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Land Suitability Analysis for Maize Cultivation Using Remote Sensing Data and Multicriteria Decision Process

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ABSTRACT

The increase in population, urbanisation, mining of solid minerals, excavation, and sand mining for construction purposes are increasingly shrinking and reducing land sizes and shapes for agricultural purposes. However, the identification, location, and suitability of the study area for maize crop production have not been fully explored or documented. Remote sensing data from Landsat 8 OLI were processed to produce layers for the Normalised Difference Vegetation Index (NDVI), Soil Adjusted Vegetation Index (SAVI), Land Surface Temperature, Slope, Land Cover, Digital Elevation Model (DEM), Soil Texture, and Rainfall. These were considered for obtaining the criteria maps, which were used as input into the multicriteria analysis algorithm. The weighted overlay analysis was conducted in a Geographic Information Systems (GIS) environment. The maize suitability map shows that 18.92% of the land is highly suitable, 58.80% is moderately suitable, 12.57% is marginally suitable, and 9.71% is marginally unsuitable. The methodology enabled the identification of land suitable for maize farming and can be considered for sustainable agricultural planning and management. Though the approach provides meaningful insight into maize crop suitability, other methodologies can be explored and compared. In sum, the paper provides a guide for future land-suitability analyses of other crops to ensure food security.

Keywords: AHP, GIS, Land Suitability.

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1. INTRODUCTION

"The source of material wealth", according to Simpson (1976), is land from which we obtain everything that is valuable to use, including metal, precious stones, food, clothing, fuel, and shelter. At death, human remains would be committed to the land for interment. Similarly, for humans to survive, land must be available, and how it is used and distributed is crucial. The significance of land and its worth to humans are encapsulated in Simpson's definition. Given the value of land, it is understandable why families, communities, states, and nations engage in a feud to seize and hold control of it. Along with urbanisation, mining, and population growth, the amount of available land for farming and agriculture has decreased due to rising demand for space and the desire for ownership and acquisition. The effects of climate change have worsened the problems. The first and most crucial step in making the most of the limited land resources for crop farming is to determine whether the land is suitable, given rural-urban drift and the shrinking land space, which has made optimal land utilisation for precision agriculture inevitable.

In Nigeria, maize is one of the main cereal crops. It is a staple of the African diet. It is well known that Nigeria is the second-largest producer of the crop in Africa and a prominent producer worldwide (Wossen *et al*., 2023). In Nigeria, maize is roasted and eaten as a snack, boiled for popcorn, ground into flour, and cooked into morsels with soup. Maize is also used as feed for birds, sheep, and goats. The increase in maize production in the country is very significant to meet the food demand of the ever-growing human and animal populations, particularly in the study area. Aside from effective land planning, relevant and reliable data are needed to identify the most appropriate sites for maize cultivation. The FAO (1976) defines crop suitability analysis as the process of assessing the appropriateness or ability of a given type of land for a particular crop based on the crop's growing conditions. Suitability is a function of crop requirements and land characteristics. It is a measure of how well the qualities of a land unit match the requirements of a particular crop in each area (Shaloo *et al.,* 2022). Remote sensing and biophysical parameters, namely slope, land cover, soil moisture, and texture, are utilised for the assessment of land suitability (Seleshi *et al.,* 2016). Previous studies have extensively applied multicriteria decision-making (MCDM) approaches in agricultural land suitability analysis. For instance, Ayehu *et al*. (2015) used GIS and AHP in Ethiopia to evaluate crop suitability under varying climatic conditions. Pragati *et al*. (2018) applied MCDM techniques for sustainable crop planning in India,

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while Pramanik (2016) integrated GIS-based AHP to assess suitability for multiple crops in South Asia. Similarly, Victor and Samson (2019) employed GIS and decision-support tools in parts of Nigeria to evaluate land suitability for maize. Collectively, these studies demonstrated the value of MCDM and the analytical hierarchy process (AHP) in integrating climatic, soil, and topographic variables to support agricultural planning.

1.1. Research Question

This study was guided by the following research questions:

1. What are the climatic, soil, and topographical requirements for maize cultivation in Kwara State?
2. Which areas in Kwara State are most suitable for maize production when assessed using MCDM-AHP integrated with GIS and remote sensing?
3. How does the integration of vegetation indices (NDVI and SAVI) improve the accuracy of land suitability mapping compared to conventional approaches?
4. What proportion of land in Kwara State falls into highly suitable, moderately suitable, marginally suitable, and marginally not suitable classes for maize cultivation?

These questions provided the basis for systematic evaluation and guided the research's methodological framework.

1.2. Research Objectives

The main aim of this study is to assess the suitability of land for maize cultivation in Kwara State using Multicriteria Decision-Making (MCDM) techniques integrated with GIS and remote sensing.

To achieve this aim, the study is guided by the following specific objectives, which are to:

1. Determine the climatic, soil, and topographical requirements necessary for maize cultivation in Kwara State.
2. Identify and map areas that are most suitable for maize production in Kwara State using the MCDM–AHP approach integrated with GIS and remote sensing techniques.
3. Evaluate how the integration of vegetation indices (NDVI and SAVI) improves the accuracy of land suitability mapping compared to conventional approaches.

4. Classify and quantify the proportion of land in Kwara State into different suitability classes (highly suitable, moderately suitable, marginally suitable, and marginally not suitable) for maize cultivation.

This study utilises the multicriteria decision-making method, the analytical hierarchy process, in conjunction with climatic, topographical, environmental, and soil factors to map and identify areas suitable for maize cultivation in the study area.

1.3. Summary of Literature, Research Gaps, and Justification for the Study

The reviewed literature indicates that integrating Geographic Information Systems (GIS), Remote Sensing (RS), and Multicriteria Decision Analysis (MCDA), particularly the Analytical Hierarchy Process (AHP), has become an essential approach for agricultural land evaluation. Studies such as those by Malczewski (2004), Ziadat (2007), and Kassawmar *et al*. (2022) demonstrate that combining GIS and AHP enables effective evaluation of land suitability by integrating multiple environmental factors, including soil texture, rainfall, slope, elevation, and temperature. These studies also confirmed that GIS–AHP models provide a transparent and replicable decision-making framework for identifying and mapping suitable areas for specific crops.

Despite these advances, the existing literature shows several gaps relevant to the present study. Firstly, while land suitability analysis has been applied to various crops across Nigeria, few studies have specifically focused on maize cultivation in Kwara State, where differences in soil composition, rainfall distribution, and temperature conditions influence yield potential. Secondly, many earlier studies have depended on coarse-scale or outdated datasets and have not incorporated recent satellite-derived variables such as Land Surface Temperature (LST), Normalised Difference Vegetation Index (NDVI), and Soil Adjusted Vegetation Index (SAVI), which are critical for capturing up-to-date biophysical and climatic conditions. Thirdly, although the FAO (1976) framework for land evaluation provides a solid theoretical base, its local adaptation through GIS-AHP integration has not been adequately explored for maize in the study area. Finally, most previous studies end with the generation of suitability maps but do not provide practical recommendations that can guide decision-making for farmers, agricultural planners, and policymakers.

This study was therefore conceived to fill these gaps by integrating current remote sensing data and multicriteria analysis techniques within a GIS framework to evaluate land suitability for maize cultivation in Kwara State. The approach utilises key parameters, including soil texture, rainfall, elevation, slope, vegetation indices, and land surface temperature, to produce a reliable, spatially explicit land suitability map. Unlike many previous works, this study also provides detailed interpretations and recommendations that address the needs of directly concerned stakeholders such as farmers and policymakers. Through this integration, the study not only enhances the methodological approach to land suitability assessment but also contributes to evidence-based agricultural planning and sustainable maize production in Kwara State and similar agro-ecological environments.

2. METHODOLOGY

2.1. Study Area and Research Design

The study was conducted in Ilorin in Kwara State, Nigeria. Kwara State was created on May 27, 1967. Ilorin, the state capital of Kwara State, is located on a latitude of 8º30' and 8º50'N and a longitude of 4º20' and 4º35'E. Ilorin city covers an area of 765 sq km and is situated in the transitional zone between the forest and the guinea savannah regions of Nigeria. The annual rainfall ranges between 1000 mm and 1500 mm, and the general elevation varies between 273 m and 364 m above sea level, and 290 meters above mean sea level. The land surface temperature ranges from 24 °C to 34 °C, and the relative humidity ranges from 65% to 80%, while the state's geology consists of Precambrian basement rocks (Akpenpuum, 2013). It covers an area of approximately 36,835 km2 (14,218 sq. miles) and a population of 3,192,893, based on the 2016 projected population (NBS, 2017). The state has sixteen local governments, namely: Asa, Isin, Irepodun, Ifelodun, Ilorin West, Ilorin East, Ilorin South, Baruten, Moro, Kaima, Oke Ero, Oyun, Offa, Ekiti, Edu, and Pategi.

2.2. Data Collection and Evaluation Criteria for the Study

The study considered a number of significant factors, namely, slope, land use/land cover, elevation, soil type (Ayehu & Besufekad, 2015; Aymen *et al.,* 2020), vegetation indices (NDVI, SAVI), rainfall, and land surface temperature (LST), which were the parameters considered for

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determining whether land was suitable for cultivation. The selection of these criteria was influenced by the literature review.

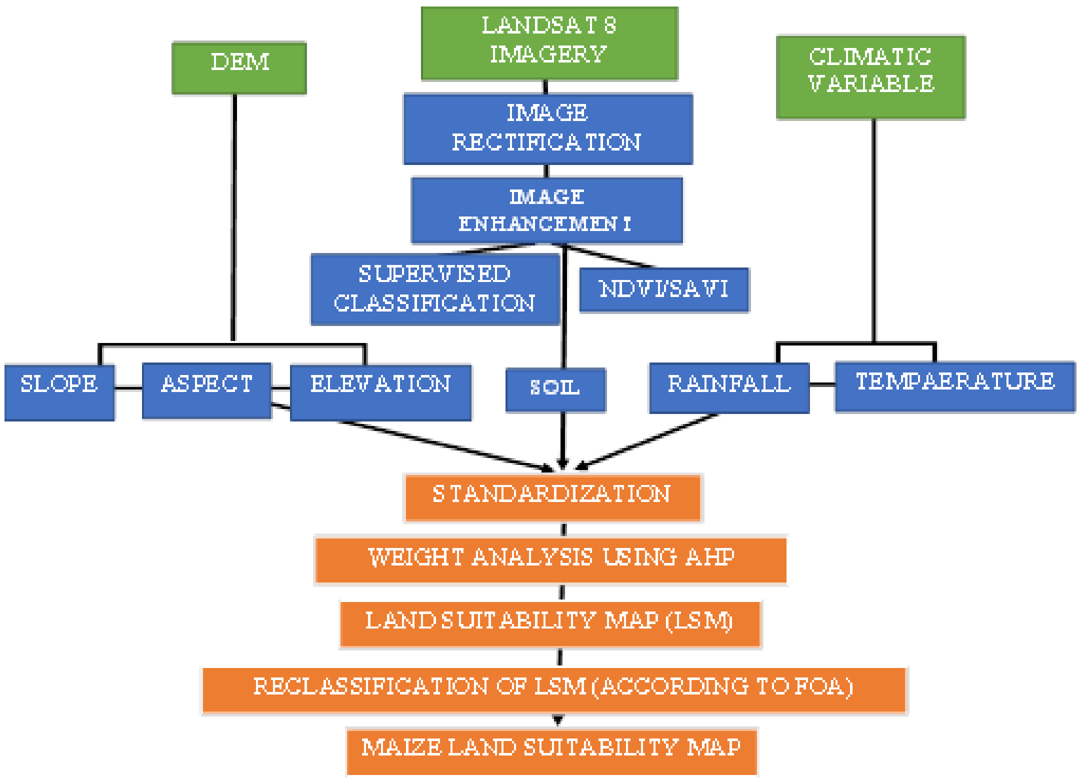
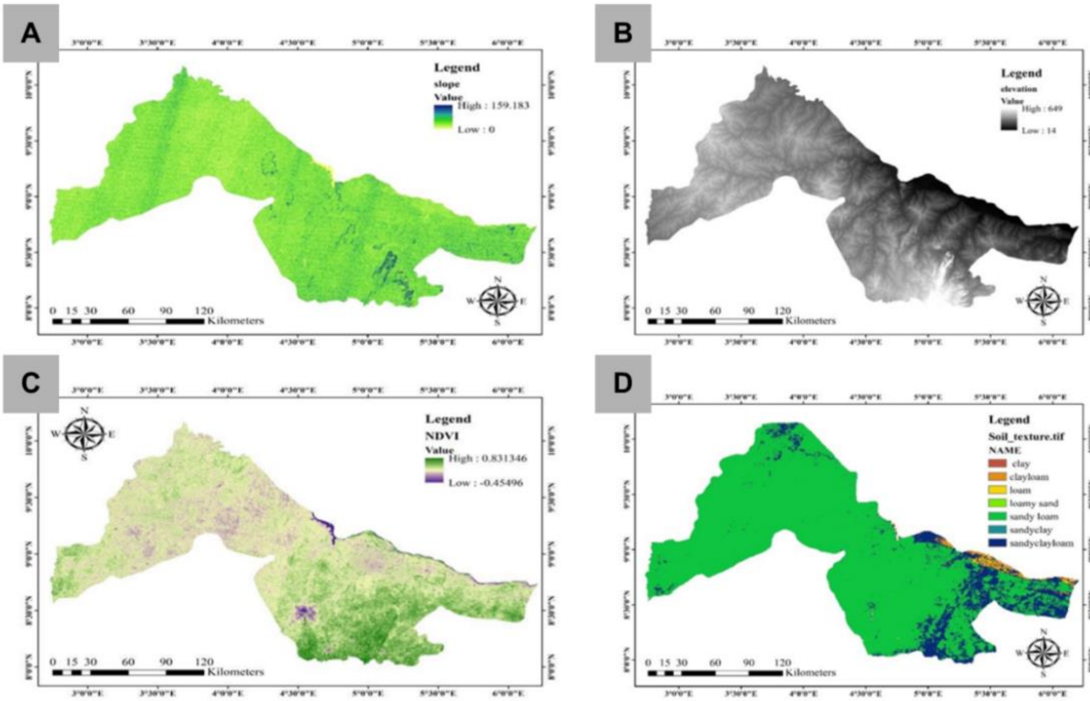


FIGURE 1: Methodology Flow Chart


A
Legend
slope
Value
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Low : 0
0 15 30 60 90 120
Kilometers
B
Legend
elevation
Value
High : 649
Low : 14
Kilometers
C
Legend
NDVI
Value
High : 0.831346
Low : -0.45496
0 15 30 60 90 120
Kilometers
D
Legend
Soil_texture.tif
NAME
clay
clayloam
loam
loamy sand
sandy loam
sandyclay
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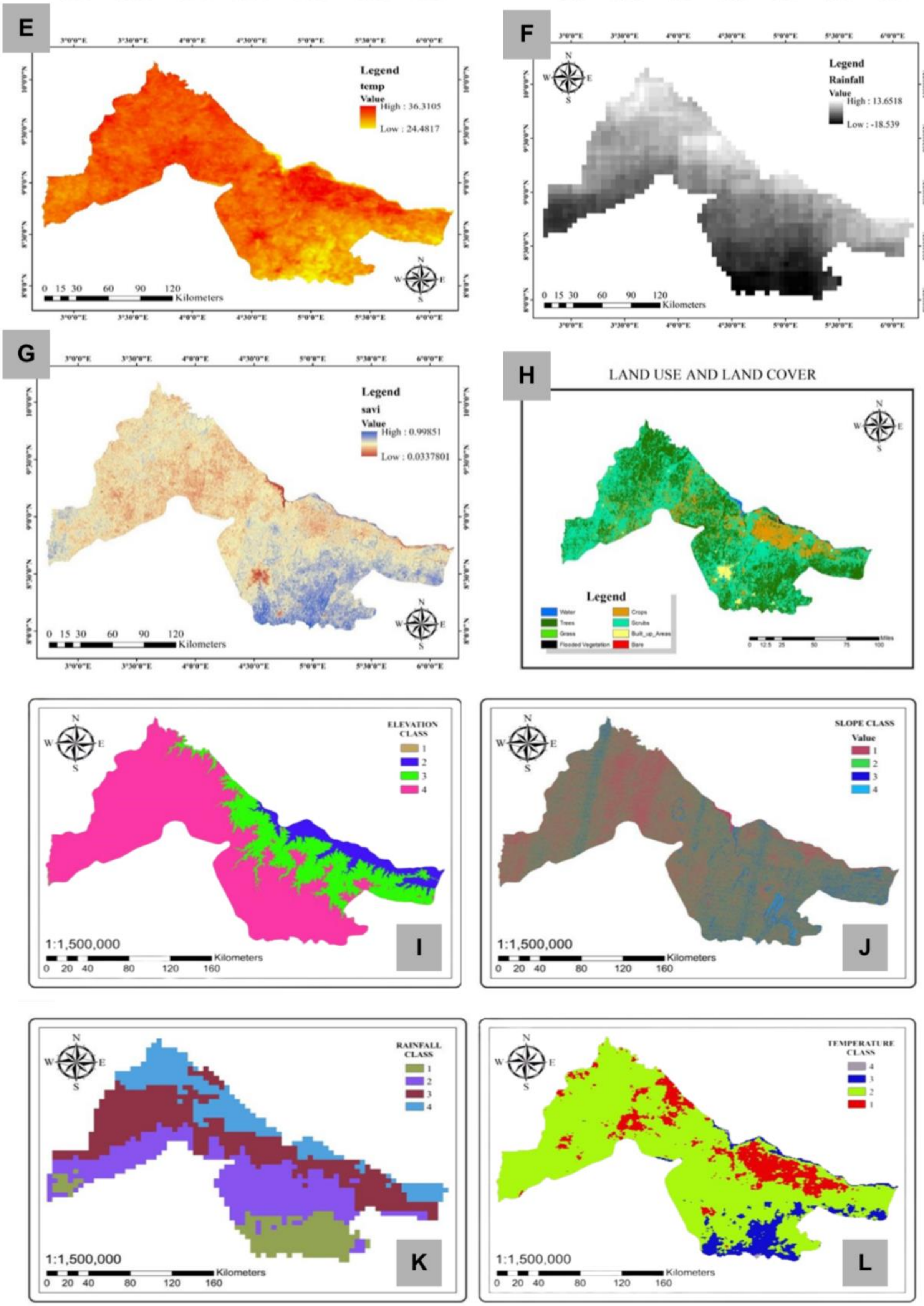
Kilometers


E
Legend
temp
Value
High : 36.3105
Low : 24.4817
0 15 30 60 90 120
Kilometers
F
Legend
Rainfall
Value
High : 13.6518
Low : -18.539
0 15 30 60 90 120
Kilometers
G
Legend
savi
Value
High : 0.99851
Low : 0.0337801
0 15 30 60 90 120
Kilometers
H
LAND USE AND LAND COVER
Legend
Water
Trees
Grass
Flooded Vegetation
Crops
Scrubs
Built_up_Areas
Bare
0 12.5 25 50 75 100
Miles
ELEVATION CLASS
1
2
3
4
1:1,500,000
0 20 40 80 120 160
Kilometers
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SLOPE CLASS
Value
1
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1:1,500,000
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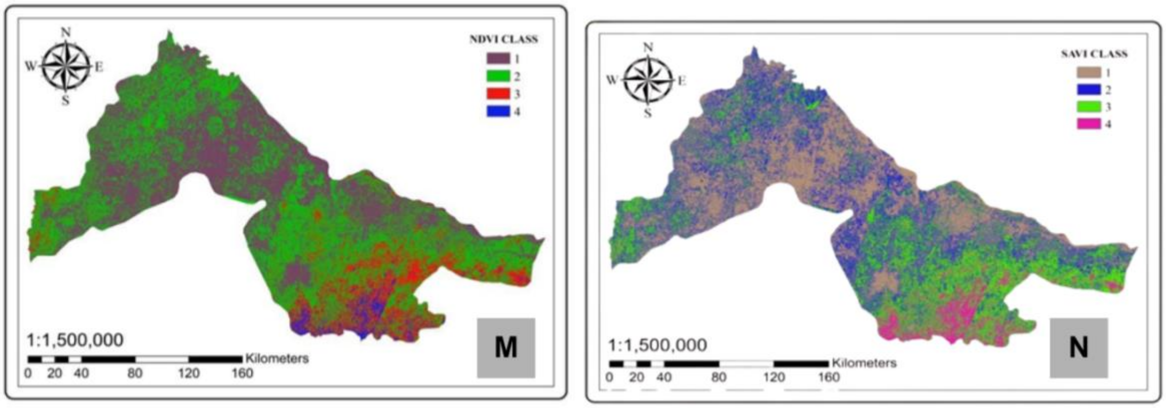

FIGURE 2 (A-N): A= Elevation, B= Slope, C= NDVI, D = Soil, E= Temperature, F =Rainfall, G= LULC, H = SAVI, I=Elevation class, J=Slope class, K=Temperature class, L=Rainfall class, M =NDVI class, N= SAVI CLASS

2.3. Topographical Factors

Elevation and slope were the topographical features used in this study. Slope is a topographic feature in site analysis and suitability prediction when combined with other variables. The USGS provided the 30m spatial resolution DEM data used in this investigation. The slope layer was then created using ArcGIS 10.7's spatial analyst toolbox. It was possible to calculate the proportions of the slopes using the cell output. Every cell in the output raster has a slope value assigned to it, along with a level surface appropriate for growing maize.

2.4. Slope

Slope affects land quality and is one of the factors used to determine whether a given area is suitable for growing crops. Seasonal plants typically require soil that is level, barely sloped, or has a slope of 0 to 6%, and it is not at risk of erosion (Zoleker & Bhagat, 2015). Slope data (DEM) were extracted from the elevation model. The DEM resolution was reduced to 30m.

2.5. Normalised Difference Vegetation Index (NDVI)

The NDVI is a vegetation index that correlates with and generates multiple crop indices and is related to numerous important biophysical parameters (Ahmed *et al.,* 2000). Knowing the amount of vegetative biomass present in the area being sensed or captured in satellite data is essential for crop monitoring. Crop stages can also be ascertained using NDVI data, as stated by Holzka *et al*. (2013). The 96-128-day maize production in Indonesia begins with planting at various dates. In this study, NDVI was extracted from Landsat images for a maize field using temporal data (Figure 2G). NDVI was extracted from Landsat and OLI datasets using a mask to distinguish regions within the Tuban Regency. The NDVI data were averaged over a 5-year window. The data were compared to protect the yield from one statistical dataset. Every year, a simple raster was created. Over the five years of observation, five raster images were created and eventually merged into a single MPR raster.

2.6. Soil Texture

Different locations have different soil qualities. Therefore, understanding the chemical and physical properties of soil is essential for mapping and analysing crop land suitability. Any agricultural crop, including maize, can grow in soil. The physical properties, specifically texture, drainage, and depth soil texture was categorised by the United States Department of Agriculture (USDA) namely sand, loamy sand, sandy loam, silt loam, loam, sandy clay loam, silty clay loam, clay loam, clay, sandy clay, silty clay, and silt clay loam, out of which clay, loam, sandy clay and clay-loam textures of the soil allow maize crop to flourish.

2.7. Climatic Factor

The climate has a major impact on the developmental growth and yields of agricultural crops, particularly maize. The two most important climatic factors considered in this study were temperature and precipitation (Widiatmaka *et al.,* 2016). As a tropical and sub-tropical crop, maize is typically grown in regions with warm temperatures and adequate rainfall. Its land surface temperature ranges from 20 to 28 °C, and the rainfall ranges from 600mm to 1500mm. The region has a good climate with high precipitation.

2.8. Precipitation/Rainfall

Raster data are created by processing rainfall data. Rainfall data from April through August were gathered from the local meteorological station. The analysis of maize production growth stages was conducted using rainfall data over a 12-month period. Rainfall during these growing stages

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varied from 600 to 1500mm. To obtain a single raster, the rainfall data were averaged monthly. Subsequently, the individual raster data were assigned to a weighted rainfall class.

2.9. LULC Processing

This image was produced by a deep learning model that was trained on over 5 billion manually labelled Sentinel-2 pixels and samples from over 20,000 sites located throughout the world's major biomes. The underlying deep learning model uses Sentinel-2 surface reflectance data from six bands: visible blue, green, red, near infrared, and two short-wave infrared bands. The model is executed across multiple data of the gathered imagery, and the results are combined to produce a final map of the year 2020.

2.10. Soil-adjusted Vegetation Index (SAVI)

The spectral signature of soil is distinct from those of the various land cover types. Reflectance rose in the visible and near infrared region in direct proportion to wavelength expansion. For the study area, SAVI was derived from Landsat 8 OLI using a mask. As with the NDVI, the SAVI was also used with a moving average. Based on the observed data, the predicted yield was compared with the moving average. The single raster was constructed using this. The single raster comprised a collection of raster datasets from several years. A single raster was produced for each year. There is also an MPR, like NDVI.

$$SAVI = \frac{p_{NIR} - p_{RED}}{p_{NIR} - p_{RED} + L}(1 + L) \tag{1}$$

2.11. Digital Image Processing

Under this section, feature and image datasets were considered. A 1:50,000 map, including information on temperature, soil type, elevation, distance from rivers, and land cover types, was used for the analysis. This information was acquired using LST, SAVI (Rubaiya *et al.,* 2021), and NDVI data (Purnamasari *et al.,* 2018). Landsat 8 OLI vegetation data, including NDVI and SAVI, were used to monitor crops at the field level.

2.12. Reclassification of Criteria

To understand the raster data, a single value was replaced with the new value or ranges of values were categorised into a single value. For each criterion source map, four categories were assigned. The four classifications were proposed based on appropriateness, with classes being extremely suitable (S1), moderately suitable (S2), marginally suitable (S3) and marginally not suitable (N1). Spatial data, including vector data sets, was processed in ArcGIS 10.7 to create raster layers. The NDVI, SAVI, and LST were computed using multilayer datasets and the moving-average technique.

TABLE 1: Reclassification of Criteria

Parameters	**Highly suitable (S1)**	**Moderately suitable (S2)**	**Marginally suitable (S3)**	**Marginally not suitable (N1)**
Temperature(˚C)	23–28	20–23 & 28– 30	16–20 & 30–34	<16 & > 34
Rainfall/ Precipitation (mm)	800 - 1500	500 – 800	200 – 500	<200
Elevation (m)	<150	150–250	250–400	>400
Slope (%)	0–2	2–6	6–12	>12
Soil factors				
Soil texture	Loam, clay loam, sandy clay and clay	Sandy loam and sandy clay loam	Loam, sandy, silty loam and silty clay loam	Silty clay, sandy, and Silty

2.13. Areas Suitable for Maize Cultivation

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The area suitable for growing maize is determined by analysing land suitability using a variety of classification schemes proposed by the FAO. The suitability classification was developed to determine whether each land unit is eligible for a particular user. The FAO's land appraisal framework assigned the first class a designation of suitable (S) or not suitable (N). The land that is somewhat and poorly suitable for growing maize is then usually designated in practice using the suitability classes, which can then be further divided into three categories (S1), (S2) and (S3) as needed. The evaluation of land suitability was based on criteria and subsequently divided into 4 groups. Ultimately, the classes were determined by applying a weighted overlay, in which the study area was assigned equal weights to maize production. The analytical hierarchy process (AHP) is a decision-making technique based on a range of variables developed by Saaty (1990). At first, we created a hierarchy out of the factors that influence decisions, with a higher class (the Goal), a lower class (the Criteria), and Alternatives. Through the process of pairwise comparison with the AHP, each pair of criteria's degree of importance is evaluated on a scale from 1-9, where 1 denotes "equal" significance of the input parameters.

$$Weighted\ Overlay = \sum_{i=1}^{n} C_i * W_n \tag{2}$$

2.14. Analytical Hierarchy Process (AHP)

The AHP is a method for making choices based on a set of variables developed by Saaty (1990), Malczewski (1999), Zolekar & Bhagat (2015), and Choudhary *et al*. (2023). Initially, the factors involved in decision-making were arranged into a hierarchy with an upper class (goal) and a lower class (criteria) alternative. In AHP, a measure of how significant the input parameters are is examined through the process of pairwise comparison in which the degree of importance of each pair of criteria is valued on a scale of 1–9 (Table 2), where 1 indicates "equal importance", 3 represents "Moderate importance", 5 denotes "Strong importance", while 7 and 9 signify "Very strong/Extreme importance" respectively (Taherdoost, 2018). The eigenvector and eigenvalue (λ_{max}) are obtained from the pairwise comparison matrices. One of the advantages of AHP is that it provides a mechanism for verifying the reliability of the final decision from the pairwise comparison process through the assessment of the consistency ratio (CR), which indicates whether the ratings were randomly generated (Saaty, 2013; Rubayet & Karmaker, 2016). The most difficult stage included selecting the goal. The middle class of the hierarchy is based on the goal's guidelines or standards, while the bottom class is based on other options. The AHP model is carried out within the geographic information system (GIS) environment (Ostvari *et al.,* 2019; Rafal & Abdulhalim, 2023).

TABLE 2: Saaty's Pairwise Comparison Scale

Scale	Compare Factor of I & J
1	Equally important
3	Weakly important
5	Strongly important
7	Very strongly important
9	Extremely important
2,4,6,8	An intermediate value between adjacent scales

The stepwise procedure of AHP is presented as follows:

Step 1: Construct the structural hierarchy.

Step 2: Construct the pairwise comparison matrix.

For instance, the pairwise comparison of attribute I with attribute j yields a square matrix $A_{n\times n}$ where a_{ij} denotes the comparative importance of attribute I with respect to attribute j. In the matrix, $a_{ij} = 1$ when i = j and$a_{ij} = 1/a_{ij}$ (Karim & Karmaker, 2016).

$$A_{n\times n} = \begin{array}{c} \text{Attribute} \\ 1 \\ 2 \\ 3 \\ \cdots \\ \cdots \\ n \end{array} \begin{vmatrix} & & & & & \\ a_{11} & a_{12} & a_{13} & \cdots & \cdots & a_{1n} \\ a_{21} & a_{22} & a_{23} & \cdots & \cdots & a_{2n} \\ a_{31} & a_{32} & a_{33} & \cdots & \cdots & a_{3n} \\ \cdots & \cdots & \cdots & \cdots & \cdots & \cdots \\ \cdots & \cdots & \cdots & \cdots & \cdots & \cdots \\ a_{n1} & a_{n2} & r_{n3} & \cdots & \cdots & a_{nn} \end{vmatrix}$$

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Step 3: Construct a normalised decision matrix.

$$c_{ij} = a_{ij} \, / \sum_{j=1}^{n} a_{ij} \qquad (1)$$

$$i = 1, 2, 3, \ldots\ldots, n, j = 1, 2, 3, \ldots\ldots, n$$

Step 4: Construct the weighted, normalised decision matrix.

$$w_i = \sum_{j=1}^{n} c_{ij} \; / \, n, j = 1, 2, 3, \ldots\ldots, n \qquad (2)$$

$$W = \begin{vmatrix} w_1 \\ w_2 \\ . \\ . \\ w_n \end{vmatrix} \qquad (3)$$

Step 5: Calculate the Eigenvector and Row matrix.

$$E = N^{th}\text{root value} \; / \sum N^{th}\text{root value} \qquad (4)$$

$$\text{row matrix} = \sum_{j=1}^{n} a_{ij} * e_{j1} \qquad (5)$$

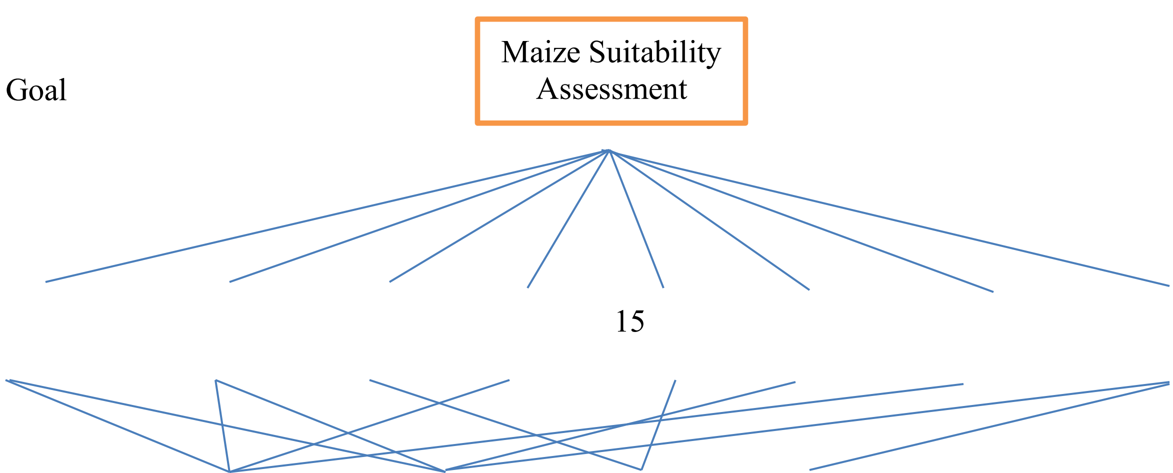
Step 6: Calculate the maximum Eigenvalue, λ_{max}.

$$\lambda_{msax} = \text{row matrix} / \text{E} \qquad (6)$$

Step 7: Calculate consistency index and consistency ratio.

$$CI = (\lambda_{max} - n) \, / \, (\text{n} - 1) \qquad (7)$$

$$CR = CI \, / \, RI \qquad (8)$$



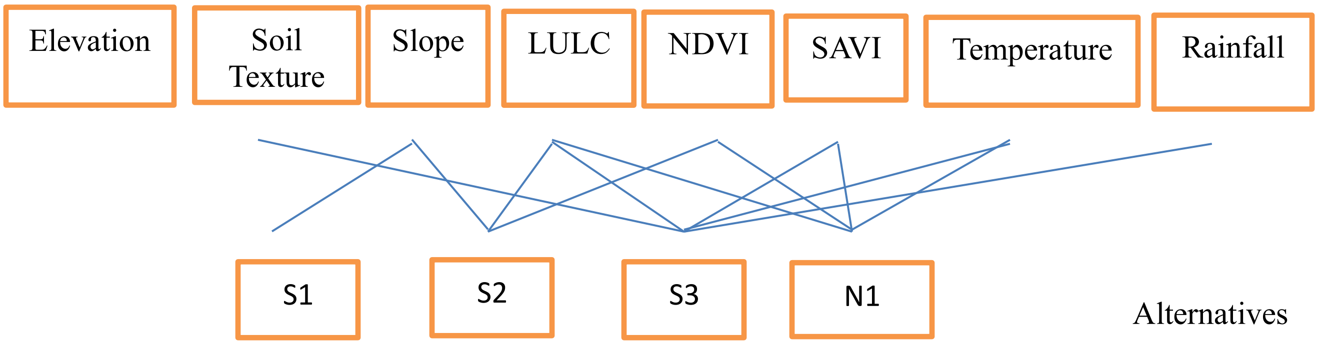


FIGURE 3: The AHP Framework for the Selection of Maize Cultivation

TABLE 3: Weights for Criteria Based on Authors' Pairwise Comparisons

	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**
1	1	0.5	4	1	0.20	1	0.17	2
2	2	1	5	4	2	3	1	4
3	0.25	0.20	1	0.33	0.20	0.25	0.20	0.33
4	1	0.25	3	1	0.25	0.33	0.20	1
5	5	0.50	5	4	1	3	0.25	3
6	1	0.33	4	3	0.33	1	0.20	3
7	6	1	5	5	4	5	1	6
8	0.50	0.25	3	1	0.33	0.33	0.17	1

Principal Eigen value = 8.611

Eigenvector solution: 6 iterations

Priority ranking

These are the resulting weights for the criteria based on the pairwise comparisons. After the matrix pairwise comparison was obtained, factor weights were determined, and the computed weights were presented as the consistency ratio, as shown in Table 4.

TABLE 4: Priority Ranking

Cat		Priority	Rank	(+)

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1	SLP	7.2%	5	2.7%
2	LULC	21.3%	2	7.1%
3	DEM	2.8%	8	1.6%
4	SAVI	5.2%	6	1.6%
5	NDVI	17.2%	3	8.5%
6	TEMP	8.9%	4	3.5%
7	SOIL	32.5%	1	15.9%
8	RF	4.8%	7	1.5%

AHP Scale: 1- Equal Importance, 3- Moderate importance, 5- Strong importance, 7- Very strong importance, 9-Extreme importance (2, 4, 6, 8 values in-between). Number of comparisons = 28, consistency ratio CR = 6.2

3. RESULTS AND DISCUSSION

This section focuses on the discussion of the research results.

3.1. Data Presentation and Analysis

At every significant level, the primary objective of data analysis is to integrate and synthesise spatial data from multiple sources into pertinent information that meets the needs and objectives of decision-makers. The selective search of data within a database is known as data retrieval. Tasks in this category are typically carried out on a single vector or raster and often involve attribute data. The main objective of data analysis is to combine and transform data from diverse disciplinary sources into useful information that meets the requirements of decision-makers at all levels. However, experts must decide which map to use and how to integrate it.

3.2. Land Use and Land Cover Classes in Kwara State

Acquired in 2020, Landsat 8 OLI satellite imagery of land use and land cover, the analysis of land use and land cover resulted in the creation of five classes. Water bodies account for 0.54% (19,762.69ha) of the state's total land area, with the Niger and Asa rivers constituting the majority of these bodies. The vegetation, categorised as Sudan savannah, comprises grassland and forest. Most of the forest is found next to water bodies and is mainly composed of trees, grasses, shrubs, and flooded vegetation. The total area of the forest makes up 33.53% (1,218,904.34 ha), while grasses make up about 42.70% (1,551,755.17 ha). The bare land, which accounts for 14.48% (526,481.40ha) of the total area and is more prevalent, includes rock and sparse vegetation, while the built-up areas make up 8.75% (318, 128.29 ha) of the state, as presented in Table 5.

TABLE 5: Land Use Land Cover

Land use	**Area(ha)**	**%**
Grass	1,551,755.17	42.70
Built-up area	318,128.29	8.75
Water bodies	19,762.69	0.54
Forest	1,218,904.34	33.53
Barren land	526,481.40	14.48
Total	3,635,031.89	100

3.3. Slope Analysis

Using the digital elevation model (DEM), the slope map was generated. There were various grades of slope, from flat to undulating. According to the classification, the slope of the region varies from one place to the next, ranging from 0% to 4%, 4% to 10%, 10% to 15%, 15% to 25%, and greater than 25%.

3.4. Reclassification of Criteria

After the data were entered into the GIS, the criteria were standardised and categorised. According to practice, professional experience, and literature, the applicability of the criteria was evaluated in this study using a linear standardisation scale from 1 to 4, with 1 denoting the highest suitability and 4 the lowest for a maize site. Using the Reclassify Software Package, a Spatial Analyst tool included in the ArcGIS 10.7 toolbox, the criteria were reclassified (assessed).

3.5. Suitability Criteria for Maize

The suitability analysis considered land use/cover, slope, elevation, soil texture, rainfall, temperature, SAVI, and NDVI. Metric weighting was performed while also accounting for other factors, such as slope and land use. The geo-processing model executed the series of commands generated by the AHP model for each characteristic or element, producing the final suitability map. SAVI is an important parameter in soil monitoring. It is a modified form of the normalised difference vegetation index (NDVI). Soil has a distinct spectral signature that differs from that of other land cover types.

Elevations in Kwara state range from 14 to 649 meters. The best height for maize production is between 15 and 125 meters, even if the bulk of the land is suitable for it. The effects of rainfall are more pronounced at higher topographic levels. The elevation data were extracted from the digital elevation model (DEM) at a 30 m resolution. Seasonal plants need flat, gently sloping, or level land with a slope of 0% to 6% that is not prone to erosion. The result shows that areas with Marginally not suitable (N1) elevation occupy 1.32% (46,651.16ha), Marginally Suitable (S3) 11.76% (427,479.75ha), Moderately suitable (S2) 32.46% (1,180,294.85ha), and Highly suitable (S1) 54.46% (1,979,638.37ha).

To extract slope data, a digital elevation model (DEM) was used. The DEM's resolution was reduced to 30 meters. The presence of slopes between 0% and 35% defined the topography's steepness. Since slope gradient is the primary determinant of soil erosion, large soil sediment losses persist after crop cessation when the gradient is relatively steep (4%). The result shows that areas with Marginally not suitable (N1) slope are 1.41%(50047.09ha), while Marginally suitable (S3) is 0.48%(17156.32ha), while Moderately Suitable (S2) is 26.01% (567092.77ha), and Highly Suitable (S1) is 72.10%(1271437.47ha).

Soil texture is the determinant of the potentiality of a soil to hold nutrients, and most of the physical characteristics of the soil depend upon the texture class because it is the relative proportions of the various size groups of individual soil grains in a mass of soil. In this study, the suitability of Maize was assessed, and four soil texture classes (Table 1) were identified in the area: Loam, Clay-loam, Sandy-clay, and Clay. The result shows that areas with Highly Suitable (S1) texture are 20.85% (757,904.15ha), while Moderately Suitable (S2) is 75.29% (2,736,815.51ha), Marginally suitable (S3) is 2.43% (88,331.27ha), and Marginally not suitable (N1) is 1.43% (51,980.96ha).

Temperature was computed for specific maize fields with minimal cloud cover using Landsat 8 OLI image temporal data. From 2000 to 2020, LST values between 15°C and 38°C were recorded from photos, but the highest temperature in the study area occurred in 2014, when temperatures exceeded 32°C. The result shows the area with Highly Suitable temperature as 17.34% and 630,314.514, Moderately suitable as 69.66% and 2,532,163.21, Marginally suitable with 10.43% and 379,133.82, and Marginally not suitable area with 2.57% occupying 93,420.32.

Rainfall levels in the area are classified into 800–1500 mm and 500–800 mm, and these were defined and studied. According to the results, there are 25.11% of Moderately suitable (S2) areas (889,546.30 ha) and 74.89% of Highly suitable (S1) areas (2,652,485.59 ha).

The integrated AHP-based suitability analysis revealed that 18.92% of the land in Kwara State is highly suitable(58.80%), moderately suitable (12.57%), marginally suitable, and 9.71% marginally not suitable for maize cultivation. This outcome indicates that most of the state has favourable environmental and topographic conditions, particularly in areas with gentle slopes, fertile soils, and optimal climatic conditions. The predominance of moderately suitable zones underscores the region’s strong agricultural potential, while the marginal areas highlight the influence of elevation, soil texture, and slope on crop performance.

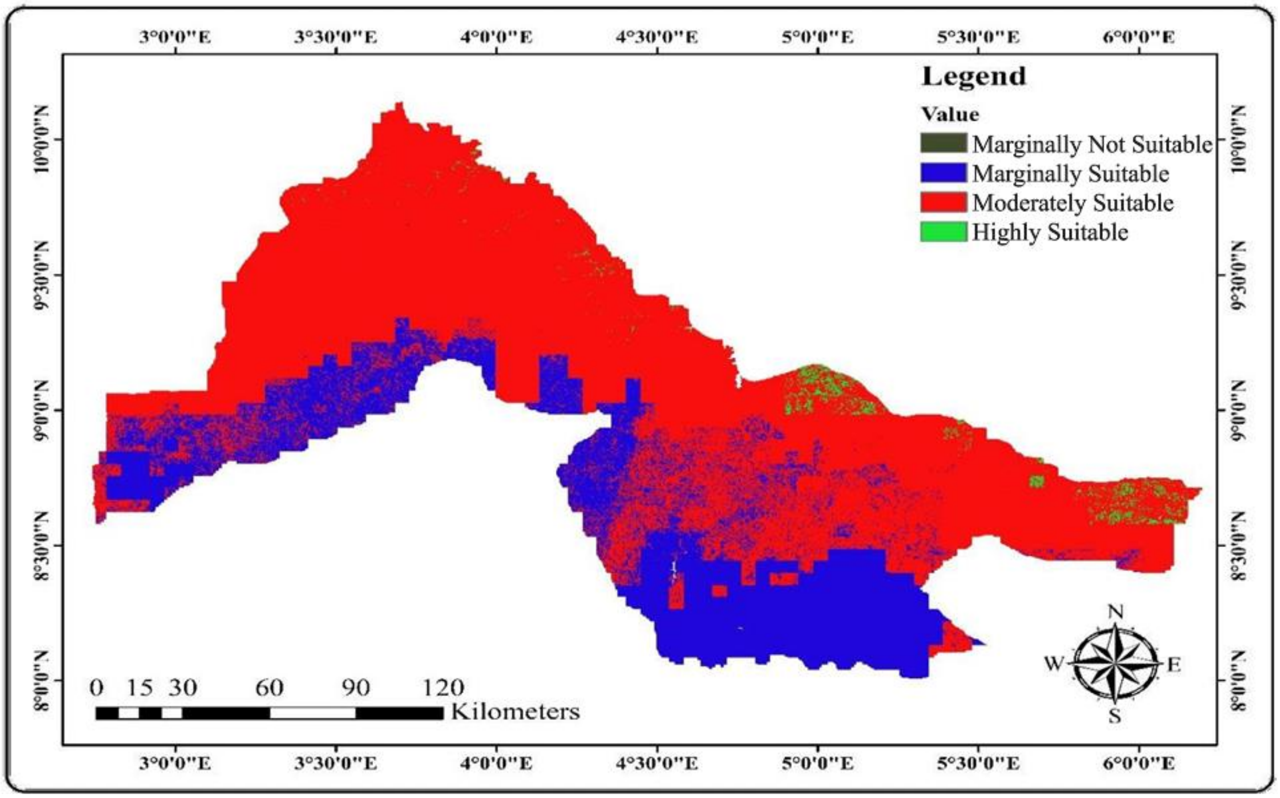

FIGURE 4: Land Suitability Map for Maize Cultivation in Kwara State

3.6. Study Limitations

While this study provides valuable insights into the spatial distribution of land suitability for maize cultivation, it is limited by the temporal resolution of satellite data and the lack of ground-truthing across multiple field sites. Additionally, the analytical hierarchy process (AHP) relies on expert-based weighting, which introduces subjective bias. Future research should integrate field-based validation and explore hybrid approaches combining AHP with machine learning to improve prediction accuracy.

4. CONCLUSION AND RECOMMENDATIONS

This research applied a multicriteria analysis in conjunction with remote sensing data in a GIS environment to identify the most suitable areas for maize production, with a unique focus on integrating eight biophysical and climatic factors and producing a spatially explicit suitability map tailored to the study area. This was done to ensure that maize is cultivated in the most optimal parts of the state and to provide an evidence-based guide to enhance land-use efficiency and support sustainable maize production. The multicriteria decision analysis for the suitability assessment considered eight factors: slope, land use and land cover, elevation levels, soil texture, vegetation indices (NDVI and SAVI), rainfall, and land surface temperature. Based on the findings of this research, 18.92% of the land was highly suitable, 58.80% was moderately suitable, 12.57% was marginally suitable, and 9.71% was marginally not suitable, resulting in an equally weighted land suitability analysis. It is recommended that farmers prioritise maize cultivation in areas classified as highly and moderately suitable, which together account for more than 77% of the state's land area. Cultivating maize in these zones will maximise yields, reduce production risks, and enhance resource efficiency. Farmers are further encouraged to avoid investing in areas identified as marginally suitable or marginally not suitable, as these locations are more likely to result in poor performance and low returns The study demonstrates how AHP, remote sensing data and GIS can be used to provide planners, farmers, and decision makers who are evaluating whether or not to use a given piece of land for agriculture to achieve high productivity and food sufficiency with a thorough and accurate database and sample map. The findings from this study provide an evidence-based tool for guiding agricultural zoning and investment in Kwara State. Integrating these suitability maps into state agricultural policies will not only enhance land-use efficiency but also promote sustainable food production and reduce the risks associated with cultivating maize in marginal or unsuitable zones.

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