

Spatial Assessment of Biophysical Suitability for Climate-Smart Agriculture across Nigeria

Bimbola Rasheed Bashorun

bimbola.bashorun@unilorin.edu.ng

University of Ilorin

Lanre Tajudeen Ajibade

University of Ilorin

Toluwalope Mubo Agaja

University of Ilorin

Davies Ojo Ajewole

University of Ilorin

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Abstract

Climate change continues to threaten agricultural productivity and food security in Nigeria, highlighting the need for spatially targeted Climate-Smart Agriculture (CSA) interventions. This study evaluated environmental suitability for CSA across Nigeria using an integrated Remote Sensing, Geographic Information System (GIS), and Multi-Criteria Decision Analysis (MCDA) framework. Five environmental indicators, Normalized Difference Vegetation Index (NDVI), mean annual rainfall, mean temperature, soil organic carbon, and surface-water occurrence, were derived from Sentinel-2, CHIRPS, ERA5-Land, SoilGrids, and JRC Global Surface Water datasets and processed using Google Earth Engine and ArcGIS Pro. The indicators were standardized and integrated using a Weighted Linear Combination (WLC), while criterion weights were determined using the Analytic Hierarchy Process (AHP). The pairwise comparison matrix produced a consistency ratio (CR) of 0.000, indicating acceptable consistency. Results revealed a pronounced south–north gradient in CSA suitability, with relatively higher suitability concentrated in southern Nigeria and parts of the Middle Belt. Very Low and Low suitability accounted for 42.33% and 37.77% of Nigeria, respectively, while High and Very High suitability covered 5.91% and 0.89%. Overall, 80.10% of the country was classified as Very Low or Low suitability, compared with 6.80% classified as High or Very High suitability. The findings provide a national-scale biophysical baseline for prioritizing context-specific climate adaptation, sustainable land management, and agricultural planning.

1. Introduction

Agriculture is fundamental to economic development, employment generation, and food security in Nigeria, where a substantial proportion of rural livelihoods depend on climate-sensitive agricultural production. The country's agricultural systems are increasingly exposed to climate variability and environmental degradation, including changing rainfall regimes, rising temperatures, drought, flooding, and declining land and water resources. These pressures create growing challenges for maintaining agricultural productivity and food-system stability, particularly where production depends heavily on rainfall and natural resource availability. Climate change can alter crop growth conditions, water availability, soil processes, and ecosystem productivity, thereby increasing uncertainty in agricultural production and food security [1–3].

The implications are particularly important in sub-Saharan Africa, where agricultural production is closely linked to climatic conditions and where many farming systems have limited capacity to absorb climatic shocks. Climate variability and change can affect agricultural productivity through changes in temperature and precipitation, increased frequency of extreme events, and modifications in the availability and quality of natural resources. Consequently, strengthening the resilience of agricultural systems requires approaches that simultaneously consider productivity, adaptation, resource conservation, and the environmental conditions within which agricultural activities occur [1, 2].

Nigeria presents a particularly relevant setting for such assessment because of its pronounced environmental and climatic gradients. The country extends from humid tropical environments in the

south to increasingly dry and semi-arid conditions in the north, producing substantial spatial variation in rainfall, temperature, vegetation productivity, soil properties, and water availability. Such environmental heterogeneity means that the potential for climate-resilient agricultural development cannot be assumed to be spatially uniform. Instead, agricultural adaptation and resource-management interventions require consideration of local biophysical conditions and their geographical distribution [4, 5].

Climate-Smart Agriculture (CSA) has emerged as an important framework for addressing the interconnected challenges of agricultural productivity, climate change adaptation, resilience, and environmental sustainability. The Food and Agriculture Organization (FAO) conceptualizes CSA around three principal objectives: sustainably increasing agricultural productivity and incomes; adapting to climate change and building resilience; and, where possible, reducing or removing greenhouse-gas emissions [3]. CSA therefore represents an approach for guiding agricultural development toward production systems that are simultaneously productive, resilient, and environmentally sustainable rather than a single standardized agricultural technology or production practice [6, 7].

The relevance of CSA is particularly strong in regions where agricultural productivity is constrained by climatic and environmental variability. Sustainable intensification, improved resource-use efficiency, better risk management, diversified production systems, and locally appropriate adaptation measures can contribute to resilient agricultural development while reducing pressure on natural resources [7]. However, the suitability of particular agricultural landscapes for climate-smart interventions varies according to their environmental characteristics. Areas with favourable vegetation conditions, adequate rainfall, suitable temperatures, productive soils, and accessible water resources may provide more supportive biophysical conditions than areas characterized by moisture limitations, thermal stress, degraded soils, or limited water availability.

Food security further strengthens the need to identify environmentally favourable areas for resilient agricultural development. Food security encompasses the availability, access, utilization, and stability of food, all of which can be affected by disruptions to agricultural production and resource availability [6]. Climate-related pressures can increase production risks and undermine the stability of food supplies, particularly where agricultural systems are highly dependent on climate-sensitive resources. Spatially identifying areas with relatively favourable environmental conditions for CSA can therefore complement broader food-security and agricultural-development strategies by providing evidence for geographically differentiated interventions.

Despite the growing importance of CSA, determining where interventions should be prioritized remains a major spatial planning challenge. Agricultural suitability is influenced by multiple environmental dimensions rather than a single variable. Vegetation condition provides an indication of ecosystem productivity, rainfall influences water availability and crop development, temperature affects crop growth and evapotranspiration, soil organic carbon contributes to soil fertility and water-holding capacity, while surface-water availability can provide opportunities for irrigation and strengthen resilience to rainfall

variability. Evaluating these factors jointly is therefore more informative than assessing individual environmental variables independently.

Remote sensing and Geographic Information Systems (GIS) provide effective tools for evaluating these spatially distributed environmental characteristics over large geographical areas. Satellite observations enable the characterization of vegetation condition and land-cover patterns across extensive landscapes, while spatial climate, soil, and hydrological datasets provide complementary information for environmental assessment. Vegetation indices such as the Normalized Difference Vegetation Index (NDVI), for example, have been widely applied to characterize vegetation condition and agricultural landscapes, particularly where conventional ground observations are spatially limited [7, 10].

The integration of remote sensing and GIS with Multi-Criteria Decision Analysis (MCDA) provides an appropriate framework for combining heterogeneous environmental indicators within a common spatial decision-support model. MCDA allows variables with different units and spatial characteristics to be standardized, assigned relative importance, and integrated to produce a composite suitability surface. The Analytic Hierarchy Process (AHP) provides a structured approach for determining criterion weights through pairwise comparison, while Weighted Linear Combination (WLC) allows the weighted criteria to be integrated into a single suitability index [10]. Such an approach has been applied in agricultural and climate-smart planning to identify spatially differentiated intervention priorities based on multiple environmental and land-use considerations [11, 12].

Although CSA has received increasing attention in agricultural development and climate adaptation research, much of the existing work has focused on adoption, farmer perceptions, socioeconomic determinants, individual CSA practices, or localized agricultural systems. These perspectives are important but do not, by themselves, provide a national-scale representation of the spatial distribution of biophysical conditions that may support climate-smart agricultural development. A spatially explicit environmental assessment can therefore provide a complementary baseline for understanding where the biophysical environment is relatively favourable or constrained for CSA implementation across Nigeria.

Accordingly, there is a need for a national-scale framework that integrates vegetation productivity, climatic conditions, soil characteristics, and water availability into a consistent spatial suitability assessment. Such an approach can help reveal geographical patterns of environmental potential and provide a basis for differentiating areas according to their relative suitability for climate-smart agricultural planning. Importantly, such an assessment should be interpreted as a biophysical suitability analysis, rather than a direct measure of CSA adoption capacity, agricultural profitability, or farmer-level resilience.

Therefore, this study applies an integrated remote sensing–GIS–MCDA framework to evaluate the spatial suitability of Climate-Smart Agriculture across Nigeria. Specifically, the study integrates NDVI, mean annual rainfall, mean temperature, soil organic carbon, and surface-water occurrence using AHP-derived criterion weights and a Weighted Linear Combination approach. The resulting national-scale

suitability assessment provides a spatial baseline for identifying areas of relatively favourable and constrained biophysical conditions and supports the prioritization of context-specific climate adaptation, agricultural planning, and sustainable resource-management interventions across Nigeria.

2. Materials and Methods

Nigeria is located in West Africa between approximately 4°N–14°N latitude and 3°E–15°E longitude, covering an area of about 923,768 km². The country contains diverse ecological zones ranging from humid tropical regions in the south to semi-arid environments in the north.

Agriculture remains a major component of Nigeria's economy, with production systems strongly influenced by climatic conditions. The variation in rainfall, temperature, vegetation characteristics, and soil conditions across ecological zones creates differences in agricultural productivity and climate vulnerability.

The spatial diversity of Nigeria provides an appropriate case study for evaluating Climate Smart Agriculture (CSA) suitability using remote sensing and GIS techniques.

Source

Authors' GIS Analysis (2026)

This study employed an integrated Remote Sensing–Geographic Information System (GIS)–Multi-Criteria Decision Analysis (MCDA) framework to evaluate the spatial suitability of Climate-Smart Agriculture (CSA) across Nigeria. The framework was developed on the premise that CSA suitability is governed by the interaction of multiple environmental factors, including vegetation productivity, climatic conditions, soil characteristics, and water availability. Integrating these factors within a spatial modelling environment enables the identification of areas with varying potentials for climate-smart agricultural development.

The methodological framework was guided by the three pillars of Climate-Smart Agriculture proposed by the Food and Agriculture Organization (FAO): (i) sustainable agricultural productivity, (ii) climate change adaptation and resilience, and (iii) mitigation of environmental impacts. Accordingly, environmental indicators representing vegetation, climate, soil, and hydrological conditions were derived from remotely sensed and geospatial datasets and integrated within a GIS environment to produce a composite CSA suitability index.

The analytical workflow comprised five sequential stages: (1) acquisition and preprocessing of geospatial datasets; (2) derivation of environmental indicators; (3) standardization of the indicator layers to a common suitability scale; (4) determination of criterion weights using the Analytic Hierarchy Process (AHP); and (5) integration of the weighted indicators through a Weighted Linear Combination (WLC) approach to generate the final CSA suitability map. The overall methodological framework adopted in this study is presented in Fig. 2.

Environmental datasets representing vegetation, climate, soil properties, and surface water resources were acquired from globally recognized geospatial databases to support the Climate-Smart Agriculture (CSA) suitability assessment (Table 1). Sentinel-2 Level-2A imagery was used to derive vegetation productivity, the Climate Hazards Group InfraRed Precipitation with Station (CHIRPS) dataset was used to characterize rainfall conditions, ERA5-Land reanalysis data were used to represent temperature, SoilGrids provided soil organic carbon information, and the Joint Research Centre (JRC) Global Surface Water dataset was used to assess surface water availability. In addition, the European Space Agency (ESA) WorldCover dataset was employed to generate the land use/land cover (LULC) map used for environmental interpretation.

All datasets were processed within the Google Earth Engine (GEE) and ArcGIS Pro environments. Google Earth Engine was used for data acquisition, image preprocessing, and derivation of environmental indicators, whereas ArcGIS Pro was used for raster harmonization, spatial analysis, weighted overlay modelling, and map production. To ensure spatial compatibility, all datasets were clipped to the Nigerian boundary, projected to a common coordinate reference system, and resampled to a consistent spatial resolution where necessary before subsequent analyses.

Table 1
Geospatial datasets used for Climate-Smart Agriculture suitability assessment

Dataset	Source	Resolution	Period	Application
Sentinel-2 MSI Level-2A	Google Earth Engine	10 m	2015–2025	NDVI (vegetation productivity)
ESA WorldCover v200	European Space Agency	10 m	2021	Land use/land cover mapping
CHIRPS Precipitation	Climate Hazards Center	~ 5 km	2005–2024	Mean annual rainfall
ERA5-Land	Copernicus Climate Data Store	~ 9 km	2005–2025	Mean temperature
SoilGrids	ISRIC	250 m	Static	Soil organic carbon
JRC Global Surface Water	European Commission	30 m	Long-term occurrence	Surface water availability

Footnote

All datasets were clipped to the Nigerian boundary, projected into a common coordinate system, and resampled where necessary to enable spatial integration.

Source

Authors’ GIS Analysis (2026)

Vegetation productivity was assessed using the Normalized Difference Vegetation Index (NDVI) derived from Sentinel-2 Level-2A surface reflectance imagery available through Google Earth Engine (GEE). Sentinel-2 was selected because its 10 m spatial resolution and multispectral bands provide reliable information for monitoring vegetation condition and agricultural landscapes. Surface reflectance products were used to minimize atmospheric effects, while cloud and cloud-shadow pixels were removed using the quality assessment (QA) band to ensure that only high-quality observations were retained.

To reduce the influence of cloud contamination and seasonal variability, a median composite of cloud-free Sentinel-2 imagery acquired between 2015 and 2025 was generated. NDVI was then calculated using the red (Band 4) and near-infrared (Band 8) spectral bands following Tucker [10]:

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

where *NIR* represents the reflectance of Sentinel-2 Band 8 and *RED* represents the reflectance of Sentinel-2 Band 4.

NDVI values range from – 1 to + 1, with higher values indicating denser and healthier vegetation. Within the Climate-Smart Agriculture (CSA) framework, NDVI was used as a proxy for vegetation condition and productivity within the CSA suitability assessment, based on the assumption that areas with healthier vegetation provide more favourable conditions for sustainable agricultural production. The resulting NDVI raster was subsequently standardized and incorporated into the multi-criteria suitability analysis.

Land use/land cover (LULC) was mapped using the European Space Agency (ESA) WorldCover Version 200 dataset, which provides a globally consistent land cover product at 10 m spatial resolution for the year 2021. The dataset integrates Sentinel-1 Synthetic Aperture Radar (SAR) and Sentinel-2 multispectral imagery using a machine learning classification approach, making it suitable for regional and national-scale environmental assessments [12].

To support the Climate-Smart Agriculture (CSA) assessment, the original ESA WorldCover classes were reclassified into five generalized categories: cropland, forest, grassland, built-up areas, and water bodies. This reclassification simplified the thematic structure while retaining the major land cover types relevant to agricultural planning and environmental assessment across Nigeria.

The resulting LULC map was used to characterize the spatial distribution of major land cover types and to support the interpretation of CSA suitability patterns. Although LULC was not incorporated as a weighted criterion in the multi-criteria decision analysis (MCDA), it provided important environmental context for explaining the spatial variability of vegetation productivity and the final suitability classes. The ESA WorldCover dataset was selected because of its high spatial resolution, standardized classification scheme, and suitability for national-scale environmental and agricultural analyses.

Climate suitability was assessed using rainfall and temperature because these variables strongly influence crop growth, soil moisture availability, evapotranspiration, and agricultural productivity. Long-term climatic conditions were represented using the Climate Hazards Group InfraRed Precipitation with Station (CHIRPS) dataset for rainfall and the ERA5-Land reanalysis dataset for temperature. These datasets provide spatially consistent climate information suitable for regional environmental and agricultural assessments.

Rainfall conditions were derived from the Climate Hazards Group InfraRed Precipitation with Station (CHIRPS) dataset, which combines satellite observations with ground-based rain gauge measurements to produce precipitation estimates at approximately 5 km spatial resolution [13]. Pentad rainfall data covering the period 2005–2024 were aggregated to annual totals, from which the long-term mean annual rainfall surface was calculated as:

$$P_{mean} = \frac{\sum_{i=1}^n P_i}{n}$$

where:

P_{mean} = mean annual rainfall,

P_i = annual rainfall for year i ,

n = total number of years.

Temperature was assessed using the ERA5-Land Monthly Aggregated reanalysis dataset developed by the European Centre for Medium-Range Weather Forecasts (ECMWF). ERA5-Land provides monthly land surface climate variables at approximately 9 km spatial resolution through numerical weather modelling and data assimilation [14]. Monthly temperature data for 2005–2025 were averaged to generate the long-term mean temperature surface using:

$$T_{mean} = \frac{\sum_{i=1}^n T_i}{n}$$

where:

T_{mean} = mean temperature,

T_i = monthly temperature observation,

n = total number of observations.

Soil organic carbon (SOC) and surface water availability were used to represent the edaphic and hydrological components of Climate-Smart Agriculture (CSA). SOC was obtained from the SoilGrids database at 250 m spatial resolution, which provides globally consistent predictions of soil properties

based on machine learning and environmental covariates[15]. Higher SOC values were considered indicative of improved soil fertility, nutrient availability, water-holding capacity, and long-term agricultural sustainability.

Surface water availability was derived from the Joint Research Centre (JRC) Global Surface Water dataset, which maps long-term surface water occurrence using Landsat observations [16]. Areas with greater surface water occurrence were considered more suitable for CSA because they provide opportunities for irrigation and improve agricultural resilience under increasing climatic variability. Both datasets were subsequently standardized before integration into the suitability model.

To ensure comparability among environmental indicators with different units and value ranges, all raster layers were standardized to a common suitability scale ranging from 0 to 1 using percentile-based min–max normalization. The 2nd and 98th percentile values were used as the lower and upper normalization limits to reduce the influence of extreme outliers. For indicators positively associated with CSA suitability (NDVI, rainfall, soil organic carbon, and surface water availability), higher normalized values represented more favourable conditions. Conversely, inverse normalization was applied to the temperature layer because higher temperatures generally reduce agricultural suitability. The standardized datasets were subsequently used as inputs to the multi-criteria suitability analysis.

The five standardized criteria were integrated using a Multi-Criteria Decision Analysis (MCDA) framework and Weighted Linear Combination (WLC). Relative criterion weights were established using an AHP-based pairwise comparison structure following Saaty [8]. The resulting weights were 0.25 for NDVI, 0.20 for rainfall, 0.20 for temperature, 0.20 for SOC, and 0.15 for surface-water occurrence (Table 2).

The consistency of the comparison matrix was assessed using the Consistency Index (CI) and Consistency Ratio (CR):

$$CI = \frac{\lambda_{max} - n}{n - 1} CR = \frac{CI}{RI}$$

The pairwise comparison matrix produced a maximum eigenvalue (λ_{max}) of 5.000, CI = 0.000, and CR = 0.000, indicating an internally consistent weighting structure and satisfying the recommended CR < 0.10 threshold [8].

The final CSA suitability index was calculated as:

$$CSA = \sum_{i=1}^n W_i X_i$$

where CSA is the suitability index, W_i is the weight assigned to criterion i , and X_i is the standardized value of criterion i .

The weights assigned to each criterion are presented in Table 2.

Table 2
Pairwise comparison matrix and criterion weights used in the CSA suitability model

Criterion	NDVI	Rainfall	Temperature	SOC	Water occurrence	Weight
NDVI	1	1.25	1.25	1.25	1.667	0.25
Rainfall	0.8	1	1	1	1.333	0.2
Temperature	0.8	1	1	1	1.333	0.2
SOC	0.8	1	1	1	1.333	0.2
Water occurrence	0.6	0.75	0.75	0.75	1	0.15
Source: Authors' GIS Analysis (2026)						

The standardized environmental layers were integrated in ArcGIS Pro using the weighted overlay technique to generate the final CSA suitability surface. The resulting suitability index ranged from 0 to 1, with higher values indicating increasingly favourable environmental conditions for Climate-Smart Agriculture implementation.

For interpretation and spatial decision-making, the continuous suitability index was classified into five equal-interval classes: Very Low (0.00–0.20), Low (0.20–0.40), Moderate (0.40–0.60), High (0.60–0.80), and Very High (0.80–1.00). The classified suitability map was used to identify priority areas for climate-smart agricultural planning across Nigeria.

3. Results

Source

Authors' GIS Analysis (2026)

Figure 3 presents the spatial distribution of land use/land cover across Nigeria. Cropland and natural vegetation occupy extensive portions of the country, while built-up areas are concentrated around major urban centres. The distribution provides important contextual information for interpreting CSA suitability because the environmental potential identified by the model occurs within an existing landscape of agricultural, natural, and developed land uses. However, LULC was retained as a contextual layer rather than an MCDA criterion because the study evaluates biophysical suitability for CSA rather than existing agricultural land availability.

Source

Authors' GIS Analysis (2026)

Figure 4 indicates substantial spatial variation in vegetation condition, with NDVI values ranging from – 0.668543 to 0.881646. Higher values are concentrated mainly in southern Nigeria and parts of the

Middle Belt, while lower values occur predominantly towards the northern ecological zones. The pattern corresponds broadly with the country's rainfall and ecological gradient, with greater vegetation productivity under wetter conditions. Negative or very low values are associated largely with water, built-up surfaces, exposed soil and other sparsely vegetated areas. NDVI therefore provides a useful spatial indicator of vegetation condition and was assigned the highest criterion weight (0.25) in the AHP model.

Source

Authors' GIS Analysis (2026)

Figure 5 illustrates mean annual rainfall for 2005–2024, with values ranging from 129.27 to 3,875.22 mm. Rainfall generally increases towards southern Nigeria, particularly the coastal and Niger Delta areas, while lower values characterize northern Nigeria. Central Nigeria forms an intermediate transition between these climatic regimes. This spatial gradient is consistent with the influence of the seasonal movement of the Inter-Tropical Convergence Zone and associated moisture distribution across West Africa. The rainfall pattern has direct implications for agricultural water availability and therefore contributes substantially to the spatial differentiation of CSA suitability.

Source

Authors' GIS analysis (2026)

Figure 6 presents mean temperature values ranging from 18.92 to 29.65°C. Higher temperatures generally characterize northern Nigeria, whereas comparatively lower temperatures occur towards the south, with intermediate conditions across the central region. The spatial pattern reflects broad climatic differences across the country and is important for CSA planning because temperature influences crop development, evapotranspiration and soil-water dynamics. Within the suitability model, temperature was therefore treated as an inverse criterion, such that relatively higher temperatures contributed lower suitability scores.

Source

Authors' GIS Analysis (2026)

Figure 7 shows soil organic carbon (SOC) concentrations ranging from 0 to 66 g kg⁻¹. The lowest SOC class (0–2.85 g kg⁻¹) covers extensive areas, particularly in northern Nigeria, whereas higher concentrations occur increasingly towards southern Nigeria. The highest values (24.85–66.00 g kg⁻¹) are concentrated in localized coastal and Niger Delta environments. SOC is important to agricultural resilience because soil organic matter contributes to nutrient cycling and soil physical properties. The spatial representation of SOC is consistent with the purpose of SoilGrids, which provides gridded predictions of soil organic carbon and other soil properties using environmental covariates and machine-learning methods [15]

Source

Authors' GIS Analysis (2026)

Figure 8 depicts surface-water occurrence, ranging from 0 to 100%. Very low occurrence (0–5.88%) dominates much of mainland Nigeria, while higher occurrence is concentrated around major rivers, reservoirs, wetlands and coastal environments. The highest occurrence class (73.73–100%) corresponds primarily to persistent water bodies and major water channels. This spatial distribution is consistent with the JRC Global Surface Water product, which characterizes the location and persistence of surface water using long-term Landsat observations [16]. Because surface water can provide supplementary opportunities for irrigation and water management, it was incorporated into the CSA suitability model with a weight of 0.15.

Source

Authors' GIS Analysis (2026)

Figure 9 presents the final CSA suitability index derived from the weighted integration of NDVI, rainfall, temperature, SOC and surface-water occurrence. The results reveal clear spatial differentiation in environmental suitability across Nigeria, with higher suitability concentrated predominantly in southern and selected central areas, while lower suitability dominates much of the north. As shown in Table 3, Very Low suitability covers 391,014.00 km² (42.33%), while Low suitability covers 348,928.00 km² (37.77%). Moderate suitability accounts for 121,013.00 km² (13.10%), whereas High and Very High suitability cover 54,613.00 km² (5.91%) and 8,200.00 km² (0.89%), respectively. Overall, 80.10% of Nigeria falls within the Very Low and Low suitability categories, compared with 6.80% within the High and Very High classes.

The dominance of lower suitability classes is largely associated with the combined effects of reduced rainfall, higher temperatures, lower vegetation productivity and relatively low SOC across much of northern Nigeria. Conversely, southern and selected central areas benefit from comparatively favourable moisture conditions, vegetation productivity and soil characteristics. This spatial differentiation supports the broader CSA principle that adaptation interventions should be context-specific rather than uniformly applied across agricultural landscapes [3].

Table 3
Spatial distribution of Climate Smart Agriculture suitability classes across Nigeria

CSA suitability class	Area (km ²)	Percentage (%)
Very Low	391014.00	42.33
Low	348928.00	37.77
Moderate	121013.00	13.1
High	54613.00	5.91
Very High	8200.00	0.89
Total	923768.00	100
Source: Authors' GIS Analysis (2026)		

The spatial pattern indicates that CSA interventions should be differentiated according to environmental conditions. Areas within the High and Very High classes may provide comparatively favourable conditions for sustainable agricultural intensification, whereas the extensive Very Low and Low suitability zones require greater emphasis on adaptive measures such as water conservation, irrigation, soil-management practices and climate-resilient production systems. The results therefore provide a national-scale spatial screening framework for prioritising CSA interventions. However, the suitability index represents biophysical potential rather than actual CSA adoption capacity. Socioeconomic conditions, infrastructure, market accessibility, land tenure and farmers' adaptive capacity were not incorporated and should be considered in subsequent assessments.

4. Conclusion

This study evaluated the spatial suitability of Climate-Smart Agriculture (CSA) across Nigeria using an integrated Remote Sensing, GIS, AHP, and Weighted Linear Combination framework. The results demonstrate substantial spatial variation in biophysical conditions for CSA, characterized by a clear south–north gradient. Higher suitability was concentrated mainly in southern and parts of central Nigeria, where comparatively favourable vegetation conditions, rainfall, temperature, soil organic carbon, and surface-water availability prevail. In contrast, much of northern Nigeria recorded low suitability, reflecting comparatively limited moisture availability, higher temperatures, and less favourable vegetation and soil conditions.

The suitability assessment indicates that 80.10% of Nigeria falls within the Very Low and Low suitability classes, whereas only 6.80% falls within the High and Very High suitability classes. These findings highlight the need for spatially differentiated CSA interventions rather than a uniform national strategy. Areas with lower biophysical suitability may require greater emphasis on water conservation, irrigation,

soil management, and climate-resilient agricultural practices, while areas with higher suitability may offer greater opportunities for sustainable agricultural intensification.

The study provides a national-scale geospatial decision-support framework for identifying areas where CSA interventions can be prioritised. However, the assessment represents biophysical suitability only and does not account for socioeconomic and institutional factors such as market accessibility, infrastructure, land tenure, farm management, or farmers' adaptive capacity. Future research should integrate these dimensions with the environmental suitability framework to provide a more comprehensive basis for CSA investment, agricultural planning, and food-security interventions in Nigeria.

Declarations

Ethics Approval

Not applicable. This study did not involve human participants, animals, or the collection of personal or sensitive data. The analysis was conducted using satellite imagery and publicly available geospatial datasets.

Consent to Participate

Not applicable. This study did not involve human participants.

Consent to Publish

Not applicable.

Competing Interests

The authors declare that they have no competing interests.

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Author Contribution

B.B.R. conceived and designed the study, developed the methodology, conducted the data acquisition, processing and analysis, performed the GIS and remote sensing analyses, and wrote the manuscript. L.T.A., T.M.A., and D.O.A. provided academic guidance and supervision. All authors approved the final manuscript.

Data Availability Statement

The datasets generated during and/or analysed during the current study are available from the corresponding author on reasonable request.

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Figures

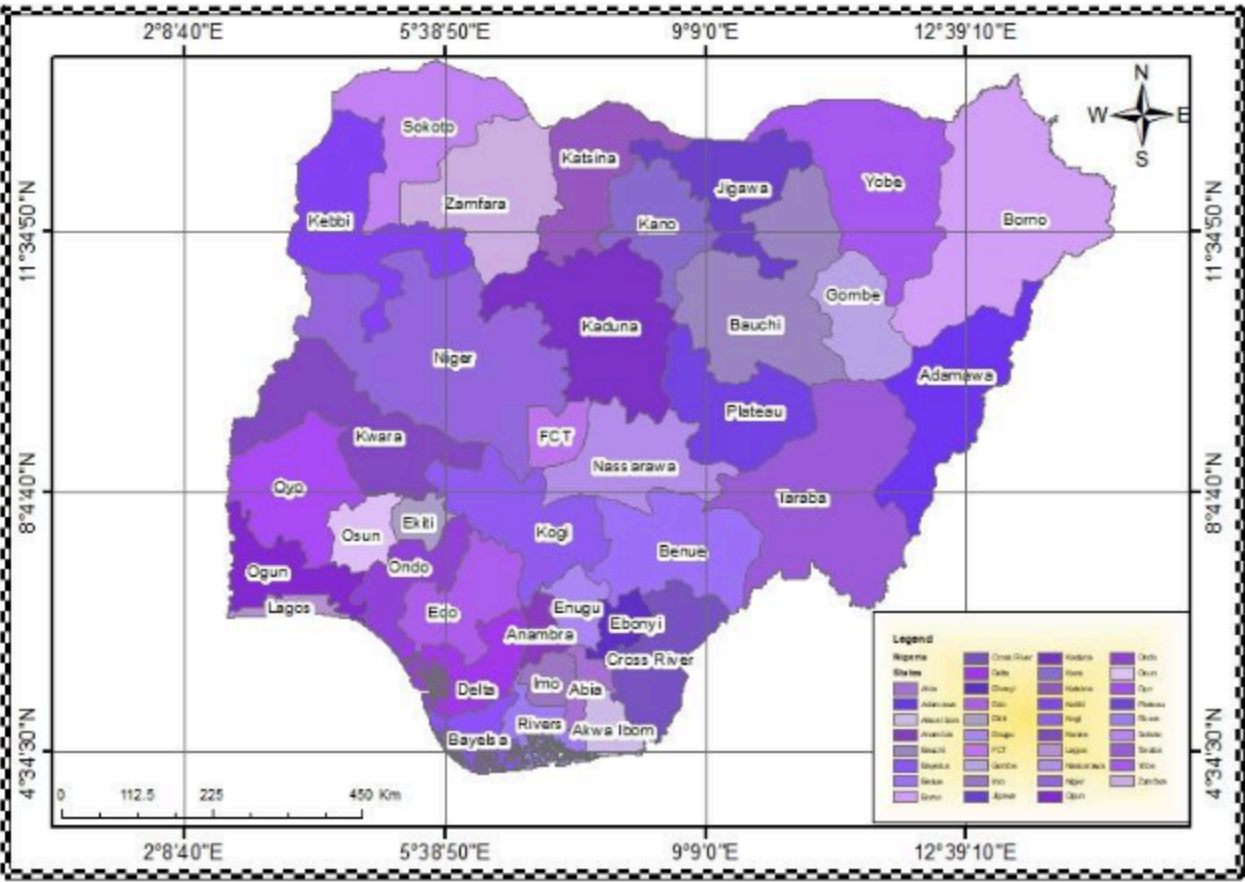


Figure 1

Map of Nigeria

Source: Authors' GIS Analysis (2026)

CSA Suitability Assessment Process

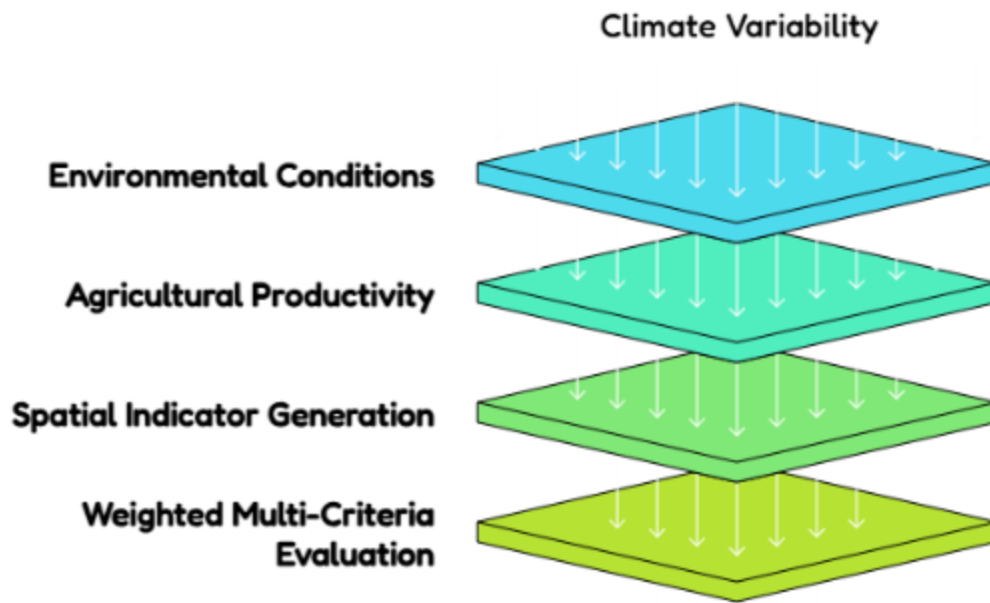


Figure 2

CSA suitability assessment

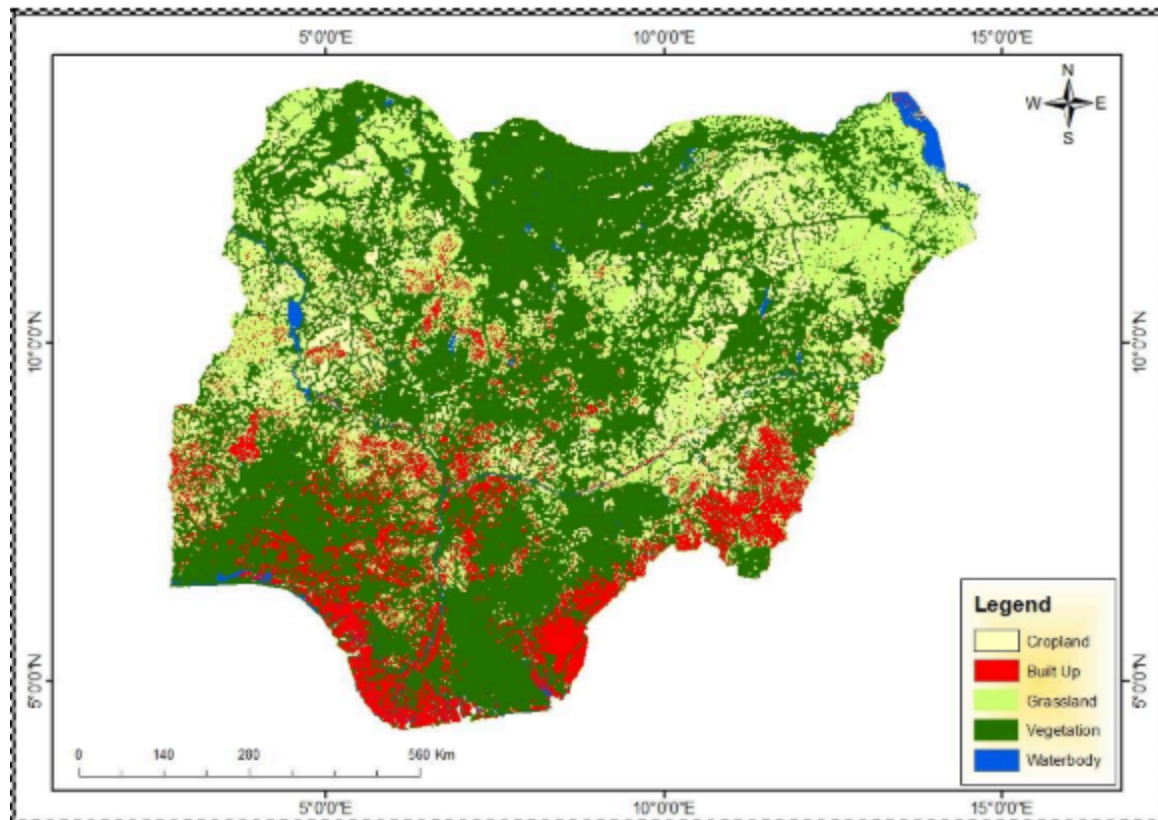


Figure 3

Source: Authors' GIS Analysis (2026)

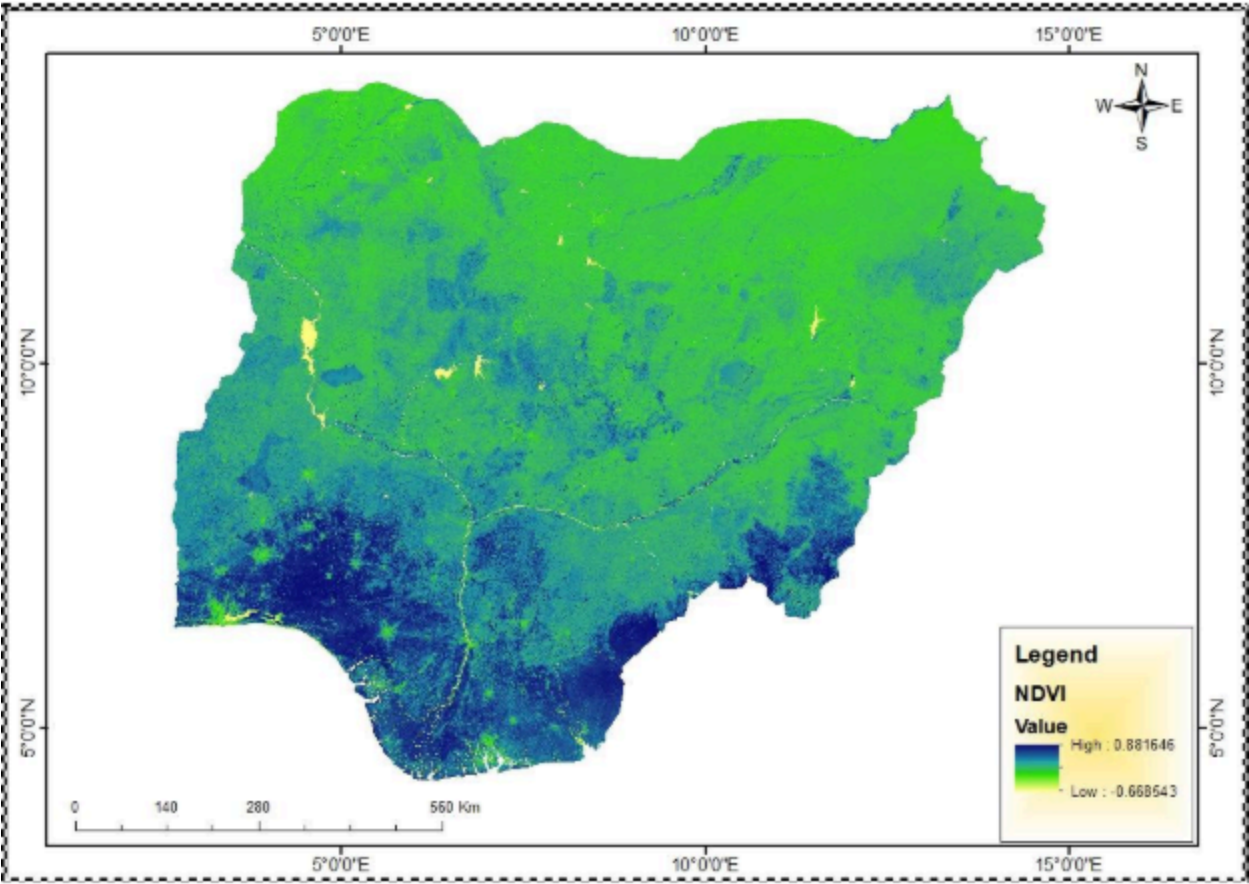


Figure 4

Normalized Difference Vegetation Index (NDVI) of Nigeria

Source: Authors' GIS Analysis (2026)

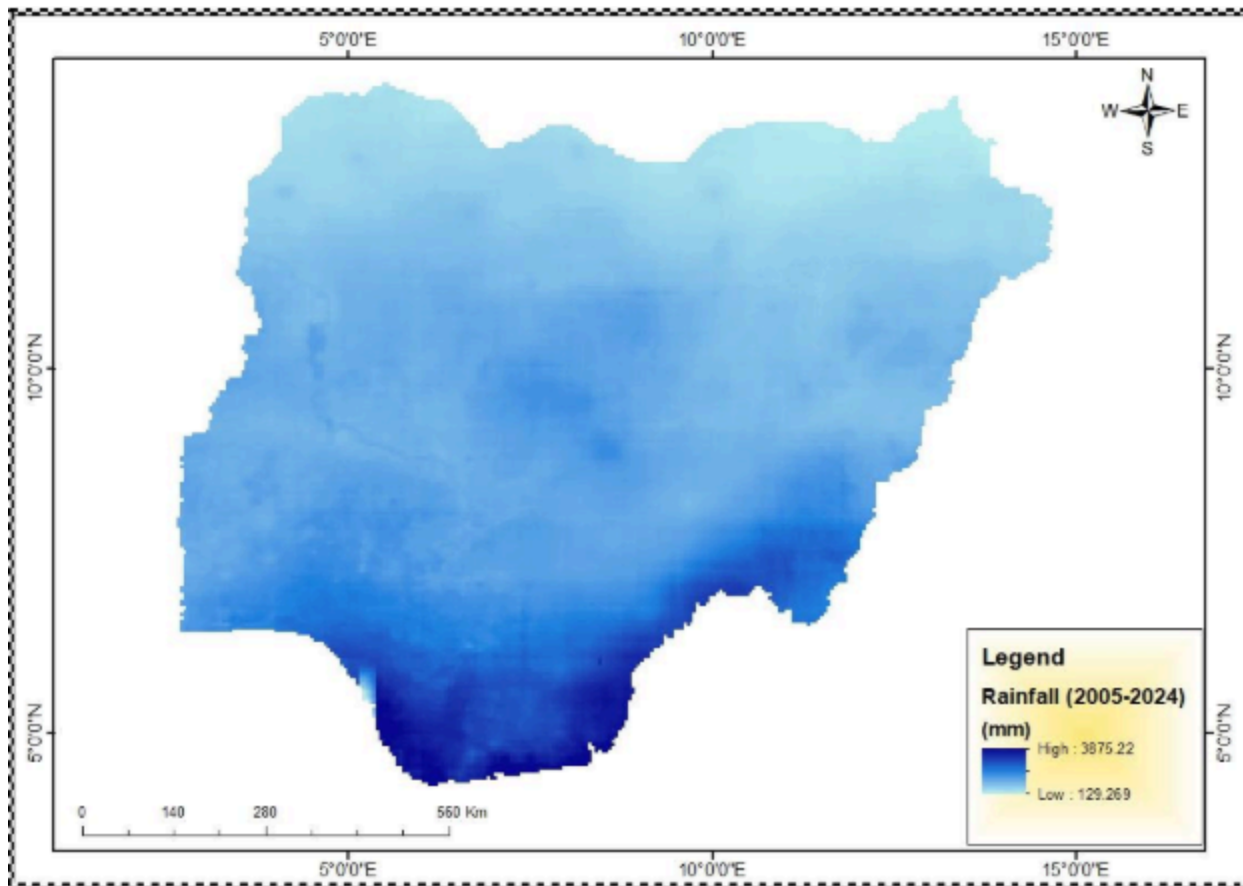


Figure 5

Rainfall Map of Nigeria

Source: Authors' GIS Analysis (2026)

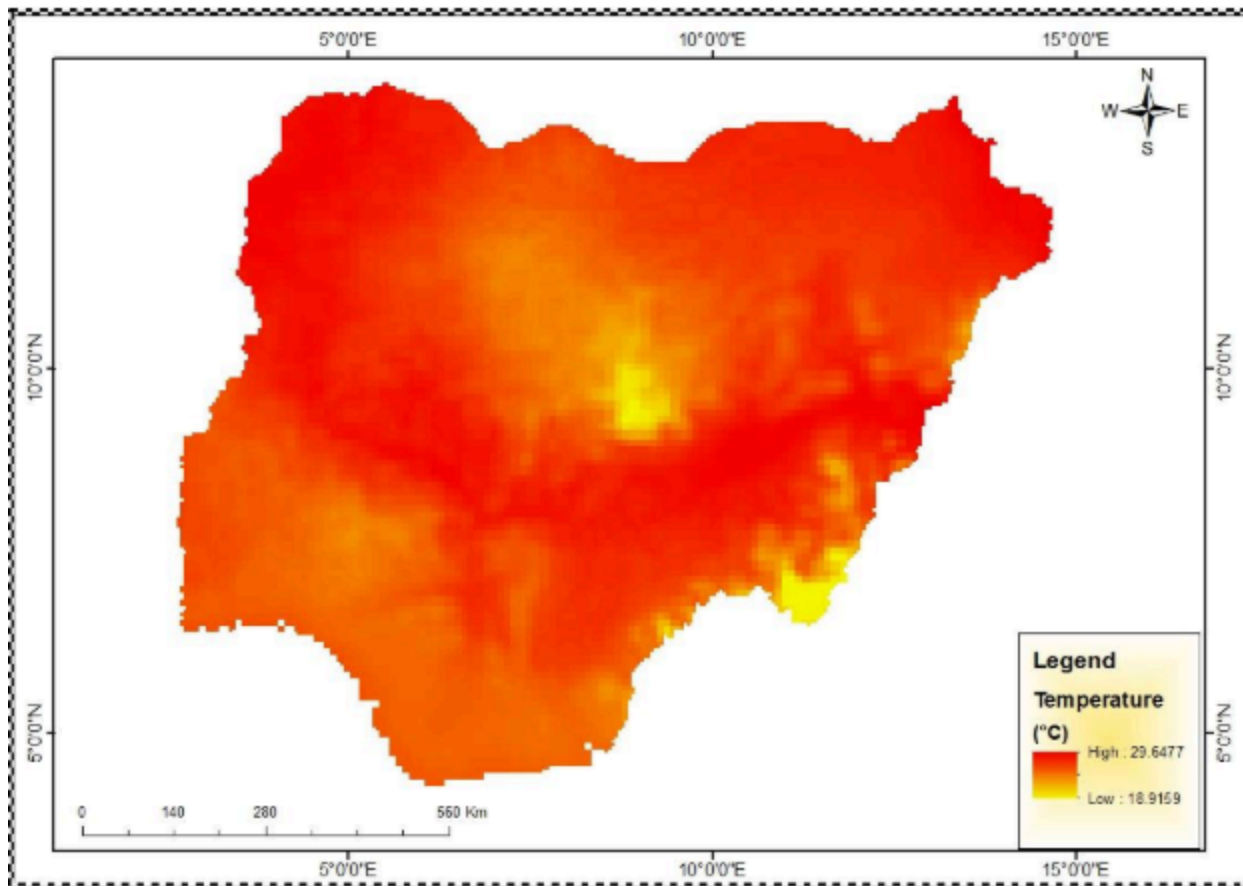


Figure 6

Mean Temperature Distribution

Source: Authors' GIS analysis (2026)

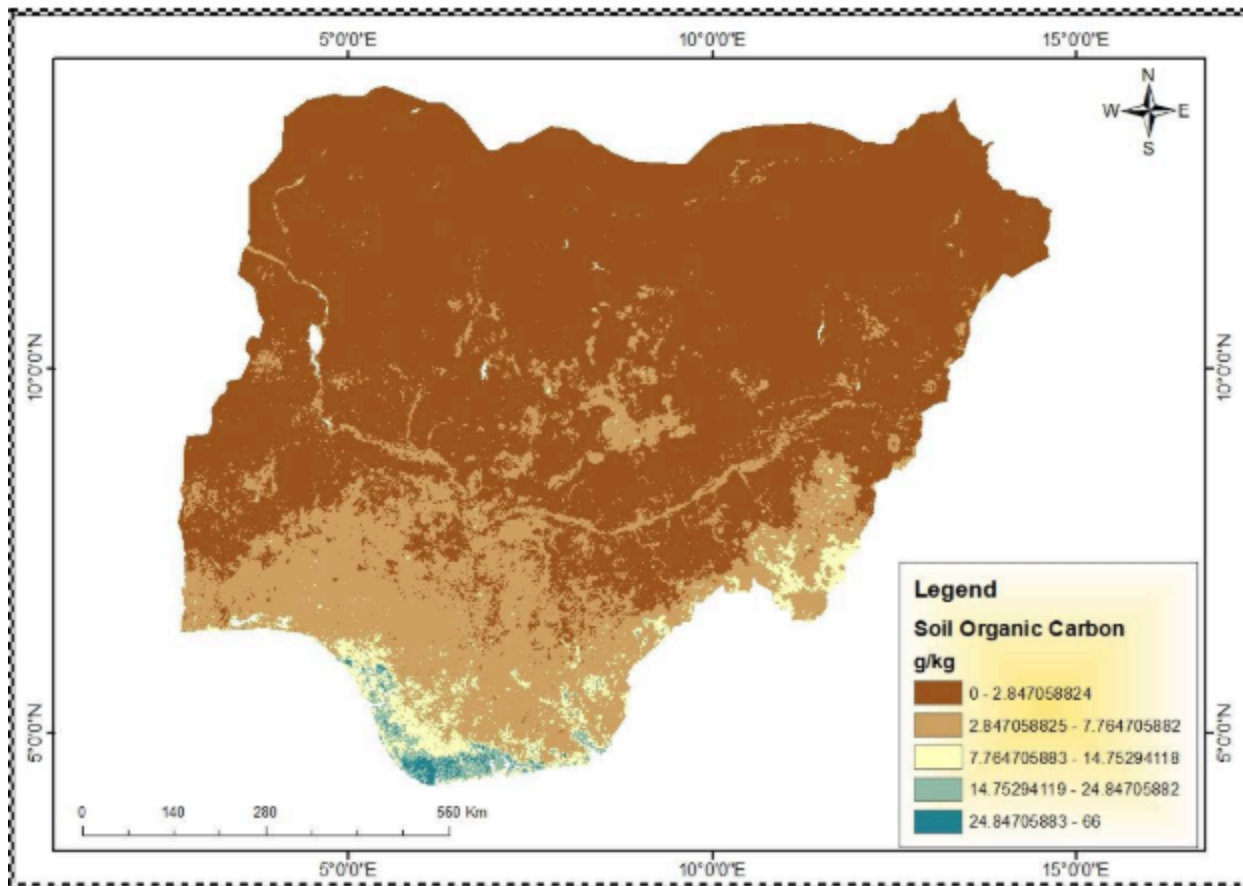


Figure 7

Soil Organic Carbon Map of Nigeria

Source: Authors' GIS Analysis (2026)

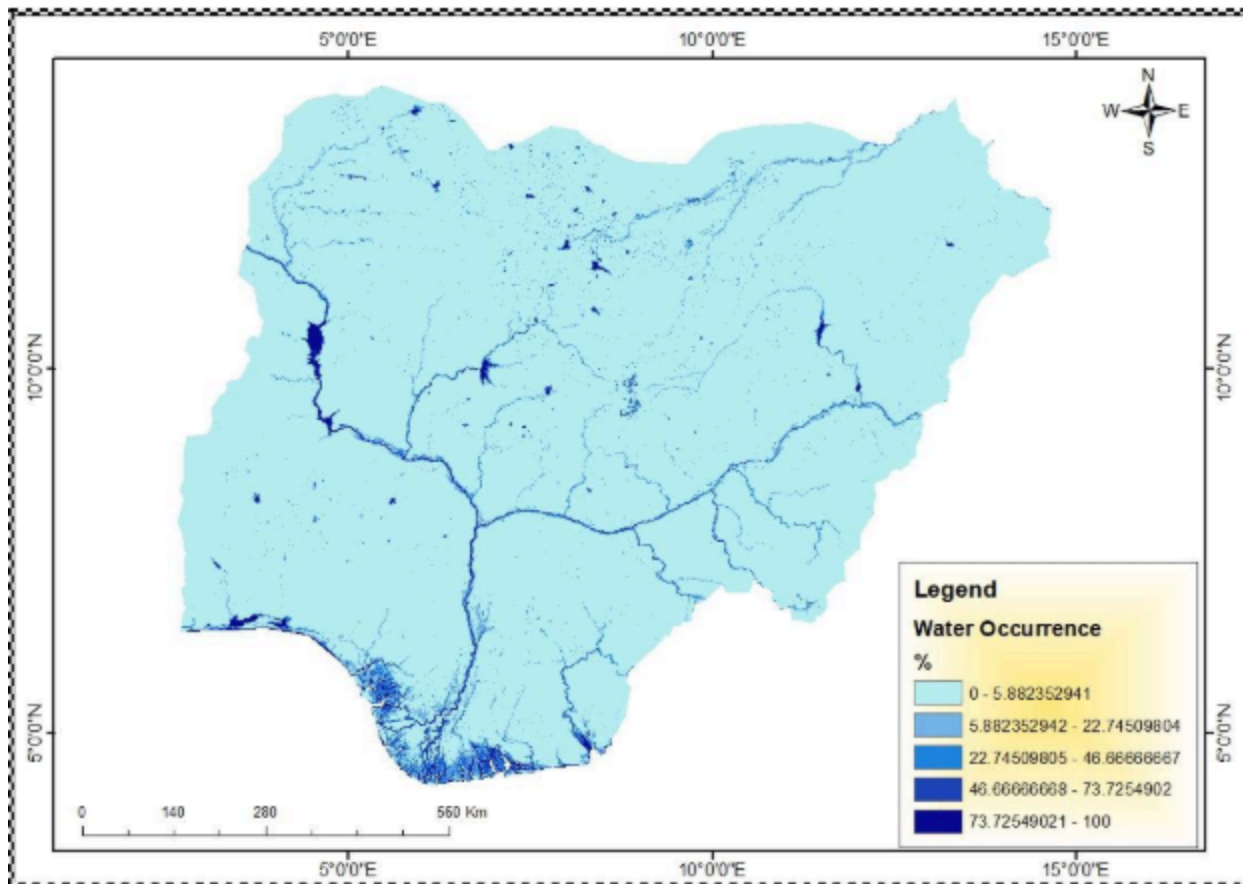


Figure 8

Water Occurrence Map of Nigeria

Source: Authors' GIS Analysis (2026)

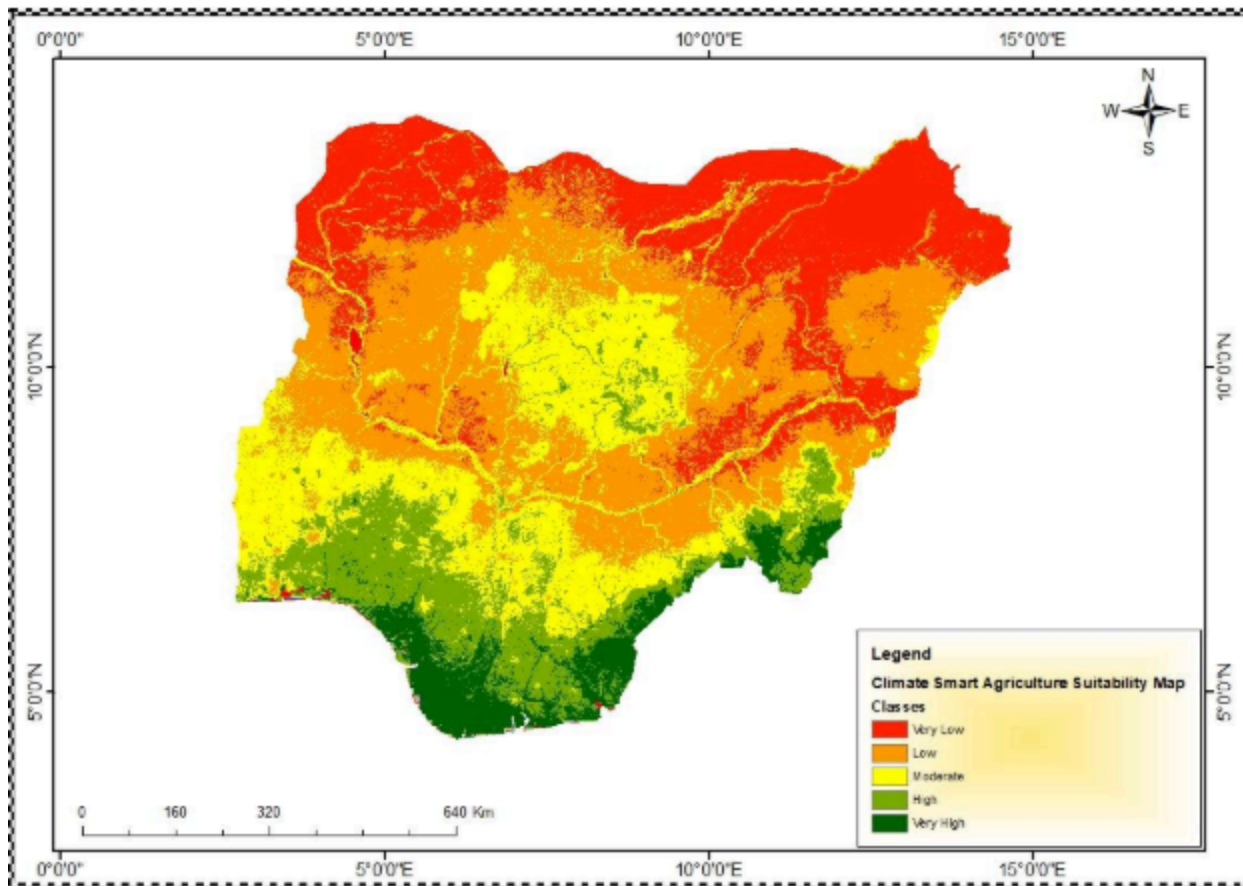


Figure 9

Climate Smart Suitability Map of Nigeria

Source:Authors' GIS Analysis (2026)