Shahid Beheshti University

**Sustainable Earth Trends**

Journal homepage: http://sustainearth.sbu.ac.ir

# Machine learning techniques for gully erosion susceptibility mapping (Case study: Mukhtaran watershed, south Khorasan province, Iran)

Javad Momeni Damaneh[a], Hadi Memarian[b*], Ali akbar Safdari[c]

[a] Department of Natural Resources Engineering, Agriculture and Natural Resources Faculty, Hormozgan University, Bandarabbas, Iran
[b] Department of Watershed Management, Faculty of Natural Resources and Environment, University of Birjand, Birjand, Iran
[c] Department of Natural Resources Engineering, Natural Resources Faculty, Tehran University, Tehran, Iran

**ABSTRACT**

Gully erosion, a significant environmental issue, can lead to severe consequences like soil loss, habitat destruction, and water pollution. To mitigate its impact, accurate mapping of land sensitivity to gully erosion is crucial. Machine learning models offer a powerful approach to predict and map gully erosion susceptibility. This study focuses on the Mukhtaran basin in South Khorasan province, Iran. By employing various machine learning techniques, including GLM, GBM, CTA, ANN, SRE, FDA, MARS, RF, and MaxEnt, the researchers aimed to identify the most suitable model for predicting gully erosion. Twenty-two environmental factors were selected and analyzed, with a focus on physiographic, climatic, hydrological, soil, land surface/cover, and geological variables. The results showed that the random forest (RF) and ensemble (ESMs) models demonstrated the highest accuracy in predicting gully erosion susceptibility, with a TSS index of 0.97. Sensitivity analysis revealed that the digital elevation model, soil electrical conductivity, bare soil percentage, land unit components, geology, runoff coefficient, and maximum storage capacity were the most influential factors. The study emphasizes the potential of machine learning models in generating accurate gully erosion susceptibility maps. However, further research is needed to explore additional factors and improve data quality. By combining topographic/hydrologic indices with machine learning models, more precise estimates of gully paths can be obtained for use in process-based models.

**ARTICLE INFO**

**Keywords:**
Arid watershed
ML performance
Random forest
Vulnerability assessment

**Article history:**
Received: 15 Dec 2024
Accepted: 07 Jan 2025

*Corresponding author
E-mail address:
hadi_memarian@birjand.ac.ir
(H. Memarian)

**Citation:**
Momeni Damaneh, J. et al., (2025). Machine learning techniques for gully erosion susceptibility mapping (Case study: Mukhtaran watershed, south Khorasan province, Iran), *Sustainable Earth Trends:* 5(3), (63-75).

**DOI**: 10.48308/set.2025.237956.1093

## 1. Introduction

Gully erosion is a major form of soil degradation and an important environmental concern that can have devastating effects such as soil loss, habitat destruction, water pollution, and sediment deposition in water bodies (Amiri et al., 2019). Temporary or ephemeral gully is often formed in low-lying land at the junction of rivers. A temporary gully is usually located in the depth of the plow layer (20 cm) and its width is 30 to 50 cm. The gully is generally cut in the plow layer with a width and depth of more than 50 cm (Liu et al., 2018). In order to reduce the negative effects of gullies and implement effective management programs, accurate mapping of gully erosion susceptibility is very important (Gomez et al., 2009; Roy and Saha, 2021). Statistical models based on different data have been successfully used to predict and prepare gully erosion sensitivity maps. These models can be divided into three groups: machine learning models, multi-criteria decision-making models, especially analytical hierarchy process (AHP) and categorized bivariate and multivariate statistical models (Garosi et al., 2018; Zabihi et al., 2018; Arabameri et al., 2019; Domazetovi et al., 2019; Lei et al., 2020; Soleimanpour et al., 2021; Mrad et al., 2024). Machine learning techniques have revolutionized gully erosion prediction by surpassing traditional statistical models through their ability to analyze large data sets, identify complex patterns, avoid human bias, and discover hidden relationships (Senanayake and Pradhan, 2022). These algorithms continuously learn and improve accuracy, expertly handling complex changes and unpredictable scenarios, especially in data-poor environments (Luo et al., 2021). In addition, machine learning-based models have an advantage in evaluating the impact of runoff caused by climate change on gully erosion compared to alternative models (Senanayake and Pradhan, 2022). Choosing the right machine learning model to create an accurate gully erosion susceptibility map (GESM) is very important because the model's performance can show different accuracy and efficiency in various environmental conditions (Roy and Saha, 2021).

The RF model or random forest as a powerful machine learning algorithm for GESM offers several advantages, including high accuracy, the ability to manage large input variables, to capture nonlinear relationships, to identify important variables, and to manage missing data well (Setargie et al., 2023).

This method efficiently handles large amounts of data, handles sparse data and samples the weight coefficients, and provides accurate estimations using advanced tree learning algorithms and weighted quantum design techniques (Gumus and Kiran, 2017).

Wise management of gully erosion in the watershed is a critical strategy for successful gully erosion control (Gayen et al., 2019; Roy and Saha, 2021). This approach addresses an important research gap in the field of gully erosion studies (Mahala 2020; Majhi et al., 2021). To develop effective strategies for preventing gully erosion, a comprehensive GESM to analysis the damage caused by gully erosion is necessary. Rainfall is an important factor in causing gully erosion. Soil saturation caused by rainfall and moisture infiltration causes undercutting of the head and wall of the ditch and its collapse with the lowering of the bottom of the ditch (Anderson et al., 2021). In Tennessee, USA, rainfall duration and accumulation were more critical than rainfall intensity in the formation and development of gully erosion (Luffman et al., 2015). The linear retreat rate of the gully head varies between 0.01 and 135 meters per year on a global scale (Vanmaercke et al., 2016).

Revival of vegetation is an important measure to reduce the intensity of gully erosion. Plant stems in the bed can reduce gully growth by increasing infiltration, reducing runoff, and reducing flow velocity (Bastola et al., 2018; Li and Pan, 2018). In general, soil and water loss due to gully erosion decreases with increasing vegetation (Gao et al., 2009; Zhao et al., 2013). And when the vegetation reaches the maximum coverage, erosion is no longer obvious (Zhang et al., 2010). In general, one of the most important and influential factors in developing gully erosion is soil type and rainfall magnitude, and the most important controlling factor for this type of erosion is the increase in soil surface coverage.

The main purpose of this study is to develop an accurate gully erosion susceptibility map of the Mukhtaran basin using machine learning techniques, especially GLM, GBM, CTA, ANN, SRE, FDA, MARS, RF, and MaxEnt models with determining and prioritizing the best model for preparing a gully erosion map. The findings of this study provide valuable spatial guidance for managing gully erosion and help to achieve sustainable development goals.

## 2. Material and methods

### *2.1. Case Study*

Mukhtaran watershed is located on the southern side of the Bagheran highlands in South Khorasan province with an area of 2421 km$^2$. Its geographical location is between 59° 02′ 32″ to 59° 08′ 59″ E longitude and 36° 25′ 18″ to 36° 31′ 43″ N latitude (Fig. 1). This area is further east-west extension (along the plain) than its north and south sides. The total surface of this region, which includes lands with diverse morphology, contains mountainous and hilly lands, vast plains, as well as desert lands that lack any vegetation cover. The region's climate according to the modified Dumarten method is cold and dry in low-altitude plains and mountains and higher areas (above 2100 m of sea level) are dry and cold. The annual rainfall of Mukhtaran range varies between 150 mm in low places and 220 mm in high places. The average annual temperature is 14.3 °C, the average annual minimum temperature is 5.6 °C, and the average annual maximum temperature is 22.7 °C.

*2.2. Data used*

First, in this stage, various basic maps including drainage network, slope, geology, geomorphology, soil series, and land use were studied and the map of specific work units was prepared. Then with the interpretation of existing aerial photos (Scale: 1:50000), the range of gully erosion forms on the map was separated. The field survey also helped us to collect 61 points of gully erosion presence by GPS (Fig. 1).

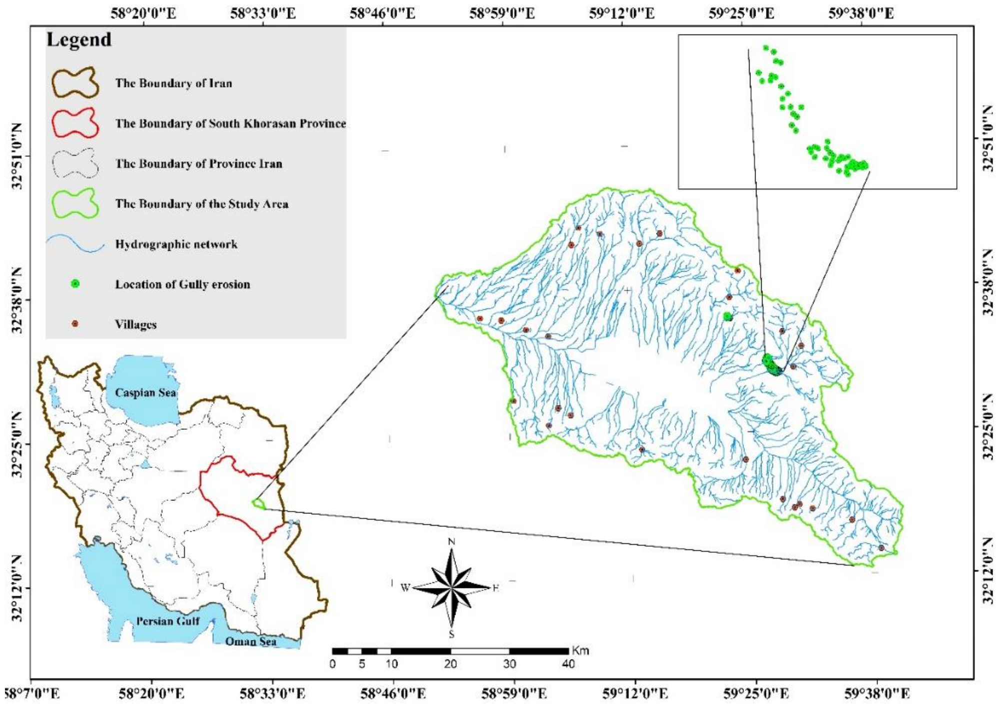



**Fig. 1.** Geographical location of the studied area and distribution of gully erosion sampling points.

*2.3. Input environmental variables*

By reviewing the studies and considering the nature of gully erosion with attention to the basic information sources available in the region, 25 important and effective variables in gully erosion formation were identified, and the related layers were prepared from different sources. Using the available information, 25 environmental variables including 5 topographic variables, 2 climatic variables, 4 hydrological variables, 8 soil variables, 4 land surface cover variables, and 2 geological variables were considered for model development. In this study, physiographic and geomorphological variables were prepared using topographic maps with a scale of 1:25000 of the country's mapping organization. Climatic variables were obtained from weather stations of the National Meteorological Organization. Soil and geological variables were procured with a scale of 1:50,000 based on a field survey and 1:100,000 base maps of the Geological Organization of Iran. Since all the input information layers of the model must have the same coordinate system and scale, the preparation of the information layers and the matching of the layers with the pixel size of 20 x 20 meters was carried out in Idrisi Selva software. Using Pearson's correlation coefficient, the variables that have a correlation coefficient of 0.8 and greater with each other were selected and eliminated to prevent the duplication of information (Damaneh et al., 2022; Momeni Damaneh et al., 2023a) (Fig. 2). Finally, to prepare a map of erosion forms, 22 environmental parameters were selected as predictive variables (Fig. 2-a, b) in Grid format along with the presence points of the dominant form of gully erosion for modeling in R software package using the GLM, GBM, CTA, ANN, SRE, FDA, MARS, RF, and MaxEnt models. The relationships between gully erosion and environmental factors were identified. Assessing the validity of the models was performed using the KAPPA, TSS, and ROC measures which are prominent and widely used indicators for validation analysis (Momeni Damaneh et al., 2023b). Table 1 shows the list of influential variables in the modeling process.

**Table 1.** List of influential variables in gully erosion modeling.

| Category | | Variable name | Abbreviation | Unit |
|---|---|---|---|---|
| Climate | | Annual precipitation | Precipitation | mm |
| | | Precipitation 24 hour | Precipitation 24 hour | mm |
| Hydrological | | Flooding | Flooding | Unitless |
| | | Curve number | CN | Unitless |
| | | Drainage density | Densitywat | (Km/Km2) |
| | | Maximum storage capacity | Coefficien | mm |
| Land surface cover | | Litter | Dryplant | % |
| | | Crown cover | Crowncover | % |
| | | Stones pebbles | Stonespebb | % |
| | | Bareground | Bareground | % |
| Soil science | Physical characteristics | Sand | Sand | % |
| | | Silt | Silt | % |
| | | Clay | Clay | % |
| | | Hydrologic soil group | Soilhidro | Dimensionless |
| | | Landsource | Landsurc | Dimensionless |
| | Chemical properties | Soil pH | pH | pH * 10 |
| | | Soil EC | EC | dsm/m |
| | | T.N. V | T.N. V | % |
| Geology | | Geology | | Dimensionless |
| | | Permeability | Permeabili | Dimensionless |
| Physiography | | DEM | DEM | m |
| | | Topographic wetness index | TWI | Dimensionless |
| | | Stream power index | SPI | Dimensionless |
| | | Aspect | Aspect | Dimensionless |
| | | Slope | Slope | % |

### *2.4. Modeling*

In this work, ten algorithms in the Biomed package within the R environment (Thuiller et al., 2009) were used to model gully erosion. The same software package was used to generate non-attendance points (Table 2), as well. In the modeling process, 70% of the dominant erosion position points were used to generate the models and 30% of the presence points were used to evaluate the performance of the applied models. Moreover, to increase the accuracy of modeling and achieve algorithm convergence, the number of repetitions was considered at 5.

**Table 2.** The list of models employed for gully erosion modeling.

| **Abbreviation** | **Name** |
|---|---|
| GLM | Generalized Liner Model |
| GBM | Generalized Boosting Method |
| CTA | Classification Tree Analysis |
| ANN | Artificial Neural Network |
| SRE | Surface Range Envelope |
| FDA | Flexible Denotative Analysis |
| MARS | Multivariate Adaptive Regression Spline |
| RF | Random Forest |
| ESMs | Techniques and their ensembles |
| MaxEnt | Maximum entropy model |

### *2.5. Model evaluation*

Accuracy assessment of the models was performed using three statistical coefficients. The first method is Receiver Operating Characteristic (ROC) which is a graphical method that evaluates the ability of a model to predict the presence and absence of species based on related environmental variables (Fielding and Bell, 1997). The second method is to calculate the amount of TSS (Eq. 1), that is used for the models with the presence and absence of ground truth points (Momeni Damaneh et al., 2023a). Research shows that the ROC has a high correlation with the TSS; therefore, in the studies whose results are in the form of presence and absence maps, TSS can be a suitable alternative to ROC (Walther et al., 2002).

Cohen's kappa is the agreement between two assessors, each of whom evaluates N items in C mutually exclusive classes (Eq. 2) (Smeeton, 1985; Galton, 1892).

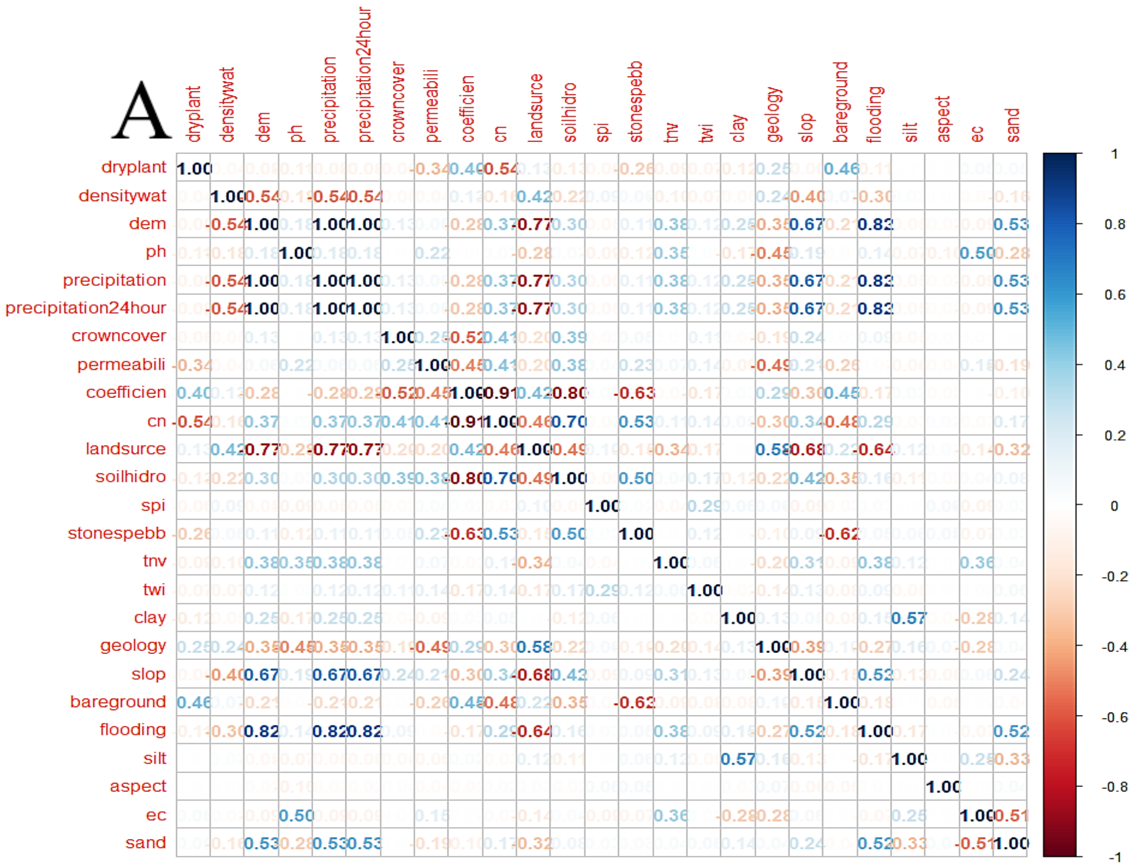
$$TSS = TPR + TNR - 1 \qquad (1)$$

$$Kappa = \frac{PA_O - PA_E}{1 - PA_E} \qquad (2)$$

The metric values of ROC, Kappa, and TSS less than 0.5 indicate inappropriate modeling performance, between 0.5 and 0.6 show very poor fit, between 0.6 and 0.7 confirm a poor fit, between 0.7 and 0.8 indicate moderate fit, between 0.8 and 0.9 designate a good fit and the range 0.9-1 indicates a high (desirable) fit of modeling (Swets, 1988; Yi et al., 2016; Momeni Damaneh et al., 2023b). To achieve a geographical view of the areas that have suitable climatic and environmental conditions for gully erosion, the optimal maps were depicted in discrete and continuous forms (Fig. 4). The values of gully erosion susceptibility obtained by the habitat suitability models were expressed from 0 to 1000. Zero is the lowest probability and 1000 is the highest probability for gully erosion incidence. To better understand the distribution of gully erosion in the study watershed, the probability map was classified into four classes including unfavorable habitats between 0 and 250, habitats with low desirability between 250 and 500, habitats with medium desirability between 500 and 750, and desirable habitats between 750 and 1000 (Table 3). The reclassification process was performed within the Arc GIS 10.5 environment utilizing the Natural Breaks method (Jenks algorithm) (Momeni Damaneh et al., 2022).

## 3. Results and discussion

The Pearson's correlation test for the predictive variables is shown in Fig. 2. Negative correlation is depicted with red color and positive correlation with blue color. Furthermore, the numerical value of correlation is shown inside each cell. According to Fig. 3a-b, 22 environmental variables that were less than 80% correlated with each other (to prevent the replication of input information) were chosen to be used in the modeling of gully erosion-prone areas.



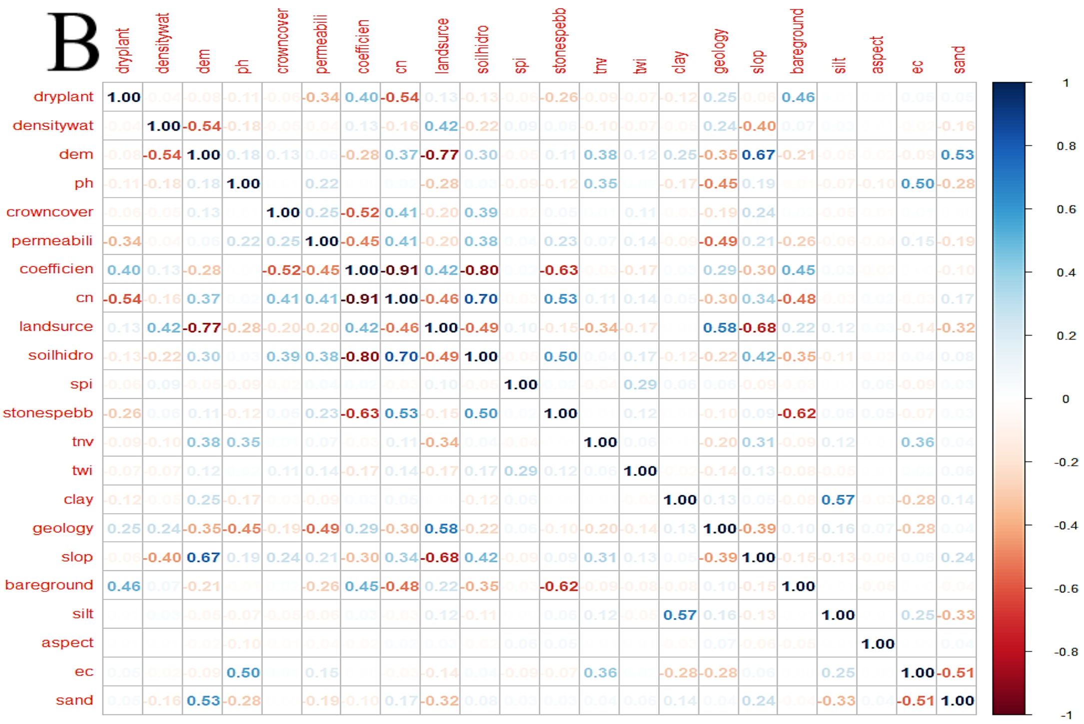


**Fig. 2.** Pearson correlation test for predictive variables with 80% correlation. Negative correlations are shown in red and positive correlations are shown in blue, (A) Correlation of total data, (B) Correlation of the data used in modeling.

### *3.1. Efficiency evaluation of the employed models*

The KAPPA and TSS index values with ROC which are the prominent and widely used indicators for determining and identifying potential areas are illustrated in Fig. 4. Based on the TSS metric, the best modeling for gully erosion is obtained using the random forest (RF) and ensemble (ESMs) models with an accuracy of 0.97. Although most of the models are implemented at a high level of efficiency, in the end, random forest (RF) and ensemble (ESMs) models were selected due to the highest accuracy. Therefore, the selected models were used as a basis for further calculations (Fig. 4). Marker et al. (2011) compared the susceptibility maps (inter-rill and gully erosion) for the Orme River basin, Italy. The comparison of models using AUC, Kappa index, and $R^2$ showed that although both TN and RF models provided good accuracies, however, TN model established higher efficiency than the RF model. The TN model showed a large difference between training and validation accuracies due to the overfitting problem. In contrast, the RF model was more stable in the training and validation phases. These results were consistent with the findings of our research, as well. Other researchers also confirm the results of this study which include the works by Kuhnert et al. (2010), Shruthi et al. (2014), Rahmati et al. (2017), Amiri et al. (2019), Garosi et al. (2019), Gayen et al. (2019), and Pourghasemi et al. (2020). The excellent forecasting performance of the RF model for gully erosion mapping can be established based on the following evidence: 1- It can use all various predictors without dropping any parameter during the modeling process. 2- It can work with very large data sets. 3- Since the RF model can generate multiple predictions of any phenomenon using a combination of trees, it can efficiently find non-linear relationships between predictors and predicted variables. 4- It combines different types of data in the analysis to overcome problems related to the non-distribution of assumptions about the input data. 5- It shows less sensitivity to noise in the input data (Kantardzic, 2011; Zhang et al., 2018).

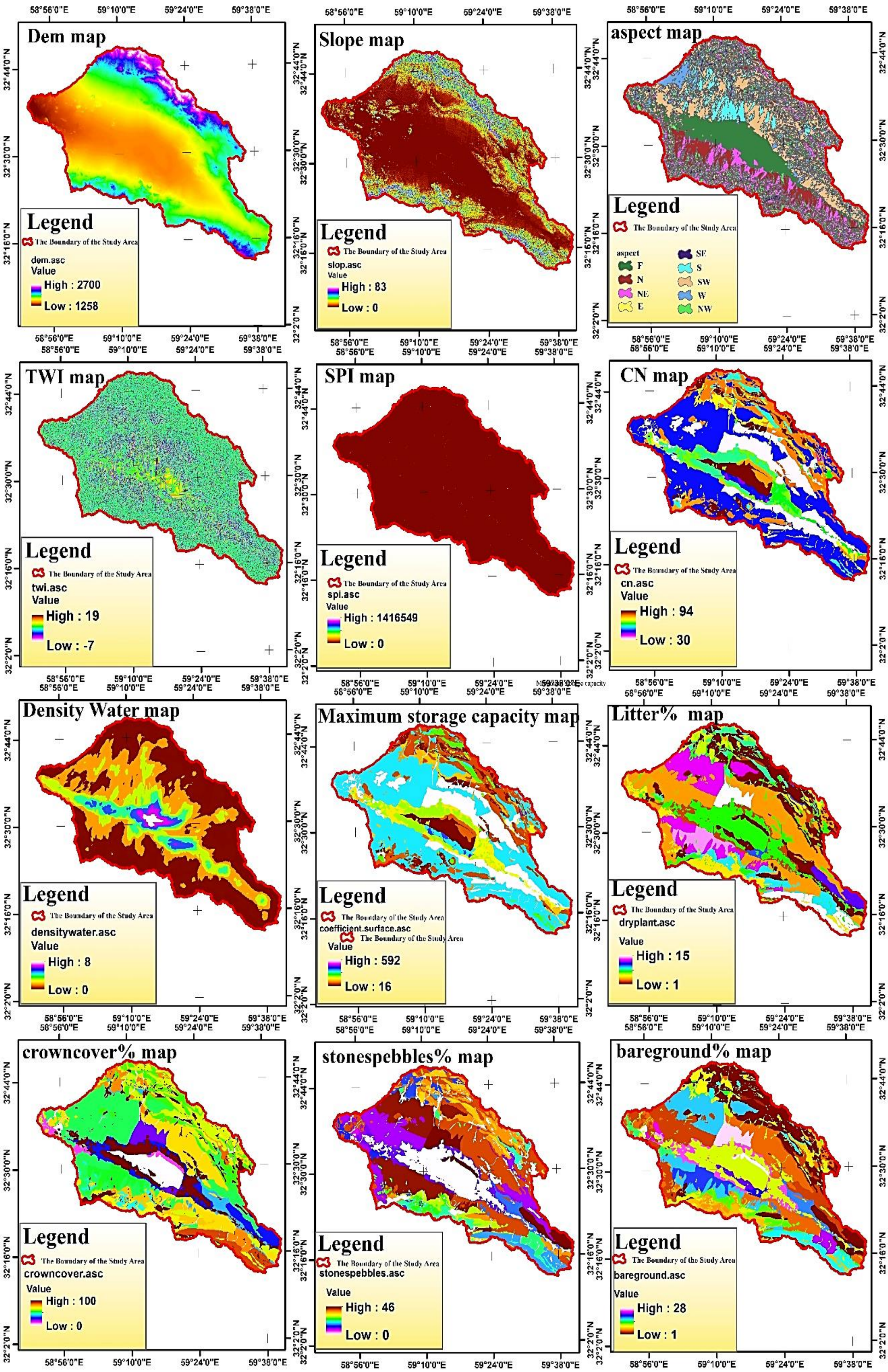



**Fig. 3.** (a) Variables selected for gully erosion modeling.

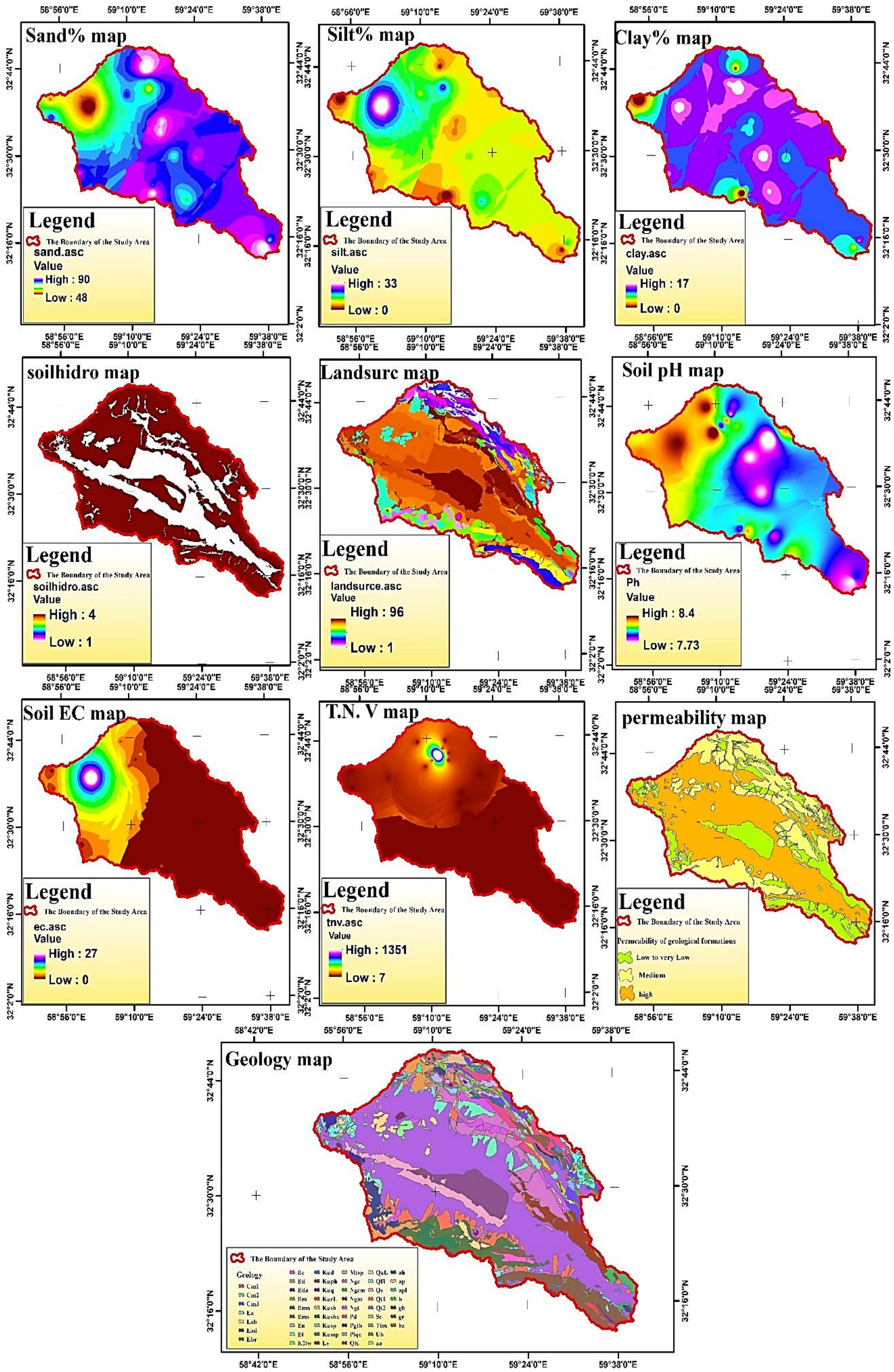



**Fig. 3.** (b) Variables selected for gully erosion modeling.

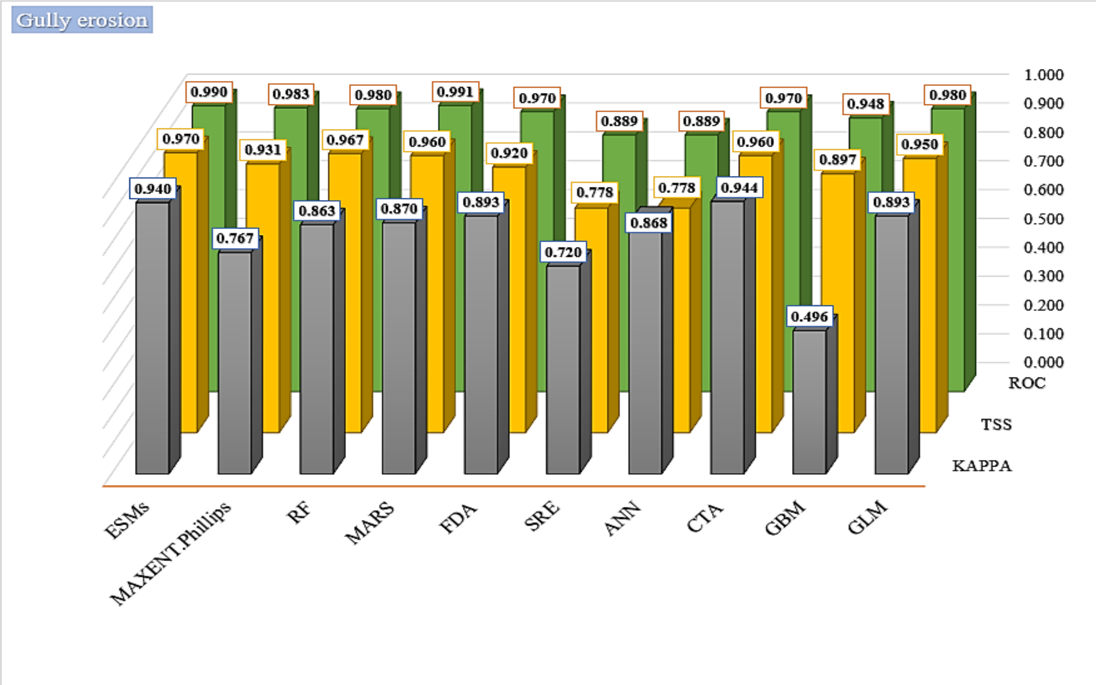



**Fig. 4.** Assessment of accuracy in the modeling of gully erosion-prone areas.

### *3.2. Sensitivity analysis*

The percentage of the relative importance of environmental variables in mapping gully erosion shows that the most important environmental factors include digital elevation model (DEM), electrical conductivity (EC) of the soil, the percentage of bare soil (uncovered soil), land unit components, geology, runoff coefficient and the maximum holding capacity of soil that respectively had the greatest effect on the geographical distribution of gully erosion (Fig. 6). In sum, the relative importance of all the environmental factors of gully erosion in the studied area showed that physiographic factors, soil, and geological factors are of significant importance in the geographical distribution of gully erosion in Mukhtaran watershed (Fig. 5). The findings are also supported thru the research work by Mohebzadeh et al. (2022).

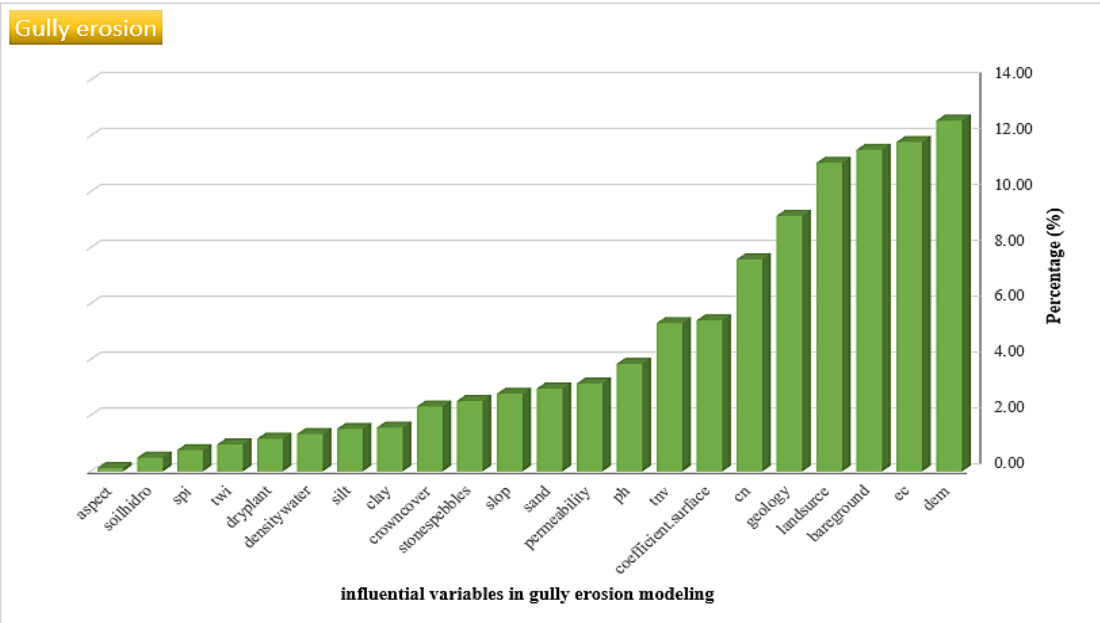



**Fig. 5.** The percentage of the relative importance of environmental parameters affecting the intensity of all types of gully erosion.

Finally, the area and the areal percentage of gully erosion classes of the Mukhtaran watershed based on the ensemble (ESMs) and random forest (RF) models are shown in Table 3 and Fig. 6.

**Table 3.** The area and the frequency of gully erosion extents in the Mukhtaran watershed.

| Erosion severity class | Model ESMs | | Model RF | |
|---|---|---|---|---|
| | Area (km$^2$) | Area (%) | Area (km$^2$) | Area (%) |
| Low | 2408.03 | 99.43 | 2415.55 | 99.74 |
| Medium | 5.64 | 0.23 | 1.05 | 0.04 |
| high | 3.86 | 0.16 | 0.45 | 0.02 |
| Very high | 4.20 | 0.17 | 4.67 | 0.19 |

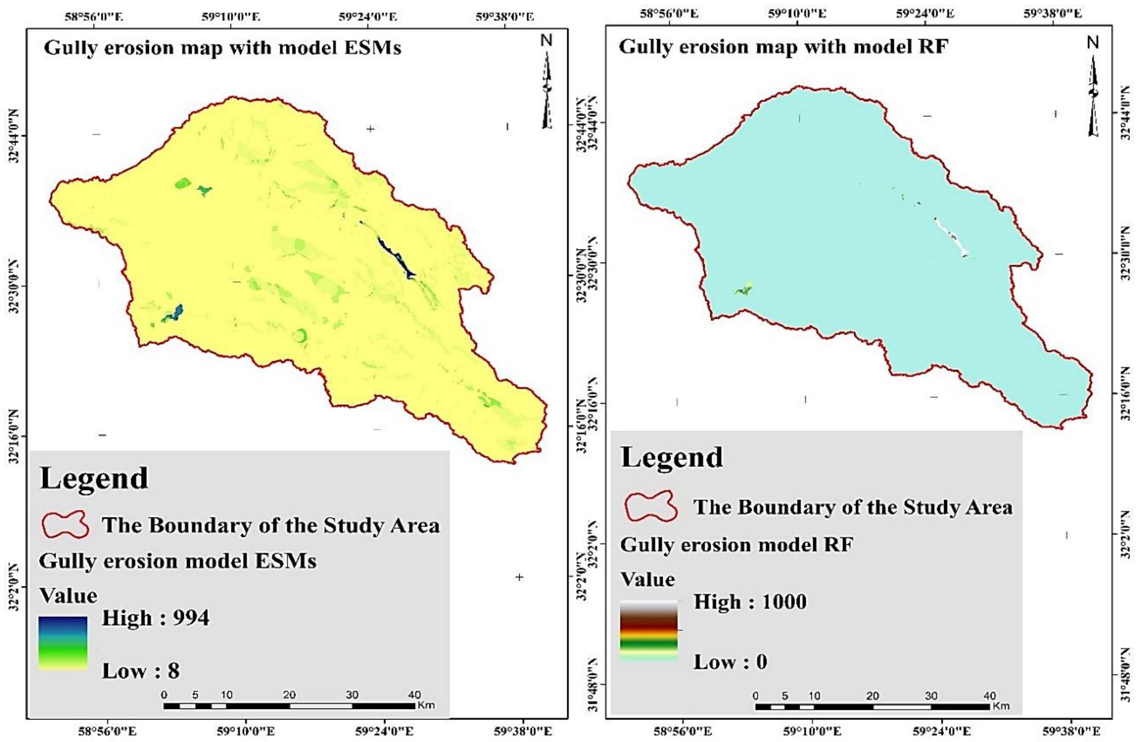



**Fig. 6.** Land susceptibility maps to gully erosion.

## 4. Conclusion

Gully erosion is an important problem that has a great impact on agricultural and economic activities with the spread of land degradation. Machine learning techniques in developing gully erosion susceptibility maps are considered valuable tools for regional managers by identifying the locations where gullies occur, as well as the locations prone to gully initiation. They are also effectively employed to assess the environmental impacts of gullies, to plan gully erosion controls, and to mitigate the gullies' negative impacts. This work examines the efficiencies of machine learning models for the preparation of gully erosion susceptibility maps in the Mukhtaran watershed, Iran. The modeling process was carried out in four main steps: (1) Preparing a distribution map of existing gullies, (2) Extracting factors influencing gully formation, (3) Multi-linear evaluation, and (4) Model development and performance analysis. In this study, ten machine learning models were employed to map the gully erosion susceptibility. The two methods, i.e., RF and ESMs models showed the best performance for preparing the gully erosion map. In validation analysis, two types of performance measures were utilized, i.e., threshold-dependent methods such as the kappa coefficient and threshold-independent methods like ROC and TSS.

As confirmed in this research, most studies also have shown that primary topographical features, e.g., altitude, slope, geological and soil characteristics such as land/vegetation unit components are among the factors that especially affect the quality of erosion modeling (Mohebzadeh et al., 2022). Despite the promising results in machine learning-based modeling for the preparation of gully erosion susceptibility maps, some suggestions are presented to improve the quality of prediction. First, further studies are recommended to test different factors, e.g., topography and hydrologic features in different geographic locations that may affect the proficiency of machine learning models. Second, strong data mining models should be used to improve the quality of the data set based on a comprehensive analysis of the relationship between the occurrence of gullies and the causative factors. Third, a set of models should be executed to combine the ability of models to increase accuracy and reduce forecast uncertainty. Among the reviewed articles, it can be revealed that, in addition to preparing a map of areas prone to permanent gully erosion, some studies also seek to use machine learning techniques to prepare a rill erosion map (Marker et al., 2011; Angileri et al., 2016), and ephemeral gully map (Garosi et al., 2019).

Although these maps can be utilized as a valuable tool to detect degraded lands by gully erosion, the generated maps cannot reliably represent the gully paths that are the main input of some process-based models. Therefore, by combining topographical indices and machine learning models, a more accurate estimate of the gully path can be provided, which can be used in process-based models to estimate soil loss from gullies.

## Acknowledgments

The authors confirm that this article was not under any financial support.

## References


Amiri, M., Pourghasemi, H.R., Ghanbarian, G.A. & Afzali, S.F., 2019. Assessment of the importance of gully erosion effective factors using Boruta algorithm and its spatial modeling and mapping using three machine learning algorithms. *Geoderma*, 340, 55–69.

Anderson, R.L., Rowntree, K.M. & Le Roux, J.J., 2021. An interrogation of research on the influence of rainfall on gully erosion. *Catena*, 206, 105482.

Angileri, S.E., Conoscenti, C., Hochschild, V., Marker, M., Rotigliano, E. & Agnesi, V., 2016. Water erosion susceptibility mapping by applying stochastic gradient treeboost to the Imera Meridionale river basin (Sicily, Italy). *Geomorphology*, 262, 61–76.

Arabameri, A., Pradhan, B., Rezaei, K. & Conoscenti, C., 2019. Gully erosion susceptibility mapping using GIS-based multi-criteria decision analysis techniques. *Catena*, 180, 282–297.

Bastola, S., Dialynas, Y.G., Bras, R. L., Noto, L.V. & Istanbulluoglu, E., 2018. The role of vegetation on gully erosion stabilization at a severely degraded landscape: A case study from Calhoun Experimental Critical Zone Observatory. *Geomorphology*, 308, 25–39.

Damaneh, J.M., Ahmadi, J., Rahmanian, S., Sadeghi, S.M.M., Nasiri, V. & Borz, S. A., 2022. Prediction of wild pistachio ecological niche using machine learning models. *Ecological Informatics*, 72, 101907.

Fielding, A.H. & Bell, J.F., 1997. A review of methods for the assessment of prediction errors in conservation presence/absence models. *Environmental Conservation*, 24(1), 38-49 .

Galton, F., 1892. Finger prints (No. 57490-57492). Macmillan and Company.

Gao, Y., Zhu, B., Zhou, P., Tang, J.L., Wang, T. & Miao, C.Y., 2009. Effects of vegetation cover on phosphorus loss from a hillslope cropland of purple soil under simulated rainfall: A case study in China. Nutrient Cycling in *Agroecosystems*, 85(3), 263–273.

Garosi, Y., Sheklabadi, M., Pourghasemi, H.R., Besalatpour, A.A., Conoscenti, C.& Van Oost, K.,2018. Comparison of differences in resolution and sources of controlling factors for gully erosion susceptibility mapping. *Geoderma*, 330, 65–78.

Garosi, Y., Sheklabadi, M., Conoscenti, C., Pourghasemi, H.R. & Van Oost, K., 2019. Assessing the performance of GIS-based machine learning models with different accuracy measures for determining susceptibility to gully erosion. *Science of the Total Environment*, 664, 1117–1132.

Gayen, A., Pourghasemi, H.R., Saha, S., Keesstra, S. & Bai, S., 2019. Gully erosion susceptibility assessment and management of hazard-prone areas in India using different machine learning algorithms. *Science of the Total Environment*, 668, 124–138.

Gomez Gutierrez, A., Schnabel, S. & FelicIsimo, A.M., 2009. Modelling the occurrence of gullies in rangelands of southwest Spain. *Earth Surface Processes and Landforms: The Journal of the*

*British Geomorphological Research Group*, 34, 1894–1902.
Gumus, M. & Kiran, M.S., 2017. Crude oil price forecasting using XGBoost, 2017. In: International Conference on Computer Science and Engineering (UBMK). IEEE, pp. 1100–1103.
Kantardzic, M.E.H.M.E.D., 2011. Data mining: concepts, models, methods and algorithms, A John Wiley & Sons. Inc. Hoboken, New Jersey.
Kuhnert, P.M., Henderson, A.K., Bartley, R. & Herr, A., 2010. Incorporating uncertainty in gully erosion calculations using the random forests modelling approach. *Environmetrics*, 21, 493–509.
Lei, X., Chen, W., Avand, M., Janizadeh, S., Kariminejad, N., Shahabi, H., Costache, R., Shahabi, H., Shirzadi, A. & Mosavi, A., 2020. GISbased machine learning algorithms for gully erosion susceptibility mapping in a semi-arid region of Iran. *Remote Sensing*, 12(15), 2478.
Li, C. & Pan, C., 2018. The relative importance of different grass components in controlling runoff and erosion on a hillslope under simulated rainfall. *Journal of Hydrology*, 558, 90–103.
Liu, J., Gao, G., Wang, S., Jiao, L., Wu, X. & Fu B., 2018. The effects of vegetation on runoff and soil loss: Multidimensional structure analysis and scale characteristics. *Journal of Geographical Sciences*, 28, 59–78.
Luffman, I. E., Nandi, A. & Spiegel, T., 2015. Gully morphology, hillslope erosion, and precipitation characteristics in the Appalachian Valley and Ridge province, southeastern USA. *Catena*, 133, 221–232.
Luo, D., Caldas, M.M. & Goodin, D.G., 2021. Estimating environmental vulnerability in the Cerrado with machine learning and Twitter data. *Journal of Environmental Management*, 289, 112502.
Mahala, A., 2020. Land degradation processes of Silabati river basin, West Bengal, India: a physical perspective. Gully erosion studies from India and surrounding regions, pp.265-278.
Majhi, A., Nyssen, J. & Verdoodt, A., 2021. What is the best technique to estimate topographic thresholds of gully erosion? Insights from a case study on the permanent gullies of Rarh plain, India. *Geomorphology*, 375 107547.
Marker, M., Pelacani, S. & Schroder, B.A., 2011. functional entity approach to predict soil erosion processes in a small Plio-Pleistocene Mediterranean catchment in Northern Chianti, Italy. *Geomorphology*, 125, 530–540.
Mrad, D., Boukhari, S., Dairi, S. & Djebbar, Y., 2024. Mapping the potential for erosion gullies using frequency ratio and fuzzy analytical hierarchy process: case study Medjerda basin, northeast algeria. *Eurasian Soil Science*, 1-17.
Mohebzadeh, H., Biswas, A., Rudra, R. & Daggupati, P., 2022. Machine learning techniques for gully erosion susceptibility mapping: a review. *Geosciences*, 12(12), 429.
Momeni Damaneh, J., Ahmadi, J. & Jafarpour Chekab, Z., 2023b. Identification of Suitable Areas for Cultivation of Saffron (Crocus sativus L.) Using Artificial Intelligence-Based Models in Khorasan Razavi Province. *Journal of Saffron Research*, 11(2), 328-345, (In Persian).
Momeni Damaneh, J., Tajbakhsh, S.M., Ahmadi, J. & safdari, A.A., 2023a. Determining The Areas Prone to The Growth of *Rhume ribes* L. Specie in Razavi Khorasan Province Using Vector Machine Models. *Water and Soil Management and Modelling*, 4(3), 75-94, (In Persian).
Momeni Damaneh, J., Tajbakhsh, S.M., Ahmadi, J. & Safdari, A.A., 2022. Comparison of species distribution models in determining the habitat landscape of *Pistacia vera* L. specie in Razavi Khorasan province. *Water and Soil Management and Modelling*, 3(4), 77-92, (In Persian).
Pourghasemi, H.R., Sadhasivam, N.,Kariminejad, N. & Collins, A.L., 2020. Gully erosion spatial modelling: Role of machine learning algorithms in selection of the best controlling factors and modelling process. *Geoscience Frontiers*, 11, 2207–2219.
Rahmati, O., Tahmasebipour, N., Haghizadeh, A., Pourghasemi, H.R. & Feizizadeh, B.,2017. Evaluation of different machine learning models for predicting and mapping the susceptibility of gully erosion. *Geomorphology*, 298, 118–137.
Roy, J. & Saha, S.,2021. Integration of artificial intelligence with meta classifiers for the gully erosion susceptibility assessment in Hinglo river basin, Eastern India. Advances in Space Research. 67(1), 316–333.
Senanayake, S. & Pradhan, B., 2022. Predicting soil erosion susceptibility associated with climate change scenarios in the Central Highlands of Sri Lanka. Journal of Environmental Management, 308, 114589.
Setargie, T.A., Tsunekawa, A., Haregeweyn, N., Tsubo, M., Fenta, A.A., Berihun, M.L., Sultan, D., Yibeltal, M., Ebabu, K., Nzioki, B. & Meshesha, T.M., 2023. Random Forest–based gully erosion susceptibility assessment across different agro-ecologies of the Upper Blue Nile basin, Ethiopia. *Geomorphology*, 108671. https://doi.org/10.1016/j. geomorph.2023.108671.
Shruthi, R.B., Kerle, N., Jetten, V. & Stein, A., 2014. Object-based gully system prediction from medium resolution imagery using Random Forests. *Geomorphology*, 216, 283–294.
Smeeton, N.C., 1985. Early history of the kappa statistic. Biometrics, 41, 795=
Soleimanpour, S.M., Pourghasemi, H.R. & Zare, M., 2021. A comparative assessment of gully erosion spatial predictive modeling using statistical and machine learning models. Catena, 207, 105679.
Swets, J. A.,1988. Measuring the accuracy of diagnostic systems. Science, 240(4857), 1285-1293.
Thuiller, W., Lafourcade, B., Engler, R. & Araujo, M.B., 2009. BIOMOD–a platform for ensemble forecasting of species distributions. *Ecography*, 32(3), 369-373.
Vanmaercke, M., Poesen, J., Van Mele, B., Demuzere, M., Bruynseels, A., Golosov, V., et al. 2016. How fast do gully headcuts retreat? *Earth-Science Reviews*, 154, 336–355.
Walther, G. R., Post, E., Convey, P., Menzel, A., Parmesan, C., Beebee, T.J. & Bairlein, F., 2002. Ecological responses to recent climate change. *Nature*, 416(6879), 389-395.

Yi, Y.J.X., Cheng, Z.F., Yang, S. & Zhang. H., 2016. Maxent modeling for predicting the potential distribution of endangered medicinal plant (H. riparia Lour) in Yunnan, China. *Ecological Engineering*, (92), 260-269.

Zabihi, M., Mirchooli, F., Motevalli, A., Darvishan, A.K., Pourghasemi, H.R., Zakeri, M.A. & Sadighi, F., 2018. Spatial modelling of gully erosion in Mazandaran Province, northern Iran. *Catena*, 161, 1–13.

Zhang, X., Wenhong, C., Qingchao, G. & Sihong, W., 2010. Effects of landuse change on surface runoff and sediment yield at different watershed scales on the Loess Plateau. *International Journal of Sediment Research*, 25(3), 283–293.

Zhang, X., Fan, J., Liu, Q.& Xiong, D.,2018. The contribution of gully erosion to total sediment production in a small watershed in Southwest China. *Physical Geography*, 39, 246–263.

Zhao, G., Mu, X., Wen, Z., Wang, F. & Gao, P., 2013. Soil erosion, conservation, and eco-environment changes in the Loess Plateau of China. *Land Degradation & Development*, 24(5), 499–510.