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GIS-Based Multi-Criteria Decision Analysis and Wind Energy Potential Assessment Using Weibull Distribution in Tunisia

Wedyan G. Nassif
Laboratoire de Modélisation Mathématique et de Simulation multi-échelle pour la Physique et l'Ingénieurie (2MSiPI), Faculté des Sciences de Tunis- Université Tunis El Manar, 2092, Tunis. Tunisia
Department of Atmospheric Science, College of Science, Mustansiriyah University, Baghdad, Iraq
Dalila Elhmaidi
Laboratoire de Modélisation Mathématique et de Simulation multi-échelle pour la Physique et l'Ingénieurie (2MSiPI), Faculté des Sciences de Tunis- Université Tunis El Manar, 2092, Tunis. Tunisia
Yaseen K. Al-Timimi
Department of Atmospheric Science, College of Science, Mustansiriyah University, Baghdad, Iraq

Abstract

This study presents an integrated framework for assessing potential sites for large-scale wind energy projects across Tunisia, considering regional development plans, geography, climate, and infrastructure. The methodology combines Geographic Information Systems (GIS) and Multi-Criteria Decision-Making (MCDM), applying the Analytic Hierarchy Process (AHP) to assign weights to key indicators, including wind speed, wind power density, proximity to infrastructure, road accessibility, elevation, slope, land use, and urban proximity. Wind speed analysis and potential energy estimation were performed using the Weibull distribution, enhancing the accuracy of site suitability maps. Results indicate that approximately 3.7% of Tunisia's land (6,053 km²), primarily in the southeastern regions (Tataouine, Medenine, southern Gabes, eastern Kebili) and selected northeastern coastal areas (Bizerte, Sidi Daoud), is highly suitable for large-scale wind energy projects, with potential annual energy production exceeding 30,440–39,566 MWh/km². Central regions are moderately suitable for medium-scale or hybrid solar-wind projects, while northwestern and densely populated central areas are less favorable for wind energy but suitable for solar generation. This framework provides a valuable reference for strategic renewable energy planning, supporting informed decision-making to fully exploit Tunisia's wind energy potential.

Key Words: Geographic Information System (GIS, Multi-Criteria Decision-Making (MCDM), Analytical Hierarchy Process (AHP), Wind Power Potential, Weibull Distribution.

Nomenclature

GIS	**Geographic Information Systems**	**SI**	**Suitability Index**
MCDM	Multi-Criteria Decision-Making	LU	Land Use
AHP	Analytical Hierarchy Process;	CR	consistency ratio
WS	Wind Speed	RI	Random consistency index
WPP	Wind Power Plants	DEM	Digital Elevation Model
WOM	Weight Overlay Model	SM	Suitability Maps
WPD	Wind Power Density	AEP	Annual Energy Production

1. Introduction

Amid the global transition toward ecologically safe, sustainable, and clean energy, renewable energy has become a fundamental necessity to address the growing environmental challenges resulting from climate change and the depletion of fossil fuels [1]. The Middle East and North Africa (MENA) region faces escalating environmental issues, including prolonged droughts, air pollution, and rising temperatures, further emphasizing the need to develop solar and wind energy to enhance energy security and support sustainable development [1].

Selecting suitable sites for renewable energy projects is a critical step, as infrastructure can be effectively deployed only in locations where wind and solar resources are sufficient [2,3]. With the advancement of remote sensing and Geographic Information Systems (GIS), it has become possible to collect and analyze multi-disciplinary spatial data, including topography, climate, and economic factors, supporting efficient spatial planning for renewable energy projects [2,3]. High-quality spatial datasets, such as Digital Elevation Models (DEMs), multispectral satellite imagery, and land cover classifications, play a crucial role in identifying technically and economically feasible locations for photovoltaic and wind energy systems [4]. These datasets can be combined with climate variables (e.g., wind speed) and infrastructure factors (e.g., distance to roads and power grids) using GIS to support broad spatial analysis for environmentally and economically efficient planning [5].

Globally, integrating GIS with remote sensing in renewable energy planning has proven successful, enhancing resource assessment accuracy while reducing project costs. GIS-assisted wind farm siting can reduce overall project costs by up to 20% (Janke, 2010). Furthermore, these technologies help mitigate socio-environmental conflicts by excluding ecologically sensitive zones and densely populated areas from development [6]. GIS-enabled spatial analyses also help break down data silos and promote equity in energy planning, providing policymakers with operational decision-support tools, including interactive maps and scenario models that can adapt to shifting environmental and infrastructural conditions [7].

Despite robust energy transition planning, Tunisia remains underexploiting its renewable energy potential. Renewable energy production is still far below domestic demand and achieves very limited results toward meeting greenhouse gas (GHG) emissions reduction targets [3]. Challenges include limited access to high-resolution national geospatial data, insufficient measurement networks, gaps in resource modeling, limited financing, inadequate infrastructure, lengthy regulatory processes, and low public awareness of the strategic role of renewable energy [8].

Tunisia has shown increasing interest in developing renewable energy projects, particularly wind energy, due to promising wind resources, rising national electricity demand, and commitments to reduce GHG emissions while promoting the sustainability of the energy sector. Favorable climatic conditions and availability of large undeveloped land areas create the need for precise scientific assessment of renewable energy sites, considering technical, economic, environmental, and logistical factors to ensure optimal site selection [9,10].

Several studies in Tunisia have applied spatial analyses and Multi-Criteria Decision-Making (MCDM) methods to evaluate renewable energy potential. GIS-MCDM tools have been used to assess national solar and wind resources, with a particular focus on Al-Thamrat (2020) [11]. Rekik and El Alimi (2024) spatially integrated energy capacities in the southern governorate of Tunisia [12]. Attig-Bahar et al. (2021) highlighted the socio-environmental consequences of expanding reliance on wind energy and suggested key planning principles [13]. Integration of GIS with MCDM frameworks, particularly the Analytic Hierarchy Process (AHP), has been found highly effective in site selection, prioritizing environmental suitability and infrastructure accessibility [14, 15, 16].

Despite previous studies on renewable energy potential in Tunisia, a comprehensive evaluation of optimal wind energy sites that integrates climatic, geographic and infrastructure factors along with technical and economic considerations remains limited. In contrast, the present study develops an integrated GIS–AHP framework combining spatial and statistical analyses to provide a data-driven decision-support tool for identifying the most suitable wind energy locations, addressing gaps in previous Tunisian studies. Finally, adopting a data-centric approach that aligns with national energy security objectives, emission reduction targets, and clean energy job creation contributes to achieving United Nations Sustainable Development Goals 7 and 13 [9]. Based on this background, the main objective of this study is to identify the most suitable locations for wind energy development in Tunisia and assess both the theoretical and technical wind energy potential. This is achieved through an integrated GIS–AHP framework enabling comprehensive spatial and multi-criteria analysis, providing decision-makers with a data-driven tool to support sustainable wind energy planning.

2. Materials and Methods

This study employs a spatially driven, data-oriented methodology to identify optimal locations for wind energy development in Tunisia. An integrated framework combining Geographic Information Systems (GIS) and Multi-Criteria Decision Making (MCDM) was implemented across two analytical phases. The MCDM structure is theoretically supported by the Analytic Hierarchy Process (AHP), which provides a robust foundation for weighting and prioritizing technical, environmental, and economic criteria.

The proposed framework enables a systematic evaluation of diverse geospatial factors to identify candidate sites that meet or exceed current standards for wind energy infrastructure siting. The methodology enhances overall evaluation performance, including cost–benefit analysis, site suitability assessment, and simulation-based impact analysis, thereby supporting more informed investment decisions for wind energy projects.

Figure 1: presents the GIS–MCDM workflow adopted in this study. The process begins with reclassifying technical datasets, particularly annual wind speed, to delineate high-potential wind zones. Economic parameters, such as slope derived from the Digital Elevation Model (DEM), are incorporated to minimize construction costs by favoring areas with suitable terrain characteristics. Proximity to critical infrastructure roads, power lines, and urban centers is quantified using Euclidean distance, ensuring that accessibility considerations are integrated alongside the objective of reducing environmental disturbance.

Environmental constraints are incorporated through land-cover analysis and the exclusion of protected or restricted areas to ensure the selection of developable land. A weighted overlay analysis is then performed to merge all spatial layers into a comprehensive suitability map. n the final stage, wind assessments were integrated with the results of spatial suitability analysis to obtain theoretical technical outputs, represented by a power density map and an annual energy production map. This enables the identification of areas with maximum potential for wind energy generation in terms of technical performance and theoretical feasibility.

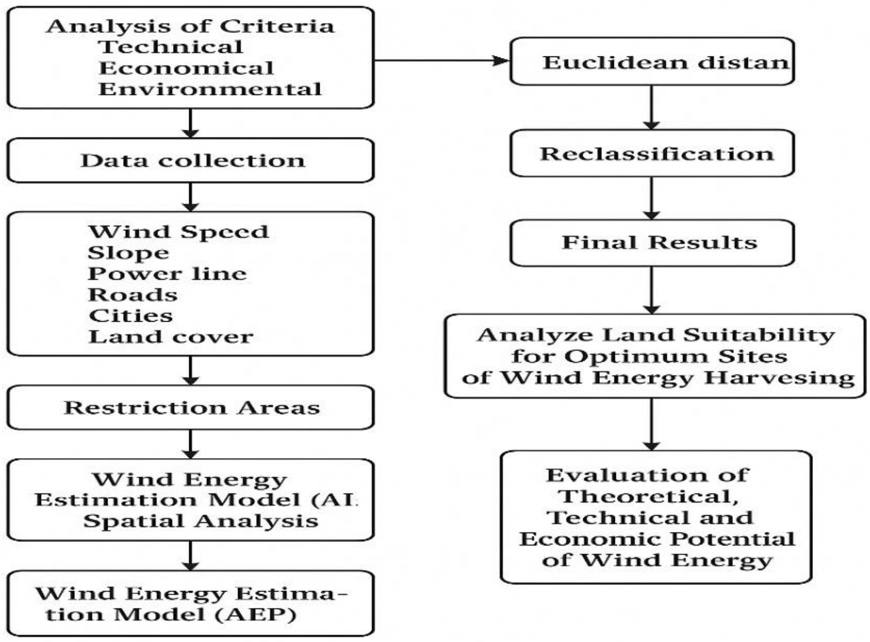

Figure 1: Methodology Flowchart for Optimal Wind Energy Site Selection Using GIS-MCDM and AHP

2.1. Data Collection

In the first phase of this study, all essential datasets required for accurately assessing wind energy potential were identified and collected. These datasets included wind speed to represent the available resource, land-use data to determine suitable areas for development, slope to evaluate topographic constraints, and distances from power transmission lines, roads, and urban centers to assess accessibility and infrastructure requirements.

Additional climatic and meteorological variables were incorporated to provide a comprehensive characterization of the environmental conditions at the studied sites. The datasets were subsequently integrated into a GIS-based framework within a Multi-Criteria Decision-Making (MCDM) methodology using the Analytic Hierarchy Process (AHP). This framework enabled a systematic and rigorous evaluation of geographical, environmental, and infrastructural factors and the precise determination of their relative weights, facilitating the identification of the most suitable locations for wind energy development in Tunisia. The data sources used in this analysis are documented in Table 1.

Table 1: Content of the required data

No.	Data Source / Organization	Data Type	Data Format	Scale / Resolution	Website / Reference
1	Earth Data / NASA	Wind speed	Raster Grid (MapInfo-based)	Cell size: 500 m	https://www.earthdata.nasa.gov / [18]
2	National Environmental Authority / Protected Areas Database	National Park Boundaries / Wetland Zones / Protection Zones	ESRI Shape File	1:25,000	Reference [19,20]
3	Agricultural Authority	Agricultural Areas	ESRI Shape File	1:100,000	Reference [21]
4	Tunisia Ministry of Water Resources	Power Lines / Transmission Lines	ESRI Shape / Polyline	Vector data	—
5	Tunisia Ministry of Water Resources	Roads	ESRI Shape / Polyline	Vector data	—
6	Tunis Ministry of Water Resources	Cities / Settlement Areas	ESRI Shape / Point	Vector data	—
7	Tunis Ministry of Water Resources	Water Bodies / Boundaries	MapInfo TAB	Vector data	—
8	Derived from DEM (USGS)	Slope	ESRI Grid	Cell size: 100 m	https://earthexplorer.usgs.gov [22]

Study Area

Tunisia is a North African country located at approximately 32°–38° North latitude and between approximately 7°–12° East longitude (Figure 2). It borders Libya to the southeast, the Mediterranean Sea to the north and east, and Algeria to the west. As we can see, Tunisia is located between 32° and either end of the Mediterranean, an ideal location in terms of geography where these environmental conditions are reflected. Tunisia is characterized by important climatic and geographic diversity [23]. The climate in the northern part is closer to a Mediterranean type, with mild, wet winters and hot, dry summers. Such vegetation disappears towards the center and south in accordance with an acidification process from mesophytic areas through zones of semiarid conditions. The significance of these variations determines the suitability of different areas for renewable energy development, especially wind and solar applications [24]. The study area also includes critical infrastructure such as population centers, significant road corridors, and electric transmission lines, all of which are key factors to understanding the technical, logistical, and economic feasibility of renewable energy projects. Northeast Algeria provides Transboundary Rivers in the northern part of the country, which consequently improves agricultural productivity with enough irrigation potential and vegetation cover to support biodiversity. All these factors push Tunisia forward as a suitable location for the deployment of renewable energy projects [25].

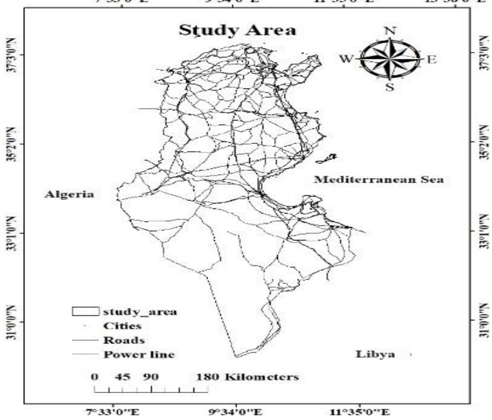

Figure 2. Location map of the study area, Tunisia

3. Methodological Framework

The present study adopts an integrated methodological framework that combines GIS-based multi-criteria decision analysis (MCDA), the Analytic Hierarchy Process (AHP), and statistical wind energy assessment using the Weibull distribution. GIS is employed to manage and analyze geographically referenced criteria relevant to wind farm site suitability, while AHP is applied to determine the relative importance of these criteria through pairwise comparisons, thereby addressing the multi-criteria nature of the decision-making process. The resulting weighted spatial layers are subsequently integrated using a weight overlay model to generate a preliminary site suitability map. Nevertheless, spatial suitability alone does not guarantee energy feasibility; therefore, the Weibull distribution is utilized to statistically characterize wind speed variability and to estimate wind energy potential at the identified suitable locations. This integrated approach ensures that site selection is spatially consistent, decision-oriented, and physically viable.

3.1. Multi-Criteria Decision Analysis and GIS (MCDA-GIS)

GIS has become a tool for mapping the location of solar, hydropower, wind, and biomass resources. All this is obviously of interest to those whose job it is to find out where renewable energy facilities can be built economically [26]. In turn, GIS puts in accordance with this theory a range of decision-support tools which systematically assess a variety of conditions such as wind speed, altitude and distance to theatres. An example of the combination of GIS and analytic hierarchy process (AHP) was carried out in multi-criteria analysis of alternative energy resource regions which resulted in distinct criteria for the implementation of a large scale wind power project. As a result, multi-criteria analyses that are spatially explicit and make use of human and physical constraints have improved the precision and effectiveness in siting of energy projects to maximize both technical functionality and environmental axiality [27]. MCDM methods offer efficient techniques to help select sites for renewable energy installations, analytically weighing a number of relevant criteria pertaining to the decision-making process [28]. Weighted Overlay Model (WOM) is one of the frequently used techniques in Multicriteria Decision-Making (MCDM) using GIA, assigning weights to each criterion and aggregating as is shown [29]. Combining GIS with MCDM involves the ultimate goal of developing a series of databases on spatial distribution and topography. At the same time, it will help to ensure that precision for decision-making on siting renewable energy systems can further refined with greater accuracy as well [30].

3.2. Weight Overlay Model (WOM*)*

In the context of GIS, this is an analysis tool widely used for assessing factors like place suitability together with relevant spatial factors and best siting program in order to evaluate these items at one stroke. Such close melding is enabled courtesy of Weighted Overlay with no required steps added. A comprehensive thematic work which summarizes the means to incorporate several geospatial layers overlying each other, with each layer representing a major factor considered in the study. Each layer carries different weights or importance coefficients corresponding to its level of significance [31, 32]. Weighted overlay method provides a statistical way to combine several themes of information for more comprehensive spatial analysis and bring to light the relationship between different phenomena [33]. To unify the input values into a common naming standard, the Reclassify tool will be used here [34]. Layers that have been reclassified are overlaid by weight overlay based on the classification scale using a criterion of BEST, which means that not only is each cell in the map suitable for irrigation within an area but also represents support preference or risk [35]. The relative influence of each thematic layer is estimated by weighting the respective layers [36, 37]. Cell values are normalized with the suitability index (SI) according to Eq. 1

:

$$SI = \sum_{i=1}^{n} v_i * w_i \tag{1}$$

i is the corresponding indicator and n is the total number of indicators, respectively. Where r_i is the normalized value of indicator i, and w_i is the weight to be assigned (in proportion of its importance) for that indicator.

3.3. Analytic Hierarchy Process (AHP)

Given the selected criteria, Analytic Hierarchy Process (AHP) found its application in the present study to rank and provide weightages to the criteria. To solve complex decision problems, AHP breaks them down into a hierarchical structure including both main and sub-criteria, facilitating an orderly and analytical evaluation process [38]. The estimated weights were then entered to the GIS-based Multi-Criteria Decision Making (GIS-MCDM) analysis to create a digital integrated spatial suitability map [39]. Each criterion was given a weight based on the pairwise comparison procedure and scored a value from 1 (lesser weight) to 9 (greater weight) [40]. Using procedure outlined in Eq 2. After building the comparison matrix, individual weight for each criterion was calculated [41].

$$F = \begin{bmatrix} x_{11} & x_{12} & x_{13} & \cdots & x_{1n} \\ x_{21} & x_{22} & x_{23} & \cdots & x_{2n} \\ x_{31} & x_{32} & x_{33} & \cdots & x_{3n} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ x_{m1} & x_{m2} & x_{m3} & \cdots & x_{nn} \end{bmatrix} \tag{2}$$

The element xij of the matrix A(F) which is of size (n×n), where i and j ranges from 1 to n, defines how much more important criterion i is with respect to the criterion j.

At first, the values in each of the columns of the comparison matrix Aij are summed up. Dividing each element by the sum of its own column gargles outputting a new matrix, normalizing it. The mean of the values in each row of the normalized matrix is then calculated in order to determine how much (the weight) we value each criterion. This vector, shown in the form of a column, signifies our priority vector or how much weight we gave to each criterion.
In the next step, consistency of pairwise comparison is scrutinized due to the fact that judgments should be consistent and rational. The level of consistency in the pairwise evaluations. This is measured through calculating Consistency Ratio (CR) which tells us how consistent are pairwise evaluations and so on The CR is calculated from the Consistency Index (CI), described as Equation (3). This stage is essential in order to check the consistency of weights generated and how acceptable it is any inconsistency in comparison matrix [42].

$$CI = \frac{\lambda_{\max} - n}{n-1} \quad (3)$$

Where:

$\lambda_{\max}$ number of the criteria (n) is the eigenvalue of the pairwise comparison matrix..

Finally, this step aims to see how much the judgments are coherent by calculating a single indicator called Consistency Ratio (CR), which tests the consistency of that Pairwise comparison matrix: This calculation can be expressed, for example, from Equation 4 [43] involving the integer value of n as:

$$CR = \frac{CI}{RI} \quad (4)$$

RI is the Random Consistency Index

Table 2**:** Value of RI [44].

n	1	2	3	4	5	6	7	8	9	10
RI	0	0	0.58	0.90	1.12	1.24	1.32	1.41	1.45	1.49

A value of Consistency Ratio (CR) less than or equal to 0.10 indicates an acceptable level in consistency between the pairwise comparisons. If the CR exceeds 0.10, it indicates more substantial heterogeneity, and a repeated evaluation process with ensuing results is recommended to improve reliability.
Based on the data in Table 3, all the Consistency Ratios (CR) for wind power sites fall within an acceptable range of under 4.01 percent. In the AHP model, wind speed was the most important factor, rated a 40% weighting. underscore The next most important factor was slope, which brought along 19.8% of the weight; and land use lay third with 10.7%. Infrastructure accessibility, such as roads and main power lines, accounted for 10% of the total weight. Proximity to urban areas represented 9.8% in this evaluation. For the purpose of a comprehensive analysis, input data were normalized or reclassified. Then the weights generated by the AHP method were used to produce weighted layers; hence, land was classified into four levels of suitability. Sites chosen for wind energy development needed to be at least 1 km² in size to ensure enough space for viable projects.

Table 3: Final WPPS weights.

Factor	**Criteria**	**Relative Weight Wind Speed**	**Indicator**	**Suitability**
Climatology	Annual Wind Speed (at 150 m)	40%	4.7-4.9 4.9-5.1 5.1-5.4 5.4-5.6	Unsuitable Low Suitable Moderate Suitable High Suitable
Topography	Slope degree	19.8%%	1-3 % 3-7 7-10 10-82	High Suitable Moderate Suitable Low Suitable Unsuitable
	Land cover/use	10.7%	Water Bodies Other	Restructure Suitable
Availability	Distance from Cities	9.8%	0-2 km 2-5 5-20 >20	Unsuitable Low Suitable Moderate Suitable

			High Suitable
Distance from Roads	10%	0-0.5 km	Low Suitable
		0.5-5	High Suitable
		5-20	Moderate Suitable
		>20	Unsuitable
Distance from power line	10%	0-0.5 km	Low Suitable
		0.5-5	High Suitable
		5-20	Moderate Suitable
		>20	Unsuitable
RI	1.24	–	–
λ_{max}	6.25	–	–
CI	0.057	–	–
CR	4.1%		

3.4. Assessment of Wind Energy Generation

Large-rotor, high-capacity wind turbines are essential for achieving efficient power generation in regions characterized by moderate or low wind speeds, which is the case in many parts of Tunisia. In this context, the Vestas V150-4.2 MW turbine represents a highly suitable option due to its design optimization for enhanced performance in low-wind sites.

This turbine features a rotor diameter of 150 meters and a swept area of 17,671 m², allowing for significant wind energy capture even under modest wind conditions. The machine starts operating at a cut-in wind speed of 3 m/s and shuts down at 22.5 m/s (cut-out), offering a wide and practical operational range for onshore applications. Various hub height configurations are available (145 to 166 meters), enabling improved energy yield by accessing higher and more stable wind speeds [45].

Technical assessments and the V150-4.2 MW Life Cycle Assessment (LCA) indicate that this turbine achieves high annual energy production in moderate-wind environments. The expected capacity factor ranges between 35% and 40%, with approximately 40% being a realistic value for well-exposed sites, making this model a competitive choice for wind power projects in Tunisia and across North Africa [46]

Table 4. The Vestas (V150- 4.2 MW) wind turbine [47.48]

Specification	Value
Rated Power	4.2 MW
Rotor Diameter	150 m
Swept Area	17,671 m²
Cut-in Wind Speed	3 m/s
Cut-out Wind Speed	22.5 m/s
Hub Height	145–166 m (depending on configuration)
Expected Capacity Factor	35%–40% (recommended for calculations: 40%)

The method for extrapolating wind speeds at varying heights is addressed. The formula for this extrapolation is provided in Equation 6 [48].

$$V_2 = V_1 \left(\frac{Z_2}{Z_1}\right)^{\alpha_m} \quad (6)$$

Where the exponent α varies with surface roughness, atmospheric stability, and diurnal cycles. A continuous wind speed surface was generated using kriging interpolation due to sparse meteorological data. The wind speed distribution was modeled using the Weibull distribution with shape K and scale C parameters estimated from the mean μ and standard deviation σ of wind speeds [49, 50] :

$$K = 0.9846 \left(\frac{\sigma}{\mu}\right)^{-1.0944} \quad (7)$$

Where :k: Weibull shape parameter,σ: Standard deviation of wind speeds ,μ: Mean wind speed

$$C = \frac{\sigma}{\Gamma(1 + K^{-1})} \quad (8)$$

C: Weibull scale parameter (m/s),σ: Wind speed standard deviation,K: Weibull shape parameter,Γ: Ga mathematical function that generalizes factorials for continuous numbers.

The wind power available in the wind flow through an area *A* at a speed *V* is given by the equation: [51].

$$P(V) = \frac{1}{2}\rho A V^3 \quad (9)$$

P (*V*): Power of the wind (W),ρ: Air density (kg/m^3),A: Blade sweep area (m^2),V: Wind speed (m/s)

Wind power density D was calculated using [52] :

$$D = \frac{P}{A} = \int_0^{\infty} P(V) f(V)\ dV = \frac{1}{2} \rho C^3 \text{Gamma} \left(\frac{K+3}{K} \right) \quad (10)$$

The annual wind energy production was calculated using Equation 7 [53]

$$E_i = D \times A \times C_p \times \eta \times \text{he} \quad (11)$$

Where: Ei , D, A, Cp, η , h_e are the annual energy production, the wind power density, the represents the area through which wind flows, the capacity factor, the efficiency of the turbine, and he = 365*24 =8760 hours.

4. Results

In Fig. 3-a we can see the distributions of annual average wind speeds in Tunisia at 150 meters above ground level, reflect some regional variations with respect to wind power potential. The highest values 9.3—10.2 m/s appear at several stations in South Tunisia, particularly Tataouine which enjoys 10.1m/s. This is because these areas are flat desert zones where the parched and rugged terrain is almost devoid of vegetation or other surface structures such as buildings or tower masts. They thus make the perfect setting for building sizeable wind farms. On the other hand, the middle regions of Tunisia, such as Sidi Bouzid and Kasserine, exhibit wind speeds ranging from a 7.3 to 8.9m/s sustained over some period of time that is fairly long. This means the area may be developed for wind power use. Meanwhile northern Tunisia proper generally presents a picture of low wind speeds: in places like El Kef those numbers hover around 6—7 m/s. This is primarily due to the lack of land for projects in steeply forested mountainous areas. Only some coastal locations are exceptional to this. Sidi Daoud (Nabeul) and parts of Bizerte, for example, exhibit high wind speeds entirely because they face Mediterranean Sea which is directly exposed to incoming ocean-borne airstreams. Figure 3-b reclassifies the data into four suitability categories (high, moderate, low, and unsuitable). Once again, the southern regions dominate high suitability, and certain coastal sites in the north stand out despite being limited in area. This effectively means these sites should be exactly those with which the national strategy in terms of plans for renewable energy development could not dispense.

(a) (b)

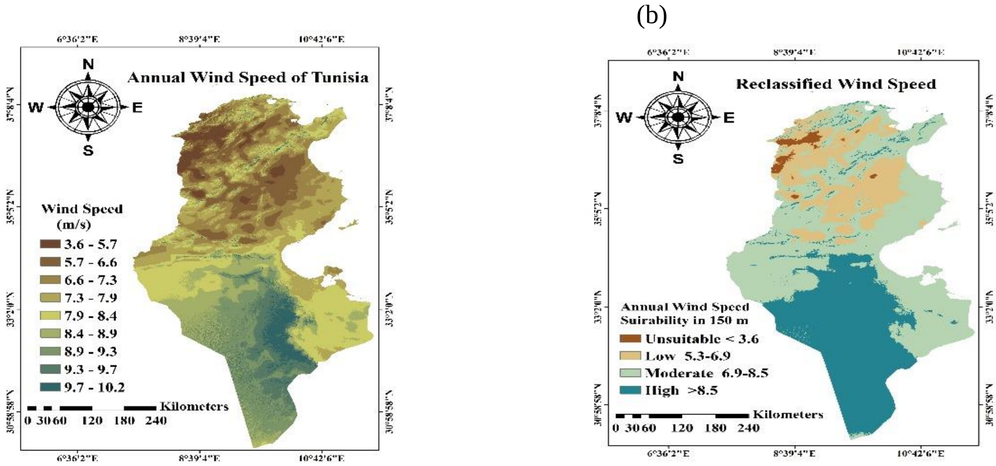

Figure 3. The mean wind Speed at 150 m over Tunisia: a) Annual wind speed b) Reclassified wind speed

In Figure 4-a, you can see Tunisia's Digital Elevation Model (DEM), divide elevation into categories spanning from 0–1 meters in the low-lying southern plains, through 1–2 m, 2–3 m, 3–5 meters m and 5–8 meters up to 8-16 meters in northern mountain areas such as Tell Atlas. These regions reflect gradations in class. Figure 4-b shows slope categories recoded into four main classes: 0–1 (highly suitable for construction, agriculture, and energy development), 1–3 (moderately suitable), 3–6 (low suitability) and 6–16 (unsuitable because of steep slopes and related hazards). Integrating elevation and slope data with wind speed maps furnishes crucial support for sustainable planning of energy and infrastructure schemes by identifying the best locations and minimizing environmental impacts in Tunisia's diverse landscape.

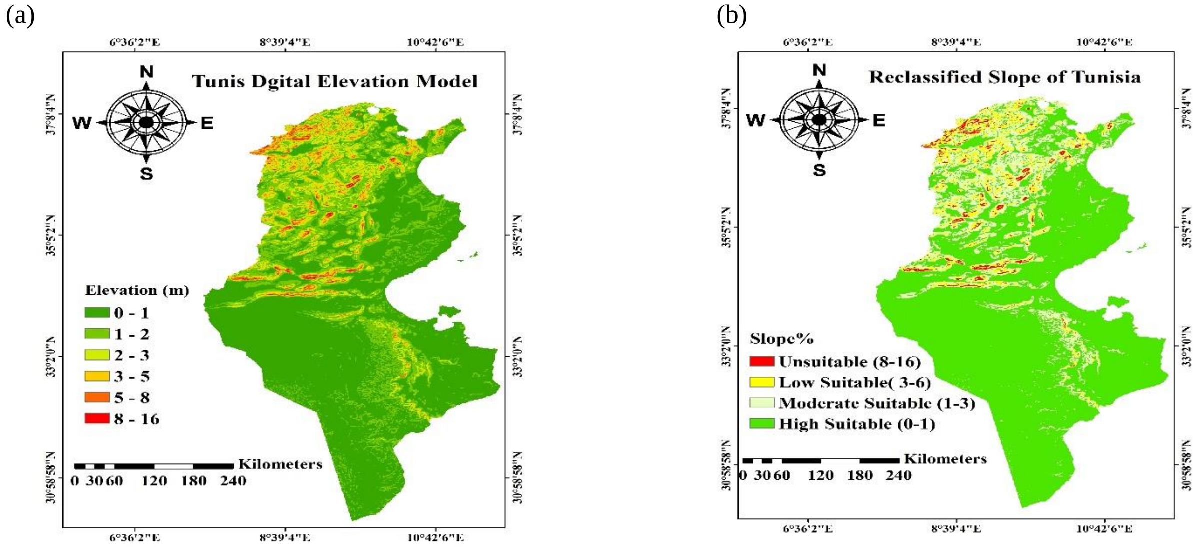

Figure 4: a) Tunisia digital elevation model, b) the reclassified slope

In Figure 5-a shown there is a regional variability in terms of power line density throughout the Tunisia. The largest networks are set up in the northern and central regions, where proximity to electricity infrastructure is high. Similarly, power line coverage is less in the southern desert regions, and therefore larger distances from the grid point to the difficulties of electrification in the remote areas. This distribution indicates an almost binary divide between the highly populated northern and northeastern urban and industrial hubs, benefitting from strong connectivity, and the isolated southern rural and desert regions, suffering from infrastructural deficit.

In Figure 5-b, the territory of the country has been classified according to the distance to existing power lines, with four categories of suitability class for energy projects: high suitability (mainly north and northeast); moderate suitability (adjacent zones); low suitability (some central areas); and unsuitable (mainly south) regions [66]. The classification not only aids in the strategic planning of renewable energy projects by locating places where projects can be plugged-in into the grid with least cost and efforts, but also points out areas which require development of infrastructure to meet, if not energy for every individual, but at the least to ensure access to equitable energy.

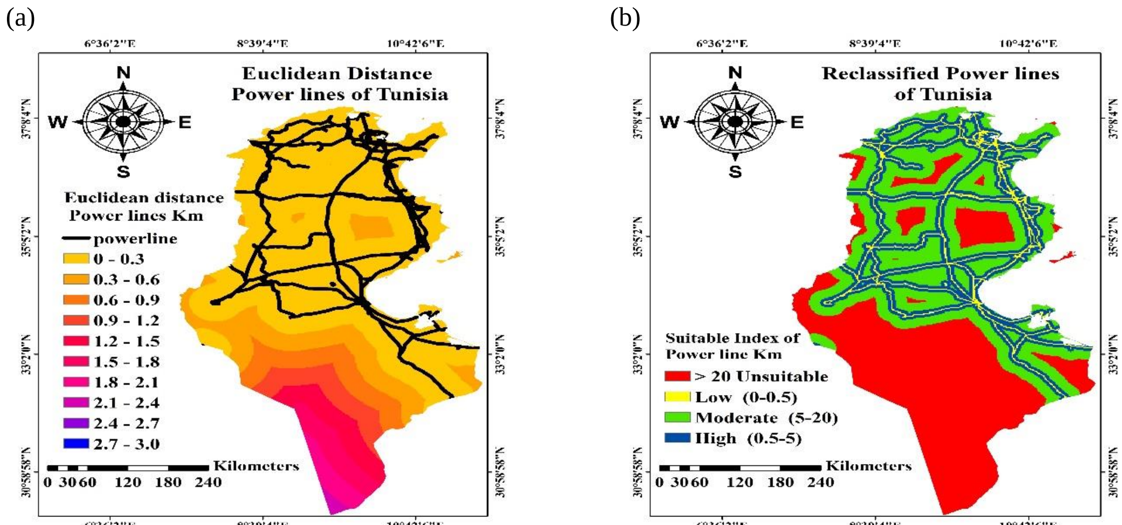

Figure 5: a) Euclidean distance power line, b) Reclassified power lines of Tunisia based on the suitability index.

Figure 6-a shows the varying accessibility of highways in Tunisia, represented by six graded distances from intensive connectivity of the north-central region 0–0.2 km and corresponding recommendations for that zone to limit low accessibility levels (1.9-2.0 km) in sparsely linked southern desert areas.

Figure 6-b divides the whole nation into classifying four degrees of suitedness for development according to distance from a road to people living there: from useless(over 20 kms) down excellent locale for a plant(situated between 0·5 and 5 km)Classification results indicate that most of these northern and central districts belong to type one, which provides greater ease in material supply and lower transport costs than the other three types.This document can thus provide a framework for power to be created in these places plan–and the right site for projects selected at affordable cost.

(a) (b)

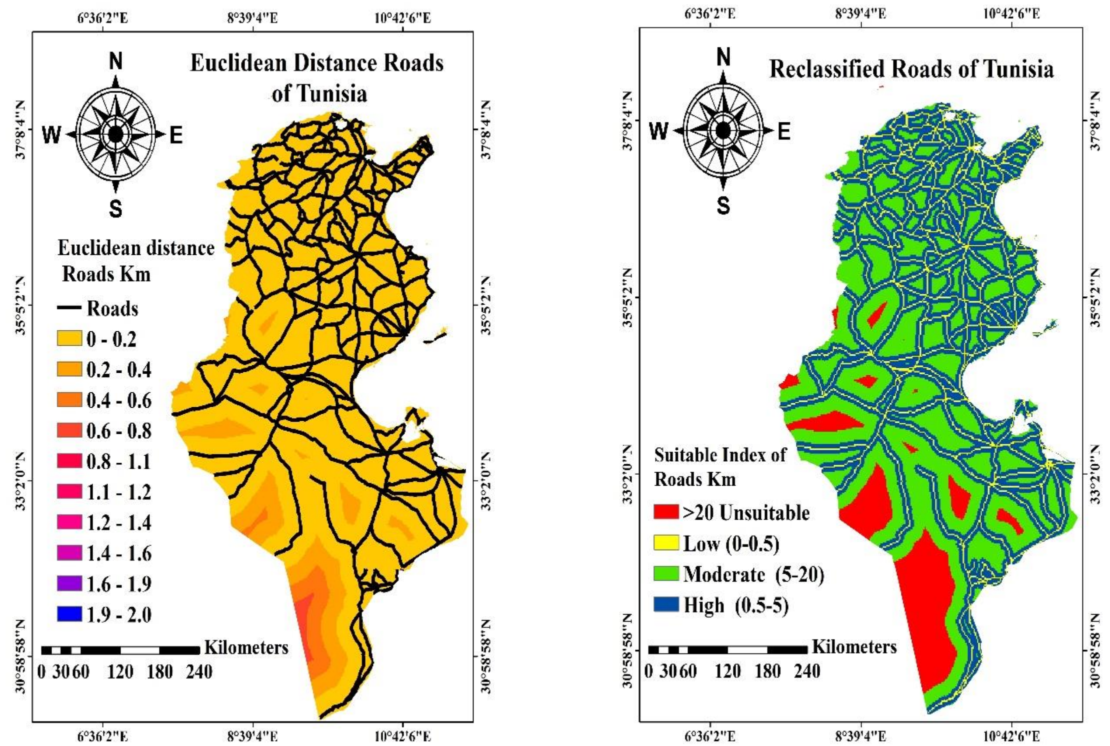

Figure 6: a) Euclidean distance, Road b) Reclassified Road of Tunisia based on the suitability index.

In Figure 7-a on the Euclidean distances between cities across Tunisia there are recognizable and identifiable patterns of city integration. The densely dotted urban network characterizes northern regions and especially those adjacent to the Mediterranean coast. This represents high connectivity and accessibility to infrastructure and services. On the other hand, the southern and hinterland regions have a wider spacing between cities, indicating more dispersed urbanization and lower traffic flow between them.

Figure 7-b further reclassifies areas of different urban proximity suitability based on our index. Four types are broken down and classified according to the distance from city centers. Less than 2km is for areas that are unsuitable because of high density and limited land. Purely available. Zoning of between 2 and 5 km shows slight unsuitability and is often located in moderately urbanized regions, eg, the north. Medium suitability areas (5–20 km) strike a balance between accessibility and land available for development, making them suitable for peri-urban development or residential growth. The farthest areas, over 20 km, are classified as highly suitable Perhaps especially so in Tunisia's southern and hinterland areas and places where land is available to support large projects such as renewable energy or agriculture conventional equipment.

This spatial assessment provides valuable input for regional planning and infrastructure development. By identifying regions with high suitability far away from dense urban cores, funding resources can be more strategically planned for and set up in advance. For example, in Decentralized development channels. By integrating urban proximity data with other planning factors, such as the accessibility of roads or energy infrastructure, we can help Tunisia achieve balanced and sustainable territorial development.

(a) (b)

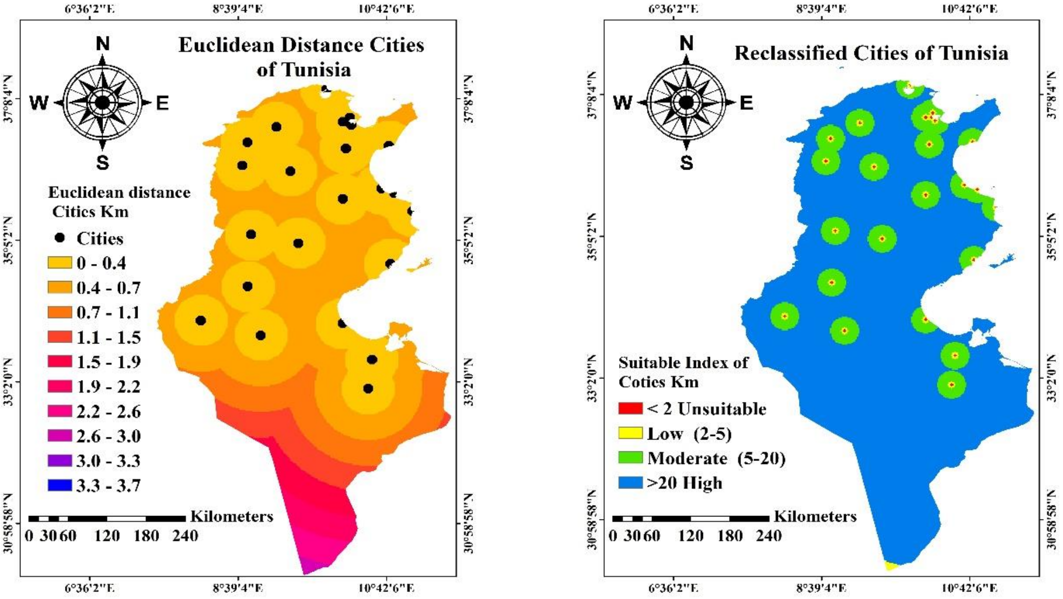

Figure 7: a) Euclidean distances of the cities, b) Reclassified cities of Tunisia based on the suitability Index

Figure 8 provides a graphical account of the land cover and land use in Tunisia, which also provides an insight into the country's ecological diversity and regional distinction. The rich Mediterranean climate as well as an abundance of rainfall, makes the north area characterized with urban zones, forests, large areas of intensive agriculture. The central region deal synonymously transformative lies between areas of productive agriculture and bushland or salt-infected barren soil. This moderate land use potential is quite typical here. Extensive arid and semi-arid deserts are the characteristics of the south region, where expansive territories consist sandy or rocky earth and limit agricultural productivity. This classification is the standard way of guiding national development strategies. The South's open desert areas have considerable suitability for solar energy projects; while in rocky regions, depending on local wind patterns, wind machines can also be set up. Knowing where various types of land are located can guide better planning on renewable energy deployment, infrastructure construction, and effective sustainable development.

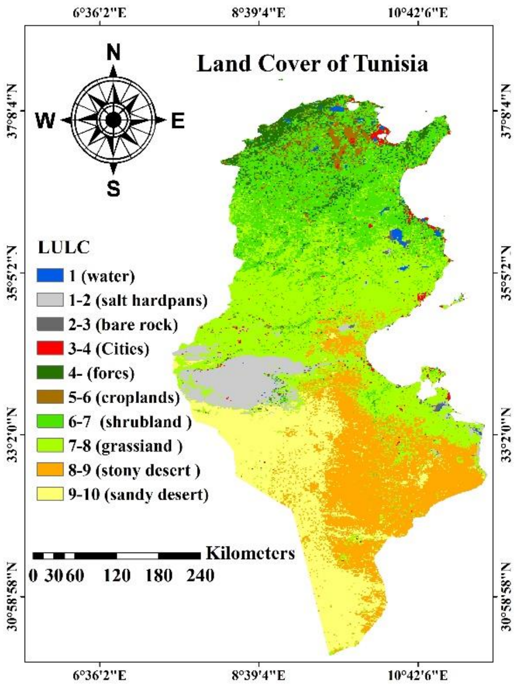

Figure 8: Land cover of Tunisi

Tunisia's land can be divided into four categories by its wind energy suitability as indicated in Table 5 and Figure 9: high, moderate (or low), and unsuitable. Areas highly suitable for wind energy cover 3.7%of the country (approximately 6,053 km²), nearly all of these in southeastern regions such as Tataouine and Medenine, where conditions are ideal, yet it is not impossible to envision large projects taking place here. Bizerte and Sidi Daoud in the northeast are two other high-suitability zones identified. Moderately suitable areas account for the bulk (65%or 106,347 km²), particularly in central districts such as Gafsa and Kairouan where decent potential exists for middle-sized wind farms. Low-suitability zones make up 26%of the country (approximately 42,539 km²), the majority being in northwestern areas where winds are not strong enough to carry big projects. Unsuitable areas (5.3%or 8,672.2 km²) include many of Tunisia's urban centers like Tunis, where progress is at a standstill. At the strategic level, therefore, both this map and the data bring up the need to rationally plan for development–a task that will require region-wide analysis as well as fine-grained local studies if Iran wishes its enviable wind energy potential tapped fully. As such, investments might best go into the southeastern and central regions with high to moderate suitability; but also those particular northern coastal sites which mode little way out from the dominant landform are nevertheless up and running. Northern sites might be ones of special promise. This shows the importance of integrating such overall geographic studies with local–on-the-ground research into how best and most environmentally friendly to use Tunisia's wind resources as part of its renewable energy scheme.

Table 5: Wind area estimations of Tunisia

Suitability	Estimated Percentage (%)	Available area for wind power plants (km2)
High	3.7%	6,052.6
Moderate	65%	106,346.5
Low	26%	42,538.6
Unsuitable	5.3%	8,672.2

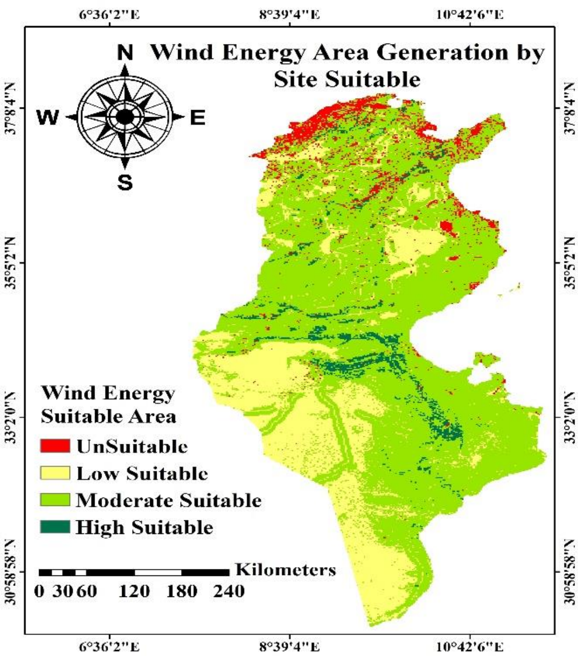

Figure 9: Suitable areas for WPPs

Wind speed and power density data (Figure 10 and Table 6) show the highest potential in the southeast (Tataouine, Medenine, southern Gabes, southern Kebili) with wind speeds exceeding 9.0 m/s and power density around 500 W/m². Northwestern and central-western areas (Béja, El Kef, Siliana, Kasserine) exhibit mild winds of 1.6–3.6 m/s and WPD below 200 W/m² due to terrain and vegetation. Northeastern coastal areas near Bizerte and Nabeul also show promising potential (>400 W/m²) due to Mediterranean airstreams. Large-scale projects are best suited to Tataouine, Medenine, and Gabes, while medium-scale projects are feasible near Bizerte and Nabeul, benefiting from proximity to the grid and potentially lower costs.

Table 6: Classification of wind energy density capacity based on potential suitability

Potential Level	WPD (W/m²)	Geographical Location in Tunisia
Very Low Potential – Unsuitable for Production	62 – 211	Limited areas in El Kef (west), Siliana (northwest), northern Kasserine, northwest Kairouan
Low Potential – Marginal Feasibility	211 – 278	Western Medenine, parts of western Gafsa, southwest Sidi Bouzid, western Kébili
Moderate Potential – Possible Feasibility	278 – 345	Sidi Bouzid, Kairouan, northern Gafsa, parts of El Kef and Siliana, southern Zaghouan
Good Potential – Suitable for Development	345 – 405	Central coast (Sousse, Monastir, Mahdia), northern Sfax, southern Zaghouan, parts of inland Nabeul
High Potential – Suitable for Large Wind Farms	405 – 502	Southern Sfax, northern Gabes, eastern Medenine, Djerba Island, northern Tataouine, northeastern Kébili, parts of coastal Nabeul
Very High Potential – Ideal for Major Projects	502 – 653	Eastern Medenine (Jérjis, Ben Gardane), southern Tataouine, Djerba Island, northeastern Kebili, eastern coastal Bizerte

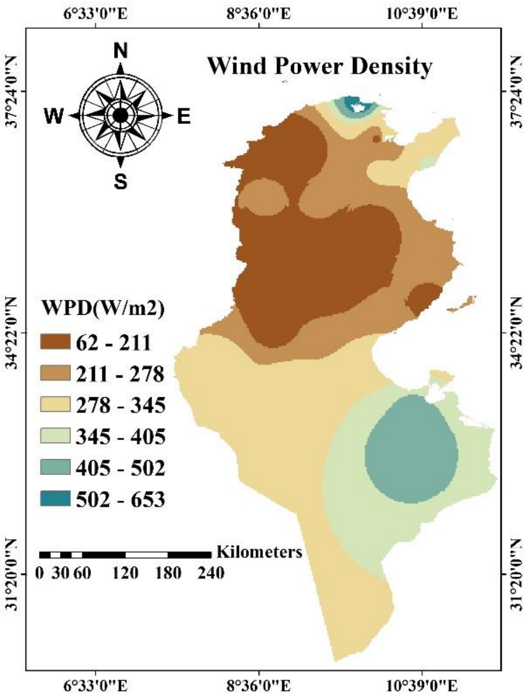

Figure 10: Spatial distribution of annual mean wind power density of Tunisia

Annual Energy Production analysis (Figure 11 and Table 7) indicates that southeastern Tunisia, particularly Tataouine, southern Medenine, southern Gabes, and eastern Kebili, is best suited for large wind projects, with AEP exceeding 30,440 – 39,566MWh/km². Central regions (Kairouan, Sidi Bouzid, Sfax, Mahdia) are suitable for medium-scale or hybrid solar-wind projects, whereas northwestern and densely populated central areas have lower energy densities (3,766–12,751 MWh/km²), making large wind projects less feasible but suitable for solar energy. Administrative studies confirm southeastern Tunisia and the Cap Bon region as priority areas for wind energy development.

Table 7. Annual Energy Production (AEP) Classification in Tunisia

Wind Energy Production Level	AEP (MWh/km²)	Corresponding Geographical Areas
Very Low Production – Not Suitable	3,766 – 12,751	Western and southwestern regions (Tozeur, western Kebili, and parts of the western highlands)
Low Production – Marginal Feasibility	12,751 – 16,823	Portions of the western-central and southern areas (e.g., western Gafsa, western Sidi Bouzid)
Moderate Production – Possible Feasibility	16,823 – 20,894	Central Tunisia (Gafsa, Sidi Bouzid, parts of Kasserine)

Good Production – Suitable for Medium Wind Farms	20,894 – 24,544	Central-eastern and transitional regions (Mahdia, southern Kairouan, parts of Sfax)
High Production – Suitable for Large Wind Farms	24,544 – 30,440	Southeastern Tunisia (Medenine, southern Gabes, parts of Tataouine, eastern Kebili)
Very High Production – Ideal for Large-Scale Projects	30,440 – 39,566	Northeastern coastal zones (Bizerte, Cap Bon peninsula)

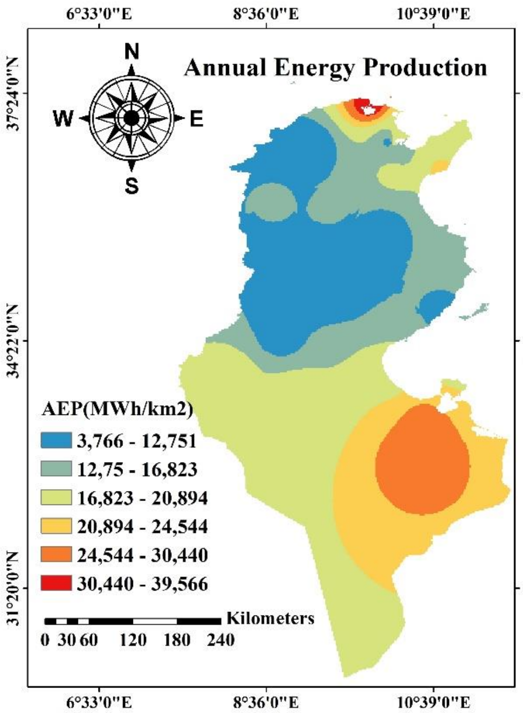

Figure 11: Spatial distribution of technical wind energy potential of Tunisia

4. Discussion

The spatial patterns identified in the study align with established scientific literature on wind resource distribution, where surface roughness, topographic slope, and exposure to maritime influences are recognized as key factors governing wind speed gradients and variability. The findings confirm that southeastern Tunisia, particularly the governorates of Tataouine, Medenine, southern Gabes, and southern Kebili, constitutes the most favorable region in terms of wind resources. This is due to its flat, obstacle-free desert landscape, which enables strong and consistent wind flows. These results correspond with previous studies examining wind-energy potential in the desert environments of North Africa.

The northeastern coastline also shows important potential, benefiting from continuous exposure to Mediterranean sea winds. Meanwhile, central Tunisia forms a transitional zone with moderate wind resources suitable for decentralized or hybrid projects that combine wind and solar power.

In contrast, the mountainous areas of the northwestern region are the least suitable for large wind farms due to rugged terrain that increases turbulence and reduces wind regularity. The study also highlights the critical role of infrastructure, such as roads and electrical grids, in determining suitable project locations. Northern and central regions benefit from more extensive network coverage, while the south requires stronger grid integration to reduce investment costs.

Overall, the results clearly indicate that southeastern Tunisia represents the core zone for the future of wind energy in the country, whereas major urban areas such as Greater Tunis are more suitable for solar energy. Accordingly, the study recommends an energy strategy that diversifies renewable sources based on the characteristics of each region, ensuring sustainable development and strengthening national energy security.

5. Conclusion

The spatial analysis results for assessing wind energy potential in Tunisia reveal a clear regional disparity in which the southeastern region, particularly the governorates of Tataouine, Medenine, southern Gabes, and eastern Kebili, stands out as the most efficient area in terms of wind speed, power density, and annual energy production. This makes it the most suitable region for hosting large-

scale wind projects. The data also confirm that the northeastern coastal areas, such as Bizerte and Cap Bon, offer significant opportunities due to maritime influences that provide strong wind resources.
In contrast, the central regions show moderate potential, enabling them to accommodate medium-scale or hybrid projects that combine wind and solar power. Meanwhile, major urban areas and the northwestern region exhibit low levels of wind suitability, directing these areas toward solar energy as the more viable option.
By integrating wind factors with topography, infrastructure, road networks, and proximity to urban centers, the analysis shows that successful energy planning in Tunisia requires a multi-criteria approach that considers the natural and economic characteristics of each region. It also becomes clear that strengthening the electrical grid in the south is essential for harnessing its high wind potential and ensuring its integration into the national grid.
Accordingly, the study underscores the need to direct investment toward the southeast as the country's primary wind-energy hub, support medium-scale projects in the central region, capitalize on marine-influenced resources in the northeast, and guide urban areas toward solar power. This should be accompanied by improved energy and transport infrastructure in the south to enhance project viability.
Overall, the findings demonstrate that Tunisia possesses substantial yet underutilized renewable energy potential, and that adopting a comprehensive national vision for renewable energy can enable a sustainable energy transition while strengthening energy security and promoting balanced regional development.

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