State, northwestern Nigeria, lies in the sub-Saharan Sudan belt of West Africa in a zone of savannah-type vegetation (Adegboyega et al., 2016). As part of the Sokoto Basin, the State is located between latitudes 10°30' N to 14°00' N and longitudes 3°30'E to 7°00'E (Bonde et al., 2014). Figure 1 presents an overview of the study area. With a land area of 28,232.37km^2, Sokoto State is bordered by the Republic of Niger to the north and west for 363km, and the states of Zamfara to the east, Kebbi to the south and west ('Sokoto', 2024). The state occupies an area of short-grass savanna vegetation in the south and thorn scrub in the north. It is a generally arid region that gradually merges into the desert across the border in Niger (Adegboyega et al., 2016). The foundation of Sokoto's economy and the anchor of its socioeconomic structure is agriculture. Rich riverine floodplains in the area are ideal for growing a wide variety of cash crops, including rice, cotton, and peanuts (groundnuts)(Adams, 1986). The vast farming methods that include the growth of cotton and rice further define the agricultural environment (Last, 2021).

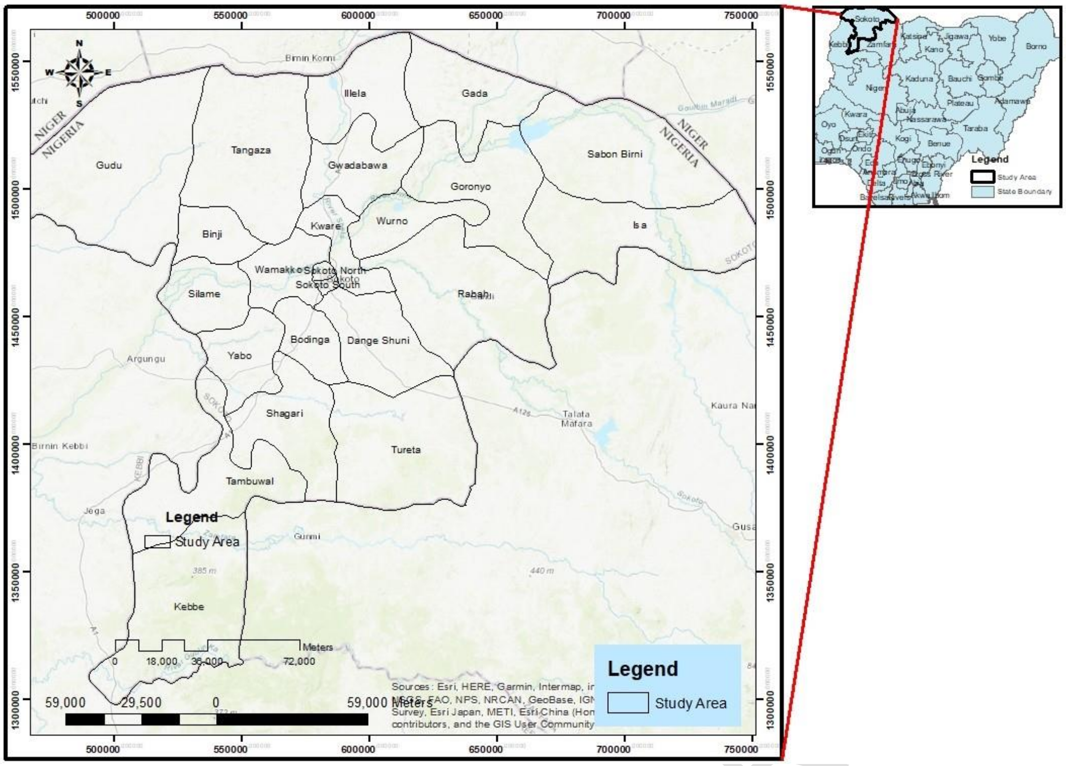

Figure 1 Study Area

Materials and Methods

The study applies an integrated geospatial and machine-learning workflow to map crops, estimate cultivated area, and predict crop yield across agricultural training sites in Sokoto State, Nigeria. Using FAO GAUL administrative boundaries, the analysis focuses on two polygons totaling 3,167.57 hectares. Key datasets include 690 scenes of Sentinel-2 SR Harmonised imagery (January–December 2023), CHIRPS rainfall, and TerraClimate temperature data. After cloud masking with QA60, creating a median composite, and clipping to the study extent, agriculturally relevant spectral bands and vegetation indices (NDVI, EVI, NDWI, GNDVI, NDRE, SAVI) were generated. Climate variables were resampled and added as predictor layers to strengthen model performance. These datasets form a unified predictor stack used for both crop classification and yield modelling. The workflow (Figure 2) follows a logical sequence: dataset preparation, Random Forest crop classification, crop area estimation, yield modelling, spatial yield prediction, and productivity zonation into low, medium, and high categories. Crop maps and yield surfaces are validated using accuracy metrics such as Overall Accuracy, Kappa, R^2, RMSE, MAE, and Pearson correlation. The final conceptual framework links remote sensing inputs, climatic variables, machine-learning processes, and spatial analysis outputs to produce decision-support products such as crop distribution maps, yield prediction surfaces, and productivity zones. Figure 3 and Table 1 illustrate the study workflow and Study area characteristics respectively.

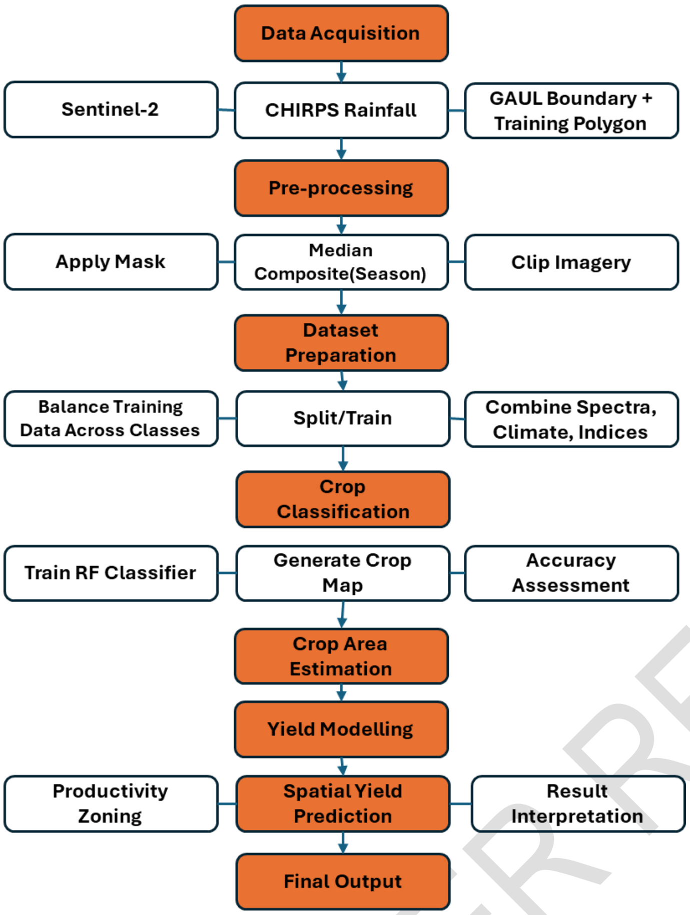

Figure 2 Study Workflow

Table 1: Study Area Characteristics

Parameter	Value	Data Source
Location	Sokoto State, Nigeria	GAUL Admin Level 1
Study area polygons	2	FAO GAUL 2015
Agricultural area (training)	3,167.57 ha	Training polygons
Imagery source	Sentinel-2 SR Harmonized	ESA Copernicus
Temporal coverage	January-December 2023	690 images
Cloud cover threshold	<40%	Pre-processing filter
Imagery after cloud mask	690 scenes	QA60 band filtering

Crop Monitoring Using Spectral Indices

Table 2 summarises the key spectral indices derived from Sentinel-2 imagery and applied in this study for crop classification and yield estimation in Sokoto State, Nigeria. Each index utilizes specific spectral bands to capture different aspects of vegetation status. NDVI and EVI quantify vegetation vigor and biomass, with EVI reducing atmospheric and soil background effects. GNDVI and NDRE provide insights into chlorophyll content and nitrogen status, enhancing nutrient monitoring. SAVI adjusts for soil brightness, improving detection in sparsely vegetated areas. NDWI measures water content in vegetation and soil, supporting assessment of crop water stress. Collectively, these indices serve as critical input features for the Random Forest machine-learning models used in this study, enabling precise crop mapping and accurate yield predictions.

Table 2. Spectral indices used for crop monitoring and yield prediction, including formulas and applications

Spectral Index	**Formula**	**Application in This Study**
NDVI	(NIR - Red) / (NIR + Red)	Measures vegetation vigor and biomass; used for crop health assessment and general vegetation mapping.
EVI	2.5 × (NIR - Red) / (NIR + 6 × Red - 7.5 × Blue + 1)	Reduces atmospheric and soil background effects; improves sensitivity in high-biomass areas for precise crop monitoring.
NDWI	(NIR - SWIR) / (NIR + SWIR)	Detects water content in vegetation and soil; used to assess crop water stress and moisture conditions.
GNDVI	(NIR - Green) / (NIR + Green)	Sensitive to chlorophyll content; helps estimate crop nutrient status and photosynthetic activity.
NDRE	(NIR - RedEdge) / (NIR + RedEdge)	Monitors canopy chlorophyll and nitrogen content; useful for late-season crop monitoring.
SAVI	(1 + L) × (NIR - Red) / (NIR + Red + L), L = 0.5	Minimizes soil brightness effects; improves vegetation detection in areas with sparse crops or exposed soil.

Crop Classification and Area Estimation

Ground truth polygons for rice, pepper, and onions were used in the classification. To reduce class bias, the dataset, which was initially largely composed of onion samples, was divided into around 4,040 samples for training and 1,009 for validation. Using both spectral indices and meteorological variables as input features, a Random Forest (RF) classifier was trained on 80% of the data. Overall accuracy, the Kappa coefficient, and a confusion matrix were used to evaluate classification accuracy. By masking the categorised map by each crop class and using pixel-based area computation, the crop area was approximated.

The crop categorisation model's overall performance is summarised in Table 3. With a good Kappa Coefficient of 0.82 and an outstanding Overall Accuracy of 99.70%, the classifier demonstrated significant agreement between predicted and actual classes. To ensure a reliable and evenly distributed dataset for model training and evaluation, 4,040 balanced training samples and 1,009 validation samples were utilised.

A thorough confusion matrix illustrating the classification of each crop class—onion, pepper, and rice—is presented in Table 4. Due to their tiny sample sizes, rice and pepper samples exhibit minor misclassifications, whereas onion samples were classified with nearly perfect accuracy (999 correctly identified). While Producer's Accuracy is highest for Pepper and Rice

(100%) and slightly lower for Onion (99.70%), User's Accuracy varies from 60% for Pepper to 99.90% for Onion. The matrix shows that the model performs exceptionally well generally, with a small amount of misunderstanding in classes with less examples.

Table 3: Classification Accuracy Assessment (Overall Metrics)

Metric	**Value**
Overall Accuracy	99.70%
Kappa Coefficient	0.82
Training samples (balanced)	4,040
Validation samples	1,009

Table 4: Classification Accuracy Assessment (Class-wise Performance)

Crop Class	**Producer's Accuracy (Precision)**	**User's Accuracy (Recall)**	**F1-Score**
Onion (Class 0)	100%	99.70%	99.85%
Pepper (Class 1)	60%	100%	75.00%
Rice (Class 2)	80%	100%	88.89%

The classification model's class-wise performance metrics are shown in Table 5, which provides more information on the accuracy with which each crop type—onion, pepper, and rice—was classified. Producer's Accuracy (Precision), User's Accuracy (Recall), and the F1-Score are among the measures that show how well the model minimises misclassification and how reliable its predictions are. This thorough analysis aids in identifying the classes that were most accurately identified and areas that might still require improvement.

Table 5: Classification Accuracy Assessment (Confusion Matrix)

	Predicted Onion	**Predicted Pepper**	**Predicted Rice**	**Row Total**	**User's Accuracy**
Actual Onion	999	0	0	999	99.90%
Actual Pepper	2	3	0	5	60.00%
Actual Rice	1	0	4	5	80.00%
Column Total	1,002	3	4	1,009	-
Producer's Accuracy	99.70%	100%	100%	-	-

Yield Modelling and Productivity Zonation

Using yield data from the ground, onions were chosen for yield modelling. The Interquartile Range (IQR) approach was used to clean the data, standardise it to kg/ha, and eliminate outliers. Temperature, rainfall, reflectance bands, and spectral indices were used as explanatory variables in a Random Forest regression model. Of the small total dataset of 14 samples, the model was trained on 70% (11 samples) and validated on 30% (3 samples). Pearson, RMSE, MAE, and bias were used to assess performance. Lastly, using the 33rd and 67th percentiles as thresholds, the estimated yield map was divided into zones of low, medium, and high productivity. The following tables present the performance and statistical characteristics of the yield prediction model developed for this study. Table 5 outlines the specifications of the Random Forest Regression model, including the number of trees, input features, and the distribution of training and validation samples. Table 6 summarizes the model's performance metrics, highlighting the goodness-of-fit (R²), correlation, error measures (RMSE and MAE), and bias, providing an assessment of prediction accuracy and reliability. Finally, Together, Tables 6, 7, and 8 provide a comprehensive summary of the yield prediction model, starting with its technical setup, moving on to its predicted performance, and ending with the descriptive statistics of the observed yields. The Random Forest Regression technique, number of trees, input features, and sample distribution are all specified in Table 6. The model's significant predictive capacity and related error levels are highlighted in Table 7, which assesses the model's accuracy using important performance measures like R2 correlation, RMSE, MAE, and bias. In order to contextualise and assess the model's performance, Table 8 presents the statistical features of the yield data, displaying its distribution through metrics such as mean, range, quartiles, and interquartile spread.

Table 6: Yield Model Performance (Model Specifications)

Parameter	**Value**
Algorithm	Random Forest Regression
Number of trees	500
Input features	15 variables
Total samples	14
Training samples (80%)	11
Validation samples (20%)	3

Table 7: Yield Model Performance (Performance Metrix)

Metric	**Value**	**Interpretation**
R²	0.84	84% of variance explained
Pearson Correlation (r)	0.92	Very strong positive relationship
RMSE	10,870 kg/ha	Root mean squared error
MAE	9,244 kg/ha	Mean absolute error
Bias	+9,244 kg/ha	Systematic over-prediction
Relative RMSE	51.80%	RMSE / mean yield
Relative MAE	44.10%	MAE / mean yield

Table 8: Yield Model Performance (Yield Statistics)

Statistic	**Value (kg/ha)**

Mean yield	20,971
Minimum yield	7,000
Maximum yield	40,000
Q1 (25th percentile)	18,000
Q3 (75th percentile)	30,000
IQR (Interquartile Range)	12,000
Range	33,000

RESULT & DISCUSSION

Crop Classification Accuracy

With a strong Kappa Coefficient of 0.82 and an Overall Accuracy of 99.70%, the crop categorisation model performed quite well. Rice fared well (F1-score: 88.89%), and onion categorisation was almost flawless (F1-score: 99.85%). The most difficult class was pepper, which had a lower F1-score of 75.00% and some misclassification, indicating strong recall but low precision. This was probably because there were only five real validation samples or spectral overlap. With a kappa coefficient of 0.82, your model matches the performance reported by Park, Jin-Ki & Park, Jong-Hwa, (2015), and the overall accuracy of 99.70% even surpasses most previous results, approaching the high accuracies of 97–98% achieved by Zhang et al., (2016). These results align with trends in recent UAV-based crop classification studies. Class-wise performance also aligns with literature, as onion and rice showed strong F1-scores similar to the high accuracies reported by Zheng et al., (2024), whereas the lower pepper F1-score of 75% reflects challenges noted by Nansen et al., (2013), who emphasized issues of over-fitting and reduced reliability when classes have very small sample sizes or spectral overlap.

With all samples exhibiting the same absolute error (+9,244 kg/ha) and substantial relative errors (40.2–132.1%), the validation results in Table 9 demonstrate a clear systematic bias, indicating constant overestimation of yields. These results are in line with earlier studies emphasising the difficulties in predicting agricultural productivity. For example, Hao et al., (2021) found root mean squared errors around 1 t/ha with decreasing accuracy under stressed conditions; Lal & Niwas, (2024) reported percentage errors between 8.70% and 10.98% for wheat yield predictions; and Martre et al., (2015) reported relative errors of 24–38% for end-of-season crop variables. The current model shows larger relative errors than earlier investigations, indicating more systematic over-prediction. Overall, the current findings and the body of literature support the idea that crop yield models frequently fail to accurately predict actual yields, especially in situations with changing environmental conditions.

Table 9: Results of Validation (Actual vs. Predicted)

Sample #	Actual Yield (kg/ha)	Predicted Yield (kg/ha)	Error (kg/ha)	Relative Error (%)
1	7,000	16,244	+9,244	+132.1%
2	18,000	27,244	+9,244	+51.4%
3	23,000	32,244	+9,244	+40.2%
Mean	16,000	25,244	+9,244	+57.8%

Note: All three validation samples show identical absolute error (+9,244 kg/ha), indicating systematic bias.

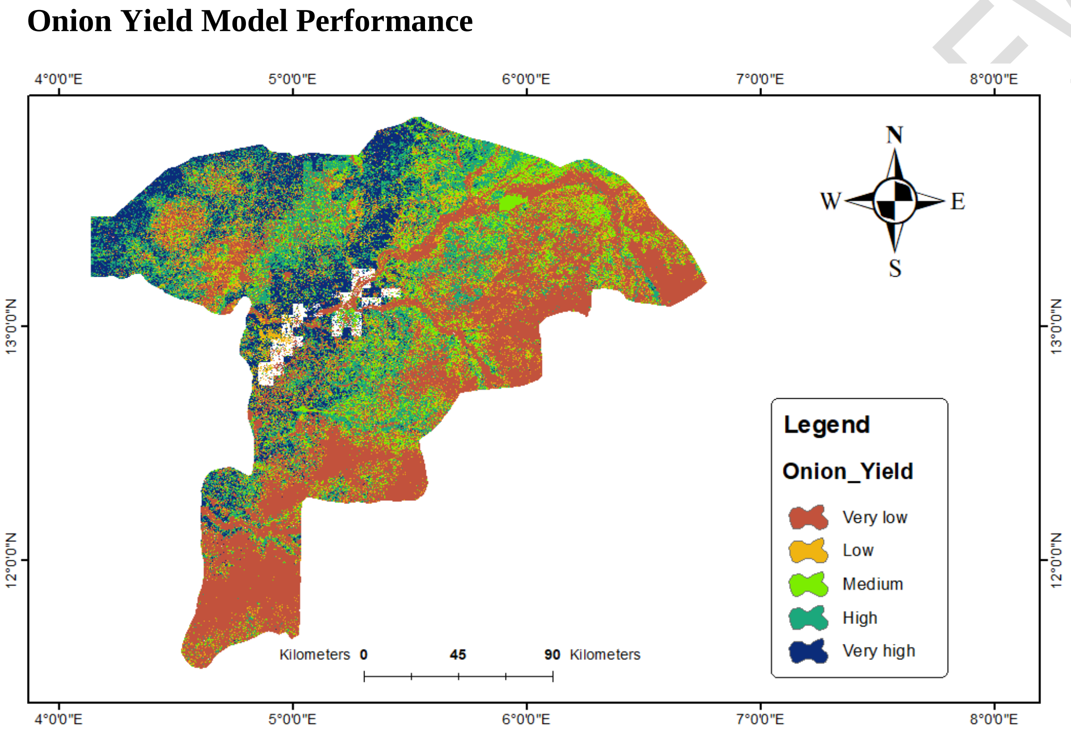

Figure 3: Onion Yield Distribution.

The result illustrated by Figure 2 shows that the Random Forest regression model demonstrated a strong statistical fit, despite the small sample size (n=14), accounting for 84% of the variation and producing a very high Pearson correlation (r=0.92) between the predicted and observed yields.

Nevertheless, the model showed consistent bias and substantial prediction error:

High Error: The Root Mean Square Error (RMSE) was 10,870 kg/ha, and the Mean Absolute Error (MAE) was 9,244 kg/ha.

Systematic Over-prediction: The model continuously overestimated yield projections, as seen by the positive bias of precisely +9,244 kg/ha. Rather than random fluctuation, this consistent inaccuracy across all three validation samples is a clear indication of systematic bias.

Relative Error: The high absolute error translated to a significant Relative RMSE of 51.80% and Relative MAE of 44.10%.

While error metrics can vary by context, Chai & Draxler, (2014) suggests that both RMSE and MAE are valuable for model evaluation. The high error rates here suggest the need for model refinement, potentially through improved calibration or incorporation of additional environmental factors (Hao et al., 2021; Kovvuri & Khushalani, 2025).

Yield Distribution and Productivity Zone Distribution

Table 10: Productivity Zone Distribution

Zone	**Threshold (kg/ha)**	**Description**	**Est. Area (%)**
Low	<18,000	Below average yield	~33%
Medium	18,000−24,000	Typical yield	~33%
	>24,000	Above-average yield	~33%

Note: Thresholds determined by: 33rd and 67th percentiles of filtered yield data (n=14)

With yields ranging from 7,000 kg/ha to 40,000 kg/ha (average: 20,971 kg/ha), the data show considerable variation in crop performance (Table 9 and Figure 2). About one-third of the land falls into the low (<18,000 kg/ha), medium (18,000–24,000 kg/ha), and high (>24,000 kg/ha) productivity zones, according to the productivity zonation, which indicates a balanced distribution across the region (Table 9). The study's results align with earlier agricultural research findings. Grain yields in northeastern Colorado ranged from 6.9 to 15.5 Mg/ha, according to Sopheap et al., (2012), showing significant geographic differences in crop performance across management zones. In Ethiopia’s central Rift Valley, Getnet et al., (2016) identified notable yield gaps of 4.2-9.2 t/ha for maize and 2.5-4.7 t/ha for wheat across agricultural zones. The smallest gaps appeared in the central lowlands, where water-limited potential yields also decreased. Hornung et al., 2006) observed even greater variation in cassava yields, ranging from 12.7 to 37.2 t/ha in Cambodia, with yield gaps of 8.9-24.4 t/ha attributed to soil nutrient shortages, crop duration, and weed competition. Collectively, these studies support the idea that significant yield differences across productivity zones are common across various crops and regions worldwide. Panwar & Singh, (2024) highlight that such variations reflect crops' sensitivity to climate, environment, and management factors.

The current findings of yield heterogeneity are supported by recent studies, which consistently confirms considerable crop production variances across various agricultural locations. According to Karan Veerbhan & Anita Malik, (2025), there is significant fluctuation in the average sugarcane yield among regions, which is 77.84 T/Ha. This is further supported by Mahalakshmi et al., (2025), who classify crops according to their production swings into high and low productivity groups. A specific example in maize production is given by Jogender et al., (2024), who identified three productivity zones: low (<2726 kg ha-1), medium (2726-2924 kg ha-1), and high (2924-3122 kg ha-1). This closely resembles the three-zone productivity classification used in the original research. The intrinsic diversity of agricultural production, which highlights the necessity for focused agricultural interventions, is a recurring topic across studies, even while the precise yield ranges vary.

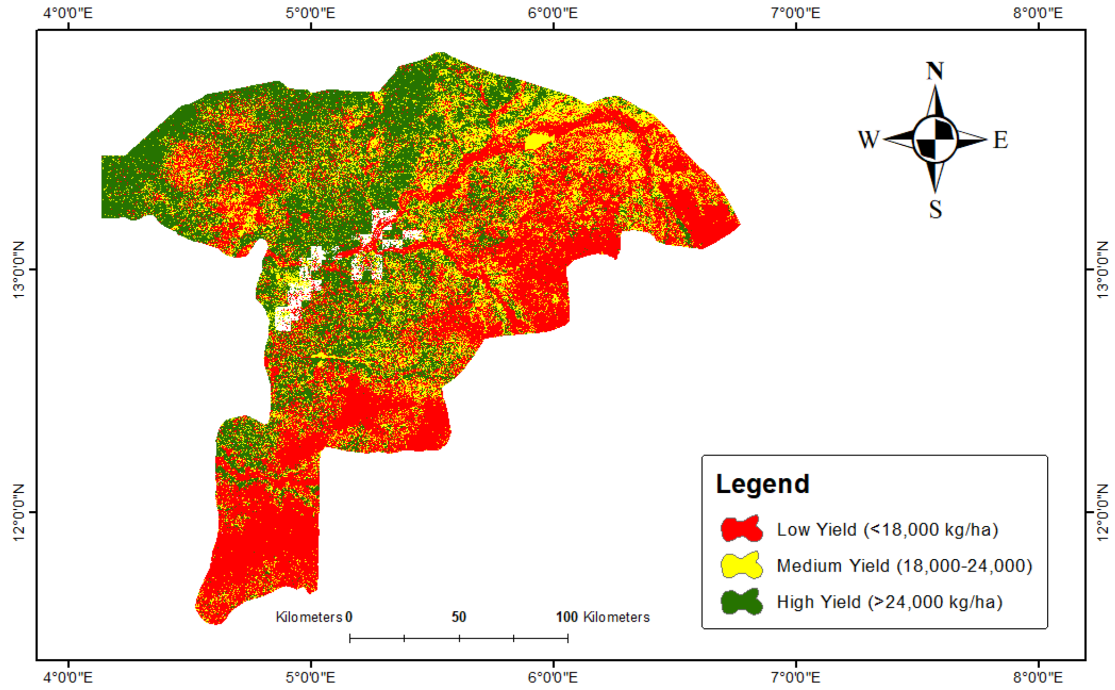

Figure 4: Production Zones

Conclusion

Crop classification in Sokoto State was significantly enhanced by the integration of Sentinel-2 indices and climate variables using a Random Forest model, which yielded nearly flawless accuracy for key crops such as rice and onions. The approach effectively differentiated between crop varieties, providing a solid basis for agricultural monitoring based on remote sensing. In terms of capturing the underlying relationship between biophysical and climatic parameters and onion yield, the yield modelling component showed high statistical potential (R 2=0.84, r=0.92). However, because of the high and persistent systematic over-prediction bias (Bias = +9,244 kg/ha), the model is currently unreliable for precise field-level prediction. The model's practical usefulness for making real-world predictions is severely limited by this high error magnitude, which translates to a 51.80% relative RMSE. The study emphasises that while there are high-performing fields, targeted interventions in low-productivity zones and actions like dataset expansion, model recalibration, improved feature selection, and guided agricultural practices are crucial for enhancing GeoAI-driven yield predictions and sustainable agriculture. A small, heterogeneous yield dataset limits model reliability.

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Details of the AI usage are given below:

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