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(Research Article)

Developing a localized vegetation classification system for sustainable land use management in Kebbi State, Nigeria

Abubakar Abubakar [1] and Usman Lawal Gulma [2, *]

[1] *Department of Biology, Adamu Augie College of Education, Argungu, Kebbi State, Nigeria.*
[2] *Department of Geography, Adamu Augie College of Education, Argungu, Kebbi State, Nigeria.*

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Abstract

Accurate vegetation classification is crucial for environmental monitoring, natural resource management, and climate change modelling. This study develops a localized vegetation classification system using the Normalized Difference Vegetation Index (NDVI) and machine learning algorithms for Kebbi State, Nigeria. Landsat 8 imagery and field observations were used to train a Random Forest model, achieving an overall accuracy of 88.2%. The results show significant differences in NDVI values across vegetation types, effectively distinguishing between grasslands, shrubs, and barren lands. The classification system demonstrates the potential of NDVI for vegetation classification in Kebbi State, supporting sustainable land use management practices such as reforestation, crop selection, and land degradation monitoring. This study contributes to developing localized vegetation classification systems, addressing regional specificities in vegetation characteristics and promoting informed decision-making for environmental conservation.

Keywords: Vegetation Classification; NDVI; Machine Learning; Land use management

1. Introduction

Accurate vegetation classification is crucial to various environmental applications, including environmental monitoring, natural resource management, and climate change modelling [1]. Vegetation classification systems are widely used for land cover mapping [2]. However, existing global systems often fail to capture regional specificities in vegetation characteristics, leading to inaccurate classification [3]. This is particularly problematic in regions with unique vegetation communities or complex land cover patterns [4]. To address this issue, there is a growing need for localized vegetation classification systems that can accurately capture regional specificities in vegetation characteristics [5]. It has been demonstrated that localised systems, which may be created using field data and machine learning algorithms, increase the precision of vegetation classification [6-8].

Sustainable land use management is crucial for maintaining ecosystem services, biodiversity, and human well-being [9]. Vegetation classification is a critical component of land use management, enabling policymakers to make informed decisions [10]. However, traditional methods of vegetation classification are often time-consuming, costly, and limited in spatial coverage [11]. Remote sensing techniques, particularly the Normalized Difference Vegetation Index (NDVI) offer a promising alternative [12].

The limitations of global systems are particularly pronounced in regions with unique vegetation communities or complex land cover patterns, where localized classification systems are essential [4]. To accurately capture regional variations in vegetation characteristics, there is a growing demand for localized vegetation classification systems that leverage machine learning algorithms, field data and remote sensing techniques [13, 14]. The combination of NDVI with

* Corresponding author: Usman Lawal Gulma

field data and machine learning algorithms could potentially address the shortcomings of global methods [6, 15]. Such systems can provide policymakers with timely and accurate information for informed decision-making, ultimately supporting sustainable land use management and the maintenance of ecosystem services [16]. This study aims to use remote sensing methods and machine learning algorithms to create a localized vegetation classification system. Examine how the localised system might be used to manage land use sustainably. This study advances the creation of precise and local vegetation classification systems for Kebbi State, which supports better natural resource management and environmental monitoring. Maintenance of ecological services, managing land use sustainably, and assisting stakeholders and policymakers in making well-informed decisions.

2. Review of Related Literature

The development of a localized vegetation classification system using NDVI for sustainable land use management in Kebbi State, Nigeria, is rooted in various theoretical and empirical studies. This review synthesizes existing literature on NDVI, vegetation classification, remote sensing, and machine learning approaches.

There has been growing recognition of how remote sensing revolutionized land use management by providing valuable information for decision-making [17]. Studies have showcased the potential of remote sensing in monitoring land degradation [18]. Studies have demonstrated the effectiveness of NDVI, a widely used remote sensing index, in classifying vegetation health and density [19-22]. NDVI values range from -1 to 1, with higher values indicating healthier vegetation. Previous studies have developed various classification systems using NDVI. For example, Nse, Okolie [23] used NDVI statistics derived from multispectral Landsat imageries to quantify different land cover transitions in Uyo, Akwa Ibom State, Nigeria. They found that built-up areas constitute a significant proportion of the area compared with vegetation cover, indicating rapid urban growth. Idrees, Omar [24] used wet, dry and harmattan seasons Landsat 8 NDVI for vegetation cover classification in Ilorin, Kwara State, Nigeria. They found that the NDVI threshold is a practical alternative to classify vegetation cover.

Research has also demonstrated that localised systems may be created with field data and machine learning techniques, increasing the precision of land cover mapping [25, 26]. Machine learning algorithms, such as decision trees, random forests, and support vector machines, have been widely used for vegetation classification [27-29]. These algorithms can handle large datasets and complex relationships between variables, making them suitable for vegetation classification [30]. Field data, such as field surveys and remote sensing are essential for developing localized vegetation classification systems [31, 32]. Field data can provide detailed information on vegetation characteristics, such as species composition, structure, and spectral reflectance, which can be used to develop accurate classification models (Yang et al., 2017).

Vegetation classification systems are widely employed for sustainable land use management [17, 33]. Several studies have highlighted the importance of localized vegetation classification systems [4, 34]. For example, Yang, D'Alpaos [35] used field data and machine learning algorithms to create a localised vegetation classification system for the Venice Lagoon in northeastern Italy. They obtained a 90% accuracy rate overall. They achieved an overall accuracy of 90%. Meng, Liang [36] used field data and machine learning algorithms to create a localised vegetation categorization system with an overall accuracy of 89% for the Tibetan Plateau in China.

In summary, localized vegetation classification systems are essential for accurate land cover mapping and can be developed using machine learning algorithms and field data. This study builds on the existing literature to quantify vegetation in Kebbi State, Nigeria using remote sensing and machine learning approaches.

3. Materials and Method

3.1. Study Area

Kebbi State (Figure 1) is located between latitude 10^0 N to 14^0 N and longitude 4^0 E to 7^0 E with a total land area of 36,229 square kilometers. The state shares borders with Sokoto State to the north, Zamfara State to the east, Niger State to the south, and Benin Republic to the west.

Kebbi State has a tropical savannah climate with two distinct seasons (the wet season and the dry season). The state's vegetation comprises of grasslands, shrubs, and deciduous forests. The state is home to several tree species, including the iconic baobab, acacia, and mango trees. The state's vegetation is also influenced by the Niger River, which supports a variety of riparian forests and wetlands. The state's agricultural land is suitable for cultivation of rice, millet, sorghum, and cowpeas.

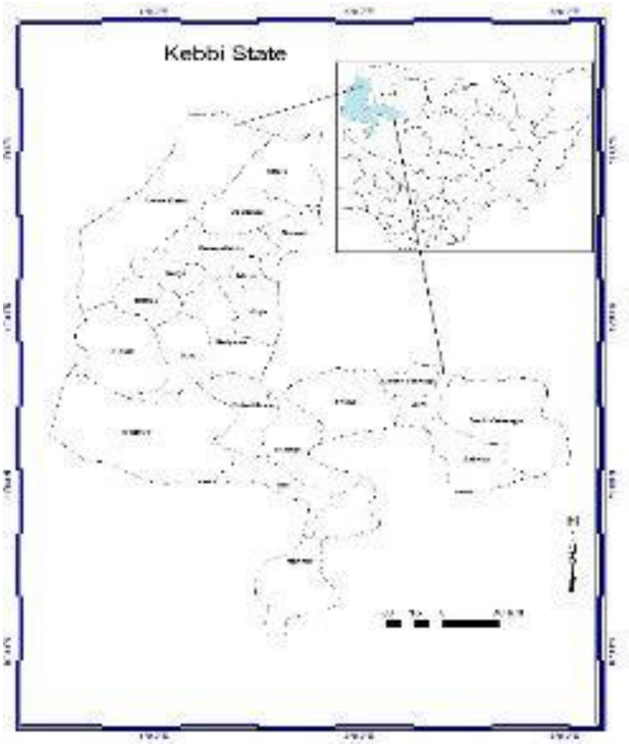

Figure 1 Location map of Kebbi State in Nigeria

3.2. Data

The United States Geological Survey (USGS) database provided the Landsat 8 imagery (30m resolution) acquired in 2024 for the study area (Table 1). Band 1 is coastal, Band 2 is blue, Band 3 is green, Band 4 is red, Band 5 is near infra-red, Band 6 is shortwave infra-red 1, Band 7 is shortwave infra-red 2, and Band 8 is panchromatic. Field observations of various vegetation types were gathered using a GPS device and vegetation survey technique [37]. Data on the species composition, structure, and spectral reflectance of the vegetation were also collected [38].

Table 1 Landsat 8 imagery scenes of Kebbi State

Path	Row	Resolution (30)	Number of bands
190	52	30	8
191	21	30	8
191	52	30	8
191	53	30	8

3.3. Method of Data Analysis

First, we created a single image by stacking the bands of each Landsat 8 image. Second, for spatial accuracy using the ArcGIS environment, those four images were mosaicked and masked using a vectorized map of the study area (Figure 2). Following the first image processing step, the R programming environment was used to calculate the NDVI from the image's subset (bands 2, 3, and 4). NDVI Equation 1, Tucker [12] is given below:

NDVI = (NIR - RED) / (NIR + RED) (1)

where NIR is the near-infrared band and RED is the red band

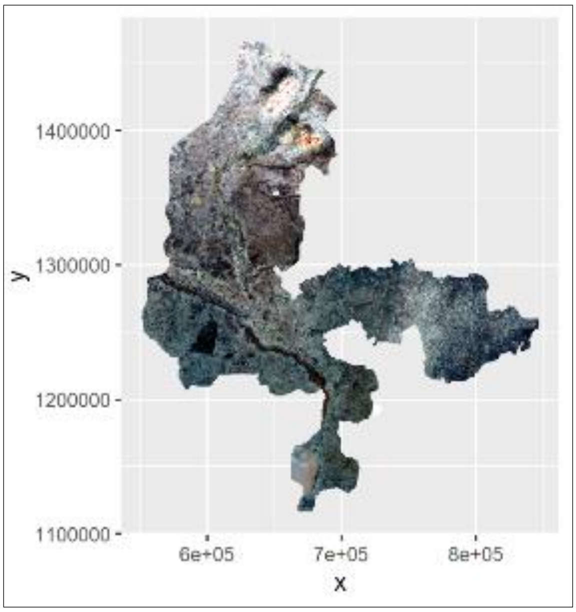

Figure 2 Stacked Landsat image of Kebbi State

Cleaning and formatting are crucial to preparing data for machine learning modelling [39]. We conducted a data-cleaning exercise to extract relevant variables from the data using NDVI values and field observations. We then develop a robust localized vegetation classification system using machine learning algorithms such as decision trees, random forests, and support vector machines [40]. The classification models were evaluated for accuracy using confusion metrics, kappa coefficient, and overall accuracy. The study area is grouped based on the various vegetation classes identified using the proposed classification models [41, 42].

4. Results

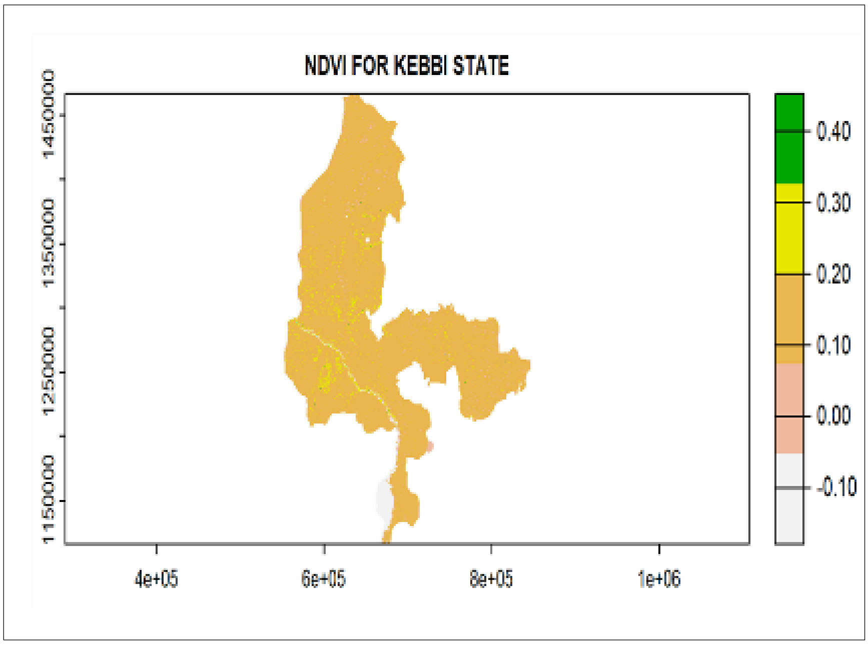

Figure 3 NDVI values of the study area

This section presents the study's findings, highlighting the differences in NDVI values across vegetation types, the classification model's performance, and the resulting vegetation classification map. Significant differences in NDVI values were observed across vegetation types. The NDVI values indicate that grassland areas have moderate vegetation density (NDVI: 0.3-0.4), and shrubs areas have low vegetation density (NDVI: 0.1-0.2). Areas of barren lands show very low NDVI values (0-0.1). Those areas having NDVI values below 0 are generally regarded as riverine. A classified vegetation map highlighted, grassland, and shrubs (Figure 3).

The map illustrates that barren areas are predominantly located across the state. Grassland areas are scattered around the central areas including Koko/Besse, and and Bagudo Local Government Areas. Patches of grasslands are also found in the eastern regions including Zuru and Danko/Wasagu Local Government areas. The southern areas including Yauri and Shanga are riverine with a mixture of grasslands. The northern parts of the state including Argungu, Augie and Arewa Local Government Areas are predominantly characterized by the presence of shrubs. The histogram of the distribution of various vegetation classes is shown in Figure 4.

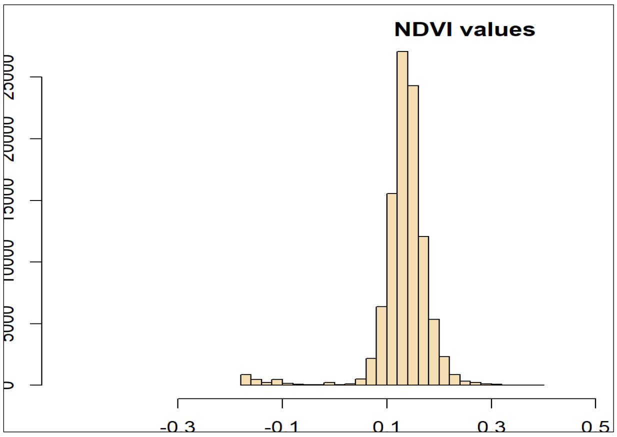

Figure 4 Histogram of the NDVI values for the study area

The classification model, the Random Forest model achieved an overall accuracy. Grasslands areas exhibiting the highest accuracy (88.2%), shrubs areas showing moderate accuracy (82.1%), barren land areas demonstrating relatively lower accuracy (80.5%).

5. Discussion

The results indicate that NDVI values can effectively distinguish between vegetation types. The Random Forest classification model accurately distinguished between grassland, shrubs and barren lands. The vegetation classification map provides valuable information for land use management, conservation efforts, and environmental monitoring.

The developed classification system demonstrates the potential of NDVI for vegetation classification in Kebbi State. The results align with previous studies, indicating NDVI's effectiveness in distinguishing vegetation types [15, 20]. The classification system can support sustainable land use management practices. Identifying areas with low NDVI values for reforestation efforts, optimizing crop selection based on NDVI-derived vegetation characteristics and tracking changes in NDVI values to monitor land degradation.

6. Conclusion

This study demonstrates the effectiveness of NDVI-based vegetation classification for sustainable land use management in Kebbi State. The developed classification system can support informed decision-making, promote sustainable land use practices, and protect environmental conservation.

While previous studies have utilized NDVI for vegetation classification, this research offers several novel contributions such as a regional specificity focusing on Kebbi State, providing insights into local vegetation characteristics. We also employ a hybrid approach combining NDVI with machine learning to enhance accuracy and efficiency. However, data quality enhancement efforts are applied in this analysis. Notwithstanding, image quality and atmospheric conditions may affect NDVI accuracy. Temporal variability in vegetation cover are not accounted for in this research. Additionally, limited field observations may impact classification accuracy.

We recommend future research to explore the use of multispectral and hyperspectral imagery for improved vegetation classification. Additionally, NDVI with other remote sensing indices (e.g., enhanced vegetation index (EVI)) could improve the accuracy of the results. EVI refines NDVI's approach, it is less sensitive to atmospheric influences.

Compliance with ethical standards

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Disclosure of conflict of interest

The authors have declared no conflict of interest.

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