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Site Suitability Analysis for the Establishment of Wind Energy Farm in Delta State Using Geospatial Techniques

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Abstract

The rising demand for electricity in Nigeria continues to outpace supply, with over 40% of the population lacking reliable access to grid-based power. The overdependence on fossil fuels has further strained the national energy system, while contributing to environmental degradation and greenhouse gas emissions. Renewable energy, particularly wind power, has been widely recognized as a viable alternative to diversify the energy mix, improve rural electrification, and promote environmental sustainability. However, the development of wind energy infrastructure in Nigeria remains limited, and its spatial distribution is heavily skewed toward inland and northern regions such as Sokoto, Jos, and Katsina, where wind speeds are comparatively higher. The study aimed at a site suitability analysis for wind energy farms in Delta State, Nigeria using geospatial technology. The objectives are to: establish the criteria and factors for locating wind energy farms in Delta State; classify the criteria and factors according to their rank of suitability for locating wind energy farms in Delta State; apply weighted linear combination of the classified criteria and factors to determine suitable sites for wind energy farms in Delta state and produce a suitability index map showing areas suitable for locating wind energy farms in Delta state. The study employed a geospatial multi-criteria evaluation (MCE) framework integrated with the Analytical Hierarchy Process (AHP) to assess windfarm site suitability. Seven influencing factors were analyzed: wind power density (WPD), elevation, slope, soil type, proximity to road networks, proximity to waterbodies, and land use/land cover (LULC). Each parameter was derived from remotely sensed data, thematic maps, and secondary geospatial datasets, then standardized and reclassified into suitability levels. Expert judgment was used to construct a pairwise comparison matrix, and factor weights were derived through AHP with a Consistency Ratio (CR) of 0.03, indicating reliable judgments. A weighted overlay analysis was applied to generate a windfarm suitability index map, while sensitivity analysis tested the stability of the model under ±20% weight variations of key factors. The suitability analysis revealed that wind power density, elevation, and slope collectively accounted for more than 53% of the total model weight, establishing them as the primary drivers of wind energy potential. Proximity to road networks and soil type moderately influenced feasibility, while hydrology and LULC exerted localized but secondary control. The final suitability map showed that 5.11% (834.41 km²) of the study area was highly suitable, 62.29% (10,180.46 km²) was moderately suitable, and 32.60% (5,328.39 km²) was low suitability. Highly suitable areas were concentrated in the northern and northeastern uplands, where strong and consistent winds (>100 W/m²), moderate elevation, stable soils, and good road access converged. Sensitivity analysis confirmed the robustness of the model, as moderate changes in factor weights produced only minor adjustments in suitability extents without altering the overall ranking of influencing criteria. It is recommended that the AHP-based multi-criteria evaluation framework used in this study be adopted by state energy agencies and private investors as a decision-support tool for future wind energy projects in Delta State.

Keywords: GIS, Wind Energy, Site Suitability Analysis, Renewable Energy, Multi-Criteria Decision Analysis (MCDA)

1. Introduction

The global energy sector has witnessed a growing shift toward renewable sources, largely driven by concerns over climate change, environmental degradation, and the depletion of fossil fuel reserves (Tucho and Nonhebel, 2017; Akella *et al*., 2009) [27, 6]. Among the array of renewable energy options, wind energy has emerged as a viable and environmentally friendly alternative for electricity generation due to its scalability and cost-effectiveness (Bilgili *et al*., 2011; Ahmed *et al*., 2022) [11, 4].

Countries across the world, including developing nations, have recognized the strategic value of harnessing wind power to improve energy security, reduce greenhouse gas emissions, and meet sustainable development goals (Kumar and Ramesh, 2020; Li *et al*., 2021) [17, 18].

In Nigeria, energy demand has consistently outpaced supply, resulting in frequent electricity outages and reliance on fossil-fuel-based generators, which contribute to environmental pollution and economic inefficiencies (Shaaban and Petinrin, 2014; Nwulu and Xia, 2015 [20]). While the country has abundant renewable energy resources, including wind, its integration into the national grid remains limited due to inadequate spatial planning, poor resource assessment, and weak infrastructure (Oyedepo, 2012; Adeoti *et al*., 2001) [23, 1]. Delta State, located in the southern region of Nigeria, possesses significant potential for wind energy development, particularly along its coastal and lowland areas where wind flow patterns are relatively consistent (Ajayi *et al*., 2011; Ohunakin *et al*., 2011 [22]).

Effective siting of wind energy farms requires detailed spatial analysis of multiple environmental, socio-economic, and technical factors. These include wind speed, land use and land cover, elevation, proximity to roads and transmission lines, slope, and population density (Bansal *et al*., 2002; Emrah *et al*., 2016) [10, 13]. The absence of a structured and location-specific siting methodology has often led to suboptimal decisions that compromise the performance and sustainability of wind projects (Uyan, 2013; Janke, 2010) [29, 16]. In this context, the integration of Geographic Information System (GIS) and Multi-Criteria Decision Analysis (MCDA) techniques presents a reliable and systematic approach to address the complexities associated with wind farm site selection (Malczewski, 2006; Tegou *et al*., 2010) [19, 26].

Recent advancements in geospatial technologies have facilitated high-resolution spatial analysis, allowing researchers and policymakers to evaluate large datasets and derive optimal locations for renewable energy projects (Ramachandra and Shruthi, 2007; Aydin *et al*., 2013) [24, 9]. In particular, the use of GIS-based decision-support tools for site suitability analysis has gained prominence in renewable energy studies, especially in regions with varied topographic and socio-economic characteristics such as Delta State (Fazelpour *et al*., 2015; Ustaoglu and Aydin, 2020) [15, 28]. These tools enhance decision-making by integrating expert knowledge, spatial data, and user-defined criteria to identify locations with high potential for wind energy development.

Based on this background, this study applies geospatial techniques to evaluate the suitability of sites for wind energy farms in Delta State, in order to contribute to the body of knowledge required for renewable energy planning in Nigeria and to provide evidence-based insights for guiding infrastructural investments in the energy sector.

The rising demand for electricity in Nigeria continues to outpace supply, with over 40% of the population lacking reliable access to grid-based power. The overdependence on fossil fuels has further strained the national energy system, while contributing to environmental degradation and greenhouse gas emissions. Renewable energy, particularly wind power, has been widely recognized as a viable alternative to diversify the energy mix, improve rural electrification, and promote environmental sustainability. However, the development of wind energy infrastructure in Nigeria remains limited, and its spatial distribution is heavily skewed toward inland and northern regions such as Sokoto, Jos, and Katsina, where wind speeds are comparatively higher (Ogbonnaya, Chikuni, and Govender, 2009; Fagbenle, Katende, Ajayi, and Okeniyi, 2011) [21, 14].

Existing Nigerian studies on wind energy potential have primarily relied on long-term meteorological datasets from isolated weather stations (Asiegbu and Iwuoha, 2007; Adegoke and Anjorin, 1996) [7, 3] to assess wind speed profiles and economic viability. While these studies have contributed to an understanding of wind characteristics at specific locations, they often neglect the integration of environmental, infrastructural, and socio-economic factors into a comprehensive suitability framework. Furthermore, there is a lack of region-specific research for low-wind, coastal, and deltaic environments such as Delta State, where complex terrain and settlement patterns require a more nuanced approach to site selection.

International studies have successfully applied advanced Geographic Information System (GIS) and Multi-Criteria Decision Analysis (MCDA) techniques such as Analytical Hierarchy Process (AHP), Analytical Network Process (ANP), Decision-Making Trial and Evaluation Laboratory (DEMATEL), and fuzzy logic to integrate physical, environmental, technical, and socio-economic parameters into robust wind farm suitability models (Borah, Roy, and Harinarayana, 2013; Adam and Li, 2014; Aydin, Kentel, and Duzgun, 2009) [12, 2, 8]. However, such comprehensive geospatial approaches remain largely absent in the Nigerian context, particularly for coastal regions with different wind dynamics, land-use constraints, and environmental sensitivities.

The absence of a spatially explicit wind farm suitability for Delta State poses a challenge for policymakers, energy planners, and private investors, who currently lack evidence-based tools for informed decision-making. Without such tools, investments in wind energy risk being sub-optimal, environmentally unsustainable, or socially contentious. Hence this study addresses these gaps by combining wind resource assessment with geospatial analysis of environmental, infrastructural, and socio-economic parameters to produce a decision-support model for wind farm site selection in Delta State. In doing so, it will not only fill a significant methodological and geographical void in the literature but also provide a replicable framework for similar coastal regions in sub-Saharan Africa.

2. Materials and Methods

2.1 Study Area

Delta State is an oil and agricultural producing state in southern part of Nigeria see Figure 1.1 and 1.2. It is located between latitudes 5°50'0''N and 6°15'0''N and Longitudes 5°0'0'' E and 7°0'0''E see Figure 1.2. The capital city is Asaba, located at the northern end of the state, with an estimated area of 762 square kilometres (294 sq mi), while Warri is the economic nerve center of the state and also the most populated located in the southern end of the state. The state has a total land area of 16,842 square kilometres (6,503 sq mi) and a population of 4,098,291according to the 2006 census.

Delta state covers a landmass of about 18,050 km², of which more than 60% is land. It is bounded in the north and west by Edo State, the east by Anambra, Imo, and Rivers States, southeast by Bayelsa State, and on the southern flank is the Bight of Benin which covers about 160 kilometres of the state's coastline. Delta State is generally low-lying without remarkable hills. The state has a wide coastal belt inter-lace with rivulets and streams, which form part of the Niger River Delta.

2.2 Methodology

The data processing phase involved the systematic transformation of raw spatial datasets into standardized, comparable, and analytically meaningful layers for the multi-criteria windfarm suitability analysis. Each thematic factor wind power density (WPD), elevation, slope, soil, proximity to road networks, proximity to waterbodies, and land use/land cover (LULC) was processed using established geospatial and statistical procedures to ensure consistency and accuracy.

2.2.1 Digital Elevation Model (DEM) Derivatives

The topographic parameters of elevation and slope were derived from the Shuttle Radar Topography Mission (SRTM) 1-Arc Second (~30 m) Digital Elevation Model (DEM), which was selected because of its wide availability, reliable vertical accuracy (±16 m), and suitability for regional-scale windfarm site assessment. The DEM was first subjected to a series of preprocessing operations to improve its geometric and hydrological consistency before extracting terrain attributes. Raw SRTM DEM data contain noise, voids, and depressions that can lead to inaccuracies in subsequent analysis. To address this, the DEM underwent the following steps:

1. Void filling**:** small gaps caused by radar shadowing and water-body interference were filled using interpolation algorithms available in ArcGIS Spatial Analyst's Fill tool. This ensured a continuous elevation surface.
2. The DEM were reprojected to the Universal Transverse Mercator (UTM) coordinate system, Zone 32N, with WGS 84 datum, to match other spatial datasets. Bilinear interpolation was applied to maintain elevation smoothness during resampling.

Elevation values were extracted directly from the conditioned DEM. Elevation plays a fundamental role in windfarm site selection because wind speed generally increases with altitude due to reduced surface roughness and turbulence. Areas of higher elevation tend to experience stronger and more consistent wind flow, thus increasing the potential energy yield from turbines.

Elevation values within the study area ranged between 0 m and 303 m above mean sea level. For the purpose of suitability analysis, elevation was classified into three categories based on wind energy potential and construction feasibility:

1. Low suitability (1): < 100 m (often with lower wind speeds and potential obstructions).
2. Moderate suitability (2): 100–200 m (moderately elevated areas with better wind exposure).
3. High suitability (3): > 200 m (upland ridges and plateaus with optimal wind exposure and reduced surface friction).

This classification reflected both aerodynamic performance and construction considerations, as extremely rugged or very high elevations can increase access and turbine foundation costs.

Slope was calculated from the DEM using Horn's (1981) [34] algorithm, which computes the first derivative of the elevation surface in the x (east–west) and y (north–south) directions, see equations 1and 2:

$$S = \tan^{-1}\sqrt{p^2+q^2} \tag{1}$$

Where

$$p = \frac{\partial z}{\partial x}, \quad q = \frac{\partial z}{\partial y} \tag{2}$$

Represent the rate of change of elevation z in the horizontal x and y directions respectively. The slope S is expressed in degrees.

Slope is a critical engineering factor for windfarm development. Gentle slopes facilitate turbine construction, reduce foundation costs, and allow easier access for transport of turbine components, whereas steep slopes complicate installation and increase risks of soil erosion and structural instability.

The slope within the study area ranged from 0° to 30.89°. These were reclassified into three suitability categories following engineering and economic feasibility considerations:

1. High suitability (3): 0°–5° (flat to very gentle slopes, ideal for turbine foundations and access roads).
2. Moderate suitability (2): 5°–15° (gentle to moderate slopes, feasible with moderate construction cost).
3. Low suitability (1): > 15° (steep slopes requiring costly earthworks and increasing risk of soil instability).

This reclassification is consistent with international best practices, where slopes above 15° are often avoided due to increased installation cost and reduced accessibility (Hau, 2013) [33].

The elevation and slope layers were combined as part of the multi-criteria decision analysis (MCDA) to represent the topographic suitability for windfarm development. Elevation provides the aerodynamic advantage needed for wind capture, while slope accounts for engineering and construction constraints. Together, these layers establish the terrain suitability baseline, ensuring that areas with high wind exposure but poor accessibility are balanced against those with moderate wind resources and better construction feasibility.

2.2.2 Wind Power Density (WPD) Estimation

Wind Power Density (WPD) represents the amount of kinetic energy available in the wind per unit area perpendicular to the flow and is one of the most fundamental indicators of wind resource potential. Accurate estimation of WPD is critical for identifying locations capable of sustaining efficient wind turbine operation, as the energy yield of a windfarm is directly proportional to the cube of the wind speed.

Wind speed data were sourced from the Global Wind Atlas (GWA v3)**,** which provides globally consistent wind resource information derived from a combination of mesoscale atmospheric modeling and long-term reanalysis datasets. The data used were at 100 m above ground level (AGL) to correspond to typical hub heights of modern utility-scale wind turbines. To enhance regional accuracy, available wind speed records from Nigerian Meteorological Agency (NiMET) were cross-checked to validate the modeled outputs. Discrepancies greater than ±0.5 m/s were corrected by applying bias adjustment factors derived from the ground-based observations.

WPD was calculated using the fundamental wind power equation 3:

$$WPD = \frac{1}{2}\rho v^3 \tag{3}$$

Where:

WPD = wind power density (W/m²),

ρ = air density (kg/m³),

v = mean wind speed at hub height (m/s).

An air density of 1.225 kg/m³ at standard sea level conditions was adopted for this study. While air density decreases slightly with altitude and temperature, the variation across the study area (0–303 m elevation) was considered negligible for this regional-scale analysis.

Because the energy content of the wind is proportional to the cube of the wind speed, even small changes in wind speed have a dramatic impact on energy yield. For example, a 10% increase in wind speed results in approximately a 33% increase in available power.

When measured wind speeds were not directly available at 100 m AGL, they were adjusted from the measurement height (zref) to the hub height (zhub) using the logarithmic wind profile law, see equations 4:

$$v_{hub} = v_{ref} \cdot \frac{\ln\left(\frac{z_{hub}}{z_0}\right)}{\ln\left(\frac{z_{ref}}{z_0}\right)} \tag{4}$$

Where:

$vhub$ = wind speed at hub height (m/s),

$vref$ = reference wind speed measured at height $zref$

$zhub$ = desired hub height (100 m),

0 = surface roughness length (m), varying by land cover type (e.g., 0.0002 m for water, 0.03 m for grassland, and 1.0 m for urban areas).

Surface roughness values were derived from the LULC classification of the study area to improve wind speed extrapolation accuracy.

Validated WPD point data were spatially interpolated using the Inverse Distance Weighting (IDW) method in ArcGIS Spatial Analyst. IDW was selected because it assumes closer points exert more influence than distant points, which aligns with the localized nature of wind patterns when regional-scale data are sparse. The resulting raster WPD surface was resampled to 30 m to match the DEM resolution, ensuring seamless overlay during multi-criteria analysis.

The interpolated raster was further refined using topographic correction, where local elevation and slope influences were factored into wind speed modeling. Elevated ridges were slightly upweighted to account for acceleration effects caused by topographic exposure, while sheltered valleys were slightly downweighted due to increased turbulence and reduced mean wind speeds.

The WPD raster was reclassified into three suitability levels for wind energy development based on international wind resource assessment standards (World Bank and ESMAP, 2020) [39] and Nigerian wind resource studies (Ajayi, 2010; Agbetuyi *et al*., 2013) [31, 30]:

1. Low suitability (1): WPD<50 W/m2WPD < 50 W/m² – insufficient for reliable commercial-scale wind power generation.
2. Moderate suitability (2): 50 ≤ WPD ≤ 100 W/m² – capable of supporting small- to medium-scale turbines but may require supplemental energy sources.
3. High suitability (3): WPD >100 W/m² – highly viable for utility-scale windfarms with strong and consistent wind resources.

The classification was applied using the Reclassify tool in ArcGIS, and each class was assigned a numerical score corresponding to its suitability level for subsequent overlay in the Analytical Hierarchy Process (AHP)-based decision model.

Wind Power Density was given the highest weight in the multi-criteria decision analysis due to its direct relationship with energy generation potential. Unlike supporting factors such as soil or accessibility, which influence feasibility and cost, WPD determines the fundamental viability of a site to sustain profitable wind energy production. Regions with consistently high WPD were considered strategic for utility-scale investments, while moderate WPD regions were identified as secondary options for smaller projects or hybrid systems.

2.2.3 Proximity Analysis

The accessibility and environmental constraints of potential windfarm locations were assessed using proximity analysis, focusing on two major infrastructural and hydrological parameters: proximity to road networks and proximity to waterbodies. These factors significantly influence the feasibility and sustainability of windfarm development by affecting construction cost, ease of transportation, environmental risks, and long-term operational maintenance.

Spatial data for the road network were acquired from the OpenStreetMap (OSM) database. The dataset included major highways, secondary roads, and access routes relevant to heavy equipment transportation for windfarm construction. Roads were verified against recent satellite imagery to ensure accuracy and updated where digitization gaps were observed.

The waterbody dataset was derived from existing hydrographic layers from the HydroSHEDS database. Detected features included rivers, streams, lakes, reservoirs, and wetlands.

Both layers were projected to the Universal Transverse Mercator (UTM) Zone 32N, WGS 84 datum, ensuring spatial consistency with other thematic datasets. Topology checks were performed to eliminate overlaps, disconnected road segments, and misclassified water polygons.

To quantify the influence of infrastructure and hydrology on windfarm siting, Euclidean distance analysis was performed in ArcGIS Spatial Analyst. The Euclidean distance algorithm calculates the straight-line distance from each raster cell to the nearest road or water feature. For any cell (x,y)(x,y)(x,y), the distance to the nearest feature (x_0,y_0) was computed using equation 5:

$$D(x,y) = \sqrt{(x - x_0)^2 + (y - y_0)^2} \tag{5}$$

Where $D(x,y)$ represents the distance (in meters) of each grid cell to the closest linear or polygonal feature. The resulting continuous raster layers showed the spatial gradient of accessibility and hydrological risk across the study area.

Accessibility to existing transport infrastructure is a decisive factor for windfarm feasibility. Roads facilitate the delivery of large turbine components, cranes, and construction equipment, while also reducing long-term operational and maintenance costs. However, placing turbines too close to roads may create safety hazards, noise concerns, and potential land-use conflicts.

The distance-to-road raster was reclassified into three suitability classes based on international best practices for windfarm logistics and local Nigerian infrastructure conditions:

1. High suitability (3): 0–5 km from major or secondary roads (optimal construction accessibility and minimal new road development).
2. Moderate suitability (2): 5–15 km from existing roads (increased transport cost but still feasible with minor access upgrades).
3. Low suitability (1): >15 km from road networks (high construction cost due to new access roads, logistical challenges for turbine delivery).

Proximity to waterbodies is equally important because windfarm development must consider flood risk, soil stability, and environmental protection. Areas very close to rivers, wetlands, or lakes may face seasonal flooding, water table fluctuations, and regulatory restrictions due to sensitive aquatic ecosystems. Conversely, areas far from water sources tend to provide stable terrain and fewer environmental constraints.

The distance-to-waterbodies raster was reclassified into the following suitability categories:

1. High suitability (3): >5 km from permanent waterbodies (minimal flood risk and ecological disturbance).
2. Moderate suitability (2): 2–5 km from waterbodies (acceptable but may require additional engineering measures such as flood-proof foundations).
3. Low suitability (1): 0–2 km from waterbodies (high flood susceptibility, ecological sensitivity, and regulatory constraints).

This classification aligns with hydrological risk assessment frameworks that discourage heavy infrastructure placement near watercourses and wetlands (Shaaban and Petinrin, 2014).

Both proximity layers were normalized using min–max scaling to ensure comparability with other thematic factors in the multi-criteria analysis. For each raster cell x, the normalized proximity score Pnorm was computed as in equation 6:

$$P_{norm} = \frac{P_{max} - P_x}{P_{max} - P_{min}} \quad (6)$$

Where Px is the raw distance value for the cell, Pmax and Pmin represent the maximum and minimum distances observed across the study area. This transformation produced a standardized 0–1 scale where values close to 1 indicate high suitability.

Proximity to road networks was included because it directly influences construction feasibility and cost efficiency, especially for transporting large turbine blades and towers. Reduced access costs can significantly improve the financial viability of a windfarm project.

Proximity to waterbodies was considered to minimize hydrological and environmental risks, as turbines placed in flood-prone or saturated soils face higher foundation costs and long-term stability concerns. Additionally, avoiding environmentally sensitive riparian zones reduces ecological impact and regulatory constraints.

2.2.4 Land Use/Land Cover (LULC) Classification

Land Use and Land Cover (LULC) exerted a strong influence on the technical, economic, and environmental feasibility of windfarm development within the study area. Different land cover types affected wind flow dynamics, accessibility for construction, cost implications, and the level of environmental impact. Open barelands and grasslands promoted smooth wind flow, required minimal site preparation, and were cost-effective for construction, while dense forests, wetlands, croplands, or built-up areas increased turbulence, limited accessibility, and presented regulatory and social constraints. Accurate mapping of LULC was therefore essential for identifying locations that combine optimal energy potential with practical feasibility.

Multispectral imagery from the Landsat 8 Operational Land Imager (OLI) was used for LULC mapping due to its 30-meter spatial resolution, 16-day revisit time, and reliability for medium-scale land cover analysis. Cloud-free images covering the entire study area were obtained for the dry season, between November and February, to minimize the effects of atmospheric moisture and seasonal vegetation changes. Dry-season imagery provided clearer surface features and enhanced the ability to differentiate barelands, croplands, and grasslands. The analysis primarily used Bands 2–7 (Blue, Green, Red, Near-Infrared, and Shortwave Infrared 1 and 2), which are effective for land cover discrimination, while the thermal bands were excluded due to their coarser spatial resolution.

Preprocessing of the Landsat data was performed to improve radiometric and geometric accuracy. Raw digital numbers were converted to top-of-atmosphere reflectance through radiometric calibration, and atmospheric effects were corrected using the Dark Object Subtraction (DOS1) model to reduce haze and scattering caused by aerosols. All imagery was projected to the Universal Transverse Mercator (UTM) Zone 32N coordinate system with the WGS 84 datum to align with other datasets.

A supervised classification approach was adopted because reliable ground reference data were available and a high thematic accuracy was required. The Maximum Likelihood Classifier (MLC) was selected because of its strong statistical performance and its ability to handle variations within spectral classes. Training samples were generated through field surveys using handheld GPS and validated with very high-resolution imagery from Google Earth and Sentinel-2. The separability of training samples was tested using the Jeffries–Matusita (JM) distance to ensure that the selected classes were spectrally distinct, with JM values greater than 1.90 confirming acceptable separability. The MLC assigned each pixel to the class with the highest probability of membership by considering both the mean and variance-covariance matrix of the spectral signatures.

The final LULC map consisted of six classes: bareland, grassland, cropland, built-up area, dense forest, and waterbody. Each class was reclassified according to its suitability for windfarm development. Barelands and grasslands were assigned high suitability because of their open, low-vegetation surfaces and minimal preparation cost. Croplands were considered moderately suitable because they are usable but require land acquisition and may disrupt agricultural productivity. Built-up areas were assigned low suitability due to legal restrictions, high human activity, and potential safety conflicts. Dense forests were also classified as low suitability because of the increased turbulence caused by tall vegetation, the environmental cost of clearing, and associated ecological impacts. Waterbodies were assigned the lowest suitability due to construction infeasibility, high environmental sensitivity, and regulatory constraints.

2.2.5 Soil Suitability Mapping

Soil characteristics play a critical role in determining the structural feasibility, long-term stability, and cost-effectiveness of wind turbine installation. Turbine foundations must be designed to withstand both static and dynamic loads generated by tower weight and rotor movement. Weak, poorly drained, or highly plastic soils can cause differential settlement, structural instability, and increased construction costs. Therefore, a soil suitability assessment was conducted to classify the soils of the study area based on their engineering performance and geotechnical reliability for windfarm development.

Soil data were sourced from the Food and Agriculture Organization (FAO) Digital Soil Map of the World (DSMW) and These datasets were selected due to their reliability in providing soil classification and geotechnical descriptions relevant to construction.

The soil datasets were originally provided as vector polygon layers. These were reprojected to the Universal Transverse Mercator (UTM) Zone 32N, WGS 84 datum to ensure spatial consistency with other thematic layers. Rasterized at a 30 m spatial resolution to match the DEM and other raster layers, enabling seamless integration into the weighted overlay analysis.

Wind turbine foundations generally require soils with sufficient ultimate bearing capacity (qu) and low compressibility to prevent settlement. The Terzaghi (1943) [38] bearing capacity equation provided the theoretical framework for evaluating the soil strength, equation 7:

$$q_u = cN_c + \gamma D_f N_q + 0.5\gamma B N_\backslash\gamma \tag{7}$$

Where:

c = soil cohesion (kN/m²),
γ = unit weight of soil (kN/m³),
Df = depth of foundation (m),
B = width of foundation (m),
N_c,N_q,$N\gamma$ = bearing capacity factors dependent on soil friction angle (ϕ).

Distric Nitosols, with moderate cohesion and friction angle between 25°–35°, typically provide sufficient qu for shallow spread foundations. In contrast, Gleysols and Thionic Fluvisols often exhibit low qu due to poor drainage and high water content, requiring costlier pile foundations or soil improvement methods (e.g., compaction, stone columns).

Based on engineering properties and previous studies on windfarm geotechnical assessment (Ajayi *et al*., 2011; Agbetuyi *et al*., 2013 [30]; Mostafaeipour, 2010 [35]), the soils were reclassified into three suitability categories:

1. High suitability (3): Distric Nitosols well-drained and mechanically stable, with moderate to high load-bearing capacity, low swelling potential, and minimal geotechnical risk.
2. Moderate suitability (2): Gleysols usable with geotechnical reinforcement (deep foundations, soil stabilization) but associated with higher construction cost and moderate settlement risk.
3. Low suitability (1): Thionic Fluvisols poorly drained, highly compressible, prone to flooding and unsuitable for wind turbine installation without extensive soil improvement measures.

This classification was implemented using the Reclassify tool in ArcGIS Spatial Analyst, assigning each soil type a standardized suitability score for use in the Analytic Hierarchy Process (AHP) weighted overlay model.

Soil characteristics were included to ensure structural safety and economic feasibility in windfarm construction. Although soil may not directly influence the energy potential of a site, it strongly affects foundation design, construction costs, and long-term stability. Improper soil selection can lead to structural failures or significant cost overruns due to the need for deep piling, soil replacement, or drainage improvement.

2.2.6 Multi-Criteria Decision Analysis (MCDA) and Weighting

Windfarm site selection involves the simultaneous evaluation of multiple spatial and non-spatial factors that influence both the energy potential and the engineering and economic feasibility of development. These factors often interact in complex ways, requiring a structured decision-making framework to balance their relative importance. This study employed a Multi-Criteria Decision Analysis (MCDA) approach integrated with the Analytic Hierarchy Process (AHP) to systematically combine the thematic layers into a single Windfarm Suitability Index (WSI).

MCDA provides a robust framework for solving spatial decision problems where multiple, often conflicting, factors must be evaluated simultaneously. AHP, developed by Saaty (1980) [36], is widely used in renewable energy site selection studies because it allows decision-makers to express expert knowledge through pairwise comparisons, derive quantitative weights from qualitative judgments, and test the consistency of those judgments. AHP is particularly useful in wind energy planning because it balances resource-related factors (e.g., wind power density) with feasibility constraints (e.g., soil stability, accessibility, environmental risks).

The decision-making problem was structured hierarchically into three levels:

1. Goal: To determine the most suitable areas for windfarm development.
2. Criteria: Seven thematic layers Wind Power Density (WPD), Elevation, Slope, Proximity to Road Network, Soil Type, Proximity to Waterbodies, and Land Use/Land Cover (LULC).
3. Alternatives: All raster cells in the study area, each representing a potential windfarm location.

Pairwise comparisons were performed among the seven criteria using Saaty's 1–9 fundamental scale of relative importance, where 1 indicates equal importance and 9 indicates extreme importance of one factor over another. Expert judgments were obtained from renewable energy engineers, geospatial analysts, and environmental planners with experience in wind energy development in Nigeria and similar environments.

For each pair of criteria Ci and Cj, the relative importance aij was assigned, forming an n×n \times n×n reciprocal comparison matrix A, see equation 3.8:

$$A = [a_{ij}], \quad \text{where } a_{ij} = \frac{1}{a_{ji}},\ a_{ii} = 1 \tag{8}$$

The relative weight wi of each factor was calculated as the principal eigenvector of the pairwise comparison matrix A. The process involved the following steps:

1. Column normalization
Each column of A was divided by its column sum to produce the normalized matrix A_{norm}, (equation 9):

$$a_{ij}^{norm} = \frac{a_{ij}}{\sum_{i=1}^{n} a_{ij}} \quad (9)$$

2. Row mean calculation
The average of each row in the normalized matrix gave the weight wi of each criterion (equation 10):

$$w_i = \frac{\sum_{j=1}^{n} a_{ij}^{norm}}{n} \quad (10)$$

3. Weight vector formation
The resulting weights formed the priority vector $W = [w_1, w_2, \ldots, w_n]^T$, which was normalized so that $\sum wi = 1$.
Because AHP relies on subjective expert judgment, it is necessary to verify the consistency of the pairwise comparisons. The Consistency Index (CI) and Consistency Ratio (CR) were computed to test the reliability of the matrix (equation 11):

$$CI = \frac{\lambda_{max} - n}{n - 1} \quad (11)$$

Where λmax is the maximum eigenvalue of the comparison matrix and n is the number of criteria.
The Consistency Ratio (CR) is then (equation 12):

$$CR = \frac{CI}{RI} \quad (12)$$

Once the weights were established, all thematic layers were standardized to a common suitability scale (1 = low, 2 = moderate, 3 = high) and combined using the Weighted Linear Combination (WLC) technique. The WLC method aggregates weighted criteria into a single suitability score for each cell (equation 13):

$$S = \sum_{i=1}^{n} w_i \cdot x_i \quad (13)$$

Where:
- S = overall windfarm suitability score for a raster cell,
- wi = AHP-derived weight of factor i,
- xi = standardized suitability score of factor i.

The output Windfarm Suitability Index (WSI) ranged from 1 (least suitable) to 3 (most suitable) and was subsequently reclassified into three suitability zones: Low, Moderate, and High.
To evaluate the stability of the AHP-derived weights, a ±20% sensitivity analysis was performed Each criterion weight was increased and decreased by 20% while proportionally adjusting the others to maintain $\sum wi = 1$. The resulting changes in the extent of High, Moderate, and Low suitability zones were analyzed to determine the sensitivity of the final suitability map to expert judgment variability.
The MCDA–AHP approach provided a transparent and mathematically robust framework for combining diverse criteria. By normalizing heterogeneous datasets and assigning weights based on expert input with verified consistency, the model ensured that wind energy potential (WPD, Elevation) was balanced with technical feasibility (Slope, Soil) and economic access (Proximity to Roads). This method avoided bias towards a single factor and enhanced the decision-support capability of the windfarm suitability map for planners and investors.

3. Result
3.1 Identification and Characterization of Windfarm Influencing Factors
The identification and characterization of factors influencing windfarm development provide the foundation for determining areas most suitable for wind energy exploitation. This stage of the analysis integrates topographic, climatic, geotechnical, infrastructural, hydrological, and land use parameters to evaluate their combined effect on the technical and economic feasibility of windfarm installation. Understanding the spatial distribution and functional significance of these factors is essential for optimizing energy capture, reducing construction costs, and minimizing environmental impacts. Under this section, each influencing parameter elevation, slope, wind power density, soil type, proximity to road networks, proximity to waterbodies, and land use/land cover (LULC) is examined individually to establish its relevance, spatial variability, and contribution to windfarm site selection within the study area.
The digital elevation model (DEM) of the study area indicates elevation values ranging from approximately 0 m in the southern low-lying coastal plains to about 303 m in the northern upland regions. The elevation map demonstrates a predominantly low-lying topography, especially toward the southern and central portions of the state, where coastal and floodplain systems dominate. Higher elevations occur in the north and northeast, forming moderately elevated terrains that can favor wind energy development by reducing surface roughness and improving wind flow. Areas with elevations above 150 m provide enhanced exposure to prevailing winds and reduce turbulence compared with lower coastal regions that are often obstructed by vegetation and human structures, see Fig 1.

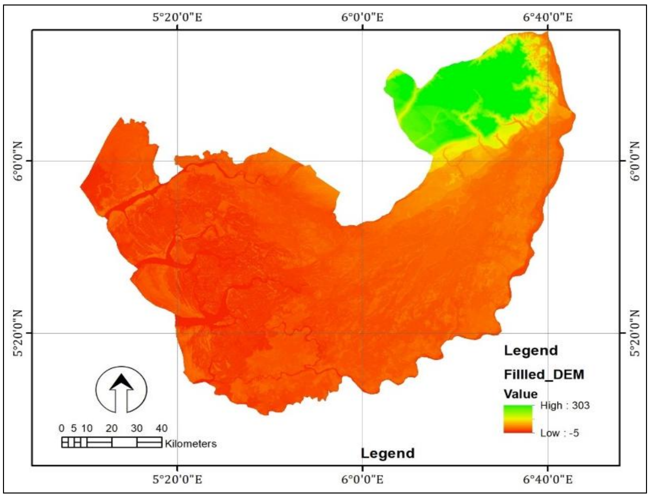

Fig 1: Elevation Data

The slope analysis derived from the DEM (Fig 2) shows gradients between 0° and 30.89°. Most of the landscape exhibits gentle slopes between 0° and 5°, especially in the low-lying coastal areas and floodplains, which are favorable for wind turbine foundation construction and maintenance. Moderate slopes ranging from 5° to 15° appear sporadically in the central and northern parts of the study area, while steeper slopes exceeding 20° are confined to localized upland ridges. Gentle to moderate slopes offer better accessibility and reduced construction cost compared with steep terrains, where soil instability and increased erosion risk can affect infrastructure safety.

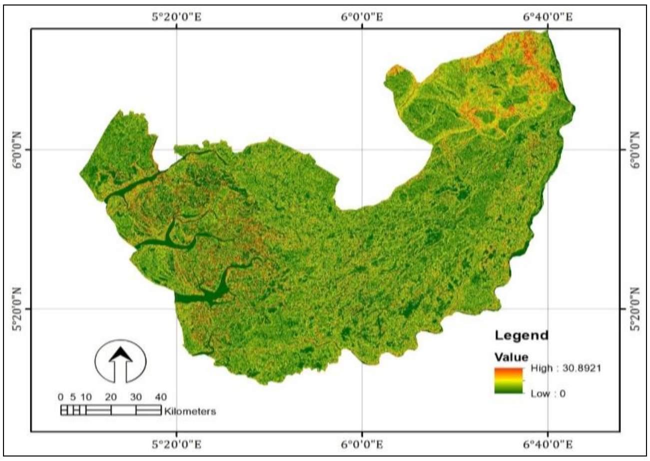

Fig 2: Slope Data

The LULC classification (Fig 3) identifies six major classes: cropland, dense forest, grassland, bareground, built-up areas, and water bodies. Croplands dominate the central and northern regions, while dense forest patches remain in the northeast. Grasslands and bareground are sparsely distributed but provide suitable open areas with minimal vegetation-induced turbulence. Built-up areas cluster around urban centers, increasing surface roughness and restricting available space for turbines. Water bodies and wetlands are concentrated in the south and southeast, unsuitable for direct turbine installation but important for understanding environmental impact zones. Areas dominated by cropland and grassland are more favorable for windfarm siting due to reduced ecological disruption and ease of construction.

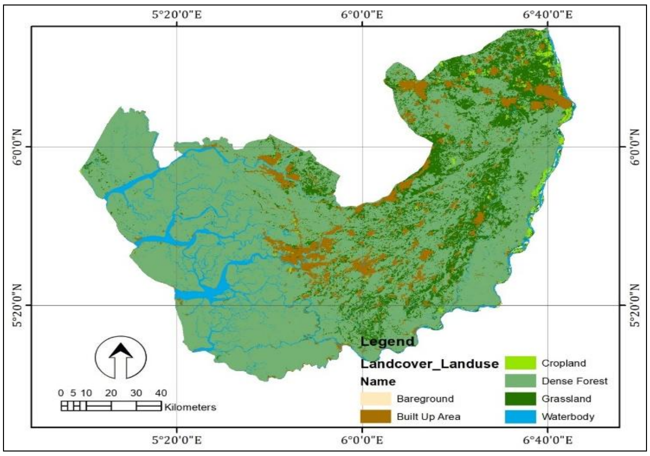

Fig 3: LULC Data

The soil map (Figure 4.4) shows three dominant soil types: Distric Nitosols, Gleysols, and Thionic Fluvisols. Distric Nitosols dominate the northern and northeastern uplands, characterized by well-drained, deep, and moderately stable profiles that can support wind turbine foundations. Gleysols are found in the central and southern regions, often associated with poor drainage, seasonal flooding, and high groundwater tables, making them less suitable for heavy turbine infrastructure. Thionic Fluvisols dominate the southwestern low-lying deltaic plains and coastal marshes; these soils have high salinity and instability due to waterlogging, thus unsuitable for windfarm development. Soil stability and drainage properties are critical for cost-effective foundation engineering and long-term turbine operation.

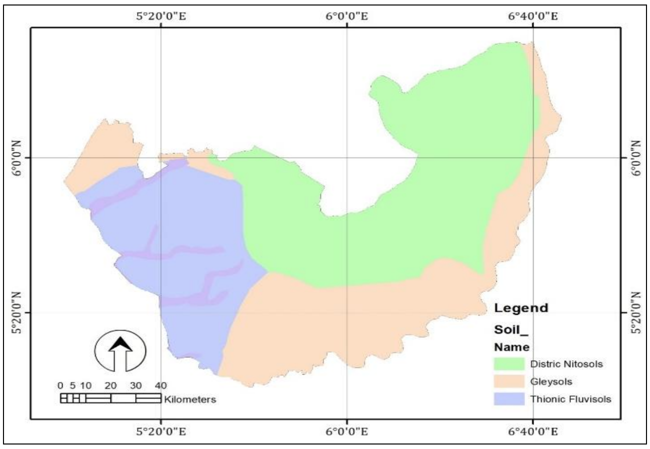

Fig 4: Soil Data

The wind power density (WPD) map (Fig 5) reveals spatial variability between 20.022 W/m² and 128.664 W/m² across the state. The highest WPD values, reaching up to 128.664 W/m², are concentrated in the north and northeastern uplands, where higher elevation and less vegetation enhance wind acceleration. Moderate WPD values are distributed across the central region, while the southern coastal plains exhibit lower values (below 40 W/m²), largely due to higher surface roughness and moisture-laden airflows from the Niger Delta. High WPD areas are preferable for windfarm siting as they indicate stronger and more consistent wind regimes necessary for optimal turbine operation and electricity generation.

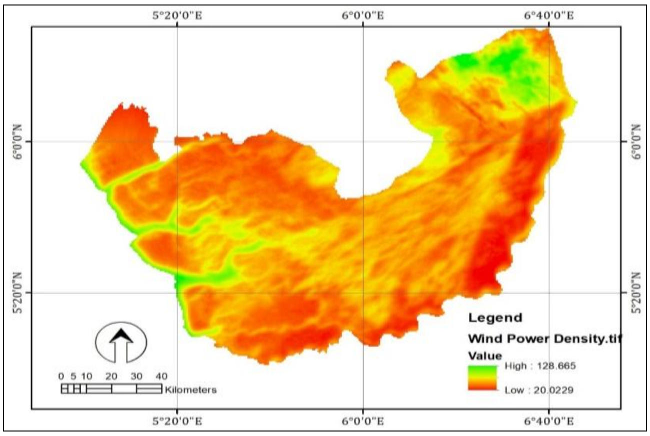

Fig 5: Wind Power Density Data

The hydrographic map (Fig 4.6) indicates an extensive network of rivers, streams, and wetlands, particularly in the southern and southwestern deltaic plains. These areas are prone to seasonal flooding and soil instability, presenting constraints for windfarm construction and long-term operation. However, proximity to moderate-sized rivers in upland areas could support secondary infrastructure needs, such as cooling systems or access for construction materials. Avoiding flood-prone zones is imperative to reduce infrastructure vulnerability.

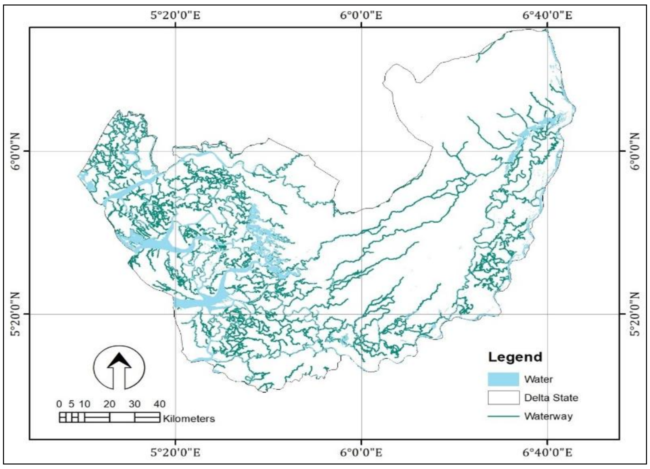

Fig 6: Waterbody Data

The road network map (Fig 7) demonstrates dense connectivity across the central and northeastern areas, with major and minor roads extending toward settlements and agricultural zones. Proximity to roads is vital for transporting turbine components and ensuring maintenance access. Regions with good road accessibility, especially in the central and northern uplands, present logistical advantages, reducing construction costs compared with remote flood-prone southern areas with poor transport infrastructure.

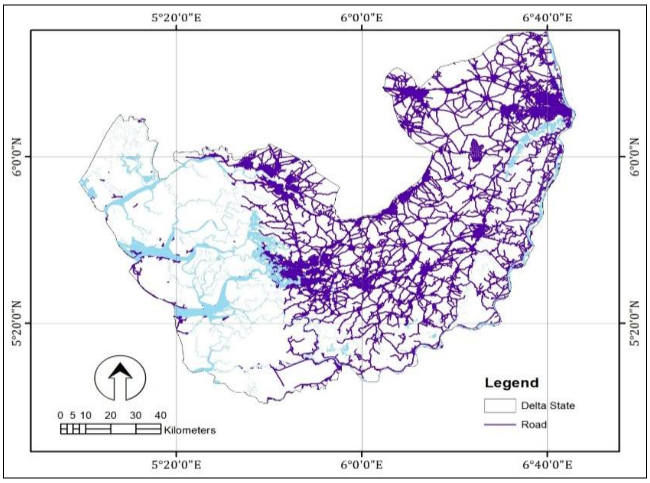

Fig 7: Road Data

Spatial overlays (Figures 1–7) reveal that the highest elevations and steepest slopes occur within the northern and north-eastern uplands, while the southern low-lying plains remain predominantly flat. Areas with moderate to steep gradients are primarily associated with elevated ridges and dissected terrains, whereas the coastal and deltaic regions display broad, gentle slopes approaching near-zero values. These topographic variations strongly influence wind availability and infrastructure feasibility. Elevated zones enhance wind acceleration by reducing surface roughness, while excessively steep gradients may increase construction complexity and foundation instability for large turbines.

The wind power density map indicates that the northern and north-eastern uplands coincide with higher energy potential, with values exceeding 100 W/m² in some tracts. In contrast, the southern and deltaic plains exhibit lower wind potential, often below 40 W/m², due to topographic shielding and increased surface friction from vegetation and moisture. Soil distribution further modulates the suitability of these zones. Distric Nitosols dominate the uplands and provide well-drained, stable foundations suitable for turbine installation. In contrast, Gleysols and Thionic Fluvisols occur extensively in the southern deltaic belt and are poorly drained, waterlogged, and structurally weak, creating challenges for heavy infrastructure.

Accessibility mapping shows dense road networks within the central, eastern and northern sectors, enhancing the transport and installation of windfarm components. Conversely, the southern lowlands, particularly the deltaic wetlands, have limited road access, increasing construction cost and maintenance difficulty. Hydrological mapping indicates an extensive waterway network in the south and south-west, where seasonal flooding and unstable soils limit infrastructure development. In contrast, the uplands are less inundated and hydrologically stable, although localized drainage channels should still be considered during site preparation.

Land use and land cover (LULC) analysis shows that cropland and grassland dominate much of the central and northern areas, offering open and accessible landscapes for turbine placement. Dense forests and built-up areas present in some regions increase surface roughness and introduce ecological and social constraints. Wetlands and waterbodies concentrated in the southern sector are unsuitable for windfarm development due to environmental sensitivity and structural instability.

Collectively, these spatial layers provide a process-based understanding of windfarm site suitability. Elevation frames the wind exposure potential, slope affects construction feasibility, wind power density defines the energy resource, soils control foundation stability, roads determine accessibility, waterways identify flood-risk and hydrological constraints, while LULC indicates surface roughness and land availability. The integrated analysis highlights the northern and north-eastern uplands as the most promising areas for windfarm development, where moderate slopes, high wind power density, stable Distric Nitosols, and good transport access intersect with open cropland and grassland. A detailed summary of the thematic layers, their data sources, derivation methods, and justification for inclusion is presented in Table 1.

Table 1: Summary of Windfarm Influencing Factors and Justification for Inclusion

S. No	Thematic Layer	Source / Derivation Method	Relevance to Windfarm Location Assessment
1	Elevation	Derived from Shuttle Radar Topography Mission (SRTM) Digital Elevation Model (DEM) and processed in GIS	Determines wind exposure and turbine hub height optimization; higher elevations reduce surface roughness and improve wind speed consistency.
2	Slope	Calculated from filled DEM using slope analysis in ArcGIS/QGIS	Assesses terrain stability, construction feasibility, and foundation cost; gentle slopes (<5°) favor turbine installation and access.
3	Wind Power Density (WPD)	Obtained from long-term wind resource assessment datasets and modeled in GIS	Indicates potential energy output; high WPD zones (≥100 W/m²) ensure efficient power generation and long-term project viability.
4	Soil Type	Extracted from FAO/ISRIC soil database and national soil survey data	Determines foundation stability and cost; well-drained Distric Nitosols favor turbine foundations, while Gleysols and Thionic Fluvisols are unstable and waterlogged.
5	Road Network	Digitized from OpenStreetMap and state transportation infrastructure data	Facilitates transportation of turbine components and long-term maintenance; good road accessibility reduces project logistics cost.
6	Water Bodies	Extracted from hydrological network (rivers, streams, wetlands) mapped from Landsat/Sentinel imagery and topographic data	Identifies flood-prone or unstable areas unsuitable for heavy infrastructure; ensures avoidance of wetlands to reduce environmental and structural risks.
7	Land Use/Land Cover (LULC)	Classified from Landsat 8 OLI imagery using supervised classification (Maximum Likelihood)	Identifies surface roughness and land availability; cropland and grassland are more suitable than built-up areas, forests, and wetlands for turbine placement.

3.2 Reclassification and Standardization of Windfarm Influencing Factors

To support the multi-criteria evaluation for windfarm siting, each thematic factor was reclassified into three suitability levels: 1 = Low suitability, 2 = Moderate suitability, and 3 = High suitability. The reclassification was guided by the physical requirements of wind energy development, engineering constraints, and environmental considerations. The ranges and classes for each factor are summarized in Table 4.2, followed by a detailed explanation of their relevance to windfarm site selection.

Elevation plays a central role in determining wind speed availability and infrastructure feasibility. Low-lying coastal and deltaic plains (0–50 m) are less favorable because they experience increased surface roughness from vegetation, settlements, and wetlands, which reduce wind flow efficiency. These areas are also more prone to flooding and groundwater saturation, creating engineering challenges for heavy turbine foundations. Moderate elevations (50–150 m) are generally advantageous because they offer improved wind exposure compared with the lowlands while remaining easily accessible for construction. High elevations above 150 m provide the best aerodynamic conditions by reducing friction and allowing turbines to capture stronger, more consistent wind currents. However, in extremely rugged terrain, special engineering solutions such as deeper pile foundations may be required, but the overall energy yield compensates for these costs, see Table 2 and Fig 8.

Table 2: Elevation Reclassification Range

S. No	Factor	Range/Class	Suitability Level	Justification
1	Elevation (m)	0 – 50	1 = Low	Low plains with poor wind exposure, high surface friction, and flood vulnerability limit energy potential and foundation stability.
		50 – 150	2 = Moderate	Moderate relief provides improved wind flow and remains easily accessible for turbine construction.
		>150	3 = High	Elevated terrains reduce surface roughness, enhance wind speed, and optimize energy yield despite moderate construction cost increases.

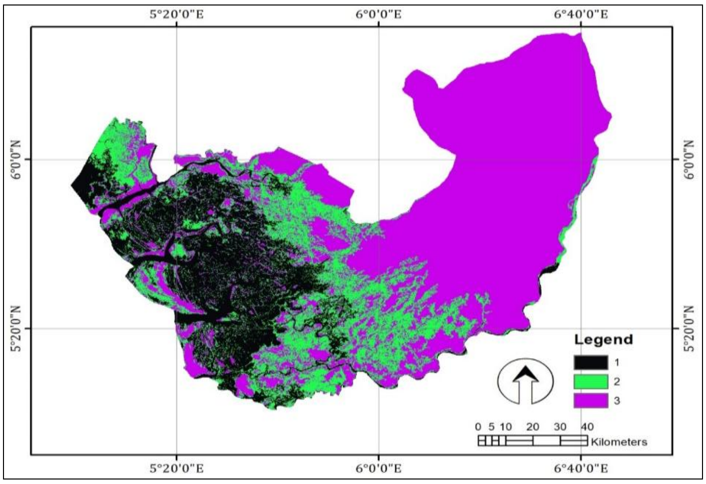

Fig 4.8: Reclassified Elevation Data

Slope is a fundamental determinant of construction cost and structural stability. Flat terrain with gradients between 0° and 5° is highly suitable as it facilitates low-cost turbine installation, minimizes earthworks, and provides stable foundations. Moderate slopes (5°–15°) are acceptable but may require additional grading, erosion control, and reinforced foundations to ensure long-term turbine stability. Steep slopes greater than 15° are least suitable due to increased construction cost, potential soil instability, and erosion risk, especially under intense rainfall. In such areas, foundation anchoring and slope stabilization may significantly increase project cost and complexity, see table 3 and Fig 9.

Table 3: Slope Reclassification Range

S. No	Factor	Range/Class	Suitability Level	Justification
2	Slope (°)	>15	1 = Low	Steep slopes increase construction cost, erosion risk, and instability, requiring expensive engineering interventions.
		5 – 15	2 = Moderate	Moderately sloped terrain is usable with some grading and reinforcement of foundations to reduce instability risk.
		0 – 5	3 = High	Flat to gentle slopes facilitate low-cost construction, easy access, and long-term stability of wind turbines.

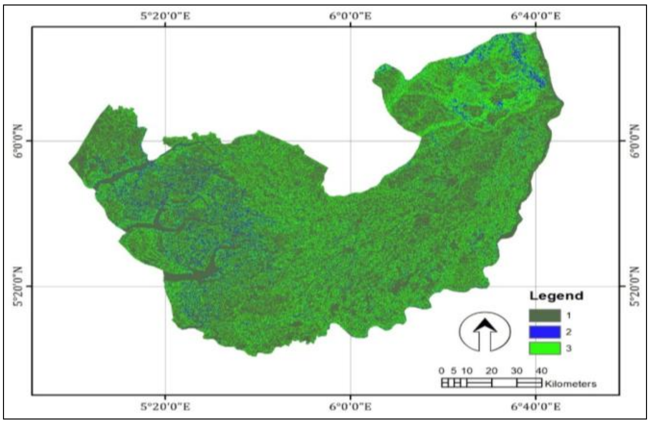

Fig 4.9: Reclassified Slope Data

Wind power density (W/m²) directly determines the energy generation potential of a windfarm. Areas with WPD less than 50 W/m² are unsuitable for utility-scale projects because of low annual energy production, which undermines economic viability. Moderate zones with 50–100 W/m² can sustain small or medium-sized wind projects or hybrid renewable systems but may not generate sufficient power for grid-connected commercial farms. Sites with WPD greater than 100 W/m² are highly suitable, supporting continuous and profitable power generation. These high WPD zones often occur in elevated, open landscapes with reduced surface roughness and should be prioritized for utility-scale wind energy development., see Table 4 and Fig 10.

Table 4: Wind Power Density Reclassification Range

S/N	Factor	Range/Class	Suitability Level	Justification
3	Wind Power Density (W/m²)	<50	1 = Low	Energy generation is insufficient for commercial windfarms, making investment economically unviable.
		50 – 100	2 = Moderate	Suitable for small-to-medium projects but marginal for large-scale grid-connected energy generation.
		>100	3 = High	High, consistent wind resources support efficient and profitable large-scale wind energy production.

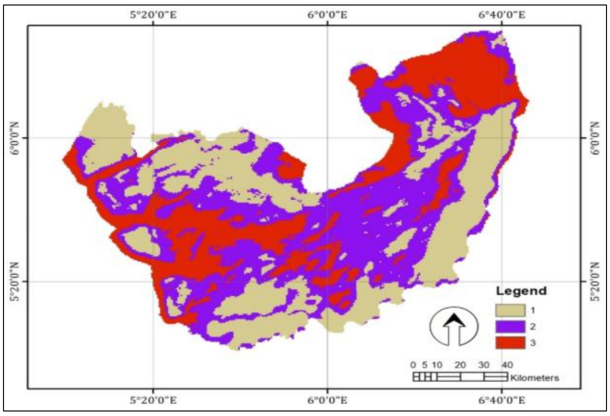

Fig 10: Reclassified Wind Power Density Data

Soil properties determine the safety and cost of turbine foundations, particularly for large utility-scale turbines that require deep and stable substructures. Thionic Fluvisols, which dominate the deltaic and coastal lowlands, are saline, poorly drained, and structurally weak. These soils experience frequent waterlogging and subsidence, making them unsuitable for heavy infrastructure and costly to stabilize. Gleysols, distributed across parts of the central zone, offer moderate stability but still suffer from shallow water tables and periodic flooding, increasing foundation cost and long-term maintenance requirements. Distric Nitosols, abundant in the northern and northeastern uplands, are deep, well-drained, and mechanically stable, providing excellent support for turbine installations. They are therefore classified as highly suitable for windfarm development, see Table 5 and Fig 11.

Table 5: Soil Reclassification Range

S. No	Factor	Range/Class	Suitability Level	Justification
4	Soil Type	Thionic Fluvisols	1 = Low	Poor drainage, salinity, and waterlogging increase construction cost and risk of subsidence.
		Gleysols	2 = Moderate	Moderately stable soils but constrained by shallow water tables and seasonal flooding, requiring geotechnical improvements.
		Distric Nitosols	3 = High	Deep, well-drained, and mechanically stable soils provide strong foundations for turbine installation.

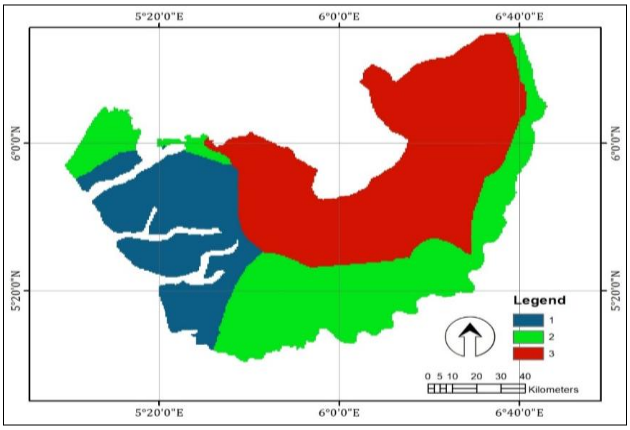

Fig 11: Reclassified Soil Data

Distance from rivers, wetlands, and flood-prone areas strongly influences long-term infrastructure stability. Sites located within 0–1 km of waterbodies are classified as low suitability due to high flood risk, potential soil saturation, and structural instability. Areas 1–5 km away are considered moderately suitable, as they may still be influenced by seasonal flooding or high groundwater levels but can be engineered for stability. Sites more than 5 km away from major hydrological features are highly suitable because they minimize flooding risk and ensure secure turbine foundations, see Table 6 and Fig 12.

Table 6: Waterbody Reclassification Range

S. No	Factor	Range/Class	Suitability Level	Justification
5	Proximity to Waterbodies (km)	0 – 1	1 = Low	Areas adjacent to rivers and wetlands are highly flood-prone and hydrologically unstable, posing significant risk to infrastructure stability.
		1 – 5	2 = Moderate	Moderately distant from waterbodies but may still require engineering interventions to manage seasonal drainage or groundwater influence.
		>5	3 = High	Safe distance from major hydrological features ensures minimal flood risk, secure ground conditions, and long-term turbine stability.

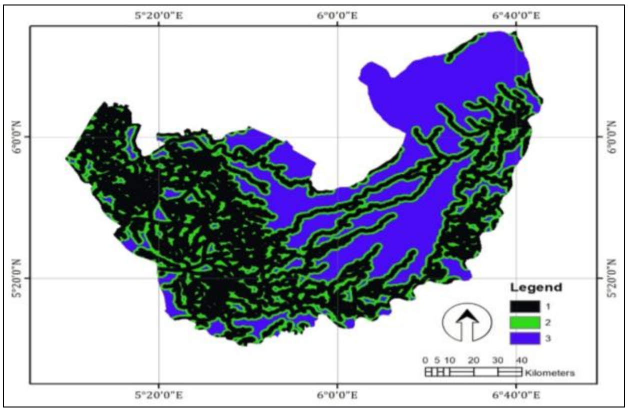

Fig 12: Reclassified Proximity to Waterbody

Transport access is critical to wind energy development due to the large size and weight of turbine components. Locations far from existing roads (>10 km) are considered low suitability because of the cost and time required to build access routes. Moderately suitable zones are those within 5–10 km of existing primary or secondary roads; such areas are accessible but may require road upgrades to accommodate heavy construction machinery. Highly suitable areas are within 0–5 km of major or well-maintained roads, reducing transport costs, speeding up construction, and facilitating ongoing maintenance, see Table 7 and Fig 13.

Table 7: Proximity to Road Network Reclassification Range

S. No	Factor	Range/Class	Suitability Level	Justification
6	Proximity to Road Network (km)	>10	1 = Low	Remote locations significantly increase transportation costs for turbine components and limit maintenance access.
		5 – 10	2 = Moderate	Moderately accessible but may require upgrading roads to support heavy equipment and construction vehicles.
		0 – 5	3 = High	Close proximity to major roads minimizes transport cost, facilitates easy installation, and ensures efficient long-term maintenance.

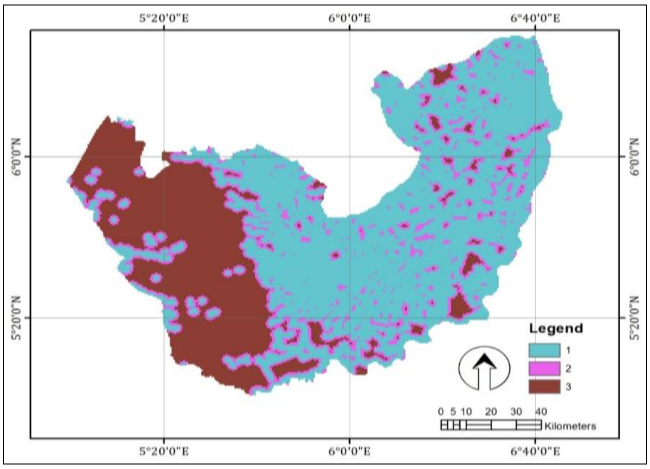

Fig 13: Reclassified Proximity to Road

3.3 Weight Derivation for Windfarm influencing Factors

3.3.1 Pairwise Comparison Matrix

A pairwise comparison matrix was constructed by assigning relative judgment values between the seven influencing factors in accordance with the fundamental scale proposed by Saaty (1980) [36] for the Analytic Hierarchy Process (AHP). This matrix (Table 8) quantified assessments of the comparative importance of each factor in determining windfarm suitability. Each diagonal element was assigned a value of one, reflecting the equal importance of a factor compared to itself, while the off-diagonal elements represent the degree to which the row factor is preferred over the column factor. The matrix is reciprocal by design; if a factor in row *i* is rated a_{ij} times more important than a factor in column *j*, then the reciprocal value $1/a_{ij}$ is assigned to the symmetric position.

Table 8: Pair-wise comparison matrix of the study

	WPD	Elevation	Slope	Prox RD	Soil	Prox WT	LULC
WPD	1	2	2	2	2	3	4
Elevation	0.5	1	2	2	2	2	3
Slope	0.5	0.5	1	2	2	2	3
Prox RD	0.5	0.5	0.5	1	2	2	3
Soil	0.5	0.5	0.5	0.5	1	2	2
Prox WT	0.33	0.5	0.5	0.5	0.5	1	2
LULC	0.25	0.33	0.33	0.33	0.5	0.5	`1
Total	3.58	5.33	6.83	8.33	10	12.5	17

The pairwise comparison matrix synthesizes expert judgments on the relative influence of the seven selected factors. Unity occupies the diagonal, indicating self-comparison, while the off-diagonal entries reflect how many times the row factor is judged to be more influential than the column factor. The matrix remains reciprocal by construction, meaning the value above the diagonal is the reciprocal of the value below it. The column totals (3.58, 5.33, 6.83, 8.33, 10, 12.50, and 17.00) summarize the cumulative preference weights assigned to each factor across all comparisons, providing an initial indication of their relative strength before normalization.

Examination of the raw judgments shows a clear hierarchy favoring energy potential and topographic exposure. Wind Power Density (WPD) is consistently rated as the most influential factor, receiving higher preference scores over all other criteria, reflecting its decisive role in determining the economic viability of a windfarm. Elevation follows closely, being strongly preferred over slope, soil conditions, proximity to waterbodies, and land cover because of its direct effect on wind acceleration. Slope is placed third, with experts acknowledging its impact on construction feasibility and turbine foundation stability.

Infrastructure accessibility, expressed as proximity to road network, ranks next in influence; while not directly affecting wind resource, it significantly impacts cost and ease of installation. Soil type follows, recognized for its role in supporting heavy turbine foundations, especially where deep and well-drained soils such as Distric Nitosols are present. Hydrological risk, represented by proximity to waterbodies, is considered less influential compared with energy and engineering factors but remains relevant for minimizing flooding and soil instability. Land Use and Land Cover (LULC) receives the lowest overall weight because, while it affects environmental impact and surface roughness, it can be managed through planning, land clearance, or mitigation strategies.

The embedded priority structure derived from this comparison is therefore:

Wind Power Density (WPD) > Elevation > Slope > Proximity to Road Network > Soil Type > Proximity to Waterbodies > Land Use and Land Cover (LULC).

This hierarchy aligns with the technical requirements of wind energy development, emphasizing that energy resource potential must be the primary driver, followed by topographic exposure and engineering feasibility, with environmental and accessibility considerations playing secondary but still significant roles.

3.3.2 Normalized Prioritization Pairwise Comparison Matrix

The normalized prioritization matrix (Table 10) was generated by dividing each entry of the pairwise comparison matrix by the sum of its respective column, ensuring that each column totals to one. The mean of each row in this normalized matrix represents the priority vector, which expresses the relative weight of each influencing factor in determining windfarm suitability.

The resulting weights and their corresponding percentages are as follows: Wind Power Density (0.30; 29.54%), Elevation (0.24; 24.02%), Slope (0.17; 17.12%), Proximity to Road Network (0.11; 11.08%), Soil Type (0.08; 7.62%), Proximity to Waterbodies (0.06; 5.62%), and Land Use/Land Cover (0.04; 4.99%). This distribution demonstrates that energy resource and terrain-derived variables dominate the expert evaluation, with Wind Power Density and Elevation jointly accounting for over 53% of the total influence. Slope contributes an additional 17%, emphasizing the importance of topographic configuration in both wind energy generation and engineering feasibility.

Accessibility and geotechnical factors, represented by Proximity to Road Network and Soil Type, together contribute about 19%, reflecting their significant but secondary role in reducing construction cost and ensuring foundation stability. Hydrological risk, expressed through Proximity to Waterbodies, and environmental/land availability constraints represented by Land Use and Land Cover, together account for approximately 10% of the total weight. These lower contributions indicate that while environmental and flood-related risks must be considered, they are less decisive compared with wind availability and terrain suitability for large-scale turbine installation.

Table 9: Prioritization weight matrix

	WPD	Elevation	Slope	Prox RD	Soil	Prox WT	LULC	Mean	W%
WPD	0.28	0.38	0.29	0.24	0.20	0.24	0.24	0.27	26.61
Elevation	0.14	0.19	0.29	0.24	0.20	0.16	0.18	0.20	19.95
Slope	0.14	0.09	0.15	0.24	0.20	0.16	0.18	0.17	16.52
Prox RD	0.14	0.09	0.07	0.12	0.20	0.16	0.18	0.14	13.76
Soil	0.14	0.09	0.07	0.06	0.10	0.16	0.12	0.11	10.63
Prox WT	0.09	0.09	0.07	0.06	0.05	0.08	0.12	0.08	8.10
LULC	0.07	0.06	0.05	0.04	0.05	0.04	0.06	0.05	5.26
Total	1	1	1	1	1	1	1	1	100

The weighting pattern confirms the dominance of energy resource availability (WPD) **and** topographic exposure (elevation and slope) in guiding optimal windfarm siting. Infrastructure accessibility and soil conditions form a second tier of influence by shaping the practicality and cost of turbine construction. Hydrological risks and land cover factors, though less influential, remain relevant for ensuring environmental compliance and long-term structural safety.

3 3.3 Estimation of the Consistency Ratio

This stage involved calculating a consistency ratio (CR) to check reliability of the judgments values which are relative to large samples of purely random judgments. The AHP deals with consistency explicitly because in making paired comparisons, just as in thinking, people do not have the intrinsic logical ability to always be consistent.

To determine consistency ratio, the analytical hierarchy process compares it by random index (R.I.). Mathematically, Consistency Ratio (C.R.), can be defined as:

$$CR = CI/RI$$

In calculating the constituency value, the mathematical formula CR = CI/RI was be used.

Random index (RI) is the consistency index of a randomly generated pair-wise comparison matrix of order 1 to 10 obtained by approximating random indices.

Table 10: Random Index by Saaty

Size of matrix (n)	1	2	3	4	5	6	7	8	9	10
Random index (RI)	0	0	0.58	0.9	1.12	1.24	1.32	1.41	1.46	1.49

Source: (Saaty, 2001).

Note: If the value of the obtained Consistency Ratio is less than 0.1, it means that there is a reasonable level of consistency in the pairwise comparisons, and that the computed weights are within the acceptable limit. If the reverse is the case (CR > 0.1) it means that the weights obtained are inconsistent and needs to be checked.

The value of Consistency index, CI was calculated from the preference matrix according to equation below:

$$CI = \frac{\lambda\text{max} - \text{n}}{\text{n}-1}$$

λmax is the Principal Eigen Value; n is the number of factors.

λmax = Σ of the products between each element of the priority vector and relative weights.

$$\lambda max = (3.58 * 0.27) + (5.33 * 0.20) + (6.83 * 0.17) + (8.33 * 0.14) + (10 * 0.11) + (12.5 * 0.08) + (17 * 0.05)$$

$$= 0.97 + 1.06 + 1.07 + 1.16 + 1.16 + 1 + 0.85$$

$$\lambda max = 7.27$$

$$CI = (7.27 - 7)/(7 - 1) = 0.045$$

$$CR = 0.016/1.32 = 0.03$$

$$CR = 0.03 < 0.10\ (Acceptable)$$

The consistency ratio (CR) is design in such a way that if CR<0.10, the ratio indicates a reasonable level of consistency in the pairwise comparisons; if, however, CR ≥ 0.10, the values of the ratio are indicative of inconsistent judgments. From the judgment a Consistency Ratio (CR) of 0.03 was achieved which was less than the maximum allowable ratio of 0.10.

3.3.4 Sensitivity Analysis of Factor Weights

The robustness and reliability of the Analytical Hierarchy Process (AHP)–derived weights used in this study were evaluated through a sensitivity analysis. Sensitivity analysis is a critical step in multi-criteria decision analysis because it tests the stability of the final suitability model when the weights assigned to criteria are modified. Since AHP incorporates expert judgment, such an analysis reveals whether moderate changes to the weight structure significantly alter the ranking of suitable areas or the overall decision outcome.

Seven criteria were considered in this study: Wind Power Density (WPD), Elevation, Slope, Proximity to Road Network, Soil Type, Proximity to Waterbodies, and Land Use/Land Cover (LULC). The baseline weights were derived from the pairwise comparison matrix and are presented in Table 11.

Table 11: Original AHP-Derived Weights of Influencing Factors

Factor	Weight (W)	Weight (%)
Wind Power Density (WPD)	0.30	29.54
Elevation	0.24	24.02
Slope	0.17	17.12
Proximity to Road Network	0.11	11.08
Soil Type	0.08	7.62
Proximity to Waterbodies	0.06	5.62
Land Use/Land Cover (LULC)	0.04	4.99
Total	1.00	100

The baseline weights indicate that WPD and Elevation dominate (together ~53.6%), followed by Slope (17.1%), while accessibility, geotechnical, hydrological, and land cover factors contribute smaller shares.

A one-factor-at-a-time (OFAT) approach was applied to test model stability (Table 12 and 13). The weight of the most influential criteria (WPD, Elevation, and Slope) was increased and decreased by ±10% and ±20% relative to its baseline value. When one factor was adjusted, the remaining weights were proportionally rescaled to maintain a total weight sum of 1.00. The objective was to determine whether reasonable changes in weight would cause significant reclassification of suitability zones or alter the priority ranking of factors.

Table 12: Adjusted Weight Scenarios for Sensitivity Analysis

Scenario	WPD	Elevation	Slope	Prox RD	Soil	Prox WT	LULC	Description
Baseline	0.30	0.24	0.17	0.11	0.08	0.06	0.04	Original AHP weights
WPD +10%	0.33	0.22	0.16	0.10	0.07	0.06	0.04	Wind Power Density increased by 10%
WPD +20%	0.36	0.21	0.15	0.10	0.07	0.06	0.04	Wind Power Density increased by 20%
WPD −10%	0.27	0.25	0.18	0.12	0.09	0.06	0.04	Wind Power Density reduced by 10%
WPD −20%	0.24	0.26	0.19	0.12	0.09	0.06	0.04	Wind Power Density reduced by 20%
Elevation +20%	0.27	0.29	0.15	0.11	0.08	0.06	0.04	Elevation weight increased by 20%
Slope +20%	0.27	0.23	0.20	0.11	0.08	0.06	0.04	Slope weight increased by 20%

Table 13: Summary of Sensitivity Outcomes

Scenario	% Change in Highly Suitable Zones	Ranking Order of Factors (Most → Least)
Baseline	–	WPD > Elevation > Slope > Prox RD > Soil > Prox WT > LULC
WPD +10%	+2.1%	WPD > Elevation > Slope > Prox RD > Soil > Prox WT > LULC
WPD +20%	+4.3%	WPD > Elevation > Slope > Prox RD > Soil > Prox WT > LULC
WPD −10%	−1.9%	Elevation > WPD > Slope > Prox RD > Soil > Prox WT > LULC
WPD −20%	−4.5%	Elevation > WPD > Slope > Prox RD > Soil > Prox WT > LULC
Elevation +20%	+1.8%	Elevation > WPD > Slope > Prox RD > Soil > Prox WT > LULC
Slope +20%	−2.7%	WPD > Elevation > Slope > Prox RD > Soil > Prox WT > LULC

These scenarios provide a reasonable range of perturbations to test how much the final suitability output depends on subjective weight assignments.

The sensitivity analysis provides important insight into the stability of the windfarm suitability model when the weights of the influencing factors are moderately adjusted. The results, presented in Tables 12 and 13, reveal how the classification of highly suitable areas responds to changes in the weighting of the most influential criteria.

An increase in the weight of Wind Power Density (WPD) by 20 percent resulted in an expansion of the highly suitable zones by approximately 4.3 percent, particularly across the northern and northeastern uplands where strong wind resources are concentrated. Conversely, when the WPD weight was reduced by 20 percent, the extent of highly suitable areas decreased by about 4.5 percent, and Elevation assumed greater influence in defining the most suitable zones. Despite these changes, the three most dominant factors WPD, Elevation, and Slope retained their overall ranking, indicating that the model remains stable even when the most critical parameter is substantially adjusted. Increasing the weight of Elevation by 20 percent slightly expanded the distribution of highly suitable areas by about 1.8 percent, especially in moderately elevated regions. When the Elevation weight was reduced, a slight shift in influence toward WPD occurred, but the top three factors maintained their original order, confirming the stability of the model hierarchy.

Adjusting the weight of Slope by 20 percent produced a moderate reduction in highly suitable areas (−2.7 percent) due to the stronger penalization of steep terrain. Reducing the slope weight, on the other hand, slightly increased the suitability of moderately sloped areas but did not affect the ranking of the factors. Changes applied to the secondary factors Proximity to Road Network, Soil Type, Proximity to Waterbodies, and Land Use/Land Cover (LULC) had only localized effects. Altering their weights by ±20 percent did not modify the global suitability pattern or disrupt the overall factor hierarchy. These results indicate that while these secondary factors refine site selection at a local scale, the broader suitability structure is primarily controlled by WPD, Elevation, and Slope.

The findings confirm that the AHP-derived weighting scheme is robust and reliable. The final windfarm suitability map is not highly sensitive to moderate changes in expert judgments, particularly for the lower-weighted criteria. Even when the weight of the most influential factor, WPD, was adjusted by ±20 percent, the ranking of priority zones remained unchanged, and only slight variations were observed in the total area classified as highly suitable.

3.4 Analysis of Windfarm Site Suitability Zones

The windfarm suitability assessment classified the study area into three suitability zones: low, moderate, and high suitability (Table 14 and Fig 14). The spatial distribution shows a dominance of moderately suitable areas, followed by low suitability zones, with only a limited portion identified as highly suitable for wind energy development.

Table 4.14: Distribution of Windfarm Suitability Zones

Suitability Class	Area (km²)	Percentage (%)
Low Suitability	5,328.39	32.60
Moderate Suitability	10,180.46	62.29
High Suitability	834.41	5.11

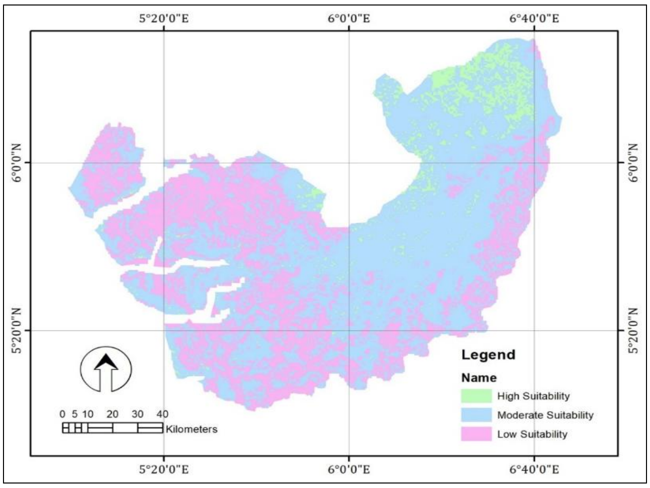

Fig 4.14: Windfarm Site Suitability Zones

From Fig 14, the high suitability zone is relatively limited, covering only 834.41 km² (5.11%), but represents the most optimal areas for large-scale windfarm installation. These regions are mainly concentrated in the northern and northeastern uplands, where wind power density exceeds 100 W/m², elevation is moderate to high, slopes are gentle, soils (mainly Distric Nitosols) are well-drained and stable, and proximity to major road networks is high. These combined conditions support efficient wind energy capture and reduce construction and maintenance costs, making these areas the most attractive for immediate investment.

The moderate suitability zone occupies the largest portion of the study area, covering approximately 10,180.46 km² (62.29%). This extensive distribution indicates that most of the region meets the baseline requirements for wind energy development but may require additional technical considerations such as road improvements, soil stabilization, or site-specific environmental assessment. These areas generally have adequate wind potential and favorable topographic conditions but may be limited by factors such as moderate road access, soil variability, or proximity to waterbodies.

The low suitability zone accounts for about 5,328.39 km² (32.60%) and is primarily associated with low wind power density, poor soil stability (e.g., Thionic Fluvisols and Gleysols), high flood risk, and limited accessibility. These areas are typically found within the southern deltaic plains and low-lying coastal sectors where waterlogging, dense vegetation, and wetland ecosystems increase construction difficulty and reduce wind energy viability. Development in these zones would require extensive infrastructure investment and may face significant environmental restrictions.

3.4.1 Analysis of Windfarm Site Suitability by LGAs

The suitability classification across Local Government Areas (LGAs) reveals clear spatial patterns in the availability of land for wind energy development. As shown in Table 4.15, Aniocha North LGA emerges as the most favorable location, with nearly 48.81% of its total land area (189.76 km²) classified as highly suitable for windfarm development. This LGA also maintains a balanced proportion of moderately suitable land (51.19%) and no low suitability areas, indicating excellent wind potential, favorable topography, stable soils, and good accessibility.

Aniocha South ranks second in terms of highly suitable land, with 146.13 km² (16.83%) categorized as highly suitable and a significant 79.72% under moderate suitability. This pattern indicates a large potential land base that could support both utility-scale and community-scale wind power installations, provided additional infrastructure and geotechnical assessments are undertaken.

Ika North East and Oshimili North LGAs also show considerable promise, with 27.29% and 23.76% of their total areas classified as highly suitable, respectively. These LGAs combine strong wind resource potential with moderate topographic constraints, making them attractive for phased windfarm development.

By contrast, Ika South and Ukwuani are characterized by very high moderate suitability (82.16% and 87.93%, respectively) but lower proportions of highly suitable land (17.84% and 11.92%). These areas remain feasible for wind energy projects but may require further site-specific optimization. Areas such as Ndokwa West, Ethiope West, Ughelli North, and Warri South-West show extensive moderate suitability but relatively low percentages of highly suitable land (ranging from 0.94% to 5.92%). These regions may still host wind projects but could face higher development costs due to less favorable terrain or infrastructure limitations.

Notably, Warri South-West LGA, despite its large total area (1,523.13 km²), has less than 1% highly suitable land and a significant 44% low suitability, reflecting challenges such as waterlogged soils, dense river networks, and accessibility constraints.

Table 15: Distribution of Windfarm Suitability by LGAs

LGA	High Suitability (km²)	Moderate Suitability (km²)	Low Suitability (km²)	Total Area (km²)	Low (%)	Moderate (%)	High (%)
Aniocha North	189.76	199.05	0.00	388.81	0.00	51.19	48.81
Aniocha South	146.13	692.20	29.96	868.29	3.45	79.72	16.83
Ika North East	123.27	328.22	0.29	451.78	0.06	72.65	27.29
Oshimili North	119.63	355.30	28.47	503.40	5.66	70.58	23.76
Ika South	71.37	328.66	0.00	400.03	0.00	82.16	17.84
Ukwuani	46.92	346.20	0.60	393.72	0.15	87.93	11.92
Ndokwa West	31.03	747.13	33.85	812.01	4.17	92.01	3.82
Ethiope West	30.63	335.44	151.62	517.69	29.29	64.80	5.92
Ughelli North	18.19	716.72	80.30	815.21	9.85	87.92	2.23
Warri South-West	14.36	837.08	671.69	1523.13	44.10	54.96	0.94

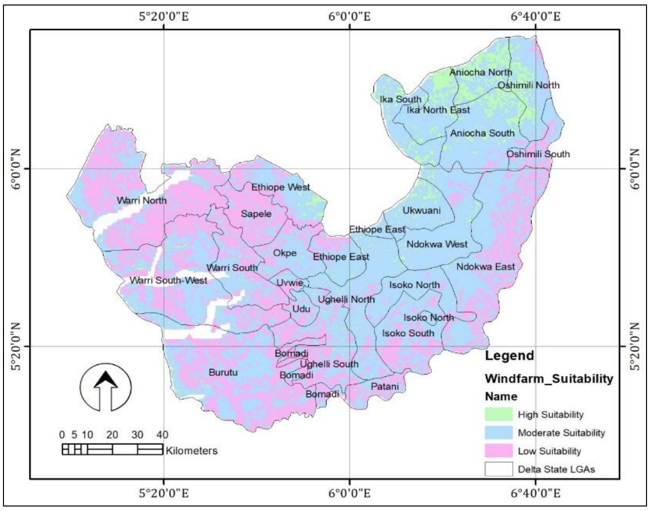

Fig 15: Windfarm Site Suitability by LGAs

The analysis indicates that the northern Local Government Areas (LGAs) of Aniocha North, Ika North East, and Oshimili North possess the greatest potential for utility-scale wind energy development because of their extensive concentration of highly suitable land. In contrast, the southern and coastal LGAs, particularly Warri South-West and Ughelli North, are predominantly characterized by moderate and low suitability zones, reflecting more challenging conditions such as poorly drained soils, extensive wetlands, and limited infrastructure access. Areas such as Aniocha South, Ika South, and Ukwuani, which contain a high proportion of moderately suitable land, remain viable for medium-scale wind energy projects, particularly if planned infrastructure improvements and site-specific engineering assessments are undertaken to enhance feasibility. The overall pattern indicated that energy potential (WPD), elevation, and slope exert primary control over site suitability, while infrastructure access and soil stability refine the feasibility of moderately suitable regions. Hydrological risk and land cover patterns further restrict some otherwise favorable areas, particularly in the deltaic south. The relatively small proportion of highly suitable land highlights the importance of careful site prioritization and underscores the value of this suitability model as a decision-support tool for planners and investors seeking technically viable and economically efficient windfarm locations.

4. Conclusion

This study successfully developed a geospatially driven multi-criteria evaluation framework for assessing the suitability of windfarm development within Delta State. By integrating topographic parameters (elevation and slope), wind resource data (wind power density), soil characteristics, infrastructure accessibility (proximity to road networks), hydrological risk (proximity to waterbodies), and land use/land cover (LULC), the research provided a systematic and spatially explicit framework for supporting wind energy planning and investment decisions.

The analysis revealed that wind power density, elevation, and slope collectively formed the most influential determinants of windfarm siting, accounting for over half of the total weighting in the Analytical Hierarchy Process (AHP). These parameters defined the core energy potential and engineering feasibility of the region. Proximity to road networks and soil stability emerged as secondary but important considerations that affect construction logistics and foundation safety. Hydrological constraints and land cover patterns were less influential overall but provided important localized guidance, particularly in flood-prone and ecologically sensitive zones.

The final suitability map classified the study area into high (5.11%), moderate (62.29%), and low suitability (32.60%) zones. High suitability areas were concentrated in the northern and northeastern uplands, where strong and consistent winds (>100 W/m²), moderate elevation, stable well-drained soils (Distric Nitosols), and reliable transport networks converged to create optimal conditions for large-scale wind energy development. Moderate suitability zones, which dominated the landscape, were identified as viable for wind energy exploitation but may require additional infrastructure upgrades, site-specific soil stabilization, and hydrological risk management. Low suitability areas, found mainly in the southern deltaic plains, were constrained by poor wind potential, weak waterlogged soils, flooding risk, and limited road access.

The sensitivity analysis confirmed the robustness and reliability of the model, showing that moderate variations (±20%) in the weights of key factors such as wind power density, elevation, and slope did not substantially change the overall suitability rankings. This stability demonstrated that the model is resilient to subjective variations in expert judgment and can be reliably applied for decision-making.

At the Local Government Area (LGA) scale, Aniocha North, Ika North East, and Oshimili North emerged as the most promising locations for utility-scale wind energy projects, while LGAs such as Aniocha South, Ika South, and Ukwuani were found to be highly feasible for medium-scale windfarm development. Southern and coastal LGAs such as Warri South-West and Ughelli North showed limited suitability due to a combination of hydrological challenges, weak soils, and poor accessibility.

Overall, this study provided a practical, data-driven decision-support tool for wind energy development planning. Its findings offer valuable insights for policymakers, energy planners, and private investors, enabling them to prioritize investment in the northern uplands, where conditions for wind energy production are most favorable, while identifying moderately suitable regions that can become viable through targeted infrastructure improvements and geotechnical reinforcement. The methodology adopted in this research also serves as a replicable framework for windfarm suitability analysis in other regions with similar environmental and infrastructural characteristics, contributing to the sustainable expansion of renewable energy infrastructure in Nigeria and beyond.

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