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Research paper

Risk-based multi-criteria decision analysis of gas power plants placement in semi-arid regions

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ABSTRACT

The purpose of this research is to determine the optimum location to construct gas power plants (GPPs) in semi-arid regions. A combination of ordered weight averaging (OWA) and analytic hierarchy process (AHP) method named OWA-AHP is utilized to prepare land suitability maps with different risk scenarios when fuzzy method is to homogenize inputs. In the proposed method, AHP is to weigh each different parameter while OWA considers risk levels. In order to validate the accuracy of the proposed method, the receiver operating characteristics (ROC) curve is investigated. Besides, the self-organizing map (SOM) algorithm and Pearson correlation are used to determine the most important parameters for constructing GPP. According to obtained results, the areas located in the north and parts of the east and south of the selected case study (about 15%) at all risk levels are the optimum areas to be hosted for GPPs. Furthermore, ROC curve shows that the Area Under the Curve (AUC) values are high for both AHP and OWA-AHP methods (AUC Fuzzy-AHP = 94.0%, AUC OWA = 89.0%). The results of the SOM algorithm and Pearson correlation with high accuracy (R_{Model1}: 0.853 and R_{Model2}: 0.940) also depict that distance to the pipeline and road are the most important parameters to identify suitable locations for GPP.

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1. Introduction

The electricity industry is dynamic and effective due to its infrastructural role and close relationship with parameters affecting economic and industrial growth; therefore, increasing its efficiency and productivity is extremely important. The power generation sector is power plants, which are the most important capital in the electricity industry. The average gas power plants are from 33% to 38% depending on the type and duration of the operation (Shu Frank, 2008; Muckerheide, 2005).

Electrical energy is considered a major contributor to the economic prosperity of a country, social welfare, and both industrial and agricultural development, therefore playing a significant role in the life of the modern human being. Among the many countries affected by the ever-increasing growth in population, Iran is currently faced with a colossal demand for electric energy given the massive rises in per capita energy consumption, further intensified through developments in industrial and agricultural sectors. To meet these demands, officials must and do take into consideration certain plans for predicting and subsequently handling future loads on the supply network for electric energy. The infrastructure of these supply networks is built upon power plants, that play a prime role in the transfer and distribution of energy. Establishing new and improved power plants could very well ameliorate the current state of the supply networks (Li et al., 2021; Zhang and Wang, 2020).

Depletion of fossil fuels, dangers of nuclear power plants, near-exponential growth of the demand for fossil fuels in industrial uses (particularly in countries closing in on becoming industrialized), obligations towards saving and adapting to the environment, controlling air pollution and the green-house effect are among the ingredients of escalations in global trends towards investments in renewable energies. On the other hand, the rather swift motion of time forewarns of the potential calamities evoked by the exhaustion of non-renewable sources of energy. Thus, it is of utmost importance that measures be taken to build new power plants run on renewable energy, which, of course, would require accurate positioning to optimize cost-effectiveness (Bolinger and Wiser, 2005; Sánchez-García et al., 2017; Demirel, 2012; Coro and Trumpy, 2020; Marques-Perez et al., 2020).

This issue is further highlighted in countries such as Iran due to their peculiar geographical situation in conjunction with the rather dispersed arrangement of cities and rural settlements in

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these countries. Operating on renewable energies and finding suitable locations for establishing new power plants is one of the foremost approaches to generating energy as opposed to other forms of transferring energy to rural sectors and margins of the country, which are accompanied by sizeable expenses in terms of transportation, maintenance, and similar procedures. This highlights the significance of finding appropriate sites for constructing power stations. Several studies have previously investigated the affecting parameters on locating suitable sites for GPP (Alavipoor et al., 2016a). GIS is used by Klassen and Marjerrison (2002) to locate coal-fired power plants and by Delaney and Lachapelle (2003) to locate wind turbines. Recently researchers have used different GIS-based methods to determine land suitability maps to GPP.

Among other candidates, the AHP method divides the process of decision making into different stages of objective, criteria, subcriteria, pairwise-comparison, and finally selection of the optimal option. Despite the commonality and prevalence of the analytical hierarchical process (AHP) model in the past few decades (Saaty, 1980), it does suffer from certain limitations that have encouraged a search for newer algorithms. These pursuits have fortunately paid off, introducing, amongst many, the analytical neural process (ANP) model, which mitigates the shortcomings of the AHP model. AHP presumes that each layer is only related linearly to the higher layers; that is not the case in real-world scenarios, wherein the relationship between different layers is generally non-linear. Cases dealing with a large number of criteria, such as multiple attribute decision making (MADM), are even more convoluted as one needs to form a pairwise comparison matrix for ascertaining the relative significance of different criteria, which is a highly time-consuming task. Furthermore, numerous categorical decision-making problems are also exceptions to the linear independence rule, working based on a mutual feedback system, which cannot be accurately implemented using AHP. Despite its many advantages, ANP is also accompanied by certain disadvantages including the inability to ensure certainty in pairwise comparisons, which is highly required in real-world scenarios. Another prevalent approach to decision making that allows for the incorporation of risk-taking and risk-aversion is the ordered weighted average (OWA) method. This model provides further flexibility compared to the previous models and incorporates interactions between contrasting objectives to accumulate data and make a collective decision. OWA was pioneered by Cheng et al. (2012). The model works by assuming an extensive range of values for weights that are assigned to different options given the significance of the corresponding item and other criteria. For this reason, OWA is primarily used in studies on decision-making processes (Chiclana et al., 2007; Makropoulos and Butler, 2006; Smith, 2006; Somlikova and Wachowiak, 2001), multi-criteria decision-making (Merigo and Casanovas, 2010; Yager, 2004; Yager and Xu, 2006), data mining (Torra, 2004), and intelligent systems (Kacprzyk and Zadrozny, 2001; Peláez and Doña, 2003). OWA is a multicriteria evaluation procedure. (Zadeh et al., 1996) first proposed the fuzzy set in multicriteria decision-making method, which is now widely used throughout the sciences.

Other scholars have applied the same approach to partial business (Priyadarshinee, 2020), distribution center (Liao et al., 2020). Tzeng et al. (2002) made a multi-criteria decision-making approach to the placement of restaurants. OWA has also been applied to natural science and engineering analysis (Van Westen et al., 2000; Malczewski, 2006; Malczewski et al., 2003).

The superiority of the OWA lies in the fact that it can assign a value from zero to one to various possible locations concerning different objectives (such as establishing a power plant). OWA considers different scenarios to be able to quantify risk at various levels (optimistic, pessimistic, or neutral), thereby facilitating the apprehension of the various decisions involved in the entire process. Accordingly, this study sought to employ OWA with 6 scenarios to locate suitable regions for the establishment of power plants.

To find suitable locations for GPP to maximize the efficiency of a sustainable city, the purpose of this research is to determine a suitable location for the gas power plant (GPP) in Isfahan province, Iran. In this study, GPP is evaluated using parameters of distance to the pipeline, distance to the road, sensitivity of formation to erosion, distance to the river and land use, slope, and altitude. It is proposed that the most appropriate method to prepare GPP maps is the OWA-AHP and AHP methods in a geographic information system (GIS).

It should be noted that in the reviewed paper, the various aspects of risk on optimal places for GPP in semi-arid areas did not study. In fact, it is essential to prepare land suitability maps according to different risk levels such that managers are able to make a proper decision according to different situations. Hence, the purpose of this research is to investigate the applicability of the AHP method in finding the optimal location to host gas power plants in a semi-arid area (Isfahan province, Iran). Moreover, the effect of risk is studied through OWA method in order to find out which output map is most appropriate according to situations. Furthermore, identifying the most important parameters to boost the decision process and reach optimum results is investigated in this paper by utilizing the SOM algorithm and Pearson correlation.

2. Materials and methods

Initially, seven parameters consist of elevation, distance to road, distance to pipeline, sensitivity classes, distance to stream, land use, slope is selected as input data. it is worth mentioning that these input parameters are chosen based on expert recommendation and a research paper that has been done in (Alavipoor et al., 2016b). Then fuzzy membership functions are used to homogenize and rescale all data to 0 through 1. The data are then overlayed using OWA to generate the final suitability map with different risk levels. Also, the AHP method is used for pairwise comparison and weighting the layers to prepare the land suitability map for GPP. The results of OWA-AHP and AHP are compared using the ROC curve. Finally, using the SOM and regression methods, the most important parameters for GPP are determined (Fig. 1). Moreover, the flowchart in Fig. 1 illustrates the methodology used in this paper.

2.1. Fuzzy method

To prepare the fuzzy map for each parameter, we need to determine membership functions. Objects are assigned a grade that ranges between 0 and 1, according to the membership function. x has value 0 if it is not a full member of the fuzzy set, while x has value 1 if it is a full member. A fuzzy set is a set that has more concepts than a classical set does. The set A in X is defined as a set of ordered pairs if X is the universe of discourse and its elements are denoted by x (Eq. (1)).

$$A = \{x, \mu_A(x) \mid x \in X\} \tag{1}$$

$\mu_A(x)$ is referred to as a membership function (or MF). A membership function maps each element of X to a membership value from 0 to 1.

To prepare fuzzy maps for each input layer, the incremental and decremental linear functions are used (Jiang and Eastman, 2000) (Fig. 2). According to Fig. 2, a decremental linear function is used for the altitude, slope, river, distance to the pipeline, distance to the road, and distance to the river, and the incremental fuzzy function is used for land use and sensitivity of formation to erosion. The optimal limits of each input parameter to the aim are a and b whose values are given in Table 1.

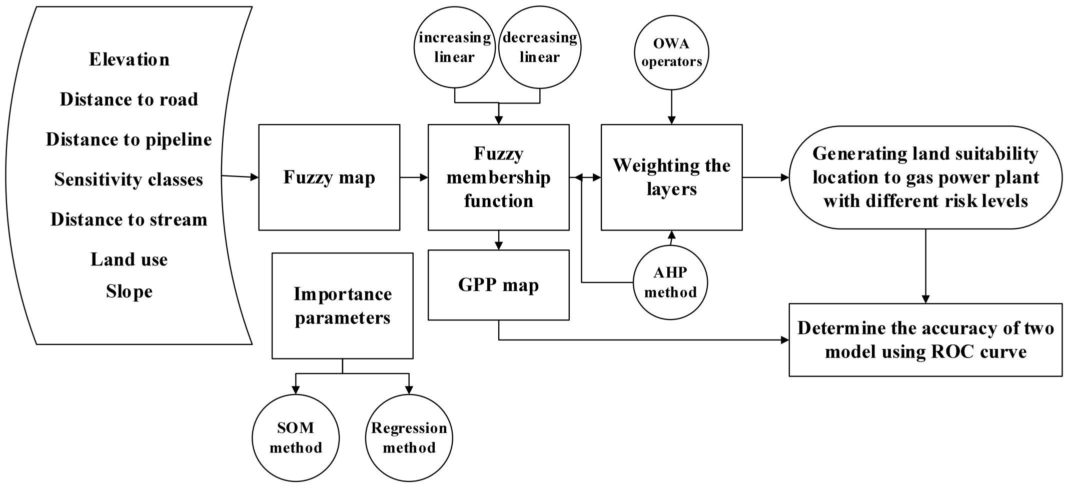

Fig. 1. Flowchart for the methodology applied in this area to determine GPP.

$$\mu_A(x) = f(x) = \begin{cases} 0 & x \le o \\ x - o / p - o & o \,\mathrm{p}\, x \,\mathrm{p}\, p \\ 1 & x \ge p \end{cases} \qquad \mu_A(x) = f(x) = \begin{cases} 1 & x \le o \\ p - x / p - o & o \,\mathrm{p}\, x \,\mathrm{p}\, p \\ 0 & x \ge p \end{cases}$$

Fig. 2. Membership functions (a): Decreasing and (b): Increasing.

Table 1
Critical limits of each effective parameters.

Layer	*a*	*b*
Altitude	<1,000 m	>1,800 m
Distance to the road	<10,000 m	>40,0000 m
Distance to the pipeline	<5000 m	>30,000 m
Sensitivity classes	>5	<2
Distance to the river	<1,000 m	>20,000
Land use	Arid land, rangeland	Military land
Slope	< 6°	>10°

2.2. OWA-AHP method

Different levels of implementation are applied to OWA and AHP methods. An AHP is a general tool that is used to evaluate the process of spatial decision-making by creating a hierarchical model. Using a linear and weighted combination, the evaluation process in AHP determines the values of each raster cell. In addition to offering a general framework for performing AHP, the OWA operator is also used to perform other processes. These two algorithms have such a structure and nature that they can be combined to create a space decision-making tool with greater power (Karimi et al., 2018). Using AHP, the hierarchical structure is formed and the relative weights of the criteria are calculated. In the future, OWA is used to assess varying levels of risk (Malczewski, 2006). Based on the three main criteria and six sub-criteria used in this study to interpolate suitable GPP locations, a hierarchical structure is used (Fig. 3).

OWA is introduced as one of the decisions making methods that can consider the priorities and mental evaluations of the decision-maker. This method can consider risk-taking and risk-averse decision-making in the decision-making process and can make the final decision based on risk-taking or risk-averse decision-making. The OWA method can calculate the level of risk-taking and risk aversion of individuals and enter it in the selection of the final option. The OWA method at this stage consists of three main steps:

(A) Determining the linguistic quantifier (Q)

(B) Obtaining ranked weights by a linguistic quantifier (Q)

(C) Calculating the total evaluations for each location of each level of the hierarchical structure, using the OWA composition function.

The overall score of the ith option can be calculated in two steps (Eqs. (2) and (3)).

$$s_{iq} = \sum_{k=1}^{l} v_{k(q)} \cdot z_{jk(q)}, \quad i = 1, 2, \ldots, m, q = 1, 2, \ldots, p \tag{2}$$

$$v_{k(q)} = (\sum_{k=1}^{l} u_{k(q)})^{\alpha(q)} - (\sum_{k=1}^{l-1} u_{k(q)})^{\alpha(q)} \tag{3}$$

Here, by reclassifying the values of the attributes related to α_q, $Z_{ik(q)}$ is the second target $u_{k(q)}$ and $x_{ik(q)}$ is reclassifying the qth weight of the attribute corresponding to k of this criterion. $\alpha_{(q)}$ is a parameter related to linguistic quantifiers related to the q target which is a class of fuzzy language quantifiers known as Regular Increasing Monotone (RIM).

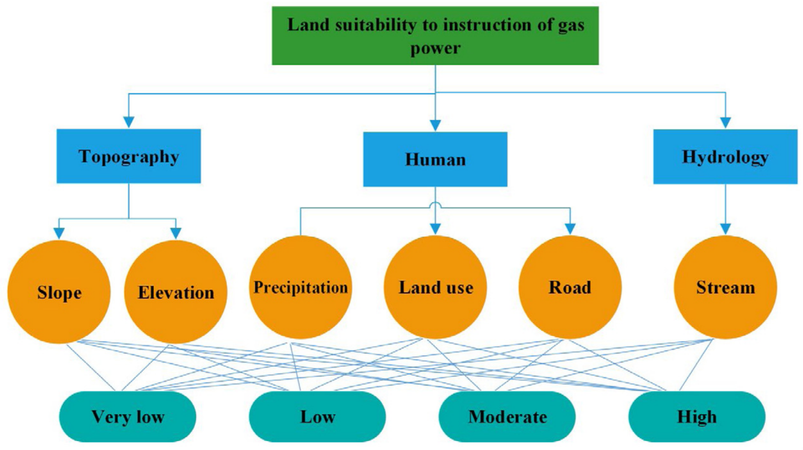

Fig. 3. Hierarchical model (criteria and sub-criteria).

The total score of each option in the final goal is obtained based on Eq. (4).

$$OWA - AHP_{(i)} = \sum_{k=1}^{l} v_k z_{iq}, \quad i = 1, 2, \ldots, m \tag{4}$$

where V_q is calculated according to Eq. (5).

$$v_q = (\sum_{q=1}^{p} u_q)^{\alpha_g} - (\sum_{k=1}^{p-1} u_q)^{\alpha_g} \tag{5}$$

By re-ranking the values of the options at the qth target level of S_{iq} and u_q, Z_{iq} is the weight q ranking of the target. α_g is the parameter linking linguistic quantifier to the ultimate goal of spatial decision-making based on a hierarchical structure.

The OWA operator consists of two main characteristics that express the behavior of this operator:

1- One measure of ORness is the position of the OR operator between AND and OR relationships. These degrees indicate the degree to which decision makers focus on better or worse values of a set of indicators or the same risk-taking and risk-averse decision-making; they can be gauged using Eq. (6):

$$ORness = \frac{1}{n-1} \sum_{i=1}^{n} (n-i) w_i \quad 0 \leq ORness \leq 1 \tag{6}$$

2- The amount of off-trade, which shows the degree of influence or exchange of one index from other indices and is defined as follows:

$$trade - off = 1 - \sqrt{\frac{n}{n-1} \sum_{i=1}^{n} (w_i - \frac{1}{n})^2} \quad 0 \leq ORness \leq 1 \tag{7}$$

2.3. SOM method

The SOM algorithm is a type of neural network model that is used in the implementation and design of nonlinear properties from multidimensional space to one-dimensional space (Kohonen, 2012). A neuron whose weight vector is close to the input variable x is called the best unit (BU) (Eq. (8)):

$$\|x - m_c\| = \min\{\|x - m_i\|\} \tag{8}$$

where x is the input vector and m the weight vector.

The vectors of the weight vectors are updated after finding the BU so that it is closer to the input vector. The method calculates the compatibility between an input vector and the neighboring BUs. Eq. (9) shows the algorithm for updating a unit weight vector. Kohonen (2012) presents the detailed algorithm of the SOM.

$$m_i(t+1) = m_i(t) + \alpha(t) h_{ci}(t)[x(t) - m_t(t)] \tag{9}$$

where the weight vector $m(t)$ indicates the output unit's location in the data space at the time t; α(t) the learning rate at time t; $ci(t)$ the neighborhood kernel around the 'winner unit' c; and $x(t)$ the input vector drawn from the input data set at time t. Using SOM, the morphometric parameters measured in this study are removed and the most relevant data are selected.

2.4. Case study

As stated, this research was conducted in Isfahan province, Iran that is a semi-arid region. It has an area of 108317 km^2 and is located between the longitudes 30° 42'- 34° 30' N and the latitudes 49° 36'-55° 25' E (Fig. 4).

Within the study area, altitudes range from 685 to 4415 m. The average annual maximum temperature in the study area is 23.5 °C, while the average annual minimum temperature is 9.2 °C. The average number of frost days as recorded by Isfahan station is 72 days per year, with the majority of frosts (i.e. 45 days) occurring during the winter and the remaining days (27) during the autumn. Frost is also reported to occur in spring as well. The highest number of annual frost days throughout the given study period is 97, occurring in 1959, while the lowest number of frost days is 39, which occurred in 1994. The earliest onset of frost occurred during the second half of October, ending in early April. January and December contributed most to the number of frost days. The highest amount of monthly sunshine hours averaged at 350 h in July, while the lowest average is reported for December at 199 h. The mean annual sunshine for the case study is 3274.

The relevant information parameters (layers) for locating suitable areas for the establishment of power plants include distance to the pipeline, distance to the road, distance to the river, sensitivity classes, land use, slope, and altitude. The required data were procured from various sources at different periods as shown in Table 2. According to Table 2, it is evident that the coordinate system, scale, and even spatial resolution of input data are different. Therefore, at this stage, the data were edited and prepared in the GIS.

3. Results and discussion

Under subsection A, we describe how to lay out input layers to better describe what OWA offers. Also, there are subsections A and B which describe fuzzy implementation and OWA procedures respectively. It is worth mentioning that all simulations are run using ArcGIS V10.2 on a Laptop (2.6 GHz, 6 GB RAM).

Table 2
Characteristics of the study area (source and scale).

Layer	Format	Source	Year	Scale
Altitude	Raster	Geographical organization	2019	1:250,000
Distance to the road	Polyline	Geographical organization	2014	1:250,000
Distance to the pipeline	Polyline	National Gas Organization	2019	1:100,000
Sensitivity classes	Polygon	Geological Survey	2010	1:100,000
Distance to the river	Polyline	Geographical organization	2015	1:250,000
Land use	Polygon	Geographical organization	2017	1:250,000
Slope	Raster	Geographical organization	2019	1:250,000

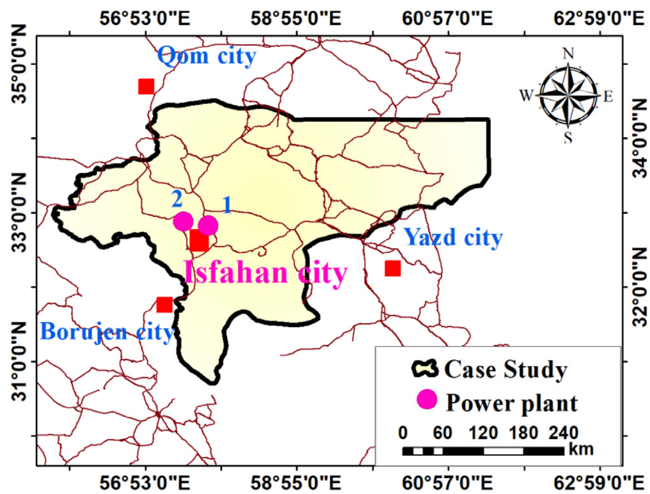

Fig. 4. Location of the region.

3.1. Preparing layers

At first, using the digital altitude model (DEM), a slope degree map is made (Fig. 5). It is worth mentioning that the altitude in most parts of the south of the case study is more than 4000 m; hence, the regions with the highest slope are located in the south (Fig. 5). Also, distance to the river, pipeline, and road maps are prepared using buffer tools in ArcGIS software V10.5. Fig. 5 depicts the results. It should be noted that to determine the effective parameters and the importance of each of these parameters for GPP, expert opinions and different studies such as Alavipoor et al. (2016a) were used.

Moreover, forest, garden, rangeland, urban, wetland, and agriculture form the land use map (Fig. 6(a)), and forests have the lowest suitability in constructing gas power plants.

Also, the sensitivity of formation to erosion map, which was used to extract formations sensitivity in ten classes, has been produced by the Iranian Geological Organization (Fig. 6(b)). As the number of classes increases, the sensitivity of formation to water erosion will increase and the importance of the area for GPP will decrease.

3.2. Fuzzy method

The fuzzy maps prepared for GPP parameters are shown in Fig. 7, in which increasing the membership function value from 0 to 1 will increase the suitability for GPP. MF associated with all parameters is defined based on Table 3.

According to Table 3, regions located at a distance of lower than 5000 meters to pipeline are the best candidates for the establishment of power plants, i.e. areas corresponding to a linear membership function (MF) of 1. On the other hand, areas located at a distance of more than 30,000 meters from power transmission lines are assigned an MF value equal to 0, and areas located in-between (at a distance of less than 30,000 and greater than 5000 m) are assigned MF values between 0 and 1. The remaining parameters (distance from rivers, distance from roads, etc.) are measured accordingly. Finally, three labels of high suitability, low suitability, and medium suitability are assigned to areas with MF values of 1, 0, and in the range (0,1), respectively.

Upon applying the membership functions to each parameter, the corresponding fuzzy maps are produced as shown in Fig. 7. According to Fig. 7(a), areas located to the north of the study region have been assigned values close to and equal to one, given their high altitude, whereas areas to the south which have a lower altitude have been allocated MF values close to and equal to one (suitable areas for the establishment of power plants). Areas located near power transmission lines, mainly found in the central regions of the study area, also correspond to MF values close or equal to 1 (Fig. 7(b)). Moreover, as shown in Fig. 7(c) (brown color), areas with lower sensitivity against erosion (comprised of stronger and more resistant geological compositions) are also suitable options for the establishment of power plants with MF values close to 1 (0.8). According to the land-use map, areas zoned as pastures and drylands (shown in blue in Fig. 7(d)) had an MF value of closer to 1 and are suitable for the installment of solar panels. The MF value for areas near waterways (shown in yellow in Fig. 7(e)) is also measured as close to one, indicating their suitability due to having ready access to water resources. Also, since areas closer to roads have greater access to transmission lines and equipment, they are assigned MF values equal to 1 and are shown in blue in Fig. 7(f). Finally, according to Fig. 7(g), areas with less slope are more suitable options for the establishment of power plants and are assigned MF values near 1.

Studies showed that fuzzy logic can be used to homogenize data (Sui, 1992; Jiang and Eastman, 2000; Mokarram et al., 2020). Next, to overlap the maps and prepare a suitable place map for GPP, the AHP method is used to weigh each parameter. Pairwise comparisons are used to weight each parameter and 20 experts, as well as several studies (Mokarram and D., 2019), are used to determine the priority of each parameter. The results of the pairwise comparison of each parameter are given in Table 4. According to Table 4, it is clear that distance to the pipeline with a weight of 0.297 is the most important and land use with a weight of 0.045 is the least important.

According to Fig. 8, it is clear that 61% of the area is not suitable for GPP and only 15% of the area is in the good class for GPP.

3.3. OWA-AHP method

Finally, to overlay the parameters and prepare the GPP map, the OWA method is used. In the present study, six order weights are applied corresponding to the seven parameters that are rank-ordered for layers. Fig. 9 gives six typical sets of order weights for 7 parameters.

As stated, OWA is used to overlay each layer with proper weight. Six quantifiers are utilized and weights for each quantifier are rank-ordered in Fig. 9. Also, GPP maps associated with these six quantifiers are represented in Fig. 9. According to Fig. 9(d),

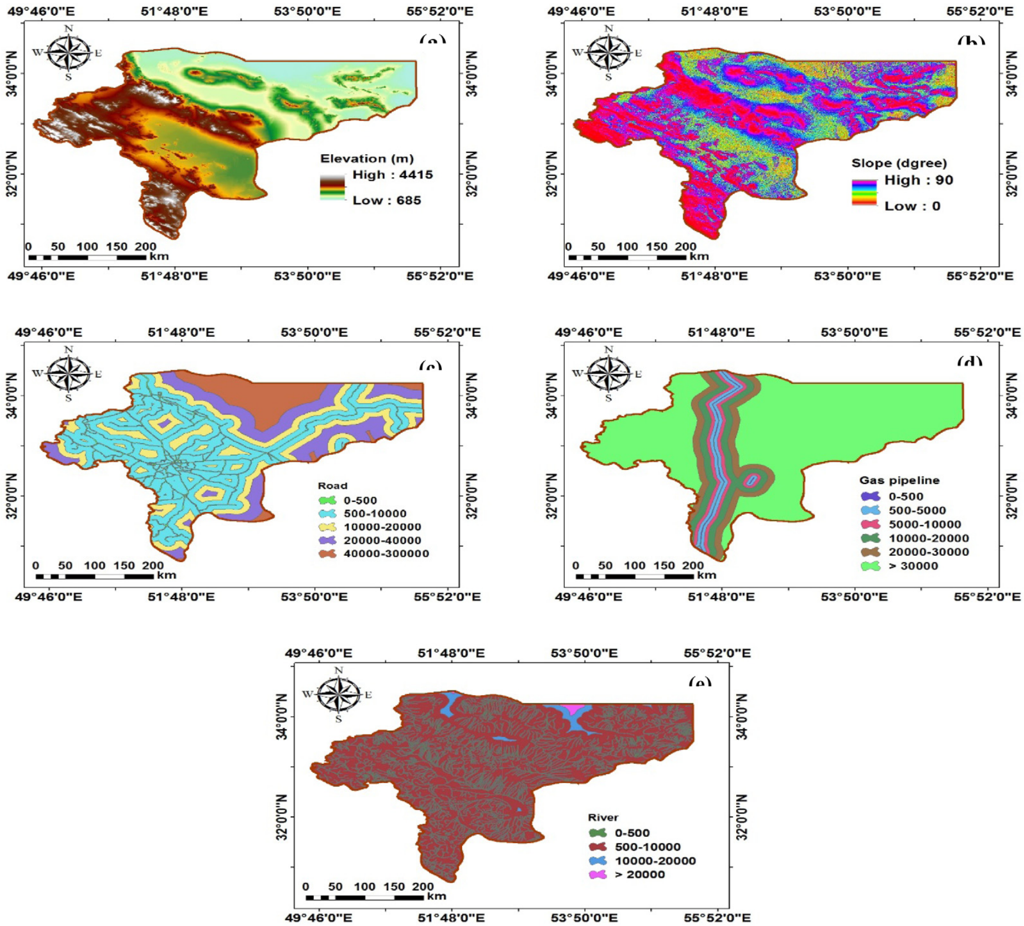

Fig. 5. Interpolation of input data. (a): altitude, (b): slope, (c): distance to the road, (d): distance to the pipeline, (e): distance to the river.

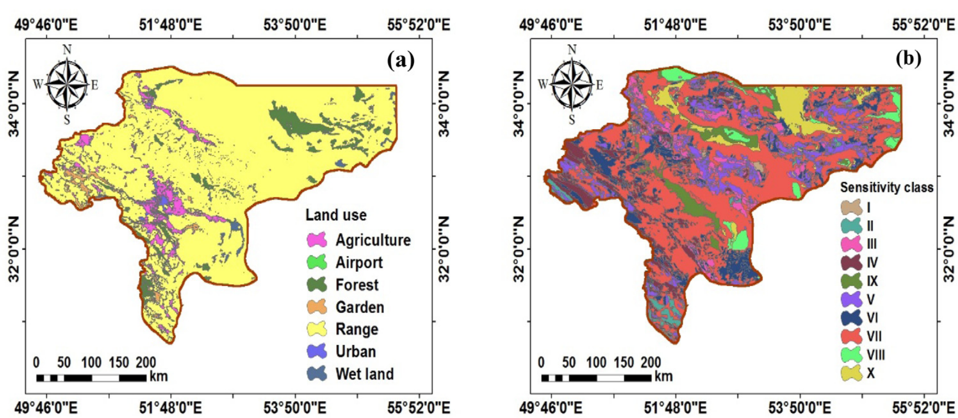

Fig. 6. Land use map (a) and sensitivity of formation to erosion map (b).

Table 3
Characteristics of each parameter to define membership function for gas power plant location.

Parameters	High suitable	Medium suitable	Low suitable
Distance to the pipeline (m)	<5000	5000–30000	> 30000
Distance to the road (m)	<10000	10000–40000	> 40000
Sensitivity classes	Class 1	Class 2–class 5	Class 6
Distance to the river (m)	<10000	10000–20000	> 20000
Land use	Arid-poor soil	Agriculture-salt land, …	Military
Altitude (m)	<1000	1000–1800	>1800
Slope (%)	<6%	6%–10%	>10%

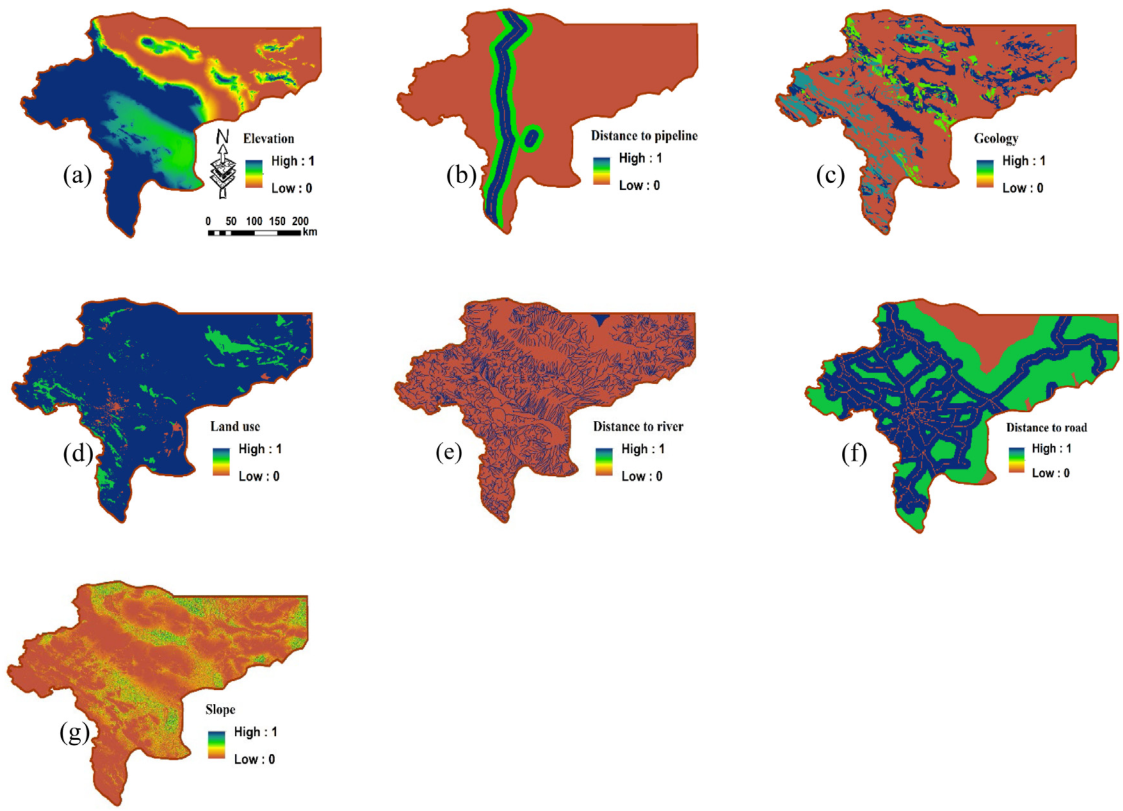

Fig. 7. Fuzzy maps for the GPP parameters; (a): altitude, (b): distance to the pipeline, (c): sensitivity, classes (d): land use, (e): distance to the river, (f): distance to the road, and (g): slope.

Table 4
Pair comparison of each parameter using the AHP method.

Parameter	Distance to the pipeline	Distance to the road	Altitude	Slope	Sensitivity classes	Distance of river	Land use	Weight
Distance to the pipeline	1	2	3	4	5	6	7	0.297
Distance to the road		1	2	3	4	5	6	0.231
Altitude			1	2	3	4	5	0.167
Slope				1	2	3	4	0.118
Sensitivity classes					1	2	3	0.082
Distance of river						1	2	0.059
Land use							1	0.045

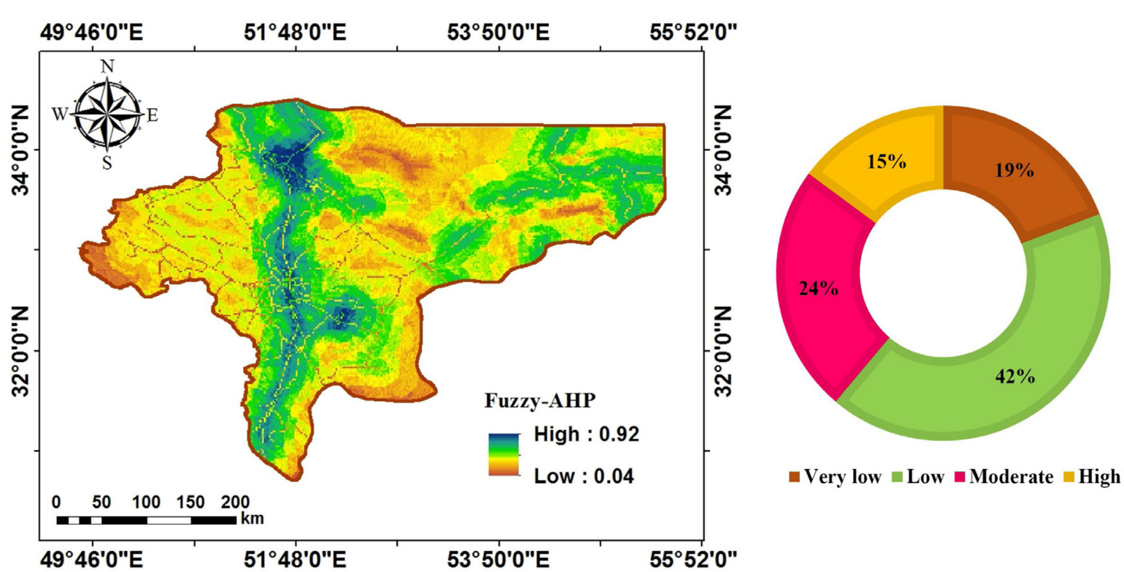

Fig. 8. Suitable areas to GPP using the AHP method.

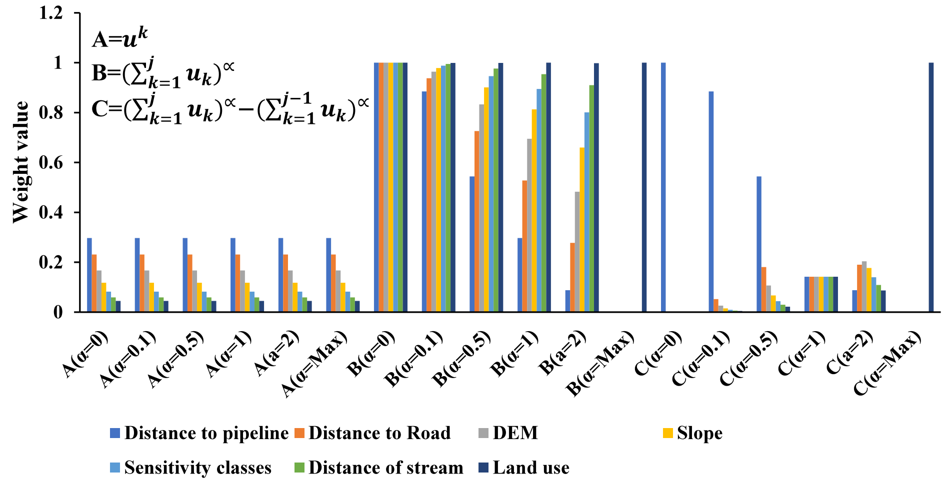

Fig. 9. Weight of each criterion using the OWA method.

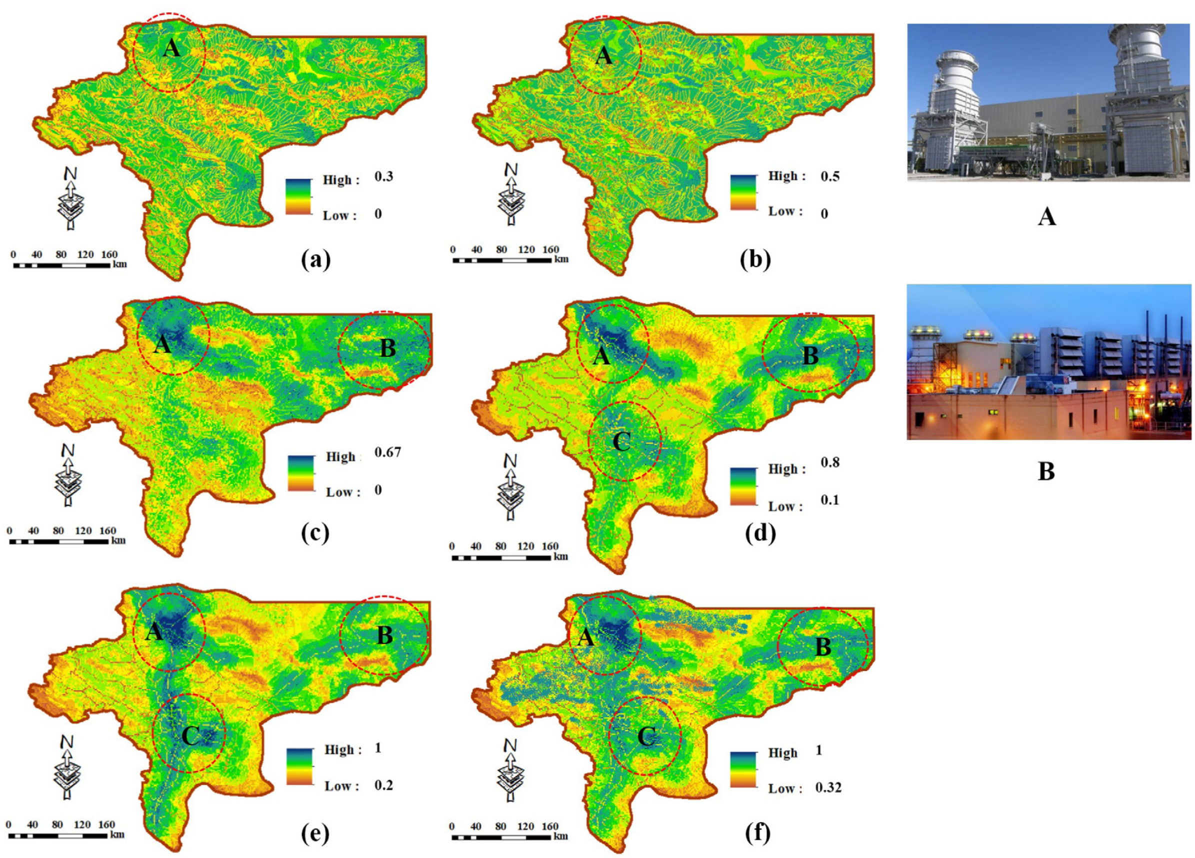

Fig. 10. GPP maps of OWA results for selected fuzzy linguistic quantifiers: (a) Low level of risk and no trade-off (LLR-NRO), (b) Low level of risk and average trade-off (LLR-ATO), (c) Average level of risk and no trade-off (ALR-NTO), (d) Average level of risk and full trade-off (ALR-FTO), (e) High level of risk and no trade-off (HLR-NTO), (f) High level of risk and average trade-off (HLR-ATO).

when the average risk (full trade-off) is selected, all parameters will give the same weights (0.142). By decreasing the risk level, the suitability of areas is reduced and, when no risk is selected, all parts of the case study have the lowest suitability to be the host of gas power plants (Fig. 10(a)). Moreover, Fig. 10(c) shows a high risk with an average trade-off that, in comparison with Fig. 10(c), has a lower risk for determining the place of GPP. It is obvious from Fig. 10(d) that the center of the case study has the highest potential to construct GPPs. Fig. 10(e) shows an average risk with no trade-off that has more risk and Fig. 10(f) shows a high level of risk and average trade-off to construct GPPs.

Finally, the proposed model is evaluated in terms of its performance in determining suitable locations for the establishment of power plants against existing gas and thermal powerhouses in Isfahan, as shown in Fig. 11. Based on the findings of the OWA method, it is clear that the model can accurately locate the suitable regions without any faults for all risk levels except level (a) (no trade-off and no risk). This justifies the aptness and reliability of OWA to be utilized in smart cities that seek to

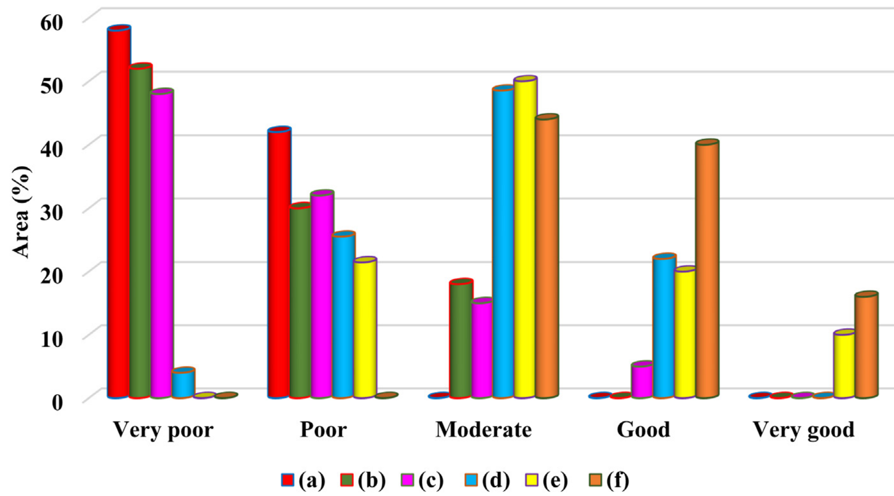

Fig. 11. The area of each class at different levels of risk.

have energy efficiency using different suitability maps generated by the model. Stated differently, the prime feature of the OWA operator is its ability to incorporate a decision matrix as a means to produce numerous solutions based on the mental characteristics of the decision-maker, who can, in turn, make use of the various generated maps based on their preferences and existing conditions.

Next, the area of each classified map of GPP was prepared, which is shown in Fig. 11. According to Fig. 11, the map prepared by the ALR-FTO operator with the low level of risk (f) is in the classes of very poor and poor for GPP. However, the ALR-FTO operator with high risk shows that the study area is in moderate, good, and very good classes for GPP. These two maps show the high and low levels of risk in this study. Other levels of risk show map in different classes for GPP, any of which can be used for GPP depending on the environmental conditions and the economic situation of the region.

In all maps prepared with different levels of risk, parts of the north, east, and south of the area marked that is specified with red circles in Fig. 11 are suitable locations for GPP. The locations are in parts of Kashan, Bidgol (A), Isfahan, and Najafabad (B), Khorbiabank (C), respectively. Part A is located near Kashan Gas Power Plant. It includes two gas units with a capacity of 162 MW (324 MW in total) in ISO conditions. Therefore, this area has acceptable accuracy by this model. Part B is located near the GPP in Isfahan (65 km southwest of Isfahan) with a capacity of 954 MW and part C is located at a distance of 400 km east of Isfahan.

Finally, to check the accuracy of the methods using the 20 points determined for GPP, the actual values are compared with predicting values using the ROC curve as well as AHP and OWA-AHP (ALR-FTO). The results of the ROC curve show that the two methods have high accuracy to predict suitable locations for GPP. According to Table 5, AUC values in both methods are high ($AUC_{AHP} = 94.0\%$, $AUC_{OWA-AHP} = 89.0\%$). It can be concluded that both methods can determine a suitable location for GPP with high accuracy.

Studies show that the use of the MCDA method shows high accuracy in determining the appropriate locations for the intended purpose. Because of this, MCDA (AHP and OWA) methods are used suitable for determining appropriate sites for the construction of the power plant. Compared to other MCDA methods, the one main advantage of the OWA method in determining suitable locations for the power plant is the preparation of land suitability maps with different levels of risk for making better decisions in the region.

3.4. Relationship between parameters using SOM and regression algorithms

Fig. 12 shows the classification map obtained from SOM results using 7 effective parameters (sensitive formation to water erosion, altitude, distance to the pipeline, distance to the road, land use, river, slope) for GPP. High-value neurons are shown in red while the small amounts are shown in blue. Using the color gradient in SOM maps, the parameters can be compared visually. According to Fig. 12, it is clear that distance to the pipeline and distance to the road have the same color gradient change, which shows such a strong positive correlation between these parameters that they can be selected as important parameters for determining suitable locations for GPP.

Lu and Yan (2020), Faradonbeh et al. (2020), and Yokota et al. (2020) showed that this method has great accuracy to examine the relationship between each of the effective parameters of the target visually, which is similar to the results of this study.

Finally, using Pearson distribution, the relationship between each parameter and related classes to suitable locations for GPP is investigated. According to the results, it is found that there is a strong relationship between suitable locations for GPP as well as distance to the pipeline and distance to the road. Therefore, with decreasing these distances, suitable places for GPP increase (Table 6).

The results of the regression are shown in Table 7. According to Table 7, it is clear that Model 1 using distance to the road and Model 2 using distance to the road and pipeline can predict land suitability classes with high accuracy (R_{Model1}: 0.853 and R_{Model2}: 0.940).

In this study, an attempt is made to investigate the suitable locations for GPP. According to the results, it is clear that using GIS can predict suitable locations for GPP spatially. Klassen and Marjerrison (2002) and Delaney and Lachapelle (2003) used GIS to determine a suitable location to construct coal-fired power plants and wind turbines. Shahi et al. (2018), Ahmadi et al. (2020) used GIS and fuzzy methods to predict suitable locations for GPP. The results of these studies, which are similar to ours, showed that the method had high accuracy to predict suitable locations.

4. Conclusions

In this paper, the optimum locations for constructing GPPs have been investigated. Hence, OWA and AHP methods have been combined to extract the land suitability map as well as considering different risk levels in the planning procedure. Besides,

Table 5
Area Under the Curve of built models.

Models	Area Under Curve (AUC)	Standard error	Asymptotic significant	Asymptotic 95% confidence interval	
				Lower Bound	Upper Bound
AHP	0.94	0.02	0.00	0.85	0.92
OWA	0.89	0.017	0.001	0.80	0.90

Table 6
Correlation between each parameter and land suitability classes to GPP.

Parameters	Gas power suitability	Distance to the pipeline (m)	Distance to the road (m)	Sensitivity classes	Distance to the river (m)	Land use	Altitude (m)	Slope (%)
Gas power suitability	1.000	−.849	−.853	−.342	−.222	−.327	.527	.326
Distance to the pipeline (m)	−.849	1.000	1.000	.367	.131	−.084	−.487	.086
Distance to the road (m)	−.853	1.000	1.000	.372	.133	−.079	−.493	.081
Sensitivity classes	−.342	.367	.372	1.000	−.104	.163	−.527	−.338
Distance to the river (m)	−.222	.131	.133	−.104	1.000	−.385	−.243	.082
Land use	−.327	−.084	−.079	.163	−.385	1.000	−.142	−.722
Altitude (m)	.527	−.487	−.493	−.527	−.243	−.142	1.000	.203
Slope (%)	.326	.086	.081	−.338	.082	−.722	.203	1.000

Table 7
The best model to predict land suitability classes.

Model	R	R square	Adjusted R square	Std. error of the estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	.853[a]	.727	.697	.1826	.727	23.994	1	9	.001
2	.940[b]	.884	.855	.1261	.157	10.872	1	8	.011

[a]Predictors: (Constant), Distance to the road (m).
[b]Predictors: (Constant), Distance to the road (m), pipeline (m).

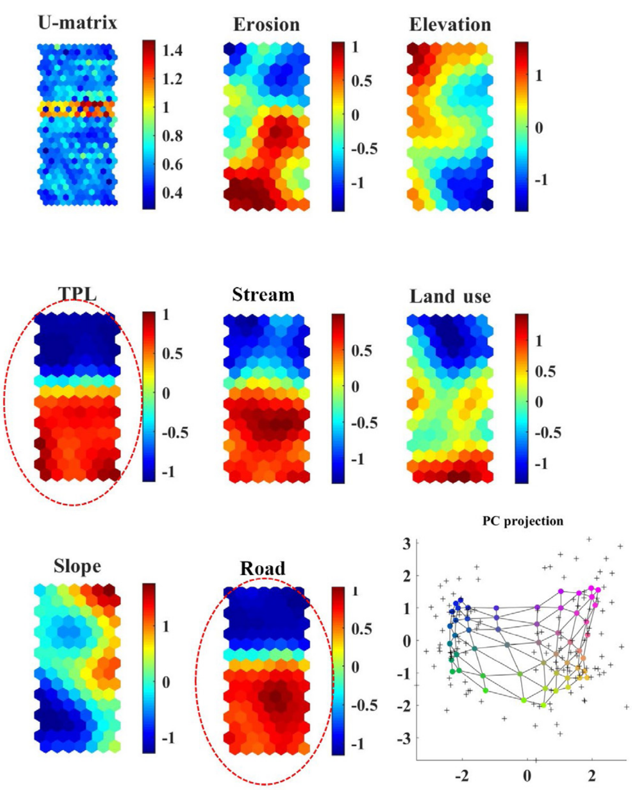

Fig. 12. Visualization of the relationship between morphometries properties and land suitability class for gas power.

the fuzzy method has been adopted to homogenize input layers. According to results, as the risk increases, the suitable zones for GPP within the case study are increased and vice versa. Moreover, according to the SOM algorithm and Pearson correlation results, distance to the pipeline and road had the biggest impact on GPP placement. Also, it has been depicted that OWA method is a powerful approach such that the best planning can be determined according to different scenarios of different risk levels. ROC curve also proved that the AUC values were high for AHP and OWA-AHP methods ($AUC_{AHP} = 94.0\%$, $AUC_{OWA-AHP}$ with average risk level = 89.0%). It means the AHP method is effective enough in such decision-making problems and, at the same time, the OWA method prepares a decision-making framework according to different risk levels.

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.

Data availability

The data is available in following link: https://drive.google.com/drive/folders/18WQObHpFemvaBNDuSNg6_SDDeI_JHbiz?usp=sharing

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