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REZA ZAKERINEJAD [1*], CHRISTIAN SOMMER [2,3],
VOLKER HOCHSCHILD [2] & MICHAEL MAERKER [5]

SPATIAL DISTRIBUTION OF WATER EROSION USING STOCHASTIC MODELING IN THE SOUTHERN ISFAHAN PROVINCE, IRAN

ABSTRACT: ZAKERINEJAD R., SOMMER C., HOCHSCHILD V. & MAERKER M., *Spatial distribution of water erosion using stochastic modeling in the Southern Isfahan Province, Iran.* (IT ISSN 0391-9838, 2021).

Soil erosion is often regarded as one of the main processes of desertification. Many parts of the world have been affected by soil erosion, resulting in major environmental problems and causing land degradation, loss of agricultural land, destroyed villages and infrastructure as well as historic places. Soil erosion particularly affects arid and semi-arid regions due to long dry periods and often-intensive precipitation events. The soil particles washed off by surface and subsurface runoff are the biggest pollution factor in terms of amount and volume. Our case study is located in the Southern Isfahan province, Central Iran. The area is severely affected by water erosion such as gullies, rills and badlands. The main aim of this study is to predict the spatial distribution of the different water related erosion types and their susceptibilities using a probabilistic Maximum Entropy Model approach based on the following environmental layers: lithology, soil textures, land use, precipitation, Normalized Difference Vegetation Index and topographic indices derived from an SRTM DEM with 30 m spatial resolution. An inventory of the erosion forms and features such as gully erosion, rill erosion and badland erosion was determined based on Google Earth images (GE), aerial photos and a field campaign conducted in 2018. In order to validate the stochastic modelling approach, we divided the entire sample in a train (70%) and test (30%) dataset. We validated the model performance using the Area Under Curve (AUC) value. The model yields good (rill and gully erosion) to excellent (badland) results for both train and test data. The spatial prediction of susceptibilities for rill, gully and badland erosion show that in total more than 40% of the study area is affected by water erosion processes (4.8% rill erosion; 23.4% gully erosion and 17.9% badland erosion). The knowledge of susceptible areas is crucial for a proper land management and related soil conservation measures to guarantee a sustainable land use.

KEY WORDS: Gully erosion, Badlands, Rill erosion, Maximum Entropy Model, Iran.

INTRODUCTION

In 1983, according to the evaluations made by FAO worldwide an area of 5-7 million hectares of agricultural land were lost due to degradation processes such as soil erosion, soil salinization, urbanization, etc.. Soil erosion processes may act on very short time scales but can also last over tens and hundreds of years. Particularly, effects of soil erosion attract special attention if they become disastrous. Soil loss becomes often critical if socioeconomic and political factors favor erosion (man-induced erosion).

In arid and semiarid regions, with scarce vegetation and particularly in areas with low infiltration capacity, e.g. due to soil compaction, stormflow is capable to effectively erode the soil. In other words, areas with low vegetation and overgrazing in large parts of the world are more exposed to water erosion and land degradation.

Many parts of Iran face various types of land degradation of which water erosion is one of the most important (Masoudi & *alii*, 2006; Masoudi & Zakerinejad, 2010; Shahrivar & *alii*, 2012; Zakerinejad & Maerker, 2014; Zakerinejad & *alii*, 2018; Zabihi & *alii*, 2018; Arabameri & *alii*, 2019a,b; Hosseinalizadeh & *alii*, 2019a). Recently large areas of arid and semiarid landscapes in Iran have been destroyed and converted to bare land by the effects of gully erosion, rill erosion, landslides and badlands (Arabameri & *alii*, 2019b). The channel type erosion (rill and gully) occur where concentrated water flows with high velocity eroding the highly erodible soils especially in the plateau areas (Masoudi & *alii*, 2006; Rahmati & *alii*, 2016). Overland flow,

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subsurface water movement, and soil piping (Kirkby & Bracken, 2009; Poesen & *alii*, 2003; Poesen & *alii*, 2018) are processes that provoke rill but also gully erosion. Since gully erosion is one of the most intensive soil erosion processes (Maerker & *alii*, 2003, 2011), particular attention should be addressed to these types of soil loss. The term "badland" refers to parts of unconsolidated sediments or poorly consolidated bedrock with low or no vegetation, which are not suitable for agriculture because of their intensely dissected landscape (Zakerinejad & Maerker, 2014).

Various researchers have studied the factors and mechanisms, which affect different types of water erosion in many parts of the world. However, processes like gullying, piping and landslides have been studied less intensively than sheet erosion processes (Kheir & *alii*, 2007; Nazari Samani & *alii*, 2010; Lucà & *alii*, 2011; Shahrivar & *alii*, 2012; Zakerinejad & Maerker, 2015; Gómez-Gutiérrez & *alii*, 2015; Gómez-Gutiérrez & *alii*, 2015; Lombardo & *alii*, 2016; Kornejady & *alii*, 2017; Cama & *alii*, 2017; Azareh & *alii*, 2019; Hosseinalizadeh & *alii*, 2019b; Yang & *alii*, 2021). Most gullies occur in unconsolidated materials, including colluvial and alluvial areas as well as deeply weathered substrates (Ahmadi & *alii*, 2007; Kirkby & *alii*, 2009; Maerker & *alii*, 2008; Conforti & *alii*, 2011; Frankl & *alii*, 2013) or aeolian deposits such as loess formations. Regarding to some studies the most important types of water erosion in the Zagros Mountains in Iran are rill, gully, landslide and badland erosion (Soufi, 2002; Rahmati & *alii*, 2017; Pourghasemi & *alii*, 2017; Zakerinejad & *alii*, 2018; Azareh & *alii*, 2019). In the recent decades, the negative impact and extent of water erosion, especially gully erosion and badland generation on human welfare and agricultural land in Iran increased drastically (Soufi, 2002; Zakerinejad & Maerker, 2014; Arabameri & *alii*, 2019a,b).

Prediction of susceptible areas to water erosion with available and low cost data is one of the main objects of this study. Many empirical models such as PSIAC, EPM, RUSL, USPED were applied for evaluating water erosion in Iran but these models are time consuming in terms of data collecting and also requiring special skills for the assessment of the input parameters (Ahmadi, 1995; Ahmadi & *alii*, 2007; Asadi & *alii*, 2017; Arekhi & *alii*, 2012). However, only a few studies exist that assess the spatial distribution of different types of water erosion on larger areas considering the relevant environmental driving factors.

There are many factors that are influencing rill and gully erosion processes like the characteristics of the catchment, soil type, climate condition, vegetation, tectonic and land use type as well as topography (Vandekerckhove & *alii*, 2001; Conforti & *alii*, 2011; Zakerinejad & *alii*, 2018; Conoscenti & *alii*, 2018; Arabameri & *alii*, 2019 b,c; Kheir & *alii*, 2007; Nazari Samani & *alii*, 2009; Zakerinejad & Maerker, 2014).

This study uses an innovative approach to predict the susceptibility of water erosion processes in the South of Semirom City in Isfahan Province (Central Iran). The area is heavily impacted by rill and gully erosion. Water erosion occurs in this area due to a complex topography, highly erodible soils and mismanagement of soil and land use/land cover (LULC) resources.

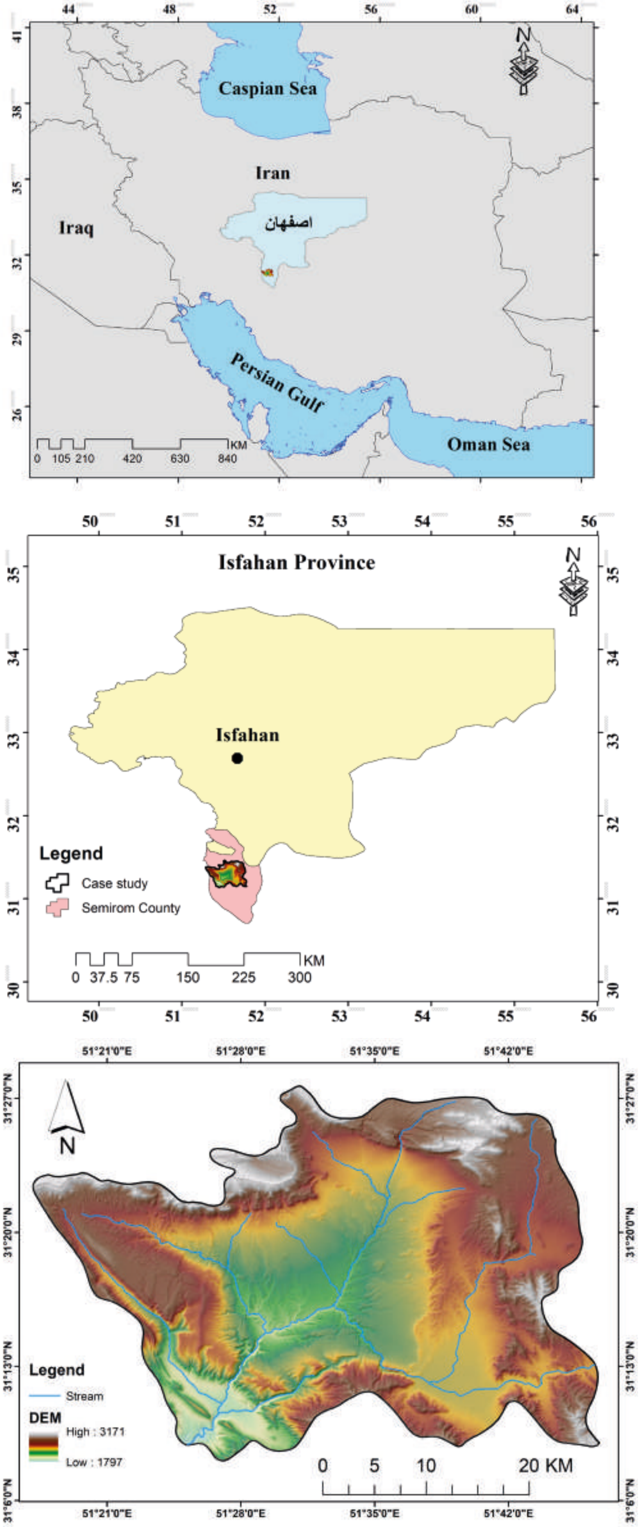

FIG. 1 - Study area of the Semirom catchment in the Southern part of Isfahan Province.

The main aim of the study is to assess the potential spatial distribution of the three most predominant types of water erosion processes (rill, gully and badland), in relation to the most important triggering factors.

STUDY AREA

The study area is located in the Semirom catchment in the Southern part of Isfahan province in the Zagros Mountains (ZM) (Central Iran, 51.774'E and 31.148 N; fig.1) and covering ca. 108.585 ha. The ZM belt extends for about 1500 km from the Taurus Mountains of southeastern Turkey, through southwestern Iran, ending near the Straits of Hormuz at the mouth of the Persian Gulf. The annual average precipitation is about 322 mm and the mean annual temperature is 23°C. The information we used in this study is based on the national geology data.

(1:100000, Geological Survey and mineral exploration of Iran), the geology consists of the following formations: Quartenary (31.42%), Mishan (mixed Marls) 4.92%, and Gourpi (Marls and limestones) 16% (Geological Survey and mineral exploration of Iran). The lowest elevation is 1797 m and the highest peak of the ZM in the study area rises to 3171 m. This catchment is characterized by a heavily dissected terrain with steep slopes, low vegetation and channels with dendritic pattern, which rapidly incise and extend headwards.

The landuse/landcover (LULC) of the study area are including poor range land with 72621 ha (66.8%), forest land 14901 ha (13.7%), mixed range and forest land 13222 ha (12.1%), agriculture 6451 (5.9%) and bare land 744 ha (0.68%). Rill features are most dominant on the slopes and show depths of less than 30 cm, while the gullies are mostly located in the central part of the study area and in the west of the catchment. Badland features are frequent in the west and east of the study area. Most of the gullies are shallow with depths around 2-3 m and lengths between 30-50 m.

FIG. 2 - Gully erosion features in the study area.

MATERIAL AND METHODS

In this research, we followed the subsequently mentioned working steps to predict the water erosion susceptible areas (rill, gully and badland):

i) In the first step the locations of characteristic gullies, rills and badlands were digitized using Google Earth (GE) images, aerial photos and fieldwork. The different erosion forms are reported as polygon shapes for gullies and badlands and polyline shapes for rill features. In this study the rill features were digitized as polylines for the reason that these features have widths of less than 30 cm, while the gully and badlands features are larger.

Subsequently, we converted the polygons and polylines into equally spaced points, which are congruent with the raster cell centroids (fig. 4).

ii) In the second step we prepared the predictor variables that are driving the erosion processes. These continuous predictor variables include: lithology, soil texture, land use/land cover (LULC), climate (annual precipitation), NDVI (Normalized Difference Vegetation Index) and topography indices such as: Topographic Wetness Index (TWI), vertical distance to channel network, convergence Index, plan curvature, profile curvature, aspect, flow length, elevation, slope, Stream Power Index (SPI) (table 1). These predisposing factors have been selected according to previous research in this area and areas with similar climates and landscape as our study area (e.g. Zakerinejad, 2019; Rahmati & *alii*, 2016; Zakerinejad & Maerker, 2014).

We converted aspect into northness and eastness as proposed by Roberts (1986).

The topographic parameters were subsequently checked for autocorrelation using the Pearson correlation coefficient in order to prevent redundant information in the model. According to the Cauchy–Schwarz inequality criteria it has a value between +1 and −1, where 1 is total positive linear correlation, 0 is no linear correlation, and −1 is total negative linear correlation (fig. 3).

Table 1 - The Environmental layers used as independent variables in the stochastic modelling approach.

Independent indices	Method
Topographic wetness Index	Olaya & Conrad, 2008
Stream Power Index	Olaya &Conrad, 2008
Slope	Zevenbergen & Thorn, 1987
LS-index	Olaya & Conrad, 2008
Profile Curvature index	Olaya & Conrad, 2008
Flow length	Olaya & Conrad, 2008
Catchment area	Olaya & Conrad, 2008
Curvature index	Zevenbergen & Thorn, 1987
Convergence Index	Köthe & Lehmeir, 1993
Vertical distance to networks	Olaya & Conrad, 2008
Aspect	Zevenbergen & Thorn, 1987
Elevation	Preprocessed in ArcGIS10.3
NDVI	Extract from Landsat 8, 2015
Soil texture	Field collection
Climate (precipitation)	Climate data from Iranian climate center
Land use	LULC map prepared in Envi, filed work and Landsat ETM data
Lithology	From Iranian geology map, 1:100000

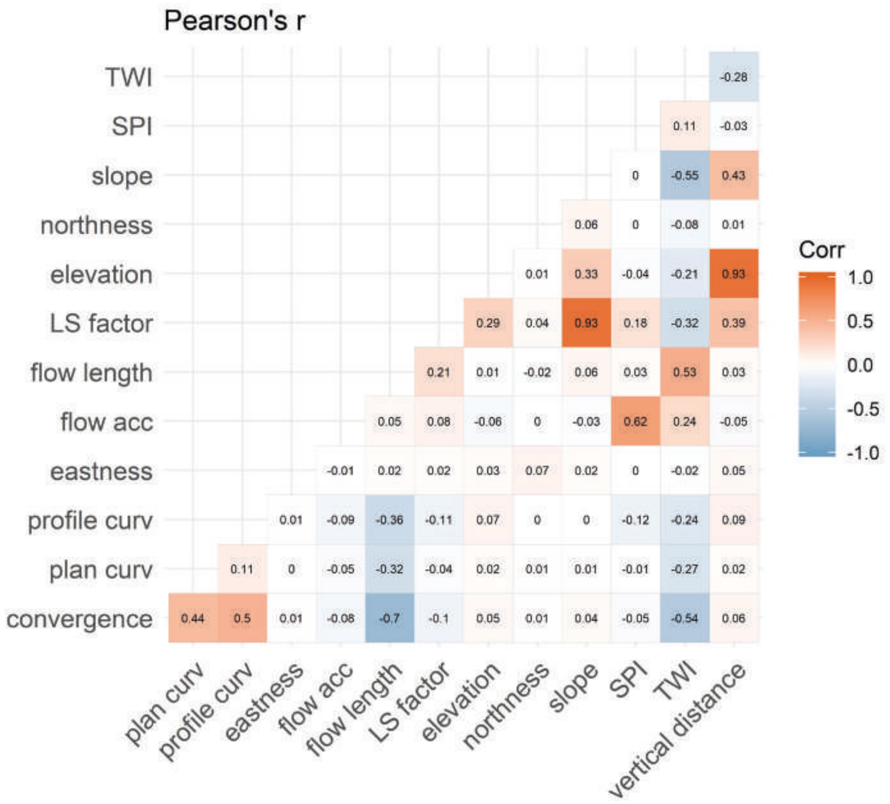

FIG. 3 - Persons coefficient correlating of the topography indices.

The topographic indices shown in table 1 were extracted in SAGA GIS 7.3.0 (Conrad & *alii*, 2015) from a SRTM DEM with 30 m spatial resolution and were then converted into an ASCII format used as input for the model runs.

Before applying the indices, the DEM was preprocessed with low pass filtering to extract artefacts and errors, like local noise and terraces (Maerker & Heydari, 2009; Vorpahl & *alii*, 2012) using ARCGIS 10.5 (ESRI, 2010). Then, the DEM was hydrologically corrected eliminating sinks using the algorithm proposed by Planchon & Darboux (2001) (fig. 5).

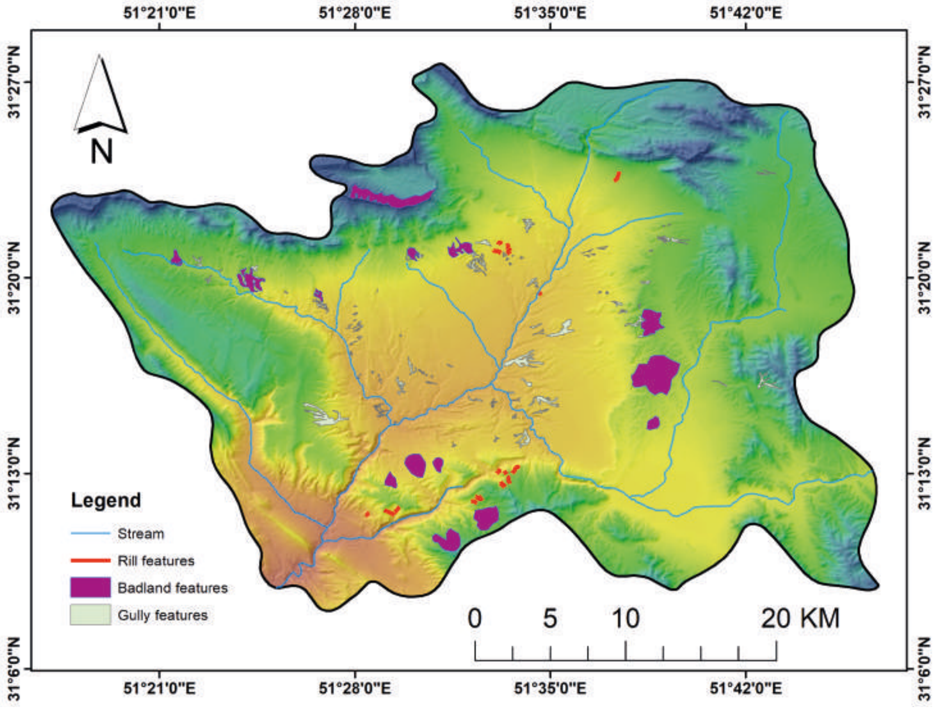

FIG. 4 - Spatial distribution of rill, gully and badland features in the study area.

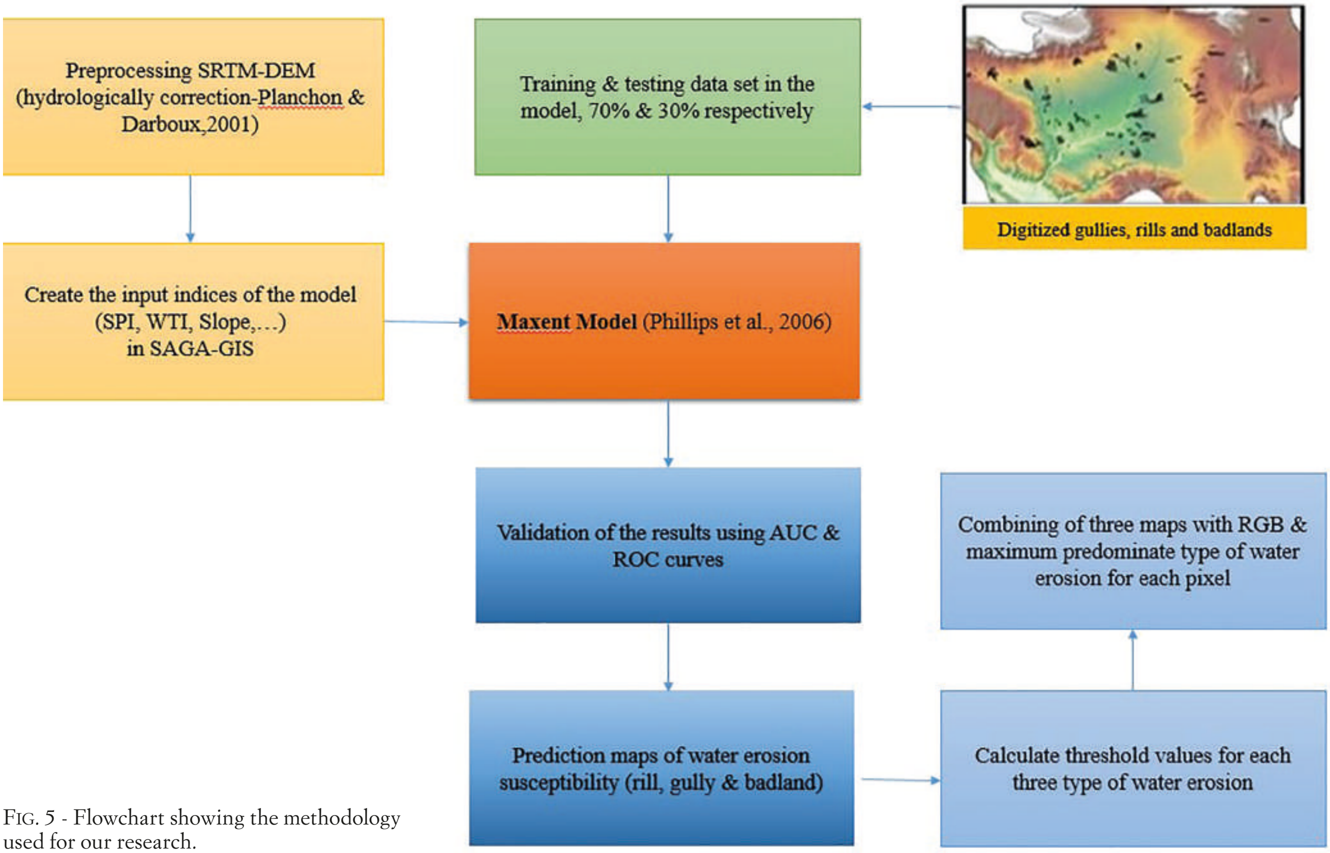

FIG. 5 - Flowchart showing the methodology used for our research.

Maximum Entropy Model (MEM)

The best probability distribution is the one that maximizes entropy (MEM). Entropy in fact is the uncertainty in the selection of an event such as different types of water erosion (rill, gully, landslide, badland). The theoretic notion of entropy quantifies the bias of a probability distribution. The entropy H of a probability distribution p is defined as

$$H(x) = H(p) = -\sum_{x} p(x) log p(x) = E[\log\left\{\frac{1}{p(x)}\right\}]$$

$H_a(x)$ is the entropy of X

The Maximum Entropy Model (MEM, Phillips & *alii*, 2006) is a general-purpose method for predictions or inferences from incomplete information. Its origins lie in statistical mechanics. MEM explores applications in diverse areas such as ecology, astronomy, portfolio optimization, image reconstruction, statistical physics and signal processing. We apply MEM here as a general approach for presence-only modeling of three different types of water erosion (rill, gully and badland). MEM is suitable for all existing applications involving presence-only datasets. The idea of MaxEnt is to estimate a target probability.

The advantages of MEM are: (1) It requires just presence data, together with environmental information for the whole study area. (2) It can utilize both continuous and categorical data, and can incorporate interactions between different variables. (3) Efficient deterministic algorithms have been developed that are guaranteed to converge to the optimal (maximum entropy) probability distribution.

Hence it is useful if we have partial knowledge about a stochastic process and we have to estimate the underlying probability distribution. The best guess is to choose among all distributions that are compatible with our knowledge, the one with the highest entropy. In this investigation, MEM is applied to predict the spatial distribution of different erosion susceptibilities and to reveal the most influencing triggering factors. MEM was successfully applied in environmental studies dealing with presence only data (Elith & *alii*, 2006; Vorpahl & *alii*, 2012; Zakerinejad & Maerker, 2014; Azareh & *alii*, 2019; Rodriguez & *alii*, 2022). In recent studies, the method was used to predict the spatial distribution of soil erodibility, landslides and gullies using important environmental parameters as independent variables (Maerker & *alii*, 2014; Zakerinejad & Maerker, 2015; Mahamane, 2015). To assess the most important variables for the spatial distribution of water erosion features (rill, gully and badland) in this study we applied the MaxEnt software version 3.3.3k (http://www.cs.princeton.edu/~schapire/maxent/). The model requires presence only data and a set of environmental variables, which are continuously distributed in spatial extent (Zakerinejad & Maerker, 2014; Zakerinejad & *alii*, 2018).

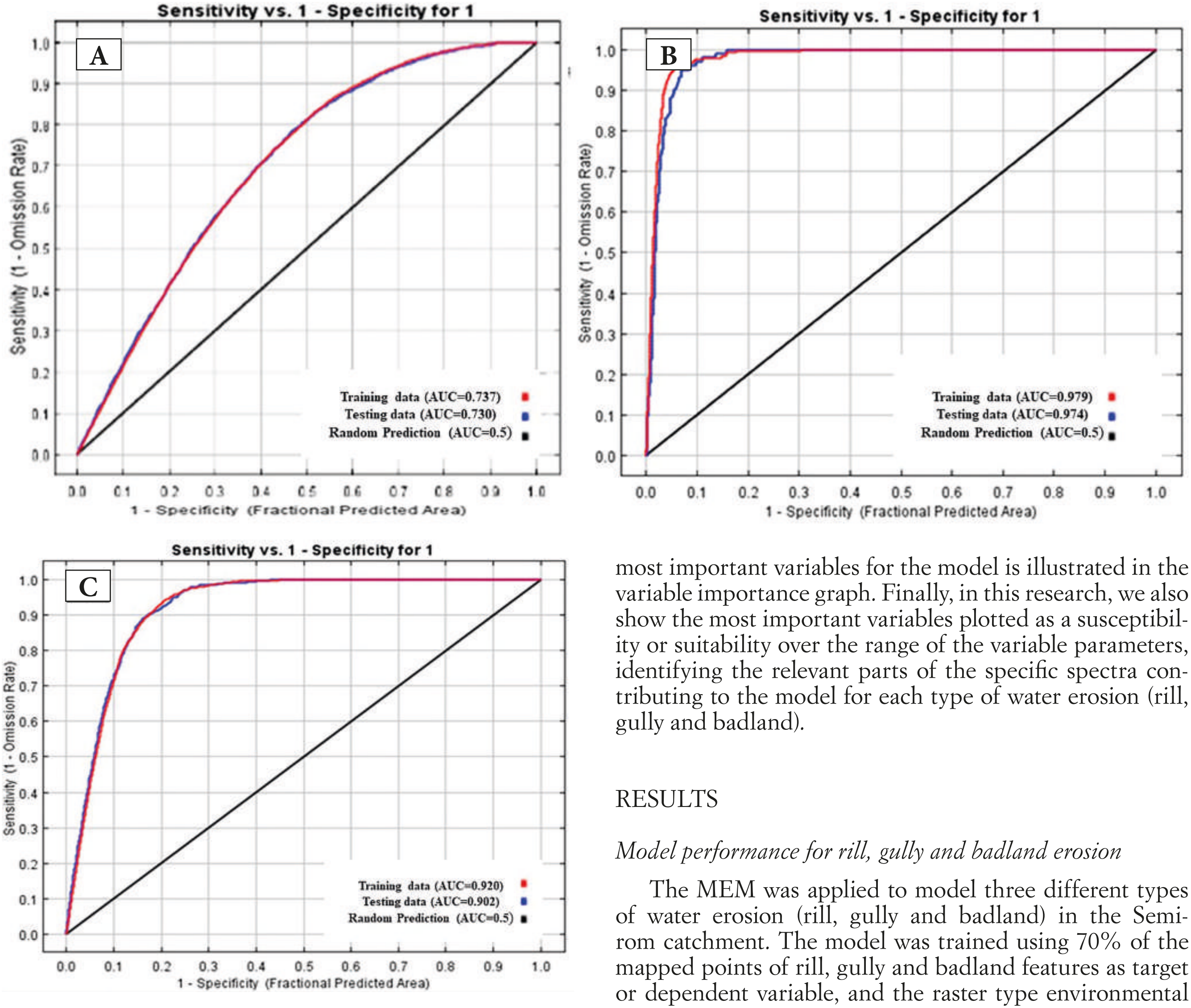

FIG. 6 - AUC for three different types of water erosion from: rill (a), gully (b) and badland (c).

Validation of the MEM model

The performance of the model was evaluated using the receiver operator characteristic (ROC) curve for training and test data. Values close to 1 indicate that the model prediction is perfect, while values near or below 0.5 indicate a random prediction (Phillips & *alii*, 2006).

In a ROC curve, the true positive rate (sensitivity) is plotted over the false positive rate (1-specificity) for all possible cut-off points (Swets & *alii*, 2000). The area under curve (AUC) is a summary measure of the accuracy of a quantitative diagnostic test. According to (Hosmer & Lemeshow, 2000), AUC values exceeding 0.7/0.8/0.9 indicate acceptable/excellent/outstanding predictions. The ROC were derived for train dataset comprising 70% of the data and a test dataset that contain 30% of the data in order to validate the model performance. The contribution of the most important variables for the model is illustrated in the variable importance graph. Finally, in this research, we also show the most important variables plotted as a susceptibility or suitability over the range of the variable parameters, identifying the relevant parts of the specific spectra contributing to the model for each type of water erosion (rill, gully and badland).

RESULTS

Model performance for rill, gully and badland erosion

The MEM was applied to model three different types of water erosion (rill, gully and badland) in the Semirom catchment. The model was trained using 70% of the mapped points of rill, gully and badland features as target or dependent variable, and the raster type environmental layers as independent variable. The resulting model is then validated using the randomly selected 30% of the mapped gully, rill and badland dataset. fig. 6 shows the ROC graph and integral (area under curve, AUC) for training data with AUC values of 0.920 for rill erosion, 0.979 for gully erosion and 0.737 for bad land erosion. The validation test data yield AUC values of 0.902, 0.974 and 0.707 for rills, gullies and badlands respectively. According to Hosmer & Lemeshow (2000) these values indicate an outstanding performance for rill and gully erosion both for training and test datasets while an acceptable performance for badland erosion was obtained. Hence, the models can be considered as highly robust in terms of sensitivity and specificity for the prediction of water erosion. Subsequently, the model was applied for the entire catchment in order to obtain the spatial distribution of specific susceptibilities for the single erosion processes. Finally, we combined the specific single process susceptibilities or occurrence probabilities in one map using probability threshold values for each soil erosion type.

Important variables for the prediction of water erosion

The most important variables to explain the spatial distribution of rill erosion susceptibilities are: land use with a contribution of 19.40%, elevation with 18.4%, lithology with 15.1% and LS-factor with 12.1% contribution.

For gully erosion the most important variables are: vertical distance to channel network with 24.8% contribution, convergence index with 15.8%, slope with 13.2% and soil texture with 10.2% contribution.

Regarding badland erosion MEM reveals as most important variable the lithology with 21.3% contribution, slope with 15.6%, NDVI with 14.2% and land use with 13.4% contribution.

Specific response of the most important variables used in the MEM approach

In this study we distinguish various types of rill, gully and badland erosion based on the specific response curves of the most important variables in the MEM application.

In fig. 8 we illustrate the four most important variables including, land use, elevation, lithology and LS factor for the rill erosion.

The LS factor (fig. 8a) shows a value range of more than 20 with very high probabilities for rill erosion. The LULC response curve (fig. 8b) reveals that the classes of rangeland with poor vegetation, dry farming and bare land are the most sensitive ones to rill erosion.

The elevation graph (fig. 8c) shows that the area ranging between 2000-2600 m is more susceptible to rill erosion whereas the lithology response curve (fig. 8d) indicates marls and alluvial sediments as the most sensitive ones to rill erosion, while the other classes consisting mostly of calcite and dolomite have less susceptibility to rill erosion. As mentioned before, gully erosion is mainly depending on the vertical distance to the network, convergence index, soil texture, and slope. The convergence index response curve for gully erosion (fig. 8e) point to values around 0 with slight emphasis on the negative values showing higher probabilities. The vertical distance to the river networks (fig. 8f), is characterized by a range of 0-400 m indicating the high potential for the gully erosion while the values more than 400 m have less probability because of the increasing distance from the stream network and hence smaller catchment areas or lower connectivities.

The soil texture graph (fig. 8g) highlights soil texture classes 2 and 3 (silty loam and silty clay loam) with the highest probabilities for gully erosion while the sandy clay areas have a low probability to rill erosion.

The slope graph (fig. 8h) also indicates that slope values between 0 and 20% are related to high probabilities, while an increase of slope over 20% result in a decrease of probability in the study area.

Regarding the MEM results the most important indicators for the prediction of susceptible areas of badland erosion are: land use, lithology, NDVI and slope.

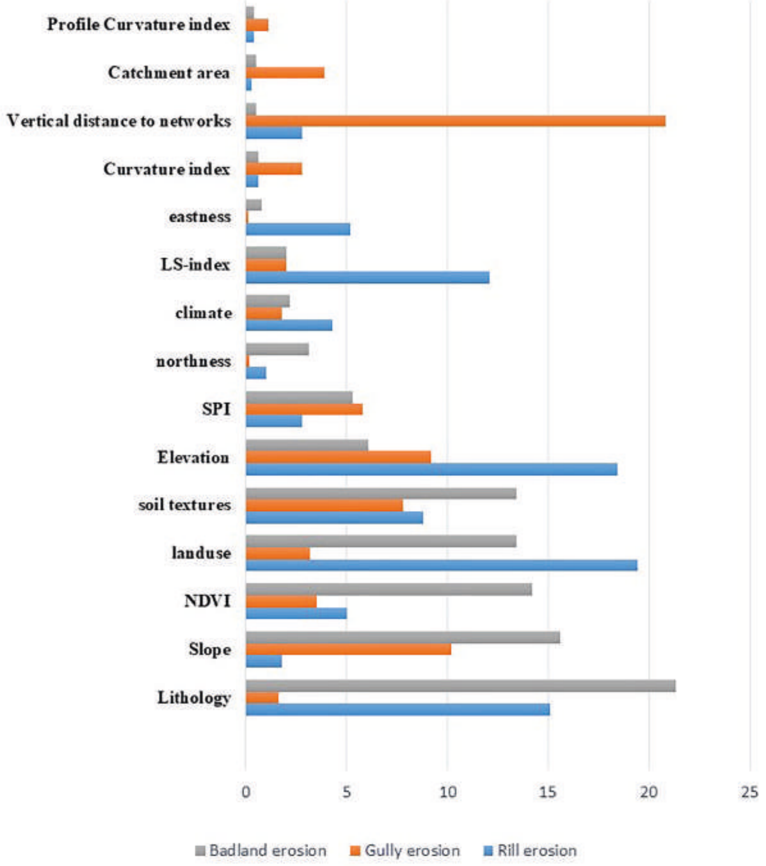

FIG. 7 - Variable importance's for the predicted types of water erosion.

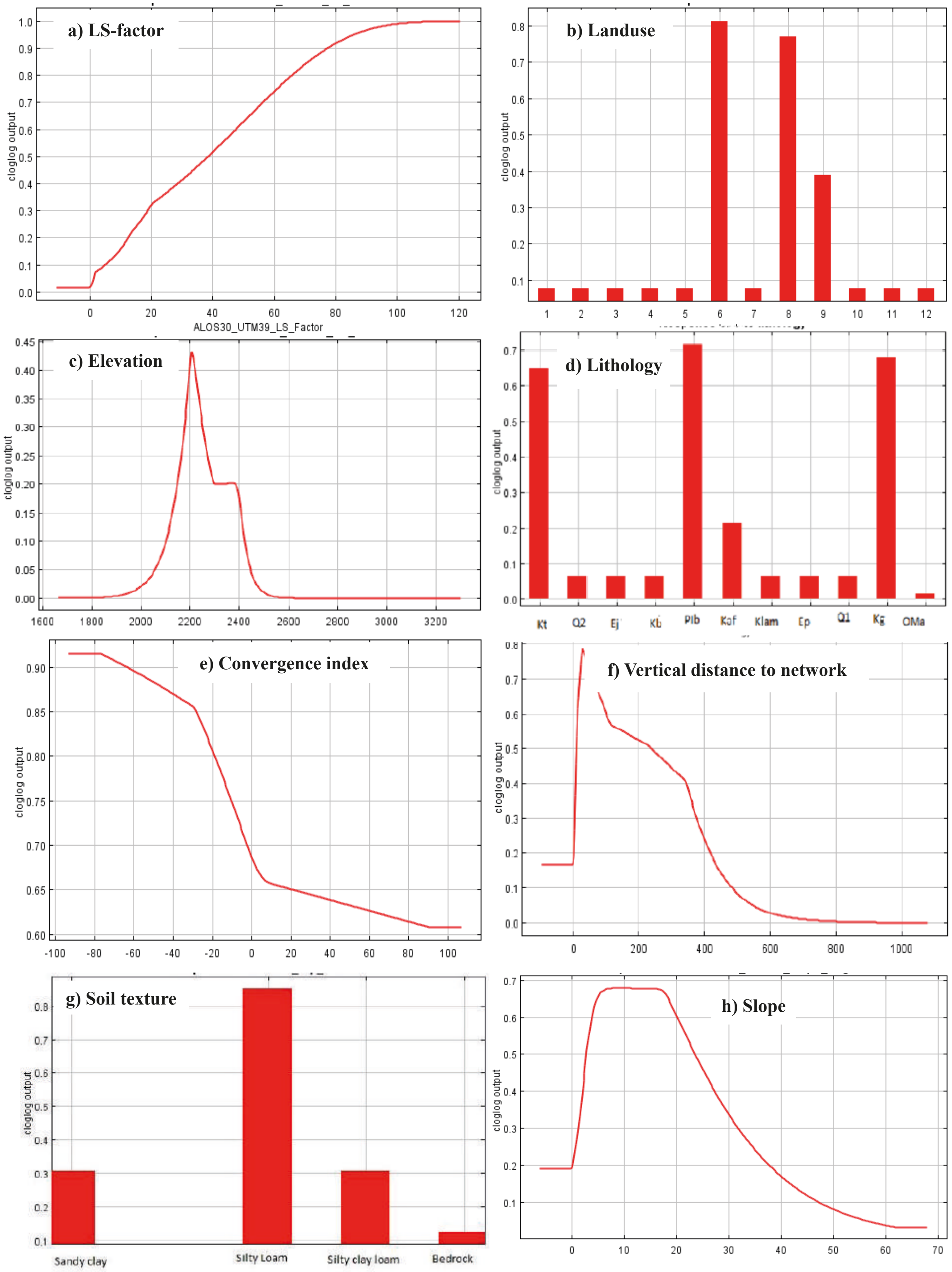

FIG. 8a -Response curves of the most important variables for rill erosion (a,b,c,d) and gully erosion (e,f,g,h)

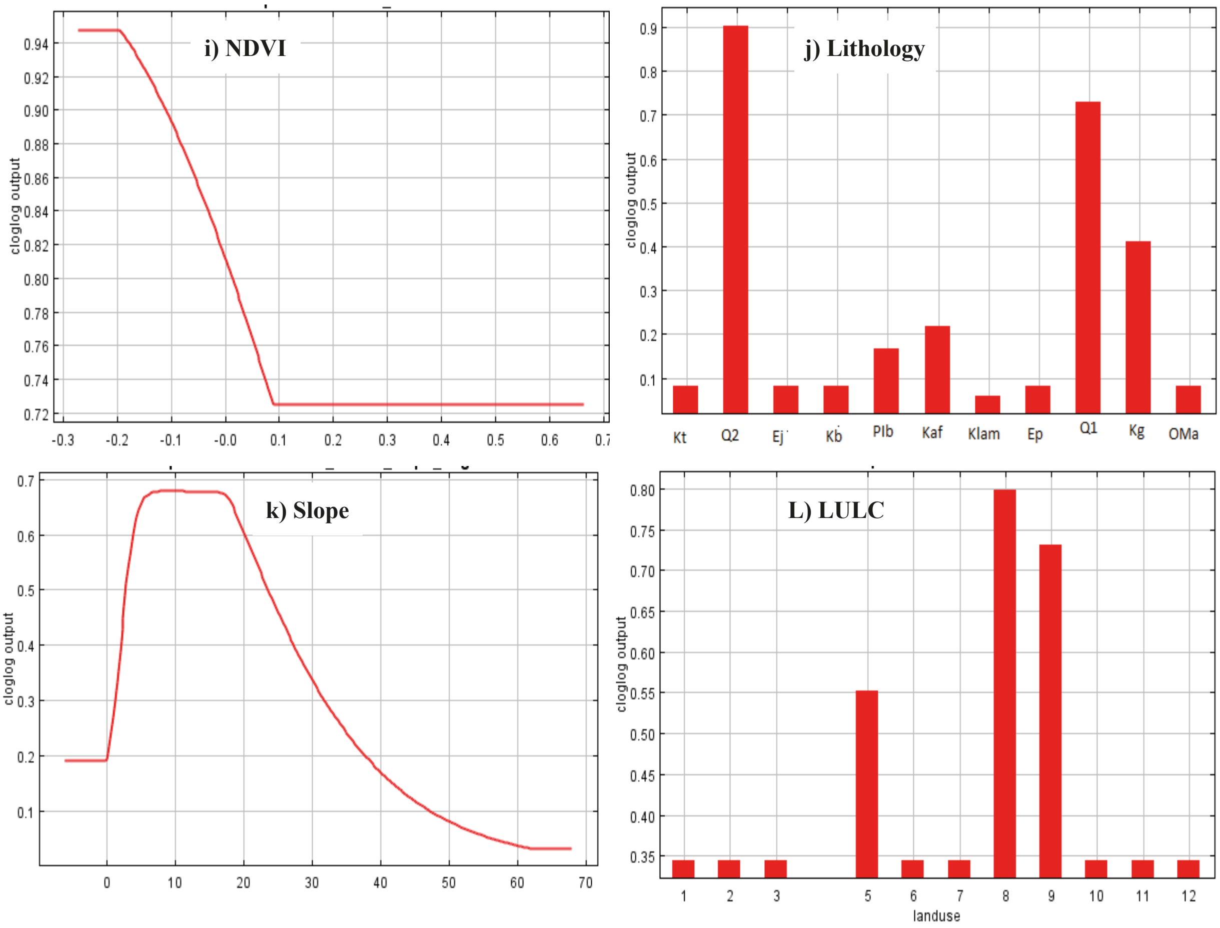

FIG. 8b -Response curves of the most important variables for badland erosion (i,j,k,L).

The NDVI response curve for badland erosion (fig. 8i) shows values of less than 0.10 having a higher probability of badland erosion. An increase of the NDVI value decrease the probability of badlands. That means, a higher density of vegetation cover can protect the area from badland erosion.

The lithology response curve (fig. 8j) indicates that the areas with alluvial and marl formations are more prone to badland erosion compared to the areas with calcite and limestone formations. The slope graph (fig. 8k) demonstrates high probabilities at slopes between 0 and 30% and thus, a higher risk of badland erosion.

Regarding to the LULC graph (fig. 8l), badlands erosion is more probable on barren and poor rangeland classes, while the area with forest and dense vegetation characterize low probabilities for badland formation.

Specific response of the most important variables used in the MEM approach

In this study we distinguish various types of rill, gully and badland erosion based on the specific response curves of the most important variables in the MEM application.

In fig. 8 we illustrate the four most important variables including, land use, elevation, lithology and LS factor for the rill erosion.

The LS factor (fig. 8a) shows a value range of more than 20 with very high probabilities for rill erosion. The LULC response curve (fig. 8b) reveals that the classes of rangeland with poor vegetation, dry farming and bare land are the most sensitive ones to rill erosion.

The elevation graph (fig. 8c) shows that the area ranging between 2000-2600 m is more susceptible to rill erosion whereas the lithology response curve (fig. 8d) indicates marls and alluvial sediments as the most sensitive ones to rill erosion, while the other classes consisting mostly of calcite and dolomite have less susceptibility to rill erosion. As mentioned before, gully erosion is mainly depending on the vertical distance to the network, convergence index, soil texture, and slope. The convergence index response curve for gully erosion (fig. 8e) points to values around 0 with slight emphasis on the negative values showing higher probabilities. The vertical distance to the river networks (fig. 8f), is characterized by a range of 0-400 m indicating the high potential for the gully erosion while the values more than 400 m have less probability because of the increasing distance from the stream network and hence smaller catchment areas.

The soil texture graph (fig. 8g) highlights soil texture classes 2 and 3 (silty loam and silty clay loam) with the highest probabilities for gully erosion while the sandy clay areas have a low probability to rill erosion.

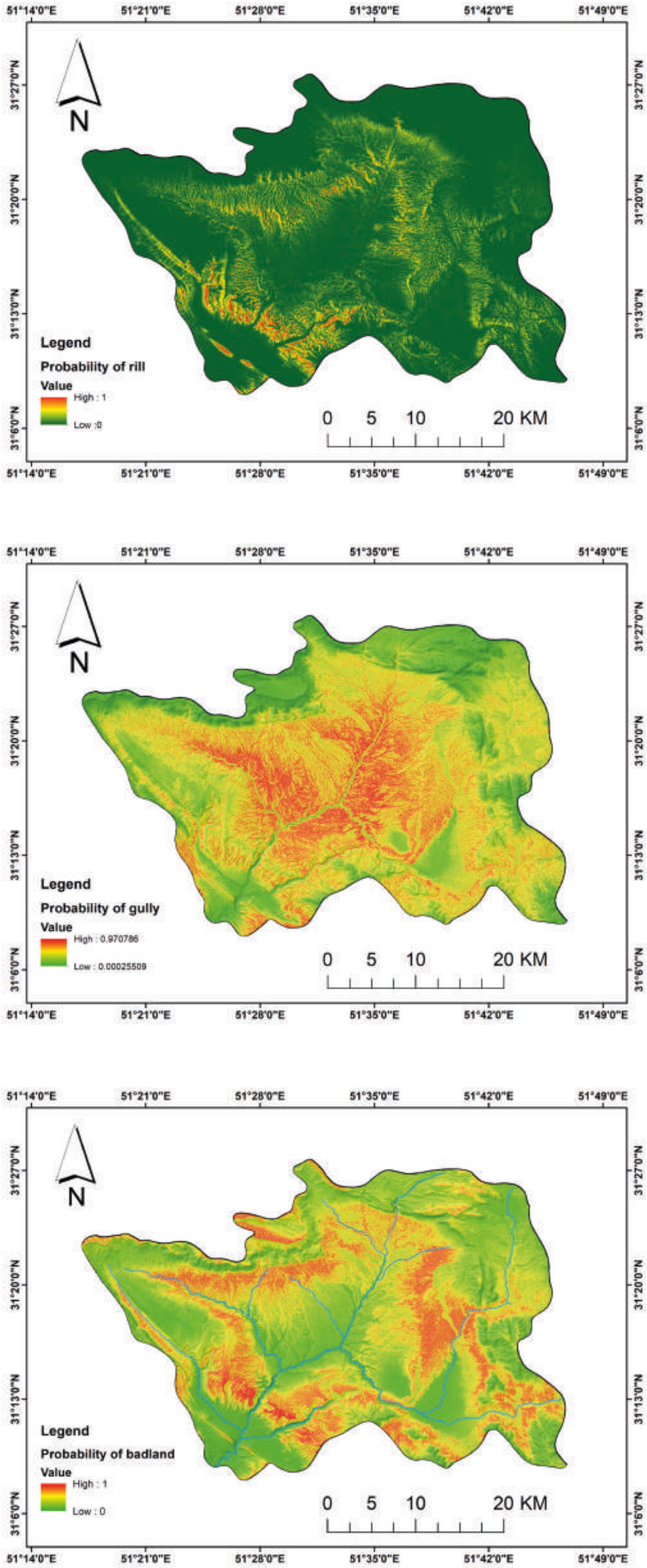

FIG. 9 -Predicted map of rill, gully and badland erosion from upper left to right.

The slope graph (fig. 8h) also indicates that slope values between 0 and 20% are related to high probabilities, while an increase of slope over 20% result in a decrease of probability in the study area.

Regarding the MEM results the most important indicators for the prediction of susceptible areas of badland erosion are: land use, lithology, NDVI and slope.

The NDVI response curve for badland erosion (fig. 8i) shows values of less than 0.10 having a higher probability of badland erosion. An increase of the NDVI value decrease the probability of badlands. That means, a higher density of vegetation cover can protect the area from badland erosion.

The lithology response curve (fig. 8j) indicates that the areas with alluvial and marl formations are more prone to badland erosion compared to the areas with calcite and limestone formations. The slope graph (fig. 8k) demonstrates high probabilities at slopes between 0 and 30% and thus, a higher risk of badland erosion.

Regarding to the LULC graph (fig. 8l), badlands erosion is more probable on barren and poor rangeland classes, while the area with forest and dense vegetation characterize low probabilities for badland formation.

DISCUSSION

As a result of problems arising from water erosion and land degradation, different models were applied to estimate and predict different types of soil erosion. In this research we applied the MEM model for a soil erosion susceptibility mapping taking into account different types of water erosion. MEM is a powerful method to assess the influencing factors for different water erosion form and features. The main advantage of the applied MEM is that this method does not require the absent dependent variables. Actually, the absence of an erosion feature does not necessarily mean that there is no potential for a specific erosion processes that might develop in future. Stochastic approaches like statistical mechanics provide a powerful tool to study the relations between locations of water erosion features and corresponding environmental characteristics. The topographic indices like slope, convergence index, distance to stream network, elevation and LS factor were important variables for the prediction of the spatial distribution of water erosion in the Semirom catchment. Regarding many studies in areas with comparatively homogeneous substrates, soils and land use, the spatial distribution of gully areas is mainly depending on topographic constraints expressed here as topographic indices (Vandekerckhove & *alii*, 2001; Flügel & *alii*, 2003; Nazari Samani & *alii*, 2009; Maerker & *alii*, 2012; Roshani & *alii*, 2013; Yang & *alii*, 2021).

In our study area, the gullies and especially the gully head cuts are frequently situated in areas with high SPI (Stream Wetness Index) and high amounts of silty textures in the top soil. The most important factors that lead to the development of gullies in the study area are: vertical distance to stream network, convergence index, slope and soil texture. It means, that those areas are susceptible that show low slopes (0-15%), low position above stream network (less than 300 m), concave surface (negative curvature values) and mostly low elevation (Zakerinejad & Maerker, 2014; Avand & *alii*, 2019; Arabameri & *alii*, 2021)

Rill erosion is one of the most abundant types of soil loss and subject of many physical based erosion models e.g. USLE, RUSLE (Revised USLE, Renard & *alii*, 1997) and USPED (Mitasova & *alii*, 1996). However, these physical based models differ considerably in the processes they represent, their data requests and complexity (Merritt & *alii*, 2003; Bosco & *alii*, 2015). As mentioned above, frequently applied models such as USPED and RUSLE do not consider the sediment yield from gullies, badlands, stream banks and stream bed erosion (Mitasova & *alii*, 1996; Maerker & *alii*, 2009; Zakerinejad & Maerker, 2015). In this study, the more important variables for prediction and mapping of rill erosion susceptibility are land use, elevation, lithology and LS factor. Areas with poor rangeland and bare land were associated with high risk of rill erosion particularly in the western and southern part of the catchment. Rill erosion appears mostly in the range of 1800-2200 m a.s.l., while the erosivity of water in the flat areas decrease (Yang & *alii*, 2021; Stefanidis & *alii*, 2021). Areas with high elevation that are less affected by grazing and intensive human use, show a lower susceptibility of rill erosion compared to the low-lying- or flat areas (Meledje & *alii*, 2021). In terms of the lithology, we observed that areas with high calcite and dolomite in the North and Northeast of the area are more resistant to water erosion due to the fact that these areas develop normally less erodible soils (Zakerinejad & *alii*, 2018; Zhang & *alii*, 2022). The LS factor has also been integrated in many empirical models for rill and sheet erosion. We show also in our application that it is one of the most important indices for rill erosion. High and steep areas are characterized by high LS factor values (Kumar & Kushwaha, 2013; Asadi & *alii*, 2017; Karásek & *alii*, 2022.)

Badland erosion is one of the most complex types of water erosion in many parts of the Zagros Mountains. The areas affected by this type of water induced sediment loss are completely unusable for any agriculture or settlement activity. In other words, the areas with badlands have seriously been destroyed. Our results show that lithology, slope, NDVI and LULC are the most relevant indictors for badland erosion. Areas in the Southwest and Northwest of the study area are illustrating a high susceptibility for badland erosion . High NDVI values, that indicate high vegetation cover, protect the soil from degradation. Typically, areas with steep slopes (more than 15%) demonstrate a high susceptibility for badland degradation processes due to the erosive power of runoff that wash away the fertile topsoil layer.

In general, investigations of the spatial relationships between locations of rill, gully and badland erosion using MEM and GIS tools show, that areas of low elevation, low slopes and flat topography, are characterized by surface runoff concentration and highly erodible alluvial deposits with high amounts of salts. These are the most prone areas to erosion processes and related forms and features. Soil texture related to both gullies and badlands shows, that high amounts of silt and silty loam are more susceptible to gully erosion. These results have been confirmed by other local studies (Bonilla & *alii*, 2010; Le Roux & *alii*, 2012; Golestani, & *alii*, 2014; Zakerinead & *alii*, 2018). The results of this study presented a time-saving, illustratable, and comparatively accurate method for rill, badland and gully mapping. Although our results show, that these types of soil erosion dominate around 50% of our study area, there are still other types of soil loss, like sheet erosion, bank erosion and landslide that need to be considered in future research in order to model water erosion in a holistic way.

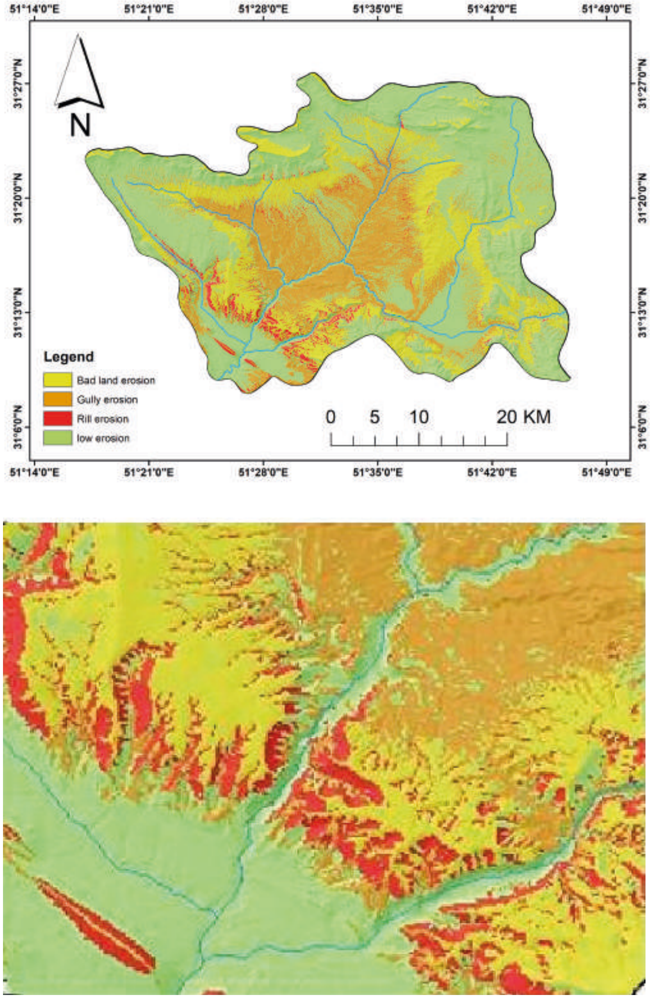

FIG. 10 -Spatial distribution of water erosion (rill, gully and badland) of the study area.

CONCLUSION

Gully, rill and badland features are common geomorphological problems in arid and semi-arid regions; therefore, it is essential to develop methods to predict water erosion with simple but highly accurate models. Although the approach applied in this study, identifies the susceptible areas, this is a mayor step forward in order to apply quantitative soil erosion models that need spatially distributed information on the driving factors but also on the spatial distribution of water erosion features and forms. The spatial risk assessment of water erosion (rill, gully and badland) in the Semirom catchment was carried out by means of a stochastic model (MEM) and a detailed terrain analysis as well as additional environmental variables. One of the issues of existing maps of water erosion in Iran is the fact, that they have been mostly prepared in a qualitative way and there is a lack of quantitative estimates of different types of water erosion. Identifying the areas, that are prone to, or susceptible to water erosion, especially in arid and semi-arid areas with the available data empirical modelling may empower ways to endorse sustainable development. In this case, applying the stochastic model as an approach to determine the susceptible areas for different types of water erosion, we show that especially in a large catchment this approach is very powerful and yield valuable results that are useful for land use management and rural policy makers to establish the best soil conservation practices. One of the advantages of the MEM model in comparison with other stochastic models is that it only needs presence only data.

The results of this research are consistent with studies that applied the MEM model to analyze other (i.e. non-gully) natural hazards such as landslides (Chen & *alii*, 2017; Kornejady & *alii*, 2017; Pandey & *alii*, 2018), debris flows (Lombardo & *alii*, 2016). In the study area soil erosion is concentrated especially in the areas with low vegetation. Actually, bare soil is highly susceptible to soil erosion therefore the protection of bare soil to reduce soil loss should be guaranteed by an appropriate cultivation (Lesschen & *alii*, 2007).

The validation of the MEM model shows that the model predictions for rill and gully are outstanding, while the result for badland illustrate an acceptable performance. Our study reveals that the combination of a stochastic model combined with remote sensing data and GIS tools yield valuable results for a proper landuse planning and soil erosion mitigation management. The simplicity and the relative low data requirements of the applied method allows an effective application also in other regions especially in arid and semi-arid areas of the world. This study emphasized the vulnerability of the study area in terms of the susceptibility towards different types of soil erosion. Thus, contributes to a progress in sustainable management and protection of these susceptible areas.

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