

Gully erosion susceptibility mapping: the role of GIS-based bivariate statistical models and their comparison

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Abstract Gully erosion is a key issue in natural resource management that often has severe environmental, economic, and social consequences. The objective of the present study is to assess the capability of weights-of-evidence (WofE) and frequency ratio (FR) models for spatial prediction of gully erosion susceptibility and characterizing susceptibility conditions at Chavar region, Ilam province, Iran. At first, a gully erosion inventory map is prepared, using multiple field surveys. In total, of the 63 gullies which have been identified, 44 (70 %) cases are randomly algorithm selected to build gully susceptibility models, while the remaining 19 (30 %) cases are used to validate the models. The effectiveness of gully erosion susceptibility assessment via GIS-based models depends on appropriate selection of the conditioning factors which play an important role in gully erosion. Learning vector quantization (LVQ), one of the supervised neural network methods, is employed in order to estimate variable importance. In this research, the selected conditioning factors are: lithology, land use, distance from river, soil texture, slope degree, slope aspect, plan curvature, topographic wetness index, drainage density, and altitude. Finally, validation of the gully dataset which has not been utilized during the spatial modeling process is applied to validate the gully susceptibility maps. The receiver operating characteristic curves for each gully susceptibility map (i.e., produced by WofE

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and FR) are drawn, and the areas under the curves (AUC) are calculated. The results show that the gully erosion susceptibility map produced by the frequency ratio model (AUC = 78.11 %) functions well in prediction compared with the WofE model (AUC = 70.07 %). Furthermore, LVQ results reveal that distance from river, drainage density, and land use are the most effective factors.

Keywords Gully erosion assessment · Bivariate statistical models · GIS · Learning vector quantization · Iran

1 Introduction

Gully erosion is a major problem for natural resource management, leading to land degradation and economic losses worldwide. This phenomenon causes different types of damage to roads, natural resources, and agriculture (Burkard and Kostaschuk 1997; Nyssen et al. 2002; Valentin et al. 2005; Choi et al. 2008; Takken et al. 2008; Akgün and Türk 2011; Chaplot 2013; Zakerinejad and Maerker 2015), which is considered as one of the principal agents of geo-environmental degradation in Western Iran. Large parts of Ilam province are affected by gully erosion (Noormohammadi et al. 2013, 2014). The gully erosion and degradation processes are related to population growth and such interrelated effects as expanding agricultural lands, overgrazing, and deforestation. Due to the semiarid climate, intense precipitation events, and deforestation processes, gully erosion is considered an important source of land degradation in Ilam.

Geo-environmental factors controlling critical conditions for gully erosion occurrence and development are primarily associated with topography, lithology, rainfall, soil, and land use (Bryan and Jones 2000; Poesen et al. 2003; Martínez-Casasnovas et al. 2004; Capra et al. 2009; Gómez Gutiérrez et al. 2009b; Cui et al. 2012; El Maaoui et al. 2012). Kirkby and Bracken (2009) stated that surface runoff is one of the principal factors contributing to the occurrence of gully erosion. The velocity and volume of concentrated surface flow are also controlled by land use and topographic attributes (e.g., contributing drainage area, slope steepness, and slope curvature) (Vandekerckhove et al. 2000; Valentin et al. 2005; Zucca et al. 2006; Dondofema 2007; Samani et al. 2009; Capra et al. 2009; Svoray and Markovitch 2009; Conoscenti et al. 2013).

Several models have been developed for assessing the gully erosion rate (USDA-SCS 1992; Poesen et al. 2003). Among these are the following physically based models: Chemicals, Runoff, and Erosion from Agricultural Management Systems (CREAMS; Knisel 1980), Water Erosion Prediction Project (WEPP; Flanagan and Nearing 1995), Ephemeral Gully Erosion Mode (EGEM; Merkel et al. 1988; Woodward 1999), and the method developed by Sidorchuk (1999). However, the above-mentioned models do not predict spatial distribution of gullies which is an essential tool for evaluating the impact of environmental changes on the occurrence of gullies and planning the erosion-control practices (Conoscenti et al. 2013). Additionally, the spatial distribution of soil erosion, especially gully erosion, is an important factor in watershed management (Popp et al. 2000; Sidorchuk et al. 2003; Kumar and Nair 2006). There are also models that allow an investigator to produce gully erosion susceptibility map (GESM) or assess the spatial probability of gully occurrence by defining statistical relationships between geo-environmental conditioning factors and the spatial distribution of gullies (Table 1).

Table 1 Methods adopted in the several studies on the spatial distribution of gullies

Article	Method
Martínez-Casasnovas et al. (2004)	Logistic regression
Chaplot et al. (2005a, b)	Linear regression
Meyer and Martínez-Casasnovas (1999)	Logistic regression
Lucà et al. (2011)	Logistic regression; information value
Akgün and Türk (2011)	Logistic regression
Conoscenti et al. (2014)	Logistic regression
Conforti et al. (2010)	Information value
Conoscenti et al. (2008)	Conditional analysis
Conoscenti et al. (2013)	Conditional analysis
Magliulo (2010, 2012)	Conditional analysis
Martínez-Casasnovas (2003)	Spatial information technology
Perroy et al. (2010)	Airborne and ground-based LiDAR
Bou Kheir et al. (2007)	CART
Geissen et al. (2007)	CART
Märker et al. (2011)	CART
Gómez Gutiérrez et al. (2009b)	CART; MARS
Hughes et al. (2001)	Gully density
Gómez Gutiérrez et al. (2009a)	MARS
Dube et al. (2014)	Weight of evidence
Kuhnert et al. (2010)	Random forests
Svoray et al. (2012)	Analytical hierarchy process; data mining techniques
Zakerinejad and Märker (2014)	Maximum entropy modeling
Zakerinejad and Maerker (2015)	Stream power index; USPED
Castillo et al. (2014)	Normalized topographic method
Gómez-Gutiérrez et al. (2015)	MARS

CART classification and regression trees, *MARS* multivariate adaptive regression splines, *USPED* unit stream power-based erosion deposition

The main objectives of this study are as follows: (1) variable contribution analysis via learning vector quantization (LVQ) algorithm, (2) analyzing the geo-environmental conditions which determine the occurrence of gully erosion, and (3) assessing the capability of frequency ratio (FR) and weights-of-evidence (WofE) models to predict gully erosion susceptibility. In order to achieve these goals, the original research was carried out in Chavar region, Ilam province, Iran, as an area prone to gully erosion. The frequency ratio and weights-of-evidence models were selected as the bivariate statistical analysis for gauging gully erosion susceptibility because of the following reasons: (1) The mentioned models can work with different types of independent variables such as binary categorical, ordinal, or continuous and (2) only few studies have tested bivariate statistical analysis for calculating gully erosion susceptibility (Dube et al. 2014). Producing the GESM will be useful to decision makers and engineers in land-use management to identify prone areas for future plans (e.g., road development and urbanization).

2 Study area

The study area is located in the northern part of Ilam province, Iran, between latitudes of $33^{\circ}21'–33^{\circ}47'N$ and longitudes of $46^{\circ}09'–46^{\circ}58'E$ (Fig. 1). It covers an area of about $2,595 \text{ km}^2$, and its altitude ranges from 423 to 2795 m above sea level, with an average of 1285 m. The study area is considered to have a semiarid climate with a mean annual rainfall of 450 mm (WRCI 2013). It receives approximately 85 % of its annual rainfall from December to April. In winter, the temperature ranges from -3 to 10.5°C , while in summer it varies from 25 to 39°C . The major rivers in the study area are Chavar and Seimare. Peak stream flows are experienced between February and June (WRCI 2013). From a geological viewpoint, the study area is located in Zagros structural zone of Iran. Zagros is identified as a region of polyphase deformation, fracture systems, and the latest reflection of the collision of Arabia and Eurasia (Alavi 1994). The central part of the study area is mostly covered by the massive limestone (Kazhdum formation). The vegetation distributed above 2500 m is mainly chestnut forests or shrub grasslands. Three main soil types occur within the study area, namely inceptisols, entisols, and vertisols. In this region, the main erosive processes that affect the landscape are related to overland flow (diffuse and/or linear) and gully formation that cause severe damages (Noormohammadi et al. 2013). The study area was selected because it is susceptible to gully erosion and land degradation due to human activities (such as extension of agriculture and deforestation, development of roads, and water transport project) and specific environmental and socioeconomic settings (Noormohammadi et al. 2014). In the case of socioeconomic setting, the people in this region earn a living by producing commodities through dry farming and irrigated agriculture.

Four photographs of the recent gullies identified in the study area are shown in Fig. 2.

From the standpoint of people's livelihood strategies, animal husbandry and agriculture production are the main incomes in this area. From the viewpoint of natural resource management, soil erosion is a major problem, especially in sub-humid, semiarid, and low- and mid-latitude areas (Lal 2001) such as Chavar region in Iran.

3 Methodology

The methodological approach applied in the current study is a statistical bivariate analysis, as illustrated in Fig. 3. It consists of six main steps:

1. Gully erosion inventory mapping
2. Preparing of maps of gully erosion conditioning factors
3. Importance analysis of gully conditioning factors
4. Application of frequency ratio and weights-of-evidence models
5. Creation of gully erosion susceptibility maps
6. Validation of the gully erosion susceptibility maps.

These steps are explained and expanded in the following sections.

3.1 Gully erosion inventory mapping

In the present study, gully erosion inventory map is a collection of gully occurrences which took place in the period of 2012–2014. To prepare a detailed and reliable gully inventory

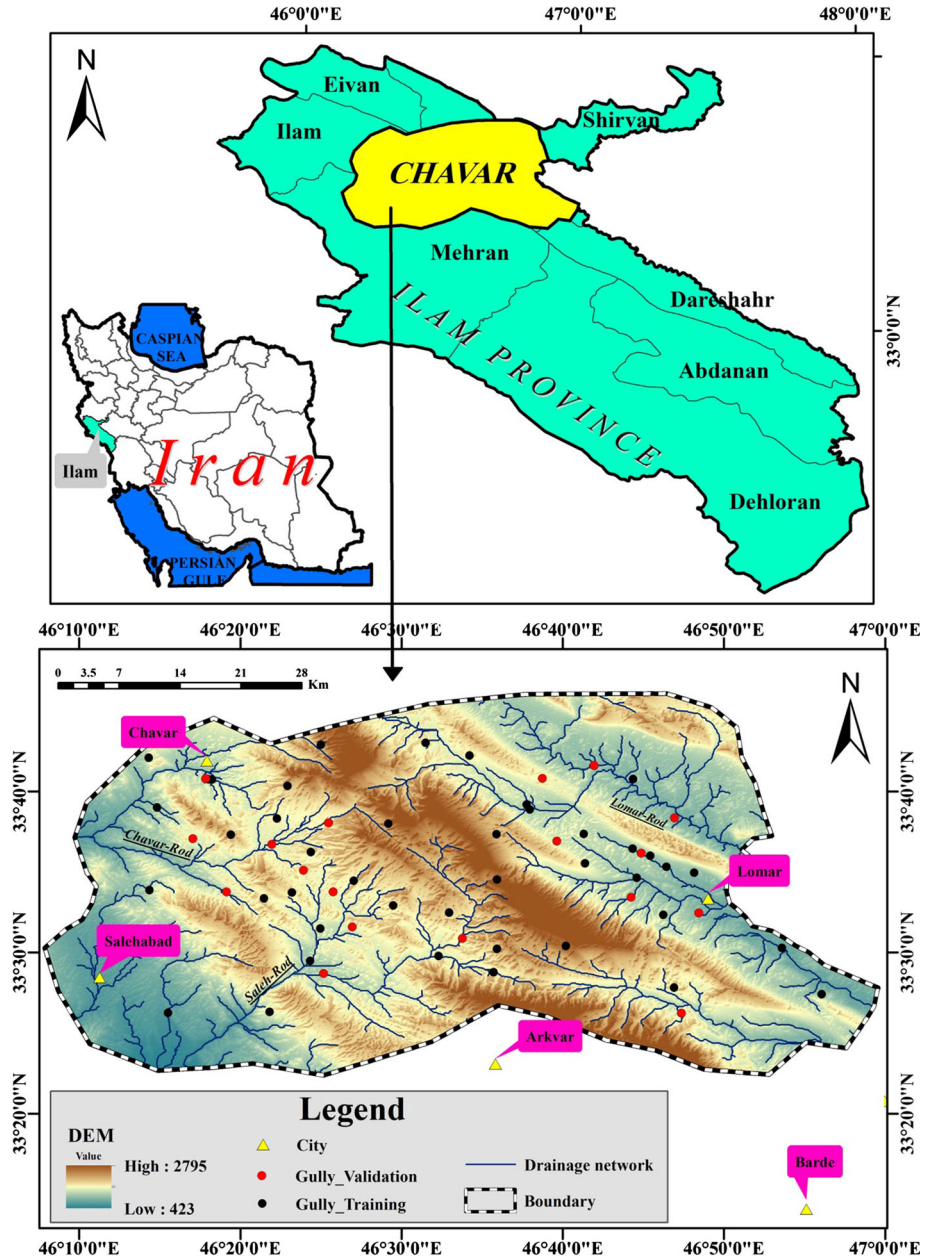


Fig. 1 Gully erosion locations with the digital elevation model map of Chavar region, Iran

map, extensive field surveys were performed in the study area (Guzzetti et al. 2000; Tien Bui et al. 2012; Frankl et al. 2013). In the second step, gully areas (i.e., polygon format) were converted to points and were used in building the gully erosion susceptibility model, while the others were applied to validate it (Conforti et al. 2010; Lucà et al. 2011; Dube et al. 2014; Zakerinejad and Maerker 2015). Among all the 63 detected gully locations,



Fig. 2 Field photographs of some gullies occurred in the study area; the gullies are hazardous to anthropogenic infrastructures such as roads and buildings (a–c), and agricultural lands (d)

70 % (44 gully cases) of them were randomly selected to train the gully erosion model, while the remaining 30 % (19 gully cases) were employed to authenticate the result (Chung and Fabbri 2003; Remondo et al. 2003; Dube et al. 2014). The locations of training and test gullies are shown in Fig. 1.

3.2 Gully erosion conditioning factors

As gully erosion process is controlled by both erosivity of runoff waters and the erodibility of soil cover, several geo-environmental attributes should be considered (Agnesi et al. 2011). It is essential to determine the gully erosion conditioning factors in order to perform gully susceptibility mapping (Conoscenti et al. 2008; De Vente et al. 2009). Therefore, in the first stage, gully erosion related to spatial database should be prepared. Through the knowledge attained from the literature, availability of data and field surveys of the conditioning factors were chosen (Kuhnert et al. 2010; Conforti et al. 2010; Lucà et al. 2011; Märker et al. 2011; Svoray et al. 2012; Conoscenti et al. 2013, 2014; Zakerinejad and Maerker 2015). Hence, ten gully erosion conditioning factors were selected to prepare the GESM of the study area. These include lithology, land use, distance from rivers, soil texture, slope degree, slope aspect, plan curvature, topographic wetness index (TWI), drainage density, and altitude (Fig. 4a–j).

Contour and survey base points were extracted from 1:50,000-scale topographic maps, and a digital elevation model (DEM) with a grid size of 20×20 m was constructed. Using the DEM, several factors such as the slope degree, slope aspect, drainage density, distance from rivers, and plan curvature can be produced. All the above-mentioned factors were

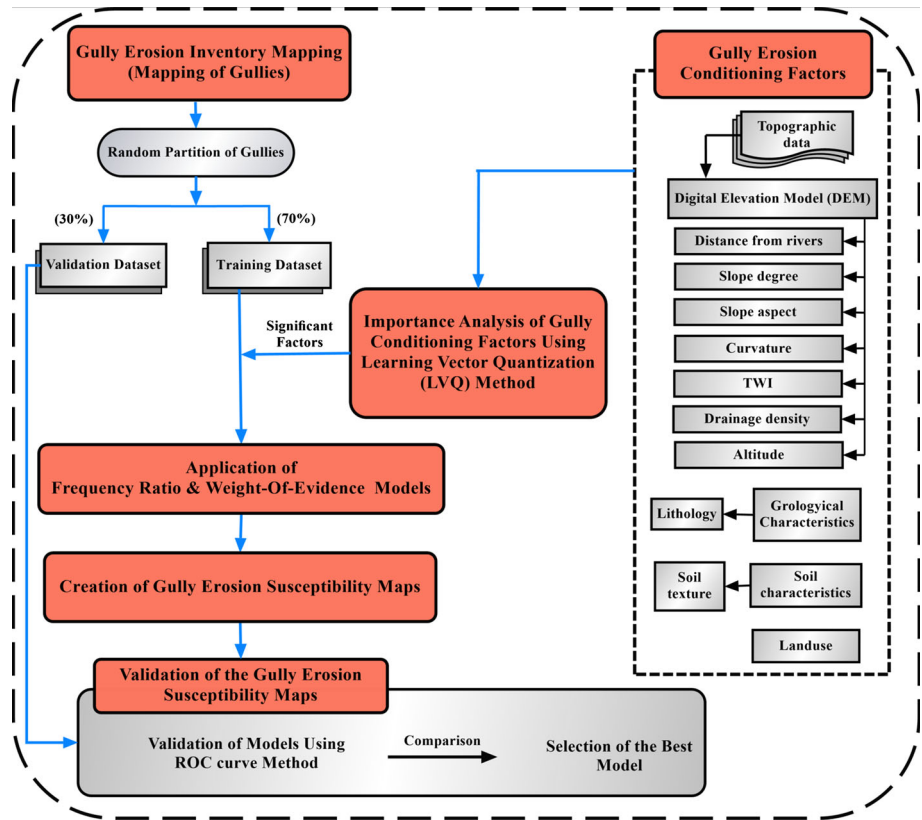


Fig. 3 Methodology flowchart including input data, six main steps (red boxes), and output of study (for details, refer Sect. 3)

converted into a raster grid format with $20\text{ m} \times 20\text{ m}$ cells for application of FR and WofE models. Furthermore, the quantile classification method was utilized to classify each conditioning factor. In this method, each class contains the same number of features. This technique is exercised in several studies due to its efficiency in classification (Tehrany et al. 2014b; Umar et al. 2014; Youssef et al. 2015).

3.2.1 Lithology

The lithology factor is known as an important variable in the natural hazard analysis (Pourghasemi and Kerle 2016). Lithological properties are associated with the geomorphological features and evaluation of a land (Dai et al. 2001; Zinck et al. 2001; Gorum et al. 2008; Zhu et al. 2014). Moreover, gully erosion is particularly dependent on the lithology properties of the material exposed or close to the earth surface (Casali et al. 1999; Stotle et al. 2003; Agnesi et al. 2011; Conforti et al. 2010; El Maaoui et al. 2012; Golestani et al. 2014). The lithology layer was concocted by digitizing the geological map (Geological Survey Department of Iran, Chavar sheet at 1:100,000 scale) (GSDI 1997). The lithology map was prepared from an available 1:100,000-scale geological map. Chavar region contains various geological formations (Table 2). The spatial distribution of lithology units in the study area is demonstrated in Fig. 4a.

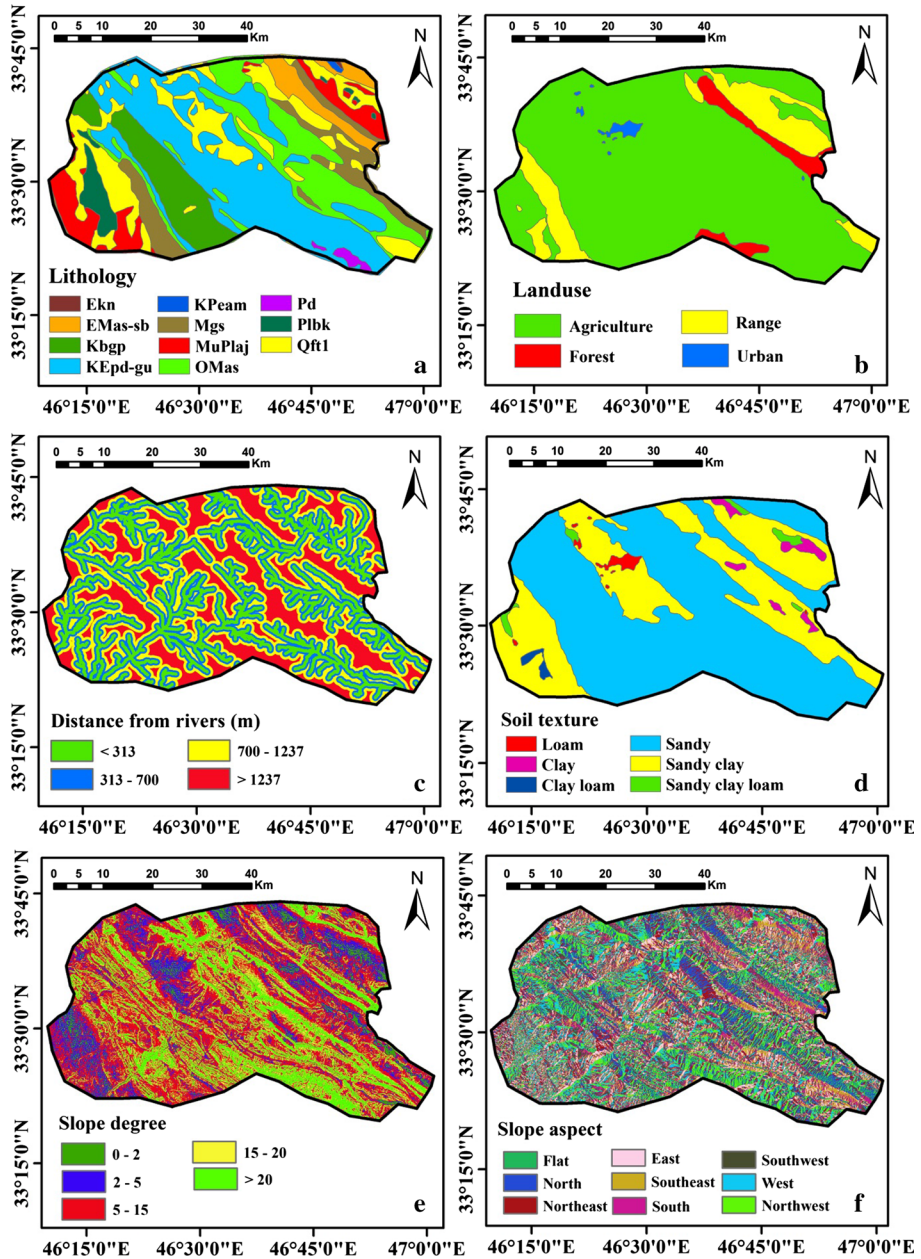


Fig. 4 Gully conditioning factors: **a** lithology (see Table 2 for legend of lithology map), **b** land use, **c** distance from rivers, **d** soil texture, **e** slope degree, **f** slope aspect, **g** plan curvature, **h** TWI, **i** drainage density, and **j** altitude

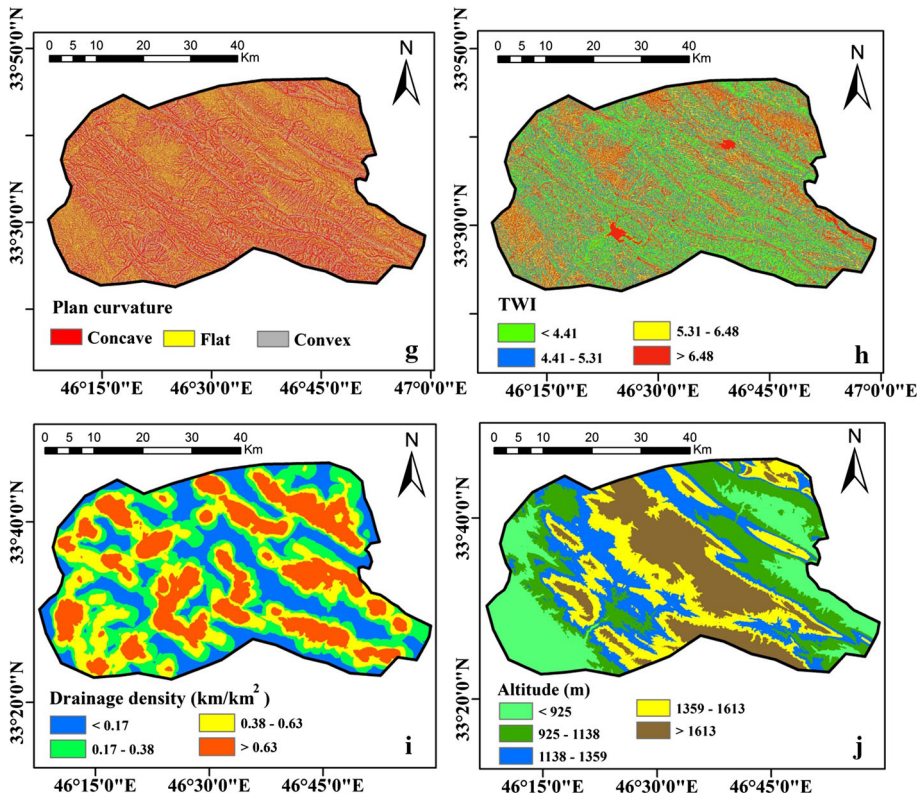


Fig. 4 continued

Table 2 Lithology of the study area

Code	Lithology	Formation	Geological age
Ekn	Tine-bedded argillaceous limestone with calcareous shale	Kandavan	Eocene
EMas-sb	Undifferentiated limestone	Shahbazan	Eocene
Kbgp	Bangestan Group; mainly limestone and shale	Surgah	Cretaceous
KEpd-gu	Massive fossiliferous limestone	Kazhdumi	Cretaceous
KPeam	Siltstone, sandstone locally with conglomerate and shelly limestone	Amiran	Cretaceous–Paleocene
Mgs	Anhydrite, salt, red marl, locally with argillaceous limestone	Gachsaran	Miocene
MuPlaj	Sandstone (brown to gray), red marl, siltstone	Aghajari	Miocene
OMas	Jointed limestone with intercalation of shale	Asmari	Miocene
Pd	Cross-bedded, quartzitic sandstone	Dorud	Permian
Plbk	Conglomerate locally with sandstone	Bakhtyari	Pliocene
Qft1	High-level pediment fan and valley terrace deposits	–	Quaternary

3.2.2 Land use

Land-use management has a significant influence on the geomorphological slope stability and gully occurrence (Anabalagan 1992; Zucca et al. 2006; Agnesi et al. 2011; Conoscenti et al. 2013, 2014; Zakerinejad and Maerker 2015). Generally barren lands and sparsely vegetated areas are more susceptible to erosion than forests where vegetation cover strongly reduces the erosive action of surface runoff (Dai et al. 2001; Çevik and Topal 2003; Gómez Gutiérrez et al. 2009a). In other words, a negative correlation exists among erosion rate and vegetation density (Snelder and Bryan 1995; Hughes et al. 2001; Chaplot et al. 2005b). The land-use map was obtained from Iranian Department of Water Resource Management (IDWRM 2012). Main land-use types having been identified in the study area were agriculture, range, forest, and urban classes (Fig. 4b). In particular, more than 81 % of the study area presents an agricultural land-use type in which the large part of the gullies (90.9 %) is included. Consequently, range land, forest, and urban areas are covered by 12.98, 4.35, and 0.79 % of the study area, respectively.

3.2.3 Distance from rivers

In most cases, gullies are linked to the drainage/stream network, facilitating the evacuation of the material eroded from upland areas (Conoscenti et al. 2014). In order to explore the influence of drainage network, the factor of distance from rivers was considered (Choi et al. 2008; Conoscenti et al. 2014; Dube et al. 2014; Zakerinejad and Maerker 2015). Hence, the distance calculation operation in ArcGIS 10.2 was exercised to derive the distance from rivers and classify it into four categories based on quantile classification scheme (Fig. 4c).

3.2.4 Soil texture

The physical properties of the surface soil play an important role in soil infiltration, runoff rate, soil resistance to erosion, and gully occurrence (Bryan and Jones 2000; Bou Kheir et al. 2007, 2008; Geissen et al. 2007; Magliulo 2012; Torri et al. 2012; Deng et al. 2015). Above all, soil texture influences hypodermic/subsurface flow and piping occurrence (tunnel erosion), which can lead to forming gullies when the roofs of pipes collapse (Bull and Kirkby 1997; Bryan and Jones 2000; Valentin et al. 2005; Pulice et al. 2012). Therefore, soil texture was selected to evaluate gully erosion susceptibility (Wells et al. 2009; Agnesi et al. 2011; Conoscenti et al. 2013). A soil texture map was digitized from soil characteristics map obtained from Iranian Department of Agriculture. Six soil texture types were in the study areas, namely loam, clay, clay loam, sandy, sandy clay, and sandy clay loam (Fig. 4d).

3.2.5 Slope degree

The gentle slope areas are highly potential areas for surface flow accumulation and consequent exposure to gully initiation (Dramis and Gentili 1977; Valentin et al. 2005; Agnesi et al. 2011; Rahmati et al. 2015b; Ghorbani Nejad et al. 2016). In the case of gully erosion, gullies in the catchment are mainly located on gentle slopes as confirmed by other researches (Flügel et al. 2003; Chaplot et al. 2005a; Kakembo et al. 2009; Le Roux and

Sumner 2012). In the current study, the slope degree was derived from the DEM and was divided into five classes (Fig. 4e).

3.2.6 Slope aspect

Slope aspect is also considered a crucial factor in natural hazard analysis and susceptibility mapping (Maharaj 1993; Baeza and Corominas 2001; Pourghasemi et al. 2013b; Umar et al. 2014). The slope aspect can indirectly influence erosion processes because it controls duration of sunlight exposition, evapotranspiration, moisture retention, vegetation cover type, and vegetation distribution on slopes (Dai et al. 2001; Sidle and Ochiai 2006; Agnesi et al. 2011; Wang et al. 2011; Jaafari et al. 2014). Moreover, it can indirectly express (proxy role) the influence of the structural setting (Conoscenti et al. 2013). The slope aspect map was constructed automatically in ArcGIS 10.2 software, using the DEM with a grid cell size of 20×20 m, and is classified into nine categories (Fig. 4f).

3.2.7 Plan curvature

The useful geomorphological information and terrain morphology description can be determined through the analysis of plan curvature (Davoodi Moghaddam et al. 2013; Chaplot 2013; Tehrany et al. 2014b). Generally, the impact of plan curvature on gully erosion occurrence is the divergence or convergence of water during downslope flow (Agnesi et al. 2011; Conforti et al. 2010; Conoscenti et al. 2013; Gómez-Gutiérrez et al. 2015). Therefore, plan curvature layer has been selected with respect to its effect on gullies triggering and development. By means of ArcGIS 10.2 software, the plan curvature map was prepared. This layer was classified into three classes of convex (positive curvature), flat (zero curvature), and concave (negative curvature) (Fig. 4g).

3.2.8 Topographic wetness index

The topographic wetness index (TWI) is a water-related and secondary topographic factor within the runoff model which is commonly applied to quantify topographic control in hydrological processes (Rahmati et al. 2016). It is clarified by the following equation (Moore et al. 1991):

$$\text{TWI} = \ln\left(\frac{S}{\tan \alpha}\right) \quad (1)$$

where S is the cumulative upslope area draining through a point (per unit contour length) and α is the slope gradient (in degrees) (Moore et al. 1991). The tendency of gravitational forces to move toward water down slope (in terms of $\tan \alpha$) and the tendency of water to accumulate at any point in the catchment (in terms of S) are considered by the TWI factor.

As stated by Gómez-Gutiérrez et al. (2015), TWI is recognized as an important factor in evaluating gully erosion proneness. Gully erosion occurs as the flow velocity exceeds the soil shear stress, which is mostly a function of S parameter and is related to energy level of surface runoff (Vandaele et al. 1996; Chaplot 2013). The erosive power of runoff in terms of flow velocity, potential discharge, and transport capacity was modeled by means of TWI (Agnesi et al. 2011; Chaplot 2013; Conoscenti et al. 2014; Tehrany et al. 2015; Tahmassebpour et al. 2016), which was derived from the DEM. A morpho-dynamic interpretation of topographic attributes (e.g., TWI, altitude, and slope angle) is given in detail

by Wilson and Gallant (2000). In the present study, TWI map is divided into four groups, using quantile classification method (Tehrany et al. 2014a) (Fig. 4h).

3.2.9 Drainage density

According to Tehrany et al. (2014b), a high drainage density causes larger surface runoff ratio. The drainage pattern of an area is affected by several factors such as the nature and structure of the geological formation, soil characteristics, vegetation cover condition, infiltration rate, and slope degree (Manap et al. 2014; Pourtaghi and Pourghasemi 2014). In order to produce drainage density map of study area, Line Density tool in ArcGIS 10.2 was applied and its values have been organized in four classes (Fig. 4i).

3.2.10 Altitude

The topographic attributes (such as altitude and slope angle) mainly control gully erosion process and, thus, determine the spatial distribution of gullies (Conoscenti et al. 2014; Hongchun et al. 2014; Gómez-Gutiérrez et al. 2015). In addition, altitude plays important roles in vegetation cover type and precipitation properties. Hence, altitude map of the study area was obtained from the DEM, and five classes (<925, 925–1,138, 1,138–1,359, 1,359–1,613, and >1,613 m) were constructed (Fig. 4j).

3.3 Importance analysis of gully conditioning factors

The learning vector quantization (LVQ) algorithm is one of the supervised neural network methods first presented by Kohonen (1995). It applies a “winner-take-all” learning approach (Pham and Oztemel 1994). Indeed, the Euclidean distance has been considered as a basic rule of competition. The distance (D_i) between the training vector X and the reference vector Z_i of neuron i is given by:

$$D_i = Z_i - X = \sqrt{\sum (Z_{ij} - X_j)^2} \quad (2)$$

where X_j and Z_{ij} are j th elements of X and Z_i , respectively. The learning equation for updating the Z_i and consequently importance analysis of variables is given as follows. If the neuron is in the wrong category (WC):

$$Z_i(t+1) = Z_i(t) - \lambda(t)h_i(t)(X(t) - Z_i(t)) \quad (3)$$

and if the neuron is in the wrong category, then

$$Z_i(t+1) = Z_i(t) + \lambda(t)h_i(t)(X(t) - Z_i(t)) \quad (4)$$

where

$$h_i(t) = \begin{cases} 1, & \text{if the } i\text{th neuron is a winner,} \\ 0, & \text{otherwise,} \end{cases} \quad (5)$$

denotes the degree of excitation of the neurons. $\lambda(t)$ is the learning rate at the time t . The details of the LVQ algorithm can be found in Ahalt et al. (1990) and Kohonen et al. (1996).

This algorithm has been successfully applied in many different fields such as landslide susceptibility zonation (Pavel et al. 2008; Borgogno Mondino et al. 2009; Pavel et al. 2011), mineral potential mapping (Tayebi and Tangestani 2015), rock type classification of

limestone (Patel and Chatterjee 2016), vegetation classification (Filippi and Jensen 2006), and environmental sciences (Erbek et al. 2004; Zhang and Xie 2012; Williams et al. 2014). Recently, Naghibi et al. (2016) have utilized the LVQ algorithm to quantify variables importance (VI) and uncertainty analysis of groundwater modeling. In the current research, the relative contribution of the independent variables to gully occurrence (i.e., dependent variable) was evaluated via LVQ algorithm—which can be performed in R statistical package.

3.4 Application of bivariate models

3.4.1 Frequency ratio model

Among several bivariate statistical approaches for gully susceptibility mapping, the frequency ratio (FR) model has been employed in the current study (Poudyal et al. 2010; Pradhan 2010). A simple geospatial assessment tool for identifying the probabilistic relationship between dependent and independent factors can be explained, using the FR model (Bonham-Carter 1994; Tehrany et al. 2013). In this study, the selected conditioning factors (e.g., lithology, land use, distance from river, soil texture, slope degree, slope aspect, plan curvature, topographic wetness index (TWI), drainage density, and altitude) and gullies location are independent and dependent variables, respectively.

The FR can be described as the ratio of the area where gullies occurred in the total study area (Conforti et al. 2010). In this model, for each conditioning factor, the density of the gullies of the training set in each class was calculated, using the following equation (Bonham-Carter 1994):

$$FR = \frac{A/B}{C/D}, \quad (6)$$

where A is the number of pixels with gully erosion for each conditioning factor, B is the number of total gully occurrences in study area, C is the number of pixels in the class area of the factor and D is the number of total pixels in the study area. By operating the FR model, the spatial relationships between gully locations and each factor's contributing gully erosion occurrence were derived. Then, the frequency ratio magnitude of each class is computed through analysis of the relationship between gully location and the attributing factors. In a given pixel, the gully erosion susceptibility index (GESI) can be obtained by summation of pixel values according to Eq. (7):

$$GESI = \sum_{R=1}^{R=n} FR, \quad (7)$$

where $GESI$ and FR are gully susceptibility index and the final weight for the FR model, respectively.

3.4.2 Weights-of-evidence model

The weights-of-evidence (WofE) model is based on a statistical Bayesian bivariate approach and has been used for landslide susceptibility mapping (Mohammady et al. 2012; Pourghasemi et al. 2013b, c) and flood susceptibility mapping (Tehrany et al. 2014b). A

detailed description of the mathematical equation of WofE model is explained by Bonham-Carter (1991, 1994).

The WofE is one of the bivariate approaches which uses the log-linear form of the Bayesian probability method to determine the relative importance of effective factors by statistical means (Lee et al. 2012; Ozdemir and Altural 2013; Rahmati et al. 2015a). By overlaying gully locations with each factor, the statistical relationship between them can be identified and assessed as to whether and how significant the effective variable is responsible for the occurrence of past gullies erosion. The WofE model is based on the calculation of positive (W^+) and negative (W^-) weights. This model computes the weight for each gully conditioning factor (A) on the basis of the presence or absence of the gully locations (B) within the study area (Bonham-Carter 1994) as follows:

$$W_i^+ = \ln \frac{P\{B|A\}}{P\{B|\bar{A}\}} \quad (8)$$

$$W_i^- = \ln \frac{P\{\bar{B}|A\}}{P\{\bar{B}|\bar{A}\}}, \quad (9)$$

where P is the probability and \ln is the natural log function. B and \bar{B} indicate the presence and absence of the gully conditioning factors, respectively. A is the presence of gully, and \bar{A} is the absence of a gully. A positive weight (W^+) explains the fact that the conditioning factor is present at the gully locations and its value is an indication of the positive correlation between the presence of the gully conditioning factor and the gullies (Bonham-Carter 1991; Mohammady et al. 2012). Similarly, a negative weight (W^-) designates the absence of the gully conditioning factor and reflects the level of negative correlation (Regmi et al. 2013). In gully susceptibility mapping, the weight contrast (C) measures and specifies the spatial association between the effective factors and gully erosion occurrences. C is negative for a negative spatial relationship and positive for a positive relationship (Pourghasemi et al. 2013b). The standard deviation $S(C)$ of W is determined by Eq. 10:

$$S(C) = \sqrt{S^2(W^+) + S^2(W^-)}, \quad (10)$$

where $S^2(W^+)$ is the variance of the W^+ and $S^2(W^-)$ is the variance of the W^- . The variances of the weights can be determined as follows (Bonham-Carter 1994):

$$S^2(W^+) = \frac{1}{N\{B \cap A\}} + \frac{1}{B \cap \bar{A}} \quad (11)$$

$$S^2(W^-) = \frac{1}{\{\bar{B} \cap A\}} + \frac{1}{\{\bar{B} \cap \bar{A}\}} \quad (12)$$

The studentized contrast (G_{Final}) is a measure of confidence and is calculated, using the following equation:

$$G_{\text{Final}} = \left(\frac{C}{S(C)} \right), \quad (13)$$

where C shows the overall spatial association between a conditioning factor and gully erosion occurrence (Bonham-Carter 1994). After applying the WofE model, the weights of

the factors (G_{Final}) were summed to give and map a gully erosion susceptibility map (GESM) based on the following equation:

$$GESI = \sum_{R=1}^{R=n} G_{Final}, \tag{14}$$

where *GESI* represents gully erosion susceptibility index.

4 Results and discussion

4.1 Relative importance analysis of gully conditioning factors

The results from LVQ technique are shown in Fig. 5. They indicated that distance from river (VI = 66.4 %), drainage density (VI = 65.9 %), and land use (VI = 63.4 %) are the most important conditioning factors, followed by slope degree (VI = 58.2 %), altitude (VI = 57.2 %), soil (VI = approximately 56 %), plan curvature (VI = 55.4 %), TWI (VI = 53.64 %), and lithology (VI = almost 49.5 %). Thus, all these layers were chosen as input variables to generate the GESMs, because they make an important contribution to gully erosion occurrence—based on the LVQ analysis—in the study area.

4.2 Application of frequency ratio model

To prepare gully susceptibility map and estimate the level of spatial correlation between gully locations and conditioning factors, the FR model was applied. Figure 5 shows the frequency ratio (FR) value that was computed for each class of the conditioning factors. There is a low correlation, provided that the FR value is less than 1; and a higher correlation exists if the FR value is larger than 1 (Oh and Lee 2010). In general, a comparatively high value of FR reveals a higher probability of gully occurrence, while a low value of FR indicates a lower probability of gully susceptibility. Lithology had an important impact on the erodibility of the study area. As shown in Fig. 5a, shale class of the Asmari formation (OMas) has the highest value of FR (1.89) followed by limestone, shale class of the

Fig. 5 Variables importance analysis using LVQ method (distance f. r.: distance from river; drainage d.: drainage density; plan c.: plan curvature)

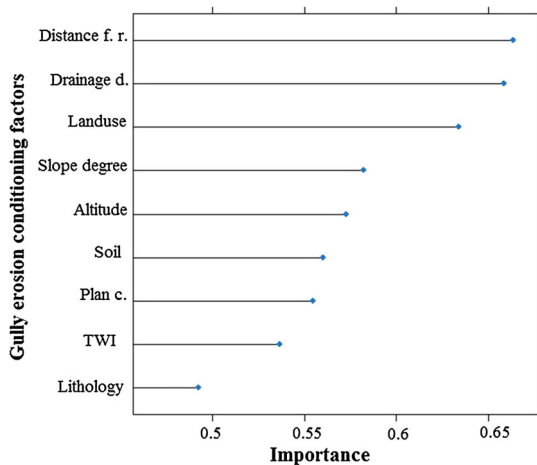
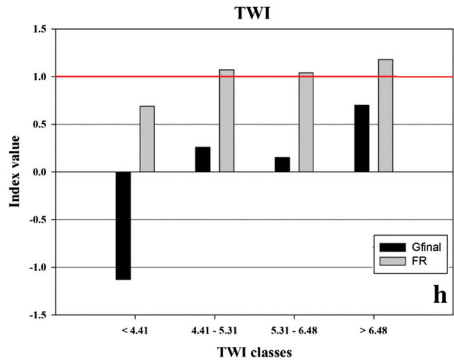
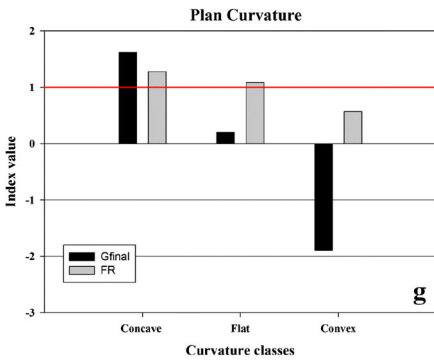
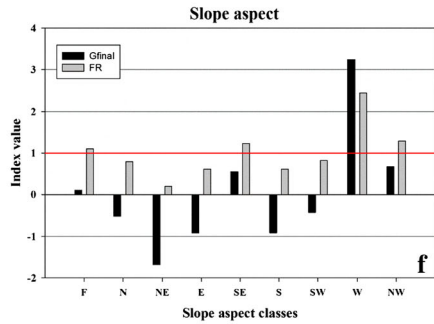
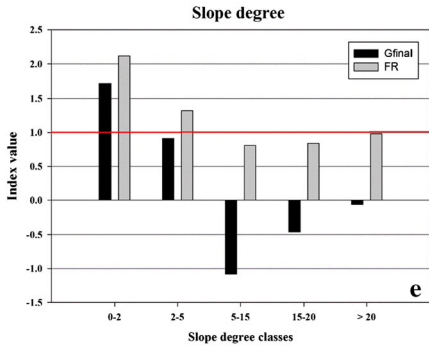
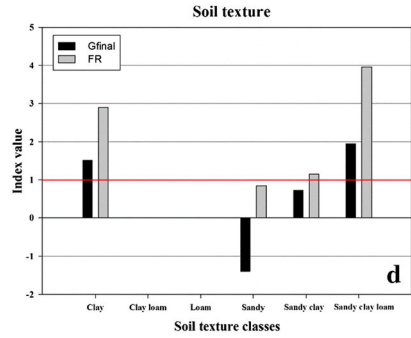
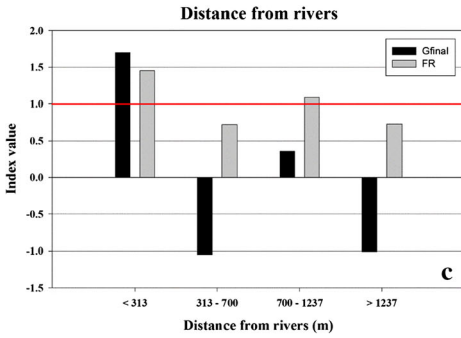
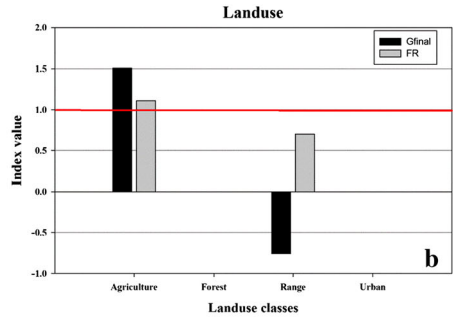
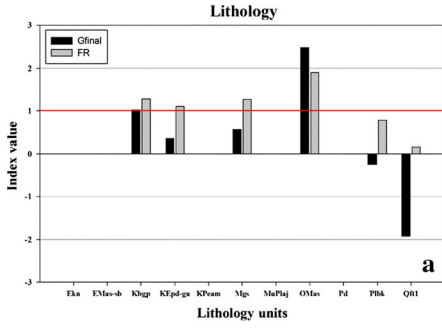


Fig. 6 The weights calculated of gully conditioning factors by FR and WofE models: **a** lithology, **b** land use, **c** distance from river, **d** soil texture, **e** slope degree, **f** slope aspect, **g** plan curvature, **h** TWI, **i** drainage density, and **j** altitude. In the case of FR model, the value of 1 (*red horizontal line*) shows an average correlation between gullies and conditioning factors. The FR values are zero, negative, and positive, of which $FR < 1$ reflects a lower correlation and $FR > 1$ reflects a high correlation. In the case of WofE model, the G_{Final} value reflects the overall spatial association between the gully conditioning factors and the gullies. A positive G_{Final} shows a positive spatial correlation and vice versa for a negative G_{Final} value

Kazhdomi formation (Kbgb) (1.28), and gray marl class (Mgs) (1.26); thus, these classes are the most influential ones in gully erosion occurrence. In the case of land-use type, it can be seen that the agriculture class has FR value of 1.10, reflecting that the gully susceptibility in this land-use type is high (Fig. 5b). In the case of distance from rivers, the results denoted that as the distance from rivers increases, the gully erosion occurrence generally decreases. In this case, the highest FR value (1.44) was obtained for <313 m (Fig. 5c). However, analysis of the frequency ratio results reveals that the FR is <1 for distance from rivers more than 1,237 m, representing a low probability of gully occurrence within this class. In the soil texture factor, the highest values were recognized for sandy clay loam (3.96), clay (2.88), and sandy clay (1.15) classes, while the remaining categories of soil texture type have FR values less than 1 (Fig. 5d). The analysis of FR for the relationship between gully occurrence and slope degree points out that slope degree class 0° – 2° has the highest value of FR (2.11) followed by 2° – 5° class (1.32) (Fig. 5e). The FR value is less than 1 for slope degree classes of 5° – 15° , 15° – 20° , and $>20^{\circ}$, indicating a low probability of gully occurrence within these slope ranges. These findings are similar to those of Conoscenti et al. (2014), stating that slope degree is a major factor which controls the overland flow concentration and the location and development of gullies. In the case of slope aspect, the FR value is more than 1 for western, northwest, southeast, and flat faces, showing a higher probability of gully occurrence compared to other slope aspect classes (Fig. 5f). Assessment of plan curvature confirmed that the concave (FR value of 1.27) class is most susceptible to gullies, followed by flat areas (FR value of 1.05) (Fig. 5g). Referring to Fig. 5h, ratios greater than 1 were recognized in the TWI range of 4.41–5.31, 5.31–6.48, and >6.48 . This result points to significant relationships between gully occurrence and TWI (in relation to runoff volume) that is in line with the findings of Dube et al. (2014). Investigation of drainage density disclosed that 0.17–0.38 and >0.63 km/km² classes have FR value >1 (Fig. 5i). This can be explained by the fact that at high drainage density, there is higher runoff water, and thus, the highest chances are present for gully occurrence. Similarly, drainage density of less than 0.17 km/km² has a lower value of FR (0.45). The analysis of FR for the relationship between gully density and altitude showed that the altitudes between 925 and 1138 m (FR value of 1.36) and 1138–1359 m (FR value of 1.02) had a high correlation with gully occurrence (Fig. 5j). Finally, based on Eq. 3, the GESM produced by the FR model is demonstrated in Fig. 6a. The GESM was classified for each model according to the four classification methods, namely quantile, natural breaks, equal interval, and geometrical interval (Fig. 7), into four different gully susceptibility zones, including low, medium, high, and very high. By comparing the results of each classification method and the distribution of training and validation gullies on the high and very high gully susceptibility zones, it was found that the quantile classification method gave the most accurate distribution. This agrees with the findings by Youssef et al. (2015) in that quantile method is a good classifier in susceptibility mapping.



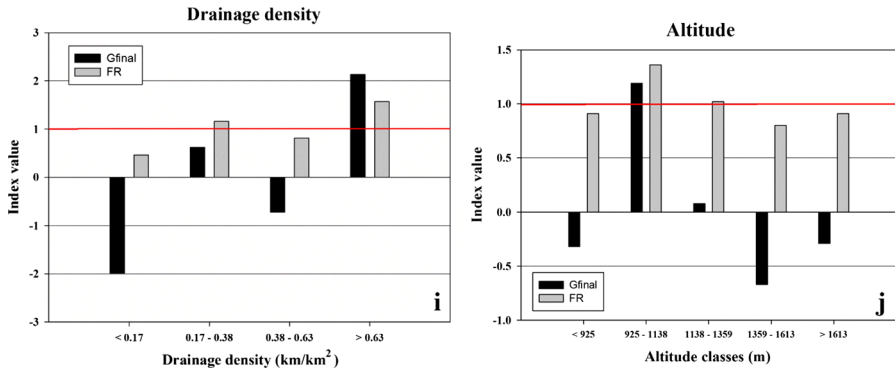


Fig. 6 continued

4.3 Application of weights-of-evidence model

As it has been explained in the previous section, all parameters of WofE model are computed for each gully conditioning factor. Figure 5 represents weights (G_{Final} values) and the relationship between the gully occurrence and classes of each conditioning factor. The G_{Final} is negative for a negative spatial association and positive for a positive spatial association. A G_{Final} equal to zero illustrates that the considered class of conditioning factors is not significant for the analysis (Corsini et al. 2009; Regmi et al. 2010). In the case of the correlation between gully occurrence and lithology, the highest G_{Final} values were +2.48 and +1.02 for OMas and Kbgp classes, respectively (Fig. 5a). These lithology units displayed the highest susceptibility to gully. Among the different land-use types, the agriculture category had the highest G_{Final} value (+1.50), indicating maximum gully susceptibility (Fig. 5b). Additionally, rangeland class acquired the weight of -0.76 , showing the negative influence on gully occurrence as the vegetated areas can decrease the surface runoff and, therefore, reduce the gully erosion. This result is in accord with the study by Zheng (2006), confirming that forested areas experience less erosion in the form of gullies in comparison with bare and agriculture areas. In the case of distance from the rivers, the class less than 313 m had the highest weight ($G_{\text{Final}} = +1.69$), demonstrating high gully erosion susceptibility in this range of distance from the rivers (Fig. 5c). The findings are in agreement with those of Dube et al. (2014) and Conoscenti et al. (2014), stating that low distances have a positive association ($G_{\text{Final}} > 0$) and that it is easier for a gully to develop on the bank of a river than on areas far from the river. The analysis of WofE model for the relationship between gully locations and soil texture indicated that both sandy clay loam ($G_{\text{Final}} = +1.95$) and clay ($G_{\text{Final}} = +1.50$) categories had positive influences on gully erosion occurrence (Fig. 5d). In the case of slope degree, the 0° – 2° and 2° – 5° classes have G_{Final} of +1.71 and +0.91, respectively (Fig. 5e). This means that the gully erosion probability is higher in these classes. In contrast, slope degrees larger than 20° have the minimum value of G_{Final} (-0.05). The relationship between the gully locations and the slope aspect can be described as follows: It is significant that high G_{Final} values were observed for southeast and flat areas (Fig. 5f), indicating a high probability of gully erosion occurrence. This was mainly due to greater vegetation cover density in the north-facing area compared with the south-facing area (Wang et al. 2011). Morphology of the topography can be described, using the curvature values. In the case of curvature, the

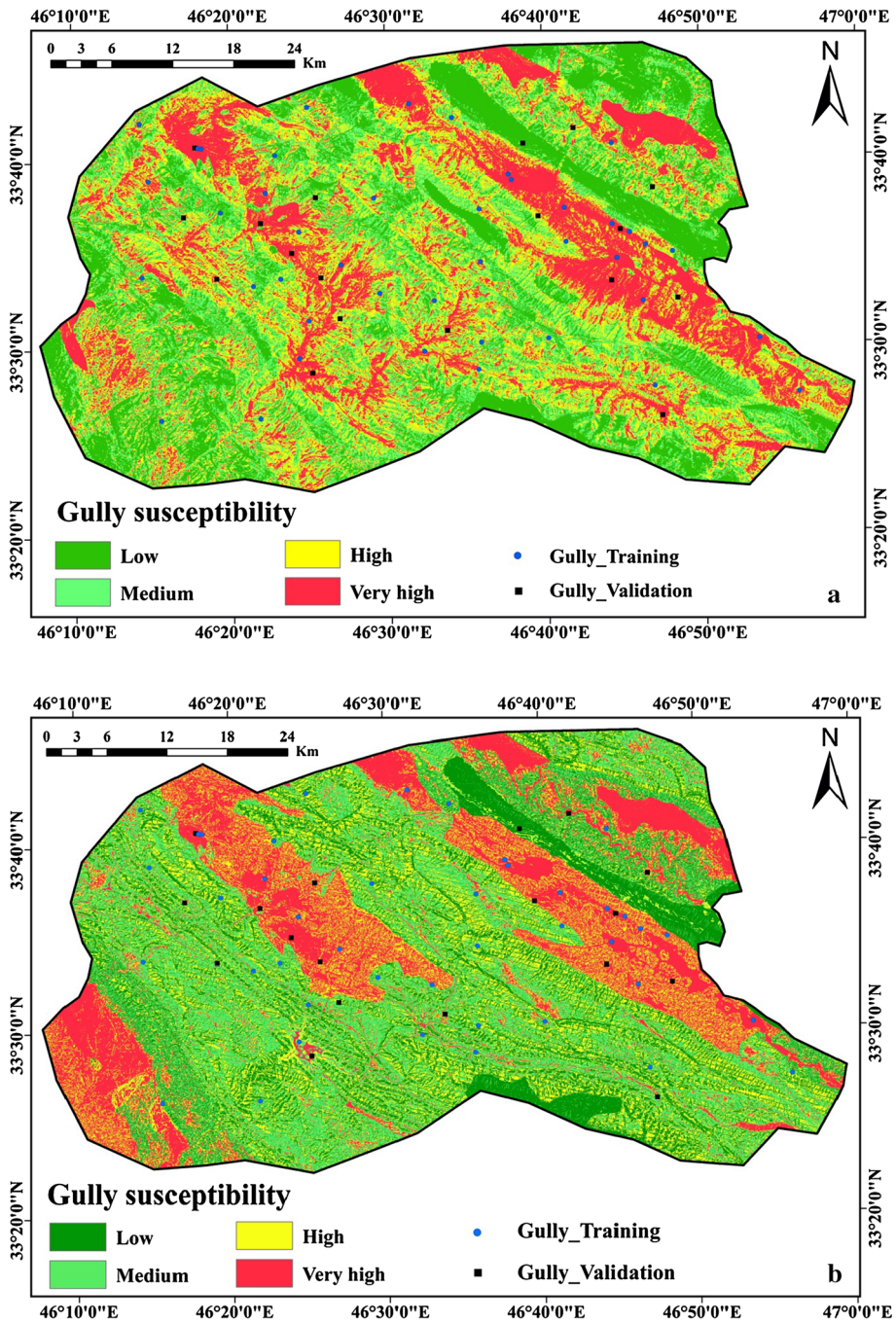


Fig. 7 Gully susceptibility maps produced based on a FR and b WofE models

analysis of WofE model indicates that concave class has the highest value of G_{Final} (+1.62), followed by flat curvature class (+0.20) (Fig. 5g). This result agrees with the findings by Conforti et al. (2010) in the Turbolo stream catchment, Italy. Their results proved that gully erosion processes commonly occur on concave slopes. Referring to Fig. 5h, TWI larger than 6.48 ($G_{Final} = +0.7$) has a high correlation with gully occurrence. Moreover, G_{Final} values generally increase by increasing TWI classes. The drainage density of 0.63–1.37 km/km² has the largest G_{Final} value (+2.13), pointing to the fact that the attributes of this class has the strongest relationship with gully susceptibility (Fig. 5i). In the case of altitude, the highest weight ($G_{Final} = +1.18$) was for the class of 925–1138 m, which has a positive effect on gully erosion occurrence (Fig. 5j). These results are in line with those of De Oliveira (1990) and Meyer and Martínez-Casasnovas (1999) in that gully distribution is mainly controlled by topographic factors (such as altitude and slope angle). Finally, based on Eq. 10, the GESM produced by using the WofE model is shown in Fig. 6b. According to the quantile classification scheme, the GESM

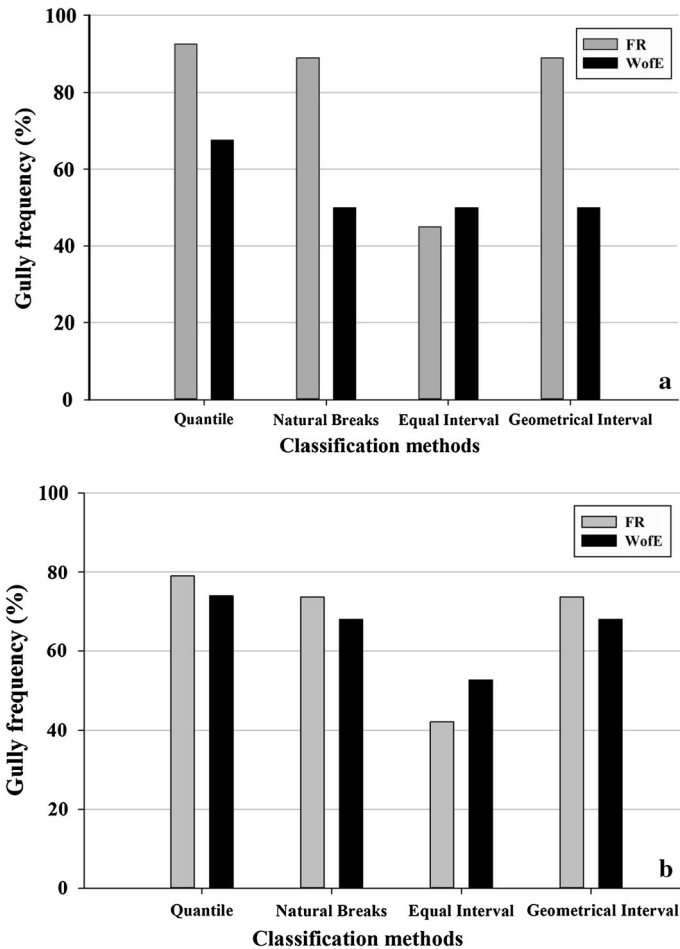


Fig. 8 Relationship between susceptibility classes (high + very high) and the percent frequency of gullies (a) training and (b) validating gully numbers of different classification methods for FR and WofE models

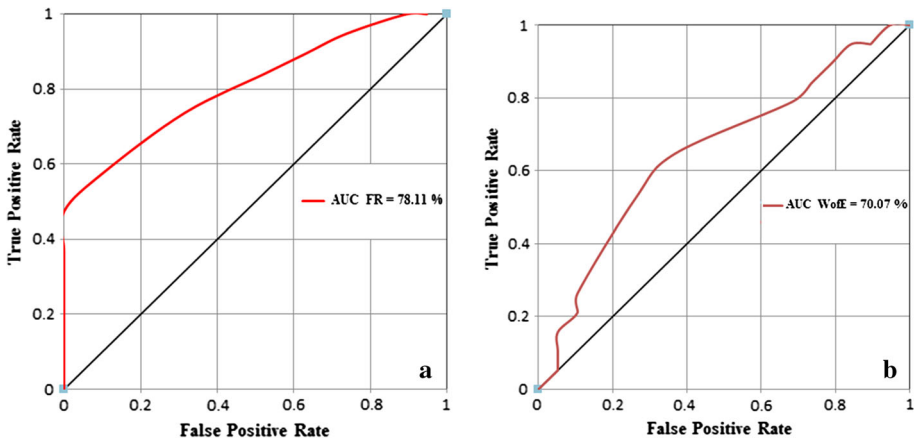


Fig. 9 ROC curve for the gully susceptibility maps produced by (a) FR and (b) WofE models

values were divided into four gully susceptible zones: low, medium, high, and very high classes (Youssef et al. 2015).

4.4 Map validation and comparison

To determine the accuracy of the different gully erosion susceptibility models applied in this study, the receiver operating characteristics (ROC) curve was employed (Mohammady et al. 2012; Pourghasemi et al. 2013c; Devkota et al. 2013; Rahmati et al. 2014). ROC curve analysis is a common technique for evaluating the accuracy of a diagnostic test (Williams et al. 1999; Zare et al. 2013; Razandi et al. 2015). The area under the curve (AUC) of the produced ROC describes the quality of a predicting system by showing the ability of the system to model the occurrence or non-occurrence of predefined “events” (Tien Bui et al. 2012; Naghibi et al. 2014). In the ROC curve analysis, the ideal model represents an $AUC = 1.0$, while an AUC value close to 0.5 shows inaccuracy in the prediction model (Fawcett 2006). According to Yesilnacar (2005), the quantitative–qualitative relationship between AUC value and prediction accuracy can be classified as follows: 0.5–0.6, poor; 0.6–0.7, average; 0.7–0.8, good; 0.8–0.9, very good; and 0.9–1, excellent. ROC curve assessment results (Fig. 8a, b) indicated that in the gully erosion susceptibility maps produced via FR and WofE, the AUCs were 0.7811 and 0.7007. Therefore, it is observed that the gully susceptibility map produced by FR model exhibited better performance than the WofE model in the study area (Fig. 9).

5 Conclusion

Due to hazardous characteristics of gullies erosion, several researchers and natural resources managers throughout the world have focused on assessing gully erosion susceptibility hazards and determining their spatial pattern for a given area. In the current study, two statistical models, frequency ratio and weights-of-evidence models, were employed for gully susceptibility mapping, and their performances were compared. At first, a gully erosion inventory map was constructed through multiple field investigations.

Of the sum total of 63 gully locations identified in the study area, 44 cases were utilized for models training and the remaining 19 for validation purposes. In the next stage, the gully conditioning factors such as lithology, land use, distance from rivers, soil texture, slope degree, slope aspect, plan curvature, topographic witness index, drainage density, and altitude were prepared. After a relative contribution assessment of each predictor variable to the models (i.e., using LVQ algorithm), the gully erosion susceptibility modeling was applied to Chavar region, Iran, via the FR and WofE techniques. Finally, for testing the accuracy of the mentioned models, the ROC curve was organized. The analysis confirms that the FR model (AUC = 78.11 %) shows a better accuracy than the WofE (AUC = 70.07 %) model. Consequently, the performance of the gully erosion susceptibility map constructed by FR model is obviously greater than that of the map produced by WofE model. According to LVQ results, the most effective factors in the prediction of gully erosion susceptibility were discovered to be distance from river, drainage density, and land-use factors, although other selected factors had reasonably acceptable importance.

In summary, the findings of the present research proved that GIS-based FR and WofE models could be successfully applied to the gully susceptibility mapping, particularly in developing and low-income countries. In fact, the above-mentioned models require data usually available for large areas (such as regional-scale resolution) or achievable without high cost- and time-consuming methods; accordingly, these models are capable of being easily reproduced and employed in other regions with the aim of gully erosion susceptibility mapping. Hence, the information provided by these gully susceptibility maps can help planners and natural resources managers reduce losses caused by focusing on “hot spot” areas of gully erosion.

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