Journal of Spatial Information Sciences

...JSIS

AGRICULTURAL LAND SUITABILITY MAPPING IN AKWA IBOM STATE, NIGERIA USING CLOUD-BASED REMOTE SENSING AND GIS

UTIBENOABASI OBOT, ANIEKAN EYOH

JOURNAL OF SPATIAL INFORMATION SCIENCES ISSN: 2354-3361
VOL. 3, ISSUE 1, PP 126–142, 2026 DOI: https://doi.org/10.5281/zenodo.20706933
PUBLISHED 15-05-2026
www.journals.unizik.edu.ng/jsis

AGRICULTURAL LAND SUITABILITY MAPPING IN AKWA IBOM STATE, NIGERIA USING CLOUD-BASED REMOTE SENSING AND GIS

[1]Utibenoabasi obot, [2]Aniekan Eyoh

[1&2]*Department of Geoinformatics and Surveying, Faculty of Environmental Studies, University of Uyo.*

Email: [1]*jessdan389@yahoo.com*, [2]*aniekaneyoh@uniuyo.edu.ng*

DOI: https://doi.org/10.5281/zenodo.20706933

Abstract

Rapid population growth and concurrent urban expansion in Nigeria have placed unprecedented pressure on arable land, necessitating precise, data-driven geospatial evaluations to secure regional food supplies. This study integrates cloud-based remote sensing and Geographic Information System (GIS) technologies to map agricultural suitability zones in Akwa Ibom State, Nigeria. Google Earth Engine (GEE) and ArcGIS 10.8 were employed for land use/land cover classification using Sentinel-2 imagery, factor weight determination via the Analytical Hierarchy Process (AHP), and weighted overlay analysis. Five biophysical factors were assessed: soil properties, climate, topography, land use/land cover, and Normalized Difference Vegetation Index (NDVI) using data spanning 2014-2024 from ISRIC SoilGrids, ALOS PALSAR DEM, CHIRPS, and ERA5. AHP assigned weights of soil properties (51.8%), climate (26.5%), topography (10.4%), land use/land cover (7.9%), and NDVI (3.4%). Results indicate 14.89% (1,002.60 km²) is very highly suitable and 28.19% (1,898.14 km²) is highly suitable for agriculture, with Nsit Ubium and Uruan Local Government Areas showing the highest suitability. Conversely, 8.96% (603.31 km²) and 17.03% (1,146.66 km²) were classified as very low and low suitability. Ground-truthing via soil sampling validated the map, confirming superior soil characteristics in high-suitability zones. The study demonstrates the efficacy of cloud-based geospatial technologies for data-driven agricultural planning and provides a replicable framework for sustainable land-use management.

Keywords: agricultural suitability mapping, cloud-based remote sensing, Google Earth Engine, Geographic Information System, Analytical Hierarchy Process.

ISSN: 2354-3361
DOI: https://doi.org/10.5281/zenodo.20706933
www.journals.unizik.edu.ng/jsis

1. Introduction

The global demand for food is increasing steadily due to exponential population growth and changing dietary patterns [13]. In recognition of this and other challenges, world leaders adopted 17 Sustainable Development Goals (SDGs) in 2015. SDG 2 specifically aims to end hunger, achieve food security and improved nutrition, and promote sustainable agriculture. Its key targets include ensuring access to safe and nutritious food for all, doubling agricultural productivity of small-scale producers, and implementing resilient agricultural practices that maintain ecosystems and strengthen adaptation to climate change [13].

In Nigeria, the path to food security is complicated by a historic shift from an agrarian to an oil-based economy following the 1956 discovery of crude oil in Oloibiri. Prior to the oil boom of the 1970s, agriculture contributed over 65% of GDP and was the main source of foreign exchange through cash crops such as rubber, groundnuts, cocoa, and palm oil [7][10]. The subsequent neglect of agriculture has left the country vulnerable to food insecurity. In September 2024, Bill Gates highlighted that Nigeria had the second-highest global rate of food insecurity, noting that the country received the largest share of his foundation's Africa intervention funds for this reason [2]. The Nigerian Economic Summit Group reported that the number of food-insecure Nigerians rose from 66.2 million in Q1 2023 to 100 million in Q1 2024, with food inflation surging to 35.41% in January 2024. Desertification in the north, over-reliance on rainfall, oil exploitation, gas flaring, land degradation, deforestation, and urbanization have further exacerbated the crisis [7][6].

Akwa Ibom State, in Nigeria's coastal Niger Delta, offers both opportunities and challenges. The state benefits from rich soils and favourable climate but faces land degradation from oil activities and indiscriminate land-use patterns. Accurate, up-to-date mapping of agricultural suitability is therefore essential for evidence-based planning. Cloud-based remote sensing and GIS technologies, particularly Google Earth Engine (GEE), provide efficient tools for processing large-scale geospatial data without local downloads [5].

Although remote sensing and GIS technologies have proven effective in agricultural mapping the world over, there exists a significant research gap in Akwa Ibom State with regards to their integration with cloud-based platforms for a comprehensive agricultural zone mapping [3]. This technological gap has resulted in inefficient agricultural resource allocation, limited understanding of suitable farming zones, and inadequate information for evidence-based agricultural planning.

This project aimed at addressing this gap by developing an integrated framework that combines cloud-based remote sensing and GIS technologies, with surveying principles, for mapping suitable agricultural zones in the state, thereby, contributing in promoting sustainable land use and enhancing food security.

The objectives of this study were to: carry out LULC classification using Sentinel-2 imagery acquired from GEE, develop a pairwise comparison matrix for agricultural suitability factors using AHP, apply spatial analysis techniques in ArcGIS for geospatial data integration and modelling, and validate results through soil testing. The study focused on biophysical factors (soil properties, climate, topography, LULC, and NDVI) using datasets from 2014-2024 across Akwa Ibom State's 31 LGAs. Socioeconomic factors and future projections were excluded.

Previous studies have successfully applied GEE and AHP for agricultural zoning in data-scarce environments, confirming the robustness of these methods.

[12] demonstrated the application of Earth observation data for mapping cropland soils, providing crucial insights for soil management practices. This work was further enhanced by [9], who developed SoilGrids 2.0 using GEE. This is a comprehensive global soil information system that provides quantified spatial uncertainty estimates, and is particularly useful for regions, like Akwa Ibom State, where detailed soil surveys are lacking. [8] showcased the integration of GEE with machine learning algorithms for mapping croplands across extensive geographical areas. This achieved high levels of accuracy in crop identification and monitoring.

[3] used remote sensing, GIS, GEE, and AHP to assess agricultural land suitability across Nigeria's six geopolitical zones, including the South-south zone (Akwa Ibom State). Key factors analysed were soil moisture, land surface temperature, precipitation, slope, elevation, and soil organic carbon. The study produced a national cropland suitability map with five categories: very high (8%), high (25%), moderate (29%), marginal (25%), and low (14% of croplands). The findings demonstrated Nigeria's substantial arable land potential for food self-sufficiency.

[4] integrated RS, GIS, GEE, ArcGIS, and AHP to assess agricultural land suitability with a focus on sustainable development. Factors analysed included soil texture, soil pH, precipitation, temperature, and soil moisture, with weights assigned based on expert opinions using AHP. The study produced four suitability classes: highly suitable (27.5%), moderately suitable (42.8%), marginally suitable (17.6%), and not suitable (12.1%).

ISSN: 2354-3361
DOI: https://doi.org/10.5281/zenodo.20706933

[11] applied a Multi-Influencing Factors (MIF) approach to assess agricultural land suitability in India's sub-Himalayan region, which has similar tropical conditions to Akwa Ibom State (approximately 2,500 mm/year rainfall, flat topography). They integrated eleven factors across topographic, land use/land cover, soil, climatic, and accessibility parameters. Satellite imagery was processed using ERDAS Imagine and ArcGIS, with the final suitability map produced via weighted overlay. Results yielded five classes: high (424.3 km²), moderate (1,191.8 km²), marginal (1,141.4 km²), currently not suitable (567.1 km²), and permanently not suitable (60.8 km²). Validation was conducted using Google Earth, Landsat 8, and GPS field visits. The authors recommended sustainable management and resilient farming practices. Although the study was not cloud-based, its RS-GIS framework can be upgraded using GEE for improved data handling.

These literatures confirm that RS, GIS, GEE, and AHP have been successfully integrated for agricultural suitability mapping globally. [12][9] established the value of Earth observation data and SoilGrids 2.0 for data-scarce regions. [3] mapped Nigeria's national suitability, finding 33% of croplands highly or very highly suitable. [4] produced a four-class suitability model with 70.3% of land being highly or moderately suitable. [11] applied an eleven-factor MIF approach in tropical sub-Himalayan India (similar to Akwa Ibom State), producing five suitability classes validated with GPS field visits. While this last study provides a strong methodological template, it lacked cloud-based processing, a gap the present study fills by leveraging GEE.

2. Study Area

Akwa Ibom State is located in the coastal southern Niger Delta region of Nigeria. It approximately lies between 330,000-430,000 mE and 490,000-610,000 mN, covering a total land area of 7,249 km². The state is bounded by Cross River State to the east, Abia and Rivers States to the west and north-west, and the Atlantic Ocean to the south. Uyo is the state capital. With an estimated population of 7.2 million and a population density of 770 persons/km², the state is one of the most densely populated in Nigeria [1].

The topography is generally low-lying with gentle slopes and an average elevation of 42.58 m above mean sea level. Geologically, the state is underlain by sedimentary formations of the Niger Delta Basin. It experiences a tropical monsoon climate characterized by two distinct seasons: a wet season (April to October) and a short dry season (November to March). The state receives an average annual rainfall of 2,509 mm, mean annual temperature of 28.47°C, with high humidity (80%) and approximately 294 rainy days per year [1]

JOURNAL OF SPATIAL INFORMATION SCIENCES
VOL. 3, ISSUE 1, PP 126–142, 2026
PUBLISHED 15-05-2026
ISSN: 2354-3361
DOI: https://doi.org/10.5281/zenodo.20706933
www.journals.unizik.edu.ng/jsis

Akwa Ibom State is divided into 31 Local Government Areas grouped under three senatorial districts: Akwa Ibom North-East (Uyo), North-West (Ikot Ekpene), and South (Eket). The larger ethnic groups are the Ibibio (the largest), Annang, and Oro, alongside smaller groups such as Obolo, Ijaw, and Ekid. The socio-economic life of the people revolves around agriculture, fishing, petty trading, and oil-related activities [1]. The state is renowned for its rich cultural heritage, vibrant traditions, and diverse local cuisines such as *ekpang nkukwo*, *efere afang*, and *efere edikanikong*. It also boasts several tourist attractions including Ibeno Beach and the Bridge of No Return.

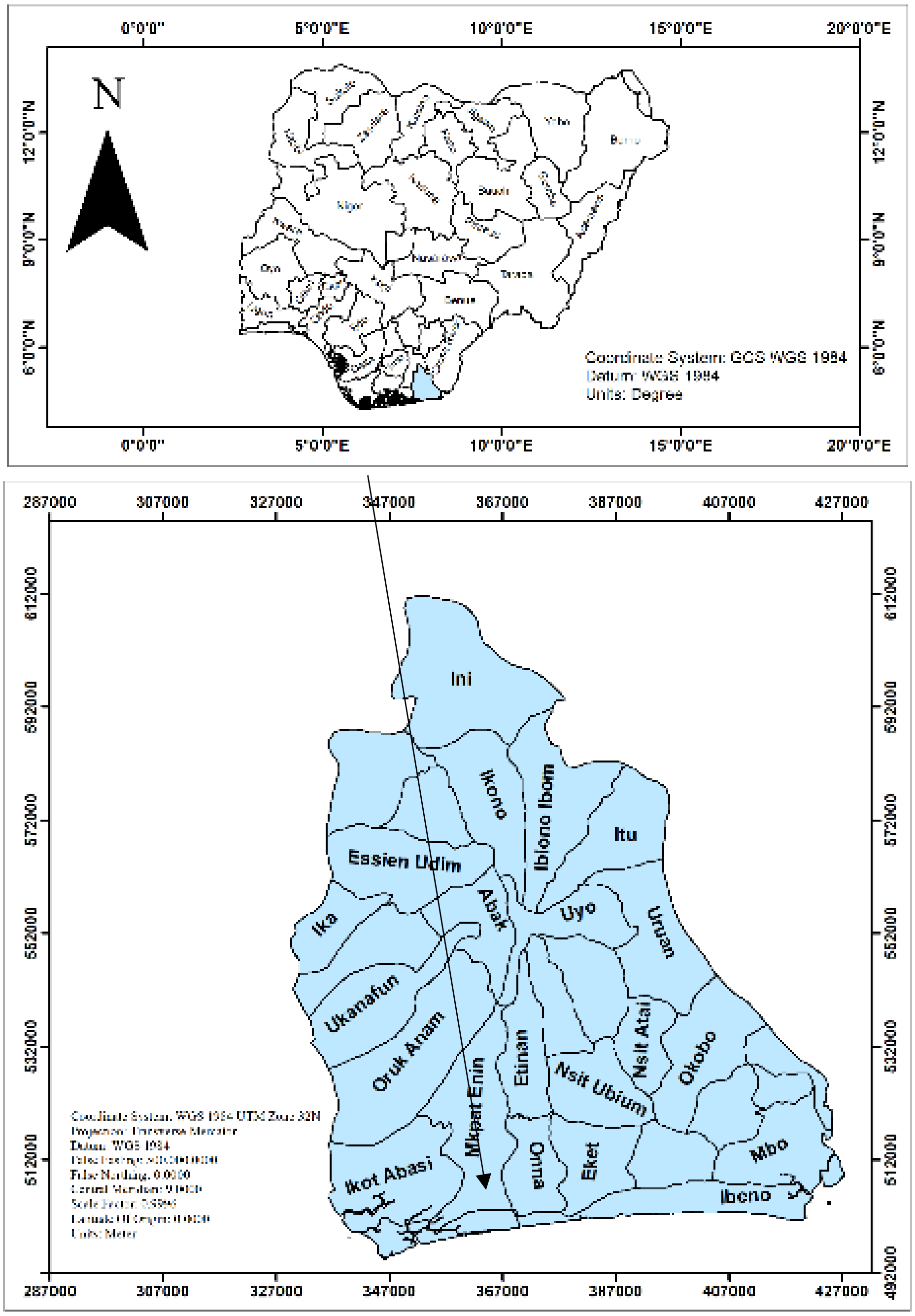

Fig. 1: Map of study area (Source: Author)

ISSN: 2354-3361
DOI: https://doi.org/10.5281/zenodo.20706933
www.journals.unizik.edu.ng/jsis

3. Methodology

The study followed a systematic research flowchart. Data acquisition was performed using JavaScript code in the Google Earth Engine code editor. Sentinel-2 surface reflectance imagery of the study area for 2024 was filtered, mosaicked, and processed.

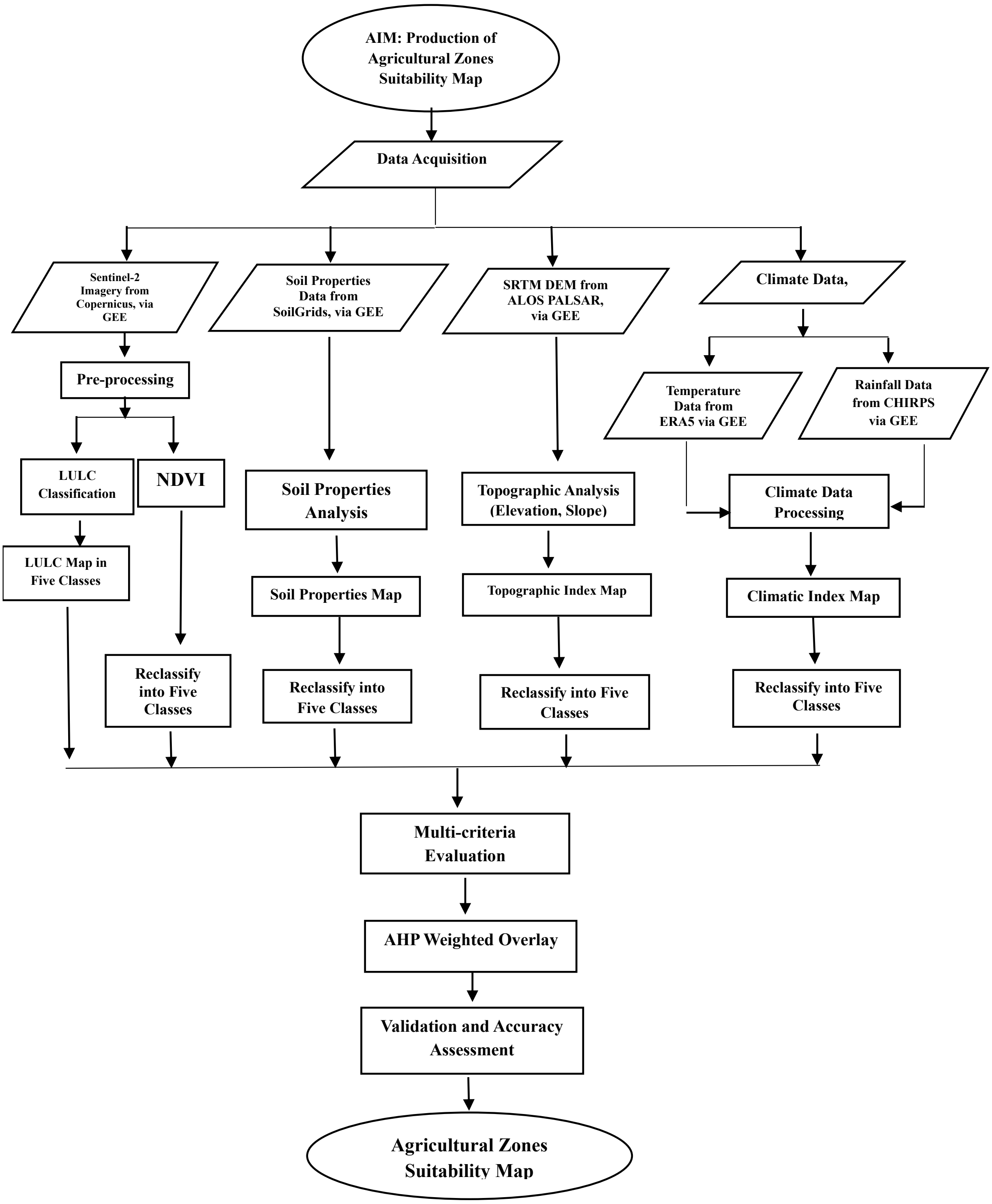

Fig. 2: Research Flowchart (Source: Author)

ISSN: 2354-3361
DOI: https://doi.org/10.5281/zenodo.20706933
www.journals.unizik.edu.ng/jsis

Land use/land cover classification was carried out using Random Forest (RF) classifier, with 150 trees, using 150 training samples for each class, with 80% of the samples for training the classifier, and 20% for testing for accuracy. The delineated classes were: Primary Vegetation, Secondary Vegetation, Built-up Area, Barren Land, and Water Body. The Normalized Difference Vegetative Index (NDVI) was extracted from the satellite imagery, using a combination of the near-infrared (NIR) band (B8) and the red band (B4), using the formula:

$$\mathbf{NDVI} = \frac{\mathbf{NIR-RED}}{\mathbf{NIR+RED}} \qquad \textbf{eqn. (1)}$$

Soil properties (texture, water content, pH, bulk density, and organic carbon content) were obtained from ISRIC SoilGrids, topographic data (elevation and slope) from ALOS PALSAR DEM, and climate data (rainfall and temperature) from CHIRPS and ERA5. All layers were reprojected to WGS 1984/UTM Zone 32N

In ArcGIS 10.8, all the data were resampled to 12.5m resolution, and reclassified into five suitability classes. AHP was used to construct a pairwise comparison matrix and calculate factor weights. Weighted overlay analysis produced the final suitability map. Validation involved ground-truthing with soil samples from Nsit Ubium (high suitability) and Eket (moderate suitability) LGAs, analysed for texture, moisture, pH, bulk density, and organic carbon.

4. Results and Analysis

4.1 Analyses of Agricultural Suitability Factors

NDVI analysis revealed that 78% of Akwa Ibom State exhibits high to very high vegetation health (46% very high, 32% high), indicating robust vegetative cover critical for crop growth. Topographic index, derived from slope and elevation using weighted overlay with AHP-assigned weights, showed 38% of the state with very high index concentrated in northern areas, while southern coastal zones recorded very low index, consistent with riverine topography. Climatic index analysis identified the north-western senatorial district as having the lowest index, while southern areas recorded the highest, driven by proximity to the Atlantic Ocean and higher rainfall intensity. Soil properties suitability index (combining bulk density, water content, organic carbon, pH, and texture) classified 31% as very highly suitable and 36% as highly suitable for agriculture, with only 1% not suitable. Land use/land cover classification showed primary vegetation (41.9%, 2,821.29 km^2), secondary vegetation (21.8%, 1,467.88 km^2), built-up areas (35%, 2,356.69 km^2), barren land (0.8%, 53.87 km^2), and water bodies (0.5%, 33.67 km^2).

ISSN: 2354-3361
DOI: https://doi.org/10.5281/zenodo.20706933
www.journals.unizik.edu.ng/jsis

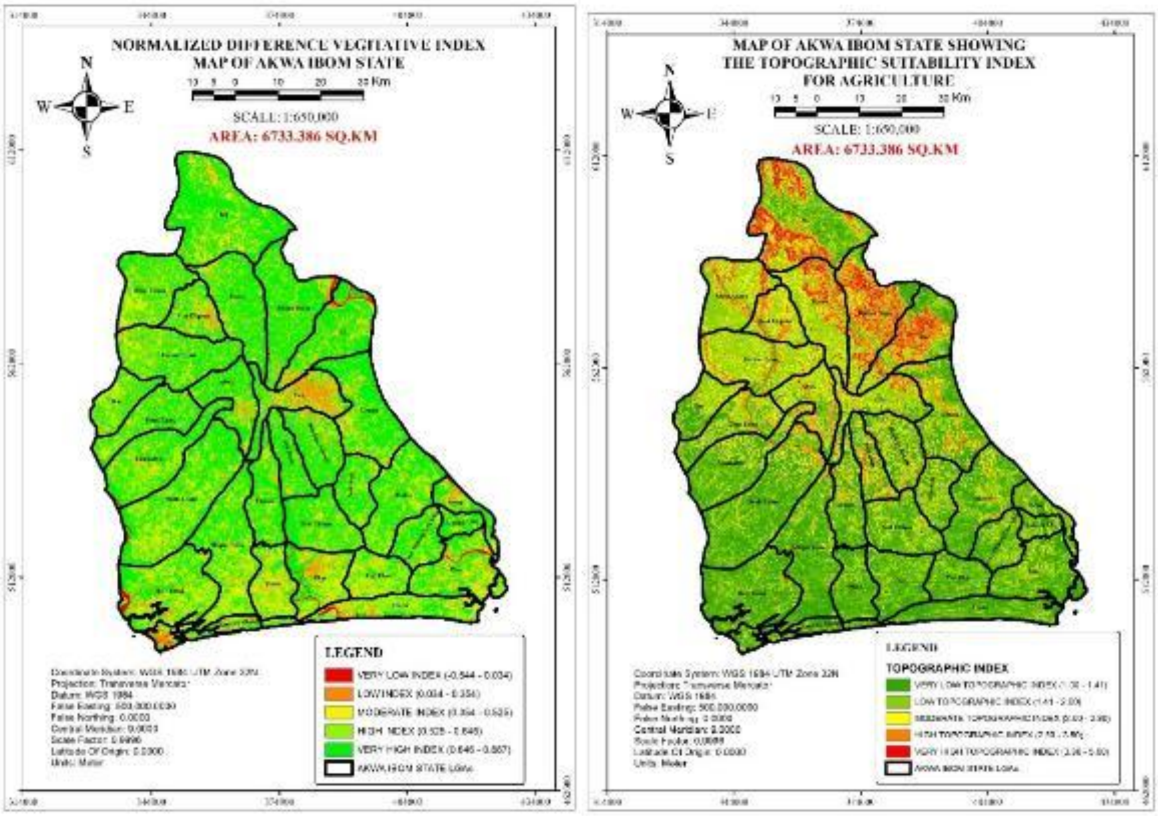

Fig. 3: NDVI Map (left) and Topographic Index Map (right) of the study area

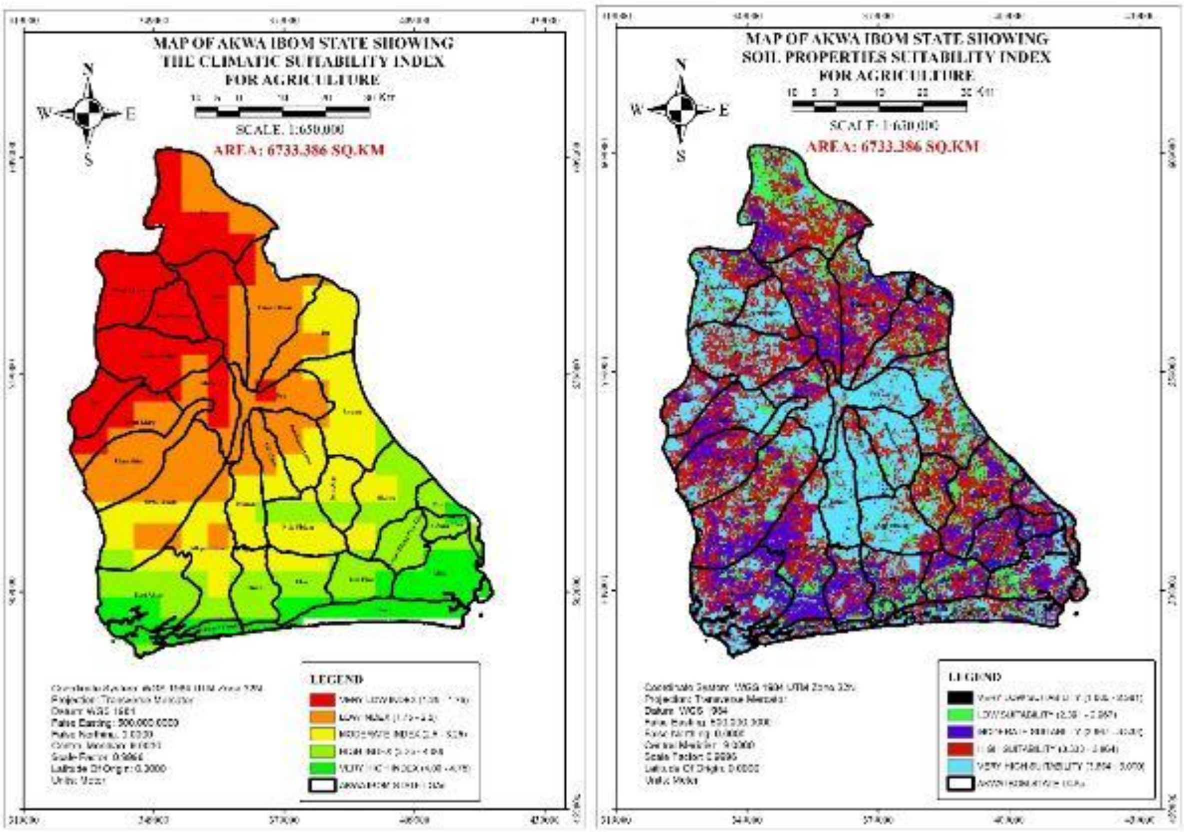

Fig. 4: Climatic Index Map (left) and Soil Properties Map (right) of the study area

ISSN: 2354-3361
DOI: https://doi.org/10.5281/zenodo.20706933
www.journals.unizik.edu.ng/jsis

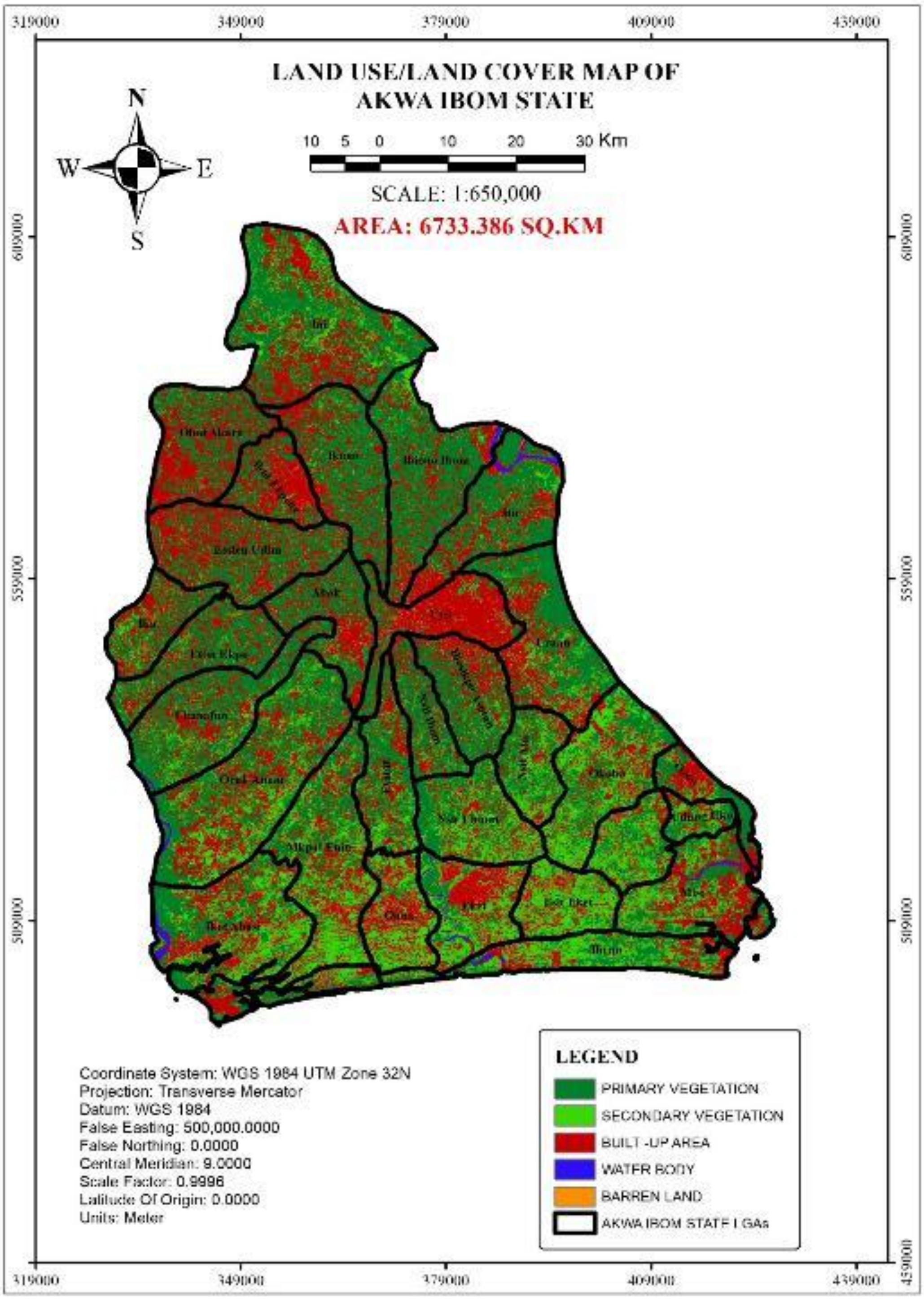

Fig. 5: LULC Map of the study area

4.2 Relative Weights of Agricultural Suitability Factors

AHP results assigned the highest weight to soil properties (51.8%), followed by climatic factors (26.5%), topographic factors (10.5%), LULC (7.9%), and NDVI (3.4%). The relative weights of each agricultural suitability factor were determined using AHP technique for AHP OS questionnaire, as

ISSN: 2354-3361
VOL. 3, ISSUE 1, PP 126–142, 2026
DOI: https://doi.org/10.5281/zenodo.20706933
PUBLISHED 15-05-2026
www.journals.unizik.edu.ng/jsis

shown in figure 3, including the overall consistency ratio (4.8%) for all participants (which is less than the 10% recommended threshold).

Breakdown by Nodes

Details Node: Agricultural Land Suitability Mapping - CR: 4.8% - AHP group consensus: 98.2% very high

Consolidated Priorities

Consistency Ratio CR: 4.8%

Cat		Priority	Rank
1	Soil Properties	51.8%	1
2	Climatic Factors	26.5%	2
3	Topographic Factors	10.5%	3
4	NDVI	3.4%	5
5	LULC	7.9%	4

Consolidated Decision Matrix

Aggregation of individual judgments for 4 Participant(s)

	1	2	3	4	5
1	1	3.00	5.92	9.00	5.92
2	0.33	1	3.87	7.00	3.87
3	0.17	0.26	1	4.40	1.73
4	0.11	0.14	0.23	1	0.29
5	0.17	0.26	0.58	3.41	1

Fig. 6: AHP Weights of Agricultural Suitability Factors

4.3 Agricultural Suitability Zones Analysis

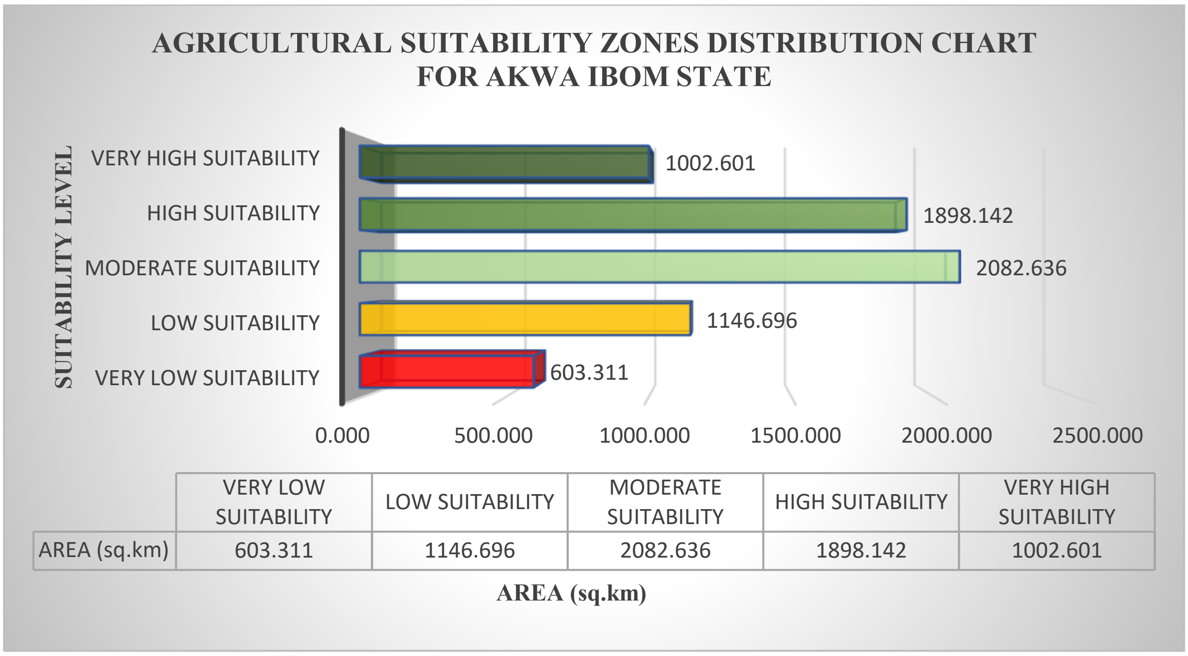

Fig. 7: Agricultural Suitability Chart of the study area

Weighted overlay analysis in ArcMap produced a final agricultural suitability map reclassified into five classes. Across Akwa Ibom State, 14.89% (1,002.60 km²) was very highly suitable and 28.19% (1,898.14 km²) highly suitable for agriculture, while 8.96% (603.31 km²) and 17.03% (1,146.66 km²)

ISSN: 2354-3361
VOL. 3, ISSUE 1, PP 126–142, 2026
DOI: https://doi.org/10.5281/zenodo.20706933
PUBLISHED 15-05-2026
www.journals.unizik.edu.ng/jsis

were classified as very low and low suitability, respectively. The remaining 30.93% (2,082.64 km²) was moderately suitable.

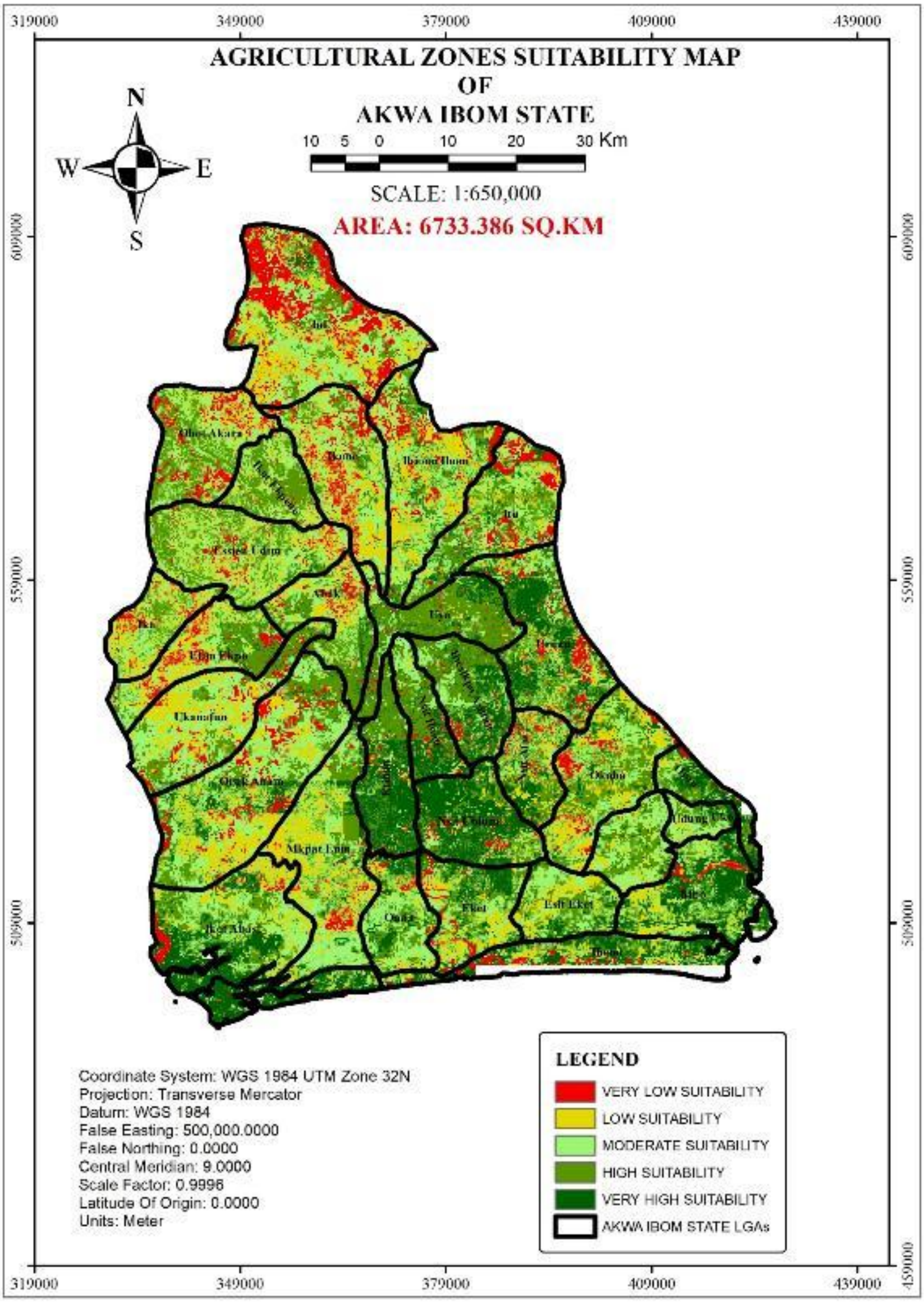

Fig. 8: Agricultural Suitability Map of the study area

ISSN: 2354-3361
DOI: https://doi.org/10.5281/zenodo.20706933
www.journals.unizik.edu.ng/jsis

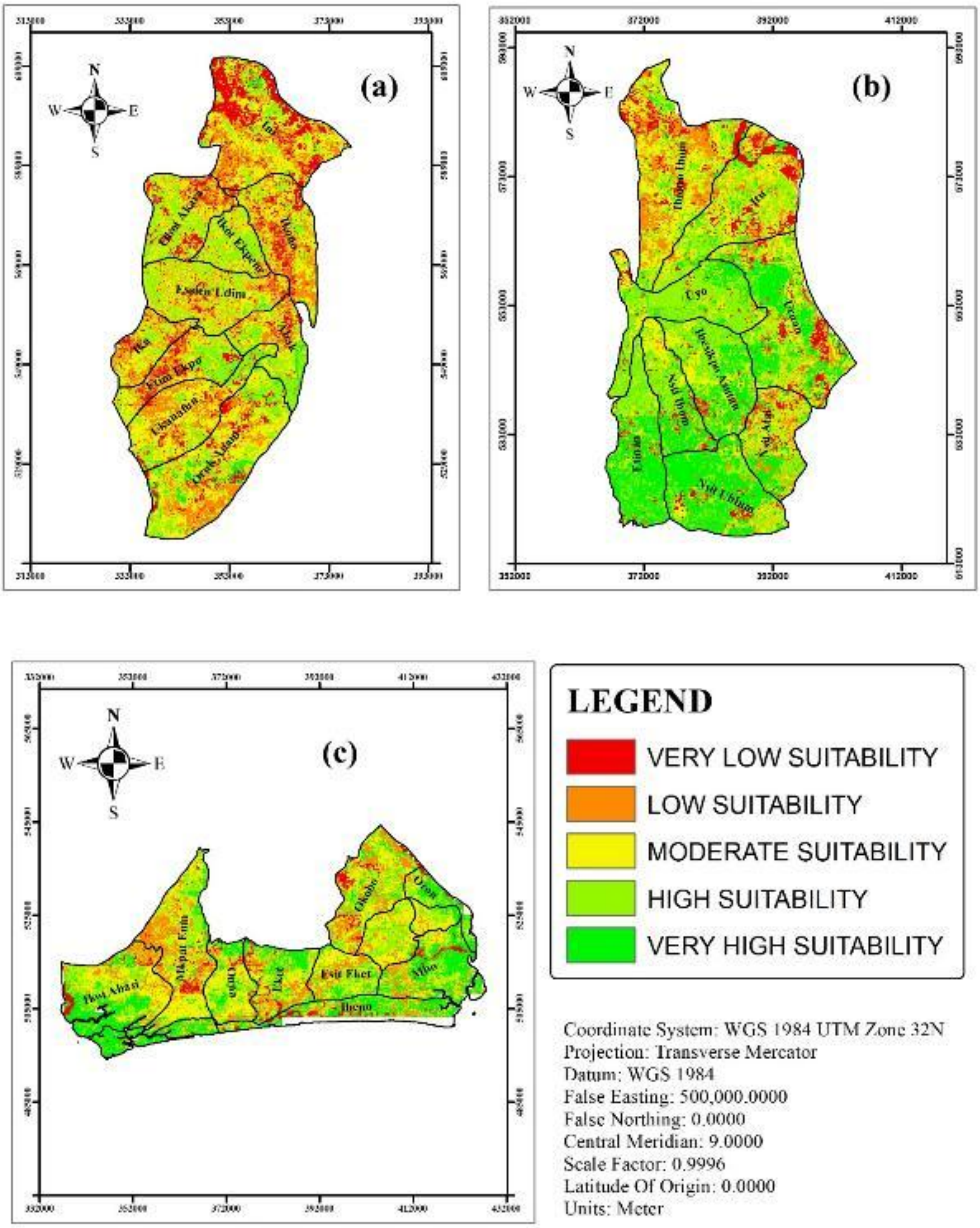

Fig. 9: Spatial Assessment of Agricultural Suitability Zones by Senatorial Districts. (a) Akwa Ibom North-west. (b) Akwa Ibom North-east. (c) Akwa Ibom South

ISSN: 2354-3361
DOI: https://doi.org/10.5281/zenodo.20706933
www.journals.unizik.edu.ng/jsis

By senatorial district, Akwa Ibom North-west recorded the lowest agricultural suitability (60.85% very low, 50.98% low suitability). Conversely, Akwa Ibom North-east recorded the highest suitability (35.39% high, 46.29% very high), followed closely by Akwa Ibom South (29.71% high, 47.85% very high).

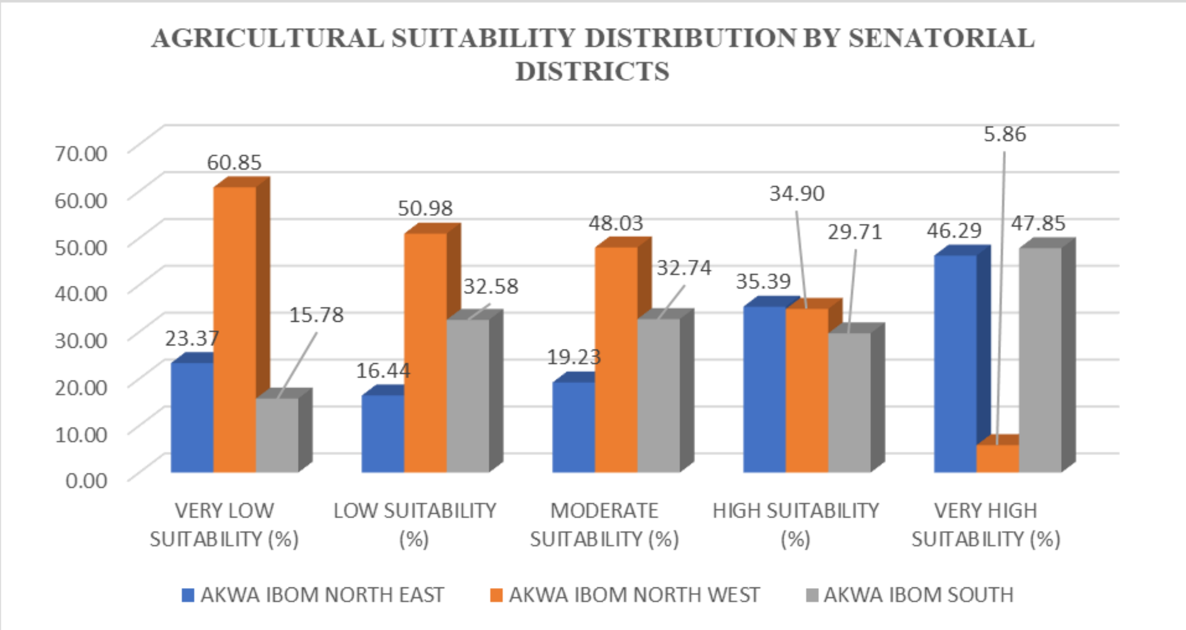

Fig. 10: Chart Showing Percentage of Agricultural Suitability Zones by Senatorial Districts

By local government areas, Nsit Ubium had the highest suitability (14.30%), followed by Uruan (13.43%), Ikot Abasi (13.33%), Etinan (12.35%), and Mbo (11.97%). Ini LGA recorded the lowest suitability (31.20%), followed by Oruk Anam (15.93%), Ikono (15.02%), Ibiono Ibom (13.02%), and Mkpat Enin (10.44%). Oruk Anam, Ini, Mkpat Enin, Essien Udim, and Ukanafun led the moderately suitable zones, ranging from 9.13% to 5.85%.

Nsit Ubium and Uruan LGAs recorded the highest suitability, while Ini and Oruk Anam LGAs were predominantly low suitability.

4.4 Data Validation and Accuracy Assessment

Ground-truthing using soil samples from Nsit Ubium (high suitability) and Eket (moderate suitability) LGAs validated the remote sensing and GIS-derived agricultural suitability map. Sample 1 (Nsit Ubium) exhibited superior soil characteristics: sandy-loam texture (71% sand, 13.76% silt, 15.24% clay), higher moisture content (31.7%), pH closer to optimal range (5.35), acceptable bulk density (1.6602 g/cm³), and higher organic carbon (3.62%). Sample 2 (Eket) showed sandier texture (81.64% sand), lower moisture (21.6%), more acidic pH (5.18), lower organic carbon (2.39%), and lower bulk density (1.4837 g/cm³). The favourable properties of Sample 1 confirmed the model's classification of Nsit Ubium as the most suitable zone, while Sample 2's less favourable profile validated the model's discriminatory ability. Despite the limited sample size, the high agreement demonstrates that integrating cloud-based remote sensing and GIS produces reliable results for agricultural planning.

5. Conclusion and Recommendations

5.1 Conclusion

This study successfully integrated cloud-based remote sensing (Google Earth Engine) and GIS (ArcGIS) technologies to map agricultural suitability zones in Akwa Ibom State, Nigeria, supporting food security and Sustainable Development Goal 2 (Zero Hunger). Data sources included Sentinel-2 imagery, ISRIC SoilGrids, ALOS PALSAR, CHIRPS, and ERA5. The methodology employed LULC classification, NDVI computation, AHP for factor weighting, and weighted overlay analysis. AHP assigned weights of soil properties (51.8%), climate (26.5%), topography (10.4%), LULC (7.9%), and NDVI (3.4%), demonstrating its efficacy as a multi-criteria decision-making tool.

Results revealed significant spatial variations in agricultural suitability: very highly suitable (14.89%, 1,002.60 km²), highly suitable (28.19%, 1,898.14 km²), moderately suitable (30.93%), low suitability (17.03%), and very low suitability (8.96%). Low suitability zones were concentrated in the north-western senatorial district (Ini and Oruk Anam LGAs), while the north-eastern and southern senatorial districts (Nsit Ubium and Uruan LGAs) emerged as the most suitable zones, driven by favourable soil properties, adequate rainfall, and flat topography. Ground-truthing using soil samples from Nsit Ubium and Eket LGAs confirmed the map's reliability, with Nsit Ubium showing superior soil characteristics (sandy-loam texture, higher organic carbon, moderate water retention).

This study demonstrates the potential of cloud-based geospatial technologies for agricultural planning in data-scarce regions. GEE enabled efficient large-scale data processing, ArcGIS enabled precise spatial analysis, and AHP provided systematic factor weighting. The findings offer a data-driven foundation for informed agricultural land-use decisions and a replicable model for regions facing similar food security challenges.

5.2 Recommendations

To enhance agricultural development and food security in Akwa Ibom State, this study recommends: (i) precision agriculture in high-suitability zones (Nsit Ubium, Uruan, Ikot Abasi, Etinan, Mbo). (ii) soil improvement interventions in low-suitability areas (Ini, Oruk Anam, Ikono). (iii)

ISSN: 2354-3361
DOI: https://doi.org/10.5281/zenodo.20706933
www.journals.unizik.edu.ng/jsis

institutionalisation of cloud-based geospatial technologies (GEE, ArcGIS) within a dedicated Ministry of Agriculture geospatial unit (iv) capacity building for farmers and extension workers. (v) sustainable land use practices (agroforestry, crop rotation). (vi) expanded ground-truthing across more LGAs. (vii) stakeholder collaboration for data sharing. (viii) development of climate-resilient agricultural systems, particularly in the north-western senatorial district. These measures would strengthen agricultural productivity, preserve fragile ecosystems, and provide a replicable blueprint for other regions.

REFERENCES

[1] Akwa Ibom State Government. *About Akwa Ibom State*. https://akwaibomstate.gov.ng/about-akwa-ibom/

[2] Bill & Melinda Gates Foundation. (2024). *Goalkeepers Report 2024*. https://knowledge4policy.ec.europa.eu/publication/2024-goalkeepers-report-race-nourish-warming-world_en

[3] Chiaka, J. C., Zhen, L., Xiao, Y., Wen, X., & Muhirua, F. (2024). Spatial assessment of land suitability potential for agriculture in Nigeria. *Foods*, 13(4), Article 568. https://doi.org/10.3390/foods13040568

[4] Choudhary, K., Boori, M. S., Shi, W., Valiev, A., & Kupriyanov, A. (2023). Agricultural land suitability assessment for sustainable development using remote sensing techniques with analytical hierarchy process. *Remote Sensing Applications: Society and Environment*, 32, Article 101051. https://doi.org/10.1016/j.rsase.2023.101051

[5] Gorelick, N., Hancher, M., Dixon, M., Ilyushchenko, S., Thau, D., & Moore, R. (2017). Google Earth Engine: Planetary-scale geospatial analysis for everyone. *Remote Sensing of Environment*, 202, 18-27. https://doi.org/10.1016/j.rse.2017.06.031

[6] Nigerian Economic Summit Group. (2024). *Policy brief on the status of food security in Nigeria*. https://nesgroup.org

[7] Okotie, S. (2017). The Nigerian economy before the discovery of crude oil. In S. Akinrinade & O. Ogen (Eds.), *The political ecology of oil and gas activities in the Nigerian aquatic ecosystem* (pp. 71-81). https://www.sciencedirect.com/science/chapter/edited-volume/abs/pii/B9780128093993000057

[8] Phalke, A. R., Ozdogan, M., Thenkabail, P. S., Erickson, T., Gorelick, N., Yadav, K., & Congalton, R. G. (2018). Mapping croplands of Europe, Middle East, Russia, and Central Asia using Landsat, random forest, and Google Earth Engine. *ISPRS Journal of Photogrammetry and Remote Sensing*, 161, 104-122. https://doi.org/10.1016/j.isprsjprs.2019.12.010

[9] Poggio, L., de Sousa, L. M., Batjes, N. H., Heuvelink, G. B. M., Kempen, B., Ribeiro, E., & Rossiter, D. (2021). SoilGrids 2.0: Producing soil information for the globe with quantified spatial uncertainty. *Soil*, 7(1), 217-240. https://doi.org/10.5194/soil-7-217-2021

[10] Revenue Mobilisation Allocation and Fiscal Commission. (2019). *Report on the Nigerian economy*. Abuja, Nigeria: RMFAC.

[11] Roy, S., Singha, N., Bose, A., Basak, D., & Choudhury, I. R. (2023). Multi-influencing factors (MIF) and RS-GIS-based determination of agriculture site suitability for achieving sustainable development of sub-Himalayan region, India. *Environment, Development and Sustainability*, 25(7), 7101-7132. https://doi.org/10.1007/s10668-022-02345-2

[12] Safanelli, J. L. (2020). *Leveraging the application of earth observation data for mapping and monitoring cropland soils* [Doctoral dissertation]. Universidade de Sao Paulo.

[13] United Nations. (2015). *Transforming our world: The 2030 agenda for sustainable development* (A/RES/70/1). https://sdgs.un.org/2030agenda