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Research Paper

A novel GeoAI-based multidisciplinary model for SpatioTemporal Decision-Making of utility-scale wind–solar installations: To promote green infrastructure in Iraq

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A R T I C L E I N F O

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A B S T R A C T

The dual use of wind and solar energy holds great promise for low-cost and high-performance green infrastructure. However, for such hybrid systems to operate successfully, comprehensive and simultaneous dimensional planning is required, a goal that single-perspective assessment approaches fail to attain. This paper proposes a novel SpatioTemporal Decision-Making (STDM) model based on Geospatial Artificial Intelligence (GeoAI) for the optimal allocation of onshore wind-solar hybrid plants, with application on a national scale in Iraq. To this end, a wide range of 21 evaluative and restrictive spatial criteria were covered. The temporal synergy factor between renewable resources was considered for the first time in this type of study. Unique global weightings for decision factors were derived using Random Forest (RF) and SHapley Additive exPlanations (SHAP) algorithms supported by sample inventories of wind and solar plants worldwide. Finally, weighted linear combination (WLC) and fuzzy overlay techniques were harnessed in a GIS environment for spatiotemporal suitability mapping of energy systems. According to the RF-SHAP model, the techno-economic criteria demonstrated substantial contributions to the placement of wind and solar systems compared with the socio-environmental criteria. The spatiotemporal suitability map identified three promising opportunities for Iraq at South Dhi-Qar, East Wasit, and West Diyala, with total areas of 780, 2166, and 649 km^2, respectively. We anticipate that our findings will encourage government agencies, decision-makers, and stakeholders to increase funding for clean energy transition initiatives.

1. Introduction

Renewable energy (RE) has become a significant source of electricity in recent years to meet the growing energy demand and contribute to the achievement of sustainable development goals (Rediske et al., 2020). In particular, wind and solar energy systems are the most mature and popular green energy sources being explored globally because of their cleanliness degree, availability, capacity factor, and construction cost compared with other clean energy sources (Adedeji et al., 2020). The challenges of providing huge lands for such investments, on the one hand, and the temporal and spatial fluctuations of wind and solar resources, on the other hand, prompted planners to shift toward the hybridization of RE systems (Saraswat et al., 2021). Such hybridization compensates for one system's weakness with another system's strength. Aside from the reliability of power supply, another advantage of wind-solar hybrid systems is lower development costs, including expenses for purchasing/renting land, the number of storage modules, operation and maintenance, and manpower (Hasan and Genç, 2022; Rezaei et al., 2020). According to some reports, deploying solar panels next to wind turbines reduces these costs by approximately 20 % (Rezaei et al., 2018).

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Wind-solar hybrid systems achieve higher efficiencies than those powered by a single power source (Amer et al., 2013). However, given that they are quite complex due to having multiple generation systems, exploring suitable sites that meet standard operating conditions for both types of energy (wind and solar) poses new challenges for researchers and decision makers.

The site suitability assessment for wind-solar systems seeks to identify potential development locations that meet technical, economic, environmental, social, and other relevant requirements. Traditionally, spatial assessment approaches have relied on a set of criteria classified into factors and constraints (Achbab et al., 2020; Ali et al., 2020). Factors determine the suitability of candidates, while constraints serve to identify proper zones in which the factors compete (Effat and El-Zeiny, 2022). In this circumstance, various multi-criteria decision-making (MCDM) methods, including analytic hierarchy process (AHP) and TOPSIS, are applied to weigh criteria and/or rank available alternatives (Rediske et al., 2020; Saraswat et al., 2021). Moreover, MCDM and geographic information system (GIS) are often combined because of the latter's unique advantages in editing, analyzing, and visualizing large geospatial databases, which enabled the implementation of spatial suitability investigations at the regional level instead of having limited alternatives (Asadi et al., 2023).

In the extensive literature, GIS-MCDM solutions have consistently played a pivotal role in the assessment of spatial suitability for RE systems. In Turkey, for instance, several publications highlight the substantial integration of GIS in spatial decision-making for deploying alternative energy equipment (Akarsu and Serdar Genç, 2022; Genç et al., 2021; Karipoğlu et al., 2022, 2021). Specifically, (Genc and Karipoglu, 2021) executed a GIS-MCDM-based methodology to investigate a broad spectrum of potential and environmental factors pertinent to the placement of hybrid wind-solar farms within the Kayseri Province of Turkey. In India, a GIS-AHP approach was adopted to perform a large-scale suitability assessment for siting solar and wind farms (Saraswat et al., 2021). AHP was employed to formulate the criteria's weights and the weighted linear combination (WLC) technique to aggregate the criterion layers into a GIS environment. In a similar study, an ordinal priority approach was applied alongside GIS to determine the land suitability to host wind and solar investments in Egypt (Elkadeem et al., 2022). The authors concluded that GIS-based solutions can be scaled to a larger country or continent if sufficient geospatial data for the decision criteria are available. Meanwhile, a study conducted on the island of Mauritius attempted to develop a conceptual approach using fuzzy logic to assess the spatial suitability of dual power plants (wind-solar) by applying topographic, climatological, and social elements (Dhunny et al., 2019). The research emphasized that the fuzzy technique outperformed linear models in terms of accuracy. The various MCDM strategies used in the context of sustainable energy were discussed in (Şahin, 2021; Shao et al., 2020). While the GIS-MCDM approaches have many advantages, they suffer from some drawbacks. For example, input factors are considered constant. Nevertheless, most of these factors are of a dynamic nature over time, such as wind speed and solar radiation (Sachit et al., 2022a). Furthermore, criteria are often weighted subjectively or objectively. Subjective weighting is criticized for bias, whereas objective weighting is not generalizable (Zardari et al., 2014).

Recently, rapid advances in artificial intelligence (AI) have improved MCDM models. New weighting methods based on AI models and feature selection algorithms have been introduced (Hanoon et al., 2022). For instance, chi-square and Fisher algorithms were applied to assign weights to criteria contributing to landslide susceptibility mapping (Sahin et al., 2015). The study suggests that weightings based on intelligent approaches should be considered when dealing with a large number of competing factors. Al-Ruzouq et al. (Al-Ruzouq et al., 2021) employed three supervised AI techniques to determine factor weights in a spatial decision-making model of waste-to-energy systems. The authors successfully implemented the proposed approach in the case of Sharjah, UAE. In another article focused on the same study area, hybrid weightings based on both AI and AHP were proposed to select the optimal sites for dam construction (Al-ruzouq et al., 2019). The study concluded that AI techniques can improve how factors are weighted in MCDM. In the field of industrial maintenance, AI algorithms (i.e., Bayesian networks and attribute relevance analysis) were employed alongside AHP to provide weights for a decision-making model (Lima et al., 2019). Although AI-based weights have been applied in various fields, their application in RE studies is still limited. In addition, the lack of sufficient training samples poses some limitations to the application of such approaches in developing countries that are just beginning to develop RE facilities.

In light of the aforementioned challenges, this study introduces a novel Geospatial AI (GeoAI)-based assessment model that considers the spatial and temporal aspects of decision-making criteria. The advantage of the proposed SpatioTemporal Decision-Making (STDM) model is not only a better understanding of the technically, economically, and environmentally feasible sites for deploying wind-solar hybrid systems but also that the sites contain temporal complementarity patterns between wind and solar resources to ensure stable power output around the clock. Furthermore, our model employs real-world experiences (in situ wind and solar plants worldwide) to develop global weights that are reliable, generalizable, and free of subjective judgments. Consequently, the need to rely on local training samples will decrease, making the STDM model potentially applicable in various regions. The novelty of this work lies in two key contributions. Firstly, it introduces new global weights that effectively trade-off between spatial assessment criteria for

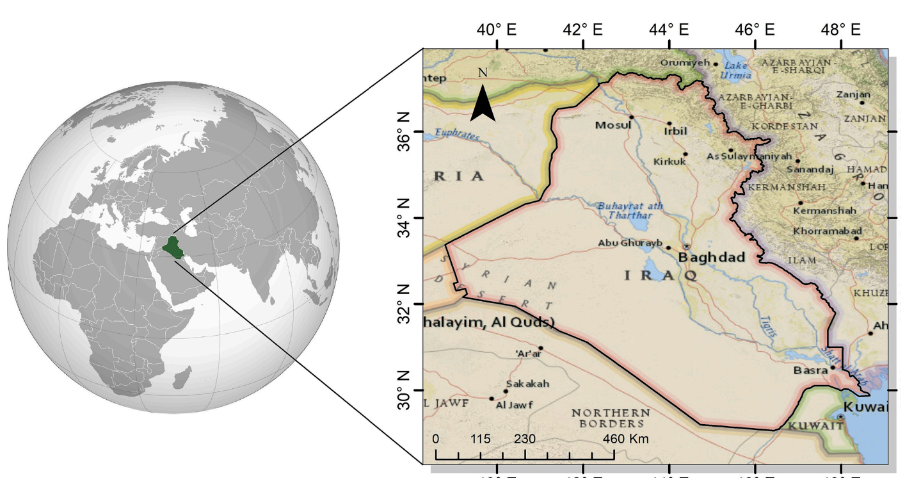


Fig. 1. Geographical location of Iraq.

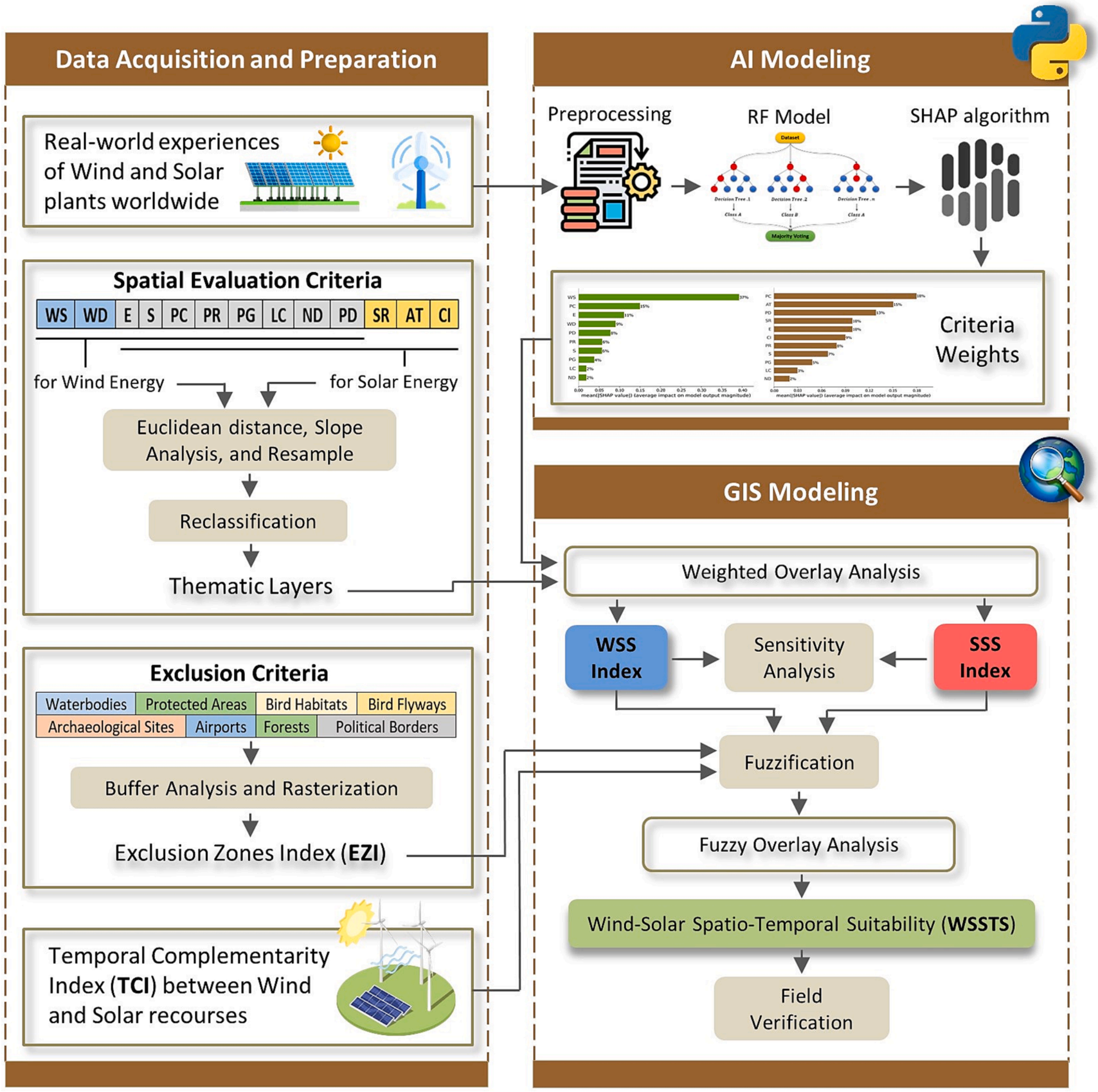


Fig. 2. Methodology flowchart of the STDM model for siting wind-solar power plants.

wind-solar hybrid farms. For this purpose, a combination of Random Forest (RF) and SHapley Additive exPlanations (SHAP) algorithms was applied to train and interpret a geospatial data-based prediction model for onshore wind and solar plants worldwide. Unlike pair-wise comparisons, which rely on experts' subjective judgments, the proposed approach benefits from real-world experiences in capturing the importance of features and selecting optimal development sites. Secondly, the work integrates temporal and spatial characteristics of renewable resources in siting dual-energy systems. Accordingly, the temporal complementarity index (TCI) between wind and solar energy is considered in a fuzzy structure along with spatial suitability indices for both types of energy. To our knowledge, TCI has not yet been incorporated into the multiobjective decision rules of RE systems; therefore, we provide a fresh research perspective that aided our comprehension of the temporal and spatial considerations pertinent to the potential of wind-solar hybrid power.

The specific objectives and contributions of our work are as follows:

To investigate an exhaustive set of 21 spatial criteria (13 factors and 8 constraints) to ensure accurate results in allocating potential sites for wind-solar development.

To develop robust, spatially transferable global weights for decision criteria by capturing their importance across global real-world experiences (global-to-local knowledge transfer).

To embed the dynamic nature of core renewable criteria in solving site problems exemplified by the TCI between wind and solar energy (the spatiotemporal solution).

To bridge the knowledge gap and encourage investment in utility-scale wind and solar energy projects by providing 1 km spatiotemporally explicit maps for the first time in the Iraqi context.

2. Context of Iraq

Iraq, a Middle East country, is located in southwest Asia within the longitudes (38° 45′–48° 40′) East and latitudes (29° 05′–37° 20′) North, as presented in Fig. 1. Iraq possesses promising potential for renewable resources due to its privileged location within the global sunbelt. However, the country still depends heavily on fossil fuels for energy production, hardly meeting the growing demand. Fortunately, Iraq's energy policy has recently begun to shift toward relying on clean energy sources, launching major investments in this sector. Therefore, investigating the spatiotemporal suitability of RE systems would support this commendable trend by highlighting promising areas for future installations.

Table 1
Range and rank of the reclassified criterion classes.

Criterion	Unit	Class range	Pixels Count	Rank
WS	m/s	> 5.00	65,467	0
		5.00 – 5.75	35,783	1
		5.75 – 6.50	178,714	2
		6.50 – 7.25	96,911	3
		7.25 – 8.00	37,364	4
		8.00 – 9.34	6058	5
WD	kg/m^3	0.84 – 1.00	2815	1
		1.00 – 1.06	9391	2
		1.06 – 1.11	49,804	3
		1.11 – 1.14	137,232	4
		1.14 – 1.17	221,539	5
SR	kWh/m^2/year	1394 – 1800	3781	1
		1800 – 1900	41,837	2
		1900 – 2000	189,321	3
		2000 – 2100	147,595	4
		2100 – 2169	39,608	5
AT	Celsius	0.07 – 15.95	10,711	1
		15.95 – 20.48	56,426	4
		20.48 – 22.87	103,940	5
		22.87 – 25.18	140,011	3
		25.18 – 27.30	110,816	2
CI	(Value × 0.01) %	657.89 – 2166.58	118,528	5
		2166.58 – 2542.58	158,701	4
		2542.58 – 3095.51	118,347	3
		3095.51 – 4157.14	22,724	2
		4157.14 – 7319.90	3606	1
E	m	> 0	785	0
		0 – 100	130,553	5
		100 – 500	214,824	4
		500 – 1000	62,020	3
		1000 – 1500	8984	2
		1500 – 3523	4812	1
S	degree	0 – 0.94	371,913	5
		0.94 – 3.23	27,914	4
		3.23 – 6.80	9741	3
		6.80 – 11.10	6742	2
		11.10 – 15.00	4031	1
		> 15	1637	0
PC	km	0 – 20	113,418	5
		20 – 40	131,800	4
		40 – 60	76,971	3
		60 – 80	50,401	2
		80 – 100	22,815	1
		> 100	26,847	0
PR	km	0 – 20	259,128	5
		20 – 40	95,463	4
		40 – 60	40,761	3
		60 – 80	13,928	2
		80 – 100	7183	1
		> 100	5789	0
PG	km	0 – 20	175,001	5
		20 – 40	79,069	4
		40 – 60	44,631	3
		60 – 80	31,790	2
		80 – 100	25,989	1
		> 100	65,772	0
LC	class	Water, Trees, Built Areas	21,223	0
		Flooded Vegetation	2575	1
		Crops	75,778	2
		Scrub/Shrub	279,237	3
		Grass	111	4
		Bare Ground	43,322	5
ND	level	Level 0	377,734	5
		Level 1	12,569	4
		Level 2	19,215	3
		Level 3	10,568	2
		Level 4	1802	1
		Level 5	364	0
PD	People per km^2	0.25 – 69.88	317,111	1
		69.88 – 235.79	74,290	2
		235.79 – 903.88	27,023	3
		903.88 – 3201.26	2594	4
		3201.26 – 7746.08	480	5

3. Methodology

The primary focus of this study is to introduce a GeoAI-based STDM model for hybrid wind-solar plants and apply it to the case of Iraq. The methodology implemented to achieve the goal includes a set of steps. Firstly, geospatial datasets were allocated, prepared, and normalized to account for the spatial, temporal, and exclusion criteria under consideration. Secondly, RF and SHAP-assisted intelligent modeling was implemented to derive global weights for the spatial criteria. Thirdly, the WLC approach was conducted in a GIS context augmented by AI weights to map the spatial suitability of wind and solar systems. Lastly, the fuzzy linear membership function and the Fuzzy-AND operator were employed to fuzzify and overlay multiple suitability evidences into a meaningful spatiotemporal suitability index. Sensitivity analysis was subsequently performed under three different weighting scenarios to verify the model's performance. Fig. 2 displays a flowchart of the applied methodology, which is discussed in detail in the following subsections.

3.1. Data acquisition and preparation

3.1.1. Thematic layers of spatial criteria

This study adopted 13 criteria for evaluating the spatial suitability of wind and solar systems based on a literature review and expert opinions (Doorga et al., 2022; Elkadeem et al., 2022; Sachit et al., 2022b). Accordingly, technical factors such as air temperature (AT), solar radiation (SR), and cloud index (CI) were deemed essential for the spatial suitability mapping of solar systems. While in the case of spatial modeling of wind farms, wind speed (WS) and wind density (WD) were considered. Elevation (E), slope (S), landcover (LC), proximity to grid (PG), proximity to road (PR), proximity to city (PC), population density (PD), and natural disasters (ND) were the other criteria used to assess both types of power sources. These indicators covered various economic, environmental, and social aspects. For a detailed discussion regarding these criteria, consult the literature (Saraswat et al., 2021; Xu et al., 2020).

For investigation purposes at the country level (Iraq), a high-resolution, up-to-date, and reliable geospatial dataset was collected. The primary reliance was on local government resources to gather data for the assigned criteria. In the case of insufficient local data, global open-source databases supported by field verification were considered for comprehensive spatial coverage. The sources and characteristics of the geospatial data considered are explained in Appendix, Table A1.

The collected data were subjected to a set of necessary functions in a GIS environment to prepare thematic layers of the spatial criteria. Firstly, the available raster data were clipped in accordance with the borders of Iraq. Secondly, Euclidean distance analysis was applied to create raster layers for the PC, PR, and PG factors using relevant vector data. Thirdly, the Feature-to-Raster tool was implemented to create a thematic layer for the PD criterion by employing the vector data of city boundaries along with population statistics. Fourthly, the prepared raster layers were resampled to standardize the spatial resolution at 1 km. Lastly, all the resampled layers were normalized by reclassifying each of them into five categories through the natural breaks (Jenks) technique. The rating scores of the classes ranged from 1 to 5 points according to their spatial relevance for the targeted RE system, as illustrated in Table 1. Points 1, 2, 3, 4, and 5 denote very low, low, moderate, high, and very high, respectively. Meanwhile, a score of 0 was assigned to the restricted categories. Essentially, the higher the category of a particular cell, the higher its suitability. The thematic maps of spatial criteria over Iraq are presented in Fig. 3.

3.1.2. TCI

Energy complementarity is the ability of two or more energy sources to work synergistically in complementing and improving electricity generation (Yan et al., 2020). TCIs determine the feasibility of using

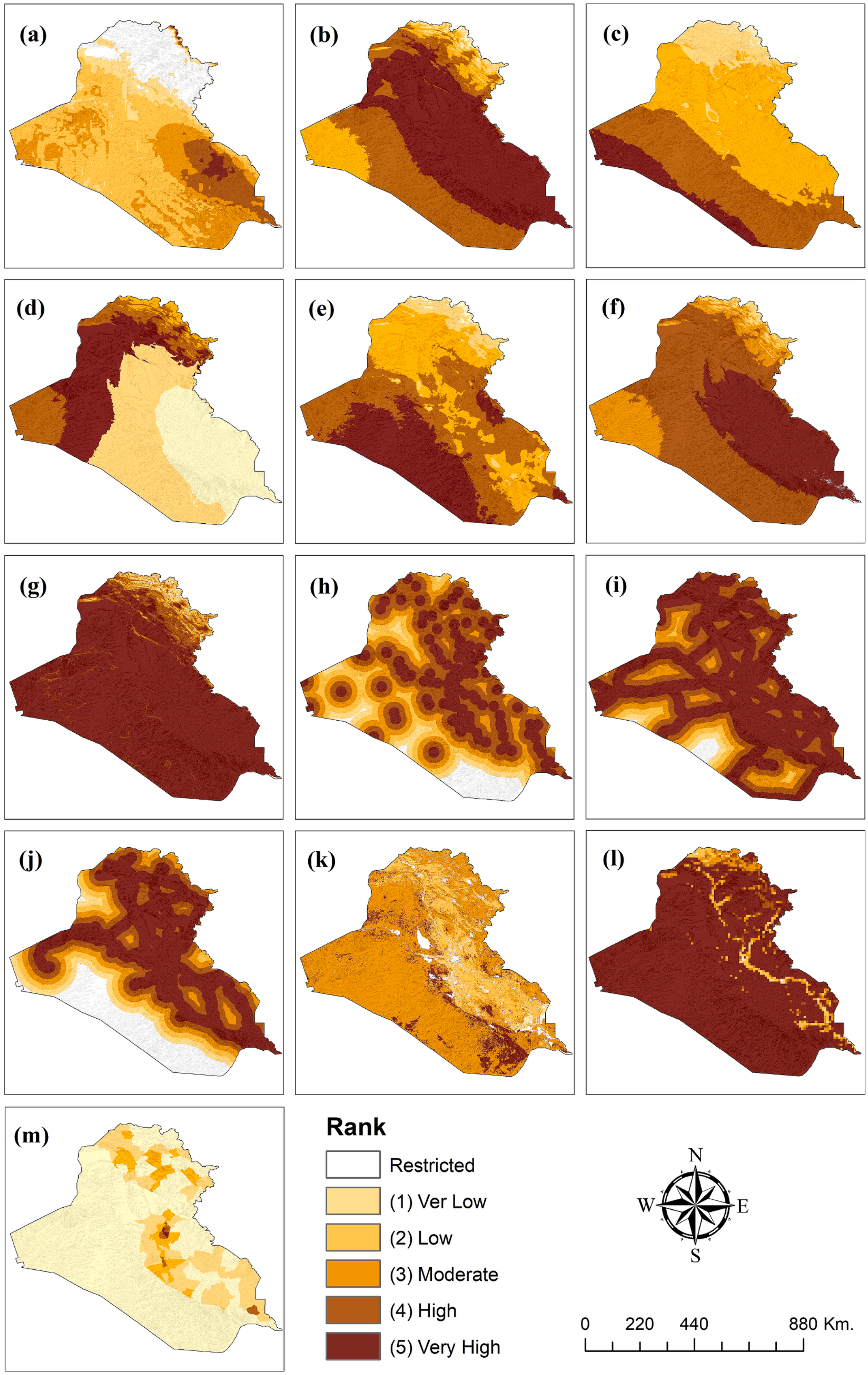


Fig. 3. Thematic maps of spatial criteria over Iraq: (a) WS, (b) WD, (c) SR, (d) AT, (e) CI, (f) E, (g) S, (h) PC, (i) PR, (j) PG, (k) LC, (l) ND, and (m) PD.

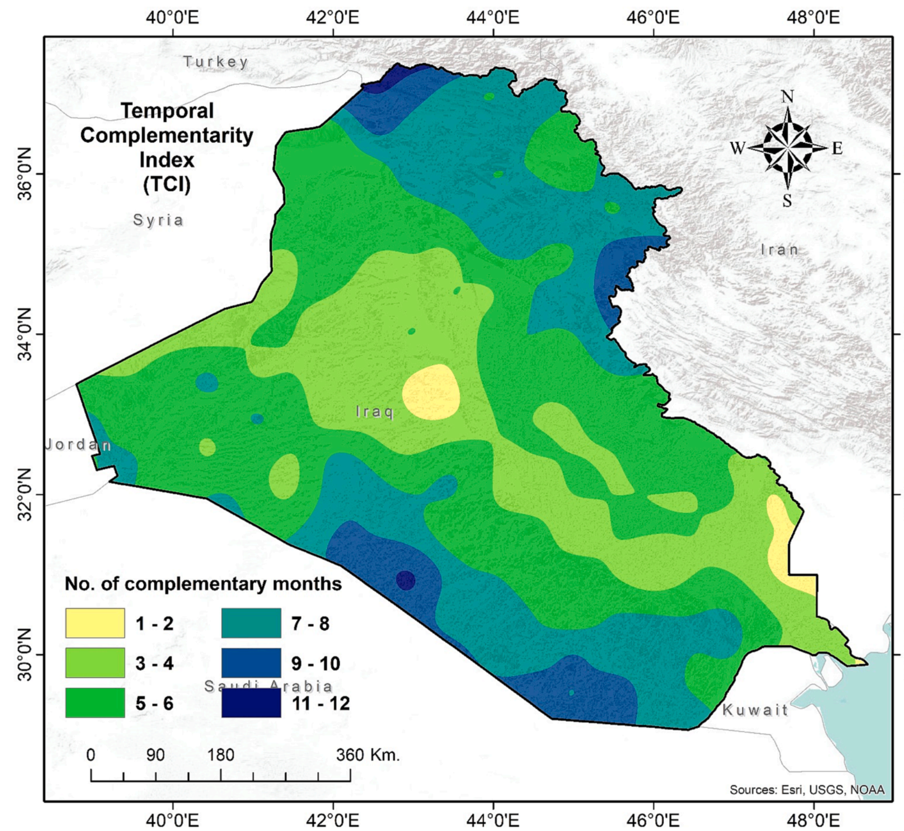
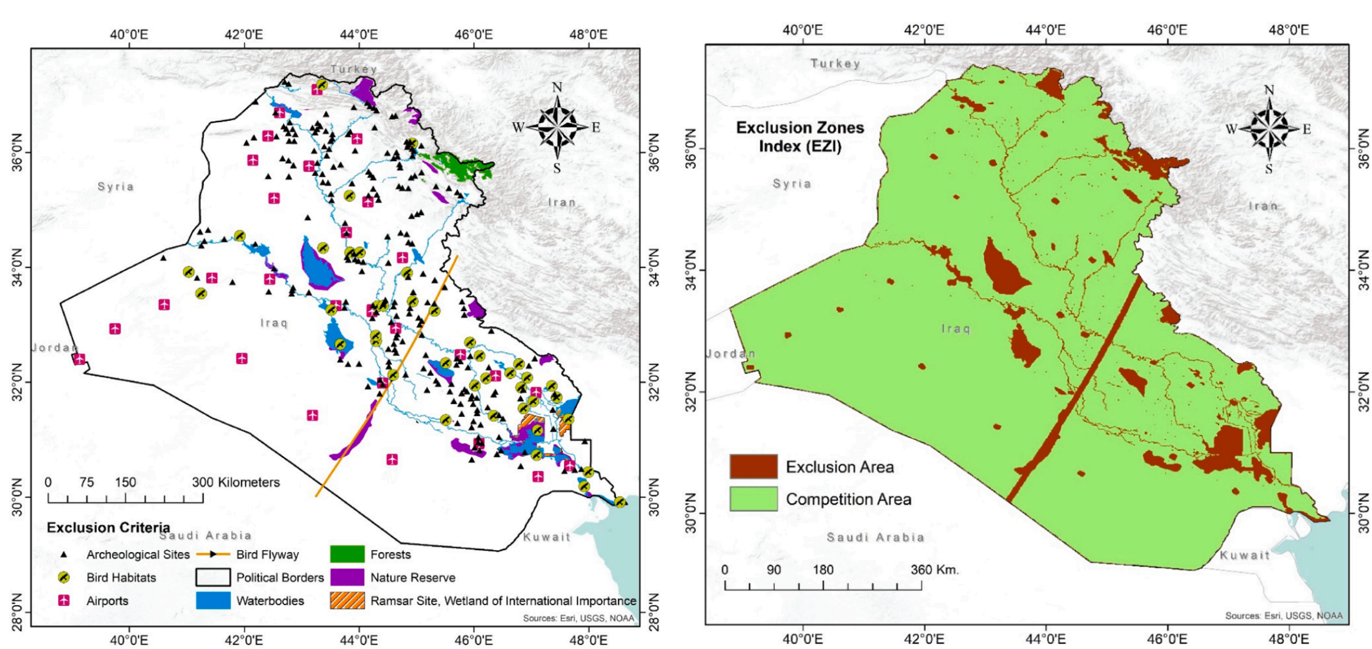


Fig. 4. TCI between wind and solar energy resources over Iraq.



(a) (b)

Fig. 5. (a) Spatial distribution of the exclusion criteria under consideration and (b) raster layers of EZI.

wind and solar energy resources together in a specific region and time and help identify potential sites for the installation of hybrid generation systems (Gallardo et al., 2020). The monthly synergistic patterns between wind and solar resources (i.e., WS and SR) across the entire Iraqi territory were recently investigated by (Sachit et al., 2022a). The results of this investigation were adopted in the TCI formulation for the current study. The assumption behind the considered TCI was that a place where the WS behavior is opposite to the SR behavior across time series is highly suitable for hosting hybrid wind-solar plants. The TCI map, which shows the number of months in a year that exhibit complementary

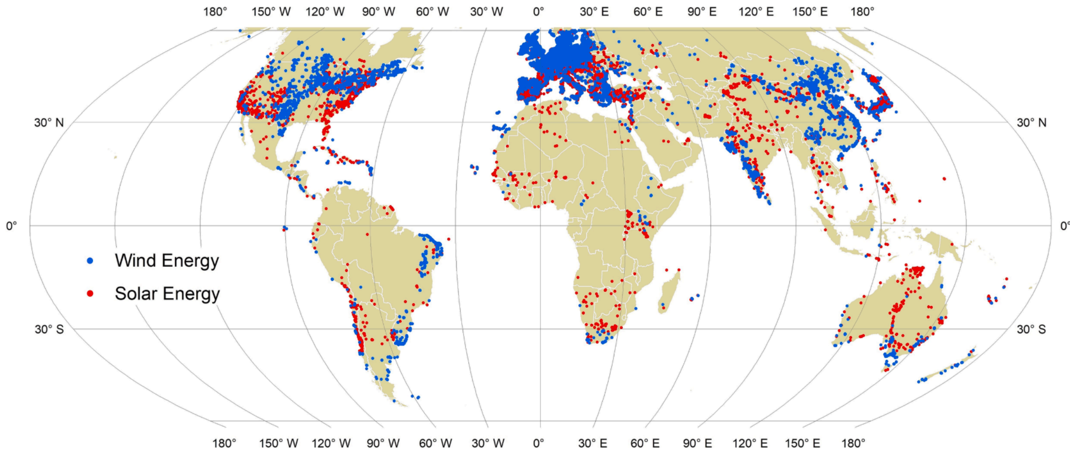


Fig. 6. Locations of wind and solar energy facilities around the globe.

behavior between solar and wind energy, is displayed in Fig. 4.

3.1.3. Exclusion zone index (EZI)

Several locations are considered unsuitable for installing power equipment, often due to environmental and security restrictions rather than a lack of evaluation indicators. This study addressed eight exclusion criteria based on previous studies and the availability of relevant data. The criteria covered airports, archeological sites, bird flyways, bird habitats, forests, political borders, protected areas, and waterbodies, as presented in Fig. 5a. Data for exclusion factors were compiled from local official sources, as listed in Appendix, Table A2.

To prepare an EZI map, a set of restrictive thresholds was imposed using the Buffer tool in ArcGIS software. Setback distances of 0.5 and 0.75 km were used around the water bodies and the protected areas, respectively. A threshold of 3 km was applied surrounding the airports. A 5 km-wide corridor was assigned for the migratory bird flyways. Moreover, an exclusion distance of 1 km was used around the rest. Finally, rasterization was implemented via the Feature-to-Raster tool to convert the vector format of the created thresholds into a raster layer with a discrete data type, as shown in Fig. 5b.

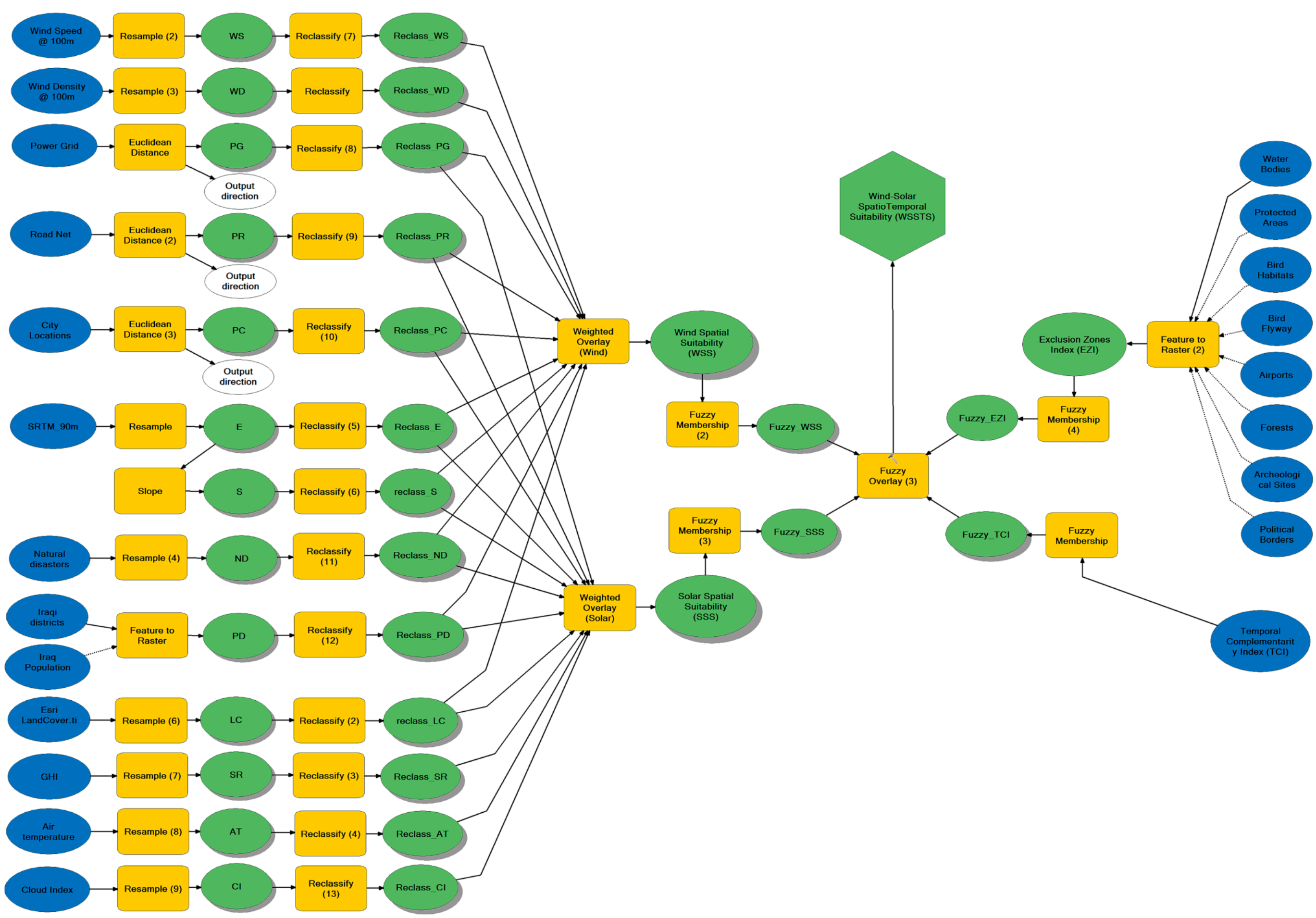


Fig. 7. Workflow and tools incorporated into the ArcGIS ModelBuilder.

3.2. AI modeling

AI-based modeling allows systems to learn and enhance performance from experiments without using explicit instructions. Essentially, AI algorithms are given the ability to make predictions by capturing the behavior of features in real-world environments. The contribution of each feature to the formulation of predictive outcomes can then be reliably measured. In this paper, the RF algorithm was considered because of its high performance in spatial suitability mapping of solar and wind energy systems (Sachit et al., 2022b; Shahab and Singh, 2019).

3.2.1. RF algorithm

The RF algorithm is an advanced decision tree model that operates by fusing a number of decision trees into a single structure known as a forest (Al-ruzouq et al., 2019). Given the lack of RE experiences in developing countries, including Iraq, this study considered wind and solar energy facilities around the world as training samples for the RF algorithm. Accordingly, the locations of 31,571 onshore wind farms and 24,048 solar photovoltaic (PV) farms worldwide were gathered using an open-access spatial database on Figshare titled "global wind solar 2020″ (Dunnett et al., 2020), as shown in Fig. 6. For each training sample, the values of independent variables (the spatial criteria under consideration for this study) were obtained from the global thematic maps prepared by (Sachit et al., 2022b).

The necessary preprocessing of the global geospatial dataset, involving cleaning, balancing, normalizing on a fuzzy scale of 0–1, and data splitting into a 70 % training set and a 30 % test set, was successfully executed. The RF algorithm was modeled using the Python programming language with the scikit-learn package (http://scikit-learn.org), in which the model's hyperparameters were carefully fine-tuned to achieve the highest accuracy. Combined with the scikit-learn defaults (Pedregosa et al., 2011), the RF model performed best when trained on 100 trees with a maximum depth of 5.

3.2.2. SHAP algorithm

SHAP, developed by Shapley (Shapley, 1953), is one of the most popular explainable AI algorithms. It estimates the direction and magnitude of each feature contributing to the AI models' development, helping humans better understand the models' output (Dikshit and Pradhan, 2021). Such merits have recently been harnessed to measure the participation and impact of attributes in formulating AI models' outcomes (Dikshit and Pradhan, 2021; Matin and Pradhan, 2021). In accordance with Equation (1), the Shapley values were calculated by averaging the marginal contribution for all possible parameter combinations (Matin and Pradhan, 2021).

$$\varnothing_i = \sum_{S \subseteq N\{i\}} \frac{|S|!(n - |S| - 1)!}{n!} [v(SU\{i\}) - v(S)], \tag{1}$$

where $\varnothing_i$ denotes the contribution of criterion i, N is the set of all criteria, n refers to the number of criteria in N, S is any subset of N that does not include criterion i, and v (N) is the base value indicating the expected output for each criterion in N. This research applied Tree SHAP, a variant of SHAP developed for tree-based AI models, to interpret the RF model mentioned earlier. This explanation estimates the global weights of the spatial criteria under consideration for both wind and solar power systems.

3.3. GIS modeling

This study involved the application of a set of weighted and fuzzy overlays along with supporting tools in an ArcGIS ModelBuilder environment, as illustrated in Fig. 7.

3.3.1. Weighted overlay

The weighted overlay is a technique for analyzing suitability in a GIS environment that relies on WLC. This method is frequently used to solve issues involving site selection, resource evaluation, and land-use suitability analysis (Abdulhasan et al., 2019). In WLC, the discrete and continuous attributes that contribute to the solution are aggregated (Tercan et al., 2021). Therefore, normalizing the criteria into a common scale is a necessary step toward a successful overlay. Thereafter, the standardized criterion layers multiplied by their assigned weights are combined on the basis of Equation (2) (Romano et al., 2015).

$$S_i = \sum_{j=1}^{n} w_j x_{ij}, \tag{2}$$

where S_i refers to the suitability index for cell i, w_j means the weightage of criterion j, x_{ij} is the normalized score of cell i for criterion j, and n denotes the total number of factors.

In this study, the reclassified factors under consideration along with their AI-based weightings were incorporated into the weighted overlay tool within ArcGIS ModelBuilder. The procedure was applied twice. In the first phase, 10 criteria related to site suitability assessment for onshore wind stations, namely, WS, WD, S, E, LC, PR, PG, PC, ND, and PD, were overlaid. Meanwhile, 11 criteria, namely, RR, AT, CI, S, E, LC, PR, PG, PC, ND, and PD, were allocated in the second stage to search for optimal places to deploy solar PV cells. These overlays generated 1 km resolution raster maps of wind spatial suitability (WSS) and solar spatial suitability (SSS) indices across Iraq. In each map, the degree of suitability was also categorized into five classes using the equal interval classification method: very low (0.0–0.2), low (0.2–0.4), moderate (0.4–0.6), high (0.6–0.8), and very high (0.8–1.0).

3.3.2. Fuzzy overlay

The fuzzy overlay is a robust GIS-based spatial analysis in which the possibility of a phenomenon belonging to multiple input sets is investigated in a multilayer overlay analysis (Baidya et al., 2014). The fuzzy overlay was implemented in this study to fuse diverse suitability indices, including WSS, SSS, TCI, and EZI, into a unique index of wind-solar spatiotemporal suitability (WSSTS). Accordingly, the crisp input layers were fuzzified to a fuzzy scale of 0–1 using the fuzzy linear membership function described in Equation (3). The Fuzzy-AND operator was then executed to combine the fuzzy layers on the basis of minimum values. Finally, the defuzzification of suitability outputs was performed in accordance with easily interpretable suitability categories.

$$f(x) = \left\{ \begin{array}{c} 0, x < a \\ \dfrac{x-a}{b-a}, a < x < b \\ 1, x > b \end{array} \right\} \tag{3}$$

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

3.4. Sensitivity analysis

Sensitivity analysis is increasingly recognized as an effective and widely applied method for addressing uncertainty and verifying the reliability of developed spatial suitability models (Rediske et al., 2020). Typically, it involves manipulating criterion weights or removing specific factors, resulting in new outputs that could be compared with the original suitability findings. In this study, sensitivity analysis was conducted considering of three different scenarios, as shown below:

1. Equal weighting scenario: The same weights are assigned to all criteria under consideration.
2. High weighting scenario: Zero weight is allocated to the most important criteria.
3. Low weighting scenario: Zero weight is allocated to the least important criteria.

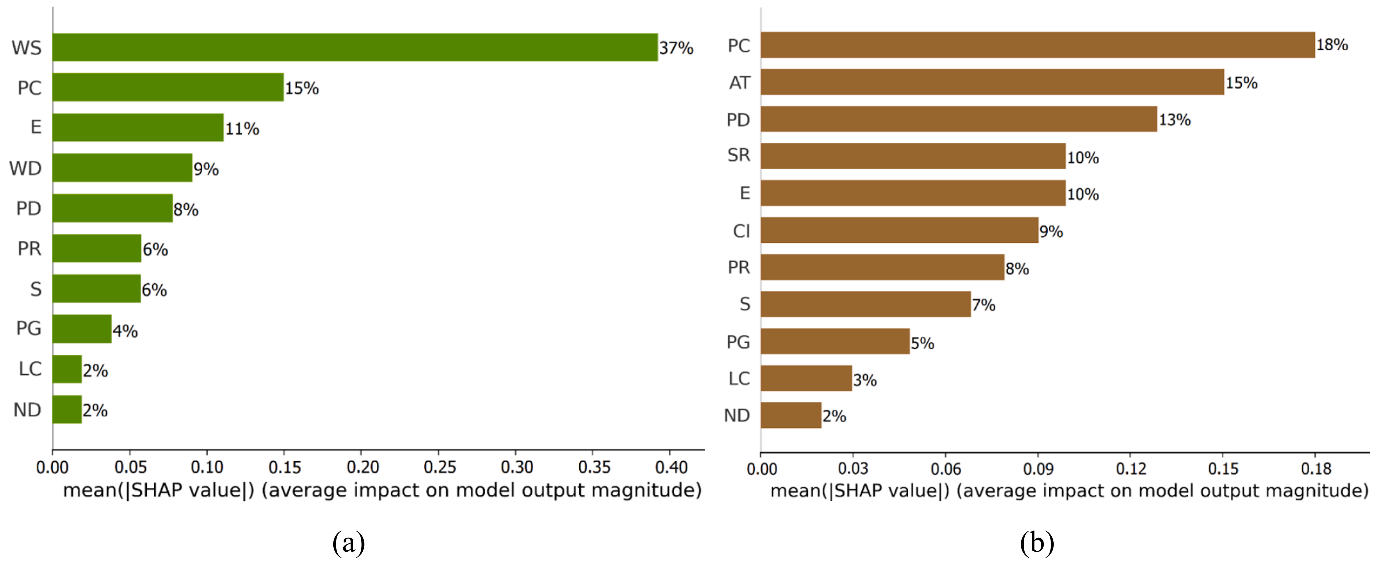


Fig. 8. AI-based weights for the spatial criteria under consideration for (a) wind energy and (b) solar energy.

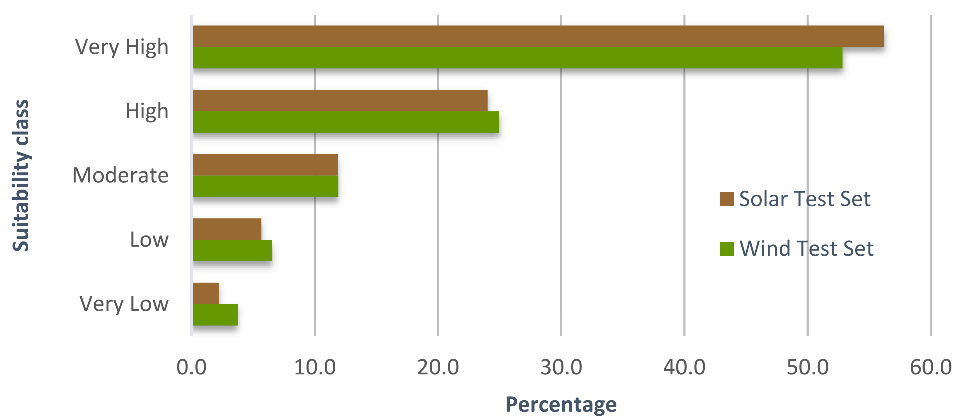


Fig. 9. Percentages of spatial suitability categories for the global test set of wind and solar farms.

In scenarios (2) and (3), all remaining parameter weights were proportionally adjusted to ensure a cumulative weight of 100. The new weights were then individually input into the weighted overlay tool to produce new spatial suitability maps comparable to the original ones. Finally, a pixel-over-pixel comparison was applied to compute the percentage change in the classification results.

4. Results and discussions

4.1. Criterion weights

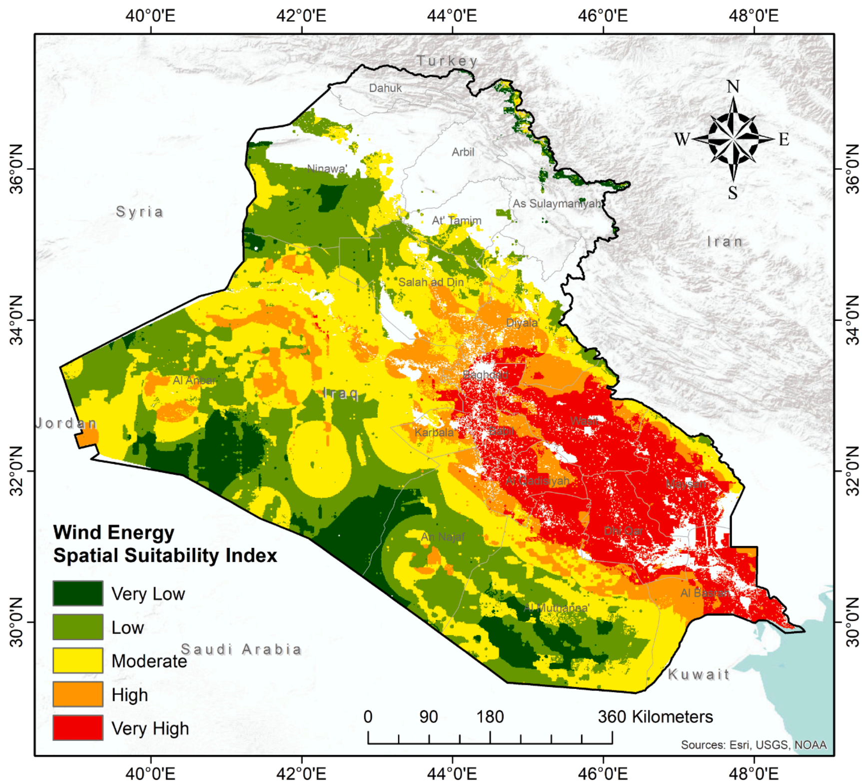
The AI techniques applied in this study (i.e., RF and SHAP) act as promising alternatives to traditional weighting methods. The RF model demonstrated high performance in classifying the geospatial dataset of wind and solar plants with an area under the receiver operating characteristic curve (AUC) of 0.96 and 0.95, respectively. The SHAP model's interpretations of measuring relative weights of each spatial criterion within the RF modeling are presented in Fig. 8. Among the spatial criteria of wind energy, WS achieved the highest weight with 37 %, followed by PC with 15 %. Meanwhile, PC and AT ranked first and second in the weighting of solar energy criteria, with 18 % and 15 %, respectively. In contrast, environmental factors received the lowest priority in both energy systems. These results highlight the significant influence of technical and economic criteria on spatial decision making for wind and solar facilities.

4.1.1. Weights' transferability

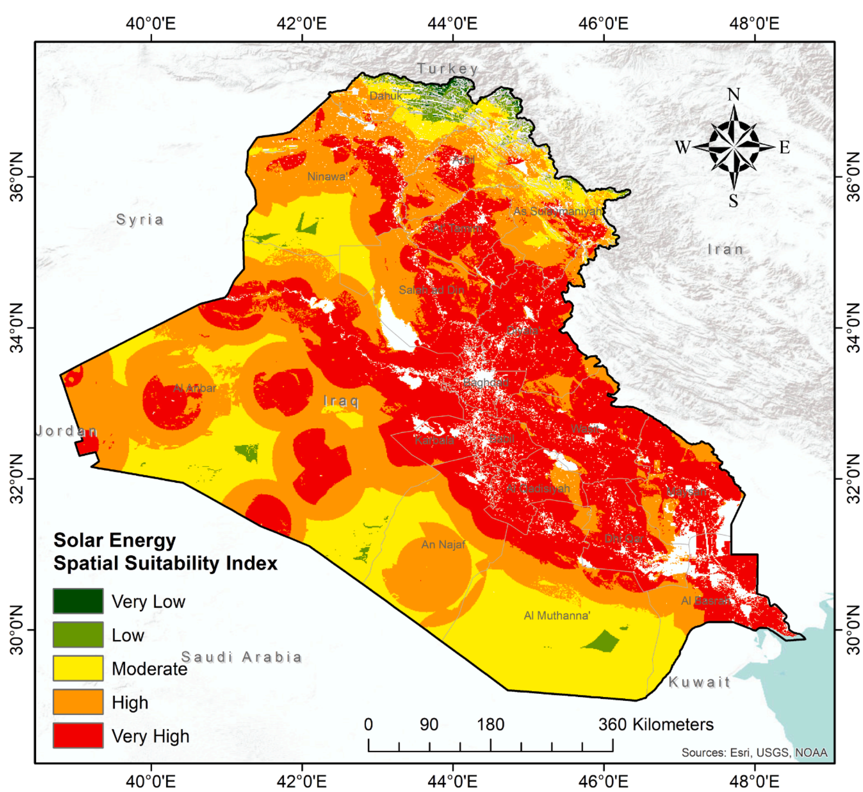
In general, developing an AI model using local data may constrain its generalizability to regions with distinct geographic and climatic characteristics. The distinctive advantage of our proposed method lies in its reliance on comprehensive global data. Nevertheless, in the interest of bolstering confidence in its performance, we conducted a spatial transferability analysis to ascertain the capacity of these model weights to yield dependable predictions across various geographic regions worldwide. For this purpose, the test set of wind and solar power plants worldwide was used as a basis for verification. In other words, we employed the reported weights from the training set (70 %) to calculate the spatial suitability scores for the test set (30 %). Fig. 9 displays the validation results, which are categorized into five suitability levels. The findings demonstrate that approximately 80 % of the test set was classified as having "high" and "very high" spatial suitability to host RE plants, which is consistent with reality. Furthermore, 11 % of the samples under verification were considered to have "Moderate" suitability, whereas the combined percentage of "Low" and "Very Low" suitability classes was 9 %. The aforementioned results highlight the high potential of our weights in predicting site suitability for wind and solar plants globally, granting them the advantage of spatial generalization.

4.2. Single-power system suitability

For the spatiotemporal assessment of wind-solar hybrid energy



(a)



(b)

Fig. 10. Spatial suitability index for (a) wind (WSS) and (b) solar (SSS) over Iraq.

Table 2
Land class statistics for the WSS and SSS indices.

Suitability Class	WSS Index		SSS Index	
	Area (km^2)	**%**	**Area (km^2)**	**%**
(1) Very Low	29,702	6.8	594	0.1
(2) Low	93,181	21.3	5,151	1.2
(3) Moderate	111,096	25.3	90,569	20.7
(4) High	44,005	10.0	141,374	32.3
(5) Very High	56,638	12.9	154,017	35.1
Unclassified	103,695	23.7	46,612	10.6
Total	438,317	100.0	438,317	100.0

farms, site suitability indices for individual wind and solar systems were first formulated, as shown in Fig. 10. The results reported in Fig. 10a indicate that the lands with high and very high suitability for hosting wind farms are distributed in the central and southeastern regions of Iraq, with an area of 44,005 and 56,638 km^2, respectively. Meanwhile, the moderate suitability category covered 25.3 % (~111,096 km^2) of the WSS map, whereas the western and southwestern regions were classified as "low" and "very low," respectively. In the SSS index, the very-high-suitability class dominated 35.1 % of the studied area, followed by the high-suitability class with 32.3 %, as shown in Fig. 10b. These high percentages clearly indicate the promising potential for the exploitation of solar energy in Iraq. About 90,569, 5,151, and 594 km^2 were

Fig. 11. Graphical comparison of the results of the WSS and SSS indices.

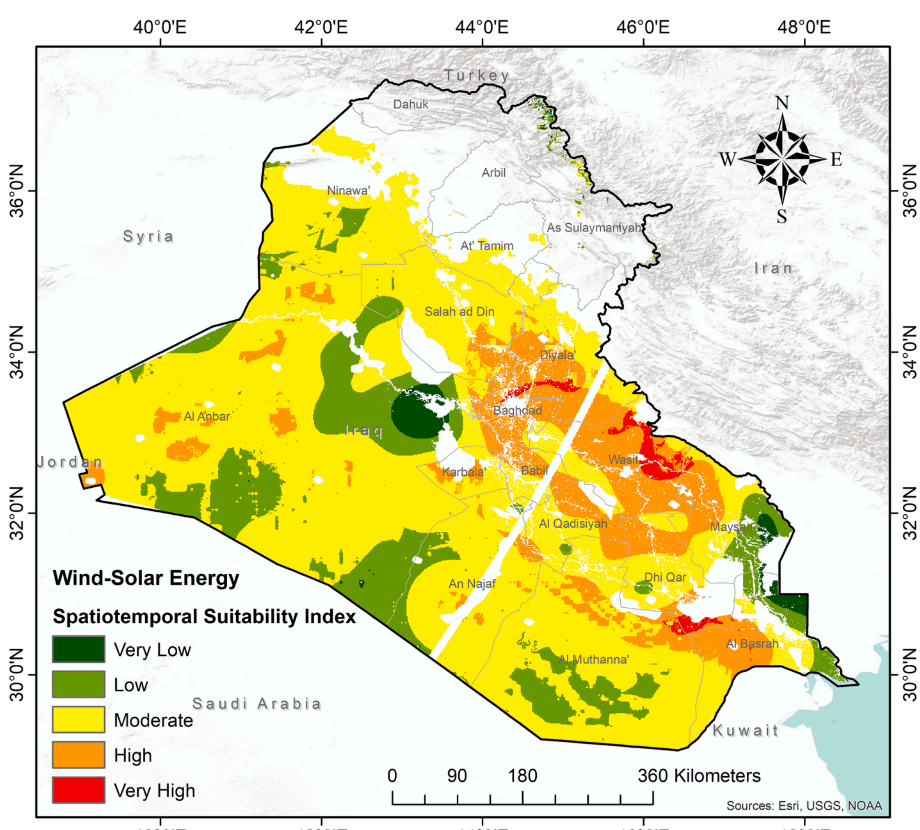


Fig. 12. Spatiotemporal suitability index for wind-solar hybrid systems over Iraq (WSSTS).

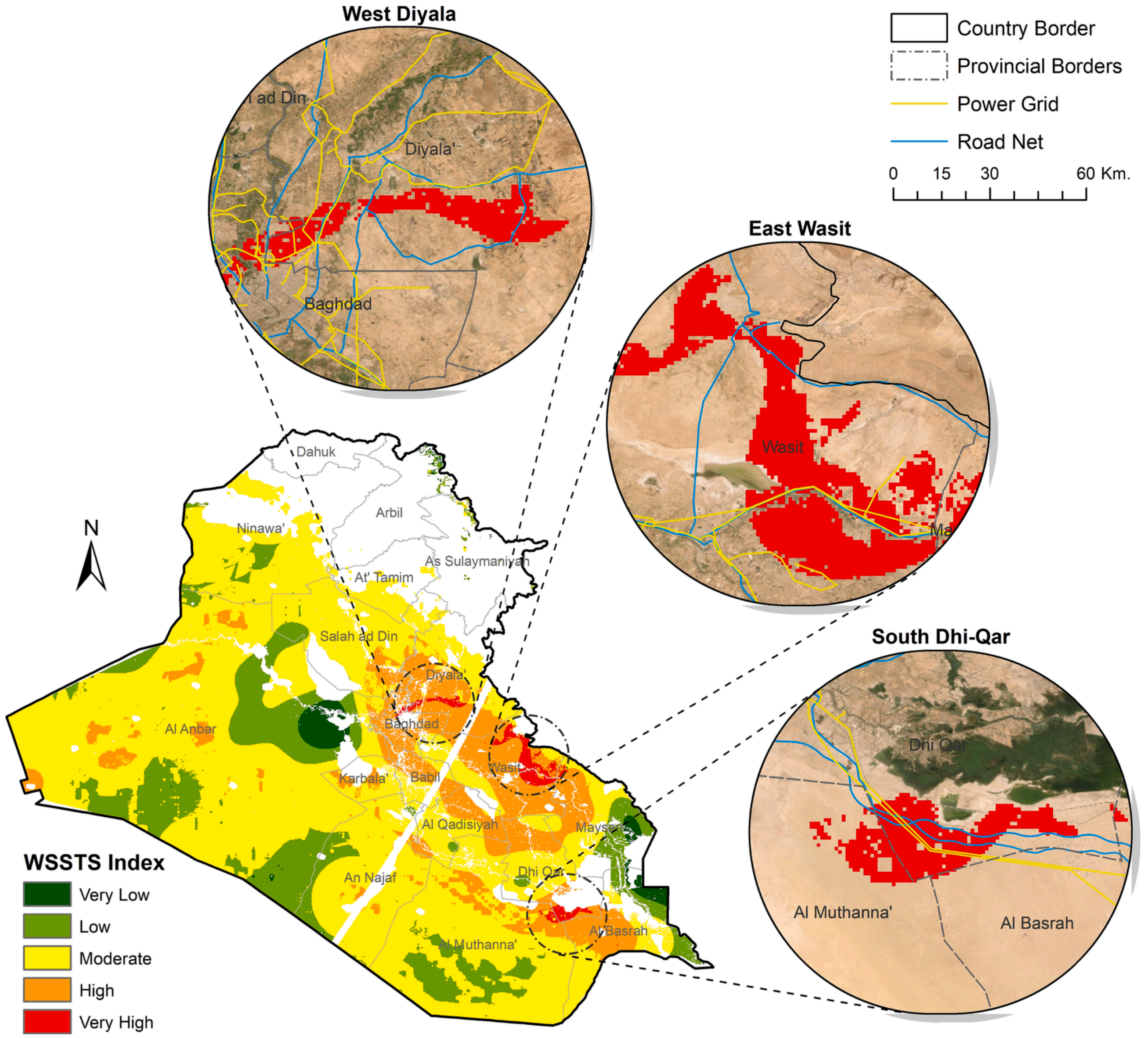


Fig. 13. Hotspots with very high spatiotemporal suitability for hosting wind-solar hybrid plants.

designated as "moderate," "low," and "very low," respectively. Pixels that did not exceed the considered restriction thresholds of the spatial criteria were not classified within any of the five suitability classes, constituting 23.7 % and 10.6 % of the WSS and SSS indices, respectively. Unclassified (unsuitable) areas are mainly found in the northern and northeastern regions of the country, characterized by steep ground slopes and low wind potential (>5 m/s). The WSS and SSS maps' findings and those of earlier local studies are in agreement (Khazael and Al-Bakri, 2021; Mohammed et al., 2020; Rasham and Mahdi, 2018). Table 2 presents the quantitative analysis of the suitability classes, while Fig. 11 compares the results of SSS with those of WSS.

4.3. Dual-power system suitability

The executed fuzzy overlay of the WSS, SSS, TCI, and EZI directories highlighted spatiotemporal opportunities for wind-solar hybrid systems, as shown in Fig. 12. The results demonstrated that the sedimentary plain region (central and southern Iraq) has a promising potential for developing wind-solar farms, in which the "high" and "very high" classes accounted for 11 % (~48,068 km^2) and 0.8 % (~3632 km^2) of the country's territory, respectively. The "moderate" suitability category dominated the majority of the studied land, covering about 47.4 % (~207,893 km^2). Meanwhile, both "low" and "very low" spatiotemporal suitability scores covered 12.4 % of the overall area, whereas 28.4 % of the WSSTS pixels were left unclassified because of the limitations of the evaluation and exclusion criteria.

In comparison with the findings on the WSS and SSS indices, a significant decrease in red pixels (very high suitability) was observed on the WSSTS map. The potential reason for the scarcity of suitable opportunities is the spatial variability of the results across the combined indices. While central and southeastern Iraq have promising prospects on the WSS and SSS indices, these areas revealed low values on the TCI scale. Moreover, regions with high temporal suitability scores on the TCI were accompanied by an absence of infrastructure, as in western Iraq, or low wind speed and steep terrain, as in the north. As a result, few lands in the convergence zones were recorded as having "very high" spatiotemporal suitability for wind-solar farms.

4.3.1. Spatiotemporal hotspots

The WSSTS map highlighted three hotspots with spatiotemporal

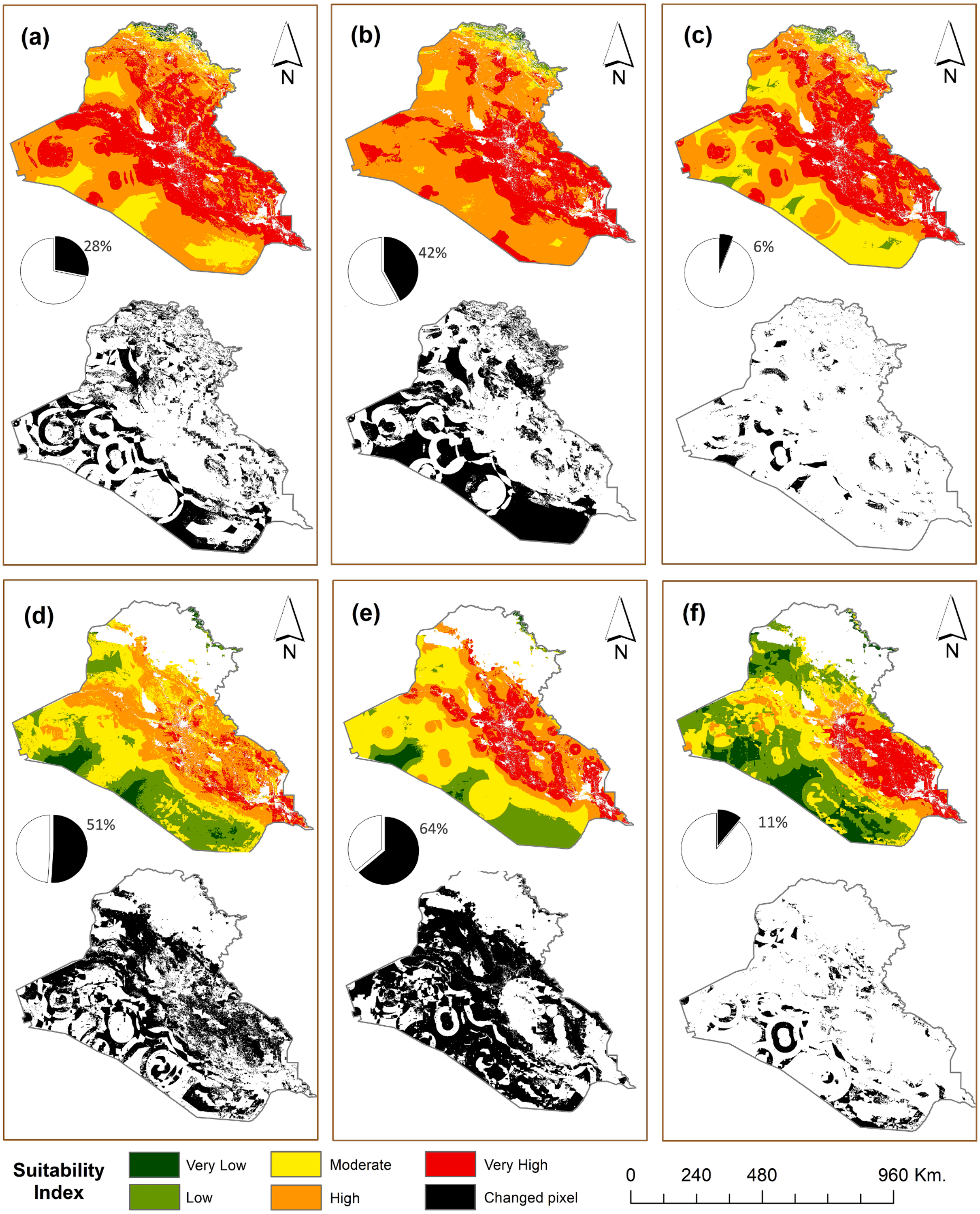


Fig. 14. Sensitivity analysis maps according to (a) scenario-1 of SSS, (b) scenario-2 of SSS, (c) scenario-3 of SSS, (d) scenario-1 of WSS, (e) scenario-2 of WSS, and (f) scenario-3 of WSS.

suitability for wind-solar hybrid systems, namely, South Dhi-Qar, East Wasit, and West Diyala, as presented in Fig. 13. The reason was that these sites exhibit a bountiful harvest of essential renewable resources along with synergistic periods of more than 6 months a year. The three hotspots are also situated in proximity to the infrastructure lines, enhancing the suitability of these sites for deploying wind turbines and solar panels side by side. Moreover, the proper land cover type and the gentle land slopes in these areas provide a suitable environment to accommodate construction. The areas of South Dhi-Qar, East Wasit, and West Diyala are ~780, ~2,166, and ~649 km^2, respectively.

4.4. Model validation

4.4.1. Sensitivity maps

Fig. 14 presents the sensitivity scenario maps considered and their pixel-over-pixel comparisons with the original suitability map for the WSS and SSS indices. The results showed that when the equal weighting scenario was applied, 51 % of the wind map's pixels switched suitability

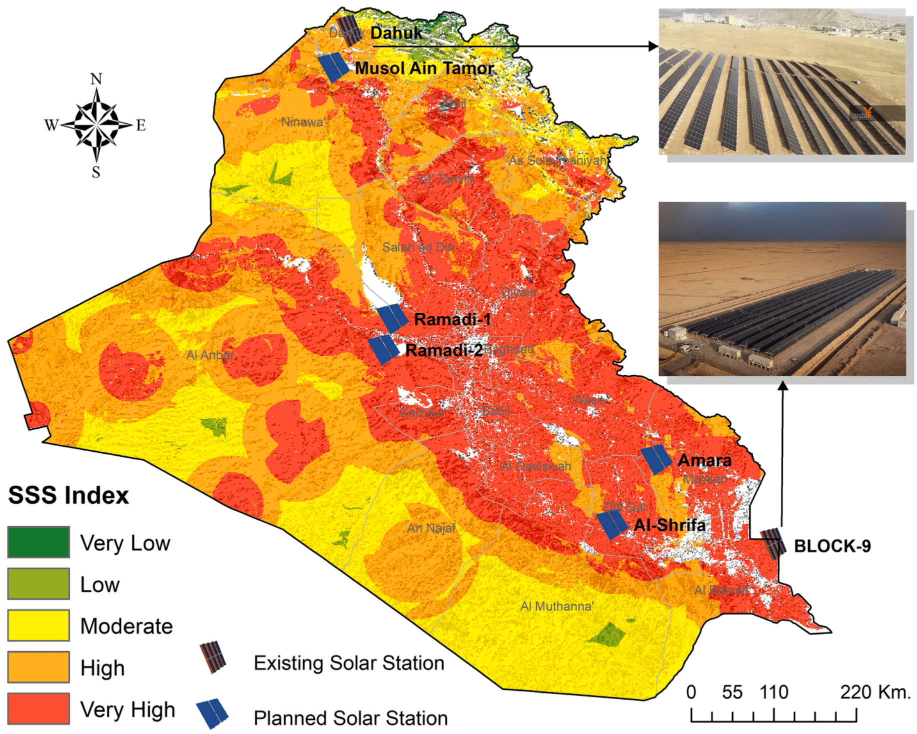


Fig. 15. SSS index validation with existing and planned solar energy projects.

classes, whereas only 28 % of the solar map's pixels were sensitized to changing weights. The "high" and "very high" suitability categories expanded notably in both the wind and solar suitability indices compared with other classes that receded. In the high weighting scenario, the sensitive pixels in the wind map increased by 64 %, and the "very high" class started to cluster around city centers. These results are consistent with the modifications made to the criterion preferences for this scenario, where the weight of WS was eliminated and the weight of PC was increased. Similarly, the solar map exhibited significant changes in suitability degrees. Withholding the importance of PC, many remote areas over Iraq showed "high" and "very high" levels of suitability for hosting solar farms. In the low weighting scenario, the sensitivity maps yielded low change rates of 11 % and 6 % for wind and solar, respectively. Similar spatial distribution patterns were observed for the suitability classes compared with the original suitability maps (AI-based weighting). The low sensitivity in this case can be attributed to the unimportant weights of the canceled criteria. The aforementioned results evidently indicate that the presented spatial suitability model is sensitive to any weight manipulation, with each addressed criterion influencing the evaluation of the study area.

4.4.2. Field verification

Recently, Iraq has established two solar plants, Block 9 (2.5 MW) and Dohuk (2 MW), and launched investment contracts for five large-scale solar farms in various places throughout the country: Musol Ain Tamor, Ramadi-1, Ramadi-2, Amara, and Al-Shrifa. For field verification, the locations of these stations were compared with the SSS index, as illustrated in Fig. 15. The comparison revealed that the existing and planned PV solar installations have "high" and "very high" suitability scores on the GIS maps, indicating that these are indeed suitable sites for development. As Iraq has not yet initiated investments in wind power, there is no real-world experience available for direct comparison with the WSS index. However, in discussions with experts, most indicated that the WSS map is clear, logical, and consistent with previous research findings.

To validate the WSSTS index, field reconnaissance was conducted in the hotspots: South Dhi-Qar, East Wasit, and West Diyala. These places were explored through field studies, including a survey of local residents' attitudes to ensure acceptance of such projects or to help design a modern structure that blends into the landscape. Fig. 16 presents the landscapes observed at representative points within these regions. In the South Dhi-Qar region, several favorable characteristics for developing wind-solar hybrid systems were noted. The land there is barren with few farms and settlements (Fig. 16a), which makes the establishment of RE plants less destructive to the environment and landscape. The highway leading to Iraqi ports runs through the region, facilitating the shipment of wind and solar equipment. Moreover, the South Dhi-Qar hotspot is located between Basra and Nasiriyah—the third and fourth most populated cities, respectively. Thus, a substantial number of people will have access to reliable electricity and stable employment if such projects are built here.

The second hot zone (East Wasit) extends from Sheikh Saad, southeast of Wasit governorate, to Badra, northeast of the province. The Tigris River separates the northern and southern halves of the region. On the basis of the site visits and the review of satellite images, fertile soils and crop fields were identified in the southern part, as illustrated in Fig. 16b. In comparison, gravelly soil and grassy landscapes were the dominant patterns in the areas north of the Tigris. Through discussions with local people in the southern part, many farmers expressed their displeasure with RE equipment being spread across their fields. In contrast, residents of the northern part expressed favorable attitudes regarding the development of their communities with sustainable energy investments. As for the West Diyala hotspot, our observations documented a mix of crop fields and shrub landscapes (Fig. 16c). This region is the smallest in size compared with other hotspots. Nonetheless, its proximity to Baghdad, Iraq's capital city, presents excellent possibilities for planning clean energy projects that can meet the needs of an important portion of the city. The aforementioned verification confirms the validity of our results for practical applications.

Fig. 16. Landscape reconnaissance at representative points within (a) South Dhi-Qar, (b) East Wasit, and (c) West Diyala.

5. Conclusions

Introducing a GeoAI-based STDM model for hybrid wind-solar facilities and applying it to the context of Iraq were the primary objectives of this study. The AI modeling highlighted the importance of technical and economic considerations in mapping the spatial suitability of RE systems. WS and PC were the most significant criteria, weighing 37 % and 18 %, respectively. The WSS and SSS indices led us to conclude that Iraq's middle and southeastern regions have promising spatial opportunities for investment in both wind and solar energy, with a total area of 46,101 km^2. Meanwhile, the WSSTS evidence established that only 3632 km^2 of land distributed across southern Dhi-Qar, eastern Wasit, and western Diyala had a "very high" spatiotemporal suitability for deploying wind-solar hybrid equipment. Furthermore, the sensitivity analysis and field verifications confirmed the high performance of our model, affirming the validity of the reported results for real-world practices.

The current study's contribution lies in providing a robust and efficient platform for selecting ideal installation sites that satisfy the temporal and spatial characteristics of RE farms. As the cost of investing in RE continues to drop, the current results could potentially encourage decision-makers and stakeholders to initiate new investments in the green energy sector to meet the rising electricity demand and mitigate global warming. This work is the first spatiotemporal suitability assessment of wind-solar hybrid systems throughout the entirety of Iraq. Therefore, this study will be helpful for local authorities in the energy planning process and land management prioritization. However, the Iraqi government is required to create an appealing investment environment for RE projects, especially in the hotspots highlighted in this study. The hindrances posed by bureaucracy and regulatory obstacles to wind and solar facility development in Iraq can be overcome through the formulation of a comprehensive national strategy for alternative energy. This strategy should outline clear objectives, priorities, and timelines, streamline procedures and regulations, offer financial and tax incentives to investors, and leverage expertise by fostering collaboration with international RE organizations.

To support sustainable development efforts in developing countries such as Iraq, more intensive investigation utilizing detailed geospatial data is urgently required to improve the exploration of ideal sites for RE installations. To further our research, the proposed approach is recommended to be applied at the micro level in certain districts of the country. A limitation of this study is that the proposed STDM model has only been applied to onshore wind and solar PV systems. As another potential avenue for future research, the presented approach could be adapted to address offshore wind and concentrated solar power installations in Iraq and Globally.

CRediT authorship contribution statement

Mourtadha Sarhan Sachit: Conceptualization, Methodology, Data curation, Investigation, Formal analysis, Validation, Writing – original draft, Writing – review & editing, Visualization, Resources. **Helmi Zulhaidi Mohd Shafri:** Conceptualization, Formal analysis, Project administration, Software, Validation, Writing – original draft, Writing – review & editing, Supervision. **Ahmad Fikri Abdullah:** Writing – review & editing, Supervision. **Azmin Shakrine Mohd Rafie:** Writing – review & editing, Supervision. **Mohamed Barakat A. Gibril:** Investigation, Writing – original draft, Writing – review & editing, Visualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix

Table A1. Sources of the Iraqi dataset used in preparing the thematic layers of evaluation criteria

Evaluation Criterion	Data Provider	Format	Access Link	Access Date
WS	Iraqi wind atlas from GEOSUN	Raster	https://www.breasc.com/en/	20 September 2022
WD	Global Wind Atlas 3.1, aided by IMS	Raster	https://globalwindatlas.info/	15 December 2022
SR	Global Solar Atlas v2.6, aided by IMS	Raster	https://globalsolaratlas.info/map	16 December 2022
AT	Global Solar Atlas v2.6, aided by IMS	Raster	https://globalsolaratlas.info/map	16 December 2022
CI	EarthEnv project aided by IMS	Raster	https://www.earthenv.org/cloud	2 January 2022
E	SRTM	Raster	https://earthexplorer.usgs.gov/	14 June 2022
S	Derived from DEM of SRTM	Raster	https://earthexplorer.usgs.gov/	14 June 2022
PC	Iraqi General Authority of Survey	CSV	https://mowr.gov.iq/en/general-survey-authority/	17 July 2022
PR	Iraqi General Authority of Survey	Vector	https://mowr.gov.iq/en/general-survey-authority/	17 July 2022
PG	Iraq Energy Institute	Vector	https://iraqenergy.org/	28 July 2022
LC	Esri	Raster	https://livingatlas.arcgis.com/landcover/	18 January 2022
ND	UNISDR	Raster	https://preview.grid.unep.ch/	14 February 2022
PD	Iraqi Central Statistical	CSV	https://cosit.gov.iq/en/	6 August 2022

Table A2. Sources of the Iraqi dataset used to identify the exclusion areas

Exclusion Criterion	Data Provider	Format	Access Link	Access Date
Airport	Iraqi General Authority of Survey	CSV	https://mowr.gov.iq/en/general-survey-authority/	17 July 2022
Archaeological Sites	Iraqi directorate of antiquities	Vector	http://mocul.gov.iq/index.php	24 July 2022
Bird Flyway	The globe of bird migration	Vector	http://globeofbirdmigration.com/	3 August 2022
Bird Habitats	CIUCN Report, Iraqi ministry of environment	CSV	http://moen.gov.iq/	7 August 2022
Forests	Iraqi ministry of environment	Raster	http://moen.gov.iq/	12 August 2022
Political Borders	Iraqi General Authority of Survey	Vector	https://mowr.gov.iq/en/general-survey-authority/	17 July 2022
Protected Areas	The World Database on Protected Areas (WDPA)	Vector	https://www.protectedplanet.net/en/thematic-areas/wdpa?tab=WDPA	6 July 2022
Waterbodies	Iraqi General Authority of Survey	Vector	https://mowr.gov.iq/en/general-survey-authority/	17 July 2022

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