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ENSEMBLE WEIGHTS-BASED GEOSPATIAL MODEL FOR OPTIMAL ALLOCATION OF WIND TURBINES: A CASE STUDY IN WASIT, IRAQ

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Abstract

Accurate spatial decision-making models are increasingly needed for wind energy planning as the globe rushes towards carbon-neutral energy. This research aims to improve existing decision-making approaches by proposing an ensemble weight-based model for mapping the spatial suitability of onshore wind systems. The model addressed three weighting scenarios: subjective weighting derived from the Analytical Hierarchy Process (AHP), objective weighting derived from the Entropy Weighting Method (EWM), and Artificial Intelligence (AI) weighting based on real-world experiences. The weight sources were harnessed in weighted and fuzzy overlays in a GIS context to create multiple suitability indices. The model was applied to the Wasit governorate in Iraq, considering 10 evaluation criteria and 6 restrictions. The results highlight the dominance of techno-economic considerations, with wind speed being an important factor in all weighting scenarios. Suitability indices suggest that the western, central, and southern areas of Wasit are most suitable for wind farms, with ideal sites identified south of Al-Hay, south of Sheikh Saad, and west of Al-Kut, covering an area of 756 km² and potentially providing more than 3.5 GW of clean electricity. The findings could encourage wind energy investment in developing countries like Iraq.

Keywords:

Wind energy;
Site selection;
GIS;
AI;
Iraq.

1 Introduction

There is unanimous agreement on the importance of renewable and environmentally friendly energy in alleviating global warming and meeting the increasing energy demand. Wind energy, in particular, is a mature and widely applied type of sustainable energy [1]. This fact is evident in the Global Wind Energy Council's (GWEC) 2023 Annual Wind Report [2]. According to the report, it is projected that in 2023, global wind energy production will surpass 100 gigawatts (GW) for the first time, with an anticipated annual growth rate of 15%. A total of 680 GW of additional capacity will be installed between 2023 and 2027 [3]. This confirms that the wind energy industry is on its way to achieving the goal of 2 terawatts (TW) by 2030 [4]. Thus, developing countries such as Iraq are required to accelerate the pace of transition towards wind energy. Thanks to the decline in prices of wind energy systems, investments in this industry are now highly competitive with other energy sector investments [5]. However, this necessitates efficient spatial planning highlighting promising development opportunities for abundant wind harvest with minimal construction costs.

Site selection, also known as site suitability assessment, is a vital step in spatial planning for wind energy projects. This procedure takes into account the availability of a set of considerations at the candidate development sites, including technical, economic, and environmental aspects [6]. The optimal candidate is then identified by trading off these indicators using multi-criteria decision-making (MCDM) methods [7]. The integration between the Geographical Information System (GIS) and MCDM, along with the accessibility of various geospatial data, has facilitated addressing more decision criteria and exploring optimal development sites within broader geographical areas [8]. With the escalation of Artificial Intelligence (AI) applications in recent years, geospatial AI (GeoAI) models have emerged as a promising alternative to traditional decision-making methods [9]. Nevertheless, AI models are not readily interpretable (often known as black-box models) and necessitate ground truth samples for effective training.

Various studies have been conducted to propose innovative methodologies for determining suitable sites for wind power plants [1]. Spatial decision-making models based on subjective or objective weightings have commonly been applied. For example, [10] utilized the Analytical Hierarchy Process (AHP) for selecting suitable sites for wind power plant installation in Pakistan based on capacity factors. A unique method for determining wind farm sites that integrates GIS, stochastic VIKOR, and the Interval AHP was reported in a study conducted in Wafangdian, China [11]. The authors used IAHP to weight multiple criteria subjectively, and Stochastic VIKOR to compute suitability indices for several alternatives. In India, a two-stage GIS-MCDM-based model was implemented to find appropriate locations for wind farm installation at a micro level, focusing on technological, environmental, economic, and social factors [8]. The algorithm employs fuzzy FAHP and Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) methodologies. Other studies have endeavored to eliminate subjectivity in decision-making by exploring objective weight methods, such as the Entropy Weighting Method (EWM), which relies on criteria data at candidate development sites [12], [13]. However, subjective weighting approaches suffer from a lack of generalizability [14]. In an attempt to mitigate the shortcomings of subjective weightings with the benefits of objective weightings, comprehensive weighting methods have been proposed by [15]. The authors derived the criteria weights by integrating the DEMATEL and Entropy methods, subsequently incorporating probability theory and the VIKOR method to prioritise the potential locations.

As an alternative approach, AI-based techniques like machine learning, deep learning, and neural networks have been utilized to enhance the spatial decision-making process of RE projects [16], [17], [14], [18]. Intelligent decision models rely on real-world experiences to develop spatial predictions and capture the significance of features. In a comparative study covering the entire USA, the performance of different AI algorithms was analyzed in classifying lands suitable for hosting RE systems, including wind power [16]. The findings indicate that among the other models examined, the random forest model performed the best. In China, the Shapley explanation algorithm and variable importance measure techniques were utilized to determine the crucial factors and their impacts on the choice of optimal places for solar power development [18]. At the global level, a study was conducted in which three machine learning models powered by Explainable Artificial Intelligence (XAI) were examined to map the global suitability of solar and wind energy farms [14]. Despite the ingenuity of AI-based decision methods, they do not negate the advantages of subjective and objective weightings, particularly in investigations at the micro-scale. Local expert judgments can refine AI's weightings due to their deep knowledge of the conditions and challenges facing local communities and environments. Additionally, examining candidates' data enhances understanding of the spatial context and its complexities, enabling more accurate and effective decisions. Thus, this study attempts to bridge this methodology gap by introducing a spatial decision approach that relies on the ensemble weight of subjective, objective, and intelligent considerations.

The primary goal of this research is to propose an ensemble weight-based model for mapping the spatial suitability of onshore wind systems. Such mapping would furnish decision-makers and stakeholders with valuable insights into potential development prospects in the wind energy domain to foster sustainable development practices. The sources of weights considered encompass subjective weights, represented by the well-known AHP method, objective weights derived from the EWM method, and AI weights captured from real-world experiences. The ensemble weights contribute to developing reliable, robust, and effective solutions for site selection problems. To the best of our knowledge, this study represents a pioneering effort in integrating the aforementioned weight sources within a spatial decision-making framework. The model was applied to Wasit Governorate, Iraq, incorporating 10 evaluation criteria and 6 constraints. Additionally, the study estimates the energy capacity across identified hotspot regions. The subsequent sections of this article are structured as follows: Section 2: Methodology covers study areas, data collection and preparation, weighting scenarios, and GIS modeling. Section 3 presents the results and discussions, including weighting outputs, suitability indices, and power estimates. Finally, the key conclusions are formulated in Section 4.

2 Methodology

This research primarily aims to introduce an ensemble weight-based geospatial model for the optimum placement of wind turbines. The methodology employed to accomplish the goal comprises a series of sequential steps, as illustrated in Figure 1. First, the spatial datasets were assigned, prepared, and standardized to accommodate the spatial requirements and exclusionary constraints under consideration. Second, three weighting scenarios supported by AHP, EWM, and AI were applied to weigh the decision criteria. Third, the weighted overlay analysis was executed in a GIS framework to plot spatial suitability indices for each scenario. Finally, the fuzzy overlay analysis was used to aggregate multiple suitability layers into an ensemble suitability index. The subsequent sections provide a detailed discussion of the methodology.

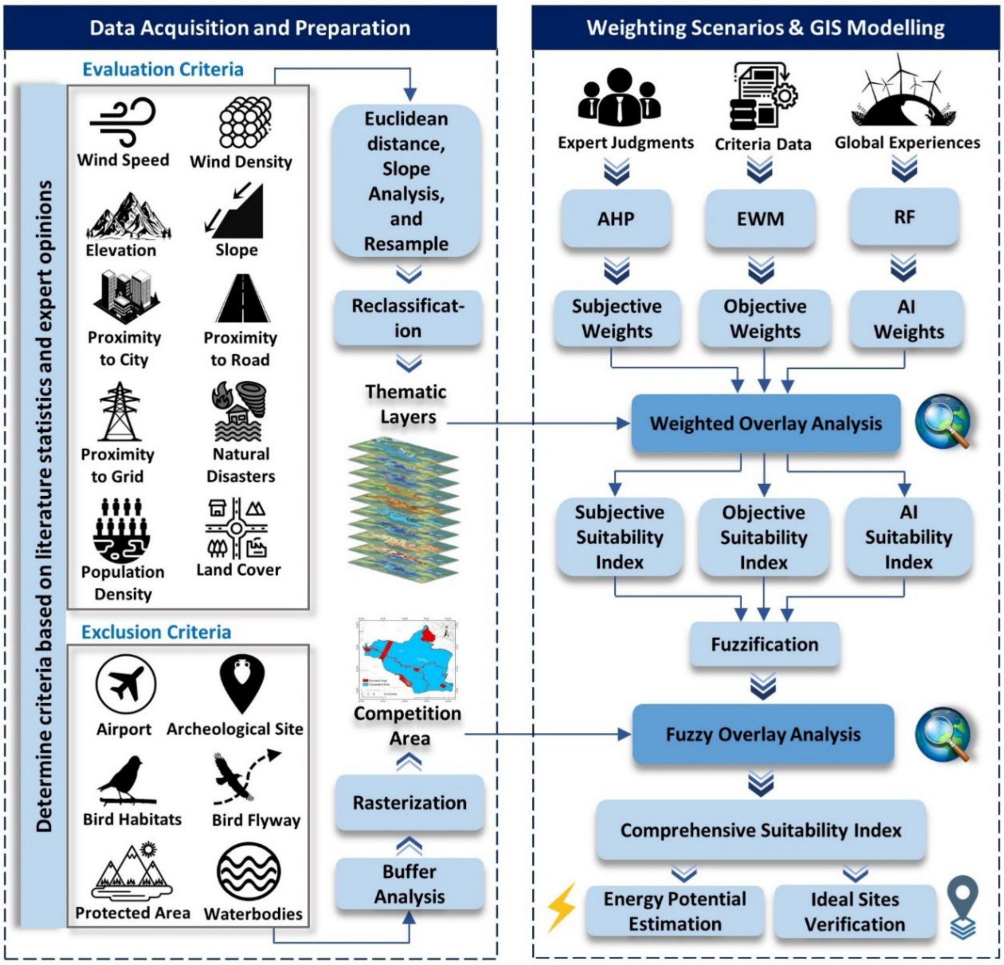


Fig. 1: Flowchart illustrating the ensemble weights-based methodology for allocation wind plants.

2.1 Study Area

Wasit governorate is located in southeastern Iraq, within longitudes (44° 30′ - 46° 40′) East and latitudes (32° 00′ - 33° 30′) North. It is bordered by Iran to the east, Maysan and Dhi-Qar governorates to the south, Al-Qadisiyah and Babel to the west, and Baghdad and Diyala to the north, as presented in Figure 2. The area of Wasit is about 16850 km². Wasit's terrain consists of wide plains covering large parts, and mountainous terrain distributed in the northern and eastern parts. Wasit has abundant wind resources, with average speeds reaching 8.4 m/s, qualifying it for investment in wind energy [19].

2.2 Data Collection and Preparation

2.2.1 Evaluation Criteria

The site selection process for onshore wind power projects necessitates several considerations to increase energy efficiency, economics, and environmental impact [6]. The wind resource, defined as the quantity of energy accessible in the wind, is a crucial factor to take into account [20]. The significance of this criterion lies in the conversion of the kinetic power of air to electrical energy [21]. Slope and elevation are also important aspects to consider when placing turbines. Steep slopes can harm the airflow around the blades of a wind turbine, while high altitudes can lead to lower air density and temperature [22]. For a wind energy project to be viable, candidate sites should have minimal obstacles, convenient accessibility, proximity to the electricity grid, and adherence to regulatory requirements [23]. Furthermore, there is an increasing proliferation of spatial modeling initiatives that include social, environmental, and risk aspects [24]. Meanwhile, proximity to cities can reduce the cost of transporting equipment and employees, as well as minimize electrical losses during power transmission. However, wind turbines should not be placed side by side with settlements to avoid noise and visual distortion [25].

In this study, the evaluation criteria were designed based on an extensive review of relevant literature supported by the opinions of local experts. Accordingly, ten very important criteria were identified, including technical criteria (wind speed and wind density); economic criteria (elevation, slope, proximity to cities, proximity to roads, and proximity to grids); environmental criteria (land cover and natural disasters); and social criteria (population density). For more details about these criteria, the reader can refer to [1], [6], [25].

To prepare the thematic layers for the evaluation criteria under consideration, a geospatial dataset was acquired from local government sources and reliable and open-source global databases, as shown in Appendix. It is noteworthy to mention that the Digital Elevation Model of Shuttle Radar Topography Mission (SRTM) was selected to determine the elevation and slope factors due to its proven accuracy within the study area, as demonstrated by [26]. The data underwent a series of essential functions in a GIS environment, including Euclidean distance analysis, slope analysis, and resampling at a 1 km resolution. Therefore, subsequent GIS analysis and visualization will be based on a 1 km cell size, which meets the requirements of macro-level spatial investigation and reduces the computational burden, storage space, and processing time.

Figure 3 displays the raster maps of the decision criteria covering the entirety of Wasit province. For advanced analysis, the raster layers were standardized by reclassifying each layer into five classes using the Jenks natural breaks technique. The classes were assigned rating scores ranging from 1 to 5 points based on their spatial importance for the wind energy system, as depicted in Table 1. Points 1, 2, 3, 4, and 5 represent categories of very low, low, moderate, high, and very high, respectively. Concurrently, the restricted categories were given a score of 0. In essence, the higher the score of a specific pixel, the greater its suitability.

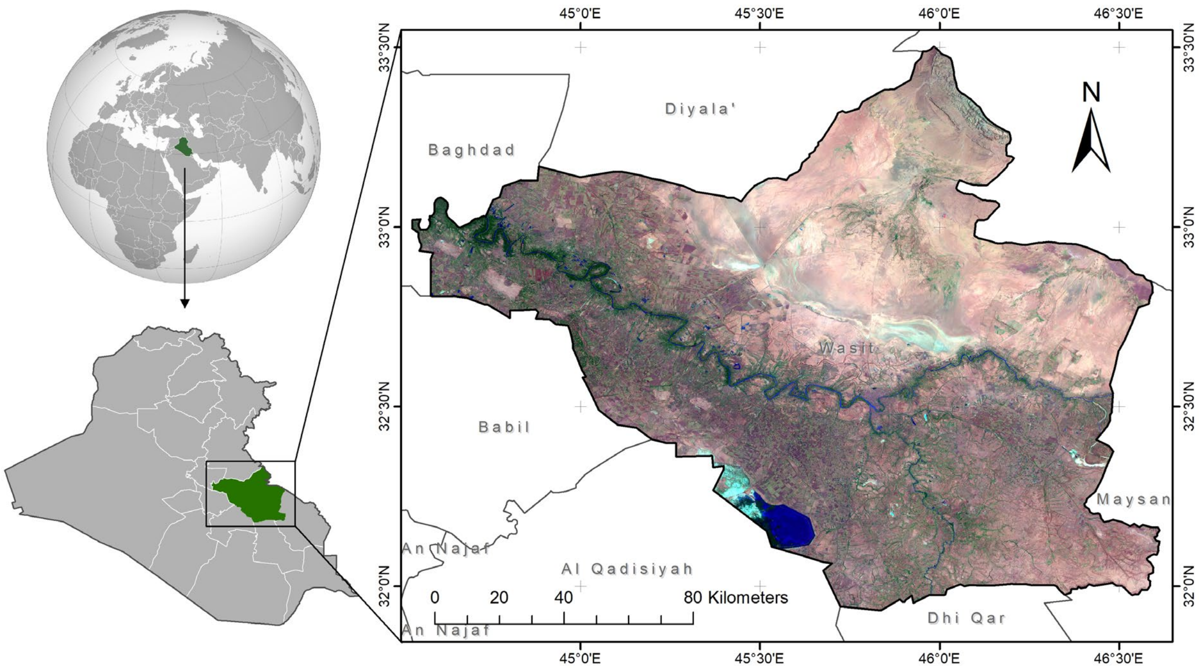
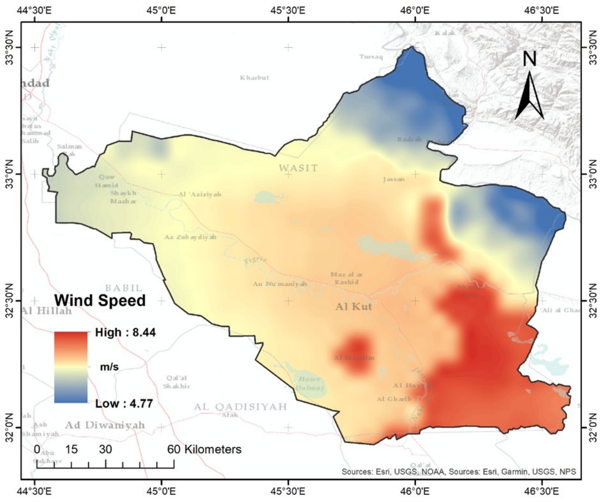
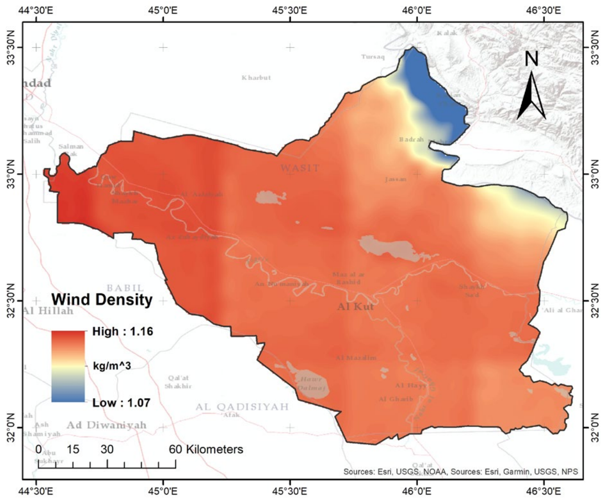


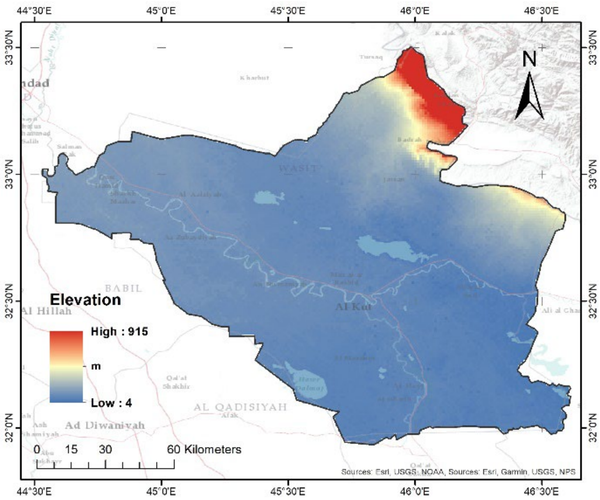
Fig. 2: Geographical location of Wasit governorate, Iraq.


Wind Speed
High : 8.44
m/s
Low : 4.77
0 15 30 60 Kilometers
Sources: Esri, USGS, NOAA, Sources: Esri, Garmin, USGS, NPS

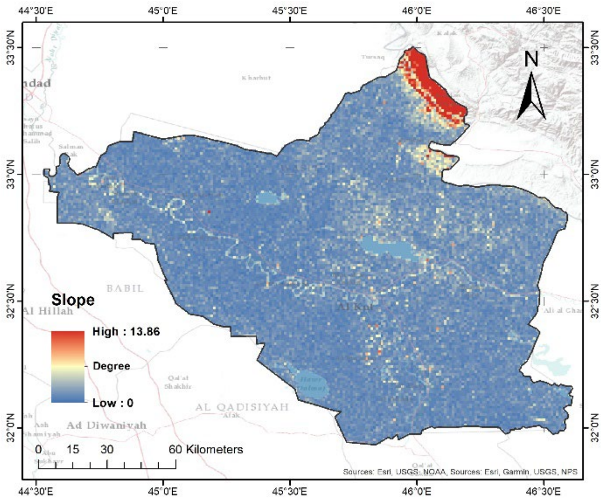
(a)


Wind Density
High : 1.16
kg/m^3
Low : 1.07
0 15 30 60 Kilometers
Sources: Esri, USGS, NOAA, Sources: Esri, Garmin, USGS, NPS

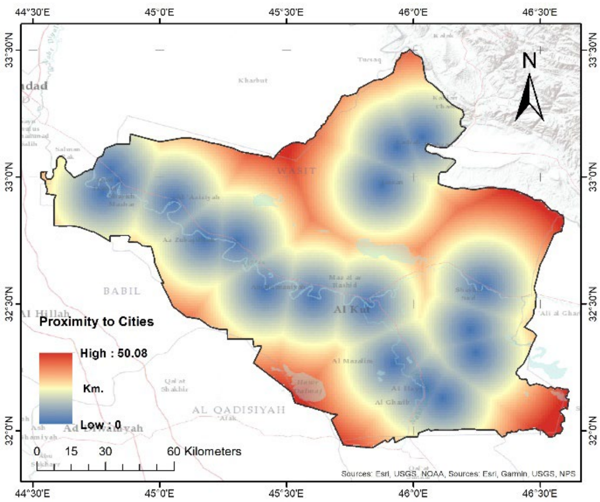
(b)


Elevation
High : 915
m
Low : 4
0 15 30 60 Kilometers
Sources: Esri, USGS, NOAA, Sources: Esri, Garmin, USGS, NPS

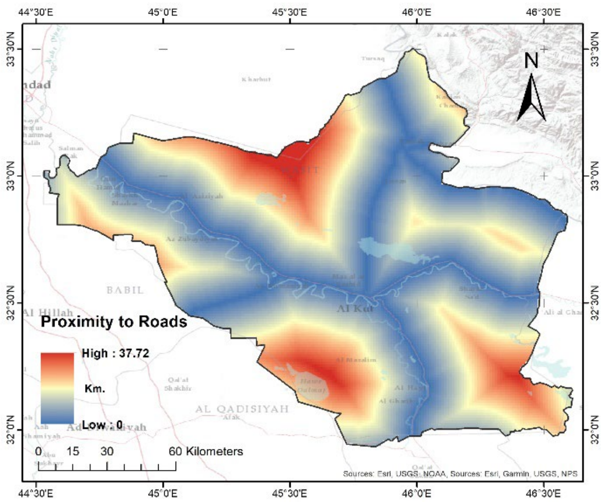
(c)


Slope
High : 13.86
Degree
Low : 0
0 15 30 60 Kilometers
Sources: Esri, USGS, NOAA, Sources: Esri, Garmin, USGS, NPS

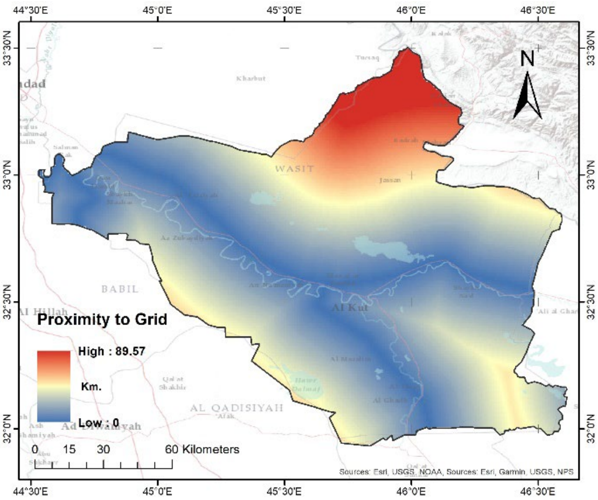
(d)


Proximity to Cities
High : 50.08
Km.
Low : 0
0 15 30 60 Kilometers
Sources: Esri, USGS, NOAA, Sources: Esri, Garmin, USGS, NPS

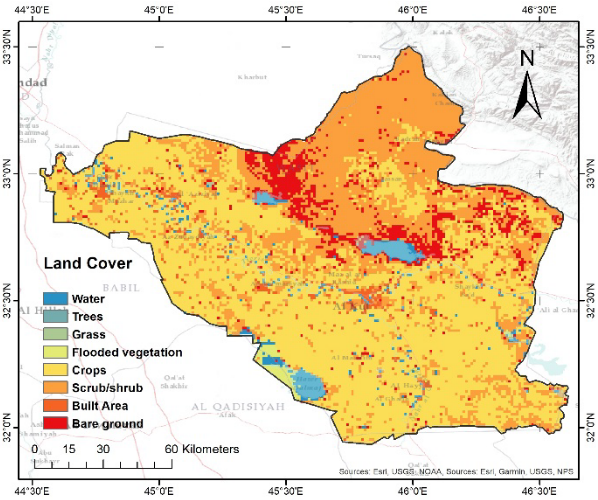
(e)


Proximity to Roads
High : 37.72
Km.
Low : 0
0 15 30 60 Kilometers
Sources: Esri, USGS, NOAA, Sources: Esri, Garmin, USGS, NPS

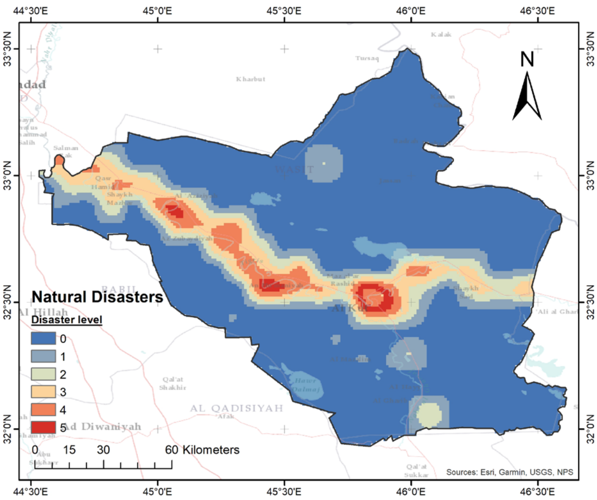
(f)



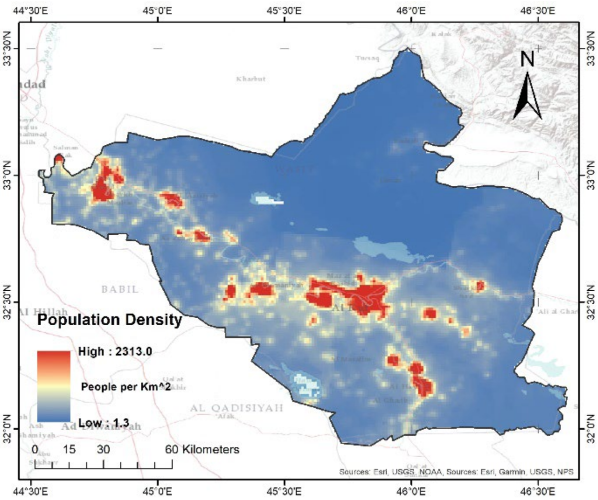
(g)



(h)



(i)



(j)

Fig. 3: The geospatial layers of evaluation factors: (a) wind speed, (b) wind density, (c) elevation, (d) slope, (e) proximity to cities, (f) proximity to roads, (g) proximity to grids, (h) land cover, (i) natural disasters, and (j) population density.

Table 1: The range and order of the reclassified factor categories.

Factor	Unit	Category Range	Order
Wind Speed	m/s	< 5.00	0
		5 – 5.75	1
		5.75 – 6.50	2
		6.50 – 7.25	3
		7.25 – 8.00	4
		8.00 – 8.44	5
Wind Density	kg/m3	1.07 – 1.15	1
		1.15 – 1.14	2
		1.14 – 1.15	3
		1.15 – 1.16	4
		1.16 – 1.16	5
Elevation	m	4 – 50	5
		50 – 100	4
		100 – 300	3
		300 –500	2
		500 – 915	1
Slope	degree	0 – 1.00	5
		1.00 – 3.00	4
		3.00 – 6.00	3
		6.00 – 10.00	2
		10.00 – 13.86	1
Proximity to Cities	km	0 – 10	5
		10 – 20	4

		20 – 30 30 – 40 40 – 50.08	3 2 1
Proximity to Roads	km	0 – 5 5 – 10 10 – 20 20 – 30 30 – 37.72	5 4 3 2 1
Proximity to Grids	km	0 – 10 10 – 20 20 – 40 40 – 60 60 – 89.57	5 4 3 2 1
Land Cover	class	Built Areas, Trees, Water Flooded-Vegetation Crops Scrub and Shrub Grass Bare Ground	0 1 2 3 4 5
Natural Disasters	level	Level-0 Level-1 Level-2 Level-3 Level-4 Level-5	5 4 3 2 1 0
Population Density	People per km2	1.30 – 84.70 84.70 – 252.70 252.70 – 595.90 595.90 – 1272.12 1272.12 – 2313.03	1 2 3 4 5

2.2.2 Exclusion Criteria

Exclusion criteria play a vital role in the selection of suitable sites for wind turbine installation. They highlight areas where evaluation factors are competitive [6]. This study focused on six exclusion criteria: airports, archaeological sites, bird habitats, bird flyways, water bodies, and protected regions. These constraints were considered depending on previous studies, characteristics of the study area, and data availability. The relevant geospatial data were acquired from authoritative sources, and their layers are shown in Figure 4. The gathered data was subjected to buffer analysis in the GIS context to identify the overall exclusion area. A buffer distance of 0.5 km was employed around the water bodies [27]. A 3 km radius was established around the airports [28]. The migratory bird flight paths were to be separated by a corridor 5 km in width [11]. Additionally, a 1 km exclusion zone was established around the rest. Ultimately, the process of rasterization was executed using the ArcGIS Feature-to-Raster technique to transform the thresholds' vector layers to raster formats with a boolean data type.

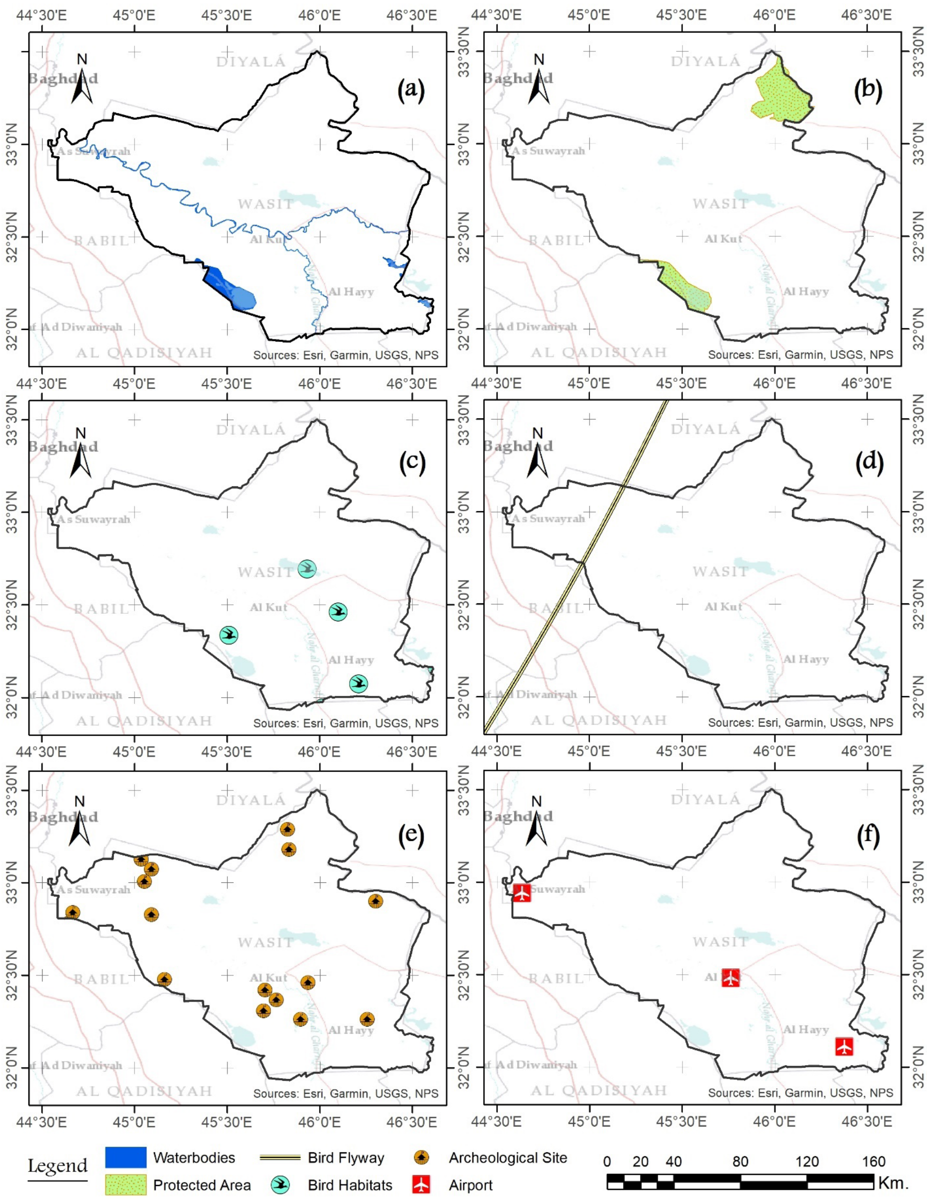


Fig. 4: The geospatial layers of exclusion factors: (a) water bodies, (b) protected areas, (c) bird habitats, (d) bird flyways, (e) archaeological sites, and (f) airports.

2.3 Weighting Scenarios
2.3.1 Analytic Hierarchy Process (AHP)

AHP, a well-known subjected weighting technique, is credited to Saaty [29]. It is based on a series of pairwise comparisons that explain experts' perceptions toward the importance of decision criteria [30]. The AHP method proposes organizing a hierarchy of factors that play a role in decision-making [31]. The goal should be placed at the top of the hierarchy. In this paper, AHP was applied as a subjective weighting method to calculate evaluation criteria weights for wind systems. The procedure is explained through the following steps:

1) Define the problem and set the goal.
2) Develop a hierarchical structure of the MCDM problem.
3) Measure the importance of decision criteria through consulting experts. In our case, 7 local experts from various disciplines were polled, including RE, regional planning, environment, and geomatics. The expert judgments are converted into numerical values using a nine-point Saaty scale, where 1 indicates equally important and 9 indicates extremely important.

4) Organize the specialists' judgments about the criteria (n) into a pairwise comparisons matrix $A_{(n \times n)}$, as shown in Figure 5. The importance of the i^{th} criterion to the j^{th} criterion is demonstrated by the element a_{ij}. If a_{ij} > 1, the i^{th} criterion is prioritized over the j^{th} criterion. If the value for both criteria is 1, then the entry is 1.

$$A_{(n \times n)} = \begin{bmatrix} 1 & \dots & a_{ij} \\ \vdots & \ddots & \vdots \\ 1/a_{ij} & \dots & 1 \end{bmatrix}$$

Fig. 5: The structure of the pairwise comparison matrix. Since this study addressed 10 criteria, the dimensions of the matrix A will be (10×10).

5) Normalize the pairwise comparisons matrix $\bar{A}_{(n \times n)}$ by making the sum of each column equal to 1, as described in Equation (1).

$$\bar{a}_{ij} = \frac{a_{ij}}{\sum_{i=1}^{n} a_{ij}} \tag{1}$$

6) Calculate the criteria weights matrix $w_{i\,(n \times 1)}$ by finding the average of each row of the matrix $\bar{A}$, as shown in Equation (2).

$$w_{i\,(n \times 1)} = \frac{\sum_{j=1}^{n} \bar{a}_{ij}}{n} \tag{2}$$

7) Validate the consistency of the pairwise comparisons matrix using Equation (3). The consistency index (CI) must meet the requirements; otherwise, the procedures should be repeated [32].

$$CI = \frac{\lambda_{max} - n}{n - 1} \tag{3}$$

where λ_{max} is the highest eigenvalue of matrix A.

According to [33], the level of consistency is reasonable if the CI/RI < 0.1. RI stands for the random consistency index shown in Table 2.

Table 2: The values of random index (RI) against n criteria [34].

n	1	2	3	4	5	6	7	8	9	10	11
RI	0	0	0.58	0.90	1.12	1.24	1.32	1.41	1.45	1.49	1.51

2.3.2 Entropy Weighing Method (EWM)

EWM is a typical objective weighing strategy that uses the entropy index to measure the dispersion of values [35]. According to EWM, an increase in the degree of dispersion of a criterion's data within available alternatives indicates an increase in the degree of differentiation, and as a result, the criterion deserves higher weight and vice versa [36]. The key steps to calculate the objective weights by EWM are as follows:

1) Initialize a data matrix P with dimension (m alternatives * n criteria) in which the value of the j^{th} criterion in i^{th} alternative is recorded as x_{ij}. In this paper, each grid cell (1 km^2) was considered as a potential alternative, hence $m = 16850$ while $n = 10$.

2) Normalize the data matrix $\bar{P}_{(m \times n)}$ using Equation (4). The standardized value is symbolized as p_{ij}.

$$p_{ij} = \frac{x_{ij}}{\sum_{i=1}^{m} x_{ij}}; \quad i = 1,2, \dots, m; \quad j = 1,2, \dots, n \tag{4}$$

3) Calculate the entropy value E_j of the j^{th} criterion using Equation (5)

$$E_j = -\frac{\sum_{i=1}^{m} p_{ij} \times \ln(p_{ij})}{\ln(m)} \tag{5}$$

4) Implement Equation (6) to derive the weight w_j of the j^{th} criterion

$$w_j = \frac{1 - E_j}{\sum_{j=1}^{n} (1 - E_j)} \tag{6}$$

2.3.3 AI Weighing Method

Essentially, AI models rely on training samples from the real world, ensuring that the weights they generate are free of subjectivity. XAI algorithms, such as Shapley's model, have contributed to understanding how factors interact within a model, enabling them to capture the significance of each factor in formulating predictions [37]. Recently, [9] introduced global weights for spatial decision criteria of wind systems. Real-world experiments of wind farms worldwide were utilized as samples to train the Random Forest (RF) algorithm. The Shapley model was applied to interpret the predictions and measure the weights of the spatial criteria, which was confirmed to be generalizable. These weights were adopted for the current study's purposes, as illustrated in Figure 6.

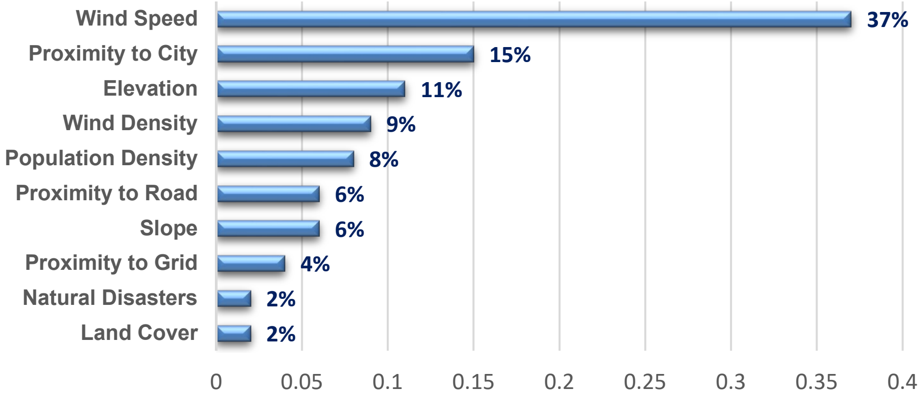


Fig. 6: AI weights for the evaluation criteria under examination [9].

2.4 GIS Modelling

2.4.1 Weighted Overlay Analysis

Weighted layering is a prevalent technique in GIS used for suitability analysis, employing a weighted linear combination (WLC) approach. It can integrate raster layers with both discrete and continuous attributes. However, for successful implementation, normalizing the layers into a common scale is necessary. Subsequently, the standardized maps are multiplied by their corresponding weights and aggregated based on Equation (7) [7].

$$S_i = \sum_{j=1}^{n} w_j x_{ij}, \tag{7}$$

where S_i denotes to the suitability index for pixel i, w_j refers to the weight of factor j, x_{ij} is the standardized score of pixel i for factor j, and n indicates the number of factors being considered.

This study utilized the weighted overlay capabilities of ArcGIS ModelBuilder to incorporate the reclassified criteria along with their assigned weights. The practice was applied three times, once for each adopted weighting scenario. These overlays produced three spatial suitability indices at a 1 km resolution for onshore wind farms across the area of interest: the subjective suitability index, the objective suitability index, and the AI suitability index. Within each index, suitability levels were further classified into five categories using the equal interval technique: (0.0–0.2) Very Low, (0.2–0.4) Low, (0.4–0.6) Moderate, (0.6–0.8) High, and (0.8–1.0) Very High. A sixth category, referred to as "Unsuitable", is assigned to pixels that do not meet the evaluation criteria thresholds.

2.4.2 Fuzzy Overlay Analysis

Fuzzy layering is a resilient spatial analysis technique in GIS. It explores the likelihood of a phenomenon being associated with various input sets through a layered overlay analysis [38]. The fuzzy overlay was executed in this work to fuse the suitability indices resulting from the weighted overlay into an ensemble index of spatial suitability for wind systems. Accordingly, the crisp input maps were fuzzified using the fuzzy linear membership function described in Equation (8), transforming them into a fuzzy scale ranging from 0 to 1. The Fuzzy-AND operator was subsequently applied to merge the fuzzy maps, using the smallest values as the foundation. This strategy allows for the identification of regions that have attained high suitability scores across the multiple indices investigated. Ultimately, the defuzzification was performed to translate the ensemble-suitability index into easy-to-understand categories.

$$f(x) = \begin{Bmatrix} 0, & x < a \\ \frac{x-a}{b-a}, & a < x < b \\ 1, & x > b \end{Bmatrix}, \tag{8}$$

where the maximum and minimum suitability thresholds are denoted by b and a, respectively.

3 Results and Discussions

3.1 Competition Areas

As a fundamental step in assessing the spatial suitability of wind farms, it is necessary to identify areas in which the evaluation criteria are allowed to compete. To this end, six exclusion criteria were considered in the context of GIS Buffer Analysis, as explained earlier in Section 2.2.2. The results yielded a raster map with two categories: the exclusion area and the competition area, as illustrated in Figure 7. Exclusion areas refer, on the one hand, to locations where the development of wind systems is not permitted due to various regulatory and environmental reasons, accounting for 14.7% of the study area (2477 km²). On the other hand, competition areas represent the appropriate scope for MCDM modeling to explore promising spatial opportunities for wind turbine deployment. Wasit Province exhibited 85.3% of its territory as competitive, allowing for a broader scope for overlaying decision criteria in subsequent steps of our methodology.

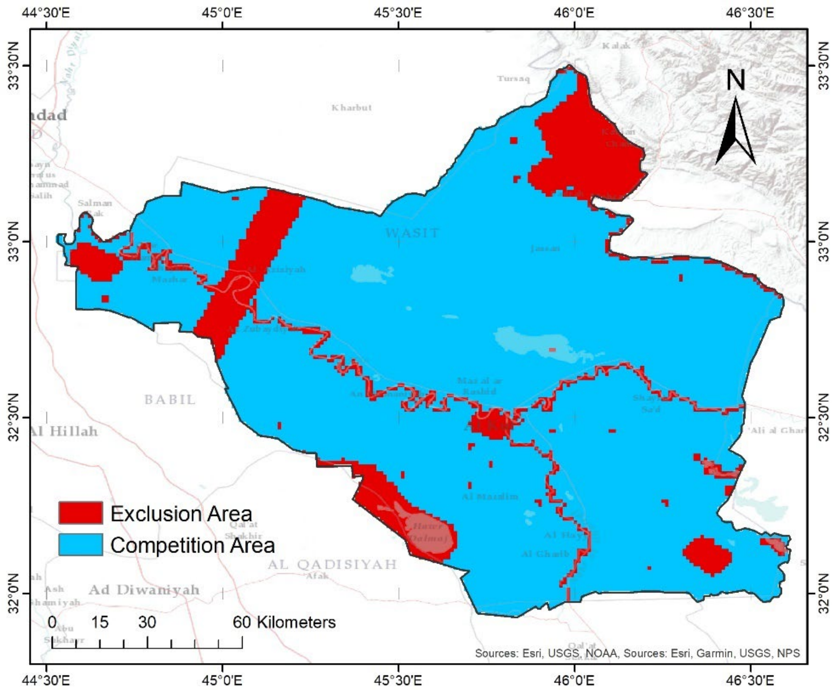


Fig. 7: Competition areas across Wasit governorate.

3.2 Weighting Outcomes

In this study, three weighting scenarios are examined: subjective, objective, and AI weightings. The application of the AHP method led to subjective weights for the decision criteria with a consistency level of less than 0.1; thus, discrepancies across expert judgments were reasonable. The results revealed that the most crucial criterion for choosing a suitable site for wind farms is wind speed (34%), followed by proximity-to-grid and proximity-to-road, with weights of 23% and 15%, respectively. Conversely, the lowest weight was recorded at 2% for the factors of elevation, slope, land cover, and natural disasters. These findings underscore the strong emphasis of experts on renewable resources and infrastructure criteria.

In the EWM-based objective weighting, the results reveal that the proximity-to-grid criterion ranked first, followed by proximity-to-city and wind speed in second and third place, respectively. The high weights indicate the large dispersion in the data for these criteria. Meanwhile, land cover and proximity-to-road were of moderate importance, each receiving a weight of 10%. These weights are generally comparable to AI weights derived from real-world experiences. However, a notable difference occurs. The proximity-to-grid in the AI scenario received low weight, despite its high importance in the other weighting scenarios. The potential reason behind this discrepancy is that the majority of RE installations worldwide are of the grid-independent type. Overall, technical and economic criteria emerged as the most superior across all considered weighting scenarios. Table 3 displays the criteria weights for each scenario considered.

Table 3: Outcomes of the three weighting scenarios.

Evaluation Criteria	Weightage Scenario (%)		
	AHP	EWM	AI
Wind Speed	34	12	37
Wind Density	9	8	9
Elevation	2	8	11
Slope	2	7	6
Proximity to City	6	14	15
Proximity to Road	15	10	6
Proximity to Grid	23	18	4
Land Cover	2	10	2
Natural Disasters	5	7	2
Population Density	2	6	8
∑	100	100	100

3.3 Suitability Indices

As stated in the methodology section, the WLC technique was utilized three times, aided by different weighting scenarios, to merge the thematic layers of the decision criteria. The overlays produced three spatial suitability indices for wind energy: the subjective suitability index, the objective suitability index, and the AI suitability index. These indices were then combined into an ensemble suitability index using fuzzy overlay. The ultimate outcomes of the indices are depicted as index maps comprising six spatial suitability categories, as illustrated in Figure 8.

The outcomes of the subjective suitability index presented in Figure 8a reveal that the central and southern regions of Wasit Governorate have a significant proportion of land, approximately 24% and 14%, with high and very-high suitability for hosting wind turbines, respectively. These areas are characterized by high wind speeds and proximity to the electricity grid, as these two criteria received the highest scores in the subjective weighting scenario. Meanwhile, 32% (~5438 km^2) of the subjective index was occupied by the low and very low suitability classes, which were primarily concentrated in the northern and southwestern regions.

In the objective suitability index (Figure 8b), an expansion was observed in the areas with high and very high suitability, with their combined percentage estimated at 56%. The rationale behind this increase is that the objective weighting scenario gave equal importance to both wind speed and economic parameters. Consequently, areas close to basic infrastructure were deemed most suitable for wind energy development. Conversely, the coverage rate of low suitability classes declined to 12% of the total land, despite their continued concentration in northern and some parts of southern Wasit. This indicates a shift towards prioritizing regions with better infrastructure and wind conditions, thus enhancing the overall feasibility of wind energy projects in the region. In both the objective and subjective suitability indices, the moderate suitability category occupied a similar area of land, estimated at 25% and 23%, respectively.

In the weighting scenario based on AI, the factors of wind speed and proximity to cities ranked highest in importance, with the combined weight of each exceeding the sum of the weights of the other factors. This result significantly affected the distribution of suitability categories in the third suitability index, shown in Figure 8c, in which the very high suitability class occupied only about 6% of the total study area. The very high degrees were concentrated in the east and south of Wasit Governorate, where wind speeds are high and proximity to city centers is favorable. On the other hand, the suitability categories of high, moderate, low, and very low dominated the AI suitability index by 30%, 31%, 23%, and 4%, respectively.

Based on the three suitability indices described earlier, it is observed that the spatial distribution of the low and very low suitability classes remains consistent throughout the northern and southern regions of Wasit. The center of the research area is primarily dominated by the high and moderate suitability classes, while the very high suitability class exhibits the greatest spatial variability. The extremely suitable category is particularly appealing to stakeholders considering investments in wind energy. Hence, this level of suitability deserves further investigation and focus.

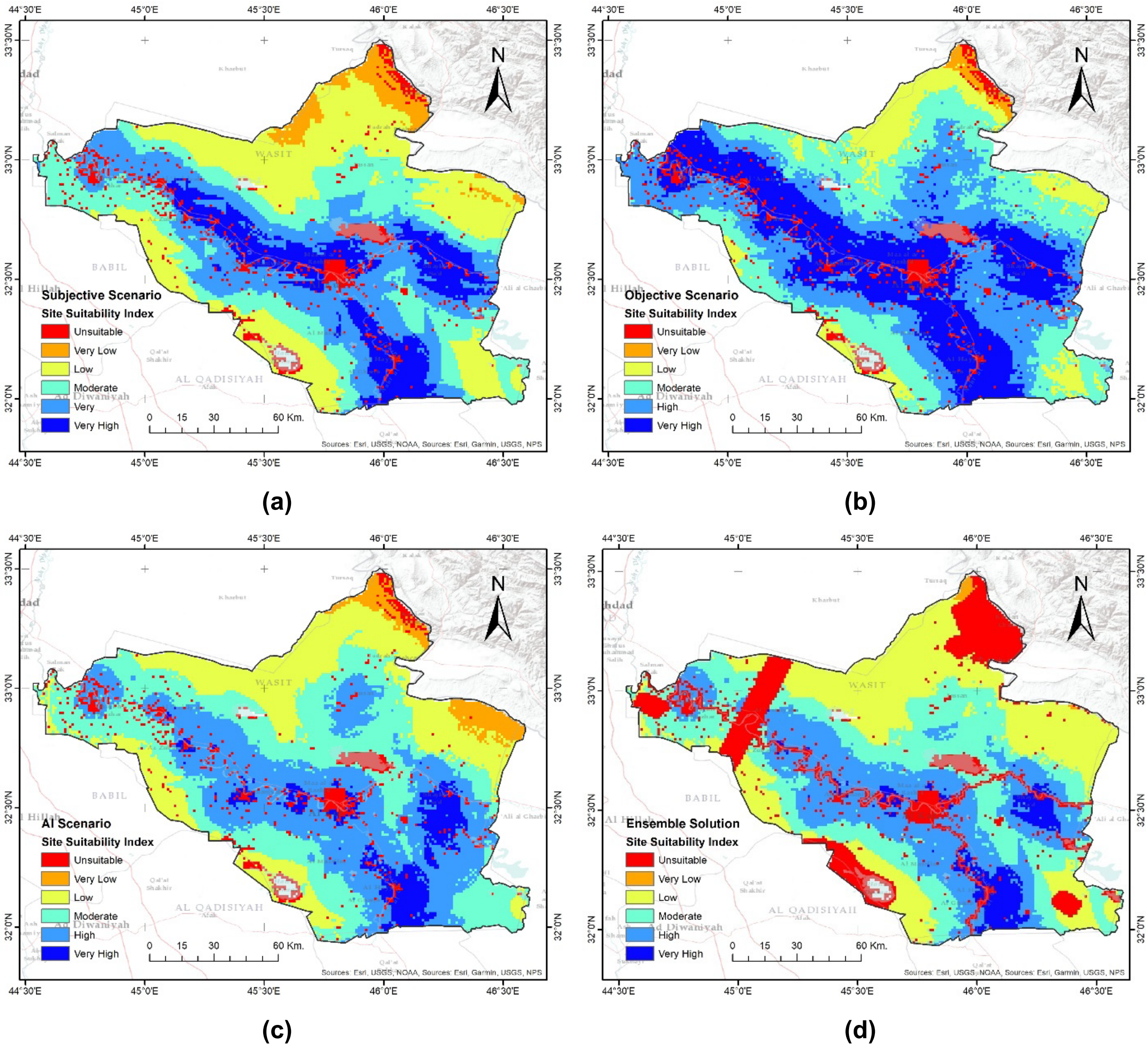


Fig. 8: Spatial suitability indices for siting wind farms across Wasit Governorate: (a) Subjective suitability index, (b) Objective suitability index, (c) AI suitability index, (d) Ensemble suitability index.

To take advantage of all reported results, the three suitability indices were integrated along with the competition area index in a fuzzy environment using the Fuzzy-AND operator. The outcomes of the ensemble suitability index are shown in Figure 8d. The suitability class assigned to any pixel on this index represents the lowest class of the corresponding overlapping pixels. Therefore, regions that showed a very high degree of suitability on the ensemble index, constituting 4% of the lands, possess the same degree of suitability across the rest of the indices. This ensures the highest degree of spatial preference is achieved across the various decision-making scenarios under consideration. Optimal pixels can be observed scattered around city centers, especially in the east and south of Wasit Governorate. Compared with the AI index, the high and moderate categories witnessed a slight decrease, while their spatial distribution remained constant. Notably, the percentage of unsuitable lands increased to 18% due to the consideration of exclusion zones in the current suitability index. Quantitative analysis of suitability categories across all indices is shown in Table 4, while results are compared in Figure 9.

Table 4: Area of suitability classes across various spatial indices for hosting wind farms in Wasit.

Suitability Class	Subjective suitability index		Objective suitability index		AI suitability index		Ensemble suitability index	
	km2	%	km2	%	km2	%	km2	%
Unsuitable	1086	6	1086	6	1086	6	3010	18
Very Low	702	4	171	1	602	4	56	0
Low	4736	28	1792	11	3794	23	4574	27
Moderate	3900	23	4200	25	5238	31	4487	27
High	4080	24	4961	29	5041	30	3943	23
Very High	2322	14	4616	27	1065	6	756	4

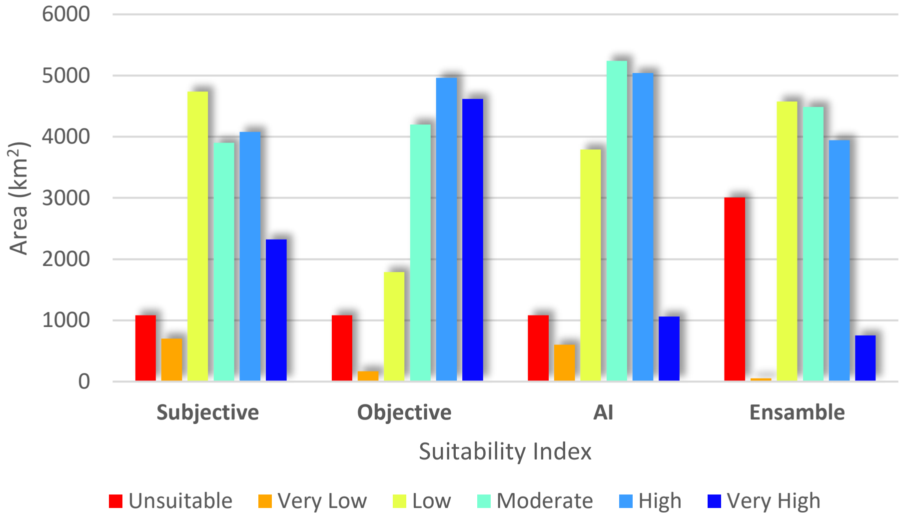


Fig. 9: Graphical comparison of suitability class areas across all indices.

3.4 Ideal Sites Verification

The ensemble suitability index identified multiple optimal locations for the development of wind energy across Wasit Governorate. The sites are located to the south of Al-Hay and Sheikh Saad cities, west of Al-Kut city, and in certain southern sections of Al-Zubaidiyah city, covering a total area of 756 km². These areas exhibit strong wind velocities ranging from 7.8 to 8.44 m/s, land elevations between 12 and 18 m, and proximity to road and electricity networks of less than 15 km.

Visual verification of highly suitable sites was conducted via comparison with their corresponding positions on satellite imagery, as depicted in Figure 10. The analysis revealed a common characteristic among these regions: vast expanses of non-settlement territory dominated by agricultural fields. This outcome aligns with the land cover classes in the reported hotspots. Additionally, crop fields typically provide large, open spaces with minimal obstructions, which is ideal for installing wind turbines as they allow for better wind flow and less turbulence. Moreover, deploying wind turbines in these areas can promote dual land use, reduce land depletion, and provide additional income to farmers by leasing their land for wind energy production without significantly affecting crop production.

The ensemble suitability index is in agreement with the literature. A study covering all Iraqi territories revealed three hotspots for investment in hybrid wind-solar energy, one of which is in the east of Wasit governorate [9]. Further investigations indicated that the city of Al-Hay, south of Wasit, was the most suitable for wind energy applications among the sites examined in Iraq [39], [40]. These conclusions are largely consistent with the announced results, confirming the robustness of the proposed model.

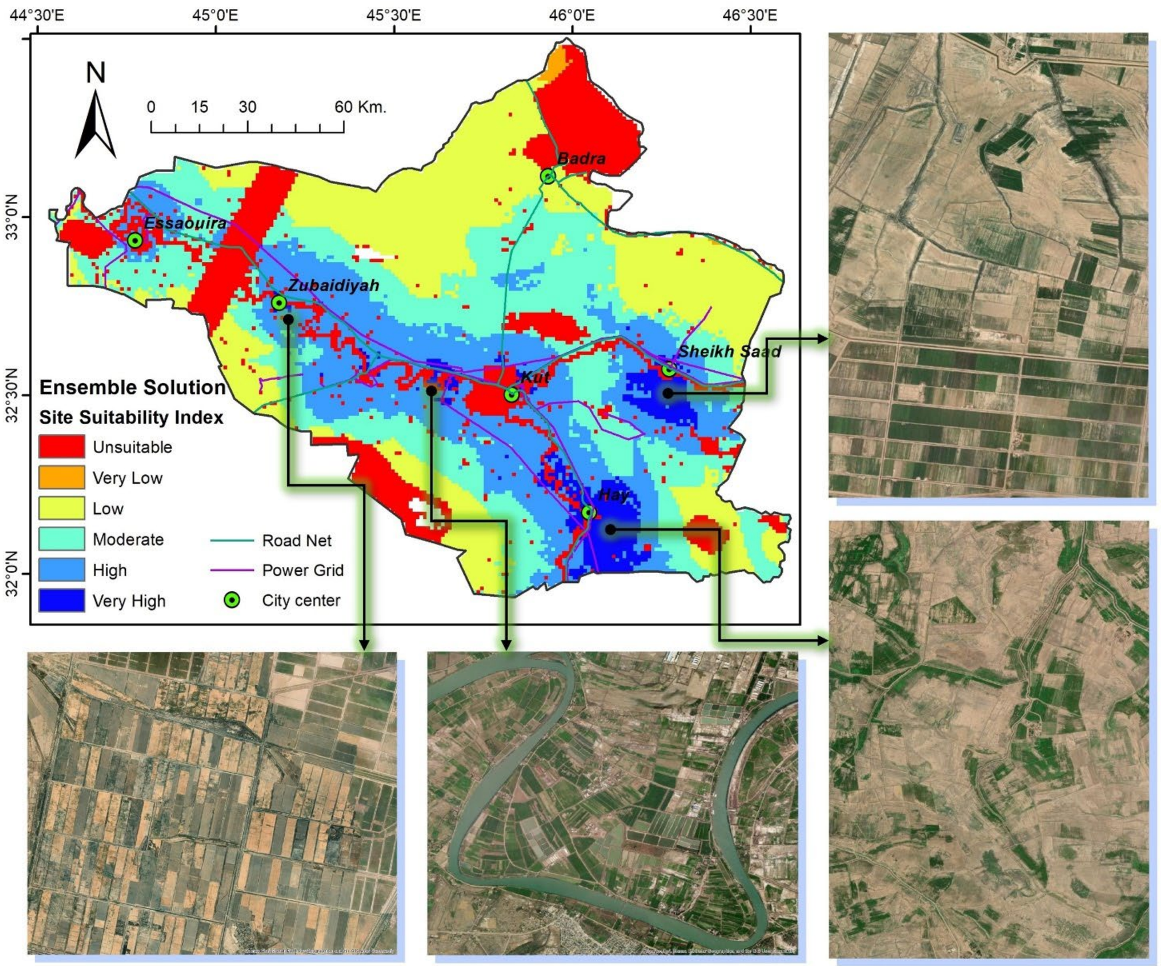


Fig. 10. Geographical visualization and availability of infrastructure for very-high suitable areas.

3.5 Energy Potential Estimation

Generally, the energy potential of a wind farm can be calculated by considering the electrical power produced by each wind turbine and the number of turbines that can be installed on the farm [24], [41]. For the analysis, the Enercon E70 with a capacity of 2.3 megawatts (MW) and the Vestas V66 with a capacity of 1.75 MW were chosen. The turbine's capacity and hub height were key factors in determining the turbine type candidacy in this work. The technical potential was estimated using Equation (9).

$$TP_W = \frac{TA}{AUT} \times P \tag{9}$$

where TP_W denotes the power potential of wind systems in gigawatts (GW); TA stands for the entire area available to host wind energy farms (km2); and AUT refers to the area beneath the turbine, which was determined in this study using the formula $(7D \times 4D)$, where D represents the rotor's diameter [42]. The letter P indicates the turbine power output, which can be extracted from the power curve supplied by the wind turbine manufacturer, as illustrated in Figure 11.

The power production of each wind turbine addressed, the AUT outcomes, and the wind energy potential are summarized in Table 5. The results demonstrate that deploying Enercon E70 turbines in areas with high and very high spatial suitability would yield expected electrical power production of 14.68 GW and 3.59 GW, respectively. When considering Vestas V66 turbines, high-suitability areas exhibit a significant increase in power potential, reaching 15.51 GW. This is attributed to the smaller AUC compared to the Enercon turbine, allowing for a larger number of turbines to be deployed. In contrast, Vestas' utilization of the very high suitability area calculations records a slight decrease in its energy potential. This discrepancy arises from the superior capacity of Enercon E70 turbines at wind speeds exceeding 8 m/s. The identified wind energy capacity has the potential to significantly impact Iraq's efforts to transition to a low-carbon future.

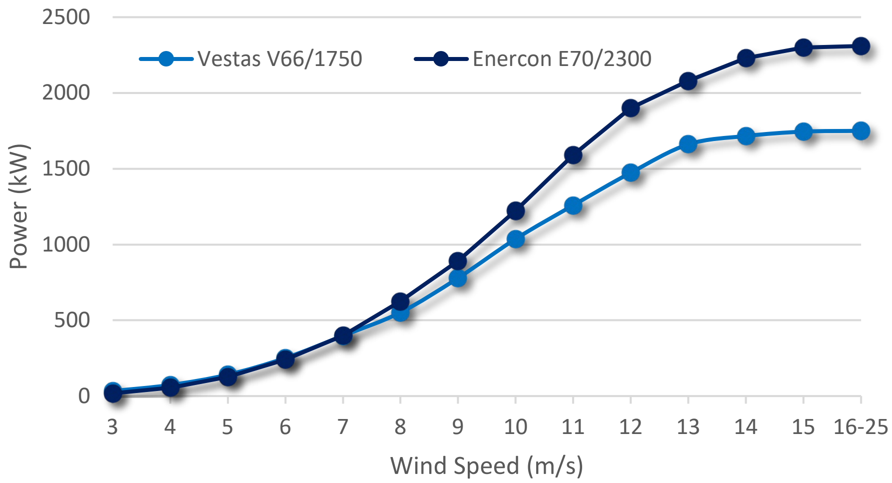


Fig. 11: Power curves of Enercon E70/2300 and Vestas V66/1750 turbines.

Table 5: Wind energy potential across the high and very high categories of the ensemble suitability index.

Suitability Category	TA (km^2)	Average wind speed (m/s)	Type of wind turbine	D (m)	P (kW)	AUT (km^2)	TP_W (GW)
High	3943	7.40	Enercon E70/2300	70	510	0.137	14.68
			Vestas V66/1750	66	480	0.122	15.51
Very High	756	8.20	Enercon E70/2300	70	650	0.137	3.59
			Vestas V66/1750	66	575	0.122	3.56

4 Conclusions

This article presents an ensemble weights-based geospatial model to identify optimal locations for onshore wind energy development. The model addresses 16 evaluation and exclusion factors and applies three different weighting scenarios: subjective weighting, objective weighting, and AI weighting. Using WLC and fuzzy overlay methods within the GIS domain, the model produced individual suitability indices for each scenario considered and an ensemble suitability index for wind turbine deployment across Wasit Governorate, Iraq. The results demonstrate the superiority of technical and economic criteria in all weighting scenarios, with the wind speed factor achieving weights of 34%, 12%, and 37% in the subjective, objective, and AI scenarios, respectively. The individual suitability indices indicate that the western, central, and southern regions of Wasit are the most likely to develop onshore wind farms, while the northern and southwestern regions are the least suitable. The ensemble suitability index highlights several ideal locations for placing wind turbines: South of Al-Hay, South of Sheikh Saad, and West of Al-Kut, covering a total area of 756 km². These regions can provide clean and sustainable energy exceeding 3.5 GW, contributing to the governorate's electricity needs and reducing its carbon footprint.

This is the first study to integrate AI-based spatial solutions with other subjective and objective approaches, offering a new perspective for decision-making models, particularly in RE planning. As the shift towards sustainable energy grows, these results could encourage policymakers and stakeholders to invest in the wind energy sector in developing countries such as Iraq. To enhance this research, it is recommended that the proposed model be applied elsewhere around the world to account for diverse data in different geographical contexts. A major limitation of this paper is the application of the proposed model exclusively to onshore wind plants. Therefore, a potential avenue for future research is to adapt this approach to address other types of green energy.

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Conflicts of Interest

The authors declare no conflict of interest.

Appendix

Table A1. Data sources used in formulating GIS databases for evaluation and exclusion factors.

	Criteria	Data Source	Format	Access website
Evaluation Factors	Wind Speed	GWA3.3 (Global Wind Atlas version 3.3)	Raster (TIFF)	https://globalwindatlas.info/
	Wind Density	GWA3.3 (Global Wind Atlas version 3.3)	Raster (TIFF)	https://globalwindatlas.info/
	Elevation	SRTM (Digital elevation model of Shuttle Radar Topography Mission)	Raster (TIFF)	https://earthexplorer.usgs.gov/
	Slope	Derived from the SRTM elevation model	Raster (GRID)	https://earthexplorer.usgs.gov/
	Proximity to Cities	Iraqi General Authority of Survey	Vector (point feature)	https://mowr.gov.iq/en/general-survey-authority/
	Proximity to Roads	Iraqi General Authority of Survey	Vector (line feature)	https://mowr.gov.iq/en/general-survey-authority/
	Proximity to Grid	Iraq Energy Institute	Vector (line feature)	https://iraqenergy.org/
	Land Cover	ESRI (Environmental Systems Research Institute)	Raster (TIFF)	https://livingatlas.arcgis.com/landcover/
	Natural Disasters	UNISDR (United Nations Office for Disaster Risk Reduction)	Raster (TIFF)	https://apdim.unescap.org/knowledge-hub/global-risk-data-platform
	Population Density	Iraqi Authority of Statistics and GIS	CSV data	https://cosit.gov.iq/ar/
Exclusion Factors	Waterbodies	Iraqi General Authority of Survey	Vector (polygon feature)	https://mowr.gov.iq/en/general-survey-authority/
	Protected Areas	The World Database on Protected Areas (WDPA)	Vector (polygon feature)	https://www.protectedplanet.net/en/thematic-areas/wdpa?tab=WDPA
	Bird Habitats	CIUCN Report, Iraqi ministry of environment	Vector (point feature)	http://moen.gov.iq/
	Bird Flyway	The globe of bird migration	Vector (line feature)	http://globeofbirdmigration.com/
	Archaeological Sites	Iraqi directorate of antiquities	Vector (point feature)	http://mocul.gov.iq/index.php
	Airport	Iraqi General Authority of Survey	Vector (point feature)	https://mowr.gov.iq/en/general-survey-authority/

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