RESEARCH ARTICLE

Integration of Gis and Multi-Criteria Evaluation for Land Suitability Assessment of Arable Crops in Ondo State, Nigeria

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Abstract

Agriculture plays a vital role in Nigeria's food security and economy, yet crop productivity depends heavily on land suitability. This study assessed the suitability of land for arable crops in Ondo State using Geographic Information System (GIS) and Multi-Criteria Evaluation (MCE) techniques. Nineteen (19) parameters, including soil, hydrogeomorphological, climatic, land-use/land-cover, and socioeconomic factors, were integrated. Datasets were obtained from sources such as Sentinel-2 Dynamic World, SRTM DEM, MODIS temperature, CHRS rainfall, ISRIC soils, and OpenStreetMap. The criteria were normalised, reclassified, and weighted using the Analytic Hierarchy Process (AHP). Weighted overlay analysis was then performed to generate suitability maps for Maize, Cassava, Yams, Plantain, and Vegetables. Results showed clear spatial variations in suitability. Plantain was the most suitable crop in S1 (12.01%). Maize followed with 7.34% in S1. Yam had the highest percentage (29.88%) in S2, indicating widespread suitability across the state. Cassava dominated in S4 (26.52%) but faced more constraints. Vegetables had the least in S1 (6.72%) and the highest in N (11.67%), making them the least suitable. Final outputs were presented as thematic maps to aid visualisation and decision-making. The study concludes that GIS-based land suitability assessment is a reliable tool for optimising arable crop cultivation in Ondo State. It highlighted highly suitable zones and identified limiting factors; the results provide evidence-based guidance for farmers, policymakers, and agricultural planners. This study recommends adopting the generated maps for land allocation, crop planning, and agricultural policy to improve yields and ensure sustainable land use.

Keywords: land suitability, arable crops, GIS, AHP, Ondo State, crop planning.

1 Introduction

Agriculture is the cornerstone of food security, economic stability, and environmental sustainability. Agriculture is practised worldwide through traditional and modern methods that coexist and evolve [1, 2]. In many developing countries, including

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Nigeria, small-scale subsistence farming remains the predominant mode of production, relying on manual labour, local soil fertility, and rainfall. In contrast, modern commercial farming, prevalent in developed nations, employs advanced machinery, irrigation systems, synthetic inputs, and high-yielding varieties [3]. Over time, agriculture has integrated technology, science, and sustainable practices to meet the demands of a growing global population [4].

The importance of agriculture in Nigeria extends beyond its economic impact. The sector is a crucial source of employment, providing livelihoods for a large share of the population, particularly in rural areas [5]. The agricultural sector grew by 14.88% year over year and accounted for 29.25% of real GDP in the third-quarter GDP Report [6]. Between January and March 2022, it accounted for 22.35% of GDP [7]. Agriculture plays a key role in employment, food security, and rural livelihoods [8]. The agricultural sector in Nigeria faces persistent problems, including soil fertility decline, climatic challenges such as drought and flooding, and complex land ownership issues that hinder effective land use and investment [9, 10]. Addressing these challenges increasingly calls for the integration of climate-smart agricultural technologies and improved soil management strategies [11]. Although technological innovations such as Geographic Information Systems (GIS) and Remote Sensing (RS) have been increasingly applied to address these challenges, a significant knowledge gap persists in their widespread adoption and integration into policy and practice [12–14].

The consequences of these gaps are far-reaching: continued low agricultural productivity, persistent food insecurity, and constrained economic growth, all of which are further compounded by inadequate investment and financing in the agricultural sector [15]. Remote Sensing and GIS offer powerful tools for analysing land use and suitability. Remote sensing provides synoptic, repetitive, and objective landscape data, while GIS integrates multiple datasets such as climate, soil, and topography into a single platform, enabling spatial and temporal analysis. Identifying suitable agricultural areas involves evaluating climatic, soil, and topographical factors and weighting them according to their importance using Multi-Criteria Evaluation (MCE) within GIS [16].

Land suitability refers to the ability of land to sustainably support crop production, guiding decisions on optimal resource use and identifying limiting factors to improve productivity [17]. Globally, the integration of GIS and Multi-Criteria Evaluation (MCE), particularly the Analytical Hierarchy Process (AHP), has become a leading developmental trend for agricultural land suitability assessments. A recent bibliometric analysis by Wijesinghe [18] revealed that GIS-based AHP models account for 43% of published suitability studies, providing highly replicable and scalable frameworks for land evaluation. Within Nigeria, several regional studies have successfully applied these geospatial techniques. For instance, Lamidi and Ijaware [19] conducted a GIS-AHP analysis for non-rice farming in Ekiti State; Omisore et al. [20] completed a geospatial assessment of agricultural land suitability in Osun State; and Taiwo et al. [21] assessed maize suitability in Ekiti State, demonstrating the critical role of combining climatic, topographic, and soil data in guiding agricultural planning.

Despite these advancements, existing studies reveal notable limitations and gaps. Methodologically, many suitability models rely on a highly restricted set of criteria. For example, studies by Zolekar and Bhagat [22] and Lamidi and Ijaware [19] utilised only seven to nine criteria, focusing almost exclusively on basic soils and topography while neglecting socio-economic or comprehensive hydro-geomorphological factors. Furthermore, most existing research in southwestern Nigeria is geographically biased toward Ekiti, Osun, and Oyo states [23, 24], leaving Ondo State significantly under-researched despite its vast agricultural potential. Additionally, previous assessments typically evaluate only one to three crops in isolation, failing to provide a comparative framework for crop diversification. Therefore, assessing land suitability is essential for guiding agricultural extension activities, optimising land use, improving yields, and ensuring food security across Local Government Areas in Ondo State [25].

Ondo State faces significant agricultural challenges due to a lack of information on the suitability of agricultural lands for specific crops. Without adequate land suitability information, farmers frequently cultivate on marginal or degraded lands, contributing to reduced yields, poor crop quality, and heightened exposure to soil degradation, pests, and diseases [26]. In this study, our objectives are I. Examine the soil characteristics and climatic factors for arable crop cultivation in Ondo State; II. Assess and determine site suitability for selected crops in the study area; and

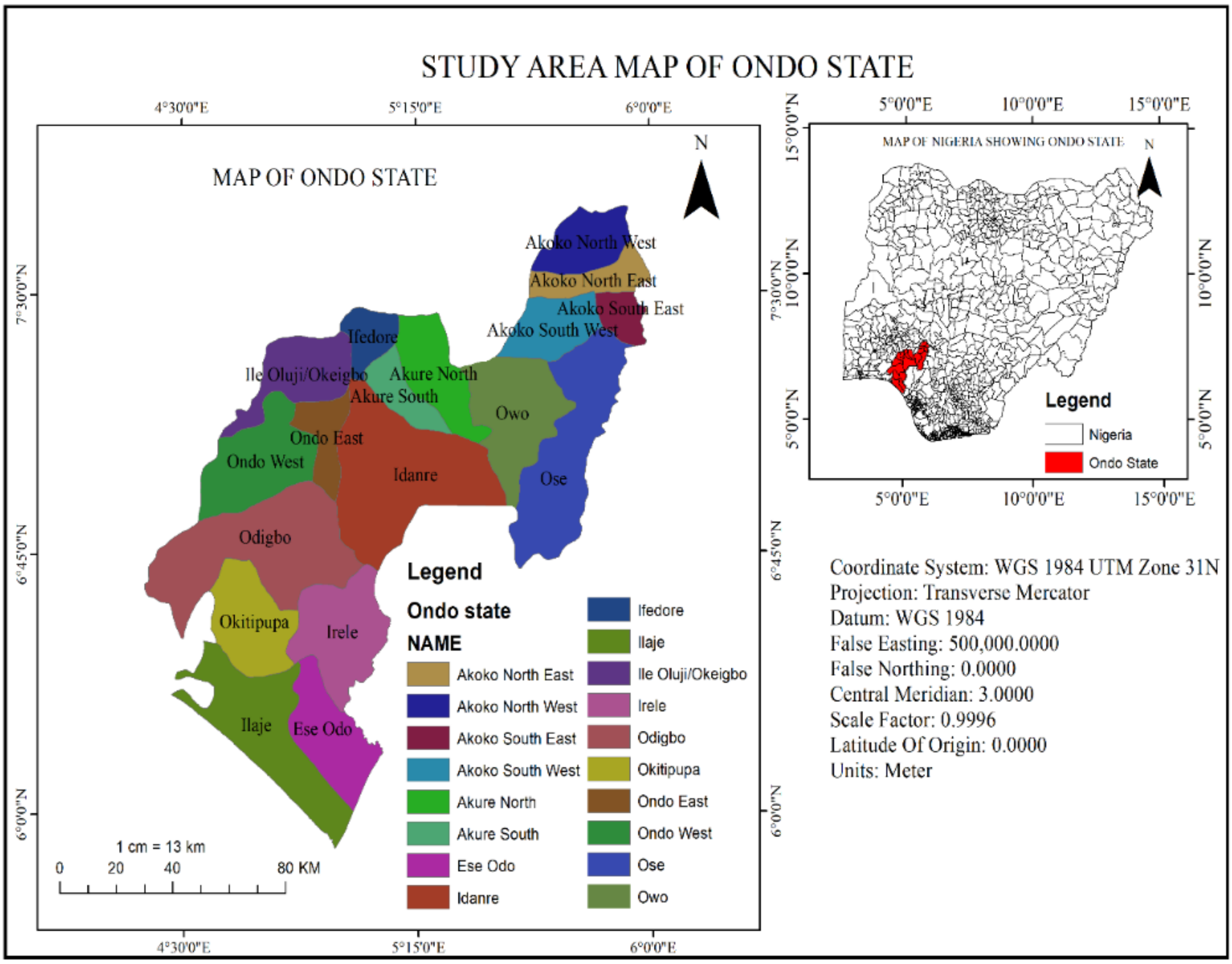

Figure 1. Study area map of Ondo State.

III. Present the results on a map to aid visualisation of suitable areas.

2 Materials and Methods

2.1 Study Area

Ondo State's study area, as shown in Figure 1, is located in southwestern Nigeria, lying approximately between latitudes 4°20′ N and 6°00′ N, and longitudes 5°50′ E and 7°45′ E. It shares boundaries with Ekiti State to the north, Kogi State to the northeast, Edo and Delta States to the east and southeast, Ogun State to the southwest, Osun State to the northwest, and the Atlantic Ocean to the south. The state covers an estimated land area of 15,031.6 km^2, comprising 18 Local Government Areas. Akure is the capital and a major commercial and administrative centre.

The state features diverse landscapes, ranging from mangrove and swamp forests along the coast to the rugged inselberg hills of Idanre, which rise over 1,000 m above sea level, making them the highest topographic points in western Nigeria. Ondo State experiences a tropical climate, characterised by distinct wet (April–October) and dry (November–March) seasons, with annual rainfall ranging from 1,500 to 2,500 mm and average temperatures between 22 °C and 30 °C. These conditions create favourable agro-ecological zones for the cultivation of a wide range of arable and cash crops.

The fertile soils, particularly in the central and southern zones, support crops such as yams (*Dioscorea* spp.), cassava (*Manihot esculenta* Crantz), maize (*Zea mays* L.), cocoa (*Theobroma cacao* L.), plantain (*Musa paradisiaca* L.), and vegetables. However, increasing population pressure, land degradation, and climate variability have heightened the need for a systematic and scientific approach to land allocation. Conducting a GIS-based land suitability assessment is essential for identifying highly productive zones, guiding

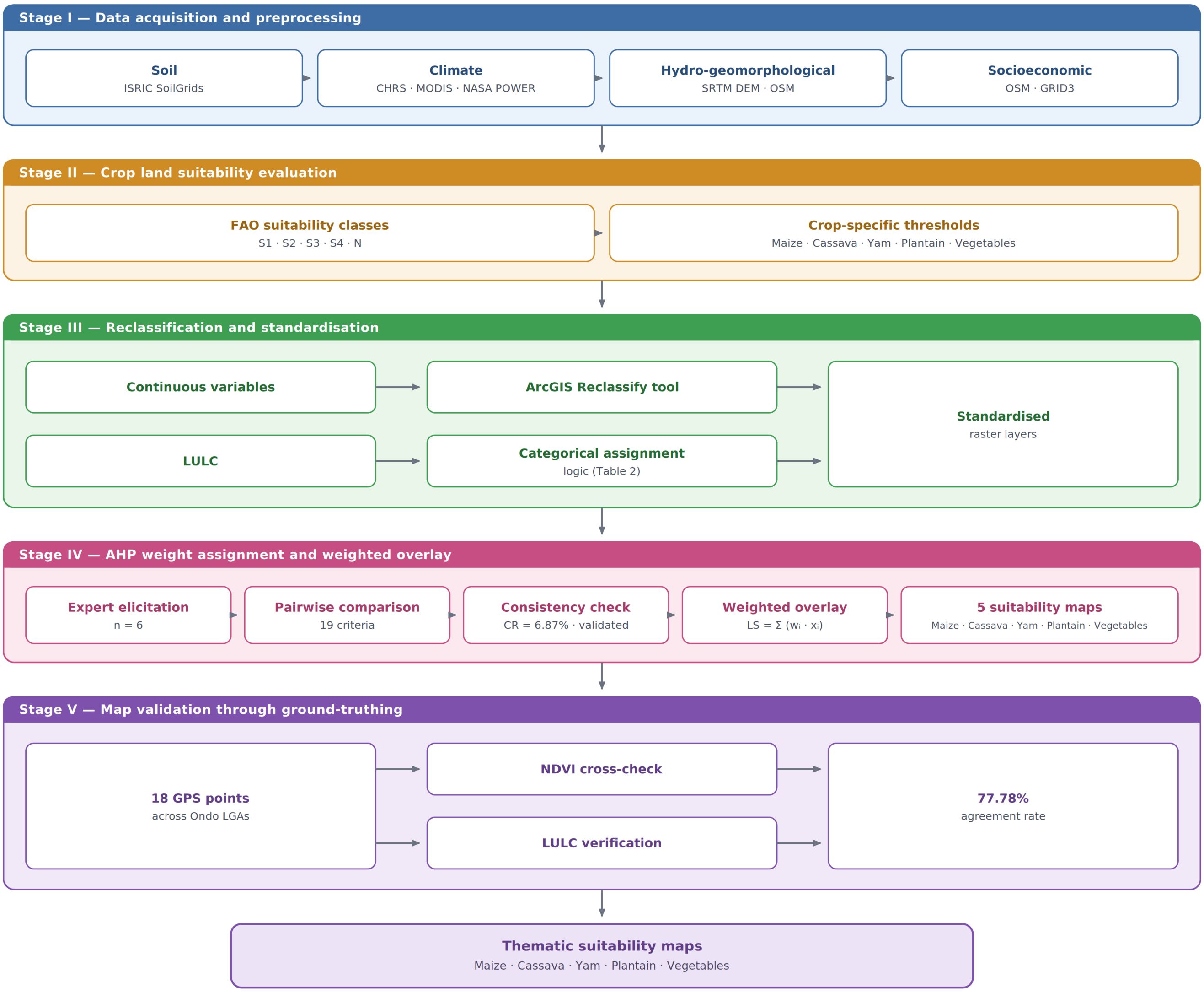

Figure 2. Methodological framework for crop land suitability assessment in Ondo State.

agricultural planning, and ensuring sustainable land management in the state.

2.2 Methodological Framework

The methodology followed five main stages (Figure 2): (i) data acquisition and preprocessing, (ii) Crop Land Suitability Evaluation, (iii) reclassification and standardisation of variables, (iv) AHP-based weight assignment and weighted overlay analysis, and (v) map validation through ground-truthing. The data and methods follow a standard land evaluation framework consistent with FAO guidelines, previous GIS-based suitability studies, and expert recommendations. Following the reclassification, the Analytical Hierarchy Process (AHP) was applied to assign weights to each criterion through pairwise comparisons, and a consistency ratio (CR) was computed to assess the reliability of the resulting weights. The weighted and standardised layers were integrated using the Weighted overlay technique in ArcGIS 10.8 to generate suitability maps for each selected crop. The outputs were classified into FAO suitability categories and presented using thematic maps to aid visual interpretation. Finally, the suitability outputs were validated through field-based ground-truthing across the 18 Local Government Areas of Ondo State to assess the model's predictive agreement.

2.3 Data Acquisition and Preprocessing

In line with typical agricultural land suitability procedures, a total of nineteen (19) variables were identified as key determinants of land suitability for selected arable crops in Ondo State, representing the soil, climate, hydro-geomorphological, socioeconomic, and land cover conditions required for the optimal

Table 1. Summary of geospatial datasets, technical specifications, and Sources used for land suitability modelling in Ondo State.

S/N	Parameter	Data Product	Resolution	Sources	Time
1	Land use and land cover	Sentinel 2	10m	Google Earth Engine Repository[1]	Fixed (2024)
2	Elevation slope	SRTM	30m	Google Earth Engine Repository[2]	Fixed
3	Climate (Precipitation)	CHRS	1km	Centre for Hydrometeorology and Remote Sensing	2014–2024
4	Climate (Temperature)	MODIS Global LST	1km	Google Earth Engine Repository[3]	1/1/2024–31/12/2024
5	Climate (Humidity)	NASA POWER Relative Humidity	2m	NASA	1/1/2024–31/12/2024
6	Soil	ISRIC SoilGrids	250m	ISRIC	Fixed
7	Rivers/surface water	OpenStreetMap (OSM) Water Layer	250m	Open Street Map	Fixed
8	Roads	OSM Road Network	250m	Open Street Map	Fixed
9	Market	GRID3 Market Locations	100m	Grid3	Fixed

[1] https://code.earthengine.google.com/c8c2a023ab1c5227fbe12041f031c83e?noload=1

[2] https://code.earthengine.google.com/c66fd74482463392fc77a0fdcb07bf83

[3] https://code.earthengine.google.com/bd5e453f2dd31c0485366749396f24dd

growth of the five selected arable crops. All datasets were obtained from primary and secondary sources and processed within a GIS environment, as shown in Table 1. The variables were grouped into five major categories representing the critical environmental and socio-economic characteristics influencing crop performance in the study area. Each variable was standardised and reclassified based on crop-specific requirements obtained from the literature, agronomic guidelines, and expert judgment, producing suitability classes consistent with FAO's land evaluation system, namely Highly Suitable (S1), Suitable (S2), Moderately Suitable (S3), Marginally Suitable (S4), and Not Suitable (N) [27].

In the crop-specific suitability analysis, all nineteen (19) biophysical and socio-economic variables were consistently integrated for each of the five selected arable crops. While climatic data were drawn from datasets spanning 2014 to 2024 to capture long-term seasonal patterns, the final discussion of the results is primarily based on environmental and land-cover conditions as of 2024. To ensure compatibility during the weighted overlay process, all thematic layers were harmonised and resampled to a uniform spatial resolution of 30 metres. Bilinear interpolation was applied to continuous variables, and nearest-neighbour resampling was used for categorical variables (LULC) to maintain class integrity. The final suitability maps are constrained by the native resolution of the coarser input datasets, particularly the 250 m SoilGrids and 1 km climatic products, and the spatial accuracy of the final maps is therefore limited by these coarser input resolutions.

2.3.1 *Climatic Variables*

The climatic variables considered in this study include rainfall, temperature, and relative humidity, which are key environmental factors that influence the growth and productivity of arable crops in Ondo State. These variables were obtained from long-term satellite-based climate datasets spanning 2014 to 2024 to capture seasonal variability and multi-year climatic patterns within the study area. Rainfall data were sourced from the Climate Hazards Centre (CHRS) PERSIANN-CDR dataset, which provides daily precipitation estimates at 0.25° resolution, and used to derive mean, minimum, and maximum rainfall values across the study area. Temperature data were obtained from the MODIS Terra and Aqua Land Surface Temperature products at 1 km resolution, from which monthly and seasonal temperature averages were extracted for the study period. Relative humidity data were acquired from the NASA POWER climate database, which provides daily humidity values at 0.5° resolution. These datasets were further aggregated and spatially interpolated to represent climatic conditions relevant to crop growth and were subsequently used as input variables in the multi-criteria evaluation framework to determine the climatic suitability of selected crops in Ondo State.

2.3.2 *Hydro Geomorphological Variable*

The hydro-geomorphologic variables considered in this study include elevation, slope, and distance to rivers, which collectively describe the physical landscape characteristics that influence water flow, drainage, erosion potential, and overall crop performance in Ondo State. These variables were derived from the Shuttle Radar Topography Mission (SRTM) Digital Elevation Model (DEM) with a 30 m spatial resolution, obtained from the United States Geological Survey. The SRTM dataset was selected for its proven reliability in hydrological and terrain analyses, as well as its widespread use in agricultural suitability studies. Slope was derived from the SRTM DEM using standard terrain processing techniques in ArcGIS 10.8, following the procedures described by Jensen [28], and provides critical information on the terrain's steepness and stability. Distance to rivers was computed using the Euclidean Distance tool based on river networks extracted from OpenStreetMap (OSM) datasets, representing the relative proximity of each location to surface water sources, which influences soil moisture availability, flood susceptibility, and irrigation potential.

2.4 Soil Factor

Soil Grids provides global predictions for standard numeric soil properties (organic carbon, bulk density, Cation Exchange Capacity (CEC), pH, soil texture fractions, and coarse fragments) at seven standard depths (0, 5, 15, 30, 60, 100, and 200 cm) [29]. According to Fan et al. [30] and Hag Husein et al. [31], most crop root biomass is located in the upper 30 cm of the soil profile. However, in their study on data-driven multilayer crop suitability prediction, Bhullar et al. [32] found that the median root depth ranged from 8.4 to 19.8 cm. They also emphasised that the model's accuracy improved when a soil depth of 10 cm was considered. In light of these observations, the extracted soil dataset for our study area was limited to depths from 0 to 30 cm. Soil Grids provides predictions with quantified uncertainties, expressed as lower and upper limits of a 90% prediction interval, and an additional uncertainty layer showing the ratio between the inter-quantile range and the median. It includes various soil properties:

1. Physical Properties: I.Bulk Density g/cm^3, Soil Texture (%), Soil Root Zone (cm), Soil Water Capacity at -33kpa.

2. Chemical Properties: Soil pH, Soil Nitrogen (mg/kg), Soil Phosphorus (mg/kg), Soil Potassium (mg/kg), Soil Calcium (mg/kg).

3. Biological Properties: Soil Organic Carbon (SOC) (g/kg), at depth 0-30 cm.

2.4.1 *Socioeconomic Variables*

The socioeconomic variables considered in this study include proximity to market and distance to major roads, both of which are essential to determining market accessibility, transportation networks, and the ease of distributing agricultural produce within Ondo State. These variables also provide insight into the availability of farming inputs, agricultural extension services, and labour, all of which influence the overall suitability of land for arable crop production. The road network dataset was sourced from OpenStreetMap, and the market dataset was sourced from grid3. Both were processed in ArcGIS 10.8 to generate Euclidean distance surfaces, following the established GIS distance modelling procedures described by Esri [33].

2.4.2 *Vegetation Variables*

The vegetation variable considered in this study is the Land Use/Land Cover (LULC) layer, which provides essential information on the distribution and characteristics of land surface features relevant to agricultural suitability in Ondo State. The LULC dataset was obtained from the Sentinel-2 Dynamic World product, developed by Google and the World Resources Institute, which provides near-real-time land-cover classification at a 10 m spatial resolution, derived from machine-learning techniques applied to Sentinel-2 imagery [34]. This dataset was used to identify land cover types that directly influence the availability and productivity of agricultural land, while filtering out features that constrain cultivation, such as built-up areas, dense forest cover, wetlands, and water bodies. After incorporating LULC into the Analytic Hierarchy Process (AHP), only areas with land cover classes suitable for crop production were retained in the final suitability evaluation. This variable provides critical insight into existing land-surface conditions and supports accurate identification of agriculturally viable areas across Ondo State.

2.5 Crop Land Suitability Evaluation

The study focused on identifying suitable areas for arable crop cultivation. The factors were compared with a standard range of conditions, and the resulting ranges were categorised as S1, S2, S3, S4, and N. The cropland suitability evaluation in this study combined literature-derived criteria with expert judgment to accurately assess the agricultural potential of land for arable crop production in Ondo State. A detailed literature review identified relevant factors influencing crop growth. This process was implemented using the Analytical Hierarchy Process (AHP), which employs pairwise comparisons of criteria to quantify their relative importance within the suitability assessment framework, following the decision-making guidelines established by Saaty [35].

In line with the Food and Agriculture Organisation land evaluation framework [27], five suitability classes were defined to reflect the degree to which each location can support sustainable crop production. These classes include Highly Suitable, Suitable, Moderately Suitable, Marginally Suitable, and Unsuitable. Highly Suitable land has minimal or no limitations and requires no significant additional inputs for optimal productivity. Suitable land has minor constraints but still supports effective crop growth with relatively low management inputs. Moderately Suitable land is characterised by more pronounced limitations that may significantly affect productivity and require substantial adjustments to inputs to achieve acceptable yields. Marginally Suitable land presents severe limitations that challenge sustainable agricultural utilisation and demand disproportionately high inputs relative to expected output. The Unsuitable class comprises areas where environmental, physical, or socioeconomic constraints are so severe that sustainable crop production cannot be achieved regardless of input levels.

There are many thresholds; for instance, cassava thrives in warm tropical conditions, requiring an optimal temperature range of 25–32 °C, with growth continuing above 32 °C. It performs best under moderate, non-erratic rainfall ranging from 400–1,700 mm, or 800–1,700 mm according to FAO standards [36, 37]. Maize, on the other hand, is highly adaptable, growing within a broad temperature range of 15–32 °C, with an optimum of 21–32 °C, and requiring between 300–1,600 mm of rainfall annually, although approximately 900 mm is often regarded as suitable for stable production [38, 39]. Yam cultivation is favoured in consistently warm environments with an optimum temperature of about 27 °C (within an 8 °C range), and it thrives under rainfall of 1,000–1,200 mm, which can extend to 1,200–1,800 mm depending on the species and soil conditions [40, 41]. These and other thresholds formed the basis for the factor reclassification used in the suitability analysis for this study.

2.6 Data Reclassification and Standardisation

Following the acquisition of the nineteen parameters, each variable was standardised into five suitability classes based on the FAO land evaluation framework: Highly Suitable (S1), Suitable (S2), Moderately Suitable (S3), Marginally Suitable (S4), and Unsuitable (N). This standardisation was essential for transforming heterogeneous spatial datasets, ranging from soil chemical properties to topographic gradients, into a uniform scale for Multicriteria integration. The comprehensive reclassification criteria and numerical thresholds for all variables across the five selected crops are detailed in Appendix (Tables A1, A2, A3, A4 and A5).

2.6.1 Reclassification of Continuous Variables

For continuous datasets, including climatic factors, hydro-geomorphological parameters, and soil characteristics, reclassification was performed using the Spatial Analyst Reclassify tool in ArcGIS 10.8. Numerical class boundaries were established by aligning the environmental attributes of Ondo State with the specific physiological requirements of each crop (Maize, Cassava, Yam, Plantain, and Vegetables), as synthesised from the agronomic literature. The

Table 2. Reclassification Logic for LULC Categories.

LULC Class (Sentinel-2)	Suitability Rank	Logic / Description
Crops	S1 (Highly Suitable)	Areas currently under active cultivation, indicating favourable soil, terrain, and climatic conditions for arable farming.
Trees	S2 (Suitable)	Forests or plantations that can potentially be converted to agricultural land, though they may require clearing and management.
Bare land	S3 (Moderately Suitable)	Exposed or sparsely vegetated areas that may require soil improvement, irrigation, or erosion control before cultivation.
Flooded vegetation	S4 (Marginally Suitable)	Seasonally or permanently waterlogged areas with drainage limitations constrain crop growth.
Built-up / Water	N (Unsuitable)	Urban areas and water bodies are unavailable for agricultural use.

specific application of these Continuous Variables within individual crop models is further detailed in the crop-specific suitability tables provided in the Appendix (Tables A1, A2, A3, A4 and A5).

2.6.2 *Reclassification of Land Use/Land Cover (LULC) Data*

The reclassification of LULC data from the Sentinel-2 Dynamic World dataset used categorical assignment logic to distinguish viable agricultural land from areas subject to physical or environmental constraints. This specific procedure follows a hierarchical priority based on existing land status and ease of conversion. The categorical reclassification for LULC is summarised in Table 2.

2.7 Analytic Hierarchy Process (AHP) and Expert Elicitation

The Analytic Hierarchy Process (AHP), developed by Saaty [35], was used in this study to assign quantitative weights to the nineteen (19) criteria influencing land suitability for arable crop production in Ondo State. AHP converts qualitative expert judgments into numerical priority weights by systematically comparing criteria through a structured pairwise assessment procedure [35]. The method is well established in GIS-based land suitability research and has been validated across multiple Multicriteria agricultural studies [42–46]. To ensure multidisciplinary robustness, an expert elicitation process was conducted involving a panel of six (6) specialists.

2.7.1 *Expert Panel Composition, Data Collection, and Weight Aggregation*

The expert panel of six specialists was intentionally segmented by domain to ensure each criterion was assessed by the most qualified evaluators: three geospatial specialists from the Department of Surveying and Geoinformatics (FUTA) evaluated LULC, elevation, slope, and climatic factors; two agronomic specialists from the Department of Crops, Soil, and Pest Management (FUTA) assessed the ten soil-related parameters including pH, texture, bulk density, and nutrient content; and one official from the Ondo State Ministry of Agriculture evaluated market proximity and road accessibility. Judgment data were collected via a structured digital questionnaire using Saaty's 1–9 scale, and within each domain-specific expert group, individual pairwise judgments were aggregated using the geometric mean method, which is the standard Aggregation of Individual Judgments (AIJ) approach [47, 48] where n reflects the number of experts per group (n = 3 for geospatial criteria; n = 2 for soil criteria). The Ministry official's socio-economic judgments were applied directly as a single-expert assessment requiring no aggregation, and the three domain-specific aggregated sub-matrices were subsequently assembled into the final consolidated decision matrix shown in Figure 3.

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
1	1	1.00	2.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	3.00	2.00	2.00	5.00	6.00
2	1.00	1	1.00	1.00	2.00	2.00	1.00	2.00	2.00	2.00	2.00	2.00	2.00	1.00	3.00	3.00	2.00	4.00	5.00
3	0.50	1.00	1	1.00	1.00	1.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	2.00	3.00	4.00	4.00	4.00	5.00
4	1.00	1.00	1.00	1	3.00	4.00	5.00	4.00	4.00	4.00	4.00	4.00	4.00	5.00	4.00	5.00	5.00	5.00	6.00
5	1.00	0.50	1.00	0.33	1	1.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	4.00	4.00	3.00	4.00	5.00	6.00
6	1.00	0.50	1.00	0.25	1.00	1	1.00	1.00	2.00	2.00	2.00	2.00	2.00	2.00	3.00	3.00	3.00	3.00	4.00
7	1.00	1.00	0.33	0.20	0.33	1.00	1	1.00	2.00	2.00	2.00	2.00	2.00	3.00	3.00	2.00	4.00	4.00	5.00
8	1.00	0.50	0.33	0.25	0.33	1.00	1.00	1	3.00	3.00	3.00	3.00	3.00	3.00	4.00	4.00	3.00	4.00	5.00
9	1.00	0.50	0.33	0.25	0.33	0.50	0.50	0.33	1	3.00	3.00	3.00	3.00	3.00	4.00	4.00	3.00	4.00	5.00
10	1.00	0.50	0.33	0.25	0.33	0.50	0.50	0.33	0.33	1	1.00	1.00	1.00	2.00	3.00	4.00	4.00	2.00	3.00
11	1.00	0.50	0.33	0.25	0.33	0.50	0.50	0.33	0.33	1.00	1	1.00	1.00	2.00	3.00	4.00	4.00	2.00	3.00
12	1.00	0.50	0.33	0.25	0.33	0.50	0.50	0.33	0.33	1.00	1.00	1	1.00	2.00	3.00	3.00	3.00	3.00	4.00
13	1.00	0.50	0.33	0.25	0.33	0.50	0.50	0.33	0.33	1.00	1.00	1.00	1	2.00	2.00	4.00	4.00	3.00	4.00
14	1.00	1.00	0.50	0.20	0.25	0.50	0.33	0.33	0.33	0.50	0.50	0.50	0.50	1	3.00	3.00	4.00	5.00	6.00
15	0.33	0.33	0.33	0.25	0.25	0.33	0.33	0.25	0.25	0.33	0.33	0.33	0.50	0.33	1	1.00	4.00	3.00	4.00
16	0.50	0.33	0.25	0.20	0.33	0.33	0.50	0.25	0.25	0.25	0.25	0.33	0.25	0.33	1.00	1	1.00	3.00	4.00
17	0.50	0.50	0.25	0.20	0.25	0.33	0.25	0.33	0.33	0.25	0.25	0.33	0.25	0.25	0.25	1.00	1	3.00	4.00
18	0.20	0.25	0.25	0.20	0.20	0.33	0.25	0.25	0.25	0.50	0.50	0.33	0.33	0.20	0.33	0.33	0.33	1	2.00
19	0.17	0.20	0.20	0.17	0.17	0.25	0.20	0.20	0.20	0.33	0.33	0.25	0.25	0.17	0.25	0.25	0.25	0.50	1

Figure 3. Final consolidated decision matrix.

2.7.2 *Weight Derivation Procedure*

The final criterion weights were derived from the consolidated pairwise comparison matrix using a seven-step mathematical procedure based on the normalised matrix row-average approach, which approximates the principal eigenvector [35]. This procedure produces two distinct outputs that serve different purposes: the priority weights (Steps 1–5), which are used directly in the weighted overlay analysis, and the consistency assessment metrics (Steps 6–7), namely the principal eigenvalue λmax and Consistency Ratio (CR), which serves exclusively as a post-derivation quality control check on the logical coherence of the expert judgements; it does not derive or alter the weights in any way.

I. We constructed the Pairwise Comparison Matrix (A), which is a 19×19 square matrix $A = [a_{ij}]$, where a_{ij} represents the relative importance of criterion i over criterion j as judged by the expert panel using Saaty's 1–9 scale. Diagonal elements satisfy $a_{ii} = 1$. For $n = 19$ criteria, this required $n(n-1)/2 = 171$ unique pairwise judgements. The full consolidated decision matrix is shown in Figure 3.

II. We then apply the Reciprocity Rule. The lower triangle of the matrix was completed using the reciprocal rule, as shown in Eq. (1).

$$a_{ij} = \frac{1}{a_{ji}} \tag{1}$$

III. We then Calculated Column Sums (C_j). The sum of all values in each column j was computed using Eq. (2).

$$C_j = \sum_{i=1}^{n} a_{ij} \tag{2}$$

Each C_j represents the total importance mass of that column and serves as the denominator for the normalisation step.

IV. We Normalised the Matrix. Each element was divided by its respective column sum, using Eq. (3).

$$\bar{a}_{ij} = \frac{a_{ij}}{C_j} \tag{3}$$

After this step, every column in the normalised matrix sums to exactly 1.0, placing all criteria on a common dimensionless scale.

V. We Computed the Priority Weights (w_j). The priority weight for each criterion was derived as the row average of the normalised matrix using Eq. (4).

$$w_i = \frac{1}{n} \sum_{j=1}^{n} \bar{a}_{ij} \tag{4}$$

where $n = 19$, these row averages constitute an approximation of the principal eigenvector of the matrix and represent the priority weight for each criterion.

VI. We determined the Principal Eigenvalue ($\lambda_{\max}$). Once weights were derived, the principal eigenvalue was computed as seen in Eq. (5).

$$\lambda_{\max} = \frac{1}{n} \sum_{i=1}^{n} \frac{(Aw)_i}{w_i} \tag{5}$$

where $(Aw)_i$ is the i-th element of the vector produced by multiplying matrix A by the weight vector w. For a perfectly consistent matrix, $\lambda_{\max}$ equals n exactly; inconsistency raises $\lambda_{\max}$ above n. In this study, $\lambda_{\max} = 20.979$.

VII. We concluded by computing the Consistency Ratio (CR). The CR was calculated as the final quality check

Table 3. AHP Priority Weights for the 19 Land Suitability Criteria.

S/N	Criterion	Category	Priority Weight	Weight (%)	Rank
1	Precipitation	Climate	0.141	14.1%	1
2	Slope	Hydro-Geomorphological	0.094	9.4%	2
3	Temperature	Climate	0.093	9.3%	3
4	Elevation	Hydro-Geomorphological	0.076	7.6%	4
5	Soil Texture	Soil	0.071	7.1%	5
6	Relative Humidity	Climate	0.062	6.2%	6
7	LULC	Land Cover	0.061	6.1%	7
8	Soil pH	Soil	0.060	6.0%	8
9	Bulk Density	Soil	0.060	6.0%	9
10	Soil Calcium	Soil	0.039	3.9%	10
11	Soil Nitrogen	Soil	0.039	3.9%	11
12	Soil Phosphorus	Soil	0.039	3.9%	12
13	Soil Potassium	Soil	0.038	3.8%	13
14	Soil Depth	Soil	0.038	3.8%	14
15	Soil Organic Carbon	Soil	0.023	2.3%	15
16	Soil Water Holding Capacity	Soil	0.020	2.0%	16
17	Distance to River	Hydro-Geomorphological	0.019	1.9%	17
18	Distance to Road	Socio-economic	0.014	1.4%	18
19	Distance to Market	Socio-economic	0.011	1.1%	19
TOTAL			**1.000**	**100%**	

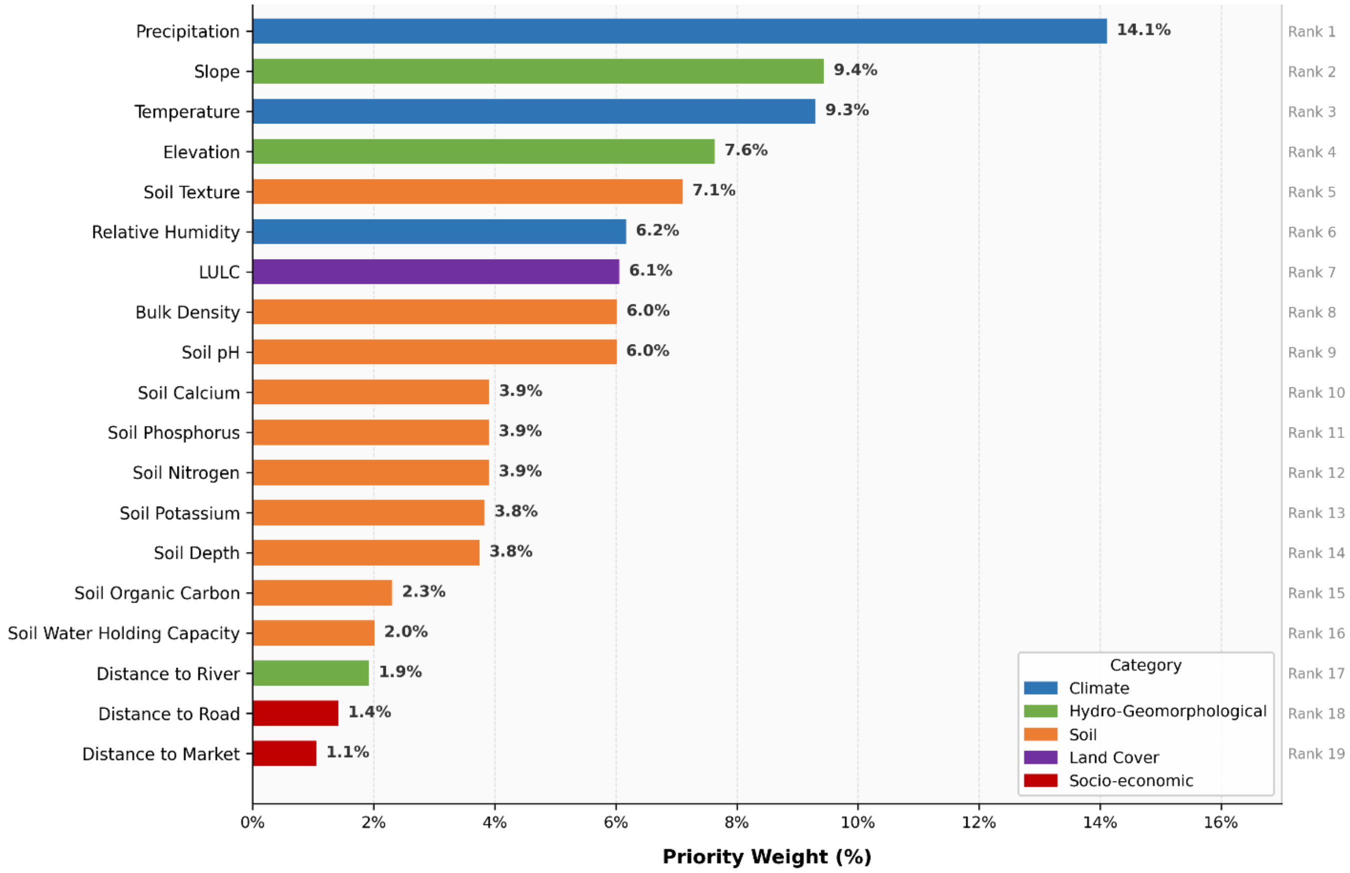

Figure 4. AHP priority weights for the 19 land suitability criteria (Ondo State, Nigeria).

using Eq. (6).

$$
\begin{aligned}
CR = \frac{CI}{RI} &= \frac{(\lambda_{\max} - n)/(n-1)}{RI} \\
&= \frac{(20.979 - 19)/18}{1.60} \\
&= \frac{0.1099}{1.60} \\
&= 0.0687 \\
&= 6.87\%
\end{aligned}
\tag{6}
$$

where $\lambda_{\max} = 20.979$, $n = 19$, and the Random Index $RI = 1.60$ for $n = 19$ [35]. Since $CR = 6.87\% < 10\%$, the expert judgments are considered consistent and the derived weights are acceptable for use in the analysis.

2.7.3 *AHP Results: Priority Weights and Consistency Verification*

The priority weights derived from Steps 1–5 is presented in Table 3 and visualised in Figure 4. These weights represent the inputs used directly in the weighted overlay analysis. Precipitation received the highest weight of 0.141 (14.1%), confirming moisture availability as the dominant driver of arable crop suitability in Ondo State. This was followed by Slope (0.094), Temperature (0.093), Elevation (0.076), and Soil Texture (0.071). The socio-economic criteria received the lowest weights, with Distance to Market at 0.011 (1.1%). The complete priority weights for all 19 criteria are presented in Table 3.

The CR was subsequently computed as the validation check on the expert judgments. The Consistency Ratio results are summarised in Table 4. The study achieved a CR of 6.87% (0.069), well below Saaty's [35] accepted threshold of 10% (0.10), confirming that the 171 pairwise comparisons were internally consistent and that the derived weight structure is statistically reliable. It is important to note that the CR validates the quality of expert judgments; it plays no role in determining the numerical values of the weights, which were derived entirely through Steps 1–5. The weighted and reclassified thematic layers were then integrated using the Weighted overlay technique in ArcGIS 10.8 to generate the final suitability maps for each of the five selected arable crops across Ondo State.

2.8 Weighted Overlay and Suitability Mapping

The weighted overlay technique was used in this study to integrate standardised criteria and

Table 4. Consistency Ratio (CR) Summary for the 19-Criterion AHP Model.

Parameter	Value	Formula / Note
Number of criteria (n)	19	—
Random Index (RI) for $n = 19$	1.60	Saaty (1980)
$\lambda_{\max}$ (Principal Eigenvalue)	20.979	Equation (5)
Consistency Index (CI)	0.1099	$(\lambda_{\max} - n)/(n-1)$
Consistency Ratio (CR)	6.87% (0.0687)	CI / RI
Threshold	< 10% (0.10)	Saaty (1980)
Verdict	**ACCEPTABLE**	CR < 0.10

their AHP-derived weights to generate final land suitability maps for arable crop production in Ondo State. This method allows heterogeneous spatial datasets to be combined by converting all thematic layers to a common suitability scale and assigning each criterion a weight that reflects its relative importance in influencing agricultural productivity, as shown in Figure 5. The weighted overlay analysis was implemented in ArcGIS 10.8, following the multi-criteria evaluation framework described by Drobne and Lisec [49], thereby enabling the systematic integration of diverse environmental and socioeconomic variables. Through this approach, each raster layer was normalised and reclassified into FAO suitability classes, after which the weight assigned to each criterion was multiplied by its corresponding suitability score. The weighted values of all criteria were then summed cell-by-cell to produce the final suitability surfaces for the selected crops, consistent with the procedures outlined by Cengiz and Akbulak [50] and Sadiq et al. [51]. This method effectively combines the outputs of the Analytical Hierarchy Process with spatial overlay modelling, ensuring that the most influential factors exert a proportionate effect on the final suitability classification. The weighted overlay technique provides a robust decision-support mechanism for evaluating complex spatial relationships and enhances the reliability of the land suitability assessment across the study area. Equation (7) below shows the relationship:

$$LS = \sum_{i=1}^{n} w_i \cdot x_i \tag{7}$$

where LS denotes suitability, w_i the weight of variable i, and x_i the score of variable i and n is the total number of criteria (n = 19 in this study).

2.9 Model Validation and Ground-Truthing

To provide a robust validation protocol for the Multicriteria Evaluation (MCE) model, a field-based ground-truthing exercise was conducted across the 18 Local Government Areas of Ondo State. One representative GPS point was collected at each of the 18 known, actively cultivated farm locations using a handheld GPS receiver, yielding 18 validation points. Each point was recorded at a central, unobstructed position on the farm to serve as a representative reference location for that site. This single-point-per-farm approach is an accepted method in GIS-based suitability validation where the objective is to confirm whether known productive farming locations fall within predicted suitable classes, rather than delineating precise farm boundaries [43, 44]. The 18 GPS points were imported into ArcGIS 10.8 and overlaid on the generated suitability maps. A point-in-polygon extraction was then performed to identify the suitability class S1, S2, S3, S4, or N assigned to each farm location by the model. Agreement was determined by assessing the proportion of the 18 farm points that fell within the 5 suitable classes.

To further strengthen validation and quality control of the suitability reference labels, two additional remote sensing indicators were assessed across the 18 farm locations. First, the Normalised Difference Vegetation Index (NDVI) derived from Sentinel-2 imagery was extracted at each farm point. NDVI provides an objective, satellite-derived measure of vegetation health and crop vigor; active, productive farms are expected to exhibit relatively high NDVI values, and correspondence between high NDVI and S1/S2 classification provides an independent, quantitative confirmation of Spatial agreement. Second, the LULC classification from Sentinel-2 Dynamic World was queried at each of the 18 farm points to verify that ground-truth locations were identified as active cropland or agriculturally compatible land-cover categories in the imagery, thereby confirming consistency between observed land use and the model's suitability predictions.

3 Results and Discussion

3.1 Climatic Factor

Ondo State experiences a tropical humid climate, with rainfall ranging from 1,758.5 mm to 2,165.6 mm (Figure 6(c)), creating favourable moisture conditions for crops such as maize, yam, cassava, and plantain. Temperature patterns in the state range from an average of 23.871°C to 35.497°C throughout

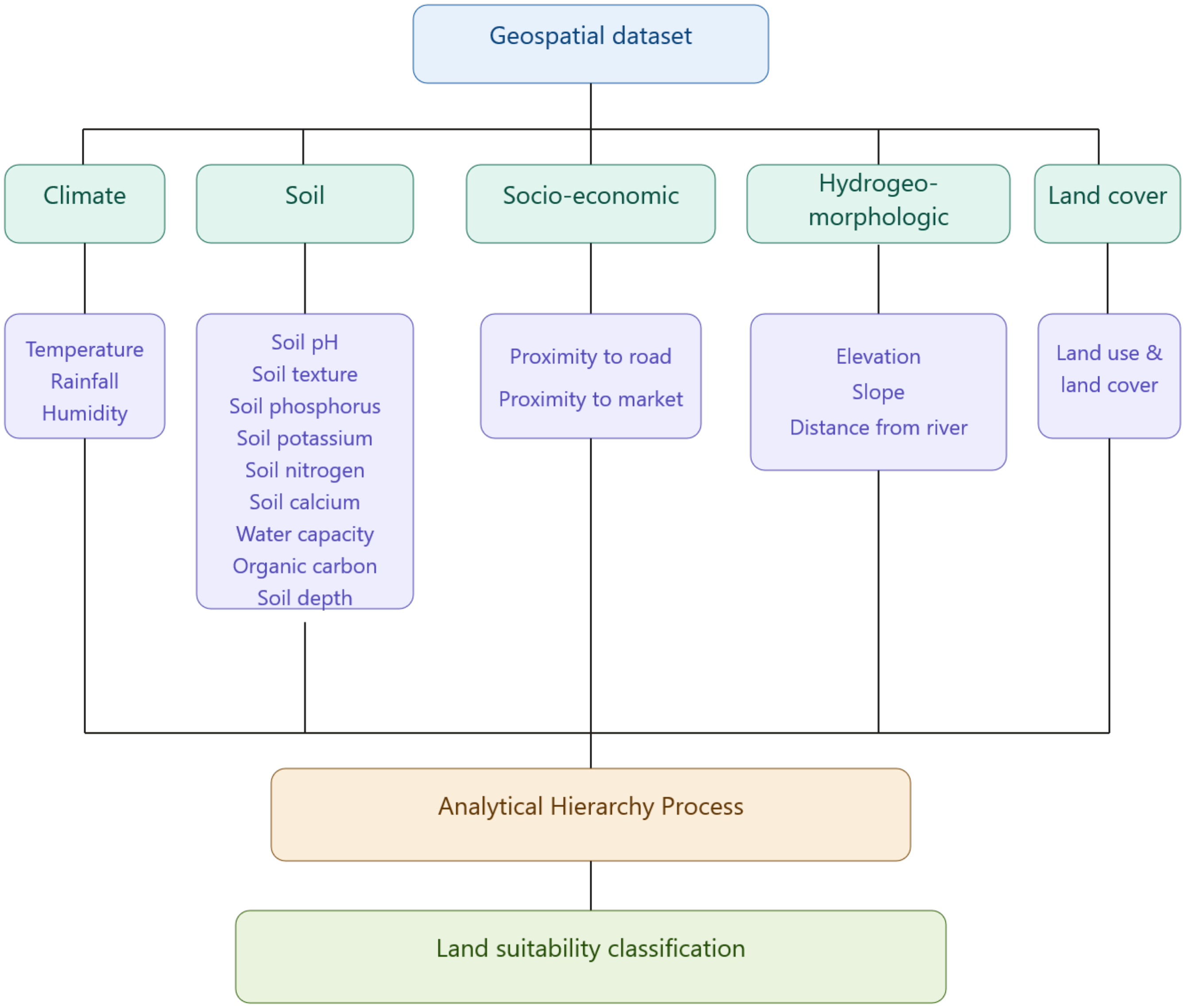

Figure 5. Workflow diagram showing geospatial datasets used as input variables for AHP criteria weighting for land suitability classification.

the year, as shown in Figure 6(b), consistent with tropical conditions reported for southwestern Nigeria by the World Bank Group [52], and generally fall within the tolerance ranges of the selected crops, which can withstand moderate heat stress. The relative humidity ranges from 34% to 70% as presented in Figure 6(a). Each climatic variable was reclassified using crop-specific thresholds documented in the agronomic literature and FAO land evaluation guidelines [27], with higher suitability assigned to areas with optimal rainfall, moderate temperatures, and adequate atmospheric moisture. These reclassified layers were then standardised and integrated into the multi-criteria evaluation framework to assess how climatic conditions influence agricultural suitability across the state. The observed environmental and socioeconomic ranges for all nineteen parameters across the study area are summarised in Table 6.

3.2 Hydro Geomorphological

The slope map of Ondo State, as shown in Figure 6(d), revealed that the majority of the land area falls within the very low (0–3°) and low (3–7°) slope categories, which are favourable for agricultural activities and settlement. Moderate slopes (7–13°) appear in patches across the central and northeastern regions and may require soil conservation measures to prevent erosion. Areas with high slopes (13–23°) and very high slopes

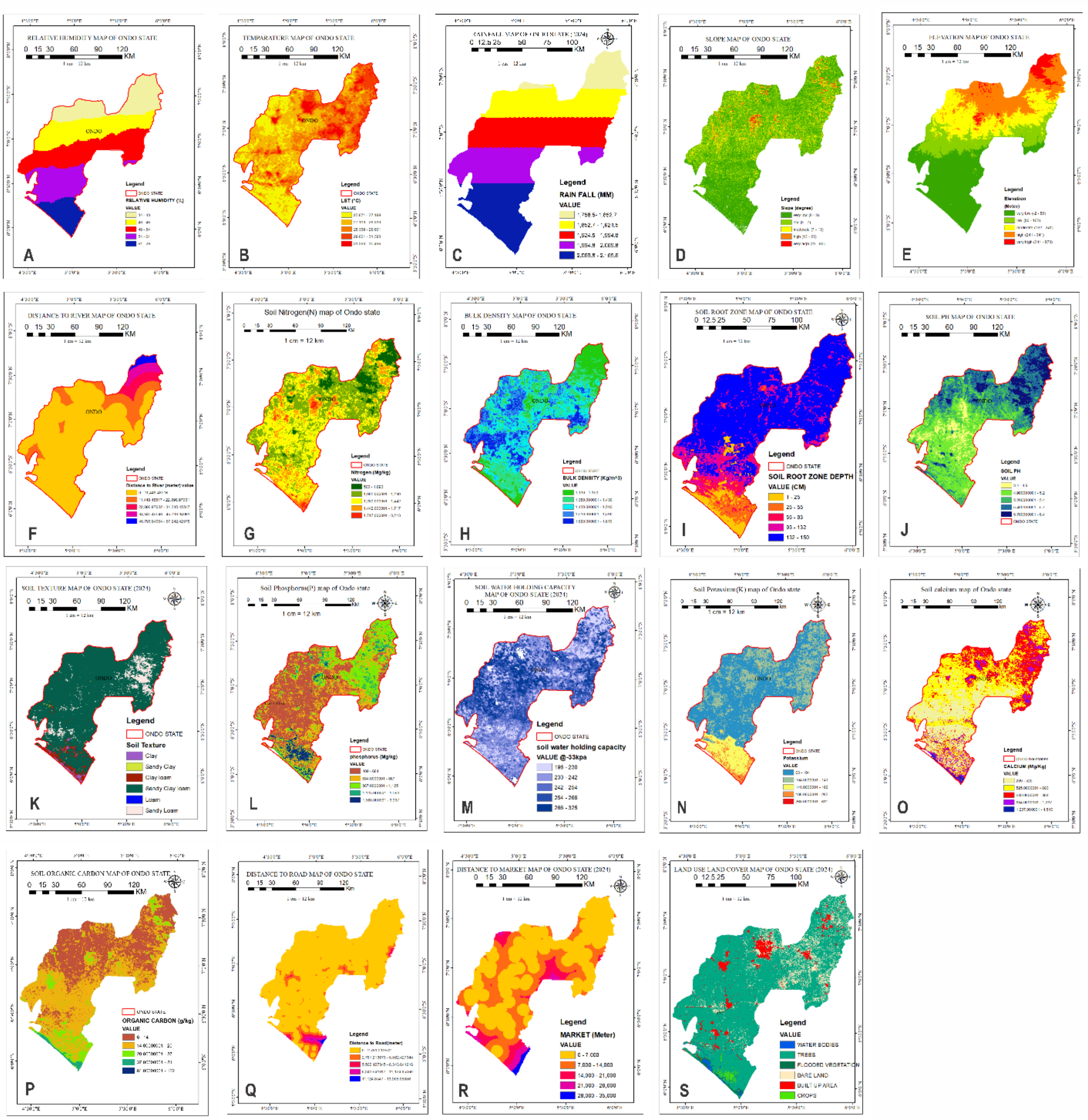

Figure 6. Spatial distribution of environmental and soil parameters across Ondo State used as input variables for crop suitability analysis. (a) relative humidity (b) temperature (°C), (c) rainfall (mm), (d) slope (degrees), (e) elevation (m), (f) distance to river (m), (g) soil nitrogen (Mg/kg), (h) bulk density (Kg/m^3), (i) soil root zone depth (cm), (j) soil pH, (k) soil texture, (l) soil phosphorus (Mg/kg), (m) soil water holding capacity (Kj/kpa), (n) soil potassium, (o) soil calcium, (p) organic carbon, (q) distance to road (m), (r) distance to market (m), and (s) land use/land cover classification.

(23–83°) are relatively limited and are concentrated mostly in hilly and rugged terrains. These steep areas may be less suitable for arable farming but could support forestry, watershed protection, and tourism activities. The elevation map of Ondo State, as presented in Figure 6(e), indicates that the southern and southwestern regions are dominated by very low ($\leq$ 80 m) to low (80–162 m) elevations, which are suitable for farming, settlements, and road networks. The central part of the state shows moderate elevation (162–241 m), providing a mix of agricultural land and slightly undulating terrain. Higher elevations (241–341

m) occur in the north and northeast, with rugged topography that may limit large-scale cultivation but is well-suited to plantation crops and forestry. The very high elevations (341–1073 m) are concentrated in the extreme northeastern axis, representing hilly landscapes that play a role in watershed management and biodiversity conservation. Overall, the elevation distribution suggests that Ondo State has a diverse terrain, ranging from coastal lowlands to upland areas, with concentrations of support in the extreme northeastern axis. There is considerable variation in Ondo's proximity to water sources, as evidenced by the range of 0 to 57,242 meters to rivers, as shown in Figure 6(f).

3.3 Soil Factor

Calcium levels in Ondo State range from 209 to 4510 mg/kg in the soil, as indicated in Figure 6(o). Deeper soils provide better conditions for root development and moisture retention, whereas shallow soils, particularly in certain areas, may limit root growth and water availability. The soil root zone ranges from 106 to 175 cm, as illustrated in Figure 6(i). Higher levels of soil organic carbon improve soil fertility and health. The range of soil organic carbon is 6-122 g/kg, as shown in Figure 6(p), demonstrating considerable diversity in soil fertility. Variability in the soil's ability to hold moisture, which is essential for controlling irrigation and ensuring crop health, is indicated by the range of 196–325 for soil water capacity at -33 kPa, as shown in Figure 6(m).

Ondo State's soil pH ranges from 3.4 to 6.4 as presented in Figure 6(j), indicating neutral to slightly acidic conditions that are generally ideal for a variety of crops. Soil nitrogen content ranges from 563 to 3213 mg/kg, as shown in Figure 6(g), with some regions having extremely low levels. This can restrict plant growth, necessitating nitrogen supplementation. Soil phosphorus levels range from 409 to 3037 mg/kg as shown in Figure 6(l), indicating that phosphorus availability is generally adequate. However, in certain regions, lower levels may necessitate supplementation to achieve optimal crop yields. Plant growth is supported by soil potassium levels ranging from 63 to 611 mg/kg, as shown in Figure 6(n); however, some regions may require more potassium to meet crop needs. Loam, sandy loam, clay loam, sandy clay loam, clay, and clay are among the soil textures that have varying effects on nutrient availability, drainage, and aeration (Figure 6(k)). While clay soils retain more water and nutrients and may present drainage challenges, loam and sandy loam soils typically offer good fertility and drainage. Bulk density ranges from 1190 to 1810 kg/m^3 as observable in Figure 6(h).

3.4 Socio-economic Factor

Road accessibility in Ondo State ranges from 0 to 13,906.06 meters (Figure 6(q)), while distance to markets ranges from 0 to 35,000 meters (Figure 6(r)). Areas closer to roads and markets benefit from better transportation networks, easier access to agricultural inputs, and improved produce distribution, all of which can enhance agricultural productivity and financial returns. Overall, most of the study area is reasonably accessible to both road networks and market centres. However, locations farther from these facilities may face higher transportation costs and logistical challenges that could limit agricultural output.

3.5 Vegetation Factor

Vegetation cover dominates Ondo State's land use and land cover (LULC) in 2024, accounting for 80% of the state's total area, as illustrated in Table 5 and visualised in Figure 6(s). Crop land has 1.13%. The prevalence of built-up and bare lands, which make up 10.98% and 6.7 % of the total area, respectively, indicates transitional and potentially degraded habitats. Water bodies account for only 0.87% of the state, demonstrating the scarcity of surface water resources, whereas flooded vegetation accounts for 0.32%.

Table 5. Land use/land cover classes and their proportional area coverage in Ondo State, Nigeria.

Land Cover Class	Area (km²)	Proportion (%)
Vegetation	12,025.28	80.00
Built-up area	1,650.47	10.98
Bare land	1,007.12	6.70
Crop land	169.86	1.13
Water bodies	130.77	0.87
Flooded vegetation	48.10	0.32
Total	**15,031.60**	**100.00**

3.6 Land suitability evaluation of Crops

3.6.1 Maize

The land suitability analysis for maize in Ondo State reveals that only 7.34% of the land is classified as highly suitable (S1), 24.27% as suitable (S2), 31.26% as moderately suitable (S3), 26.14% as marginally suitable (S4), and 10.99% as unsuitable (N). These spatial distributions are illustrated in Figure 7(a, b), which show the land suitability area covered for Maize

Table 6. Minimum and Maximum Criteria Values for crop farming in Ondo state, Nigeria.

Parameter	Minimum	Maximum
Elevation (m)	-2	1073
Slope (°)	0	83
Precipitation (mm)	1758	2165
Temperature (°C)	23.9	35.5
Relative Humidity (%)	34	70
Soil pH	3.4	6.4
Soil Nitrogen (mg/kg)	563	3213
Soil Phosphorus (mg/kg)	409	3037
Soil Potassium (mg/kg)	63	611
Soil Calcium (mg/kg)	209	4510
Soil root zone (cm)	106	175
Bulk Density (kg/m³)	1190	1810
Soil Organic Carbon (g/kg)	6	122
Soil Water Capacity @-33kPa	196	325
Distance to Rivers (m)	0	57,242
Distance to Roads (m)	0	13,906
Distance to Market (m)	0	35,000

in Ondo State. This distribution highlights both the opportunities and challenges for maize cultivation in the state. The maize suitability assessment for Ondo State shows both similarities and contrasts with the findings of Linda et al. [53]. In Ondo, only 7.34% of land is classified as highly suitable (S1), while most areas fall into the suitable (24.27%), moderately suitable (31.26%), and marginally suitable (26.14%) classes, with 10.99% deemed unsuitable. This indicates that although maize can be cultivated widely, truly optimal land is limited. In contrast, the Egbeda LGA study by Linda et al. [53] employed a three-class suitability framework and reported a more favourable distribution: 26.8% of the land was classified as highly suitable, 64.8% as moderately suitable, and only 8.4% as marginally suitable, with no areas designated as unsuitable under their classification scheme. Although a direct class-by-class comparison is constrained by the difference in classification frameworks—this study adopts the FAO five-class system (S1–S4 and N), whereas Linda et al. [53] applied a three-class scheme—the contrast in the proportions of highly suitable land (7.34% versus 26.8%) is nonetheless instructive. These differences reflect variations in spatial scale and local environmental conditions: the broader, state-level Ondo assessment captures widespread soil fertility constraints, erosion risks, and land degradation, whereas the localised analysis in Egbeda LGA highlights more optimal agro-physical conditions for maize cultivation.

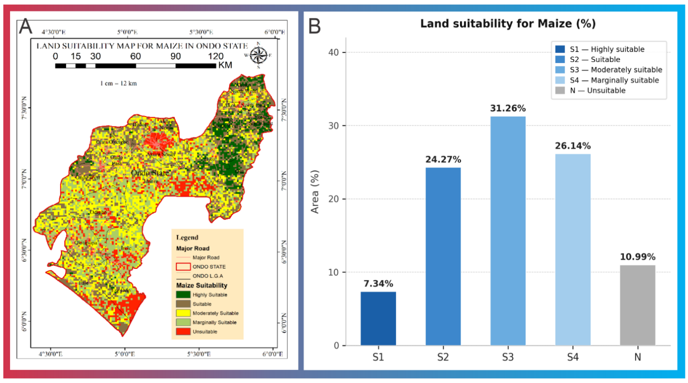

Figure 7. Land suitability assessment for maize in Ondo State. (a) Spatial distribution of maize suitability classes (S1–S4 and N) across Ondo State (b) Percentage area by maize suitability class.

3.6.2 *Cassava*

The land suitability analysis for cassava cultivation in Ondo State shows that 7.33% of the land is highly suitable (S1), 24.29% is suitable (S2), 28.59% is moderately suitable (S3), 26.52% is marginally suitable (S4), and 13.27% is unsuitable (N). These spatial distributions are illustrated in Figure 8(a, b), which show the land suitability area covered for Cassava in Ondo State. Compared with the findings of Jacob and Otti [54] in Yewa South, Ogun State, this study shows notable differences in the distribution of cassava suitability. Jacob and Otti [54] identified only 1.16% of land as highly suitable, while most land (73.66%) was classified as suitable and 25.18% as moderately suitable, with almost no marginal or unsuitable areas. Their AHP–MCE approach placed the highest weights on soil (26.8%) and land use/land cover (24.4%), followed by rainfall (18.5%) and temperature (14.9%), with terrain factors playing a smaller role. The contrast with Ondo arises mainly from methodology: the FAO land evaluation system reveals broader variability, whereas the weighted AHP–MCE method tends to group most land into the suitable class. Both studies agree that cassava is highly resilient and can grow across diverse environments, though truly optimal land remains limited. The implication is that Ondo requires improvements in soil fertility and infrastructure to uplift marginal and moderate areas, while Yewa South should focus on enhancing its widespread but less suitable land.

3.6.3 *Yam*

The analysis of yam suitability in Ondo State shows that 7.2% of the land is highly suitable (S1), 29.88% is suitable (S2), 30.60% is moderately suitable (S3), 23.72% is marginally suitable (S4), and 8.6%

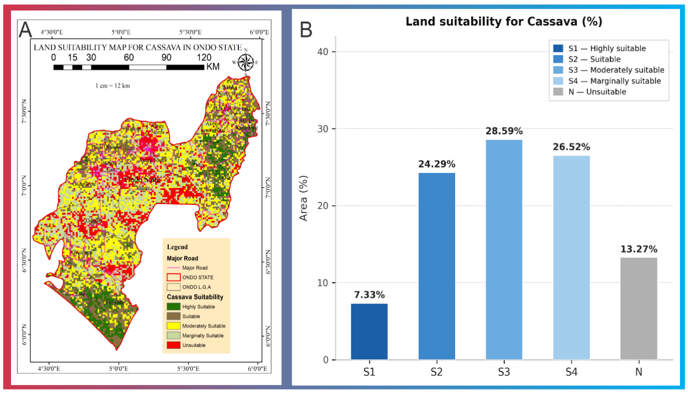

Figure 8. Land suitability assessment for cassava in Ondo State. (a) Spatial distribution of cassava suitability classes (S1–S4 and N) across Ondo State (b) Percentage area by cassava suitability class.

is unsuitable (N). These spatial distributions are illustrated in Figure 9(a, b), which show the land suitability area covered for yams in Ondo State. This distribution reflects yams' requirement for fertile, well-drained soils and favourable climatic conditions, while also highlighting localised constraints that limit their cultivation potential. The study's yam suitability results align with those of Abah and Petja [55].

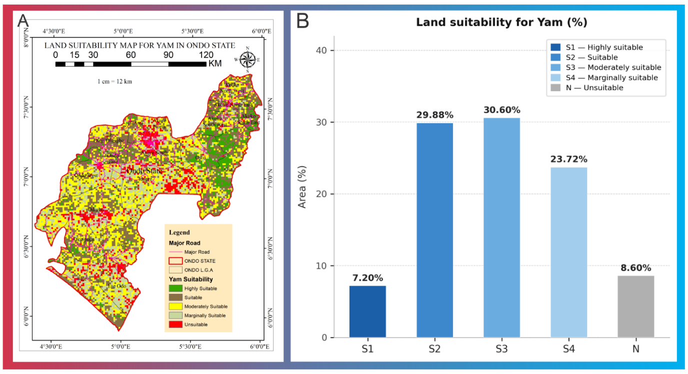

Figure 9. Land suitability assessment for yams in Ondo State. (a) Spatial distribution of yam suitability classes (S1–S4 and N) across Ondo State (b) Percentage area by yam suitability class.

But also reveal key differences, Ondo State has a higher combined proportion of highly suitable and suitable land (37.08%) than the Benue Basin's 16.7%, indicating better overall conditions for yam cultivation. However, Ondo also records a larger share of completely unsuitable land (8.6%) than the 4.88% of very low suitability reported in the Benue Basin. Conversely, the Benue Basin has a much larger proportion of moderately suitable land (48.85%) than Ondo (30.60%), suggesting that Benue's landscape is dominated by areas needing moderate improvement, while Ondo has more land closer to optimal productivity levels. Overall, both studies confirm the feasibility of yam cultivation across extensive areas, but Ondo offers greater opportunities in higher-suitability zones, whereas Benue requires targeted efforts to improve yields on its moderately suitable lands [55].

3.6.4 Vegetable

The land suitability analysis for vegetables in Ondo State shows that 6.72% of the land is highly suitable (S1), 25.82% is suitable (S2), 31.20% is moderately suitable (S3), 24.59% is marginally suitable (S4), and 11.67% is unsuitable (N). These spatial distributions are illustrated in Figure 10(a, b), which shows the land suitability area covered for vegetable farming in Ondo State, Nigeria. The findings from Ondo State differ notably from those of Magaji and Pantami [56], due to differences in scale and environmental context. Ondo's assessment reflects a broad, statewide distribution of suitability classes, with a relatively balanced spread and about one-third of the land falling into the moderately suitable category. In contrast, the Kano study focuses on a specific floodplain irrigation site where management practices strongly shape suitability outcomes, resulting in large areas classified as marginal or unsuitable, especially for onions, unless more flexible evaluation methods are used. Crop-specific outcomes also diverge: Ondo's regional-level analysis suggests that vegetables collectively face widespread ecological constraints, whereas the Kano study evaluates individual crops and shows that tomatoes and cabbage have higher potential than onions. Despite these differences, both studies agree that soil fertility and climatic factors are the major constraints to vegetable production. Overall, Ondo offers broader opportunities for expansion due to its larger share of moderately suitable and suitable land, whereas the Kano assessment highlights localised yet severe limitations [56].

3.6.5 Plantain

The land suitability analysis for plantains in Ondo State shows that 12.01% of the land is highly suitable (S1), 25.23% is suitable (S2), 27.27% is moderately suitable (S3), 24.11% is marginally suitable (S4), and 11.38% is unsuitable (N). These spatial distributions are illustrated in Figure 11(a, b), which shows the land suitability area covered for plantain farming in Ondo State, Nigeria. This study aligns with the findings of Dickson et al. [57], which recognise that plantain is well adapted to humid environments, yet truly optimal land remains limited. However, notable

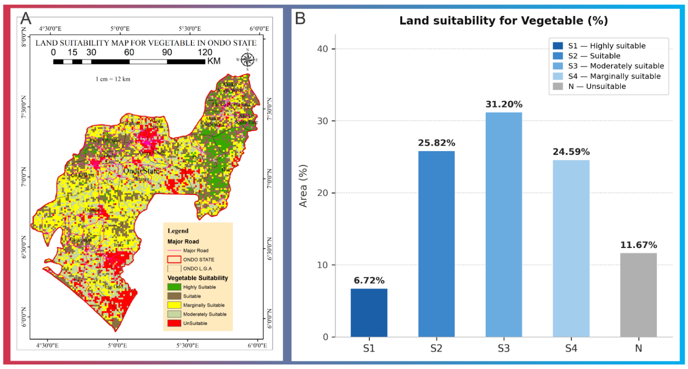

Figure 10. Land suitability assessment for vegetables in Ondo State. (a) Spatial distribution of vegetable suitability classes (S1–S4 and N) across Ondo State (b) Percentage area by Vegetable suitability class.

differences exist in the distribution of suitability classes. Ondo exhibits a wider spread of highly suitable land, whereas Dickson et al. [57] reported that Bayelsa contains only 3.51% highly suitable land, with most areas (52.63%) being moderately suitable due to poor drainage, low-lying soils, high water tables, and soil acidity. Although both regions show similar proportions of unsuitable land (about 11–12%), the underlying causes differ: soil fertility decline and socioeconomic challenges in Ondo, versus hydrological and drainage constraints in Bayelsa. Overall, while both studies emphasise plantain's adaptability, they highlight that Ondo offers greater potential for high-yield production with improved soil fertility and infrastructure, whereas Bayelsa requires targeted drainage and soil management interventions to enhance its moderately suitable land [57].

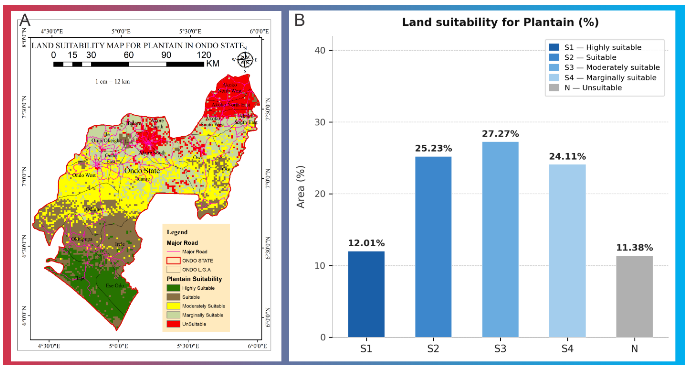

Figure 11. Land suitability assessment for Plantain in Ondo State. (a) Spatial distribution of Plantain suitability classes (S1–S4 and N) across Ondo State (b) Percentage area by Plantain suitability class.

3.7 Validation

The spatial validation results presented in Table 7 demonstrate a satisfactory level of agreement between the eighteen ground-truthed farm locations and the suitability zones predicted by the MCE model. Fourteen out of 18 farm locations (77.78%) were correctly classified within the predicted suitability zones, providing objective empirical benchmark data that confirms the predictive reliability of the nineteen-criteria framework. The agreement rate was calculated using Eq. (8). Notably, farms cultivating plantain in the high-rainfall southern zones consistently fell within S1 and S2 classes, validating the 14.1% AHP priority assigned to Precipitation as the dominant criterion. This structured, GPS-based spatial ground-truthing provides empirical support for the model's spatial plausibility, directly addressing concerns about the method's predictive agreement rate. Agreement was defined as correspondence between the predicted suitability class and observed field conditions. Farms classified as S3 were marked as agreement, where moderate yields were recorded during ground-truthing, consistent with moderately suitable conditions. The cassava farm at Uso Farm, predicted as S4, was similarly marked as agreement, given that observed reduced yields were consistent with the constraints expected under marginal suitability. The quantitative agreement rate was calculated as follows:

$$\text{Quantitative Agreement rate } (\%) = \frac{\text{Number of matches}}{\text{Total farms}} \times 100 \tag{8}$$

$$\text{Quantitative Agreement rate } (\%) = \frac{14}{18} \times 100 = 77.78\%$$

3.7.1 *Limitations of the Study and Future Directions*

Several limitations of this study should be acknowledged. First, the field-based agreement assessment relied on 18 GPS-recorded farm locations, which, while distributed across Ondo State, represent a relatively small validation sample. This limits the statistical robustness of the agreement rate and constrains its generalizability across the state's full spatial extent. Second, the absence of independent crop-yield datasets means that suitability predictions could not be validated against measured productivity outcomes. Third, the final 30 m suitability maps are constrained by the native resolution of the coarser input datasets, particularly the 250 m SoilGrids and 1 km climatic layers, which may smooth spatial variability at finer scales. Future studies should incorporate larger ground-truth datasets and yield records to improve the rigour of model validation.

Table 7. Spatial validation of land suitability predictions using ground-truth farm data.

S/N	Farm Name	Latitude	Longitude	Dom. Arable Crop	Pred. Class	Spatial Agreement with Ground-Truth
1	Aduro Farm	6.502133	4.720216	Plantain	S1	Yes
2	Futa Farm	7.305208	5.125918	Maize	S2	Yes
3	Agilo Farm	7.569594	5.843037	Cassava	S3	Yes
4	Olu Agilo Farm	6.914900	5.148032	Maize	S3	Yes
5	Mariwo Farm (Ifedore LGA)	7.371321	5.103167	Maize	S3	Yes
6	Will Farm	6.914889	5.147818	Mixed	S3	Yes
7	Glt Farmland	7.211245	5.321667	Yam	S2	Yes
8	02 FJ Arena	6.485380	4.776953	Cassava	N	No
9	Moribo Green Farm	6.422457	4.918808	Cassava	S3	Yes
10	Unnamed Farm	7.203033	4.855873	Maize	S3	Yes
11	Unnamed Farm (Ondo Town)	7.116399	4.792026	Cassava	S4	No
12	Unnamed Farm (Ondo)	7.138379	4.895263	Cassava	S3	Yes
13	Unnamed Farm (Idanre)	7.139700	5.087529	Maize	S2	Yes
14	Idanre Farm	7.110284	5.175446	Maize	S3	Yes
15	Aiyeloboro Farm	7.192112	5.290083	Cassava	S3	Yes
16	Uso Farm	7.263133	5.391666	Cassava	S4	Yes
17	Oda Farm	7.210890	5.238239	Maize	S4	No
18	Iluabo area	7.277288	5.299376	Maize	N	No
Total	**18 Farms**					**Yes = 14 / No = 4**

4 Conclusion and Recommendations

4.1 Conclusion

This study successfully assessed land suitability for arable crops in Ondo State using GIS and multi-criteria evaluation of nineteen parameters, including soil, climate, topography, land use/land cover, and accessibility. In line with the first objective, soil, climatic, hydro-geomorphological, and socio-economic factors were examined to assess their influence on crop growth requirements. The second objective was achieved by applying the Analytic Hierarchy Process (AHP) and weighted overlay techniques to integrate all criteria and generate suitability maps for crops such as yams, maize, cassava, plantain, and vegetables. Finally, the third objective was achieved by presenting the results as a map, thereby enhancing the visualisation and interpretation of suitable areas. The findings demonstrate that GIS-based land suitability analysis provides a reliable and systematic framework for optimising agricultural land use. The suitability maps produced serve as practical tools for farmers, policymakers, and stakeholders, contributing to improved crop production, better resource management, and long-term agricultural sustainability in Ondo State.

4.2 Recommendations

Based on the findings of this study, the following recommendations are proposed: The thematic suitability maps generated for all five crops should be formally adopted by the Ondo State Ministry of Agriculture and Natural Resources as a baseline spatial planning tool for land allocation, crop zoning, and the prioritisation of agricultural investment. Zones classified as Highly Suitable (S1) should be designated as priority agricultural development areas, with targeted input supply, extension services, and infrastructure investment directed toward these locations.

For areas classified as Moderately Suitable (S3) or Marginally Suitable (S4), which together account for the largest share of the state's agricultural land, targeted soil amelioration interventions are recommended. Specifically, lime application to address widespread low pH (3.4–6.4), organic matter incorporation to improve soil nitrogen levels, and subsoil drainage improvements in waterlogged zones should be prioritised to elevate these areas to higher suitability classes.

Data Availability Statement

Data will be made available on request.

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Conflicts of Interest

The authors declare no conflicts of interest.

AI Use Statement

The authors declare that no generative AI was used in the preparation of this manuscript.

Ethical Approval and Consent to Participate

Not applicable.

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Table A1. Criteria required for Maize farming in Ondo State, Nigeria.

Agro-suit class	S1 Highly Suitable	S2 Suitable	S3 Moderately Suitable	S4 Marginally Suitable	N Unsuitable
LULC	Crops	Trees	Bare land	Flooded vegetation	Built up, water
Elevation (m)	24–79.153	79.1523–182.305	182.305–281.160	281.160–405.803	405.803–1072
Slope (°)	0–5	5.01–15	15.01–30	30.01–45	45.01–83.114
Precipitation (mm)	1758.447–1800	1800–1900	1900–1950	1950–2000	2000–2165.618
Temperature (°C)	23.86–24	24–27	27–30	30–32	32–35.50
Relative Humidity (%)	49–65	44–49	39–44	65–70.15	34.131–39
Bulk density (g/cm^3)	1190–1250	1250–1400	1400–1550	1550–1650	1650–1810
Soil pH	6.0–6.4	5.8–6.0	5.6–5.8	5.2–5.6	3.4–5.2
Soil Texture (mg/kg)	Loam	Sandy loam	Clay Loam	Sandy loam	Clay loam, clay loam
Soil Nitrogen (mg/kg)	2000–3213	1500–2000	1000–1500	563–1000	563
Soil Phosphorus (mg/kg)	409	409–1000	1000–1500	1500–2200	2200–3037
Soil Potassium (mg/kg)	400–611	200–400	100–200	76.9193–99	0–76.9193
Soil Calcium (mg/kg)	209	209–1000	1000–2000	2000–3000	3000–4510
Soil Root Zone (cm)	132–150	93–132	55–93	25–55	1–25
Soil Organic Carbon (g/kg)	80–122	40–80	20–40	10–20	6–10
Soil Water Capacity @ 33kpa	295–325	270–295	245–270	196–245	196
Distance to Rivers (m)	4000–57242.435	3000–40000	20000–30000	10000–20000	0–10000
Distance to Roads (m)	0–500	501–1000	1000–1500	1500–2000	2000–13906.07
Distance to Market (m)	0–5000	5000–10000	10000–15000	15000–20000	20000–35034.523

Table A2. Criteria required for Cassava farming in Ondo State, Nigeria.

Agro-suit class	S1 Highly Suitable	S2 Suitable	S3 Moderately Suitable	S4 Marginally Suitable	N Unsuitable
LULC	Crops	Trees	Bare land	Flooded vegetation	Built up, water
Elevation (m)	24–79.153	79.1523–182.305	182.305–281.160	281.160–405.803	405.803–1072
Slope (°)	0–5	5.01–15	15.01–30	30.01–45	45.01–83.114
Precipitation (mm)	1758.447–1839	1839–1921	1921–2003	2003–2085	2085–2165.618
Temperature (°C)	23.86–24	24–27	27–30	30–32	32–35.50
Relative Humidity (%)	62–70.165	55–62	48–55	41–48	34.131–41
Bulk density (g/cm^3)	1190–1250	1250–1400	1400–1550	1550–1650	1650–1810
Soil pH	6.0–6.4	5.8–6.0	5.6–5.8	5.2–5.6	3.4–5.2
Soil Texture (mg/kg)	Loam	Sandy loam	Clay Loam	Sandy Clay loam	Sandy Clay, clay loam
Soil Nitrogen (mg/kg)	2000–3213	1500–2000	1000–1500	563–1000	563
Soil Phosphorus (mg/kg)	409	409–1000	1000–1500	1500–2200	2200–3037
Soil Potassium (mg/kg)	400–611	200–400	100–200	76.9193–99	0–76.9193
Soil Calcium (mg/kg)	209	209–1000	1000–2000	2000–3000	3000–4510
Soil Root Zone (cm)	1–39	39–59	59–79	79–100	100–150
Soil Organic Carbon (g/kg)	80–122	40–80	20–40	10–20	6–10
Soil Water Capacity @ -33kpa	295–325	270–295	245–270	196–245	196
Distance to Rivers (m)	2000–10000	10000–20000	20000–30000	30000–40000	40000–57242.425
Distance to Roads (m)	0–500	501–1000	1000–1500	1500–2000	2000–13906.07
Distance to Market (m)	0–5000	5000–10000	10000–15000	15000–20000	20000–35034.523

Table A3. Criteria required for Yam farming in Ondo State, Nigeria.

Agro-suit class	S1 Highly Suitable	S2 Suitable	S3 Moderately Suitable	S4 Marginally Suitable	N Unsuitable
LULC	Crops	Trees	Bare land	Flooded vegetation	Built up, water
Elevation (m)	24–79.153	79.1523–182.305	182.305–281.160	281.160–405.803	405.803–1072
Slope (°)	0–5	5.01–15	15.01–30	30.01–45	45.01–83.114
Precipitation (mm)	1758.447–1839	1839–1921	1921–2003	2003–2085	2085–2165.618
Temperature (°C)	23.871–26.2	26.2–28.5	28.5–30.8	30.8–33.1	33.1–35.495
Relative Humidity (%)	62–70.165	55–62	48–55	41–48	34.131–41
Bulk density (g/cm^3)	1190–1250	1250–1400	1400–1550	1550–1650	1650–1810
Soil pH	6.0–6.4	5.8–6.0	5.6–5.8	5.2–5.6	3.4–5.2
Soil Texture (mg/kg)	Loam	Sandy loam	Clay loam	Sandy loam	Clay loam
Soil Nitrogen (mg/kg)	2000–3213	1500–2000	1000–1500	563–1000	563
Soil Phosphorus (mg/kg)	409	409–1000	1000–1500	1500–2200	2200–3037
Soil Potassium (mg/kg)	400–611	200–400	100–200	76.9193–99	0–76.9193
Soil Calcium (mg/kg)	209	209–1000	1000–2000	2000–3000	3000–4510
Soil Root Zone (cm)	1–39	39–59	59–79	79–100	100–150
Soil Organic Carbon (g/kg)	80–122	40–80	20–40	10–20	6–10
Soil Water Capacity @ -33kpa	295–325	270–295	245–270	196–245	196
Distance to Rivers (m)	2000–10000	10000–20000	20000–30000	30000–40000	40000–57242.425
Distance to Roads (m)	0–500	501–1000	1000–1500	1500–2000	2000–13906.07
Distance to Market (m)	0–5000	5000–10000	10000–15000	15000–20000	20000–35034.523

Table A4. Criteria required for Plantain farming in Ondo State, Nigeria.

Agro-suit class	S1 Highly Suitable	S2 Suitable	S3 Moderately Suitable	S4 Marginally Suitable	N Unsuitable
LULC	Crops	Trees	Bare land	Flooded vegetation	Built up, water
Elevation (m)	24–79.153	79.1523–182.305	182.305–281.160	281.160–405.803	405.803–1072
Slope (°)	0–5	5.01–15	15.01–30	30.01–45	45.01–83.114
Precipitation (mm)	1758.447–1839	1839–1921	1921–2003	2003–2085	2085–2165.618
Temperature (°C)	23.871–26.2	26.2–28.5	28.5–30.8	30.8–33.1	33.1–35.495
Relative Humidity (%)	62–70.165	55–62	48–55	41–48	34.131–41
Bulk density (g/cm^3)	1190–1250	1250–1400	1400–1550	1550–1650	1650–1810
Soil pH	6.0–6.4	5.8–6.0	5.6–5.8	5.2–5.6	3.4–5.2
Soil Texture (mg/kg)	Loam	Sandy loam	Clay Loam	Sandy loam	Sandy Clay, clay loam
Soil Nitrogen (mg/kg)	2000–3213	1500–2000	1000–1500	563–1000	563
Soil Phosphorus (mg/kg)	409	409–1000	1000–1500	1500–2200	2200–3037
Soil Potassium (mg/kg)	400–611	200–400	100–200	76.9193–99	0–76.9193
Soil Calcium (mg/kg)	209	209–1000	1000–2000	2000–3000	3000–4510
Soil Root Zone (cm)	1–39	39–59	59–79	79–100	100–150
Soil Organic Carbon (g/kg)	80–122	40–80	20–40	10–20	6–10
Soil Water Capacity @ -33kpa	295–325	270–295	245–270	196–245	196
Distance to Rivers (m)	2000–10000	10000–20000	20000–30000	30000–40000	40000–57242.425
Distance to Roads (m)	0–500	501–1000	1000–1500	1500–2000	2000–13906.07
Distance to Market (m)	0–5000	5000–10000	10000–15000	15000–20000	20000–35034.523

Table A5. Criteria required for Vegetable farming in Ondo State, Nigeria.

Agro-suit class	S1 Highly Suitable	S2 Suitable	S3 Moderately Suitable	S4 Marginally Suitable	N Unsuitable
LULC	Crops	Trees	Bare land	Flooded vegetation	Built up, water
Elevation (m)	24–79.153	79.1523–182.305	182.305–281.160	281.160–405.803	405.803–1072
Slope (°)	0–5	5.01–15	15.01–30	30.01–45	45.01–83.114
Precipitation (mm)	1758.447–1839	1839–1921	1921–2003	2003–2085	2085–2165.618
Temperature (°C)	23.87–27.1	27.1–29.4	29.4–30.2	30.2–32.5	32.5–35.50
Relative Humidity (%)	49–57	57–65	41–49	65–70.165	34.131–41
Bulk density (g/cm^3)	1190–1250	1250–1400	1400–1550	1550–1650	1650–1810
Soil pH	6.0–6.4	5.8–6.0	5.6–5.8	5.2–5.6	3.4–5.2
Soil Texture (mg/kg)	Loam	Sandy loam	Clay Loam	Sandy Clay loam	Sandy Clay, clay
Soil Nitrogen (mg/kg)	2000–3213	1500–2000	1000–1500	563–1000	563
Soil Phosphorus (mg/kg)	409	409–1000	1000–1500	1500–2200	2200–3037
Soil Potassium (mg/kg)	400–611	200–400	100–200	76.9193–99	0–76.9193
Soil Calcium (mg/kg)	209	209–1000	1000–2000	2000–3000	3000–4510
Soil Root Zone (cm)	1–39	39–59	59–79	79–100	100–150
Soil Organic Carbon (g/kg)	80–122	40–80	20–40	10–20	6–10
Soil Water Capacity @ -33kpa	295–325	270–295	245–270	196–245	196
Distance to Rivers (m)	2000–10000	10000–20000	20000–30000	30000–40000	40000–57242.425
Distance to Roads (m)	0–500	501–1000	1000–1500	1500–2000	2000–13906.07
Distance to Market (m)	0–5000	5000–10000	10000–15000	15000–20000	20000–35034.523

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