Land Suitability Analysis for Rice Cultivation Using a GIS - based Analytical Hierarchy Process (AHP) Multi - Criteria Decision Making Approach: Kabba / Bunu Local Government Area, Kogi State, Nigeria

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Abstract: ***This research focused on evaluating the suitability of land for rice farming within the Kabba/Bunu local government area using an integrated approach that combines the Analytic Hierarchy Process (AHP) within a Geographic Information System (GIS). The selection of key factors such as climate, soil, topography, and land use/land cover (LULC) was guided by the FAO's guidelines and expert recommendations. Through the integration of GIS - based Multi - Criteria Decision Analysis (MCDA) and the application of AHP for prioritizing these factors, we developed weighted suitability layers, culminating in the creation of a comprehensive map indicating areas optimal for rice cultivation. The land was categorized into five suitability levels: most suitable, more suitable, suitable, less suitable, and not suitable. The findings confirm the efficacy of AHP in conducting such analyses, provided the correct variables are chosen. Notably, approximately 38% of the region, primarily in the south, was identified as moderately suitable for rice cultivation.***

Keywords: rice farming, land suitability, Geographic Information System GIS, Analytic Hierarchy Process AHP, Kabba Bunu.

1. Introduction

1.1 Background

Rice, scientifically known as Oryza sativa, stands as a fundamental food crop worldwide, particularly vital for small - scale farmers in developing countries. It serves as a primary source of nutrition for over half the global population, providing essential calories and carbohydrates, with individual consumption ranging from 100 - 240kg annually (Danvi et al., 2016). Positioned as the third most produced staple after maize and sugarcane, rice holds a significant place in global agriculture (FAOSTAT, 2012). Nigeria, notably the largest importer of rice globally and a leading producer in West Africa, predominantly cultivates rice in states such as Ebonyi, Kaduna, Kano, Niger, Benue, Taraba, and Borno (Ujoh et al., 2019).

Rice cultivation can adapt to various climatic conditions, with the majority of the production coming from irrigated systems. Over 40, 000 varieties of rice exist, spanning across long, medium, and short grain categories (Akpoti et al., 2019). The application of Geographic Information System (GIS) based Multi - Criteria Data Analysis (MCDA) has emerged as a successful approach in addressing spatial problems, including land suitability assessments for agriculture (Aldababseh et al., 2018; Ojo & Baiyegunhi, 2020). Recent studies have leveraged MCDA, along with remote sensing, to evaluate land for rice cultivation, incorporating various environmental and climatic parameters (Danvi et al., 2016; El Baroudy, 2016; Akpoti et al., 2019).

1.2 Problem Statement

Despite Benue state's recognition as a major rice producer in Nigeria, Kogi state, sharing similar climatic and soil conditions, has not achieved comparable levels of rice production. This study aims to investigate the underutilization of rice cultivation potential in Kogi state, with a focus on Kabba/Bunu local government area, proposing strategies to enhance rice production through GIS and Analytic Hierarchy Process (AHP) methodologies.

1.3 Objectives

The primary goal is to leverage AHP within GIS for a detailed assessment of land suitability for rice cultivation in Kogi state. The specific objectives include:

- Mapping land use and cover in Kabba/Bunu using satellite imagery.
- Conducting a multi - criteria analysis to evaluate the area's suitability for rice farming.
- Classifying Kabba/Bunu into distinct zones based on their suitability for rice cultivation.

1.4 Study Area Description

Kogi state, situated in Nigeria's middle belt, is known for its strategic location bordering ten other states and housing the confluence of the River Niger and River Benue. It is a hub for commercial trade and agriculture, primarily fueled by its fertile lands and favorable climate. The state is a rich source of various agricultural products including yam, cassava, soya bean, and notably rice among others. It also harbors significant mineral resources like limestone and coal (Atedhor, 2015). Spanning over 29, 833km², Kogi state is positioned within specific latitudinal and longitudinal coordinates, offering a diverse topography and rich agricultural potential.

Kogi experiences a monsoonal climate, characterized by distinct dry and wet seasons, with significant rainfall occurring between April and October. The climate, alongside its proximity to major rivers, provides a conducive environment for various forms of agriculture. Since its establishment in 1991, Kogi state has seen a notable population increase, particularly in its capital, Lokoja. This demographic shift has influenced land - use patterns, with agriculture remaining the predominant occupation.

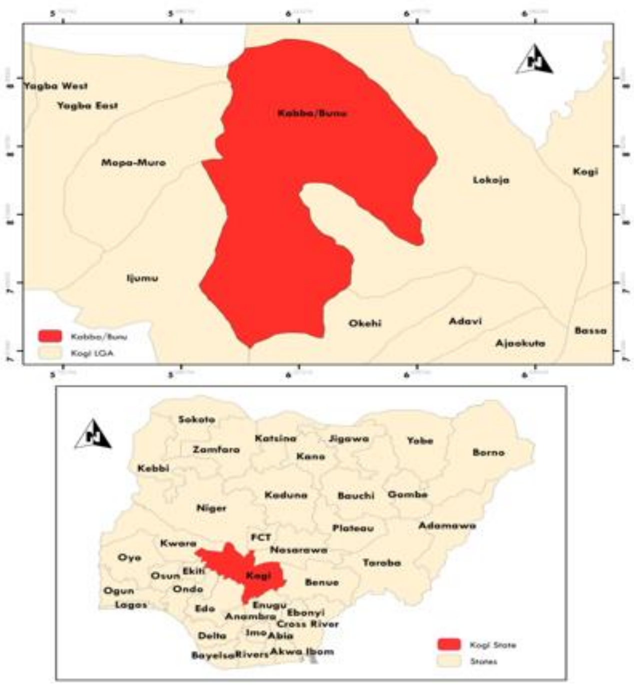

Figure 1: The study area map

2. Literature Review

2.1 Sustainability in Agricultural Land Use

The path towards enhancing agricultural land sustainability is closely tied to the comprehension of soil textures and their behaviors, given the traditional methods for assessing soil fertility are often expensive and not always reliable (Keshavarzi et al., 2020). The use of Geographic Information Systems (GIS) has emerged as a pivotal tool in pinpointing areas conducive to sustainable agricultural practices, aligning with environmental conditions (Ayehu & Besufekad, 2015). The capability of conducting suitability analyses to identify optimal lands for specific crops is instrumental in promoting agricultural land sustainability (Tey et al., 2014).

2.2 Environmental Impact on Crop Growth

The growth and distribution of plants are significantly influenced by environmental factors. A shortfall in any of these factors, such as water availability, can restrict plant growth, as observed in desert - adapted species (Armah et al., 2011). Essential environmental variables impacting plant development include light, temperature, water, humidity, and nutrients. Understanding the interplay of these factors can lead to optimized agricultural practices. Additionally, the competitive and synergistic interactions among different crops when co - cultivated can affect their growth and yield, highlighting the importance of strategic crop selection and spacing (Amini et al., 2020; Seyedmohammadi et al., 2019).

2.3 The Concept of Food Security

The definition of food security encompasses various aspects, including food availability, access, stability, and utilization as outlined by the FAO in 2006. It involves ensuring a consistent supply of food at all levels, from local to global, and the ability for populations to access this food supply. Land suitability analyses for agricultural purposes, using methodologies like AHP and fuzzy - AHP, are crucial for enhancing food security by identifying areas optimal for crop cultivation (Babatunde, 2020).

2.4 Soil Characteristics and Their Influence

Soil composition, including the mixture of sand, silt, clay, and organic matter, profoundly affects its properties and, consequently, plant growth. The texture of the soil influences its water retention and drainage capabilities, which are critical for healthy plant development. Additionally, the soil structure, shaped by organic matter and soil organisms, plays a vital role in facilitating plant growth by affecting air and water movement, root penetration, and nutrient availability (Bagherzadeh & Gholizadeh, 2018; Gosal et al., 2018; Bünemann et al., 2018).

2.5 Classifying Land for Suitability

The assessment of land suitability involves evaluating the fitness of land for specific uses, taking into account its current condition and potential improvements. This process involves appraising and categorizing land areas based on their compatibility with intended uses, which is critical for informed land - use planning and sustainable development (Komolafe E. O et al., 2019; Malczewski, 2004).

2.6 The Role of AHP in Agricultural Planning

The Analytic Hierarchy Process (AHP) has shown significant promise in agricultural planning, particularly in identifying land suitable for crops like rice. This method, coupled with GIS, enhances the precision of land suitability assessments based on soil properties, climatic conditions, and topography, adhering to established frameworks and expert insights (Amini et al., 2020). The selection of AHP over other multi - criteria analyses, such as fuzzy systems, underscores its effectiveness in the agricultural domain.

2.7 Evolution of Land Suitability Analysis

Prior to the integration of GIS in land suitability assessments, traditional methods, including various national approaches and monographic studies, were employed to evaluate the agricultural potential of lands.

The advent of GIS, alongside tools like AHP and fuzzy - AHP, has revolutionized the field, enabling more accurate and efficient suitability mapping for agricultural endeavors (Malczewski, 2004; Akpoti et al., 2019).

3. Methodology

3.1 Overview of Multi - Criteria Decision Analysis (MCDA)

Multi - Criteria Decision Making (MCDM) integrates various opinions and criteria to facilitate decision - making processes, especially when multiple, competing factors are at play (Malczewski & Rinner, 2015). The synergy between MCDA and Geographic Information Systems (GIS) creates a powerful tool for conducting spatial analyses. MCDA is pivotal in evaluating alternatives by considering multiple criteria simultaneously, which is crucial in fields such as land suitability analysis where various environmental and geographical factors are involved (Seyedmohammadi et al., 2019). GIS, with its capability to manage and analyze spatial data, enhances decision - making by visualizing geographical information and integrating it with MCDA for a comprehensive analysis (Adewumi et al., 2019). In this methodology, criteria are weighted to reflect their relevance to the decision - making context, considering the nature of alternatives and the decision - maker's preferences.

3.2 Data Acquisition and Preparation with GIS

Data acquisition and preparation are fundamental steps, accounting for a significant portion of the project's effort (Chadli et al., 2016). This research employs various GIS analytical techniques, such as interpolation and overlay, combined with MCDA and AHP to process the datasets described below:

Land Use and Land Cover (LULC): Landsat 8 OLI imagery from 2020, with a 30m resolution, was processed through supervised classification to delineate land use and cover patterns. This data was sourced from the United States Geological Survey (USGS) website. The classification accuracy was validated using a confusion matrix in ENVI software, comparing the classified imagery against ground - truth samples from the study area.

Slope Analysis: slope is a critical factor in assessing land suitability for agriculture. It was derived from Digital Elevation Models (DEMs) obtained from the Shuttle Radar Topography Mission (SRTM) via the USGS website. ArcGIS's Spatial Analyst Toolbox was utilized to calculate slope percentages, aiding in identifying terrains suitable for rice cultivation, where flatter areas are preferable for uniform water distribution.

Soil Characteristics: soil properties play a crucial role in agricultural viability. Parameters such as texture, depth, and pH were considered in this study. Soil data was acquired from the Nigeria Hydrological Services Agency (NIHSA), providing detailed information on soil physical and chemical properties. These data were transformed into raster layers in ArcGIS to facilitate analysis.

Climate Data: climate, particularly temperature and rainfall, significantly influences agricultural productivity. Rice, typically grown in warm and wet conditions, thrives in temperatures ranging from 20 to 40°C and annual rainfall between 1250mm and 2000mm. Climate data spanning 30 years for temperature and 28 years for rainfall were obtained from the Nigeria Meteorological Agency (NiMet) and processed using the Inverse Distance Weighted (IDW) interpolation tool in ArcGIS.

All raster data layers were standardized to a 30m spatial resolution and aligned to the WGS84 coordinate system. Suitability levels for each criterion were established based on a combination of literature review, expert consultation, and the author's empirical knowledge. These levels were then reclassified in ArcGIS to create criteria maps, with suitability ranked from "Most Suitable" to "Not Suitable, " following the FAO's land suitability classification framework.

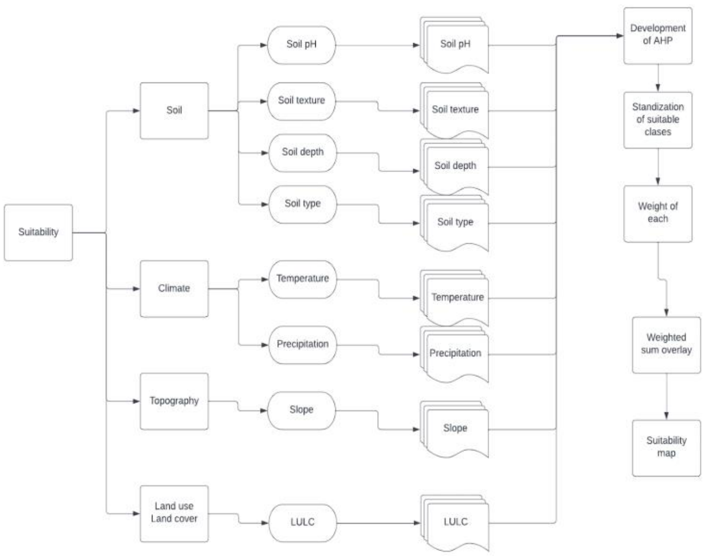

Figure 2: Flowchart of methodology used in this study

Table 3.1: Distribution of factor and their suitability scale in the study area

Properties	Description	Suitability scale
Soil type	Lf - Ferric Luvisol	3
	Ne - Eutric Nitosol	5
Precipitation	6.00 - 7.00	1
	7.00 - 9.00	2
	9.00 - 11.00	3
	11.00 - 13.00	4
	13.00 - 16.00	5
Temperature	24.00 - 24.69	5
	24.69 - 25.19	4
	25.19 - 25.71	3
	25.71 - 26.21	2
	26.21 - 26.90	1
pH	0	5
	0 - 6.0	4
	6.00 - 6.10	3
	6.10 - 6.20	2
	6.20 - 6.50	1
Slope	0 - 1.129	5
	1.129 - 3.528	4
	3.528 - 6.915	3
	6.915 - 12.701	2
	12.701 - 35.988	1
Land use/ land cover	Wetland/water body	5
	Vegetation	4
	Grassland	3
	Bare/rocky ground	2
	Settlement	1

3.3 Analytic Hierarchy Process (AHP) Application

The Analytic Hierarchy Process (AHP) is renowned for being the most widely implemented and trusted methodology within the sphere of multi - criteria decision - making. Its application, in both its classic and modified forms, has garnered significant attention from the research community (Adewumi et al., 2019; Seyedmohammadi et al., 2019). A critical aspect of decision - making involves the meticulous evaluation of pertinent information. Hence, a variety of decision - making approaches focus on determining the relative significance or weights of various alternatives against each criterion in specific decision - making contexts. The approach devised by Saaty in 1980, which employs pairwise comparisons, has been a subject of interest among numerous scholars.

To ascertain factor weights, the Analytic Hierarchy Process utilizes the Pairwise Comparison Matrix (PCM), where two factors are compared at a time. Saaty's (1980) suggested scale serves as the basis for assigning values to these pairwise comparisons within AHP. The scale allows for values ranging from 1/9 to 9, reflecting the relative importance of one factor over another. A score of 9 indicates a strong preference for one factor over another, while a score of 1/9 suggests the opposite. A score of 1 denotes equal importance between two factors. AHP calculates the weightings for each criterion by extracting the Eigenvector associated with the largest Eigenvalue of the comparison matrix and normalizing the sum of its elements, ensuring a consistent and structured approach to decision - making.

Table 3.2: Scales for pairwise AHP comparison

Intensity of importance	Description
1	Equal importance
3	Moderate importance
5	Strong or essential importance
7	Very strong or demonstrated importance
9	Extreme importance
2, 4, 6, 8	Intermediate values
Reciprocals	Values from inverse comparison

Source: Saaty (1980).

3.4 Criteria Normalization Process

In the context of land suitability assessments, criteria maps are typically categorized into ordinal classes such as S1, S2, S3, and N. These classifications reflect the relative suitability of specific land attributes for agricultural purposes, with each class representing a different level of compatibility with the crop's requirements (Chang, 1996). To facilitate a detailed analysis, it's necessary to assign a quantitative value to each class. This process helps in evaluating the importance of the highest suitability class (S1) in relation to other classes for a given criterion, essentially comparing the significance of different classes within the same criterion.

The normalization of criteria involves assigning a proportional value to each class within a criterion, thereby quantifying their relative importance (Seyedmohammadi et al., 2019). This is typically done using scales that range from 0 to 1, 0 to 10, or 0 to 100, converting ordinal data into a format that can be quantitatively analyzed. The pairwise comparison method, as outlined by Saaty (1980), is frequently employed for this purpose, enabling a systematic evaluation of the ordinal classes by comparing them in pairs.

In this study, a refined approach to the Analytic Hierarchy Process (AHP) known as the Ideal Model AHP was implemented. This method was chosen to overcome a specific limitation of the traditional AHP, where the introduction of an alternative matching an existing option could potentially reverse the ranking of the alternatives. The Ideal Model AHP mitigates this issue by ensuring a consistent and reliable comparison, even when new alternatives are introduced (Chang, 1996).

3.5 Determining Criterion Weights via AHP

In evaluating land suitability for rice cultivation, it's recognized that not all criteria hold equal significance. It becomes essential to quantify the relative importance of each factor, such as comparing the impact of slope on rice productivity to that of soil depth or other variables. This step involves comparing the various criteria to understand their individual contributions to the overall suitability assessment. Multi - Criteria Decision Making (MCDM) offers a suite of methods for organizing decision - making processes and evaluating, as well as prioritizing, different alternatives. Among these, the Analytic Hierarchy Process (AHP) stands out as a prominent tool, especially for integrating into GIS - based land suitability analyses (Malczewski & Rinner, 2015). In this phase, each criterion was assessed in relation to others to assign it a numerical value indicative of its importance. The pairwise comparison method, as formulated by Saaty (1980), provides the framework for this assessment in AHP. In this study, weights were determined based on consultations with local agricultural experts and relevant literature. The pairwise comparison matrix used in this analysis, which will be detailed in Table 3.3, assigns a value of one to elements along the diagonal (indicating a comparison of a factor with itself) and maintains symmetry across the matrix. This approach ensures a structured and quantifiable evaluation of each factor's significance in the context of rice crop suitabili

Table 3.3: Pairwise comparison matrix of selected criteria's

Parameters	Soil type	Precipitation	Temperature	pH	Slope	LULC
Soil type	1	2	2	3	4	3
Precipitation	0.5	1	2	4	2	3
Temperature	0.5	0.5	1	1	2	2
Slope	0.25	0.5	0.5	0.5	1	2
LU/LC	0.33333	0.333333	0.5	1	0.5	1

Table 3.4: Normalized pairwise comparison and computation of consistency ratio

Multiplication row	6th root of product	Criteria weight	Sum of pair wise	sum*cw	Percentage influence	Consistency index	Consistency ratio
144	2.28	0.33	2.91	0.96	33.13	0.04	0.038
24	1.69	0.24	4.58	1.12	24.57		
1	1	0.14	7	1.01	14.47		
0.16	0.74	0.1	10.5	1.12	10.73		
0.06	0.62	0.09	11.5	1.04	9.11		
0.02	0.55	0.07	12	0.95	7.96		
	6.9			6.23			

When applying the Analytic Hierarchy Process (AHP), ensuring the consistency of the judgments made in the pairwise comparison matrix is crucial. The Consistency Ratio (CR) is a measure used to assess the likelihood that the matrix judgments were made randomly (Amini et al., 2020; Keshavarzi et al., 2020). It is calculated using the formula:

$$CR=RI/CI$$

where CI is the Consistency Index, given by:

$$CI=\lambda max-n/\ n-1$$

In these formulas, λmax represents the Maximum Eigenvalue of the matrix, CI stands for the Consistency Index, CR is the Consistency Ratio, and RI denotes the Random Index, which is derived from the average consistency index based on the matrix size (Saaty, 1980). The variable n corresponds to the number of criteria or sub - criteria considered in the pairwise comparison matrix.

A Consistency Ratio (CR) value of 0.10 or below is generally accepted as indicating reasonable consistency in the pairwise comparisons (Adewumi et al., 2019; Malczewski & Rinner, 2015). In the context of this land suitability study, the calculated CR was 0.05, signifying that the comparisons made regarding land characteristics were consistent, and the relative weights assigned were appropriately determined.

3.6 Implementing Overlay Analysis

In this study, the technique of weighted sum overlay was employed to integrate various map layers, a method that allows for the amalgamation of diverse and heterogeneous datasets into a cohesive analysis by normalizing them onto a uniform scale (Seyedmohammadi et al., 2019). This approach involved assigning weights to different land suitability map layers, derived from the Analytic Hierarchy Process (AHP) as outlined previously. In the process of weighted sum overlay, the cell values within each input raster—representing the ratings for land suitability—are multiplied by their corresponding criterion weight. The resultant values are then aggregated to produce the final suitability map.

The culmination of this methodological approach is depicted in Table 3.5, which presents the results of the overlay analysis. Additionally, Figure 4 illustrates the rice suitability maps generated through this weighted sum overlay process. The comprehensive land suitability map categorizes the study area into five distinct zones based on their suitability for rice cultivation: most suitable, more suitable, suitable, less suitable, and not suitable, offering a clear and actionable guide for agricultural planning and land management decisions

Table 3.5: Results of weights obtained from multi criteria analysis

Factor	Percentage influence	Criteria weight
Soil type	33.132451	0.33132451
Precipitation	24.5788574	0.24578857
Temperature	14.471931	0.14471931
pH	10.7358048	0.10735805
Slope	9.11674524	0.09116745
Land use / Land cover	7.96421054	0.07964211

3.7 Analyzing Vegetation Cover

Understanding the current vegetation cover within the study area is essential for refining the suitability map for rice cultivation. Important environmental and economic considerations arise when suitability classes overlap with areas of dense vegetation. It's crucial to investigate how these suitability zones correlate with the existing vegetation patterns to ensure sustainable land use planning. Typically, areas classified as highly or moderately suitable for cultivation should ideally not overlap with regions of dense, valuable vegetation.

To assess the state of vegetation, the Normalized Difference Vegetation Index (NDVI) serves as a widely recognized tool for evaluating vegetation health and coverage (Tansey et al., 2004). In this study, NDVI values were derived using ERDAS IMAGINE 10, a specialized image processing software, applied to Landsat 8 OLI satellite imagery from 2020, sourced from the USGS Earth Explorer website. This analysis helps in identifying the distribution and density of vegetation across the study area, providing a critical layer of information for integrating with the land suitability map.

4. Findings and Interpretations

4.1 Analysis of Land Use and Land Cover

The analysis of Land Use and Land Cover (LULC) within the study area revealed that grassland is the predominant land cover, accounting for 30% (803.25 km²) of the total area, making it the most extensive cover type identified. This grassland is evenly distributed across the study region. Vegetation, including forests and shrubs, represents the second largest category, covering 27% (738.007 km²) of the area and also features a uniform distribution throughout the research zone.

Urban or built - up areas constitute 9% (240.320 km²) of the land cover, reflecting the human settlements within the study domain. Additionally, water bodies and wetlands make up approximately 14% (387.110 km²) of the total LULC, indicating significant aquatic and semi - aquatic environments within the area. The composite LULC map, which integrates features such as rocky terrain, dense vegetation, and wetlands, underscores the diverse landscape of the study area, as detailed in Table 4.1 of the results section.

Table 4.1: The summary of land use land covers classification

Land Use	Area (sq. km)	Percentage (%)
Built - up areas/settlement	240.32	9
Grassland	803.252	30
Bare/rocky land	537.31	20
Water bodies/drainage	387.11	14
vegetation	737.007	27
Total land area used	2, 704.999	100

Table 4.2: The result of overall accuracy assessment and kappa coefficient

Classified image	Overall accuracy (%)	Kappa coefficient (%)
OLI and TIRS	(3043907/3078836)	0.9127/1.0
	98.8655	91.27

The maps resulting from this land use land covers classification is shown in Figure 3 below.

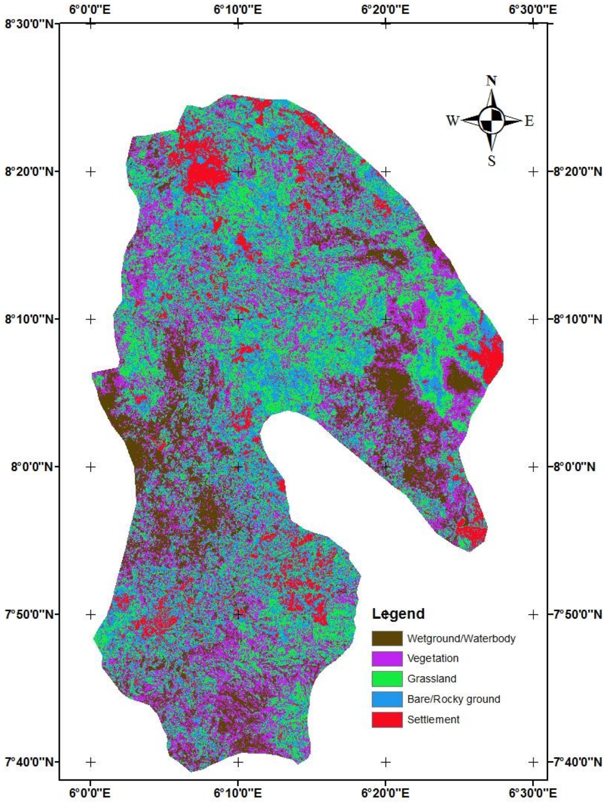

Figure 3: Land use land covers classification map

The reliability of a map derived from remote sensing technology, especially for land use and land cover (LULC) classifications, hinges significantly on the accuracy of its categorization (Bhagat et al., 2009). As shown in Table 4.2, the classification accuracy of the imagery was remarkably high, with an overall accuracy of 98.86% and a Kappa coefficient of 91.27%. This indicates a strong statistical agreement of 91.27% between the ground - truthed pixels and the classified imagery. Moreover, the minimal total error of less than 2% underscores the high precision of the map classification, affirming its reliability.

Jensen et al., (2020) suggest that Kappa coefficient values above 80% reflect a high degree of concordance or accuracy between the classified map and the reference data. In contrast, values ranging from 40% to 80% denote moderate accuracy, and values below 40% signal a low level of agreement. Therefore, the results of this classification process exhibit a high level of accuracy in alignment with the ground - truth data, underscoring the effectiveness of the classification methodology employed.

4.2 Analysis of Soil Types

The soil type analysis within the study area identified Ferric Luvisol and Eutric Nitosol as the two predominant soil categories. Ferric Luvisol was found to be the more extensive of the two, covering a larger portion of the study area. While both soil types are deemed suitable for rice cultivation, Eutric Nitosol has been observed to yield better results in terms of rice production effectiveness compared to Ferric Luvisol (Akpoti et al., 2020). This distinction is visually represented in Figure 4.

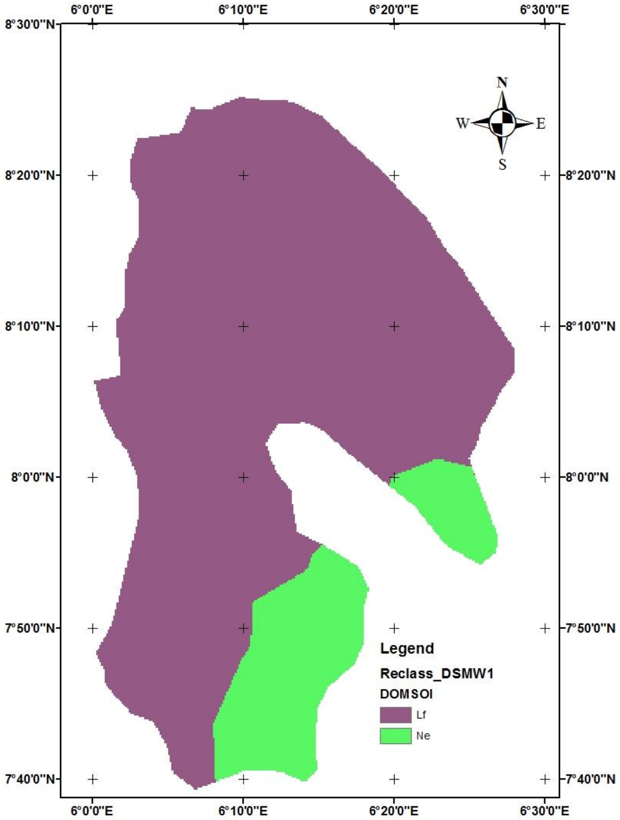

Figure 4: Soil type map

4.3 Temperature Distribution

Figure 5 illustrates the temperature variation within the study area, showcasing the range of thermal conditions. The region's temperatures were categorized into five distinct groups, with the average minimum temperatures starting at 24°C and peaking at an average maximum of 26°C.

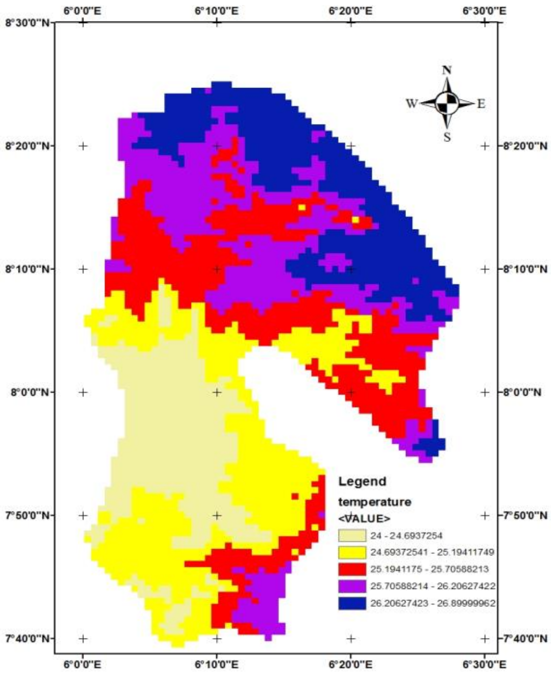

Figure 5: The distribution of temperature value in the study area

4.4 Precipitation Analysis

Within the study area, the highest recorded rainfall for agricultural lands reaches up to 1160mm, while rice cultivation areas specifically experience a maximum rainfall of 600mm. On average, the study region receives about 880mm of rainfall annually. Notably, during the dry season, the rainfall amount drops to 0mm. It's also observed that as elevation increases within the study area, the amount of precipitation tends to decrease, a trend that is clearly depicted in Figure 6.

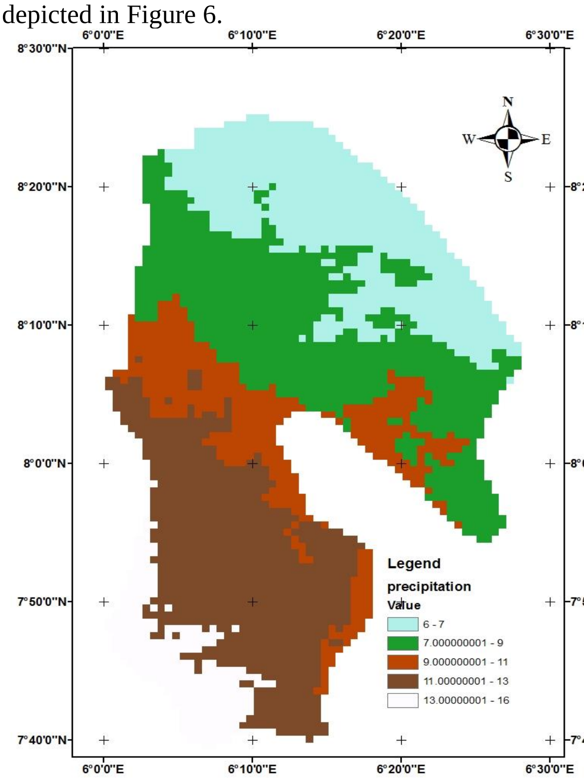

Figure 6: The precipitation of the study area

4.5 Analysis of Terrain Slope

The terrain slope within the study area, as depicted in Figure 7, varies significantly, with measurements ranging from a minimal 0 degrees to a maximum of 35.988 degrees. These measurements have been categorized into five distinct classes to facilitate analysis. The classification begins with the lowest slope value of 0 degrees, indicating the flattest areas within the study region, and extends to the highest recorded slope of 35.988 degrees.

The mapping reveals that a substantial portion of the study area, nearly 90%, is characterized by predominantly flat terrain with slopes of 0 degrees. Additionally, the area encompasses varying degrees of slope inclines: gentle slopes ranging from 3.528 to 6.915 degrees, moderate slopes from 6.915 to 12.701 degrees, and steep slopes extending from 12.701 to 35.988 degrees, further diversifying the topographical features of the research region.

4.6 Soil pH Levels

The optimal soil pH range for effective nutrient uptake by rice plants is approximately 6.6, with a permissible variance between 0.01 to 0.12, or more broadly, between pH 0.2 to 2.0, as outlined by Aondoakaa & Agbakwuru (2012). In this study, soil pH levels were categorized into five distinct groups to reflect the varying acidity levels across the research area. The highest pH category, ranging up to 6.0, covers the largest portion of the study area, indicating predominantly alkaline conditions. The category representing the lowest pH levels falls within the 6.1 to 6.2 range, highlighting areas of the study region with slightly more acidic soil conditions.

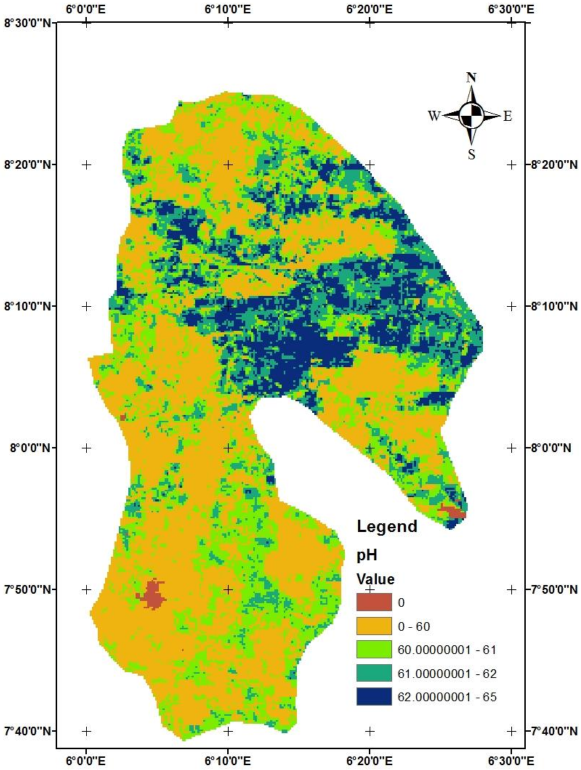

Figure 7: The distribution of pH values in the study area

4.7 Temperature Suitability map

Table 4.3: Spatial distribution of temperature

Temperature	Area converted in Km2	Percentage	Suitability scale
26.21 - 26.90	487.13	18.001	1
25.71 - 26.21	526.23	19.447	2
25.19 - 25.71	612.95	22.651	3
24.69 - 25.19	596.79	22.054	4
24.00 - 24.69	482.88	17.844	5

Figure 8: Temperature suitability map

4.8 Slope suitability map

Table 4.4: Spatial distribution of slope in the study area

Slope	Area covered (Km$^{2)}$	Percentage (%)	Suitability scale
12.701 - 35.988	9.20673841	0.34023424	1
6.915 - 12.701	37.9339075	1.40184433	2
3.528 - 6.915	143.872949	5.3168126	3
1.129 - 3.528	195.850696	7.23764583	4
0 - 1.129	2319.13571	85.703463	5

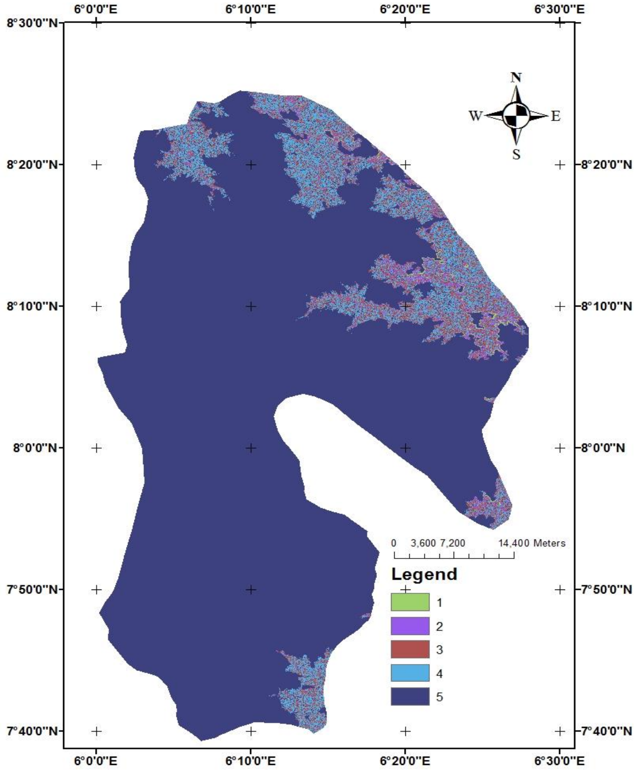

Figure 9: Slope suitability map

4.9 Precipitation suitability map

Table 4.5: Spatial distribution of precipitation

Precipitation	Area covered (Km^2)	Percentage (%)	Suitability scale
6.00 - 7.00	606.810302	22.4246231	1
7.00 - 9.00	781.034548	28.6306533	2
9.00 - 11.00	394.341709	14.5728643	3
11.00 - 13.00	712.194724	26.3190955	4
13.00 - 16.00	211.618719	7.82035176	5

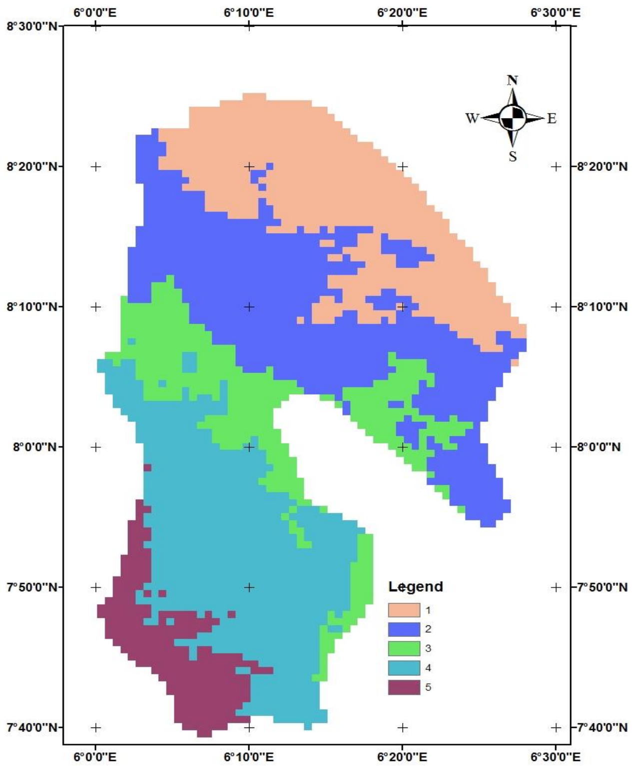

Figure 10: Precipitation suitability map

Paper ID: SR24309115421 DOI: https://dx.doi.org/10.21275/SR24309115421

4.10 Soil pH suitability map

Table 4.6: Spatial distribution of pH

pH	Area covered (Km^2)	Percentage (%)	Suitability scale
6.2 - 6.5	306.966627	11.3439256	1
6.10 - 6.20	469.430514	17.3477648	2
6.00 - 6.10	694.289045	25.6573926	3
0 - 6.0	1223.36058	45.2091862	4
0	11.9532367	0.44173085	5

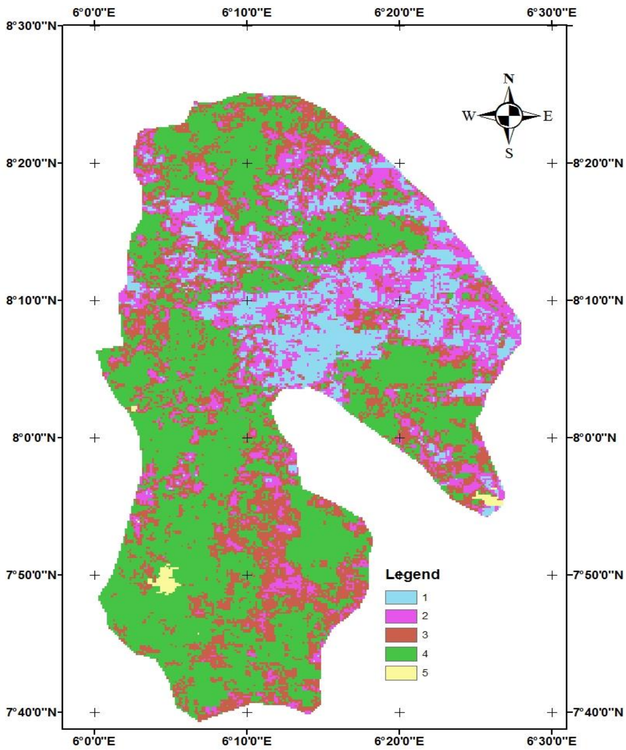

Figure 11: pH suitability map

4.11 Land use land covers suitability map

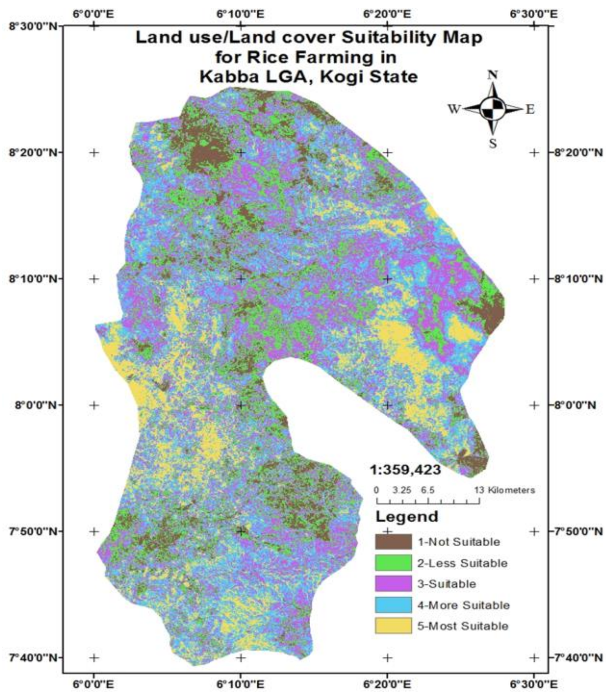

Figure 12: LULC suitability map

4.12 Generation of the Suitability Map

Utilizing the Spatial Analyst tools within ArcGIS 10.1, a weighted sum overlay technique was applied to produce the rice cultivation suitability map, as depicted in Figure 14. The analysis, detailed in Table 4.12, reveals that the most suitable areas for rice cultivation encompass 295, 547 acres, which constitutes 23.15 percent of the entire study area. This finding indicates that a significant portion of the land under investigation holds great potential for rice farming.

Table 4.6: The suitability distribution across the study area

Area (km^2)	Percent (%)	Rice suitability
526.42	19.45	2
1071.75	39.6	3
1074.32	39.7	4
33.492	1.237	5

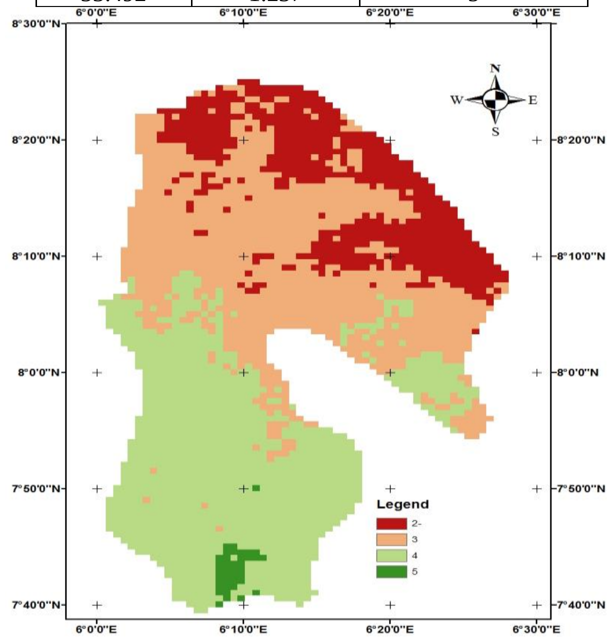

Figure 13: Rice crop suitability map

4.13 Suitability Analysis for Rice Cultivation

The analysis identified areas highly suitable for rice cultivation, characterized by specific environmental conditions: slopes between 0 - 4%, soil depth ranging from 75 - 300m, soil pH from 5.6 to 7.4, clay texture, annual rainfall exceeding 1400mm, and temperatures spanning 20 to 30°C. These criteria align with established agricultural research and were used to define the most suitable zones for rice farming.

Table 4.12 illustrates that a considerable portion of the study area, covering 1074.32 km² or 39.70%, is moderately suitable for rice cultivation. This classification accounts for a large segment of the land, indicating significant potential for rice production. Another noteworthy portion, totaling 1071.75 km² or 39.60% of the area, falls under the 'suitable' category with certain limitations related to rainfall, soil pH, and slope. Due to the challenges in economically addressing these constraints, this classification is less favored for rice cultivation.

Furthermore, a smaller fraction of the study region, encompassing 526.42 km² or 19% of the total area, is deemed not suitable for rice farming.

The distribution of suitability levels reveals that up to 40% of the land exhibits various degrees of suitability for rice production, with the combined area of highly and moderately suitable zones making up 55% of the total study area. This suggests a robust potential for rice cultivation within the region. Therefore, prioritizing rice farming in the most and moderately suitable areas, alongside exploring alternative crops for the suitable zones, could optimize agricultural productivity and economic returns in the region.

5. Conclusion and Recommendations

This study aimed to develop a suitability map for rice cultivation by integrating spatial analytic techniques and a weighted sum overlay approach. By focusing on the topography, climatic conditions, and soil properties of the study area, the research provides valuable insights for local farmers on optimal planting locations. The findings reveal that a significant portion of the study area, particularly in the south, offers moderate suitability for rice farming, presenting opportunities to enhance rice production in the region.

This methodology, which combines Geographic Information Systems (GIS) with Multi - Criteria Decision Making (MCDM) and leverages the Analytic Hierarchy Process (AHP) for decision support, demonstrates its potential applicability across various agricultural planning contexts. This approach could be replicated in other Local Government Areas (LGAs) of Kogi State, supporting the proposition that Kogi could match or surpass Benue State as one of Nigeria's leading rice producers.

The study's outcomes not only serve as a practical guide for farmers but also offer a foundation for further research. Future studies could expand the scope of suitability analysis to include additional factors such as soil fertility and socio - economic conditions. Investigating the long - term sustainability of the land and correlating suitability assessments with existing land use and cover patterns could provide deeper insights into agricultural land management strategies.

To fully realize the potential for rice production in the study area, it is recommended that stakeholders:

- Expand the scope of suitability assessments to encompass a broader range of factors affecting agricultural productivity.
- Conduct detailed analyses of socio - economic conditions to align agricultural strategies with local needs and capabilities.
- Implement sustainable farming practices to maintain soil health and ensure long - term land viability.
- Foster collaboration between researchers, local farmers, and policymakers to translate research findings into actionable farming practices.

By adopting these recommendations, the study area can enhance its rice production capacity, contributing to local economic development and food security.

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