

# Risk Assessment of Runoff Generation Using Artificial Neural Network and Field Plots in The Area of Roads and Forest Lands

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## Research Article

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# Abstract

Runoff generation potential (RGP) on hillslopes is an important issue in the forest roads network monitoring process. In this study, the artificial neural network (ANN) was used to predict RGP in forest road hillslopes. We trained, optimized, and tested the ANN by using field plot data from the Shirghalaye watershed located in the southern part of the Caspian Sea (Iran). 45 plots were installed to measure actual runoff volume (RFP) in different environmental conditions including land cover, slope gradient, soil texture, and soil moisture.

A multi-layer perceptron (MLP) network was implemented. The runoff volume was the output variable and the ground cover, slope gradient, initial moisture of soil, soil texture (clay, silt, and sand percentage) were the network inputs. The results showed that ANN can predict runoff volume within the values of an appropriate level in the training ( $R^2=0.95$ ,  $MSE= 0.009$ ) and test stages ( $R^2=0.80$ ,  $MSE= 0.01$ ). Moreover, the tested network was used to predict the runoff volume on the forest road hillslopes in the study area. Finally, an RGP map was generated based on the results of the prediction of the ANNs and the GIS capabilities. The results showed that using both an ANN and a GIS is a good tool to predict the RGP in the forest road hillslopes.

## Introduction

The monitoring of the generation of hillslope runoff generation is a crucial aspect in Sustainable Forest Management, considering that surface runoff is one of the major problems among environmental issues (Wagenbrenner et al. 2021, Iroume et al. 2021, Dalir et al. 2014, Dixon 2005, Wang et al. 2013). Runoff occurs when the soil is unable to absorb or store precipitation and results in surface and rill erosion (Brodowski and Rejman 2004). The mechanisms by which hillslopes store and release water are of crucial importance, considering that they may affect many ecological processes through biogeochemical and nutrient cycles (Stieglitz et al. 2003). It is well known that unpaved forest roads may cause many local changes to the hydrologic dynamics on hillslopes thus increasing runoff generation potential (RGP) (Nasiri et al. 2017, Al-Chokhachy et al. 2016). Such surface water is a concern on road hillslopes with important side slopes due to the risk of slope instability (Aldrich et al. 2005, Pierson et al. 2007, Akay et al. 2008, Gholami and Khaleghi 2013). Usually, the characteristics of road embankments are not suitable for the growth of vegetation (Martínez-Zavala et al. 2008) because the materials are covered with poor soil qualities which limit vegetation growth (De ona et al. 2009; Meyer et al. 2019; Naghdi et al. 2017), and as a result the soil is very erodible in the embankment (Wei et al. 2007, De ona et al. 2009). It is therefore necessary to study the runoff generation processes, runoff hazards, and define areas with high RGP in the forest area. This is a priority for conserving the endangered forest road network by preventing hydrological concerns.

This is a complex issue considering that many factors influence the RGP, i.e. slope, vegetation coverage, rainfall intensity and duration, and soil type and texture (Pastor and Castro 1995, Poesen and Hooke 1997, Martinez-Casasnovas 1998, Uson 1998, Pickup and Marks 2000, Sun et al. 2014, Dalir et al. 2015, Dalir et al. 2021). Therefore, the various factors affecting RGP must be identified prior to erosion modelling (Foster 2001). The application of models has become common in hydrology studies. In such studies the plot scale is very important. Plot scale studies are useful for the development of new RGP modelling methods and they provide access to many up-to-date runoff measurements for test new models (Zhao et al. 2009, Li et al. 2017). Examples of models tested using plot studies are the universal soil loss equation (USLE) and the revised

universal soil loss equation (RUSLE) (Wischmeier and Smith 1958 and 1978; Renard et al. 1996). Moreover, simulated rainfall is an important tool for studying hydrology because the experimental conditions can be controlled, and many kinds of natural environments can be simulated within a short period of time (Li et al. 2017).

Several techniques have been used to predict runoff generation and map runoff hazard. One of the new modelling approaches is the use of artificial neural networks (ANNs). ANNs have a flexible mathematical structure with the capability of defining sophisticated non-linear relationships between input and output parameters. ANNs provide advantages over conventional hydrological models by successfully identifying the non-linear hydrologic relationship between input and output data sets (Gholami et al. 2019, Maier et al. 2019, Abrahart et al. 2012, Wu et al. 2014). ANNs have been found to be useful and efficient as modelling tools, particularly in problems for which the characterization processes are difficult to describe via physical or statistical based equations (Gholami et al. 2019, Riad et al. 2004). Runoff volume evaluation is a time-consuming, expensive and strict step, yet it is an important part of hydrological studies. These evaluations cannot be carried out in all of the study areas such as a complete forest road network or for a high number of plots. Therefore, ANNs can be used as an excellent tool to evaluate hydrological factors based on field or experimental measurements. Therefore, the use of field plot data and ANNs can be helpful to determine runoff volume within an appropriate time and at a low cost. Nilsson et al. (2006) predicted monthly runoff generation using ANNs models as a function of precipitation, temperature, snow accumulation and seasonal information in two Norwegian river basins. He successfully predicted daily runoff volume for Maryland (USA) with temperature, precipitation, and snowmelt equivalent serving as inputs to the ANNs. Further, ANNs have been widely applied in the simulation of hydrologic processes (Choong et al., 2020, Tokar and Johnson 1999, Isik et al. 2013, Golami et al. 2016). Based on results, ANNs modelling appears to be a promising technique for the prediction of flow for catchments in semi-arid regions. Accordingly, the neural network method can be applied to various hydrological systems where other models may be inappropriate. ANNs can be used for predicting runoff with a high rate of accuracy and in a short time, but its results are given in a numerical form and the use of the results could be difficult for other users to comprehend. On the other hand, the geographic information system (GIS) has powerful capacities to solve environmental problems and has proved to be an important tool in geoscience (Picchio et al. 2019). Coupling of GIS and ANNs can help make use of the efficient processing of runoff data, quantify and collect data for another area, provide ANNs with the necessary inputs and training, and present the results in visual and user-friendly formats (Wu et al. 2011).

In recent years, the use of different models to simulate forest hydrology has become more common. This study has applied ANNs and GIS to estimate RGP. The main idea and difference is that in this study, an optimal neural network with ANNs and GIS is used to achieve more accurate results in runoff prediction by field plot data while reducing the limitations and errors. The applied methodology is of particular interest, considering that it can be applied in any study area in the world. We aimed to predict runoff for a forest road network hillslope and to develop a runoff hazard mapping by using data from field plot measurement and an ANN coupled with a GIS.

## **Materials And Methods**

## Study area

The field studies were conducted on the side slope of a forest road hillslope in the Shirghalaye basin forest, Guilan province, Southern Caspian Sea between 49° 52' to 37° 5' N latitude and 49° 55' to 50° 8' E longitude. The study area is 2588 ha (Fig. 1). This mountainous area has an altitude ranging from 1120 to 1680 m. The major soil type is clay loam soil. The general soil thickness is 0.5–1.5 m, with a humus layer of 0.15–0.50 m and a litter of 0.10–0.50 m. The soil pH varies from 6 to 7.

The forest lands were predominantly covered by Oriental beech (*Fagus Orientalis* Lipsky), Alder (*Alnus glutinosa* & *Alnus sabcordata*), and Hornbeam (*Carpinus betulus*). The mean tree height is 21 m and stand density was measured as 180 trees per hectares. The mean annual precipitation recorded at the closest climatology station is 1200 mm. The maximum mean monthly rainfall of 120 mm usually occurs in December, while the minimum monthly rainfall of 25 mm occurs in August. The mean annual temperature is 15 C° with the lowest values in February. Due to widespread timber harvesting in this area, there is a large network of forestry roads (46.8 km). The study area consists of a number of hillslopes with a slope between 17.3–51.9% and constitutes a limited area of about 4 km<sup>2</sup>.

## Runoff Measurement Using Field Plots (Rfp)

In this part of the study, 45 plots of runoff with 2 m<sup>2</sup> dimensions were established on the forest road hillslopes. The material of the plot walls was waterproof and made of aluminum.

Various embankment slopes and crop cover percentages were used (Fig. 2). The plots were established on the road hillslopes. The penetration depth of the plot walls in the soil is 10 cm. One runoff plot was established per kilometer of the road.

The coverage rate was determined by taking a digital picture at the location of each plot. Slope percentages were measured using an inclinometer.

The soil samples from the depth interval 0-10 cm were collected with a soil hammer and rings (diameter 5 cm, length 10 cm) outside of the plot (Fig. 2), put in polyethylene bags, labeled, and brought back to the laboratory where they were promptly weighed. Soil samples were oven-dried at 105° C for 24 h. The soil moisture content in the samples was measured gravimetrically after drying (Kalra and Maynard 1991). Soil texture (clay, silt, and sand percentages) was determined in the laboratory. Particle size distribution was determined by using the Bouyoucos hydrometer method (Kalra and Maynard 1991),

Soil bulk density was calculated as Equation (1):

$$Db = \frac{W_d}{VC} \quad (1)$$

where Db is the dry bulk density (g cm<sup>-3</sup>), W<sub>d</sub> is the weight of the dry soil (g), and VC is the volume of the soil cores (196.25 cm<sup>3</sup>).

Initial soil moisture was calculated as Equation (1) (Kalra and Maynard 1991):

$$M_s = [(W_w - W_d)/W_d] \times 100 \quad (1)$$

Where  $M_s$  is the soil moisture content (%),  $W_w$  is the moist soil weight (g), and  $W_d$  is the dry soil weight (g). Two rainfalls of 60 and 45 millimeters were considered as the designated storm rainfalls to evaluate the runoff generation potential. The rainfall intensities were 22 and 30 millimeters per hour, respectively, the return period of rainfall in this study was 20 years. At the end of the lower slope of each plot, a runoff collection tank was installed. Runoff volume was measured after the designated rainfall (Las Heras et al. 2010). In fact, after the rains, we emptied the reservoirs and waited for a high-intensity rainfall event to be recorded. After recording the rainfall event, that event and its data were used as designated rainfall. The amount of rainfall was more than the initial loss of soil in the area and led to runoff generation. The initial loss in this study was estimated to be 5-18 mm. The initial loss was estimated based on the amount of rainfall before the start of runoff in the entire plot area (n=45).

Finally, the plots were used to measure runoff on the selected hillslopes.

## Prediction Of Rgp Using Anns

We used a multi-layer perceptron (MLP) network in NeuroSolutions software to predict the runoff generation potential on the hillslopes. ANNs is used by an enveloping the optimization algorithm to adjust the weight of each neuron, completing the learning process for that case. A multilayer perceptron is a class of feed forward artificial neural network. An MLP consists of at least three layers of nodes. Except for the input nodes, each node is a neuron that uses a nonlinear activation function. Learning was performed in the perceptron by changing connection weights based on the error values in the comparison with the experimental values. We used a feed-forward neural network to predict the RGP volume. The factors slope gradient, vegetation canopy percent, soil moisture, clay, silt, and sand percentages (soil texture) were selected as inputs and the runoff volume as the output. Finally, RGP were evaluated for 45 plots in two rainfall events (90 samples of rainfall run off). After normalizing all data, they were then split into training/test data sets: training data (70% of all data) and testing data (30% of all data). In terms of optimizing the network structure, it was determined that the optimal transfer function, optimal inputs or the real affecting factors, the determination of optimal learning techniques, and the appropriate number of neurons. (Isik et al. 2013). After training and network optimization, the network was established. Finally, an optimized and tested MLP network was created for the reliable prediction of quantitative amounts of RGP. To determine the optimal structure of the network (optimization inputs, the optimal transfer function, and optimal learning technique) the trial-error method was used in the NeuroSolutions medium. After each trial-error, network assessment was performed by evaluating the error values and the correlation coefficient between the predicted values and the observed data. Finally, after achieving the optimal network structure, the network testing was performed.

An MLP with tangent hyperbolic transfer function, LM back-propagation technique, two hidden neurons, 1000 epoch, and the optimal inputs was selected as an optimal network to predict RGP. To evaluate the performance of the ANN model, statistical criteria was used such as the coefficient of determination ( $R^2$ ),

mean square error (MSE) and mean absolute error (MAE). The coefficient of determination is always between zero and one and how much it is closer to one, to indicate the better performance of the model (eq. 1):

$$R^2 = \left[ \frac{\sum_{i=1}^n (Q_i - \bar{Q}_i) \cdot (\hat{Q}_i - \bar{\hat{Q}}_i)}{\sqrt{\sum_{i=1}^n (Q_i - \bar{Q}_i)^2 \cdot \sum_{i=1}^n (\hat{Q}_i - \bar{\hat{Q}}_i)^2}} \right]^2 \quad (1)$$

MSE is based on the difference between actual and predicted values which are evaluated and the value which is lower and closer to zero indicates the better performance of the model (eq.2):

$$MSE = \frac{\sum (Q_i - \hat{Q}_i)^2}{n} \quad (2)$$

MAE value changes from zero to infinity. How much it is closer to zero indicates the better performance of model (Khaleghi et al. 2014) (eq.3):

$$MAE = \frac{1}{N} \sum_{i=1}^N |E_i| \quad (3)$$

Where  $Q_i$  is the observed value,  $\hat{Q}_i$  is the simulated value and  $\bar{Q}$  is the mean of the observed data and  $\bar{\hat{Q}}$  is the mean of the simulated data and  $n$  is the number of data.  $E_i$  or absolute error is the difference between the predicted and observed values. Further, a sensitivity analysis of the model inputs was performed in order to determine key parameters to RGP in forest road hillslopes. This analysis is performed after the network testing. In other words, this analysis is used to assess the affecting factors in the network output or RFP values. The ANN performance was evaluated using error values (MSE, MAE, and  $R^2$ ) and the comparison between the predicted and observed values.

## Mapping Of Rgp By Coupling Anns And Gis

One of the goals of our study was to couple an ANNs and GIS to predict RGP for the forest road hillslopes. In other words, we can predict and map RGP for runoff values by coupling ANNs and GIS on the forest road network.

At this stage, the geo-referenced layers of the network inputs (tested network) in GIS with raster format were combined. Pixel size was defined one by one meter based on field plot size and data. Finally, geographical coordinates and quantitative amounts of affecting factors in RGP were acquired for each cell. These data were transferred from the GIS to Excel medium. The output data serves as the input of the tested MLP network to predict runoff volume in the study area.

Next, the predicted RGPs were transferred from the ANNs back to GIS. An RGP map was generated using the predicted runoff values and GIS capabilities. The RGP map was prepared by classifying the map in GIS. An evaluation of ANNs performance in RGP mapping was performed through the test stage. Further, the performance of coupling ANNs and GIS was evaluated through overlaying the observed runoff values (field plots data) on the predicted runoff values in the map.

## Results

The Pearson correlation coefficients showed a significant correlation between runoff volume on the forest road hillslopes and vegetation canopy, slope, soil moisture, clay and sand (soil texture) while the correlation was not significant with silt (Table 1). According to the Pearson correlation, ground slope, soil moisture, and clay percentage have a significant positive relation with runoff volume, whilst vegetation canopy, silt, and sand showed negative relations. The runoff volume during the study period ranged from 0 to 0.65 liter per 1 m<sup>2</sup> for the study plots (Table 2).

Table 1

The Pearson correlation (correlation matrix) between the measured runoff values and the affecting factors in runoff generation on the forest road hillslopes.

	Run off (L)	Vegetation cover (%)	Slope (%)	Soil moisture (%)	Clay (%)	Silt (%)	Sand (%)
Runoff (L)	1	-0.72 <sup>**</sup>	0.42 <sup>**</sup>	0.67 <sup>**</sup>	0.64 <sup>**</sup>	-0.17	0.09
Vegetation cover (%)	-0.7 <sup>**</sup>	1	-0.04	-0.495 <sup>**</sup>	-0.70 <sup>**</sup>	0.14	0.25
Slope (%)	0.42 <sup>**</sup>	-0.04	1	0.31 <sup>*</sup>	0.23	-0.13	0.03
Soil Moisture (%)	0.67 <sup>**</sup>	-0.49 <sup>**</sup>	0.31 <sup>*</sup>	1	0.53 <sup>**</sup>	-0.33 <sup>*</sup>	-0.09
Clay (%)	0.64 <sup>**</sup>	-0.70 <sup>**</sup>	0.23	0.53 <sup>**</sup>	1	-0.59 <sup>**</sup>	-0.45 <sup>**</sup>
Silt (%)	-0.17	.14	-0.13	-0.33 <sup>*</sup>	-0.59 <sup>**</sup>	1	0.37 <sup>*</sup>
Sand (%)	0.09	0.25	0.03	-0.09	-0.45 <sup>**</sup>	0.37 <sup>*</sup>	1
<sup>**</sup> Correlation is significant at the 0.01 level (2-tailed), <sup>*</sup> Correlation is significant at the 0.05 level (2-tailed)							

Table 2  
Network inputs and outputs for predicting runoff values for some of the studied plots.

	Runoff (Liter)	Vegetation cover (%)	Slope (%)	Rainfall (mm)	Rainfall intensity (mm/h)	Initial soil moisture (%)	Clay (%)	Silt (%)	Sand (%)
Mean	0.19	42.56	32.17	59.35	29.38	30.84	30.33	39.25	30.74
Std. Deviation	0.17	34.16	15.16	5.27	2.15	4.61	4.54	3.73	2.79
Minimum	0	0	15	45	22	24	24	28	25
Maximum	0.65	90	65	80	30	46	41	42	44
N	45	45	45	45	45	45	45	45	45

The ANN was used for predicting the runoff generation volume in the forest road hillslopes with inputs and output data, and the results during the training (modeling and optimization) stage showed suitable simulation ( $R^2=0.95$ ;  $MSE=0.009$ ); the error values in the training stage were given in Table 3.

Table 3  
Performance evaluation of the MLP network at the training stage for predicting the runoff values.

Criteria N=63	Training: run off (liter)
MSE	0.009
MAE (Mean Absolute Error)	0.031
Min Absolute Error	0.001
Max Absolute Error	0.85
$R^2$	0.95

The results of the sensitivity analysis using the tested network was given in Fig. 3 and the results showed that cover percentage is the most important factor in runoff modeling. Furthermore, according to the trial-error method results, soil moisture, slope, clay, and sand percentages are optimal inputs for predicting RGP using the optimized ANN.

In the next stage, the validation or test was performed for evaluating the performance of the optimized network in RGP prediction. The comparison between the observed values (runoff volume from field plots) and the predicted values of RGP was given in Fig. 4. Moreover, Tables 3 and 4 show the results of training and testing phases in predicting RGP. According to the results, the MLP network can be used for predicting RGP.

Table 4  
Performance evaluation of the MLP network at the test stage for predicting the runoff values.

Criteria N=27	Test: run off (liter)
MSE	0.011
MAE	0.051
Min Absolute Error	0.002
Max Absolute Error	0.40
R <sup>2</sup>	0.80

Affecting factors in RGP in the forest road hillslopes consist of many aspects and the relationships between the factors are complex. Raster layers of the network inputs were obtained using overlay analysis in GIS. The tested network and GIS were coupled for mapping the RFP in the forest roads network during a rainfall event with a return period of 25 years (60 mm). The RFP map was prepared by coupling the tested MLP network and GIS and the map was given in Fig. 5.

Moreover, the coupling of ANN and GIS performance were evaluated by overlaying the observed values (field plot data) on the generated runoff map in Fig. 5. The runoff generation potential was classified into five classes based on the predicted values from low potential to very high potential in the study area. As can be seen in the resulting map, the described methodology could provide an acceptable prediction (via the comparison between observed and predicted values) for modeling the RGP.

the RFP in the forest watershed. The measured values of the filed plots have been overlapped with the map for evaluating the performance of the obtained results in RFP mapping ( $R^2=0.79$ ).

## Discussion

In this study, the RGP was evaluated on the forest road hillslopes. Previous studies have shown that among the most important factors in runoff generation are rainfall values and rainfall intensity (Tokar and Johnson 1999, Keim et al. 2006). These factors had a constant rate in our study, because in this study our goal was to predict the runoff generation potential during a return period. In this study, two rainfall events were selected in which the amount of rainfall was more than the initial soil loss. Therefore, runoff was flowing during such rainfalls. Using different plots in different coverage, slope, soil texture, soil moisture, and with instant intensity of precipitation, runoff generation was studied in different areas of forest road hillslopes. The study showed that in the case of constant rainfall intensity, the most important factor in the generation of runoff is the vegetation coverage. Furthermore, ground slope, soil moisture, clay percent, and sand percentage are the most important factors of runoff generation in the study area.

According to the results, there is a negative relationship between runoff generation and sand percentage in soil texture. Also, a negative relationship between runoff generation and vegetation cover is observed as reported in previous studies (Gholami and Khaleghi 2013, Keim et al. 2006). Slope, soil moisture content, and clay

percentage in soil texture have a positive relationship with runoff values. By increasing the percentage of vegetation on the forest road hillslopes the runoff volume was reduced in various ways. This aspect can be related to several reasons. For example, it could cause the increase of organic matter and porosity of the soil thus improving the soil structure which reduces runoff. In the case of where there is sand in the soil, the results showed a positive relationship and it showed that the more sand there was in the soil the more permeability it had. The results of this study, as well as most studies in this field, showed that runoff generation has a positive and direct correlation with the increase in the percentage or gradient of slope. As the slope increases, the velocity of water drops on the surface of the soil increases, and as a result, this speed is more than the penetration rate in the soil, so the amount of runoff increases (Las Heras et al. 2010, Sun et al. 2016). By increasing soil moisture and water absorption, the maintenance capacity in the soil decreases and runoff generation increases. Many studies have been carried out on the effect of clay content on the levels of generation of runoff, which shows that due to the increase of clay content in soil, the soil penetration strength is reduced (Renard et al. 1996, Brodowski and Rejman 2004).

According to the obtained results, the areas in the forest hillslopes with a higher percentage of vegetation and a lower percentage of sand in the soil texture, with more slope, soil moisture, and clay have more potential for runoff generation. These are the areas which should be considered. Of course, these relationships are not simple and linear, and there is a complex relationship between the affecting factors in runoff generation. After identifying the most important factors in the runoff generation, these factors were used as ANN inputs. According to the results obtained in the training and test stages, it was determined that ANN can be used with a good level of precision to predict the runoff values. Also, when the input factors of the model in different areas and the roads of the forest are measured, RFP can be easily calculated so as to reduce time input and increase cost effectiveness. Although ANN is a highly efficient tool for modelling and identifying environmental factors, it does not provide input nor identify the spatial and geographical distribution of phenomena. To solve this problem, GIS can be used for the preparation of the input values of the model, as well as the mapping and spatial distribution of the output of the model. In this study, GIS as a pre-analyzer tool was initially used to collect input data from the study area. In the next step, ANN was used as a post-analyzer to prepare the map of runoff generation potential. If the input data are accurate, an appropriate ANN can provide users with precise output. Thus, this study has demonstrated how using both ANN and GIS, the RGP for extensive areas of forests roads can be modelled and identified. By classifying the output of the model based on the runoff values, the study area can be classified based on the RGP. Therefore, the generated map can be used as a tool for planning soil conservation practices. Coupling of ANN and GIS can estimate RGP within a short time and at a low cost. Moreover, this methodology can be used in everywhere.

## Conclusions

The most important factor in runoff potential is vegetation cover. This is followed by the slope, soil moisture content, clay percentage and sand percentage in soil texture. These factors act in a non-linear manner and in complex interactions. In this study, the intensity and value of rainfall was constant. It is to be recognized that the rainfall intensity and rainfall value are the most important factors in runoff values. If accurate data is available by implementing ANN, the runoff values in the forest area can be simulated with high precision.

Due to the weakness of the ANN in spatial distribution and mapping, GIS can be used to compensate. In this study, the first step to formulating a prediction is for the GIS to provide input for the ANN data and then transfer the ANN results onto a map. The use of both GIS and ANN can be useful to predict and categorize the runoff values for different users. It is also suggested that future studies use other methods of artificial intelligence such as machine learning in the various scenarios of the forest areas.

## **Declarations**

### **Ethical approval**

Not applicable.

### **Consent to Participate**

All authors consent to participate in this manuscript.

### **Consent to Publish**

All authors consent to publish this manuscript.

### **Authors Contributions**

All authors contributed to the study conception and design. All authors read and approved the final manuscript.

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### **Conflicts of interest/Competing Interests**

There is no conflict of interest among authors.

### **Availability of data and materials**

All data and materials as well as software application or custom code support our published claims and comply with field standards.

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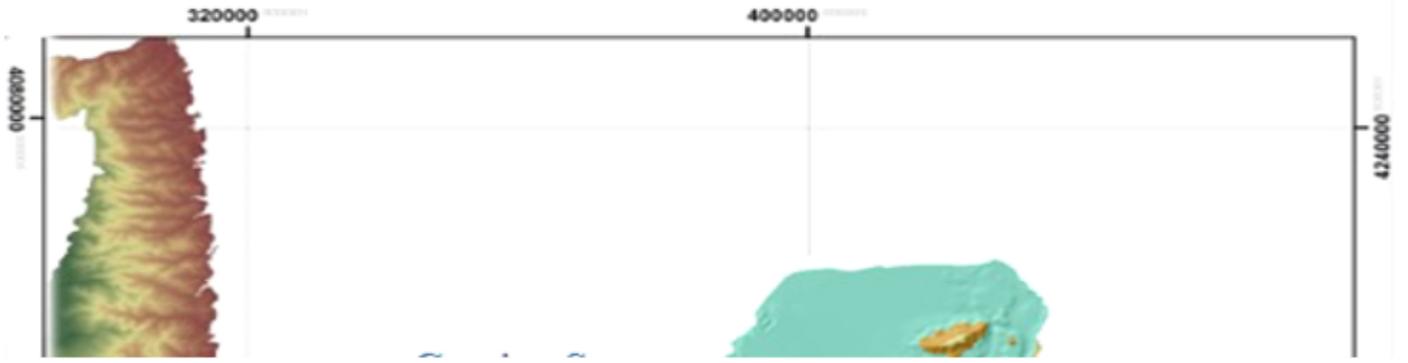
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## Figures



**Figure 1**

Location of the study area to the south of the Caspian Sea (Shirghlave watershed).



**Figure 2**

A view of the plots used for runoff measurement during the designated rainfalls

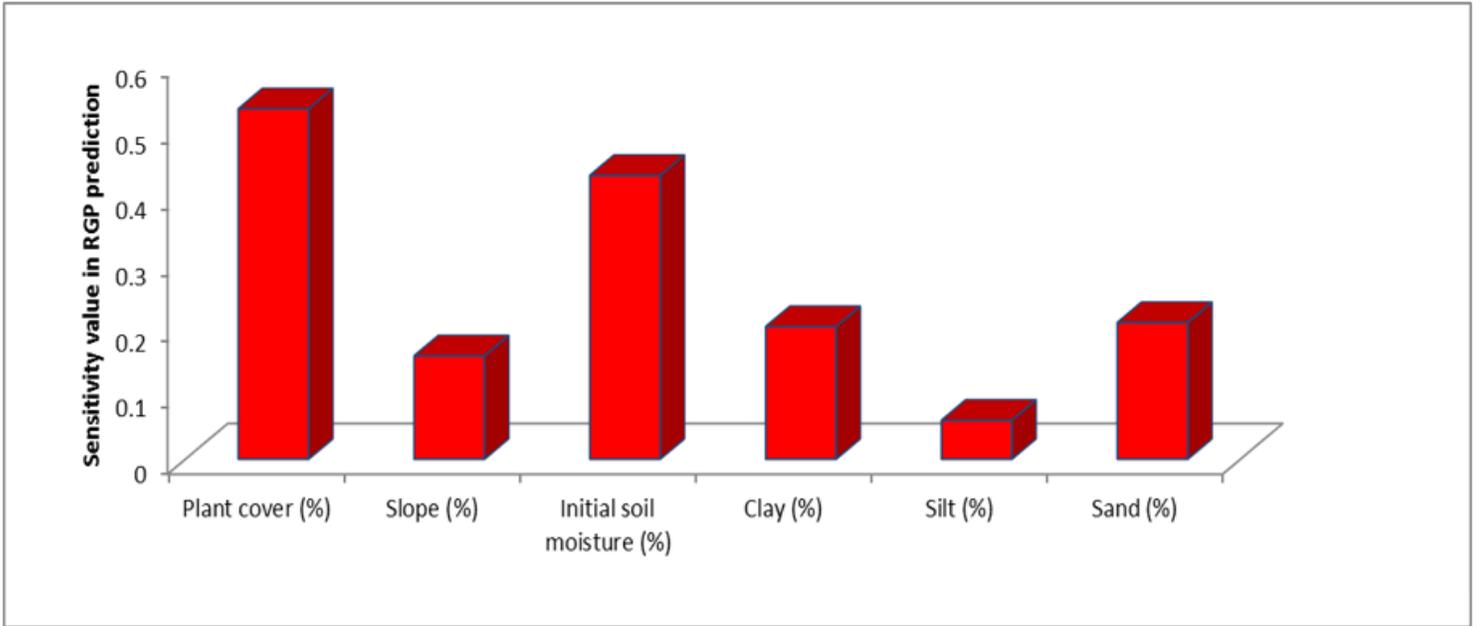


Figure 3

Results of the sensitivity analysis using the tested network for predicting runoff values.

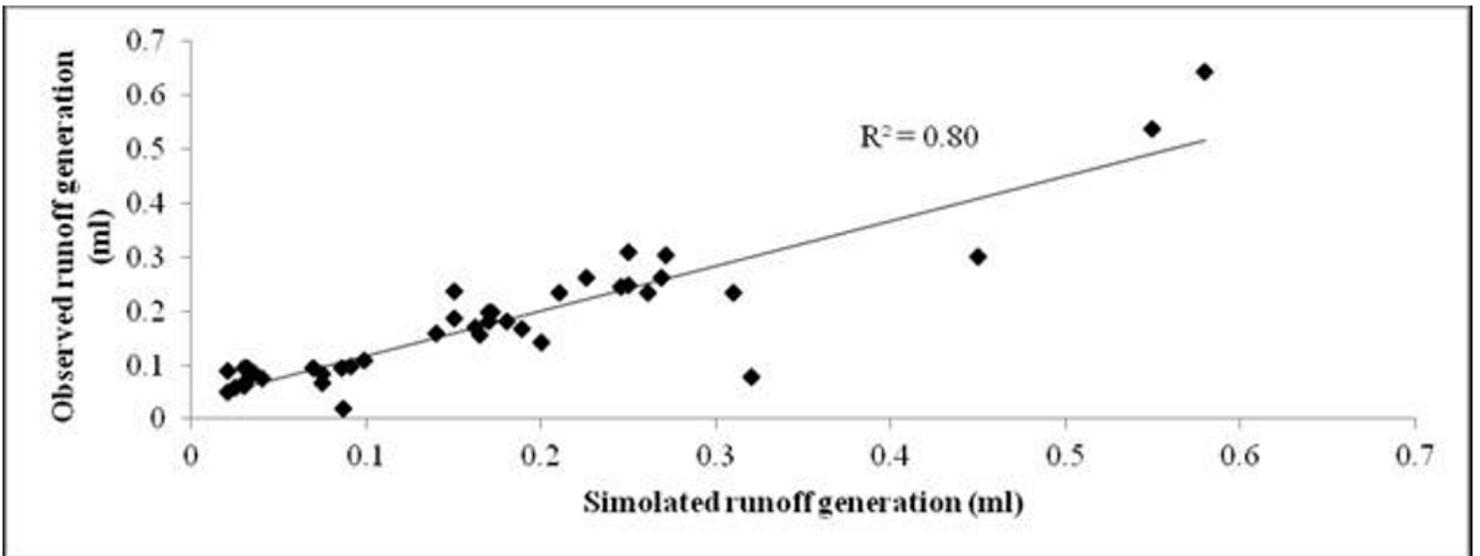


Figure 4

Comparison between the predicted and the observed run off values in the test stage

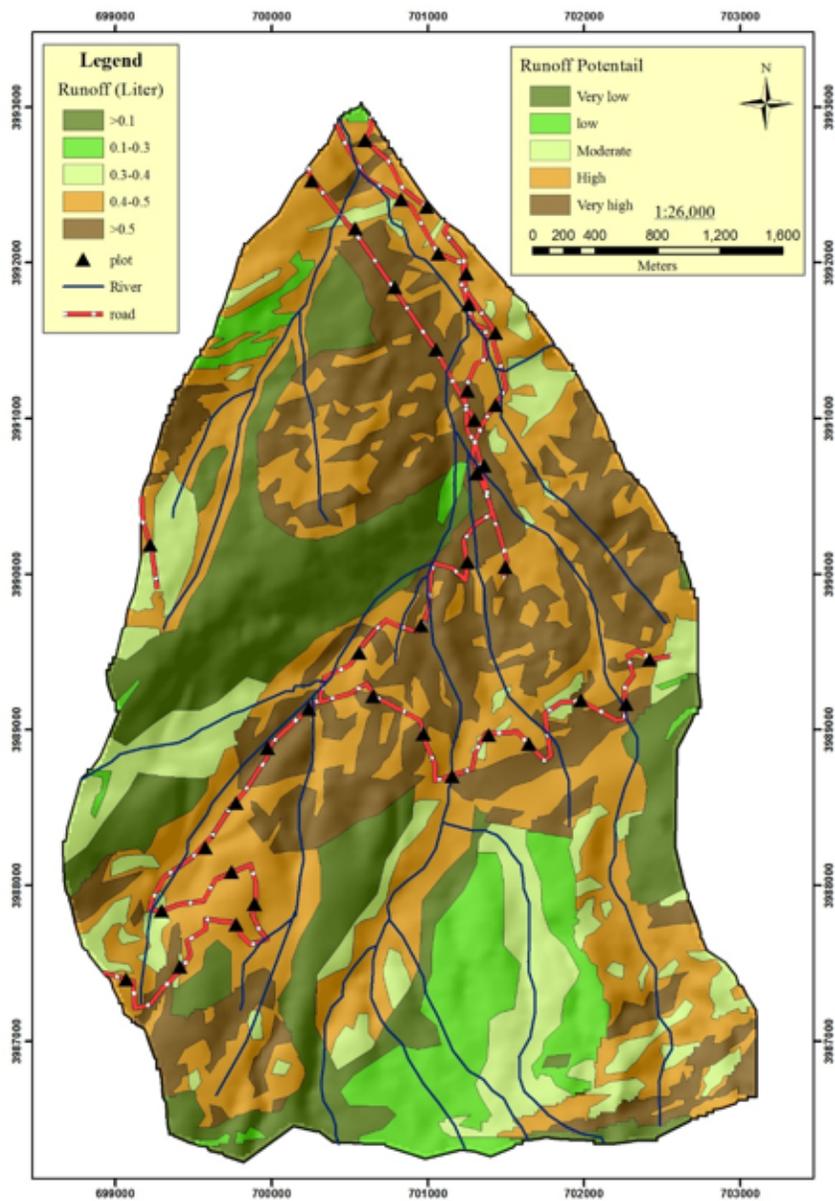


Figure 5

Map of run off values ( $l/m^2$ ) during the designated rainfall ( $T_r=25$  yr) and classification of