Using a GIS-based order weight Average (OWA) Methods to Predict Suitable Location for Artificial Recharge of Groundwater

Marzieh Mokarram (m.mokarram@shirazu.ac.ir)
Shiraz University https://orcid.org/0000-0003-4282-1950
Saeed Negahban
Shiraz University
Ali Abdolali
University Corporation for Atmospheric Research
Mohammad Mehdi Ghasemi
Shiraz University

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Marzieh Mokarram [1*], Saeed Negahban [2] and Ali Abdolali[3,4], Mohammad Mehdi Ghasemi[5]

[2]Department of Range and Watershed Management, College of Agriculture and Natural Resources of Darab, Shiraz University, Iran, Email: m.mokarram@shirazu.ac.ir

[2]Assistant Professor, Department of Geography, Faculty of Economics, Management & Social sciences, Shiraz University, Shiraz, Iran

[3]University Corporation for Atmospheric Research (UCAR), Boulder, CO 80301 USA

[4]National Oceanic and Atmospheric Administration (NOAA), College Park MD 20740 USA

[5] Research Sciences of Fars Province

[*]**Corresponding author**: Marzieh Mokarram, Tel.: +98-917-8020115; Fax: +987153546476 Address: Darab, Shiraz university, Iran, Postal Code: 71946-84471, Email: m.mokarram@shirazu.ac.ir.

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Abstract

The purpose of this study is to use the GIS-based analytic hierarchy process (AHP) and order weight average (OWA) to determine suitable locations for the artificial recharge of groundwater (ARG). Therefore, after preparing the fuzzy maps for each parameter, AHP method is used to pari comparison and determine the weight of each parameter. Then, using the OWA-AHP method based on different levels of confidence (different α values), the weighting is done for each parameter to prepare the final land suitability maps with different risk levels. Also, the adaptive network-based fuzzy inference system (ANFIS) method is used to predict land suitability classes using input parameters. Then, using the Best subset regression method, the most important effective parameters for ARG are identified. The results of the Fuzzy-AHP method show that 27% of the area (in different parts) has good and very good conditions for ARG. The results of the combined OWA-AHP method show that, in case of low-level risk and no trade-off, more area is in very low class (80 %) while in case of the high level of risk and average trade-off, the highest area is in the very low class (27 %). The results of the ANFIS method show that fuzzy c–means (FCM) and sub-clustering methods have high accuracy to predict suitable places for ARG. The results of the best subset regression method show that slope, lithology, land use, and altitude with the lowest C_p values (5.2) are effective parameters to determine ARG.

Keywords: Artificial recharge of groundwater (ARG), fuzzy -AHP method, Ordered Weight Average (OWA)-AHP, ANFIS, Best subset.

1. Introduction

Water scarcity is a major concern in different parts of the world, especially in semi-arid and arid areas. The lives of about one-third of the world's population are tied to groundwater and more than 70% of groundwater resources are consumed by agriculture (FAO, 2017). The withdrawal of these resources is increasing due to the rapid agricultural and industrial growth. Consequently, excessive groundwater consumption causes irreversible problems such as a significant drop in the water level of wells and drying, river flow reduction, lake level subsidence, water quality degradation, and an increase in pumping costs. The artificial recharge of groundwater (ARG) is among the most efficient ways for control and prevention of water level decrease in plains, which is of great importance for agriculture and industry. Artificial recharge is a series of pre-designed activities for the nourishment of groundwater either by natural replenishment or percolation of surface waters into the groundwater aquifers, leading to increase in groundwater volume (National Research Council, 1994). Thus, locating suitable areas for artificial recharge is important.

Geographical Information System (GIS) is a tool for data analysis that can be used to store, retrieve, manipulate, process and analyze different spatial and temporal datasets (Palanisamy et al. 2020). This tool provides accurate spatial information about the watershed for conservation and planning in water resources management (Karunanidhi et al. 2019). There are different ways to determine the appropriateness of a region for artificial recharge in GIS. Rajasekhar et al. (2019) used Remote Sensing (RS), GIS, and Analytical Hierarchy Process (AHP) technique to predict Artificial Groundwater Recharge in Anantapur District, India. The results showed that the accuracy of methods to determine a suitable location was 82.05%.

Kim et al. (2018) used the Artificial Neural Network (ANN) method to determine the situation of

groundwater recharge in South Korea. The results showed that if the ANN model score is less than 1.5, the possibility of artificial recharging is relatively low. Patil et al. (2019) used GIS and Remote Sensing (RS) techniques to determine suitable locations for groundwater recharge. The results showed high accuracy in classifying the area into good, medium, and poor classes for groundwater recharge. Anand et al. (2020) used the AHP method in GIS to determine suitable locations for groundwater recharge in the Bhavani River basin of South India. The results showed that the best areas for groundwater recharge are dams. Arya et al. Arya et al. (2020) used the AHP method to determine suitable locations for groundwater recharge in the Vattamalaikarai River basin in South India. They found that more than 50% of the area was in the medium or low potential group in terms of groundwater.

Das et al. (2019) used fuzzy-AHP to determine land suitability for groundwater recharge in West Bengal, India. According to their results, the plain in the east of the area was suitable for groundwater recharge. Rajasekhar et al. (2019)used the AHP method to determine artificial groundwater recharge in the Jilledubanderu river basin. They concluded that fuzzy-AHP is an accurate method for predicting land suitability for artificial groundwater recharge. Kamangar et al. (2020) used AH, ANP, and TOPSIS to weigh the effective parameters of ARG in southern Iran. The results showed that about 5% of the study area was suitable for artificial recharge of groundwater. Arya et al. (2020) used GIS and RS to prepare interpolation maps of groundwater potential. Their results indicated that more than 50% of the basin region falls under the moderate to low groundwater potential category.

One of the methods that have been used for land suitability in some recent studies is the Order Weight Average (OWA) method which, unlike other multiple-criteria decision analysis (MCDA) methods such as AHP and ANP, is able to prepare land suitability maps with different levels of

87 risk that, depending on the environmental and regional conditions, can be used by managers for
88 ARG. OWA is widely used in multi-criteria combination procedures (Bellmann , 1970;
89 Malczewski et al., 2003; Malczewski, 2006; Mokarram and Aminzadeh, 2010). It provides a
90 different decision strategy with various risks (Malczewski and Rinner, 2005; Chu and Lin, 2009;
91 Ban and Ban; 2012).
92 According to studies and the importance of ARG in arid and semi-arid regions, it is important to
93 check and determine suitable places for groundwater recharge. Considering that the uncontrolled
94 abstraction of groundwater in most arid and semi-arid regions, especially in Iran, has caused a
95 sharp drop in the water table and reduced aquifer reserves, determining suitable locations for ARG
96 is of great importance (Ghayoumian et al., 2007). Annual extraction of 520 million cubic meters
97 of groundwater out of aquifers in Bushehr province in southern Iran has reduced these aquifers.
98 Therefore, groundwater resource management and ARG in the study area is important. The
99 purpose of this research is to determine the location of artificial recharge in southern Iran, taking
100 into account the geographical and atmospheric parameters such as slope, lithology, land use,
101 drainage density, distance to fault, precipitation, and altitude. In this study, a new hybrid method
102 called OWA-AHP is used which advantageously provides us with the combination of two-by-two
103 comparisons of each parameter using the AHP method and use of different risk levels using the
104 OWA method. This makes the OWA method more efficient for weighting layers. In this study,
105 using the ANFIS method, land suitability classes for ARG are also predicted through input
106 parameters. Finally, using the best subset regression method, the most important parameters
107 affecting ARG are identified. In general, the objectives of the research are as following:
108 1- Using membership functions, the fuzzy maps for each parameter are prepared and using the
109 AHP method, the weight of each parameter is determined and the final map of suitable places for

ARG is prepared.

2- A combination of OWA-AHP is used as a new efficient tool to weigh each layer and prepare land suitability maps with different levels of risk.

3- The ANFIS method is used to predict land suitability classes.

4- The best subset regression method is used to determine the most important parameters affecting groundwater recharge.

2. Materials and methods

In this part, the membership functions are defined by the fuzzy maps for each parameter and prepared. Then AHP method is used to compare the importance of each parameter in a pairwise comparison to determine the weight of each parameter. Using the OWA-AHP method, suitability maps with different levels of risk are prepared. ANFIS is used to predict land suitability classes and the best subset regression method is used to determine the most important effective parameters in suitable places for ARG. A summary of the research method is shown in Fig. 1.

2.1. Study area

This study was carried out in Bushehr Province, located in the south of Iran. It has an area of 42,871.23 km^2 with a population of 1,163,400 and lies between the longitude of 27 ° 01 ′ to 29 ° 54 ′ N and latitude of 51 ° 12 ′ to 55 ° 42 ′ E (Fig. 2). The province connects to the Persian Gulf on its south. The temperature values in the region range between -1 and 52.5 C∘ and the average annual temperature in the province is 25.7 C^o. The vegetation of the study area varies and depends on the geographical location of the area so that, in warm and dry areas, most of the native species are Acacia. Two permanent rivers including Mand (685 km), and the Hell River (230 km) flow in

133 the study area (Pazira et al., 2016).

134

135 *2.2. Preparing raster maps*

136 In this study, slope, lithology, land use, drainage density, distance to fault, precipitation, and
137 altitude maps are used as input data to determine the suitable locations for ARG. The description
138 of factors used in the analysis of this stage of the research is listed in Table 1.

139 It is worth noting that the selection of the most important data for the intended purpose depends
140 on the region and expert opinion. For example, Rajasekhar et al. (2019) used geology,
141 geomorphology, drainage density (DD), land use/land cover (LULC), lineament density (LD),
142 slope, soils, and rainfall, or Anand et al. (2020) used drainage, lineament, geology, soil, slope,
143 geomorphology, and land use as input data to determine suitable locations for groundwater
144 recharge. To select the data in the present research, the characteristics of the region and the opinion
145 of experts are used.

146 Finally, interpolation maps are prepared for each parameter with a resolution of 30 m in GIS (Fig.
147 3). In Fig. 3, it can be seen that the southern half of the study area has lower heights and slopes
148 than the northern half. Also, Fig. 3 clearly shows that, except for a small part of the south of the
149 region, the rest of the region has less distance from the faults. The land-use status of the study area
150 is shown in Fig. 3, which shows that the southern parts mostly include rangelands. Also, the
151 susceptibility map of formations to water erosion showed that the southern half is very sensitive
152 to water erosion. The sensitive classes of formation to water erosion are shown in Table 2. Also
153 according to Fig. 3, it turned out that the northern parts have precipitation of more than 400 mm.
154 The drainage density interpolation map is shown in Fig. 3. It is obvious that the northern parts
155 have a higher drainage density.

156

157 *2.3.Methods*

158 *2.3.1. Fuzzy method*

159 To prepare fuzzy maps for each parameter, membership functions are used. A fuzzy set *A* in *a*
160 *reference set X* is shown in Eq. (1) (McBratney and Odeh, 1997).

161 $$A = x, \mu_{A(x)} \mid x \in X \quad (1)$$

162 where $\mu_A(x)$ is called the membership function (or MF) of x in A.

163 In this study, two incremental and decremental membership functions are used to prepare a fuzzy
164 map for each of the parameters, which is shown in Fig. 4. For altitude, precipitation, and drainage
165 density parameters incremental membership function is while for the other parameters decremental
166 membership function.

167

168 *2.3.2. Analytic hierarchy process (AHP)*

169 The analytic hierarchy process (AHP) is one of the most efficient methods of multi-criteria
170 decision making (Saaty and Vargas,1980). This method is based on a pairwise comparison of
171 parameters and allows managers to examine different scenarios. This method is one of the most
172 comprehensive systems designed for criteria decision making and allows the problem to be
173 formulated hierarchically. It is also possible to consider different quantitative and qualitative
174 criteria in the problem together. This method includes the following steps:

175 A) Creating a hierarchical structure

176 B) Preference of parameters

177 C) Preparation of normalized matrix and weight vector of parameters:

178 To calculate the weight of each parameter, the values of each column of the pairwise comparison
179 matrix must first be added together and each element in the matrix must be divided by the sum of

its own column (Eq. 2) Then the average of the elements in each row of the normalized matrix is calculated (Eqs. 2, 3).

$$r_{ij} = \frac{a_{ij}}{\sum_{i=1}^{m} a_{ij}} \quad (2)$$

$$W_i = \frac{\sum_{i=1}^{n} r_{ij}}{n} \quad (3)$$

Here, m is the number of columns, n is the number of rows, a_{ij} is the pairwise comparison matrix, r_{ij} is the normalized matrix assets for options i, and w_i is the weight of option i.

D) Determining the final score of options (Eq. 4).

$$V_H = \sum_{k=1}^{n} W_i(g_{ij}) \quad (4)$$

V_H is the final score of j, W_k is the weight of each criterion and g_{ij} is the weight of the options in relation to the criteria.

E) Calculating the compatibility rate

To calculate the compatibility rate, the pairwise comparison matrix (A) must first be multiplied by the weight vector (W) to obtain a good estimate of $\lambda_{max}.W$ so that $AxW = \lambda_{max}.W$. By dividing $\lambda_{max}.W$ by W, the value of λ_{max} is calculated. Then the value of the incompatibility index (I.I.) is calculated using Eq. 5 and the compatibility rate (I.R.) is calculated using Eq. 6 is calculated. If the incompatibility value is less than 0.1, the compatibility of the decision matrix is acceptable and if it is more than 0.1, it should be reconsidered.

198 $$I.I = \frac{\lambda_{\max} - n}{n-1} \quad (5)$$

199 $$I.\mathrm{R}. = \frac{I.I}{I.I.R.} \quad (6)$$

200 *2.3.3. Ordered Weight Average (OWA)-AHP method*

201 The two methods of OWA and AHP are not implemented at the same level. AHP is a general tool
202 for creating a hierarchical model of spatial decision issues, overall process processing, and
203 evaluation of each process. The evaluation process in AHP uses a simple weighted linear
204 combination to calculate the values of each raster cell. OWA operator also provides a general
205 framework for performing processes such as AHP. The nature and structure of these two
206 algorithms are such that their combination can be used to create a more powerful spatial decision
207 tool (Yager and Coleman, 1999). To achieve this framework, it is assumed that two steps of AHP,
208 namely the formation of the hierarchical structure and the calculation of the relative weights of the
209 criteria, are met by performing a pairwise comparison of the criteria. From this point on, the
210 problem is processed by OWA-guided quantifiers (Malczewski, 2006). OWA method can
211 calculate the level of risk-taking and risk aversion of individuals and enter it in the selection of the
212 final option. OWA operator, *F*, with dimension *n*, is an $R^n \rightarrow R$ mapping with weight vector w=(w1,
213 …wn)^T for an input set of data X=(x1, …xn) that are grouped together as (Eq. 7):

214 $$F(x_1,...,x_n) = \sum_{i=1}^{n} w_i b_i = W^T B \quad (7)$$

215 Which applies to the following conditions (Eq. 8):

$$Wi \in [0,1] \quad i = 1,2,...,n$$

216 $$\sum_{i=1}^{n} w_i = 1 \quad (8)$$

Where b_i and i are the largest values of the set ascending to descending. The concept of grading is defined as follows: (Eq. 9).

$$1 \le \alpha \le \infty$$

$$\sum_{i=1}^{n} (n-i) \qquad (9)$$

$$Orness(w) = \alpha = \frac{1}{n-2}$$

Here, OR-ness is between 0 and 1, which indicates the degree of emphasis of the decision-maker on the better or worse values of a set of indicators or the same risk-taking and risk aversion of the decision-maker. The degree of Orness or risk-taking indicates the position of OWA operator between AND (minimum (and OR (maximum)) relationships. A higher degree value (closer to one) indicates a more optimistic or risk-taking decision-maker, and a lower degree value (the closer it is to zero) indicates higher pessimism or risk aversion on the part of the decision-maker. In general, an OWA operator with OR-ness more than 0.5 represents a risk-averse or optimistic decision-maker; OR-ness = 1 represents a neutral decision-maker; and OR-ness < 0.5 represents a risk-averse or pessimistic decision-maker. The most important issue in using the OWA operator is determining its weights. In this paper, the minimum and maximum distance methods are used to determine the weights of the OWA operator. This model was introduced by Wang and Parkan (2005) (Eq. 10).

$$\begin{aligned} &Maximum \quad \partial \\ &\sum_{i=1}^{n} w_i = 1 \\ &w_i - w_{i+1} - \partial \le 0 \qquad i = 1,...,n-1 \\ &w_i - w_{i+1} + \partial \ge 0 \qquad i = 1,...,n-1 \\ &w_i \ge 0 \qquad\qquad\qquad i = 1,...,n \end{aligned} \qquad (10)$$

This model is a linear model that determines the weights based on the given grading. In this model, the distance between adjacent weights under the given calibration is reduced as much as possible. The weights obtained from this model are regularly distributed and follow an arithmetic progression.

2.3.4. Adaptive neuro-fuzzy inference system

This model, developed by Young in 1996, allows fuzzy systems to use the adaptive backward error propagation training algorithm in parameter training discussions (Kim, 1998). An ANFIS structure consisting of a set of fuzzy IF-THEN rules of the TSK type (for one rule only) can be used for modeling and mapping input-output data. In general, the steps of this network are as follows:

Layer 1, input Nodes: Each node in this layer generates membership values that belong to each of the appropriate fuzzy sets using the membership function (Eqs. 11, 12).

$$O_{1,i} = \mu_{A_i}(x) \qquad for\ i = 1,2 \tag{11}$$

$$O_{1,i} = \mu_{B_{i-2}}(x) \qquad for\ i = 3,4 \tag{12}$$

where y and x are non-fuzzy inputs to nodes i, and A_i and B_i are language tags that are denoted by the membership functions of μ_{Ai} and μ_{Bi}, respectively.

Second layer, rule nodes: Each neuron in this layer is fixed. The "and" operator is used in this layer until the output that represents the first part of that law is obtained (Eq. 13).

$$O_{2,i} = w_i = \mu_{A_i}(x)\,\mu_{B_i}(y) \qquad for\ i = 1,2 \tag{13}$$

Third layer, intermediate nodes: The main purpose of the third layer is to determine the ratio of

each ignition power of the law to the sum of all ignition laws. As a result, *W* is obtained as the standardized average (Eq. 14).

$$O_{3,i} = \overline{w}_i = \frac{w_i}{w_1 + w_2} \tag{14}$$

Fourth layer, result nodes: In this output layer, each node is equal to (Eq. 15):

$$O_{4,i} = \overline{w}_i f_i = \overline{w}_i (p_i x + q_i y + r_i) \tag{15}$$

where w_i is the output of the n^{th} node of the previous layer and $\{p_i, q_i, r_i\}$ are the coefficients of this linear combination

Fifth layer, output nodes: This layer calculates the total single output node by summing all the input signals. Therefore, in this layer of the non-fuzzy process, the results of each fuzzy law are transformed into non-fuzzy output (Eq. 16).

$$O_{5,i} = \sum_i \overline{w}_i f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} \tag{16}$$

The designed sample of the adaptive fuzzy-neural model is shown in Fig. 5.

2.3.5. All subset regression method

In this study, after determining the map of suitable areas and preparing land suitability classes for ARG, the correlation between all parameters with these classes in 50 sampling points is calculated using Pearson regression. In most studies, stepwise regression is used to determine the relationship between all the effective factors separately (Rencher and Pun, 1980). In this study, the best subset regression is used to solve this problem. This regression model considers the combined effects of

277 all factors and provides more information about the combination of all factors while being reliable
278 (Anthony, 1984).
279
280 **3. Results and Discussion**
281 *3.1. Fuzzy method*
282 The fuzzy maps prepared for effective parameters in the ARG are shown in Fig. 6 for the input
283 parameters of Fig. 3. The membership function value for each parameter is between 0 and 1 which
284 represent less and more suitable locations for ARG, respectively.
285 As can be seen in Fig. 6, it is clear that small parts of the north of the region with high altitudes,
286 parts of the north and south of the region with low slope, most areas with less distance from the
287 fault, areas with land use of rangeland, areas prone to erosion, areas with high precipitation in the
288 northern parts, and areas with high drainage density located in the northern and southern parts of
289 the region are prone to ARG and receive the number 1 and cole 1 from the membership function.
290 Finally, to prepare a land suitability map for ARG using the pairwise comparison matrix, the
291 weighted fuzzy maps of input parameters are prepared (Fig. 7). According to the results, the slope
292 and elevation with the weight of 0.297 and 0.045 are of high and low importance, respectively.
293 It is worth noting that the weighting is done based on the conditions of the region and the opinions
294 of experts. The values of these weights can be different in different regions. For example, in the
295 studies of Rajasekhar et al. (2019), the lowest weight was considered for soil and lineament density
296 while in the study of Anand et al. (2020) the highest weight was considered for the lineament
297 parameter.
298 Finally, using the weights assigned to each parameter (Fig. 7), the final map of suitable areas for
299 ARG is prepared which is shown in Fig. 8. According to Fig. 8, it is obvious that about 12% of the

300 area is in the very high class (0.8-1), 14% in the high class (0.6-0.8), 59% in the moderate class
301 (0.6-0.4), 14% in the low class (0.2-0.4) and about 1% in the very low (0-0.1) class.
302
303 *3.2. OWA-AHP method*
304 In the present study, six order weights (α values) are used for seven factors that are rank-ordered
305 for each parameter. Based on the corresponding criterion weights and the standardized criterion
306 maps, OWA operators are defined. According to Table 3, α values is from at least one ($\alpha = 0$) to
307 all ($\alpha = \infty$) (Table 3).
308 Fig. 9 shows six alternatives of ARG with different risk levels. Fig. 9 (LLRNTO) and (LLRATO)
309 represent a low risk with the average tradeoff in comparison to Fig. (ALRFTO) with more risk.
310 Fig. 9 (HLRATO) displays high risk with average tradeoff compared to Fig. 9 (LLRNTO) with
311 lower risk. Finally, Fig. 9 (ALRNTO) displays average risk with no tradeoff versus Fig. 9 (6) with
312 more risk. Based on Fig. 9, with reducing risk (low level of risk and no tradeoff as shown in Fig.
313 9 (LLRNTO)), the percentage of suitable location is low and only small portions of the eastern
314 part of the study area are suitable for the artificial recharge. By increasing the risk (LLRATO)
315 (Fig. 9 (LLRATO)), the eastern part of the region (blue color) turns into suitable for artificial
316 recharge. With average risk (full tradeoff as shown in Fig. 9 (ALRFTO)), all of the effective
317 parameters of drinking water quality with different weights lead to the highest appropriateness in
318 the north, south, and west parts of the region. Fig. 9 (ALRNTO) shows an average level of risk
319 and no tradeoff and has low risk compared to Fig. 9 (HLRATO). According to Fig. 9 (ALRNTO),
320 many parts of the study area have high values by a total rate of 28% (dark blue), medium value,
321 and a low value. According to Fig. 9 (HLRNTO), with a high level of risk and no tradeoff, the area
322 with appropriateness for ARG increases. So with decreasing the risk (no tradeoff), almost all parts

of the study area are found inappropriate for ARG. On the other hand, increasing the risk (no tradeoff) leads to improvement in-appropriateness for ARG.

According to Fig. 9, the area of land suitability maps with different risk levels is classified in eighty classes shown in Fig. 10. For situations, LLR-NTO, LLR-ATO, ALR-FTO, classes 0-0.125 have the most area and for situations, ALR-NTO, HLR-ATO, HLR-NTO, classes 0.625-0.75, and 0.75-0.875 have the most area. Also, based on Fig. 10, land suitability with LLR-NTO had the highest area in the very low class (80%) (between 0.125 - 0.25) while land suitability with HLR-NTO had the highest area in the very high class (27%) (between 0.75 - 0.875).

This study applied OWA operators to prepare different maps with different risk levels for ARG. Based on the financial and environmental situations, decision-makers can choose one of the maps to manage the region. A review of the literature shows that there is no study about preparing an ARG map with different risk levels using the OWA-AHP method. In the past, OWA has been used in environmental engineering studies to investigate different parameters such as flood analysis (Yalcin et al., 2004), environmental monitoring (Stroppiana et al., 2009), climate change (Zarghami and Rahmani, 2012), soil fertility (Mokarram and Hojati et al., 2017), land suitability (Mokarram andAminzadeh, 2010).

Finally, to evaluate the accuracy of the two methods (fuzzy-AHP and OWA-AHP with ALR-NTO) in 20 sample points, the values of climatic, human, environmental, topographic characteristics as well as land suitability classes predicted by the two methods and the real values are compared using the receiver operating characteristic (ROC) curve, the results of which are shown in Table 4. According to Table 4, it is clear that the area under curve (AUC) values for both models are high (AUC Fuzzy-AHP = 95.0%, AUC OWA = 90.0%), which indicates the high accuracy of the methods to determine suitable locations for artificial recharge of groundwater.

346 The results of the present study show that the AHP and OWA methods have high accuracy for
347 investigating suitable areas for groundwater recharge. The results of the study of Anand et al.
348 (2020) showed that the use of MCDA and GIS methods is an efficient and useful tool for planning
349 and improving areas suitable for groundwater recharge in the case area.
350
351 *3.3. ANFIS method*
352 Grid, sub-clustering, and FCM models from the ANFIS algorithm are used to predict land
353 suitability classes. For the three models, hybrid and back-propagation modes are used. Table 5 and
354 Fig. 11 show the results of each model. The results of FCM in hybrid mode to predict suitable
355 locations for ARG classes are shown in Fig. (11 (a)). R, MSE, and RMSE values are used to
356 determine the accuracy of the model in predicting land suitability classes. The results show that R
357 = 0.99, MSE = 0, RMSE = 0.012, indicating the high accuracy of the FCM model in hybrid mode
358 to predict suitable places for arterial recharge of groundwater. According to Fig. 11 (b), it is clear
359 that the sub-clustering method with values of R = 1, MSE = 0, and RMSE = 0 is highly accurate
360 in predicting land suitability classes. It is worth noting that the back-propagation model has more
361 errors and is not suitable for predicting land suitability classes. . Jafari et al. (2021) showed that
362 the FCM-hybrid method show high accuracy for checking groundwater status.
363 Studies show that the combination of the FCM method with hybrid mode for classification and
364 prediction of the target shows high accuracy, which is consistent with the results of this study
365 (Jaypuria et al., 2020; Jafari et al., 2021).
366 Then, to investigate the effective parameters on suitable places for ARG and to determine the most
367 important effective parameters, the best subset regression is used. Fan et al. (2020) confirmed the
368 high accuracy of the method in selecting the important data. According to Fig. 12, in the lowest

369 C_p values (5.2), slope, lithology, land use, altitude have the highest correlation and, therefore, have
370 the greatest impact on determining suitable locations for ARG.
371 Therefore, the use of the best subset regression method has a high accuracy due to the investigation
372 and selection of the most important parameters considering the combined relationship of the
373 parameters with each other (Takano and Miyashiro et al., 2020; Kwong et al., 2020).
374

375 **4. Conclusion**

376 In this study, fuzzy AHP and OWA-AHP methods are used to determine suitable locations for
377 ARG in Bushehr province, southern Iran. The results of the OWA-AHP method show that, with
378 decreasing risk level (no trade-off), almost all of the study area (i.e. about 80% or 34296.98 Km^2),
379 except for small parts in the center and north of the study area, is suitable for ARG. Also, with
380 increasing the risk (no trade-off), about 27% (11575.23 Km^2) of the study area is suitable for ARG,
381 and that the majority of these sites are spread over different parts of the study area, especially in
382 the south of the study area. By referring to land suitability maps with different risk levels, one of
383 them can be chosen depending on the financial constraints and environmental situations to
384 determine high-risk areas in the region. Therefore, based on different conditions of the study area
385 such as the people's financial status, authoritative perspectives, short and long-term plans, the age
386 distribution of the population, etc., the artificial recharge map with the appropriate risk level can
387 be used for the management of the region. Also, the results of the ANFIS method show that FCM
388 and sub-clustering are highly accurate in predicting land suitability map for ARG. Finally, the
389 results of the best subset regression method show that the slope, lithology, land use, and altitude
390 are the most important parameters to predict land suitability classes. In this study, it is also
391 suggested that in areas that are suitable for groundwater recharge, the necessary management

should be taken to feed runoff in groundwater aquifers.

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Notes on contributors: Conceptualization by M.M., S.N. and A.A.; formal analysis by M.M.; initial methodology and investigation by M.M., S.N. and A.A.; project administration by A.A.; supervision by M.M..; validation M.M., and A.A.; visualization and software by M.M.; writing—original draft by and M.M. and A.A.

Declaration of competing interest

No known

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Figure captions

Fig. 1. Flowchart of the research Method

Fig. 2. Location of the study area

Fig. 3. (a) Altitude (DEM); (b) Slope; (c) Distance to fault; (d) Land use; (e) Sensitivity classes; (f) precipitation and (g) Drainage density maps

Fig. 4. Incremental and decrement membership function for each of the effective parameters in groundwater recharge

Fig. 5. ANFIS structure

Fig. 6. Fuzzy maps for the ARG location parameters. (a) Altitude ; (b) Slope; (c) Distance to fault; (d). Land use; (e). Lithology; (f). Precipitation; and (g) Drainage density

Fig. 7. Weights for used parameters using AHP

Fig. 8. Land suitable areas for ARG using the fuzzy-AHP method

Fig. 9. (1). LLR-NTO, (2). LLR-ATO, (3). ALR-FTO, (4). ALR-NTO, (5). HLR-ATO, (6). HLR-NTO

Fig. 10. Area of each class using OWA method

Fig. 11. Results of ANFIS method. (a): Fcm:hybrid, (b): Sub:hybrid

Fig. 12. Best-subset regression results to determine the most important parameters affecting artificial recharge of groundwater

528 **Table 1.** The data source of the study area to investigate suitable places for ARG

Parameters	Scale	Format	Source	Year
Slope	Resulation 30m	Raster	USGS	2019
Lithology	1:100,000	Polygon	Bushehr Geological Survey	2015
Land use	1:250,000	Polygon	Agricultural Jihad of Bushehr Province	2017
Drainage density	1:250,000	Raster	Geographical organization of the country	2015
Distance to fault	1:100,000	Polyline	Bushehr Geological Survey	2015
Precipitation	Resolution 30m	Raster	Bushehr Meteorological Organization	2019
Altitude	Resulation 30m	Raster	USGS	2019

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530

531 **Table 2.** Description of sensitive classes of formation to water erosion

Classes	Description
1	Limestone rock
2	Bedded to massive fossiliferous limestone
3	Hale and chert, bedded to massive orbitolina limestone
4	Bedded argillaceous limestone and calcareous shale, bedded sandstone
5	Piedmont conglomerate and sandstone, shelly limestone
6	Bedded argillaceous - limestone, Low-level piedmont fan, and valley terrace deposits

532

533 **Table 3.** weighting each parameter with different αvalues (linguistic quantifiers)

j	Quantifier	Criterion Weight u^k	$(\sum_{k=1}^{j} u_k)^{\alpha}$	$(\sum_{k=1}^{j} u_k)^{\alpha}$ - $(\sum_{k=1}^{j-1} u_k)^{\alpha}$
Slope	(a) At least one, Low level of risk and no trade-off (LLR-NTO) (α=0)	0.297	1	1
Lithology		0.231	1	0
Land use		0.167	1	0
Drainage density		0.118	1	0
Distance to fault		0.082	1	0
Precipitation		0.059	1	0
Altitude		0.045	1	0
Slope	(b) At least A Few, Low level of risk and average trade-off (LLR-ATO) (α=0.1)	0.297	0.885678	0.885678
Lithology		0.231	0.938131	0.052453
Land use		0.167	0.96427	0.026139
Drainage density		0.118	0.97951	0.015241
Distance to fault		0.082	0.988968	0.009458
Precipitation		0.059	0.995302	0.006334
Altitude		0.045	0.9999	0.004598
Slope	(c) A Few, average level of risk and full trade-off (ALR-FTO) (α=0.5)	0.297	0.544977	0.544977
Lithology		0.231	0.726636	0.181659
Land use		0.167	0.833667	0.107031
Drainage density		0.118	0.901665	0.067999
Distance to fault		0.082	0.946044	0.044379
Precipitation		0.059	0.976729	0.030685
Altitude		0.045	0.9995	0.022771

Slope		0.297	0.297	0.142
Lithology		0.231	0.528	0.142
Land use		0.167	0.695	0.142
Drainage density	(d) Half, average level of risk and no trade-off (ALR-NTO)	0.118	0.813	0.142
Distance to fault	(α=1)	0.082	0.895	0.142
Precipitation		0.059	0.954	0.142
Altitude		0.045	1	0.142
Slope		0.297	0.088209	0.088209
Lithology		0.231	0.278784	0.190575
Land use		0.167	0.483025	0.204241
Drainage density	(e) Most, High level of risk and average trade-off (HLR-ATO)	0.118	0.660969	0.177944
Distance to fault	(α=2)	0.082	0.801025	0.140056
Precipitation		0.059	0.910116	0.109091
Altitude		0.045	0.998001	0.087885
Slope		0.297	0	0
Lithology		0.231	0	0
Land use		0.167	0	0
Drainage density	(g) All, High level of risk and no trade-off (HLR-NTO)	0.118	0	0
Distance to fault	(α=∞)	0.082	0	0
Precipitation		0.059	0	0
Altitude		0.045	1	1

534

535

536 **Table 4.** Area Under the Curve of built models

Models	Area Under Curve (AUC)	Standard Error	Asymptotic Significant	Asymptotic 95% Confidence Interval	
				Lower Bound	Upper Bound
Fuzzy-AHP	0.95	0.000	0.001	0.93	0.89
OWA	0.90	0.001	0.002	0.90	0.85

537

538 **Table 5.** The results of the ANFIS method

Method	Model	Train			Test		
		R	**RMSE**	**MSE**	**R**	**RMSE**	**MSE**
FCM	Back propagation	0.075	22.200	4.710	0.068	24.410	4.940
	Hybrid	0.990	0.000	0.012	0.990	0.000	0.012
Sub-cluster	Back propagation	0.430	44.230	6.650	0.570	28.400	5.300
	Hybrid	1.000	0.000	0.000	1.000	0.000	0.000
Grid-	Back propagation	0.560	0.730	0.270	0.730	10.370	3.220
	Hybrid	0.500	12.000	2.800	0.560	8.700	2.600

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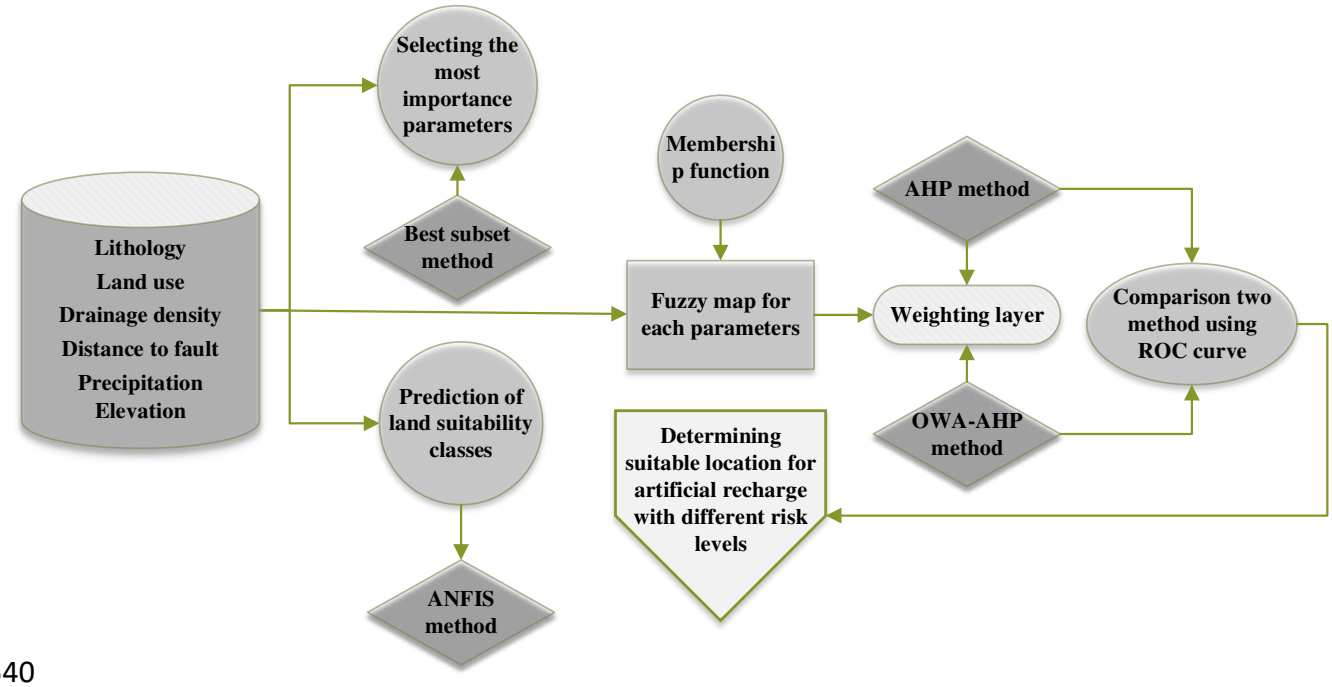

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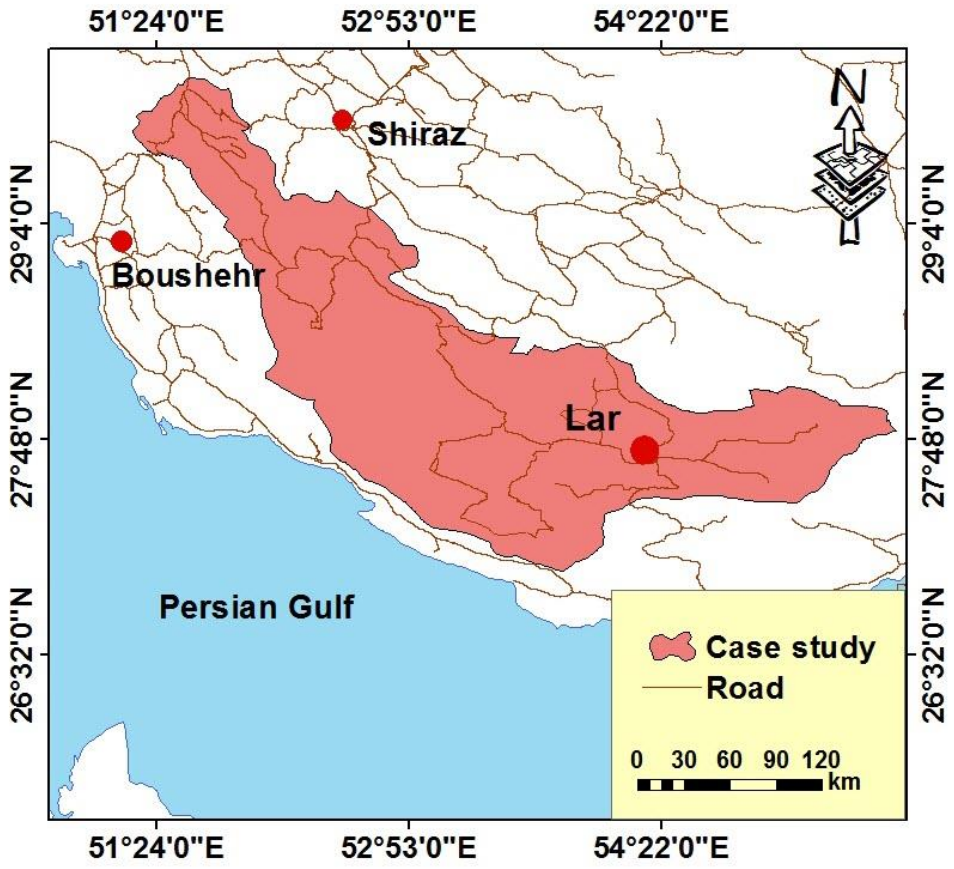
541 **Fig. 1.** Flowchart of the research Method



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543 **Fig. 2.** Location of the study area

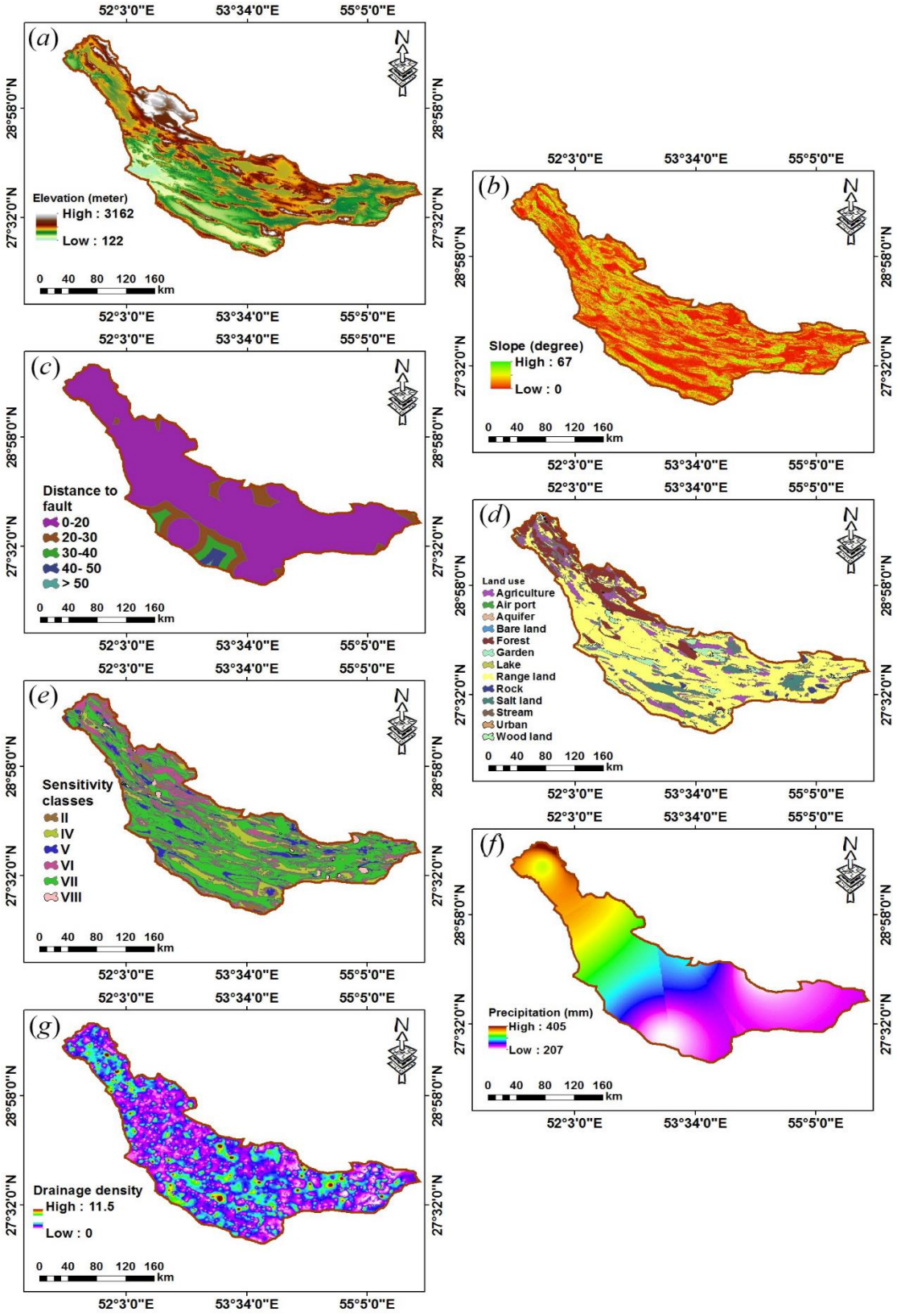
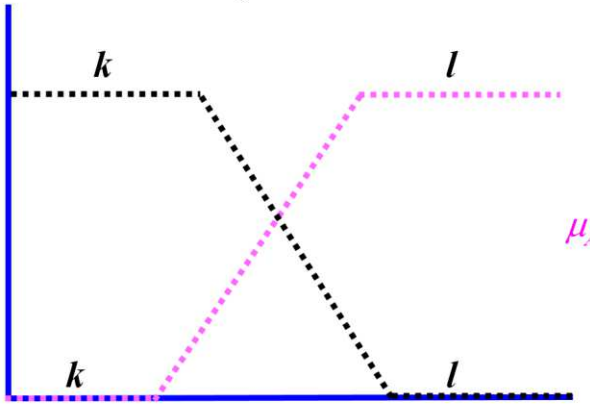


Fig. 3. (a) Altitude (DEM); (b) Slope; (c) Distance to fault; (d) Land use; (e) Sensitivity classes;

546 (f) precipitation and (g) Drainage density maps

$$\mu_A(x)=f(x)=\begin{cases}0 & x\le k\\ x-k/l-k & k\prec x\prec l\\ 1 & x\ge l\end{cases}\Bigg\}$$



$$\mu_A(x)=f(x)=\begin{cases}1 & x\le k\\ l-x/l-k & k\prec x\prec l\\ 0 & x\ge l\end{cases}\Bigg\}$$

547

548 Fig. 4. Incremental and decrement membership function for each of the effective parameters in

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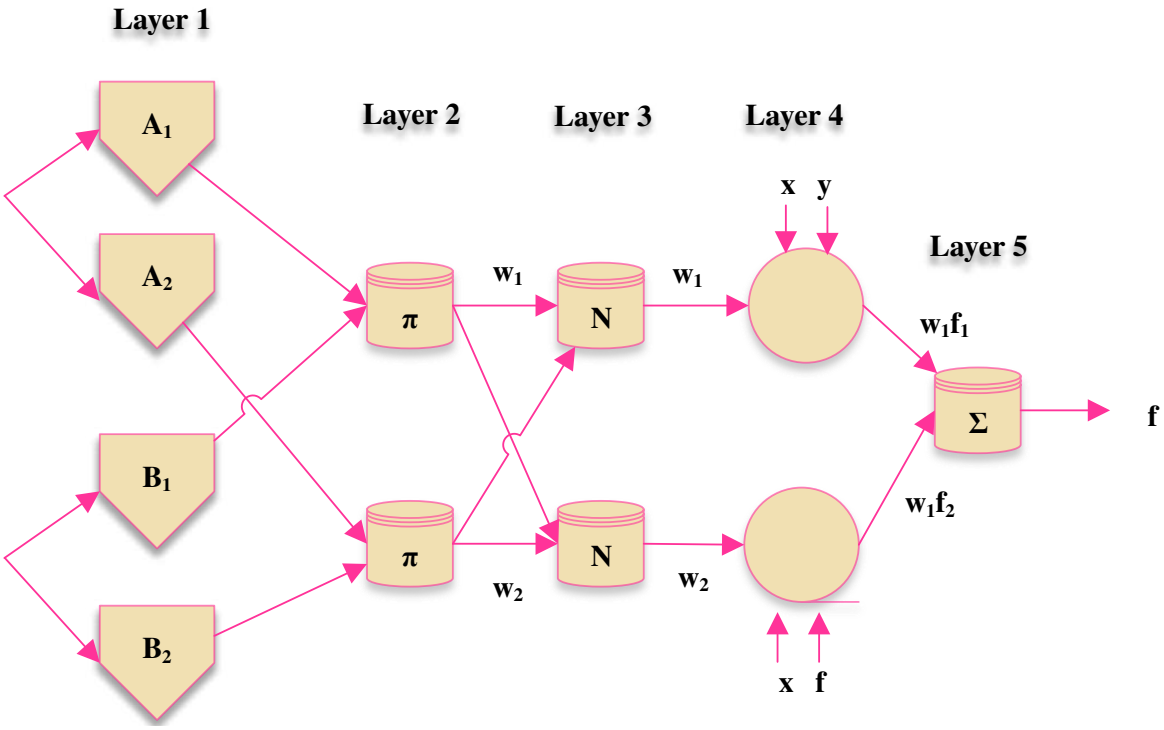

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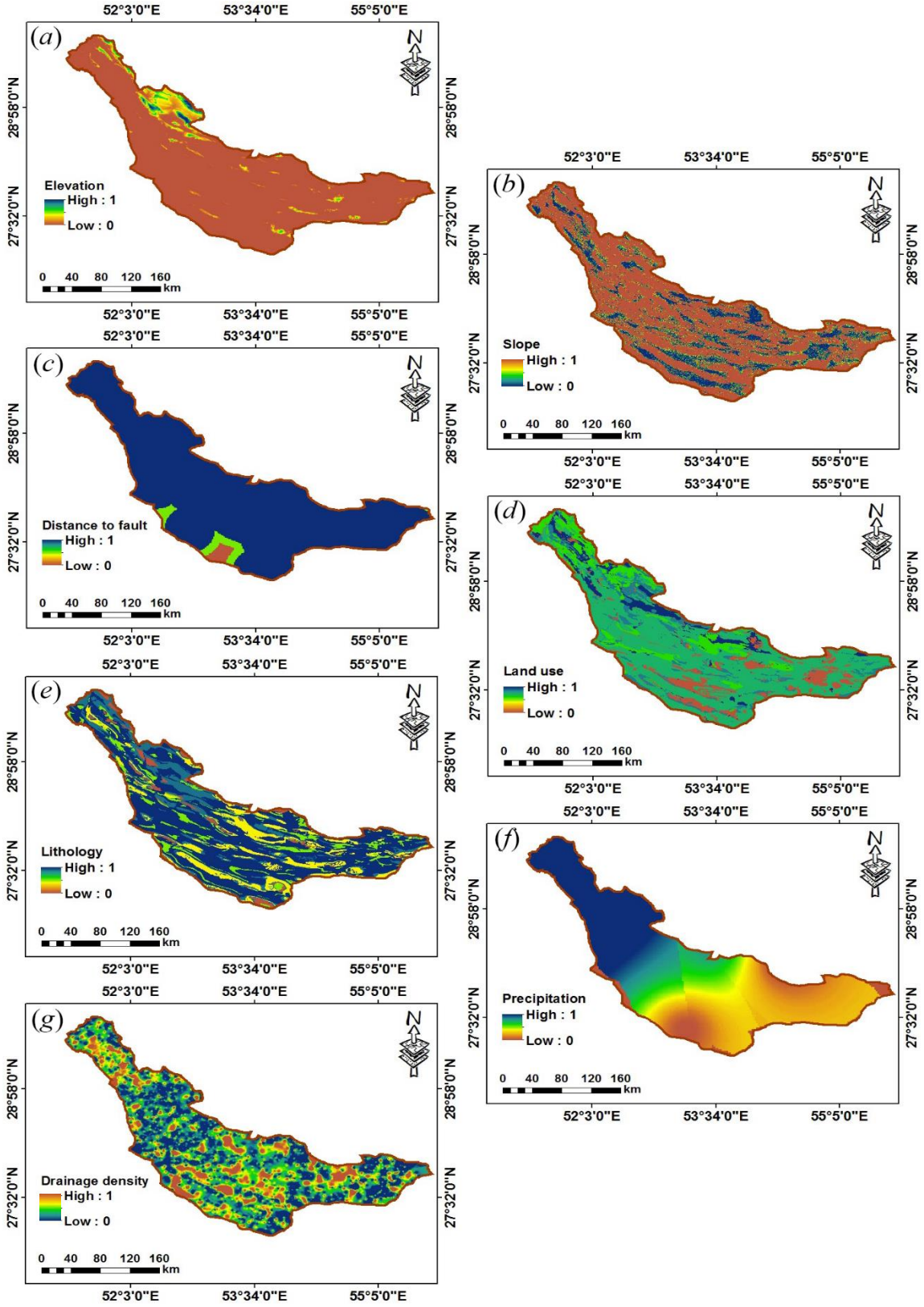

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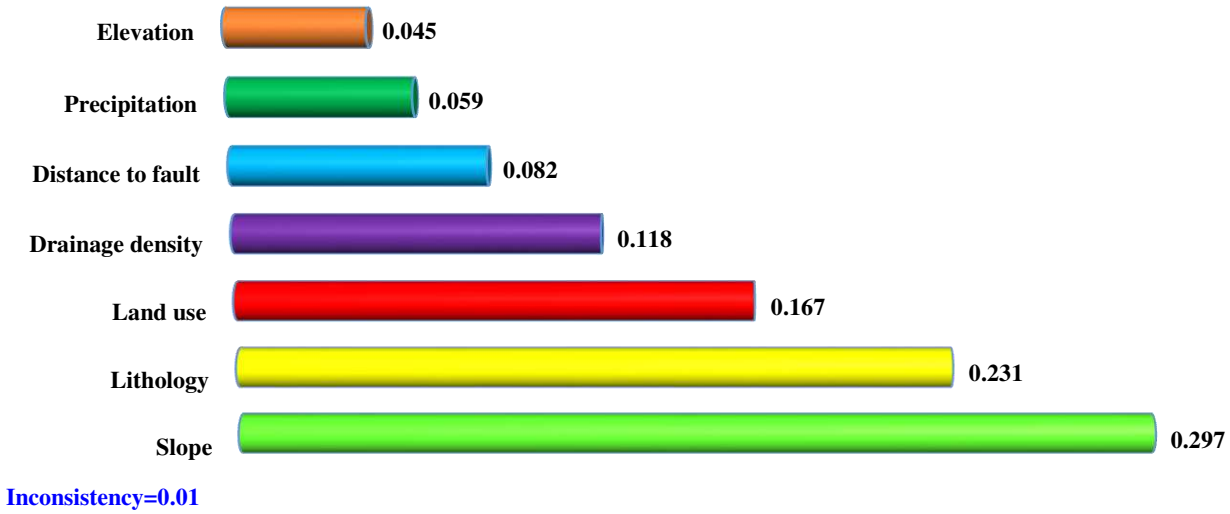

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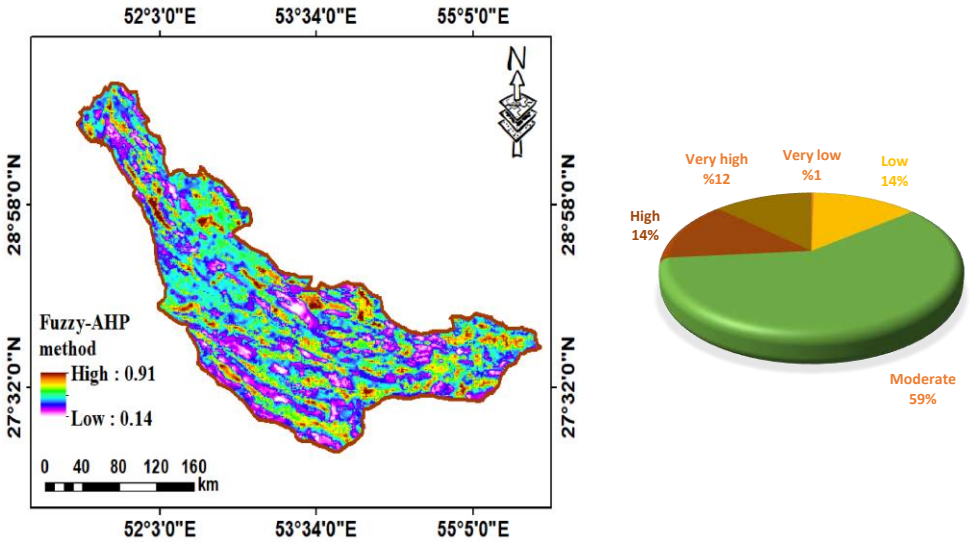
559 **Fig. 7.** Weights for used parameters using AHP



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561 Fig. 8. Land suitable areas for ARG using the fuzzy-AHP method

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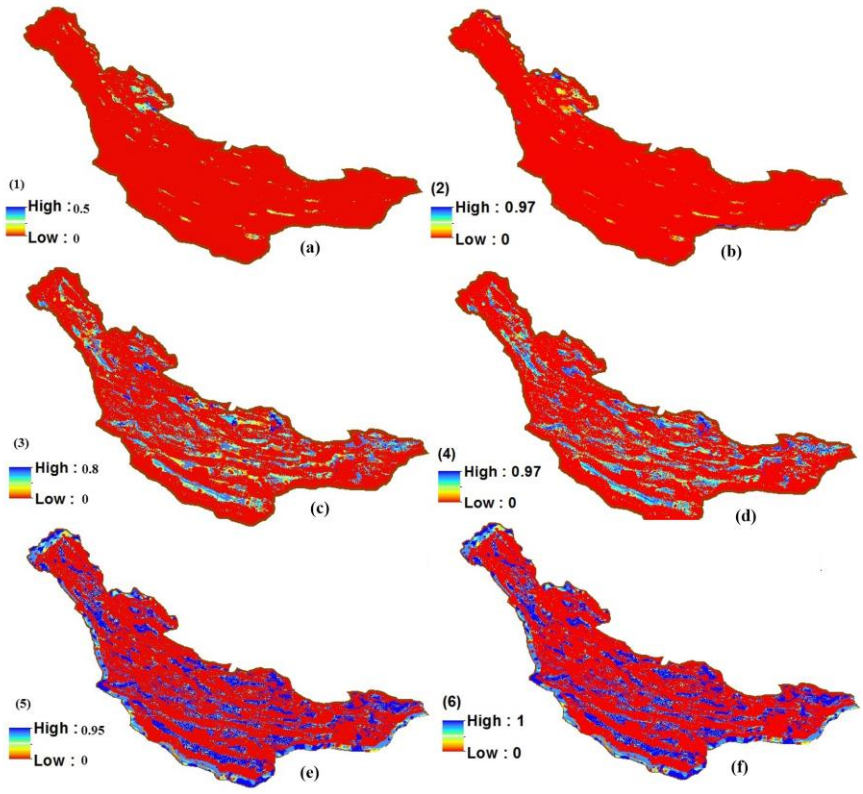
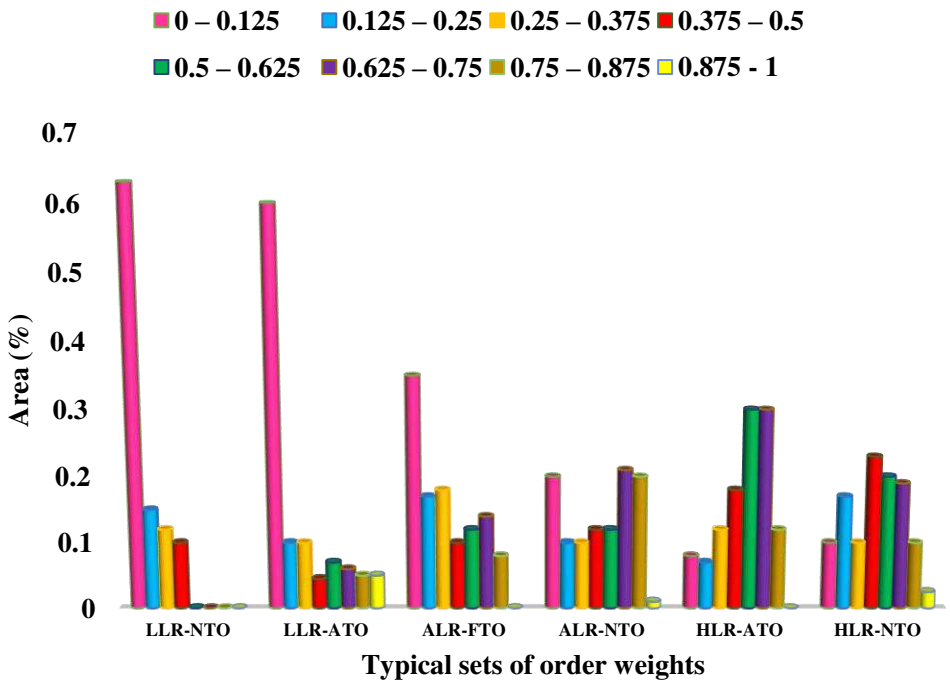


564

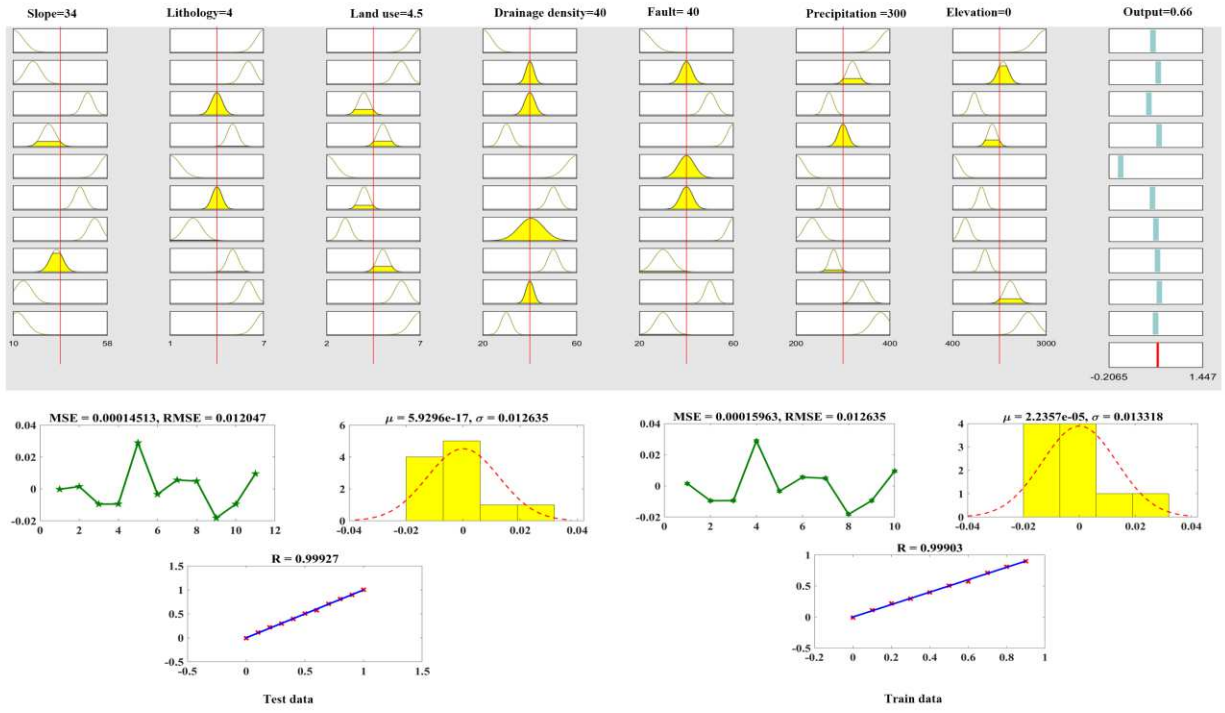
565 **Fig. 9.** (1). LLR-NTO, (2). LLR-ATO, (3). ALR-FTO, (4). ALR-NTO, (5). HLR-ATO, (6).

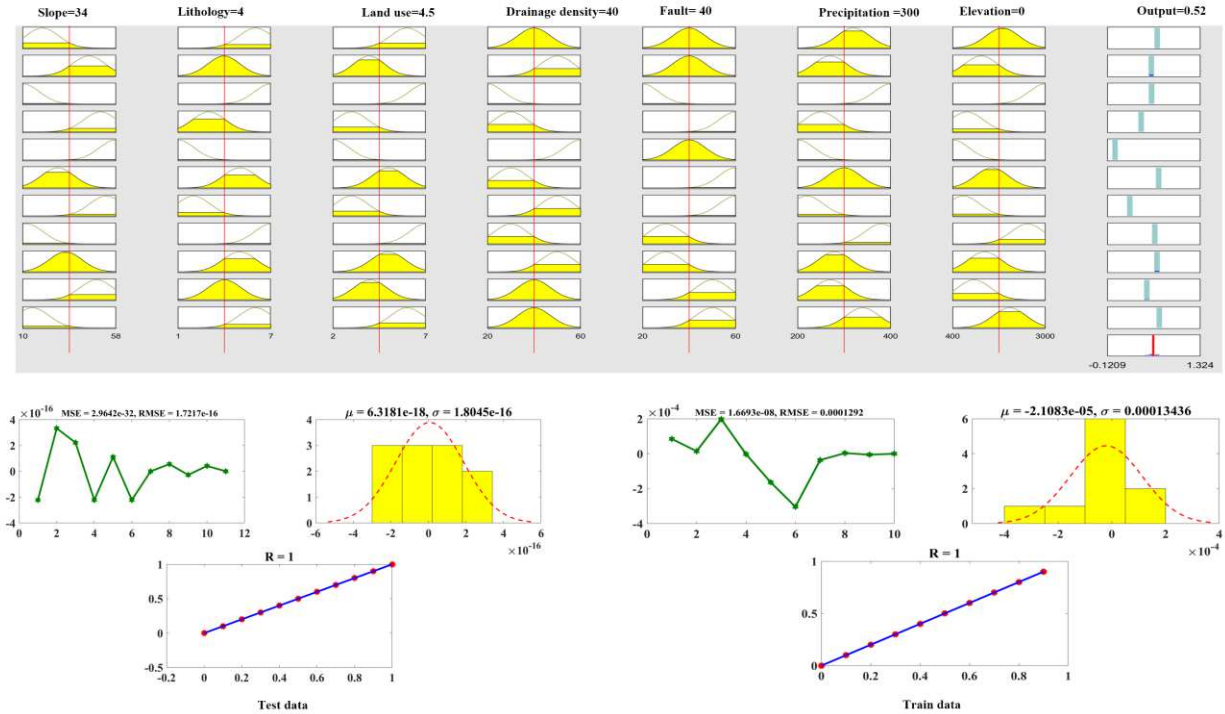
566 HLR-NTO



567

568 **Fig. 10.** Area of each class using OWA method





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Figures

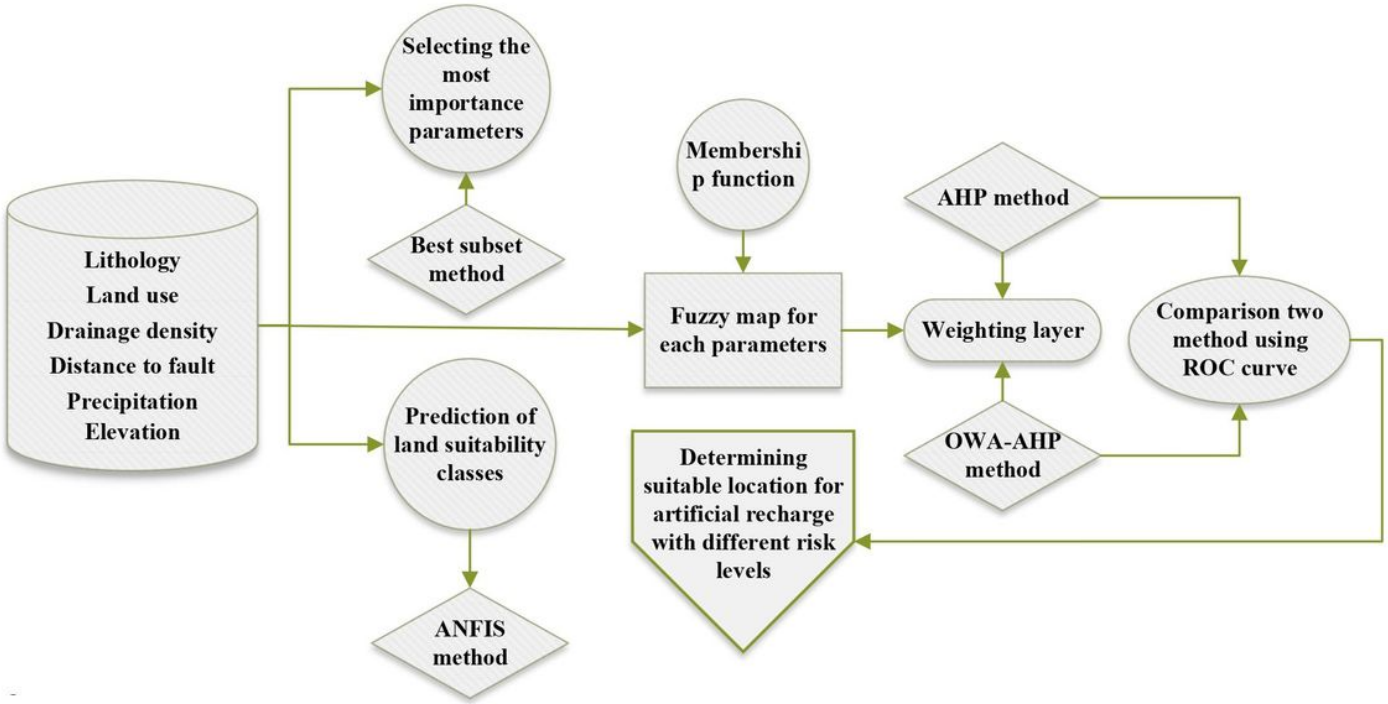


Figure 1

Flowchart of the research Method

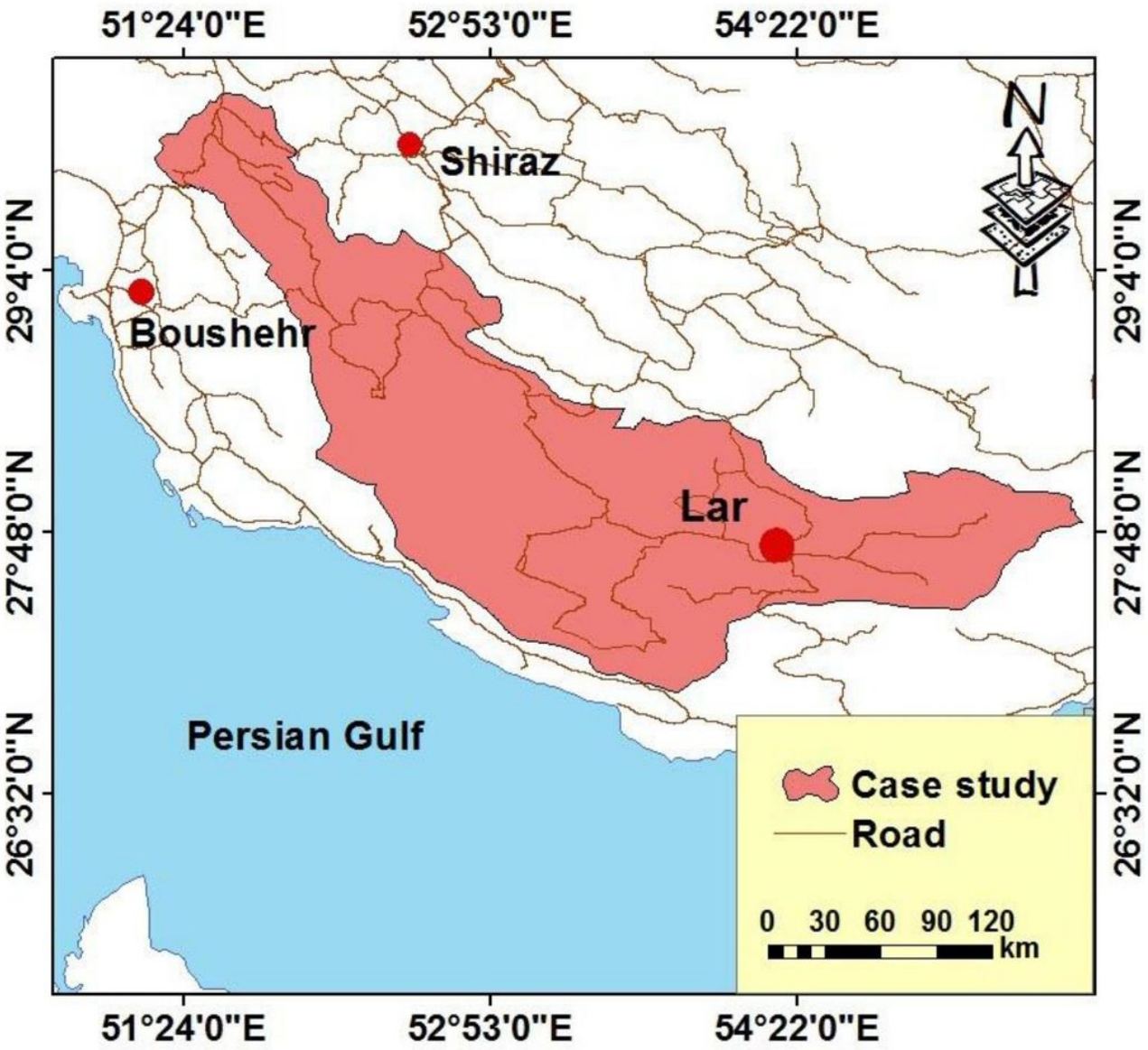


Figure 2

Location of the study area Note: The designations employed and the presentation of the material on this map do not imply the expression of any opinion whatsoever on the part of Research Square concerning the legal status of any country, territory, city or area or of its authorities, or concerning the delimitation of its frontiers or boundaries. This map has been provided by the authors.

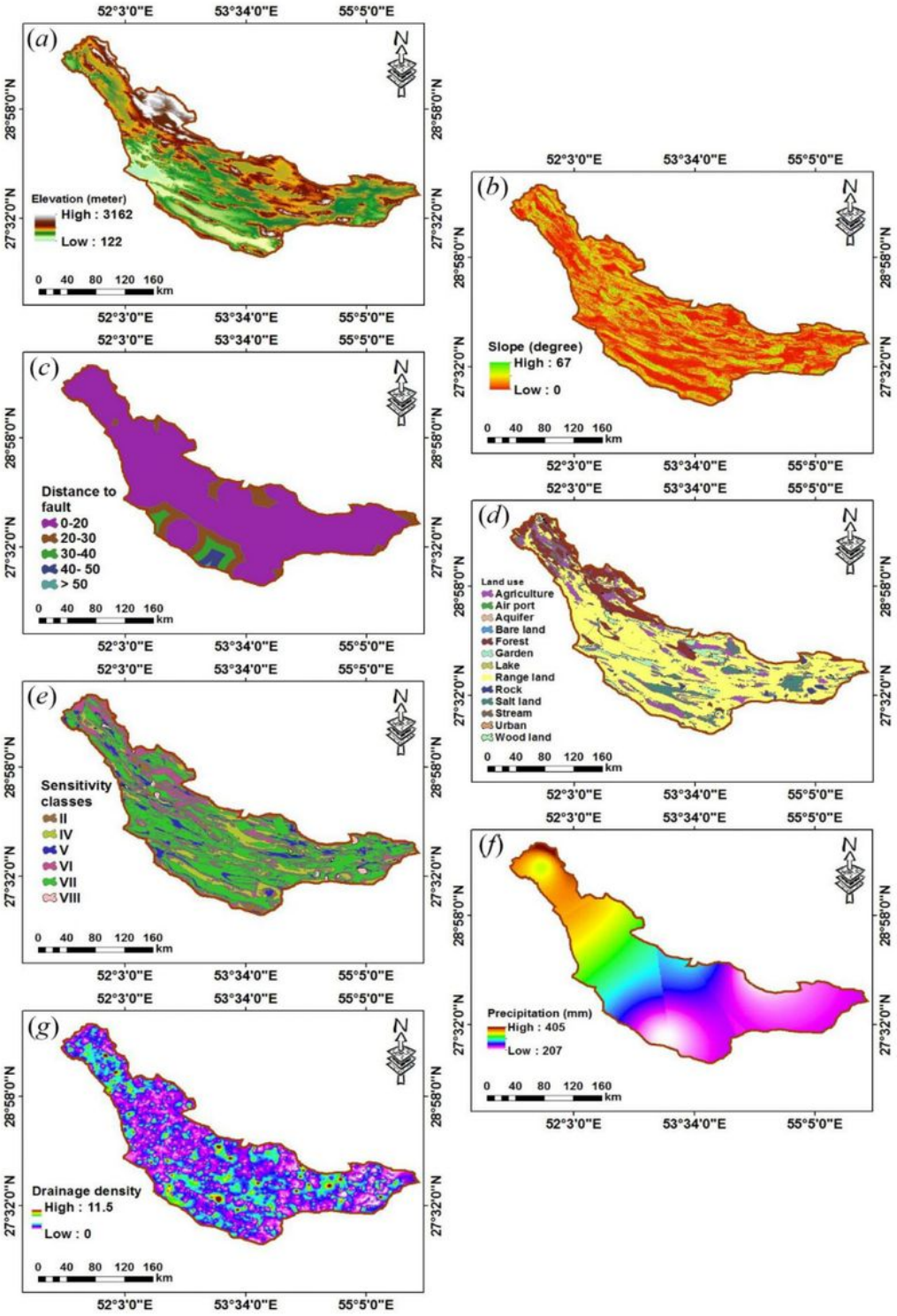


Figure 3

(a) Altitude (DEM); (b) Slope; (c) Distance to fault; (d) Land use; (e) Sensitivity classes; (f) precipitation and (g) Drainage density maps Note: The designations employed and the presentation of the material on this map do not imply the expression of any opinion whatsoever on the part of Research Square concerning the legal status of any country, territory, city or area or of its authorities, or concerning the delimitation of its frontiers or boundaries. This map has been provided by the authors.

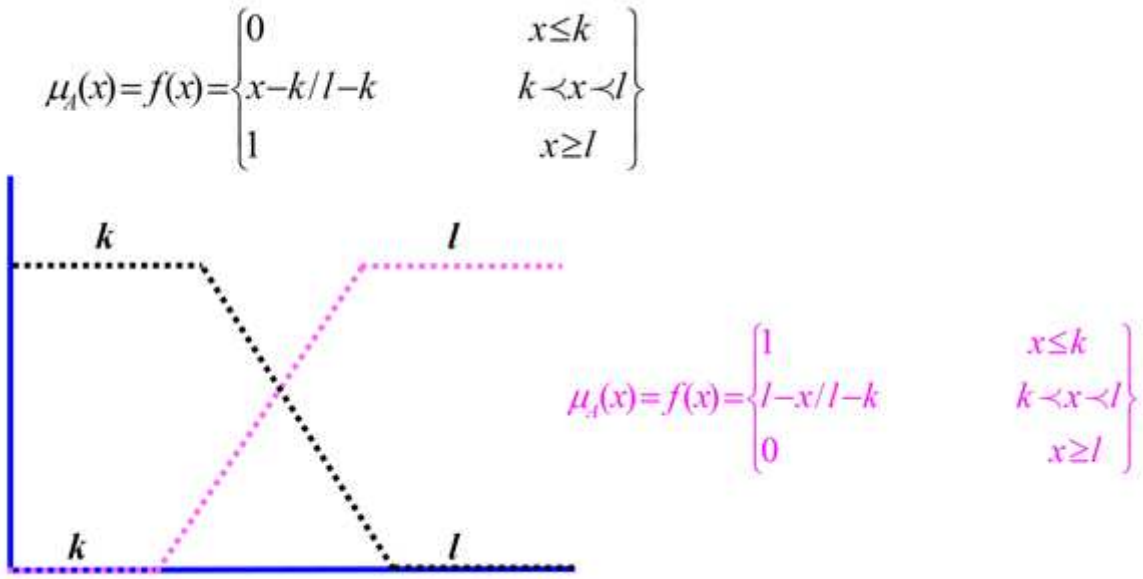


Figure 4

Incremental and decrement membership function for each of the effective parameters in groundwater recharge

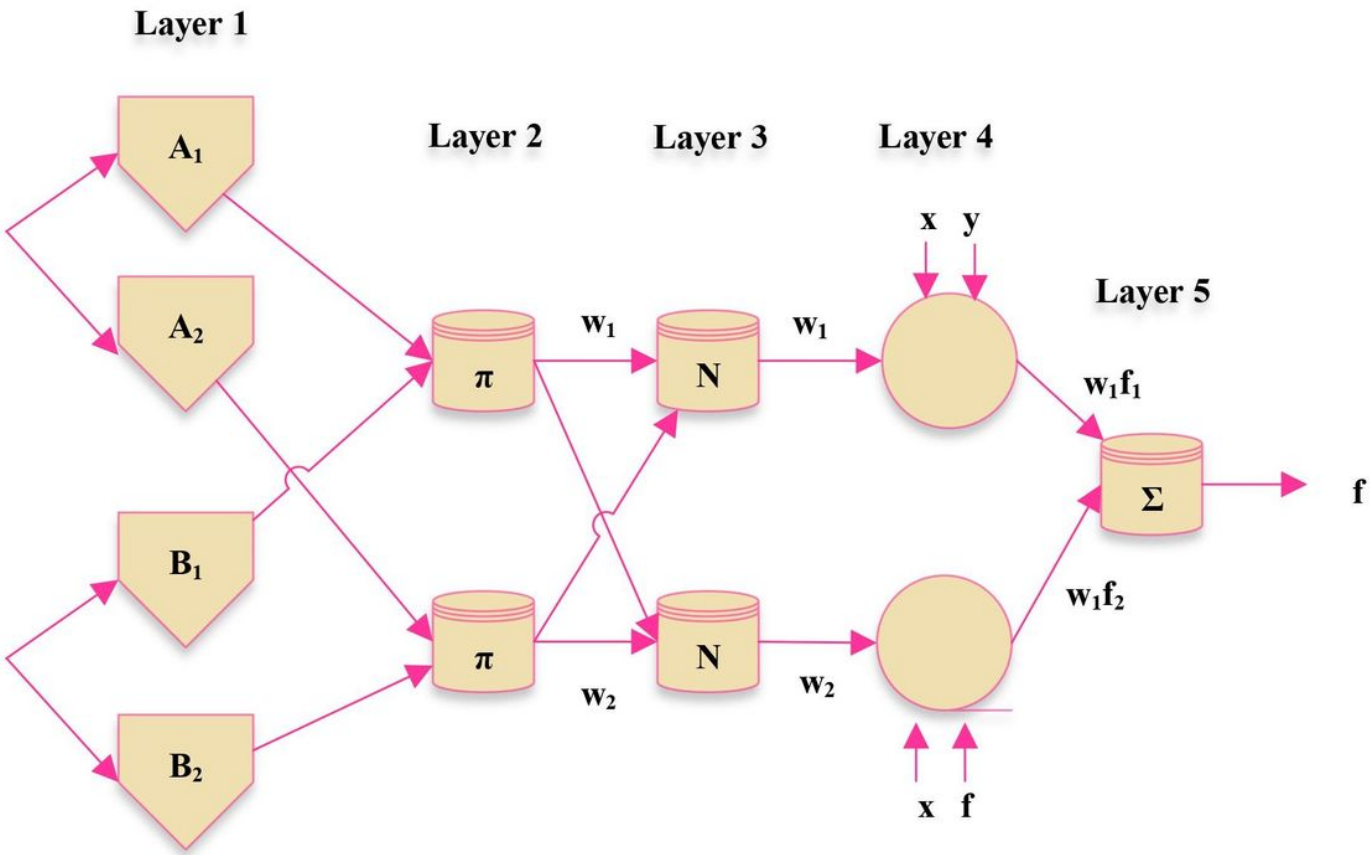
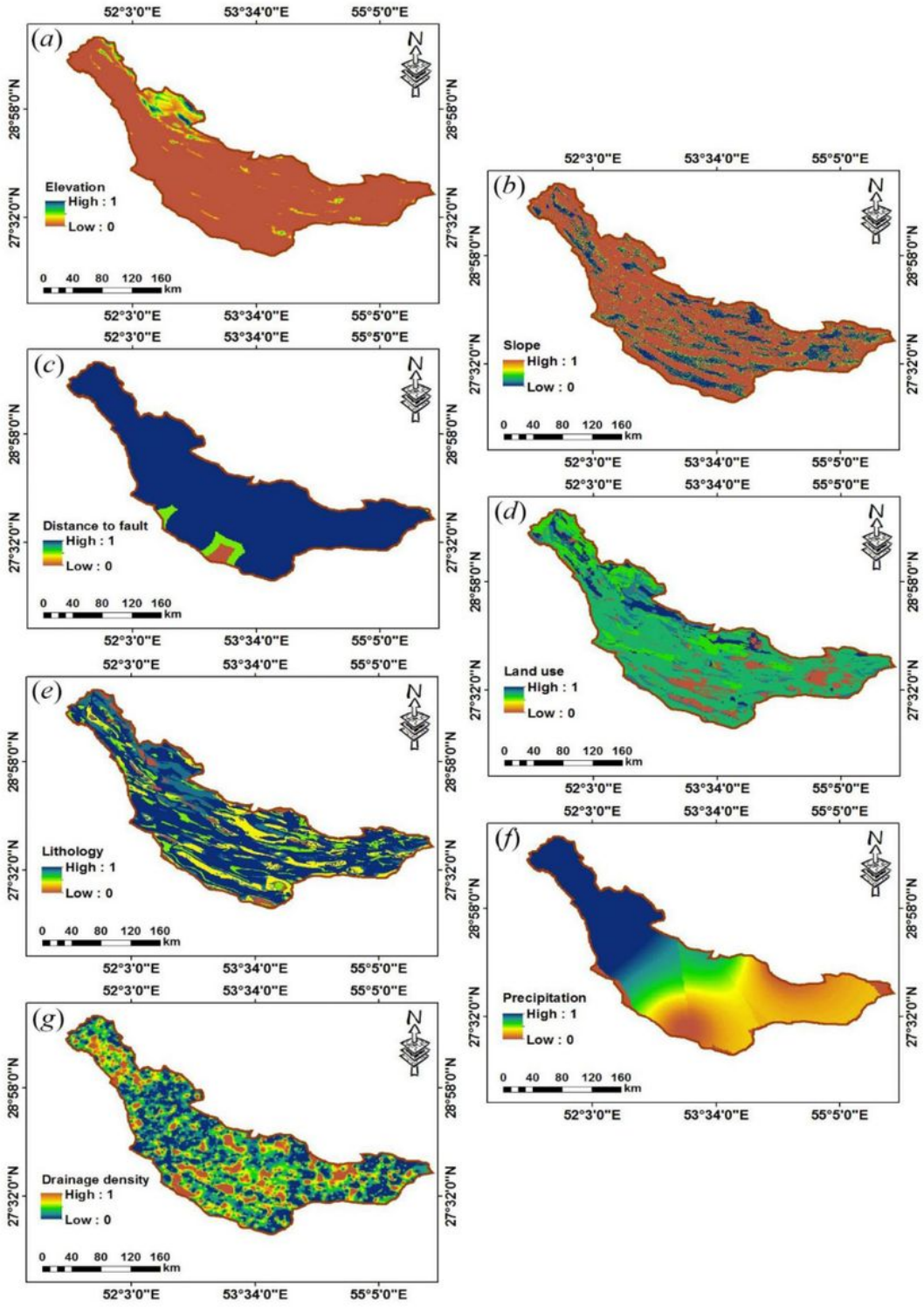


Figure 5

ANFIS structure



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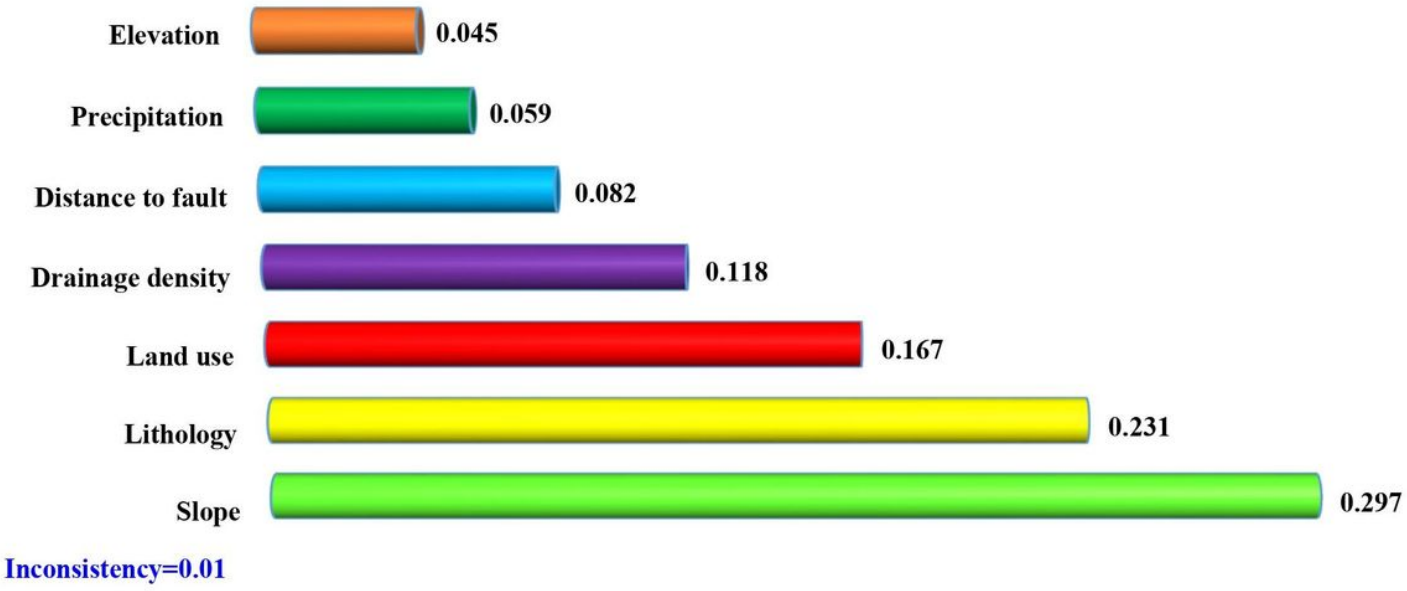

Figure 7

Weights for used parameters using AHP

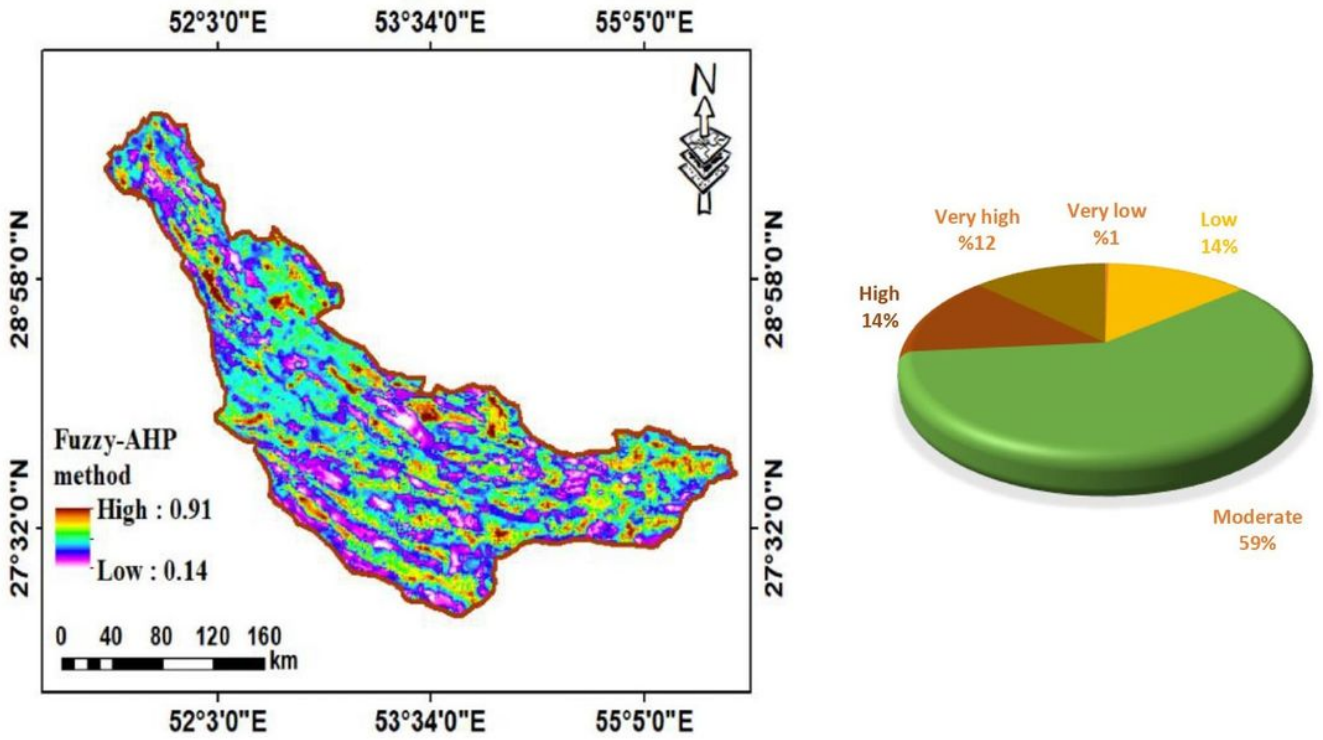

Figure 8

Land suitable areas for ARG using the fuzzy-AHP method Note: The designations employed and the presentation of the material on this map do not imply the expression of any opinion whatsoever on the part of Research Square concerning the legal status of any country, territory, city or area or of its authorities, or concerning the delimitation of its frontiers or boundaries. This map has been provided by the authors.

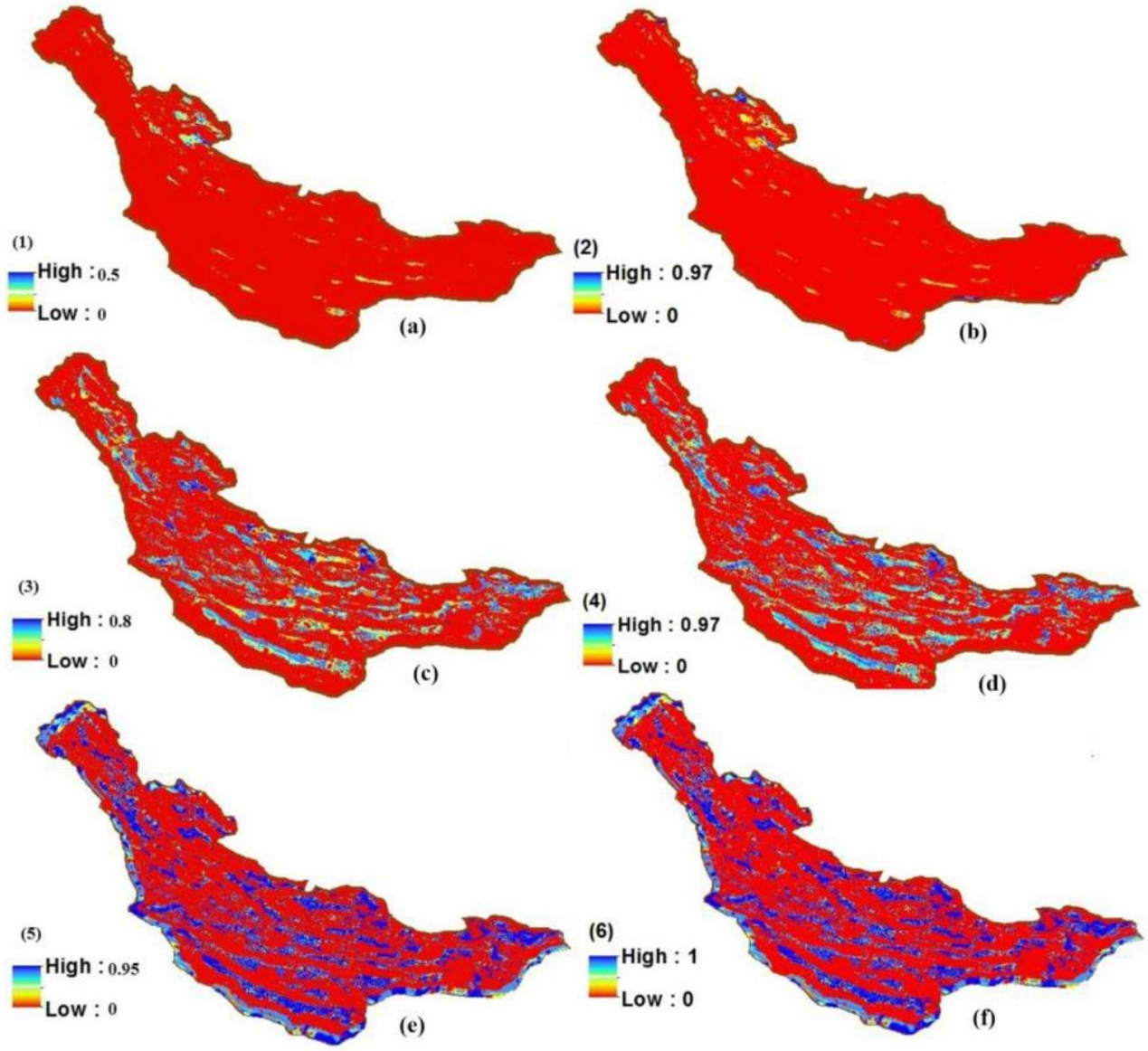

Figure 9

(1). LLR-NTO, (2). LLR-ATO, (3). ALR-FTO, (4). ALR-NTO, (5). HLR-ATO, (6). HLR-NTO Note: The designations employed and the presentation of the material on this map do not imply the expression of any opinion whatsoever on the part of Research Square concerning the legal status of any country,

territory, city or area or of its authorities, or concerning the delimitation of its frontiers or boundaries. This map has been provided by the authors.

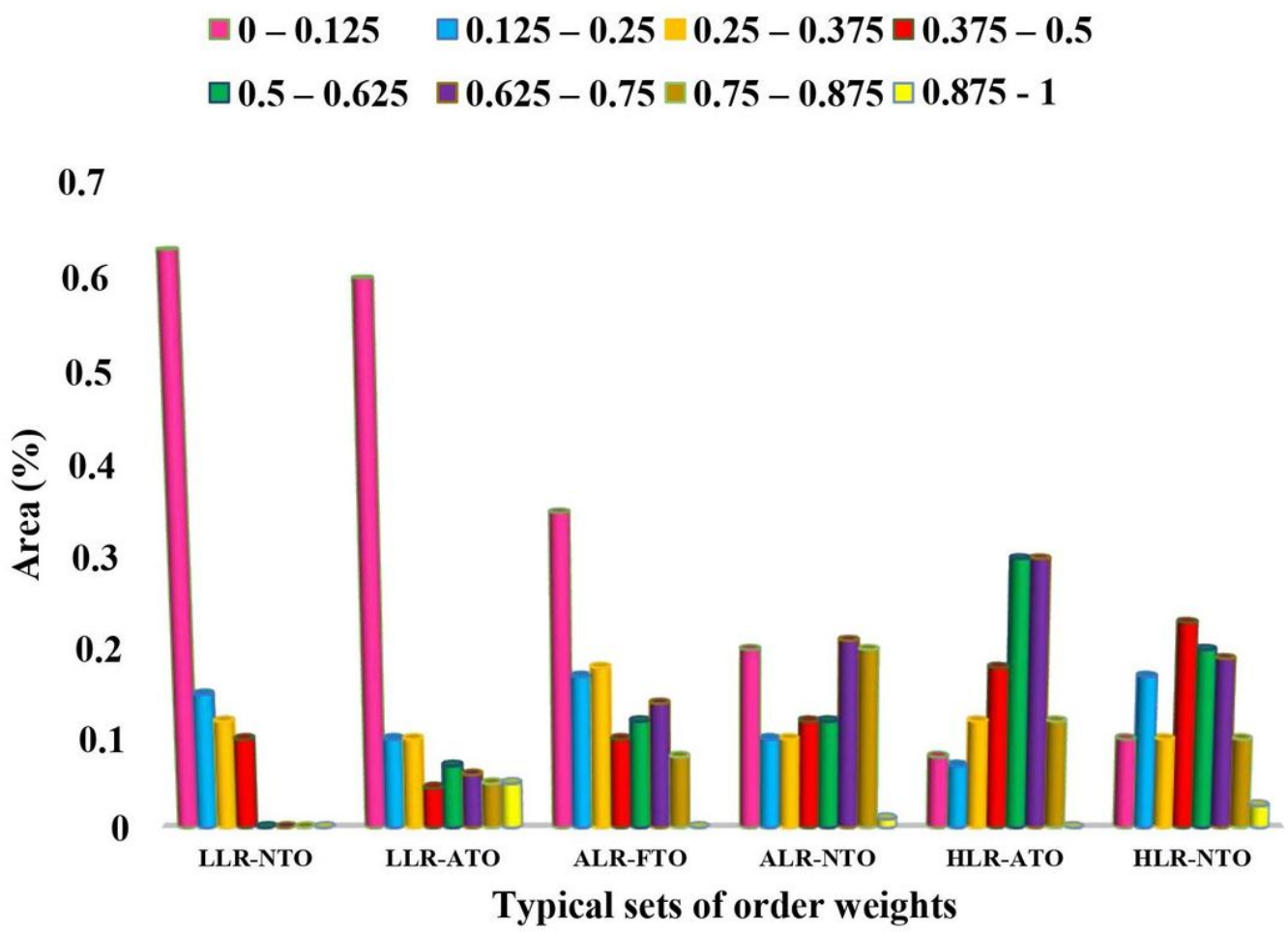

Figure 10

Area of each class using OWA method

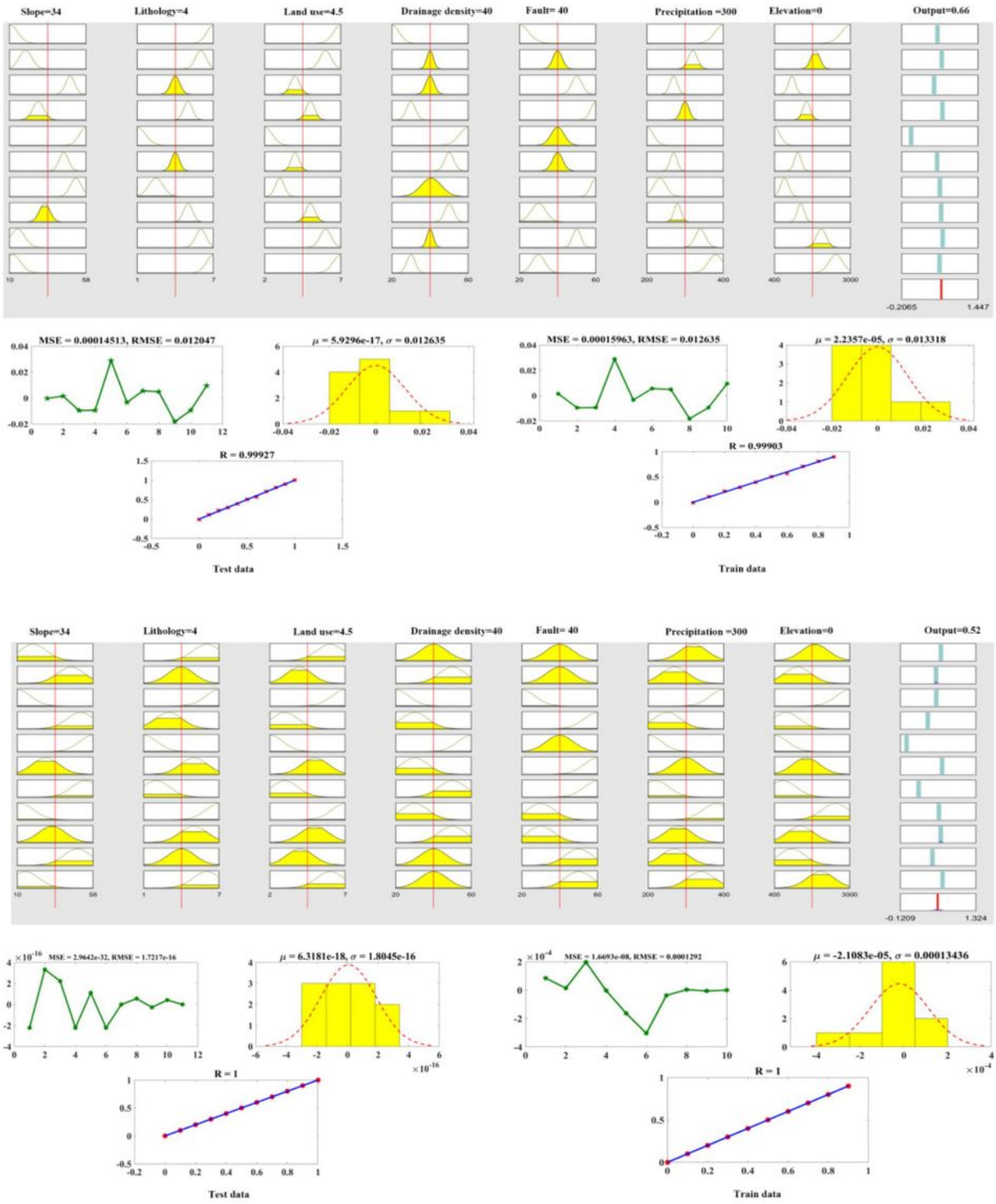

Figure 11

Results of ANFIS method. (a): Fcm:hybrid, (b): Sub:hybrid

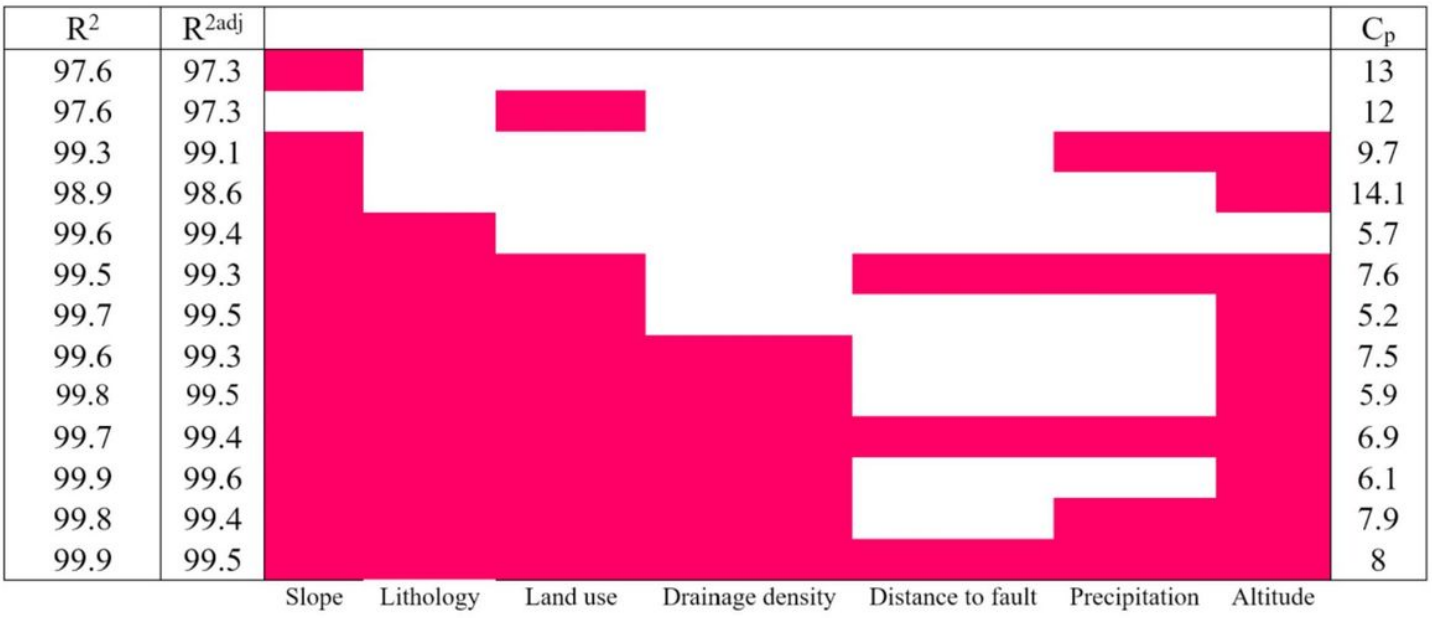

Figure 12

Best-subset regression results to determine the most important parameters affecting artificial recharge of groundwater