

Normalized Difference Vegetation Index for Rice Mapping and Estimation of Rice Area and Yield in Sudan Ecology of Nigeria

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Abstract: Rice is a vital crop for global food security, and remote monitoring and mapping are crucial for detecting crop stress and estimating cultivated areas and outputs. This study employed Normalized Difference Vegetation Index (NDVI) and supervised image classification to assess crop health and map rice-growing areas in three Nigerian states (Kano, Kaduna and Katsina). The research analyzed satellite imagery from Sentinel and Landsat missions during the 2022 growing season. NDVI values revealed variations in vegetation health, ranging from 0.044 to 0.148 in May and peaking at 0.110 to 0.450 in August. Supervised image classification identified an average rice cultivation area of 0.227 hectares. The actual rice yield was measured at 1512.624 kg/ha, while the model predicted a higher output of 4218.21 kg/ha. The prediction model exhibited an average root mean square error (RMSE) of 0.419, corresponding to an accuracy of 82%. This study highlights the potential of remote sensing technologies in tracking rice crop performance and mapping cultivated areas. These tools provide critical insights for data-driven decisions, enhancing rice sector development planning. By integrating remote sensing technologies, this research underscores their value in minimizing human involvement in estimating rice area and productivity indices. The study's findings have significant implications for rice production and food security in Nigeria and globally. The use of remote sensing technologies can help optimize rice production, reduce losses, and improve food availability and affordability. By leveraging these technologies, stakeholders can make informed decisions to enhance rice sector development, ultimately contributing to global food security.

Keywords: Rice, NDVI, Remote Sensing, Crop Monitoring and Food Security.

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I. INTRODUCTION

Rice is a vital crop that feeds nearly 50% of the global population and plays a crucial role in ensuring food security (FAO, 2020). However, extreme weather conditions like drought and flood, exacerbated by climate change, impact rice crops. To mitigate this, developing a suitable crop monitoring system for land management and spatial planning is essential. This involves extracting and assessing pre- and post-event information about paddy fields using remote sensing technologies like Sentinel-2A (Dar et al., 2020; Singha, 2020; Onyibe et al., 2024).

According to Mkhabela *et al.*, (2011), understanding the physiological stages of rice growth is crucial for monitoring, with four distinct stages: nursery, vegetative phase, reproductive phase, and harvesting. Optical remote sensing offers an attractive option for evaluating vegetation indices,

including the Normalized Difference Vegetation Index (NDVI). NDVI measures vegetation greenness and density, providing insights into crop health (Singha, 2020).

Zang et al., (2022) discovered that NDVI is essential for field management, yield estimation, optimal water resource utilization, and greenhouse gas emission monitoring. A sudden drop in NDVI values may indicate crop health deterioration, but it's crucial to counter-check with other data to avoid false alarms. Accurate NDVI interpretation can help agronomists raise healthier yields, reduce fertilizer costs, and promote environmental sustainability.

In Nigeria, the National Space Research and Development Agency (NASRDA) is responsible for wide-area satellite imagery, while small-area imagery can be obtained from Unmanned Aerial Vehicles (UAVs). The Convolutional Neural Network (CNN) algorithm can filter

and classify images, estimating the area covered by each object. Time series NDVI data have been used for crop yield predictions since the 1980s, with most studies focusing on staple crops like wheat and rice (Adebayo and Olusola, 2020).

➤ Statement of Research Problem

Significant rice yield losses in Nigeria's Sudan Ecological Zone are caused by pests, diseases, and climate-related factors, exacerbated by inadequate and delayed crop condition information. Traditional manual surveys are impractical for large-scale monitoring due to their labor-intensive and time-consuming nature. This study explores the potential of Remote Sensing technology, specifically the Normalized Difference Vegetation Index (NDVI) model, to provide timely and accurate crop monitoring. This study aims to estimate NDVI values for rice crop monitoring, develop a reliable method for crop health assessment and yield prediction, and enhance decision-making for stakeholders through data-driven insights in the Sudan Ecological Zone of Nigeria. By leveraging satellite imagery and NDVI, this study seeks to improve crop monitoring and management practices, ultimately contributing to optimized rice yields and food security in the region.

➤ The Objectives of the Study are to:

Map the rice cropland area for the study area.

Generate the NDVI to monitor the performance of rice crops using the Satellite Imagery.

Estimate the rice yield and output using the NDVI generated.

This research aims to advance crop monitoring technologies and deliver actionable insights to optimize rice production in Nigeria's Sudan Ecological Zone.

II. METHODOLOGY

➤ Study Area

The study was conducted in 2022 in the areas between latitude $11^{\circ} 08' 04.034''$ N to $11^{\circ} 53' 16.372''$ N and longitude $7^{\circ} 21' 51.831''$ E to $8^{\circ} 10' 48.902''$ E. This area is spread across three states: Kano, Kaduna, and Katsina encompassing six Local Government Area (LGA) councils that interface between the three states, sharing common boundaries. The LGAs (Figure 1) are Kudan, Makarfi, Danja, Rogo, Kafur, and Karaye. The study area covers approximately 3828.49 km².

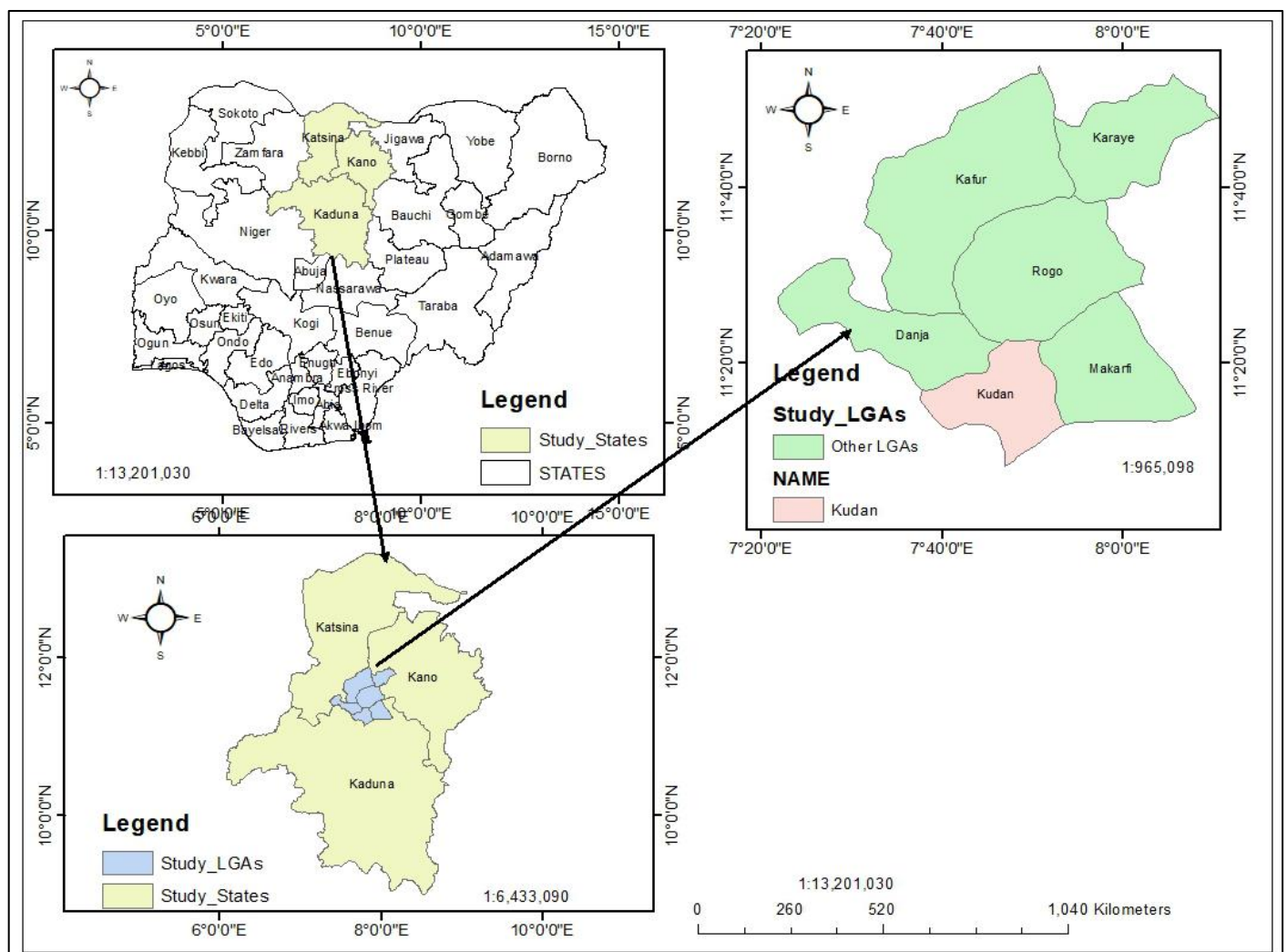


Fig 1 Study Area Map

➤ Data Types and Sources

- Primary and secondary data were used for the study.
- Satellite Data Acquisition: Landsat and Sentinel Imagery

Given the challenges posed by cloud cover in optical remote sensing, Landsat satellite images were used to complement Sentinel data. Landsat 8 and Landsat 9 images, each with a 30-meter spatial resolution, were acquired for this

study. These images correspond to path 189 and row 52, ensuring proximity to the desired observation dates of Sentinel imagery. Additionally, Sentinel-2A and Sentinel-2B satellite images, with upper-right coordinates of 12°N, 7°E, and lower-left coordinates of 11°30'18.84" N, 7°48'19.64" E, were sourced. Both datasets were collected for the entire rice-growing season, from planting (May 2022) to harvesting (September 2022). A detailed summary of the Sentinel and Landsat satellite images used is presented in Table 1.

Table 1 Satellite Data Acquisition for the Study with Dates

S/N	Satellite Image Date	Satellite Image Type	Revisit Period
1	02/05/2022	Sentinel 2A	5 days with 2B
2	07/05/2022	Sentinel 2B	5 days with 2A
3	22/05/2022	Sentinel 2A	5 days with 2B
4	27/05/2022	sentinel 2B	5 days with 2A
5	03/05/2022	Landsat 8 (OLI)	8 days with landsat 9
6	11/05/2022	Landsat 9 (OLI)	8 days with landsat 8
7	19/05/2022	Landsat 8 (OLI)	8 days with landsat 9
8	27/05/2022	Landsat 9 (OLI)	8 days with landsat 8
9	01/06/2022	Sentinel 2A	5 days with 2B
10	04/06/2022	Landsat 8 (OLI)	8 days with landsat 9
11	12/06/2022	Landsat 9 (OLI)	8 days with landsat 8
12	20/06/2022	Landsat 8 (OLI)	8 days with landsat 9
13	28/06/2022	Landsat 9 (OLI)	8 days with landsat 8
14	06/07/2022	Landsat 8 (OLI)	8 days with landsat 9
15	14/07/2022	Landsat 9 (OLI)	8 days with landsat 8
16	22/07/2022	Landsat 8 (OLI)	8 days with landsat 9
17	07/08/2022	Landsat 8 (OLI)	8 days with landsat 9
18	05/08/2022	sentinel 2A	5 days with 2B
19	10/08/2022	Sentinel 2B	5 days with 2A
20	30/08/2022	sentinel 2A	5 days with 2B
21	08/09/2022	Landsat 8 (OLI)	8 days with landsat 9
22	24/09/2022	Landsat 8 (OLI)	8 days with landsat 9

➤ Primary Data Collection

Primary data were collected through structured questionnaires administered to rice farmers using the Open Data Kit (ODK) app. This allowed for the collection of key information on agronomic practices, farm conditions, and farmer demographics. Additionally, the geographical boundaries of the farm plots were recorded using a Garmin GPS receiver. The perimeter coordinates of 1,080 rice farms across six local government areas—Rogo, Kudan, Makarfi, Danja, Karaye, and Kafur—were collected. These areas are situated at the intersection of the three selected Nigerian states: Kano, Kaduna, and Katsina. The name of each farmer, the type of crop planted, and their contact information were documented for subsequent follow-up during the yield harvesting phase. These data were crucial for the development of the yield estimation model.

➤ Secondary Data Collection

Secondary data involved the acquisition of satellite images for Normalized Difference Vegetation Index (NDVI) analysis. Sentinel-2A and Sentinel-2B imagery were utilized due to their high spatial resolution, ranging from 10 meters to 60 meters, and their ability to systematically capture optical images of terrestrial and coastal environments. The Sentinel-2 constellation, part of the Copernicus Programme, features a 5-

day revisit period (when both satellites are operational) and supports a broad spectrum of applications, including agricultural monitoring, emergency response, land cover classification, and water quality assessment.

To account for cloud cover that might obscure optical data, Landsat 8 and Landsat 9 satellite images with 30-meter spatial resolution were also included in the analysis. These images, along with the Sentinel data, provided a continuous and comprehensive temporal dataset spanning the rice-growing season from May to September 2022. By integrating Sentinel and Landsat data, the study ensured both spatial and temporal coverage, facilitating robust NDVI analysis for crop health assessment and yield prediction.

➤ Sentinel Satellite Imagery

Sentinel-2A and Sentinel-2B satellite images were integral to this study due to their high spatial resolution and regular acquisition schedule. Sentinel-2 is a multi-spectral imaging mission for land and coastal monitoring, with spatial resolutions ranging from 10 meters to 60 meters, depending on the spectral band. The constellation provides a revisit period of 5 to 10 days, which allows for frequent and up-to-date monitoring of vegetation conditions. This characteristic is particularly important for agricultural monitoring, where

timely data are needed to assess crop health and detect potential stress factors such as drought or pest infestations. Sentinel data was collected during the rice growing cycle, from planting to harvesting, to generate time-series NDVI maps.

➤ *Landsat Satellite Imagery*

To mitigate the limitations of cloud cover associated with optical remote sensing, Landsat 8 and Landsat 9 images were incorporated into the dataset. With a spatial resolution of 30 meters, these images provide complementary data to the higher-resolution Sentinel-2 imagery. The Landsat data, corresponding to path 189 and row 52, were acquired on dates as close as possible to those of the Sentinel data to ensure consistency in temporal analysis. This integration of both Sentinel and Landsat datasets enhanced the robustness of NDVI analysis, allowing for more accurate and comprehensive monitoring of rice crop health and yield predictions throughout the growing season.

By combining these datasets, the study leverages the strengths of both high-resolution and cloud-robust satellite platforms, facilitating a more reliable and complete analysis of rice crop dynamics in the study area.

➤ *Data Analysis*

The perimeter coordinates of all the farm plots were plotted as points and these were used to digitize all the farm plots as polygons using the Geographic Information System platform. For accuracy purposes, the GPS coordinates of the perimeters of each plot taken on the field were labeled differently.

➤ *NDVI Analysis*

Since one of the objectives of the study is to generate the indices that simplify Ag-statistics estimation, time series NDVI was, therefore, analyzed and the value per farm plot from the planting period to the harvest period was obtained.

The Normalized Difference Vegetation Index for the entire study area was calculated using the NDVI algorithm.

The following equation was used.

$$NDVI = \frac{NIR - RED}{NIR + RED}$$

NIR = Near-infrared band of the satellite image

RED = RED band of the satellite image

In Sentinel Satellite Image, band 8 represents Near Infrared (NIR) while band 4 represents RED. Therefore, NDVI calculation for sentinel data = band 8 - band 4/ band 8 + band 4, and for Landsat data, NDVI = (band 5 - band 4)/(band 5 + band 4). This implies that NIR for Landsat corresponds to band 5 while RED corresponds to band 4. For the generation of average NDVI for farm plots, all the digitized farm plot polygons were overlaid on the NDVI layer for the selected LGAs and the average NDVI was generated for each plot for rice, using the zonal statistics tool within the Geographic Information System Platform.

III. RESULTS AND DISCUSSION

The study showed the time series NDVI for the length of the growing season for the selected crop (rice) and the geometrically calculated area of the farm plot size. The study showed the NDVI statistics for rice from May 2022 (planting period) to September 2022 (harvesting period). These statistics include the mean, standard deviation, range, minimum, and maximum NDVI values for all the farm plots over the growing season from planting to harvesting period for the selected crop. The average NDVI value in May, which marks the onset of the growing season for rice in the study area, ranges from 0.044 to 0.148. In July, which represents the grain filling stage, ranges from 0.136 to 0.348, and in August, which was the maturity stage for harvest, ranges from 0.110 to 0.450. These approaches assume that measures of photosynthetic capacity from spectral-vegetation indices are directly related to crop yield.

Figure 2 presents the landcover area showing cropland area (July 2022) while Figure 3 and 4 shows NDVI Maps for May, July and September. Table 2 also shows the land cover for mapping for cropland area and other land cover estimations.

Table 2 Land Use, Landcover for Mapping for Cropland Area and Other Land Cover Estimation

Land use Landcover classes	Area in Square Kilometer
Cropland Area	194.973269
Vegetation Area	901.76134
Grassland Area	200.8880
waterbody coverage	48.1059
Bareland Area	2417.4291
Settlement Area	64.8444
Total	3828.0021

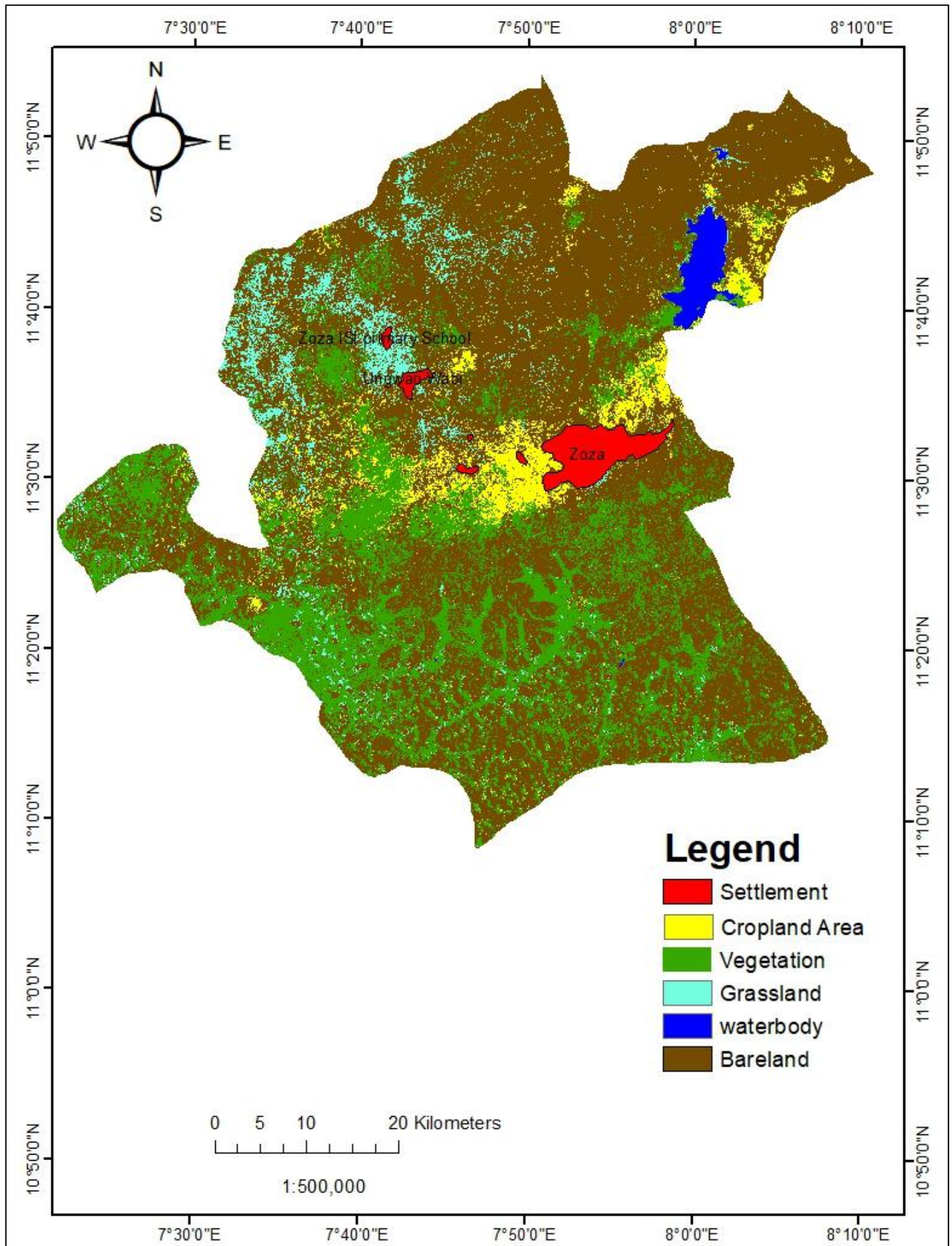


Fig 2 Landcover Area Showing Cropland Area Covered (July, 2022)

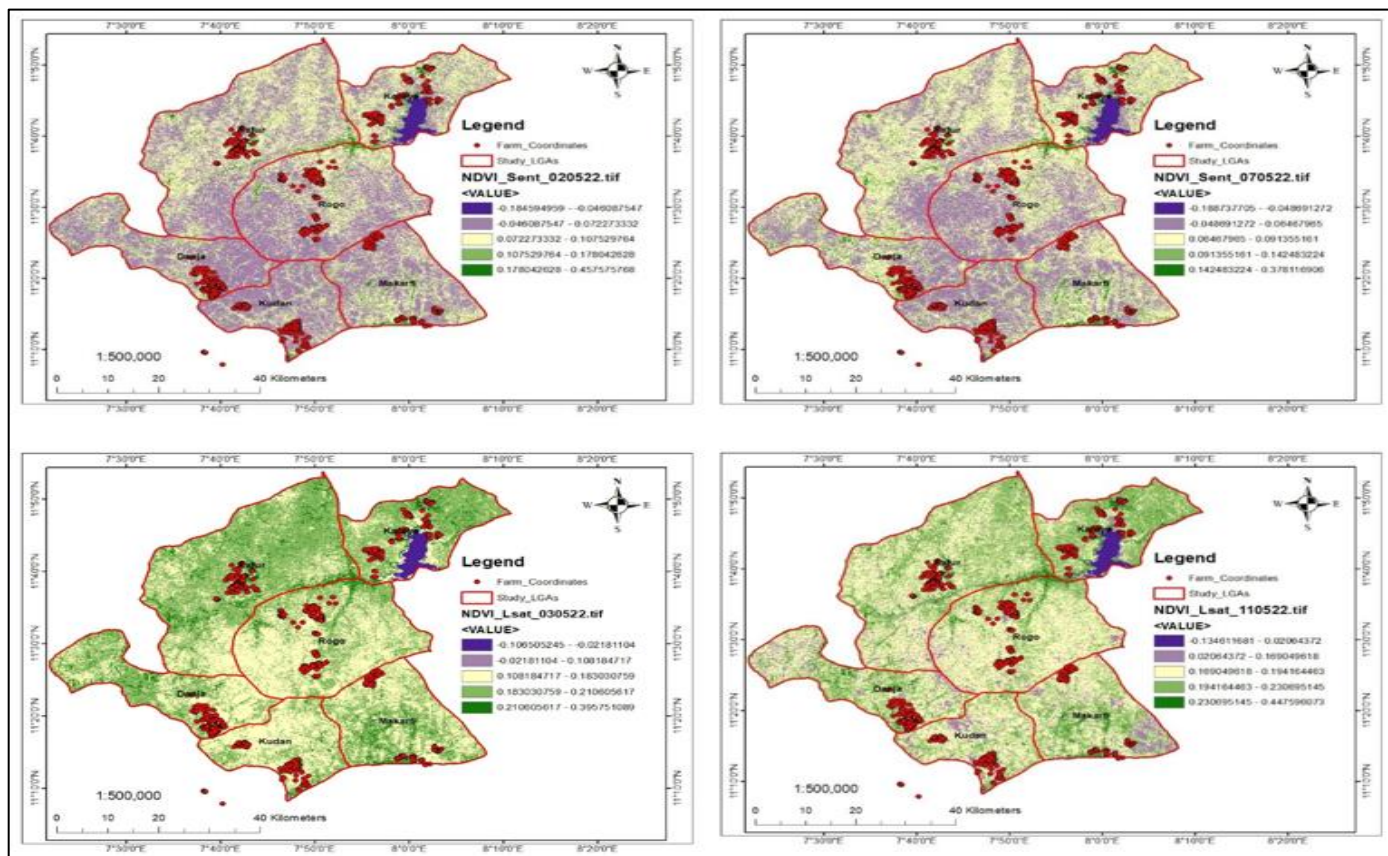


Fig 3 NDVI Maps for May

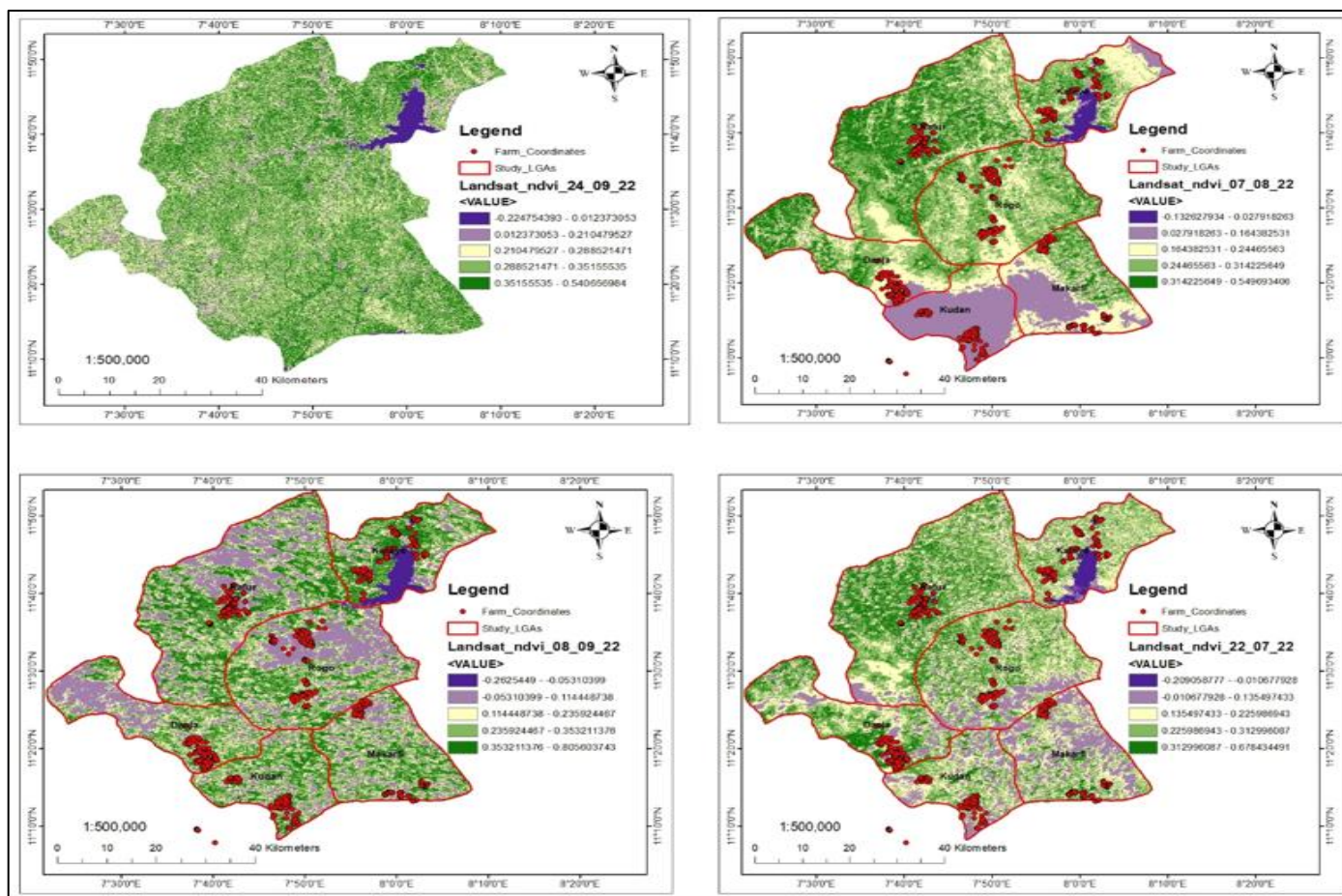


Fig 4 NDVI Maps for July – September

➤ *Predicted Model*

In the training phase for Kafur, the model correctly identified 1741 non-rice samples but misclassified 427 rice samples as non-rice. The results predicted a high accuracy for non-rice predictions at 100.0% but a very low accuracy for rice predictions at 4.5%. The overall accuracy for Kafur during training was 80.5%.

The results for Danja showed the model correctly predicted 1598 non-rice samples but incorrectly labeled 403 rice samples as non-rice. The non-rice prediction accuracy was 100.0%. The overall training accuracy for Danja was 80.2%. For Rogo, the model successfully predicted 1139 out of 1286 non-rice samples but mis-classified 276 rice samples as non-rice. The non-rice prediction accuracy was 88.6%, and the rice prediction accuracy was 50.3%. The overall accuracy for Rogo was 77.0%.

Karaye's results showed the model correctly predicted all 1456 non-rice samples but misclassified 159 rice samples as non-rice. It accurately identified only 7 out of 166 rice samples. The non-rice prediction accuracy was 100.0%. The overall accuracy for Karaye was 90.2%. However, in Makarfi, the model correctly identified 1421 out of 1421 non-rice samples but misclassified 383 rice samples as non-rice. The non-rice prediction accuracy was 100.0%. The overall training accuracy for Makarfi was 79.7%.

In Kudan, the model correctly predicted all 1652 non-rice samples but misclassified 327 rice samples as non-rice. The non-rice prediction accuracy was 100.0%. The overall accuracy for Kudan was 83.6%.

➤ *Estimation of Rice Output Across LGAs*

In Kafur, the correlation between `plot_harvest` and `NDVI_mean` was exceptionally strong for rice (0.900). This indicates that higher NDVI values, which reflect better vegetation health, are strongly associated with higher crop yield. The correlation between `plot_harvest` and `plot_size_area_m2` was moderately strong at 0.652.

Similar patterns emerged in Danja, with strong correlations between `plot_harvest` and `NDVI_mean` for rice (0.9212). The correlations between `plot_harvest` and `plot_size_area_m2` were lower, with values of 0.5268 for rice. Rogo displayed strong correlations between `plot_harvest` and `NDVI_mean` for rice (0.906). The `plot_harvest` and `plot_size` correlations were moderate, with a value of 0.300 for rice.

In Karaye, the correlation between `plot_harvest` and `NDVI_mean` was robust for the crop at 0.904. Makarfi showed strong correlations between `plot_harvest` and `NDVI_mean` for the crop at 0.911. The correlations between `plot_harvest` and `plot_size` were low, indicating that plot size had a minimal direct impact on yield. In Kudan, the correlations between `plot_harvest` and `NDVI_mean` were significant: rice (0.918). Across all LGAs, the correlation between `plot_harvest` and `NDVI_mean` was consistently strong, indicating that NDVI is a reliable predictor of crop yield.

This strong positive relationship suggests that healthier vegetation, as indicated by higher NDVI values, leads to higher yields for the crop. The correlation between `plot_harvest` and `plot_size` was generally weaker and more variable, suggesting that while plot size does have some impact on yield, it is less influential compared to vegetation health. Similarly, the correlation between `NDVI_mean` and `plot_size` varied, showing that plot size can influence vegetation health but not as consistently across different crops and regions.

Overall, these results highlight the critical role of NDVI in predicting crop yields and suggest that while plot size has some effect, it is not as strong or consistent a predictor as vegetation health. This information is valuable for agricultural planning and management, helping to focus efforts on improving vegetation health to boost crop yields.

IV. CONCLUSION

This study demonstrates the critical role of remote sensing technologies, particularly the Normalized Difference Vegetation Index (NDVI) and supervised image classification techniques, in monitoring rice crop health and mapping cultivation areas. Conducted across three Nigerian states (Kano, Kaduna, and Katsina), the study utilized satellite imagery from Sentinel and Landsat missions to assess rice fields over the 2022 growing season. The NDVI analysis captured the progression of rice growth, with values increasing from 0.044–0.148 in May (planting) to 0.110–0.450 in August (maturity), effectively reflecting the crop's health across various growth stages.

Supervised image classification identified a mean cultivated area of 0.227 hectares, with notable variability in plot sizes. The model predicted an average rice yield of 4218.21 kg/ha, although the actual measured yield was lower at 1512.624 kg/ha, with a root mean square error (RMSE) of 0.419 and a model accuracy of 82%. These results underscore the model's potential for estimating rice yield and detecting discrepancies that warrant further refinement.

Overall, the study highlights the effectiveness of NDVI and remote sensing in providing timely, data-driven insights for rice monitoring, yield estimation, and agricultural planning. These findings offer valuable contributions to national food security efforts by improving decision-making for farmers, policymakers, and agricultural managers. The integration of remote sensing technologies promises to enhance the efficiency and accuracy of crop monitoring and resource allocation in the rice sector.

RECOMMENDATIONS

- **Adoption and Upscaling of Remote Sensing Technologies:** Encourage the adoption of remote sensing technologies, such as NDVI and supervised image classification, for rice crop monitoring and yield estimation.
- **Integration with Agricultural Planning:** Integrate remote sensing data into agricultural planning and decision-

making processes to improve resource allocation and crop management.

- Capacity Building and Training: Provide training and capacity-building programs for farmers, policymakers, and agricultural managers on the use and interpretation of remote sensing data.
- Data-Driven Decision Making: Promote data-driven decision-making in the rice sector by using remote sensing data to inform policy and management decisions.
- Refinement of Yield Estimation Models: Refine yield estimation models to reduce errors and improve accuracy, using ground-truth data and other relevant factors.
- Collaboration and Knowledge Sharing: Foster collaboration and knowledge sharing among stakeholders, including researchers, policymakers, and farmers, to promote the adoption and effective use of remote sensing technologies in agriculture.

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➤ Conflicts of Interest

The authors declare no conflict of interest in the work.

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