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ORIGINAL ARTICLE

# Use of a maximum entropy model to identify the key factors that influence groundwater availability on the Gonabad Plain, Iran

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## Abstract

The purpose of this study is to identify the key factors that influence the availability of groundwater resources in a 10-year period in the Gonabad region of Iran using a maximum entropy model. For this purpose, 165 qanats were selected in 2004 that had yields of more than 3 l/s. By reviewing similar studies, 13 factors were considered to have an influence on groundwater potential exploited by the qanats, including: slope aspect; drainage density; fault density; distance from faults or other fractures; land use; lithology; plan curvature; profile curvature; qanat density; distance from rivers; land slope; stream power index (SPI); and topographic wetness index (TWI). The results indicated that qanat density had the greatest influence on the groundwater potential in a given area. Additionally, the increased importance of this factor with the occurrence of drought indicates that qanats are appropriate structures for exploiting groundwater and that they were well sited when they were originally constructed. Other important factors that influence groundwater potential are SPI, TWI and lithology factors. This indicates the importance of the slope, water accumulation area and rock characteristics in the groundwater potential. Additionally, there were significant changes in the distribution of areas with a high to low groundwater potential over a 10-year period. Reducing the number of effective factors in 2014 modeling showed that with the occurrence of drought and the limitation of areas with groundwater potential, the factors affecting zoning of the groundwater potential are also limited.


**Keywords** Drought · Maximum entropy · Qanat · Groundwater potential · Temporal changes · Spatial changes

## Introduction

Groundwater is one of the main and most important sources of water used by communities for various purposes (Pradhan 2009; Neshat et al. 2014) because of low temperature variations, better sustainability than surface water against short-term droughts, easy access and low utilization costs (Jha et al. 2007). There are limited spaces in aquifers for water storage, so it is necessary to exploit these resources with knowledge of groundwater conditions (Bera and Bandyopadhyay 2012). The infiltration of rainwater and snowmelts into the soil and/or pore space and discontinuous rocks causes the natural recharge of aquifer (Nampak et al. 2014). Accordingly, the distribution and quantity of groundwater can be influenced by climatic conditions as well as surface and subsurface characteristics of the earth such as alluvial properties, quantity and quality of fractures in subsurface rocks, land use, geomorphic facies and topographic features (Saud 2010; Senthil Kumar and Shankar 2014).

In arid zones, most human civilizations are located on the basis of ready access to water resources, especially to groundwater (Bera and Bandyopadhyay 2012). In these regions, groundwater resources are an important tool for sustainable development (Subyani 2005; Bayumi 2008). Therefore, understanding the factors influencing the availability of groundwater is important in managing the quality and quantity of these resources.

A large number of statistical models and learner machine methods can predict how to distribute groundwater potential using independent natural variables. These include: the support vector machine (SVM); the boosted regression tree (BRT); multivariate adaptive regression splines (MARS); logistic multiple regression (LMR); generalized additive model (GAM); and random forest (RF) models (Naghibi et al. 2016, 2017a; Mair and El-Kadi 2013; Sorichetta et al.

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2013; Rodriguez-Galiano et al. 2014; Naghibi and Pourghasemi 2015; Gutiérrez et al. 2009; Zabihi et al. 2016). One of the learning machine models is the maximum entropy method that operates on the basis of the statistical-probabilistic distribution of key factors. This model has been used in different fields of the natural sciences for assessing issues such as the forecasting of species distribution, crop planting zonation, landslide susceptibility evaluation, processing of earth features and groundwater characteristics mapping (Ariyanto 2015; Bajat et al. 2011; Convertino et al. 2013; Davis and Blesius 2015; Dyke and Kleidon 2010; Elith et al. 2011; Huset 2013; Jaime et al. 2015; Kim et al. 2015; Kornejady et al. 2017a; Kumar and Stohlgren 2009; Liu et al. 2012; Mert et al. 2016; Moosavi and Niazi 2016; Park 2015; Peterson 2011; Phillips et al. 2004; Pueyo et al. 2007; Rahmati et al. 2016b; Shen et al. 2015; Thuiller et al. 2005; Townsend Peterson et al. 2007; Wahyudi et al. 2012; Wang and Bras 2011; Warren and Seifert 2011; Williams 2010; Wollan et al. 2008; Yackulic et al. 2013; Yu et al. 2014).

Maximum entropy (MaxEnt) model does not define strict assumptions prior to research which can be considered as a powerful advantage. Importantly, it can also handle data from various measurement scales. Assuming that the potential of groundwater in the study area is affected by the occurrence of droughts, the following goals and innovations were considered in this study: (1) the use of the natural drainage properties of a qanat as a suitable index of the groundwater potential; (2) the assessment of spatial and temporal variations of groundwater potential using the maximum entropy model in one of the great plains of eastern Iran in a 10-year period; and (3) the determination of the most effective factors in reducing or/and sustainability the groundwater potential in the study area.

## Study area

The authors selected the Gonabad Region in the eastern part of Iran as a case study to assess temporal and spatial changes of groundwater potential. The Gonabad Region is located in the Razavi Khorasan Province, Iran, between 34°02′ to 34°26′N latitude and 58°16′ to 59°01′E longitude (Fig. 1). It covers an area of approximately 2188.91 km$^2$. The topographical elevation of the study area varies between 894 and 2774 m above sea level. The mean annual point precipitation is recorded as 160 mm in the Gonabad weather station (IRIMO 2016). Based on information provided by the Geological Survey of Iran (GSI 1997), about 44% of the lithology covering the study area falls within the units described as Qt2 including low level pediment fan and valley terraces deposit. Most of the area (89%) is covered by rangeland land use type. Exploitation of groundwater resources in this region includes semi-deep and deep wells, springs, and qanats. The Gonabad Region faces major challenges in the management of scarce freshwater resources under pressures of increasing population, economic development, climate change, pollution and overabstraction. Assessment of groundwater is very vital within this region, since groundwater supplies drinking water and irrigation requirements. Also, the people living in this region depend on irrigated and dry farming agriculture.

## Methodology

The steps in this research are presented in Fig. 2. In the first step, data preparation was carried out. Four types of data were utilized in this study: digital elevation model (DEM)-derived factors, distance factors, density factors and land factors. Then, the best factors were selected. In this research, several conditions were considered for selecting the factors that could be used in modeling: firstly, the lack of correlation performed through the PCA test; secondly, the contribution rate in modeling; thirdly, the impact of each factor on the training and testing process; and fourthly, the similarity of accuracy in the training and testing process. To evaluate time variations, the model was implemented two times and with a 10-year interval. In the next step, the model performance was evaluated using the receiver operating with a characteristic) ROC) index. Finally, after determining the most effective factors, the results were interpreted.

### Qanat inventory map

Usually, qanats areas are constructed on plains or on large waterways in mountainous areas where the groundwater table is high. In this study, the locations of qanats in 2004 were obtained from a topographical map with 1:50,000-scale and this was ground-truthed by the e field visits using a GPS device (Fig. 1). The profile of qanat system and its components can be found in Naghibi et al. (2015).

### Geo-environmental factors

After reviewing the results of studies on the potential of groundwater, 13 effective and key factors were determined and their respective maps were prepared in ArcGIS 10.3.1 software. The methods used to develop the relevant factors from these data are discussed below.

#### Slope aspect

Changes in the slope aspect lead to differences in the amount of solar energy that is received by the land surface, which in turn affects soil moisture content, the type, extent and distribution of the canopy cover, and ultimately

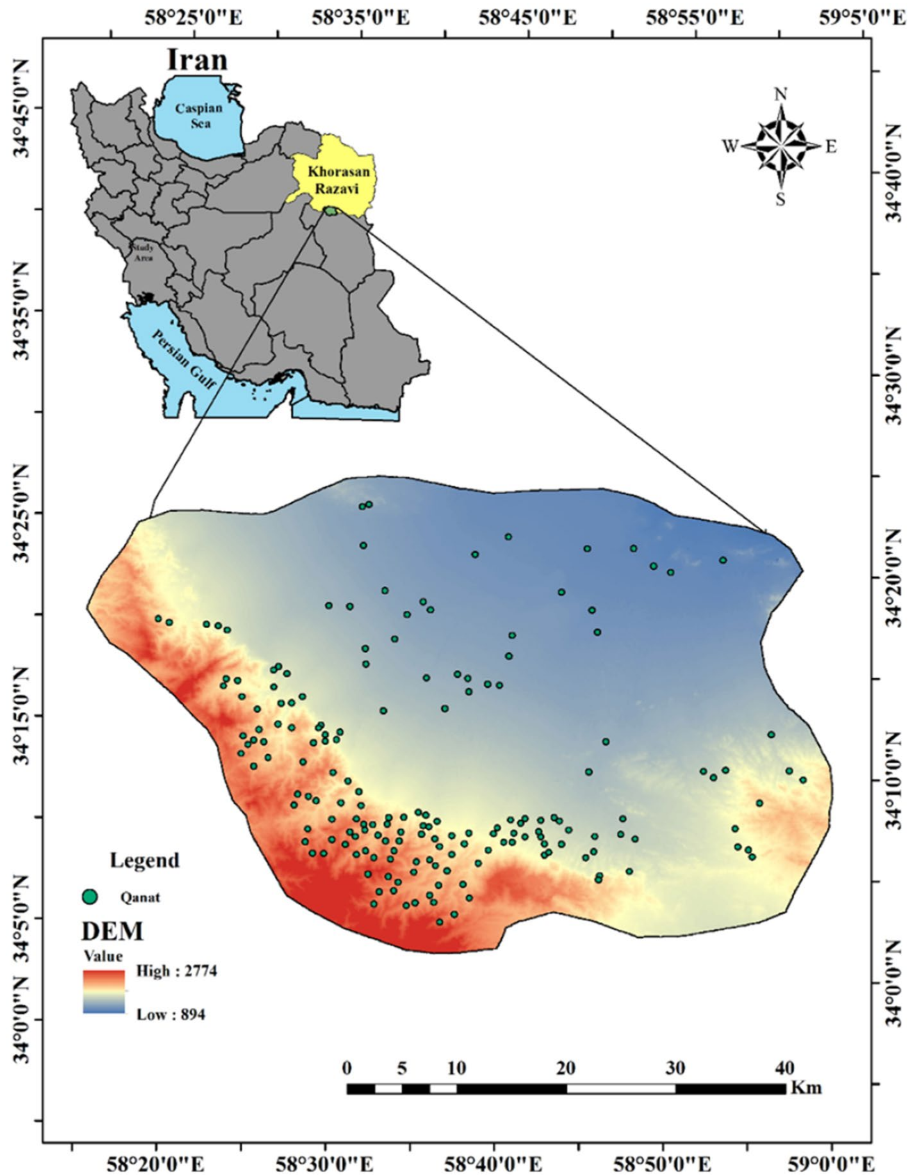



**Fig. 1** Location of Gonabad Region in Iran and Razavi Khorasan Province

evapotranspiration (Dai et al. 2001; Sidle and Ochiai 2006; Rahmati et al. 2016b; Naghibi et al. 2018). A slope aspect map was compiled from the DEM data (30 × 30 m) and has been classified into nine classes, four basic directions, four subsidiary directions and no direction or flat (Fig. 3j).

### Drainage density

In each region, the pattern and drainage density are closely related to the hydrological characteristics. Also factors such as geology, topography, soil type, infiltration, water absorption capacity in soil, canopy cover and climate affect the shape and density of drainage (Manap et al. 2013). High levels of drainage reduce the infiltration and increase the runoff. Therefore, areas with low drainage density are suitable for underground water development (Dinesh Kumar et al. 2007; Magesh et al. 2012).

The drainage network of the study area was extracted from topographic maps with a scale of 1:50,000 that were produced by Iran National Cartographic Center in 2013. Drainage density is the ratio of the total streams length to the area occupied by them (Singh and Prakash 2002). To calculate the drainage density, the total length of the stream per pixel (30 × 30 m) is divided into its area. Then the values of each pixel were assigned to its center. Finally, a drainage density map was developed using an interpolation technique. The drainage density calculated in the study area is in the range of 0–1.53 km/km$^2$ (Fig. 3e).

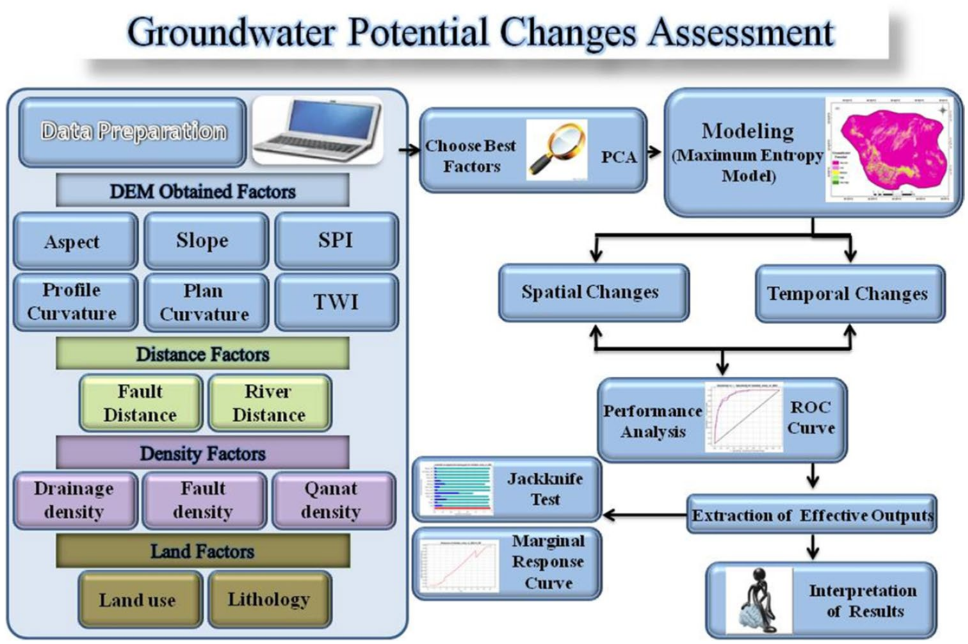



**Fig. 2** Flowchart study in this research

### Fault density

Lineaments such as faults and other deep fractures can cause surface and subsurface water exchange (Davoodi Moghaddam et al. 2013). The faults of the study area were extracted from geological maps with a scale of 1:100,000 that were produced by the Geological Survey Department of Iran (1997). The fault density map was prepared in the same way as the drainage density map and its range was between 0 and 18.64 km/km$^2$ (Fig. 3f).

### Fault distance

The map of distance to fault (m) was prepared based on the Euclidean distance algorithm using ArcGIS 10.3.1 software. The range of values for this factor is between 0 and 22,976 m (Fig. 3c).

### Land use

Land use can affect runoff, infiltration and the recharge of aquifers in different areas (Anbazhagan et al. 2005; Bhattacharya 2010; Naghibi et al. 2017b). Land use is the only factor that can change significantly during the 10-year period of study. Therefore, two land use maps for the years 2004 and 2014 were prepared. The land use map was prepared using Landsat 7 images and maximum likelihood algorithm via supervised classification (Rahmati et al. 2016a, b). In the studied area, five types of land use were identified including: agricultural land, fallow land, orchards, rangeland, and urban land. The largest and lowest land uses are rangeland and orchard, respectively (Fig. 3g).

### Lithology

Lithology influences various characteristics of an aquifer, especially its porosity and permeability (Chowdhury et al. 2010; Rahmati and Melesse 2016). These two characteristics affect the existence and movement of groundwater (Shahid et al. 2000; Ozdemir 2011). Usually, suitable aquifers have been reported in alluvial deposits of Quaternary formations (Rahmati et al. 2016b).

The lithology layer of the study area was extracted from geological maps with a scale of 1:100,000 that were produced by Geological Survey Department of Iran (1997). The lithology of investigation area consists of two sequences of sedimentary and volcanic rocks and unconsolidated deposits of Quaternary age (Fig. 3h).

### Plan curvature

The characteristics of landforms have been used as an effective factor in many geomorphological evaluation studies, such as the presence and distribution of groundwater, karst features, gullies, and landslides. The shape of the ground can alter surface drainage and sediment transfer to rivers (Jenness 2013). To prepare this layer, the digital elevation model (DEM) of the study area and ArcGIS 10.3.1 software were used (Fig. 3i).

### Profile curvature

The profile curvature can affect the flow velocity. Negative values (convex shape) increase the flow velocity and decrease infiltration, and positive values (concave shape)

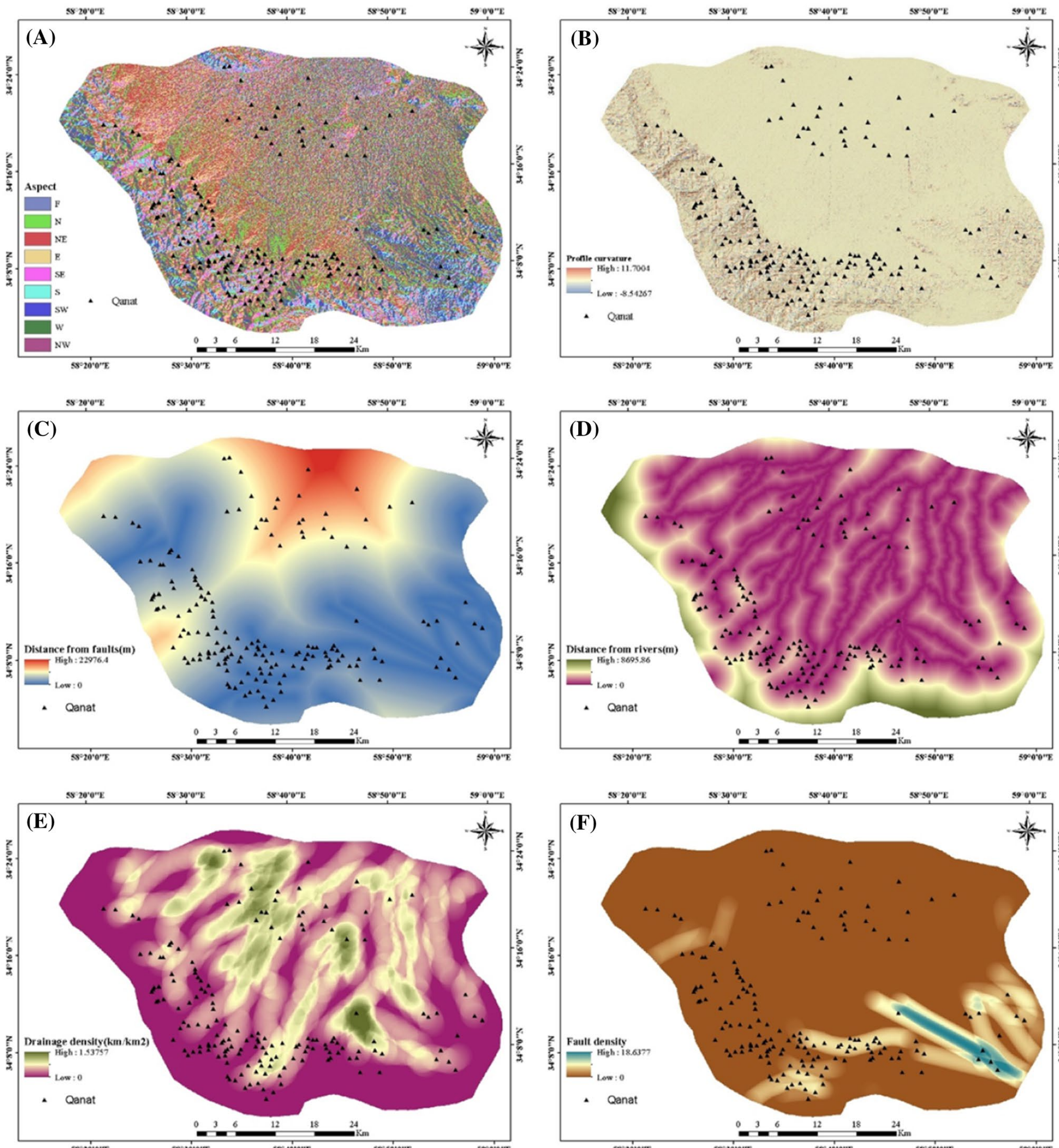



**Fig. 3** The map of factors used in the MaxEnt model. **a** Aspect, **b** profile curvature, **c** distance from faults, **d** distance from river, **e** drainage density, **f** fault density, **g** land use, **h** lithology, **i** plan curvature, **j** slope, **k** SPI, and **l** TWI

reduce the flow velocity and increase infiltration (Jenness 2013).

To prepare profile curvature like plan curvature, the digital elevation model of the study area and ArcGIS 10.3.1 software were used (Fig. 3b).

## Qanat density

Qanats act as natural groundwater drainage systems (Perrier and Salkini 1991). The existing qanats in the study area are very old and have been gradually built according to the

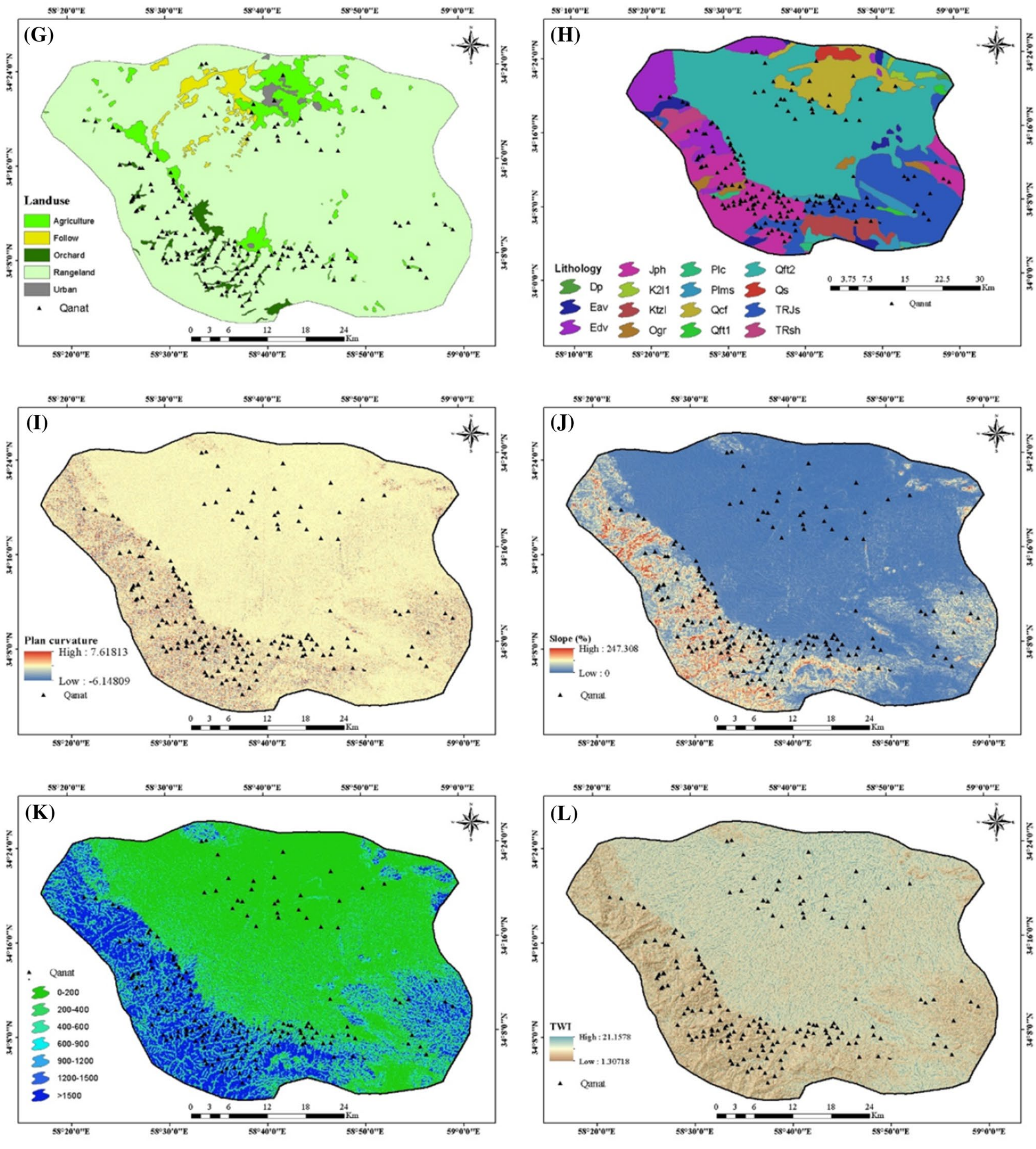



**Fig. 3** (continued)

potential of the aquifer and the need for water in the region. Therefore, an increasing density of qanats in each region indicates a suitable groundwater potential at the time of construction. The topographic maps of the study area with a scale of 1:50,000 that contain the district's qanat data were used to prepare the qanat density layer (Fig. 3m).

## Distance to river

Several studies have been conducted on the impact of river flows on groundwater status (Gooseff et al. 2005; Cardenas et al. 2004; Storey et al. 2003; Deepa et al. 2016). So increasing the distance from the rivers, especially rivers with permanent flows or rivers with a longer period of flow, can have a negative impact on groundwater potential. To provide this layer, topographic maps with a scale of 1:50,000 and Spatial Analyst extension in ArcGIS 10.3.1 were used (Fig. 3d).

#### Slope degree

Slope degree is an important factor in the study of groundwater conditions (Al Saud 2010; Ettazarini 2007; Kornejady et al. 2017b). This factor can affect the runoff, infiltration and recharge processes. As the slope increases, the runoff moves more quickly and this reduces the infiltration of water into the soil and reduces the recharge potential (Sarkar et al. 2001; Adiat et al. 2012). The DEM of the study area was used to prepare this layer (Fig. 3j).

#### Stream power index (SPI)

The stream power index is a measure of the erosive force of a stream (Moore et al. 1991). Increasing the SPI reduces the infiltration time, increases turbidity and reduces infiltration. Accordingly, this index was considered as an effective factor in determining the likelihood that recharge will take place to an aquifer from a flowing stream. The SPI was calculated using Eq. 1 (Moore et al. 1991) (Fig. 3k):

$$\mathrm{SPI} = B_{\mathrm{s}} \times \tan\alpha \tag{1}$$

where $B_{\mathrm{s}}$ is the specific catchment area ($\mathrm{m}^2$) and $\alpha$ is the local slope gradient (°).

#### Topographic wetness index

Topographic wetness index (TWI) quantifies the impact of topography on some hydrological characteristics. This index describes the process of collecting water at different places and the effect of gravity on the infiltration of water into an aquifer and to move downslope (Ghorbani Nejad et al. 2017). The index also determines the role of topography on the moisture content of soils in a given region and on the spatial distribution of soil moisture (Moore et al. 1991; Pourghasemi et al. 2013; Davoodi Moghaddam et al. 2013). The TWI index was calculated using Eq. 2 (Moore et al. 1991):

$$\mathrm{TWI} = \ln\left(\frac{\beta}{\tan\alpha}\right), \tag{2}$$

where $\alpha$ is the cumulative upslope area draining from a point (per unit contour length) and $\beta$ is the slope angle at the point (Fig. 3l).

### Combination of groundwater potential factors

The best combination of parameters used to assess the potential of groundwater was determined by checking the pairwise correlation between all factors using principal component analysis (PCA). The use of parameters that are well correlated with each other may cause errors in determining how prospective an area is for providing a groundwater resource. The optimal combination of factors is determined by eliminating inefficient factors. For this purpose, factors that are highly correlated with other factors are eliminated. The choice of these factors is based on the extent of correlation with other factors and by expert opinion. In this study, a correlation of 0.7 was considered as the maximum acceptable value for the correlation between factors (Kornejady et al. 2017a) (Table 1).

### Maximum entropy model

The theory of information and statistical principles are the basis of MaxEnt. The concept of entropy was first defined by Shannon (1948) as the expected amount (average) of the data contained in the conditions studied. This concept was presented based on Boltzmann's H-theorem as:

$$H(X) = E[I(X)] = E[-\ln(\hat{\pi}(x))], \tag{3}$$

where $E$ is the expected amount for a factor and $I$ is the data content. In this equation, the negative natural logarithm can be used to express the probability distribution of the factors. The logarithm with an increasing trend for independent sources is a suitable measure for entropy. According to the above equation, the average data were considered to be the expected amount. This is consistent with the probability theory that the mean of observational data is equal to the expected amount of a random variable (Ross 2014). Based on Jaynes' definition of maximum entropy, "the best probability distribution that can represent an unknown probability distribution function (pdf) subject to a set of testable information (expected values of different variables) is the one with the largest entropy" (Jaynes 1957a, b); if the results of a phenomenon are unknown, the information obtained will be greater and the entropy will be larger. Accordingly, when all restrictions are considered for the phenomenon under investigation, the best estimate of the pdf can be obtained, which can be accepted as the final result. In this case, the designated pdf has maximum entropy and the maximum information is obtained from the effective factors (Shannon 1948, 1951).

Like all other probability functions, two conditions for the entropy of $\hat{\pi}$ must be observed: (1) based on a statistical principle for all observable phenomena, assign a positive probability

**Table 1** Matrix of pairwise correlation between groundwater potential factors in the study area

| Factors | Aspect | Profile curvature | Fault distance | River distance | Drainage density | Fault density | Land use | Lithology | Plan curvature | Qanat density | Slope | SPI | TWI |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Aspect | 1.000 | 0.001 | −0.097 | 0.097 | −0.080 | 0.126 | 0.080 | −0.167 | 0.007 | −0.077 | 0.075 | 0.020 | −0.066 |
| Profile curvature | | 1.000 | −0.007 | 0.002 | −0.007 | 0.006 | −0.012 | −0.014 | −0.469 | −0.004 | 0.012 | 0.260 | 0.154 |
| Fault distance | | | 1.000 | −0.108 | 0.190 | −0.443 | −0.231 | 0.342 | −0.010 | 0.295 | −0.241 | −0.125 | 0.190 |
| River distance | | | | 1.000 | −0.699 | −0.063 | 0.113 | −0.449 | 0.009 | −0.256 | 0.376 | 0.134 | −0.224 |
| Drainage density | | | | | 1.000 | −0.013 | −0.123 | 0.464 | −0.013 | 0.297 | −0.413 | −0.152 | 0.243 |
| Fault density | | | | | | 1.000 | 0.055 | −0.363 | 0.008 | −0.115 | 0.048 | 0.044 | −0.062 |
| Land use | | | | | | | 1.000 | −0.141 | 0.010 | −0.047 | 0.141 | 0.036 | −0.121 |
| Lithology | | | | | | | | 1.000 | −0.022 | 0.282 | −0.412 | −0.174 | 0.261 |
| Plan curvature | | | | | | | | | 1.000 | −0.008 | 0.049 | −0.416 | −0.318 |
| Qanat density | | | | | | | | | | 1.000 | −0.186 | −0.084 | 0.127 |
| Slope | | | | | | | | | | | 1.000 | 0.288 | −0.483 |
| SPI | | | | | | | | | | | | 1.000 | 0.461 |
| TWI | | | | | | | | | | | | | 1.000 |

for each $x$; (2) the sum of all probabilities assigned to x must be one. By applying the two conditions above, Eq. 3 changes as:

$$H(X) = -\sum_{x \in X} \hat{\pi}(x) \ln \hat{\pi}(x). \tag{4}$$

In fact, in this study, there is a collection of random places $x$ from the larger set $X$, and appropriate qanat in each location is considered as the response variable ($Y$). In the spaces with these qanats, $y = 1$ and in the absence $y = 0$. MaxEnt is a generative model. This model performs learning through probability distribution $P(x, y)$ or conditional probability $P(x|y)$, while the discriminative models perform learning through the conditional probability $P(y|x)$. The implementation of discriminative models requires information about the presence and absence of phenomena, and the preparation of these data requires extensive studies) Vapnik and Vapnik 1998; Ng and Jordan 2001). Generative models can provide better predictions with little training information. This ability can be very useful in cases where accessible information is limited (Edvardsen et al. 2011; Edwards et al. 2005; Feeley and Silman 2011; Guisan et al. 2006; Niamir et al. 2011; Robertson et al. 2010).

If the existence and absence data are available, MaxEnt can be implemented as a deterministic model (Baldwin 2009; Berger et al. 1996; Halvorsen 2012). In this study, only presence data was used. Accordingly, the generative model is introduced based on Byes' rule (Elith et al. 2010; Phillips and Dudík 2008; Phillips et al. 2009):

$$P(y = 1|x) = \frac{P(x|y = 1)P(y = 1)}{P(x)}, \tag{5}$$

where $P(y = 1|x)$ is the probability for the existence of qanat on site $x$, $P(x|y = 1)$ is the probability of existence in the site $x$ given that the qanat is present (equivalent to $\pi(x)$ in MaxEnt), $P(y = 1)$ is the complete occurrence, and $P(x)$ is the probability that the $x$ site will be selected ($P(x)$ is equivalent to $1/|X|$, that is, the probability of selecting the $x$ site from the $X$-set).

Another form of the above equation is:

$$P(y = 1|x) = \pi(x)P(y = 1)|X|. \tag{6}$$

According to the probability distribution in generative models, $P(x)$ can be rewritten as:

$$P(x) = \sum_{y} P(x|y) = P(x|y = 1)P(y = 1) + P(x|y = 0)P(y = 0). \tag{7}$$

If the probability of presence and absence is equal $(P(y = 0) = P(y = 1) = 0.5)$, the equation can be simplified as:

$$P(y = 1|x) = \frac{P(x|y = 1)}{P(x|y = 1) + P(x|y = 0)}. \tag{8}$$

In this study, the potential of groundwater in the study area was determined using the maximum entropy model in the MaxEnt software 3.3.3 k. MaxEnt is a machine learning model based on the presence of a phenomenon (Graham et al. 2008; Hernandez et al. 2008; Kornejady et al. 2017a; Phillips et al. 2006; Quinn et al. 2013; Wisz et al. 2008). One of the applications of these models is to study areas with inappropriate access.

Of course, it should be noted that if the distribution of input data is not appropriate, modeling only based on the phenomenon presence will be prone to error (Austin 2007; Hortal et al. 2008; Loiselle et al. 2008; McCarthy et al. 2011; Reddy and Dávalos 2003; Robertson et al. 2010; Veloz 2009; Wolmarans et al. 2010). In the present study to resolve this problem, all the qanats in the study area were investigated. MaxEnt is able to use the data in a continuous and categorized manner. This will make the results more accurate and reduce computational errors.

This model estimates the best probabilistic distribution of potential areas by connecting input factors and existing potential areas (Elith et al. 2010; Kleidon et al. 2010; Medley 2010; Moreno et al. 2011; Nieves et al. 2011). Initially, MaxEnt prepares a first map. This map has the same pixels in terms of potential groundwater probability. Then, by adding each of the influential factors, the characteristics and limitations of the susceptible areas are extracted and the accuracy of the first map is improved. This operation continues until the best probability distribution function (using the maximum entropy function) and groundwater potential map are obtained.

### Model validation

To validate the MaxEnt model, a success rate curve (SRC) and a prediction rate curve (PRC) should be plotted. These curves are plotted using both the training and testing datasets. In both curves, the vertical axis is related to the correct detection rate of places with groundwater potential and the horizontal axis is related to the correct detection rate of places without groundwater potential. The area under the SRC (AUSRC) represents the accuracy and the area under the PRC (AUPRC) represents the prediction power or generalization of the model. When this value is closer to one, the accuracy of the model increases (Metz 1978; Pearce and Ferrier 2000; Pontius and Schneider 2001).

Determining the most important factors affecting the potential of groundwater can be useful in managing water resources. In the MaxEnt model, the jackknife test is used to determine the most important factors. In addition, the different classes and ranges of each factor have a different effect on the groundwater potential. Determining the most important range of each factor was determined using the response curve.

### Data format and the determination of parameters in MaxEnt

The map of all factors studied was converted to ASCII format and the coordinates of the used qanats were prepared in the form of a CSV file; then, both sets of data were entered into the model. The background points and convergence thresholds were selected as 10,000 and $10^{-5}$, respectively. To better learn the proper pattern and ensure the effectiveness of the plateau, the number of replicates was increased to 5000. Since the type of features and the number of samples are different, selecting the “auto” option allows the model to use the appropriate adjustment values (Phillips et al. 2006).

## Results and discussion

### Initial selection of appropriate factors

According to the results of the PCA test (Table 1), the pairwise correlation between the drainage density and the river distance has a maximum value ($-0.699$) and a pairwise correlation between the profile curvature and the slope aspect has a minimum value (0.001). Also, the results showed that the pairwise correlation of all factors was less than 0.7, so none of the considered factors were eliminated and all were entered into the model.

### Running the model at two different times

As stated above, in the present study, for the purpose of examining time variation, the potential of groundwater in the 2 years of 2004 and 2014 was investigated. With the initial implementation of the model, it became clear that aspect, plan curvature and profile curvature in 2004 and aspect, drainage density, fault distance, fault distance, plan curvature and land use in 2014 had no effect on the accuracy of the model and, even with their elimination, the accuracy of the model increased in the implementation of 2014. To compare the results of groundwater potential in the two studied times, groundwater potential maps of the study area were classified according to natural break distance into five classes as very low, low, medium, high and very high (Pourghasemi and Rossi 2017; Pourghasemi and Kerle 2016; Rahmati et al. 2016a) (Fig. 4). The density of suitable qanats, the percentage of different groundwater potential classes, the kappa index and the Chi square test results for two-time implementation are provided in Table 2. In all cases, the largest area is dedicated to classes with the least groundwater potential. By improving the groundwater potential (increase class), the area decreases. Accordingly, the percentages of different groundwater potential classes in both years 2004 and 2014 have statistically significant

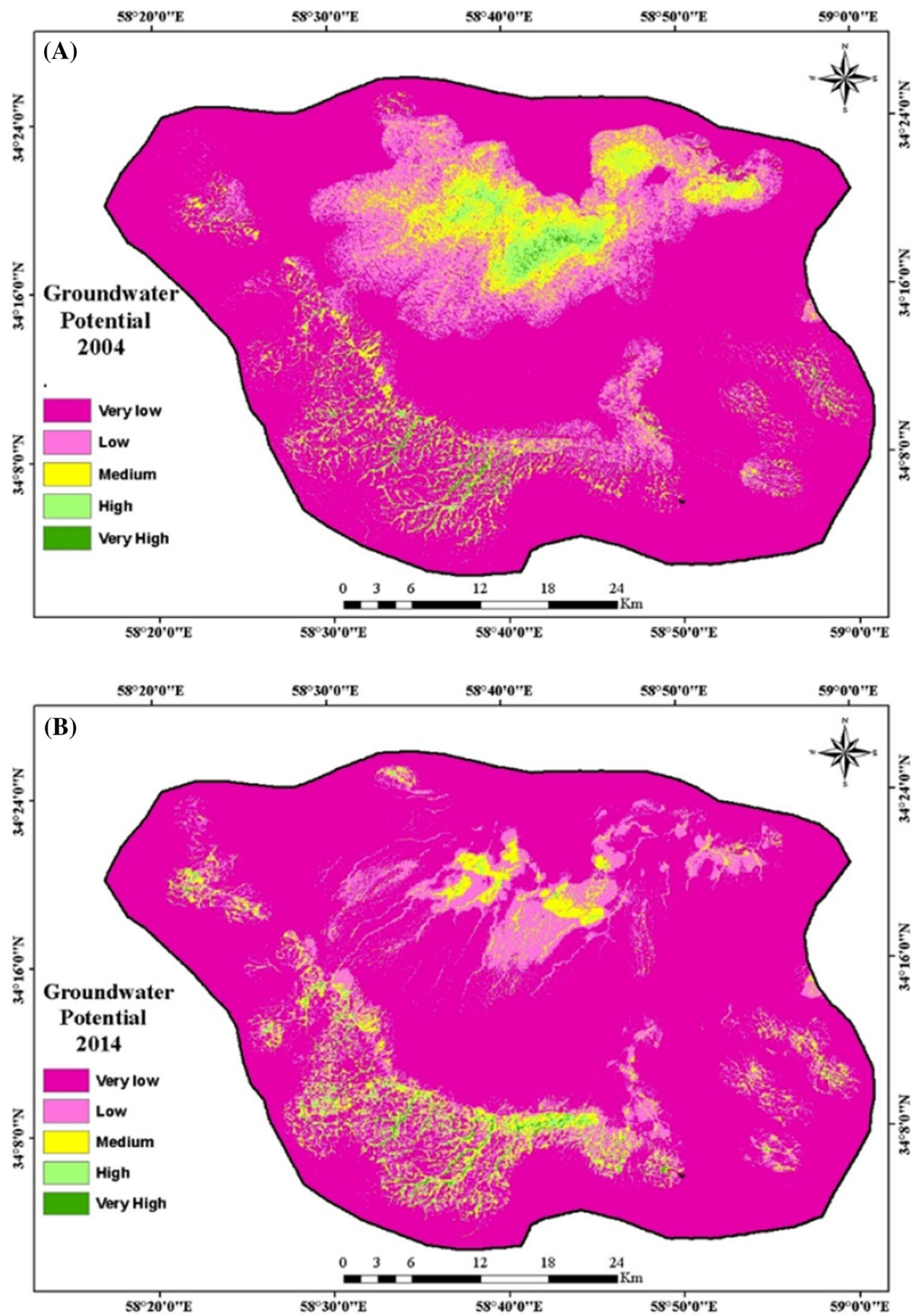



**Fig. 4** Groundwater potential maps: **a** 2004, **b** 2014

**Table 2** Areal percentage of models' classes, qanat densities, discordance and concordance (2004–2014)

| Class | 2004 | | | 2014 | | | 2004–2014 | |
|---|---|---|---|---|---|---|---|---|
| | Class area (%) | Chi square | Qanat density | Class area (%) | Chi square | Qanat density | Kappa index | Level of agreement |
| Very low | 65.73 | 139.59 | 0.0000094 | 76.81 | 207.95 | 0.0000059 | 0.77 | Strong |
| Low | 18.04 | $P$ value $<0.05$ | 0.0000870 | 14.87 | $P$ value $<0.05$ | 0.0000300 | 0.19 | Very weak |
| Medium | 11.17 | | 0.0002000 | 5.72 | | 0.0000720 | 0.13 | Very weak |
| High | 4.55 | | 0.0004200 | 2.15 | | 0.0001500 | 0.12 | Very weak |
| Very high | 0.50 | | 0.0011000 | 0.45 | | 0.0006000 | 0.14 | Very weak |

disagreement at 95% confidence level ($P$ value $b$ 0.05). This result is common in natural processes and shows the role of different natural conditions in the existence or absence of the phenomenon studied. The Kappa test results show that the groundwater potential in 2004 and 2014 have a strong agreement in very low classes and very weak agreement in low, medium, high and very high classes. The results of Table 2 indicate a decrease in the area percentage of all classes except the very low class in 2014. This result indicates that there has been a reduction in groundwater potential in the interval between the two studies. Investigating the density of appropriate qanats showed that in classes with a higher groundwater potential, the density of qanats increased. This result indicates that the model is functioning correctly.

The results obtained indicate that the MaxEnt model has a high level of accuracy (Fig. 5) for determining the groundwater potential of the study area in both 2004 and 2014. Despite the decrease in the number of suitable qanats in 2014, implementing the model at the two mentioned times, with AUC of about 0.9 for both training and testing, represents the excellent ability of the model to assess and predict the groundwater potential (Pearce and Ferrier 2000).

## Most effective factors

The relative contribution of all factors studied in the training process of the MaxEnt model in both 2004 and 2014 is presented in Table 3. The results show that in both 2004 and

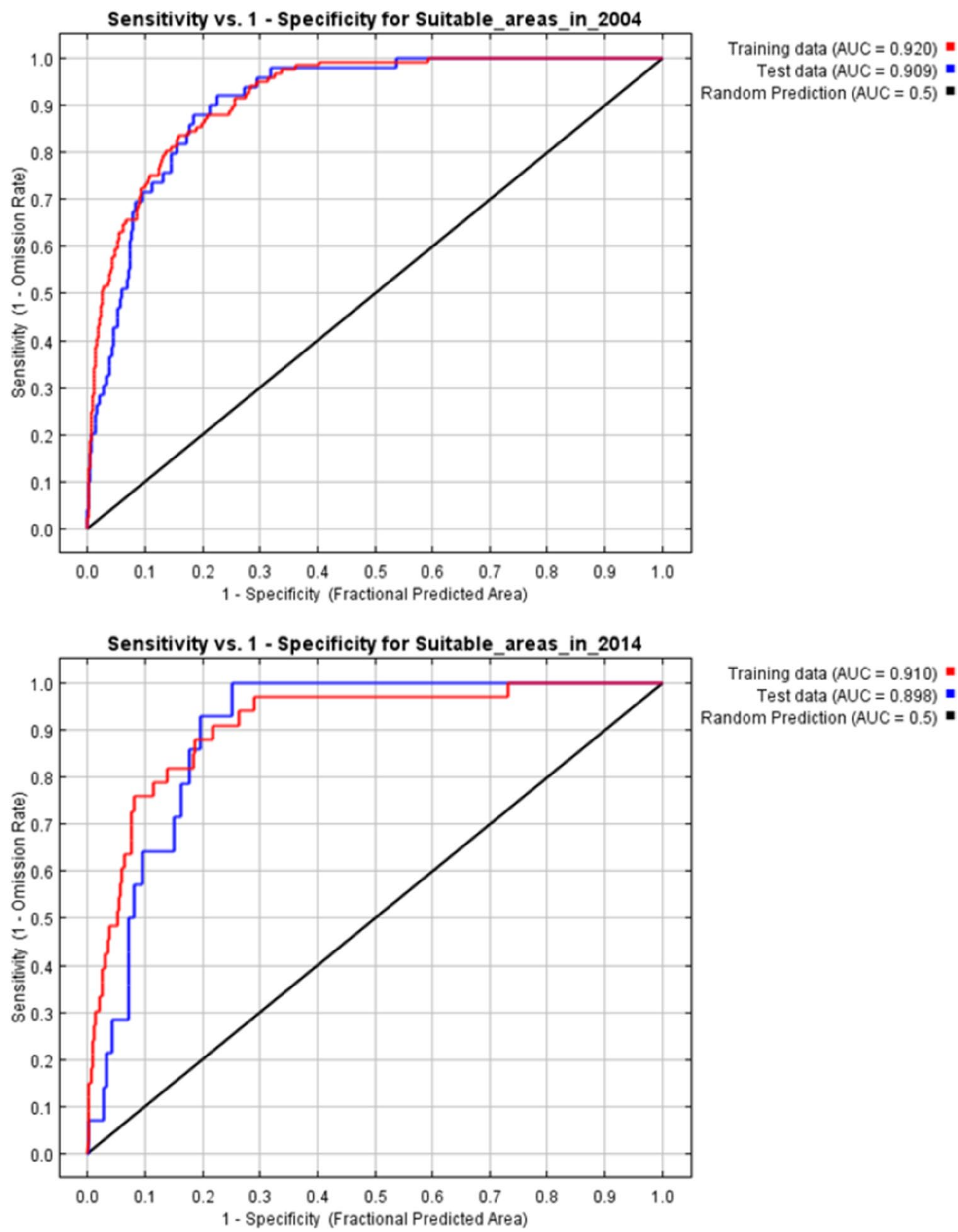



**Fig. 5** Accuracy of the model in training and validation steps in **a** 2004 and **b** 2014

**Table 3** Contribution rate of the various factors on groundwater potential modeling in the MaxEnt model

| Factor | Qanat density | SPI | Lithology | Land use | Slope | Drainage density | TWI | River distance | Fault Density | Fault distance | Profile curvature |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | *2004* | | | | | | | | | | |
| Contribution (%) | 47 | 17.7 | 7.7 | 3.5 | 7.1 | 3.5 | 7.1 | 3.8 | 1.7 | 0.9 | – |
| | *2014* | | | | | | | | | | |
| Contribution (%) | 63 | 12.8 | 5.7 | – | 5.6 | – | 9.2 | 1.8 | – | – | 1.8 |

2014, the relative contribution of qanat densities is higher than other factors and is about 50% and more than the contribution of various factors in modeling dependent on this factor. The results also indicate a relatively large change in the contribution of the investigated factors over time. In 2014, due to the reduction of groundwater potential in different parts of the study area, the contribution of qanat density, with a 16% increase, has the highest increase, and the contributions of SPI index, lithology and river distance with 4.9, 2.0 and 2.0% decrease, respectively, have the highest reduction. As there are a number of algorithms in the MaxEnt model, it is difficult to determine the specific contribution of a given factor. These algorithms can have different results in determining the contribution of factors (Phillips 2012). Accordingly, the assigned contribution, rather than reflecting the importance of factor, relates to the role of each factor in the modeling process.

The jackknife test using test data for 2004 and 2014 was implemented and its results are presented in Fig. 6. The graph obtained from the jackknife test includes three types of information: (1) model AUPRC when each factor enters the model alone (blue part); (2) the AUPRC of the model when the model runs with all the factors other than the one mentioned at the beginning of the bar (in other words, the accuracy of the model with the removal of each factor and the presence of the remaining factors—the green part); and

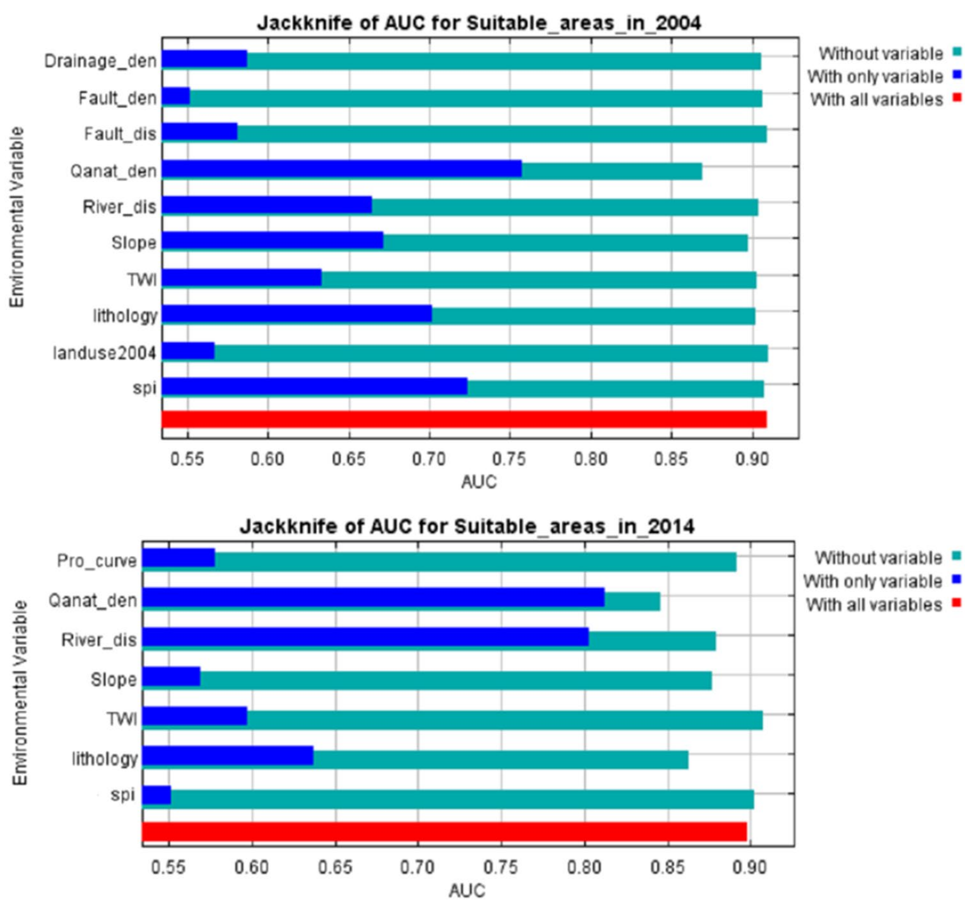



**Fig. 6** Jackknife of AUC for MaxEnt model using test data. **a** 2004, **b** 2014

(3) model AUPRC when all factors are involved in modeling (red part).

The implementation of the model with each of the factors independently showed that the qanat density and the SPI index in 2004 and the qanat density and the river distance in 2014 with the highest AUPRC had the greatest impact on the potential for groundwater availability. The results of the implementation of the progressive removal of each factor (green bar) indicate that the highest decrease in AUPRC was obtained by eliminating qanat density from the model. Therefore, the sensitivity of the model to the changes in this factor is high. The uniqueness of the impact this factor has had on other factors cannot compensate for the lack of it and the accuracy of the model is reduced. The sensitivity of the model to the SPI and river distance factors is not high and the lack of these two factors is compensable by other factors. These results are consistent with the relative contribution of the factors.

The results also showed that the drainage density, distance and density of faults and the land uses with the lowest AUPRC had little effect on the modeling of 2004, and was eliminated due to the ineffectiveness of the 2014 modeling process. A review of the data show that the limited availability of information of the number and length of faults, the predominance of plain lands and the low diversity of the land use is likely to have influenced the low impact of these factors on the model output.

The factors can be eliminated from the modeling process when they have no effect on the accuracy of the model (Kornejady et al. 2017a). With this argument, the factors of slope aspect and the plan curvature in 2004 and the slope aspect, drainage density, fault density, fault distance, plan curvature and land use in 2014 were eliminated in the modeling process. The results show that the reduction in the number of factors affecting the modeling process in 2014 indicates that with the occurrence of drought, many factors lose their role in the groundwater potential and determining the optimal areas for the potential of groundwater is limited to several key factors. However, in 2004, after qanat density and the SPI index factors which have a high impact on model output, lithology, TWI, slope and river distance factors had a moderate impact.

## The response of different factors to the groundwater potential

By increasing the qanat density in both 2004 and 2014, its effect on the groundwater potential increases. Increasing the density of the qanats increases the volume of water extracted from aquifers. This parameter should reduce the groundwater potential, but increasing the groundwater potential by increasing the qanat density indicates the proper identification of potential areas and a proper site selection when constructing these structures (Figs. 7, 8a).

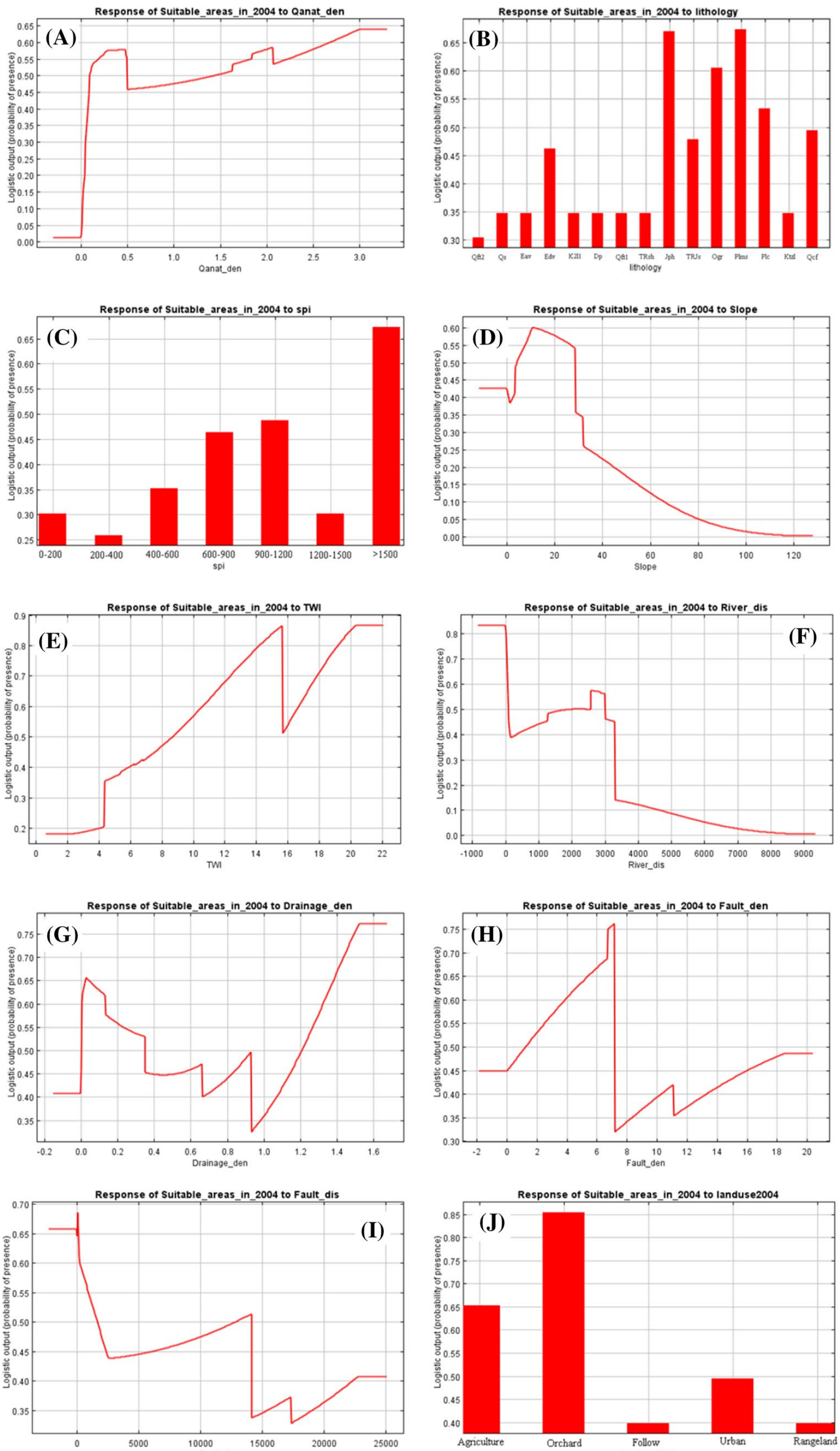
In general, in both 2004 and 2014, the groundwater potential would be reduced by increasing the slope. In 2004, the highest groundwater potential was found where slopes were about 10–30%, but in 2014 the highest groundwater potential was found where slopes were negligible. This is due to qanats in mountainous areas which were observed to have high discharge rates in 2004, but either dried up or the discharge rate dropped significantly in 2014. In 2004, the occurrence of high-yielding qanats in mountainous areas increased the groundwater potential for areas with a high slope. But with the focus of desirable qanats in plain areas in 2014, the potential of mountainous areas decreased. Thus, with the occurrence of drought, the groundwater potential in mountainous areas reduced at a greater rate than in lowland areas (Figs. 7, 8d).

The implementation of the model in both 2004 and 2014 indicates an increase in groundwater potential by increasing the TWI index. Since the TWI is increased in low slopes and extensive accumulation area, the highest TWI is related to the plain area. The existence of an increased trend in the groundwater potential with increasing TWI indicates the importance of plain areas in terms of this factor. It is likely that the decline in the 2004 curve is due to the role of the existing qanats in mountainous regions (Figs. 7, 8e).

By investigating the SPI values in the study area, it is determined that the high SPI values are related to mountainous regions and low SPI values are related to plain areas. In 2014, areas with a minimum and maximum SPI have the highest potential. This result can be interpreted based on the SPI index which is directly related to the contributing area and the slope degree. In 2004, groundwater potential increased in areas with high SPI values (class 7), but in areas with decreased SPI values it was low (class 1). Other areas with moderate SPI values (class 4 and 5) showed an increase in groundwater potential. The difference in the distribution and amount of precipitation in 2004 compared to 2014 can raise the amount of recharge to aquifers and, by compensating for the slope effect, increase the groundwater potential in higher SPI classes (Figs. 7, 8c).

Profile curvature was not used due to the lack of significant impact on modeling in 2014. Garden and agricultural land uses had the greatest impact on the model output in 2004. Since the extracted water from existing qanats is used for the development of garden and agricultural lands, increasing the groundwater potential in these two land use categories is completely reasonable (Fig. 7j).

In both 2004 and 2014, the groundwater potential was reduced with increase in distances from rivers. This is consistent with rivers in the study area being important recharge features and with their influence on groundwater recharge declining with distance. With increasing



(A)
Response of Suitable_areas_in_2004 to Qanat_den
Logistic output (probability of presence)
Qanat_den
(B)
Response of Suitable_areas_in_2004 to lithology
lithology
(C)
Response of Suitable_areas_in_2004 to spi
0-200
200-400
400-600
600-900
900-1200
1200-1500
>1500
spi
(D)
Response of Suitable_areas_in_2004 to Slope
Slope
(E)
Response of Suitable_areas_in_2004 to TWI
TWI
(F)
Response of Suitable_areas_in_2004 to River_dis
River_dis
(G)
Response of Suitable_areas_in_2004 to Drainage_den
Drainage_den
(H)
Response of Suitable_areas_in_2004 to Fault_den
Fault_den
(I)
Response of Suitable_areas_in_2004 to Fault_dis
Fault_dis
(J)
Response of Suitable_areas_in_2004 to landuse2004
Agriculture
Orchard
Follow
Urban
Rangeland
landuse2004

◂**Fig. 7** Response of different factors to the groundwater potential in 2004. **a** Qanat density, **b** lithology, **c** SPI, **d** slope, **e** TWI, **f** river distance, **g** drainage density, **h** fault density, **i** fault distance and **j** land use

'distance from river', the groundwater potentiality values reduced drastically (Figs. 7, 8f).

Survey of the lithology map of the area showed that the greatest impact on the groundwater potential is related to sedimentary rocks, unconsolidated sediments of Quaternary age and igneous rocks. Sedimentary rocks in 2004 have the highest potential and, with the transfer of potential areas to the plains, the impact of the Quaternary formations in 2014 was increased. Additionally, unconsolidated sediments of Quaternary age are considered to have a high groundwater potential, particularly in lowland areas, and fractured granite has the most potential of igneous rocks (Figs. 7, 8b).

This factor was not used due to the lack of significant impact on modeling in 2004. The impact diagram of this factor is a bell-shaped curve, and the greatest impact occurs within the range of 0–1.5. Reduced potential in these parts is due to area constraints (Fig. 8g).

The distance from the fault factor was only used in the 2004 modeling. In general, with the increase in the distance from a fault, the groundwater potential is reduced, but the reduction of impact does not have a regular trend. Due to the role of water transfer from upstream areas by faults, the reason for the potential reduction on getting away from the fault can be explained (Fig. 7i).

Fault density was only used in the 2004 modeling. The impact of this factor does not show a steady trend. Up to a density of about 7, increasing fault density causes impact increase on groundwater potential. In the following, after a sharp drop, the increasing trend continues. The reason for this result can be related to the dual role of faults in the transfer of groundwater (Fig. 7h).

Drainage density was only used in the 2004 modeling. Drainage density in the study area did not have a uniform trend. Up to drainage density factor of about one, the impact on groundwater potential decreases, and in areas with a drainage factor greater than one, the impact increases. The drainage system of the area has a dual function. On the one hand, by increasing the drainage density, the rate of water discharge during rain increases, which leads to a decrease in infiltration. On the other hand, the bed and banks of the river are a good place for infiltration and the recharge of aquifer, and with increasing drainage density, the extent of these areas is also increased. Of course, according to Fig. 7g, the declining trend is very irregular and the increasing trend is regular.

## Conclusions

Determining the spatial distribution of areas that have a high potential for groundwater availability and how these areas change over time provide information to help manage groundwater resources. Drought is one of the phenomena that can change the groundwater potential. In this study, using the MaxEnt model, which is a machine learning model, the groundwater potential was modeled for 2 years, 2004 and 2014, from the arid to semi-arid Gonabad region of eastern Iran. The major difference between these 2 years is the occurrence of a drought p in the years leading up to 2014. For the modeling of groundwater potential, 13 factors including aspect, slope, profile curvature, fault distance, drainage density, fault density, land use, lithology, plan curvature, qanat density, slope, SPI and TWI were used.

The modeling accuracy for training and testing data for both years 2004 and 2014 achieved an AUC of about 0.9, which is indicative of the very good accuracy of the model in zoning the groundwater potential. Groundwater potential was classified into five categories: very low, low, medium, high and very high. The results indicate that in 2 years of model implementation, the concordance between four categories (low, medium, high and very high) was weak.

This result also shows significant changes in the groundwater potential between 2004 and 2014. However, in both years the qanat density factor has the greatest impact on the groundwater potential in the study area. As the existing qanats are very old, the importance of this factor in the model suggests that these structures were well sited when they were constructed.

An investigation of the most significant factors that contribute to groundwater potential indicated that a number of factors could be removed from the model using the 2014 dataset without reducing the integrity of the model.

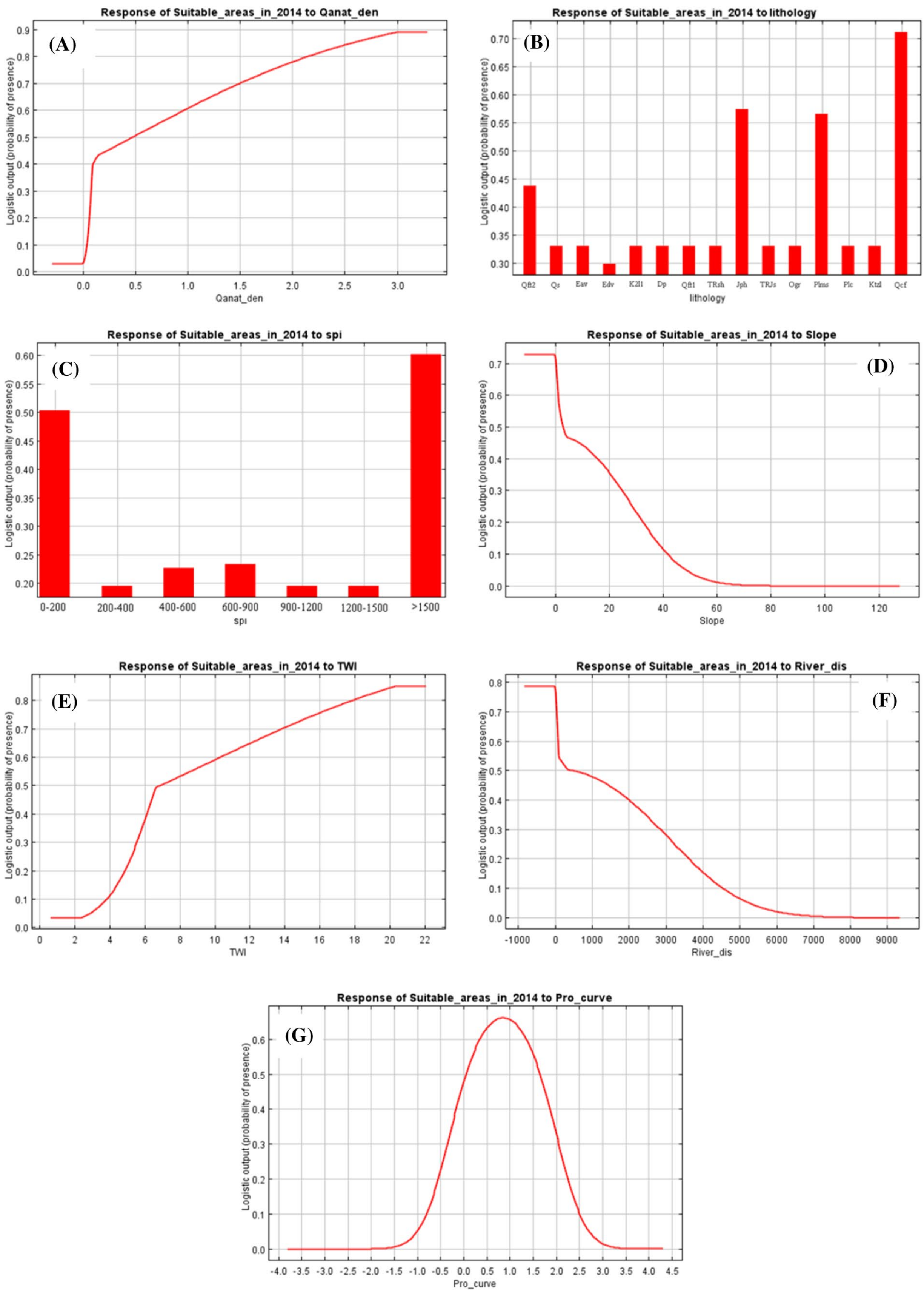



**Fig. 8** Response of different factors to the groundwater potential in 2014. **a** Qanat density, **b** lithology, **c** SPI, **d** slope, **e** TWI, **f** river distance, **g** profile curvature

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