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Spatial soil erosion estimation using an artificial neural network (ANN) and field plot data

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ABSTRACT

Soil erosion and sediment transport measurement is a time-consuming and difficult step yet important part of hydrological studies. Hence, use of models has become commonplace in estimating soil erosion and sediment transport. In this study, we used an artificial neural network (ANN) to simulate soil erosion rates. A geographic information system (GIS) was used as a pre-processor and post-processor tool to present the spatial variation of the soil erosion rate. The ANN was trained, optimized and verified using data from the Kasilian watershed located in the northern part of Iran. Field plots were used to estimate soil erosion values on the hillslopes. A Multi Layer Perceptron (MLP) network was adopted, where the soil erosion rate was the output variable and the rainfall intensity and amount, air and soil temperature, soil moisture, vegetation cover and slope were the inputs. After the training process, the network was tested. According to the test results, the ANN can estimate soil erosion with an acceptable level (coefficient of determination = 0.94, mean squared error = 0.04). The verified network and its inputs were used to estimate soil erosion rates on the hillslopes. Finally, a soil erosion rate map was generated based on the results of the verified network and GIS capabilities. The results confirm the high potential when coupling an ANN and a GIS in soil erosion estimation and mapping on the hillslopes.

1. Introduction

The soil is a vital resource for mankind and earth life, but unfortunately, this important resource is endangered due to pollution and erosion. Hence, we need information on erosion and sediment processes to support soil conservation practices (Pierson et al., 2007; Naghdi et al., 2017). However, soil erosion records are limited in the world because erosion and sediment measurements are expensive and time-consuming. Water erosion is the main factor for physical and chemical degradation of soils in humid and semi-arid regions. Runoff occurs when the soil is unable to absorb or store precipitation and can subsequently result in surface and rill erosion (Brodowski and Rejman, 2004). Soil erosion causes undesired effects such as decreasing soil fertility, reduction of vegetation and agriculture production, sediment deposition in for instance water reservoirs, water resources pollution and land degradation (Aldrich et al., 2005; Pierson et al., 2007; Akay et al., 2008; Gholami and Khaleghi, 2013). It is therefore necessary to study soil erosion processes, erosion hazards and define areas with high soil erosion potential as priority areas for conserving the endangered erodible soil.

Past studies showed that soil erosion rate is dependent on different factors such as rainfall (especially rainfall intensity), land cover and landuse, topography, and soil moisture (Pastor and Castro, 1995; Poesen and Hooke, 1997; Martınez-Casasnovas, 1998; Uson, 1998; Pickup and Marks, 2000). On hillslopes, surface runoff and hence soil erosion are influenced by soil type, slope rate and vegetation type and cover (Sachs and Sarah, 2017). In particular, the soil type affects the erosion process (Yair and Lavee, 1974; Naghdi et al., 2017). The role of vegetation and slope is a controversial subject (Masson, 1971). Descroix and Poulenard (1995) observed that the erosion rate increased with slope only below a certain slope threshold (27%). Bohm and Gerold (1995) confirmed the important role of vegetation for soil erosion and found a small effect of the soil texture and slope. Kirkby et al. (2005) found that the soil erosion rate on hillslopes generally is affected by variations in slope and vegetation. Therefore, all important elements influencing soil erosion, such as climate (precipitation) and land use, must be identified prior to erosion modeling (Foster, 2001).

Use of models has become commonplace in estimating soil erosion

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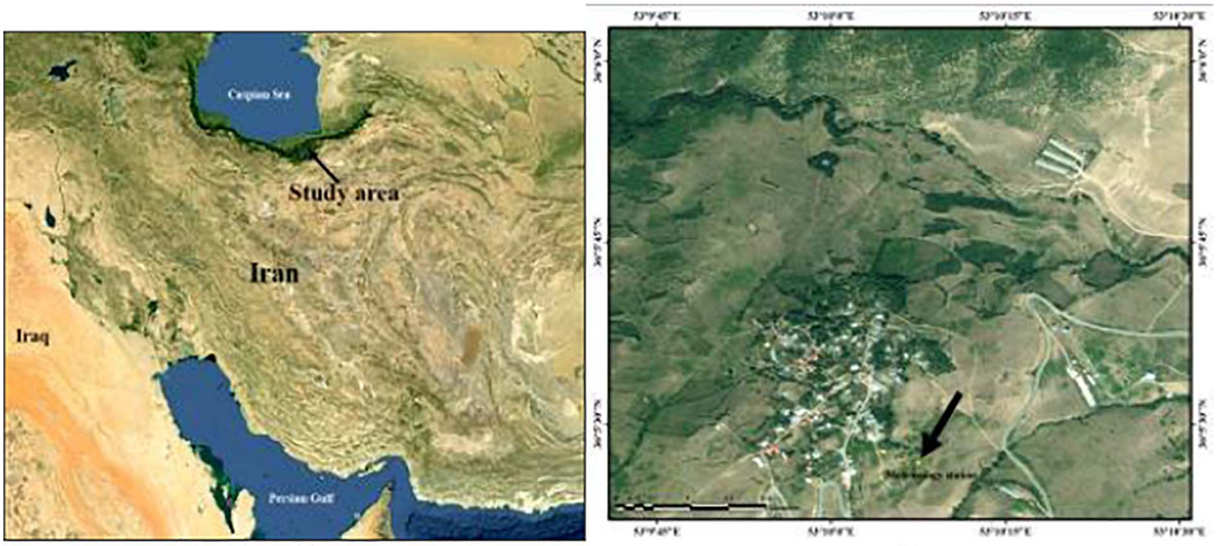


Fig. 1. (a) Location of study area (b) Location of meteorology station, landuse and land cover on the study hillslopes based on the satellite image.

rates. In soil erosion modeling, runoff generation and soil loss evaluations at the plot scale have been of crucial importance. Plot scale studies are useful for the development of new soil erosion modeling methods and they provide access to a high number of up-to-date soil erosion measurements to test new models (Lane and Nearing, 1989; Zhang et al., 1996; Ascough et al., 1997; Nearing et al., 1999). 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, 1978; Renard et al., 1996).

Different techniques have been used to simulate soil erosion and map erosion hazard. One of the new modeling approaches in soil erosion modeling is the use of artificial neural networks (ANNs). Soil erosion measurements cannot perform in all of the study area or for a high number of plots. Further, ANN can estimate hydrological parameters based on filed or observational measurements. Therefore, soil erosion estimations by using ANN can help us to decrease the costs and the studies time and ANN can possible to estimate soil erosion for every place and every time in a short time. Tokar and Johnson (1999) successfully simulated daily runoff for a river in Maryland (USA) with precipitation, temperature, and snowmelt equivalent serving as inputs to an ANN. Further, ANNs have been widely applied in the simulation of hydrologic processes (Isik et al., 2013). Different studies have evaluated ANNs for environmental forecasting (e.g. Anctil and Rat, 2005; Gholami et al., 2017). ASCE (ASCE Task committee on application of artificial neural networks in hydrology, 2000) reported about ANN applications for rainfall-runoff modeling, and reservoir operation, but only a few studies describe results of ANN models in soil erosion evaluation. Rosa et al. (1999) evaluated the interplay between land cover and land use properties and soil erosion by means of expert decision trees and ANNs. Harris and Boardman (1998) applied expert systems and ANNs as an alternative paradigm to mathematical process-based erosion modeling for South Downs in Sussex, England.

The major advantage of neural networks is that they are data driven and do not require restrictive assumptions about the form of the basic model. Neural networks learn from the analyzed data and do not require reprogramming, but they are referred to as black box models. In the modeling process, ANNs should be trained, optimized and tested. Training a neural network model essentially means selecting one model from the set of candidate models. Optimization is the process of adjusting parameters to obtain an optimized set of parameters without violating some constraints. A network performance test is any process that is used to quantitatively or qualitatively measure the performance of a computer network.

In addition, a geographic information system (GIS) is an efficient tool for mapping the soil erosion intensity and other erosion features (Martınez-Casasnovas, 1998; Zhao et al., 2009). Different studies were performed in estimation and mapping soil erosion and sediment, but most of them have different limitations such as a low accuracy or need to a high volume of data (Molla and Sisheber, 2017; Naghdi et al., 2017). However, some studies have investigated the problem of soil erosion using an ANN. An ANN can be used for estimating soil erosion with a high accuracy and in a short time, but the use of its results (without geographic coordinate) will be difficult for other users. On the other hand, GIS is a powerful tool for use in environmental problem solving and in conducting soil erosion modeling. Therefore, in order to develop a model using ANN in a GIS to simulate soil erosion rate, it is very useful to combine an ANN model with the GIS technique. Hence, a coupling ANN to GIS can present the results in a geo-referenced graphic form and usable for all of the users (Dixon, 2004). This methodology can be used in the other areas to estimate soil erosion by using a tested network and coupling to a GIS in order to decrease the cost and time of studies. The objective of the present study is to simulate the soil erosion rate and map erosion hazard (soil erosion zoning) by using data from field plots and an ANN coupled to a GIS. The main innovation of this study is the combination of an ANN and GIS for simulating and mapping soil erosion hazard on hillslopes.

2. Materials and methods

2.1. Study area

The study area is located between 53° 05′ to 53° 10′ E longitude and 36° 05′ to 37° 10′ N latitude in the Mazandaran Province, in northern Iran (Fig. 1). The climate of the study area is semi-humid (Esmaeeli Gholzom and Gholami, 2012). The mean annual precipitation and temperature are approximately 600 mm and 10 °C respectively and precipitation mainly consists of rainfall. Climatic data (precipitation and temperature) are available from the Kaleh meteorological station in the study area (Fig. 1). The study area consists of hillslopes with a slope between 10° to 20° and constitutes a limited area of about 4 km^2. The hillslopes have a soil layer of 60 cm with a clay-loamy texture. Soil studies were conducted for selecting the plot sites (Joel et al., 2002). In general, the hillslopes had the same conditions in terms of soil texture and soil depth.

2.2. Site selection for field plots

It is important to measure soil erosion rates using field plots for the evaluation of model results (Evans, 1995; Licznar and Nearingb, 2003). The first step in measuring soil erosion by field plots is to correctly select the location of the field plots. Next, the affecting environmental factors for soil erosion were determined in the study area. Different landuses and vegetation covers were defined based on satellite images. A high resolution image (Quickbird) was used for providing landuse and land cover maps by visual inspection and field studies. Then, vegetation cover percentage was measured by plotting in the different classes of land cover and vegetation cover. Vegetation cover was visually estimated on 1 m^2 quadrats. Twenty quadrats were used to estimate vegetation cover percentage of every hillslope. The mean of the vegetation cover percentages in the twenty study plots was taken as vegetation cover. Finally, a vegetation map of the study area was constructed using these field data and satellite images. Also, the annual vegetation changes were evaluated on the hillslopes for the study period (September 2014–September 2015). We had four vegetation cover measurements in the four seasons. Moreover, rainfall amount and intensity and air temperature were measured at Kaleh station. A slope map was generated using a Digital Elevation Model (DEM, 10 m resolution) in GIS. The DEM was generated using a topographic map (1:25,000 scale). Air temperature was measured automatically at the meteorological station during the study period and soil moisture was measured once a day (at the plot sites). Soil temperature was measured for each rainfall event (rainy day) at depths of 5 and 50 cm. The sum of precipitation in the preceding five days was considered as Antecedent Moisture Conditions (AMC).

Finally, three sites were selected to establish field plots. Nine plots were established to evaluate soil erosion rates on the hillslopes. The plots have slopes of 10°, 15°, and 20° and each measure 1.8 m × 22 m. We had two types of plots for the studied hillslopes; rocky plots (for one site) and metallic plots (for two sites) delimited by 35 cm high metallic sheets inserted about 10 cm into the soil (Fig. 2). In total, we established nine plots on the three hillslopes (three rocky and six metallic plots). The rocky plots were established due to rock outcrops. Most previous studies have been conducted in sites with metallic plots. Usage of metallic plots is easier. Moreover, the establishment of metallic plots will create the smallest changes in soil structure. We did not aim to compare these two types of plots, but since there were some limitations for establishing metallic plots on some of the hillslopes (because of rock existence, slope fracture and slope hardness) we used rocky plots as well.

2.3. Measurement of soil erosion using plots

Nine plots were established to measure soil erosion on the selected hillslopes (three plots at each site). At the downslope end of each plot was a reservoir for collecting runoff and sediment. A metallic pipe connects the end of the plots to a storage tank. From September 2014 to September 2015, runoff and sediment yield were monitored on the three experimental slopes. Although precipitation mainly consists of rainfall in the study area, we observed several snow days in 2013 to 2015. The resulting soil erosion of snow runoff was not evaluated in this study. Runoff collected from the study plots was measured within a day after each rainfall event, no rainfall-runoff event exceeded the storage capacity of the reservoirs. Moreover, evaporation of the stored runoff was negligible in the tanks (Las Heras et al., 2010). We measured runoff volume and soil erosion after each rainfall event. Afterward, the tanks were emptied for future measurements. The stored runoff was stirred and one liter sample was taken. Then, sediment concentrations were estimated by first oven drying the collected runoff samples and then weighing the sediment. The mean sediment concentration of the three plots was estimated for evaluating the mean soil erosion for the hillslopes. Soil erosion rates were estimated in g/m^2. We measured the soil erosion rates in the study plots for ninety days during the study period (2014–2015). Rainfall amounts and other climatic variables were directly measured by an automatic rain gauge station (Kaleh station) located between the study sites.

2.4. Simulation of soil erosion rates using ANN

In this study, a Multi-Layer Perceptron (MLP) network was applied to simulate the soil loss on the hillslopes. MLPs have been widely used for environmental modeling (Harris and Boardman, 1998; Loh and Tim, 2000) and use a supervised learning technique called back propagation in the training stage. The MLP consists of three main layers (input, hidden and output layers) of nonlinearly-activating nodes. Learning was performed in the perceptron by changing connection weights based on the error values in the comparison with the observed values. We used a feed-forward neural network to estimate the erosion rates. Rainfall and rainfall intensity, antecedent soil moisture, air temperature, soil temperature, soil moisture, slope and vegetation cover were selected as inputs and the erosion rate as the output. Finally, soil erosion rates were estimated for ninety studied days (eighty rainfall events and ten days without precipitation during 2014–2015). We have to use sunny days (days with zero rainfall values) in the modeling process, because otherwise the tested network would estimate soil erosion for days without rainfall or days without runoff. The ANN was applied using NeuroSolutions software. First, we normalized all data and divided the data into two classes: training data (70% of all data), and testing data (30% of all data). A trial-and-error approach was used to determine the optimal structure of the MLP network, the learning technique, and momentum parameter in the training stage (Isik et al., 2013). In the trial-and -error method, one of the network components is varied and the others are kept constant. The ANN performance in soil erosion modeling is evaluated by its accuracy and error values. The optimal network is the network with the optimum components for estimating soil erosion resulting in the smallest errors.

We changed the number of hidden neurons from 1 to 10 to find the optimal number of hidden neurons. The appropriate input parameters were selected by a trial-and-error method, and statistical analysis (determination coefficients). Different input parameters and their influence on model performance were evaluated and compared. Finally, the optimal inputs were selected based on their performance in soil erosion simulation. The initial inputs were rainfall intensity, rainfall amount, vegetation cover, slope, soil moisture, soil temperature and air temperature.

Finally, a MLP with a tangent hyperbolic transfer function, LM learning technique, two hidden neurons, and the optimal inputs was used to train the network for simulating the soil erosion rate. The tangent hyperbolic transfer function (activation function) and the LM learning technique are some of the best selections for hydrologic ANN modeling (Anctil and Rat, 2005). After training and optimization, the network testing was done. Criteria for simulation performance were the mean squared error (MSE), the coefficient of determination (Rsqr) and the mean absolute error (MAE) in the simulation. The mean squared error incorporates both the variance of the estimator and its bias. Minimizing MSE is a key criterion in selecting estimators. The MSE is used to determine the extent to which the model results fit to the data and whether the removal of some explanatory variables, simplifying the model, is possible without significantly harming the model's predictive ability. Rsqr is a measure of how well observed outcomes are replicated by the network based on the proportion of the total variation in the observed outcome explained by the network or model. Further, the mean absolute error (MAE) has a clear interpretation as the average absolute difference between observed and simulated outputs. In the testing stage, the ANN was verified by using MSE, Rsqr and MAE. The MSE, Rsqr and MAE are defined in Eqs. (1), (2) and (3):

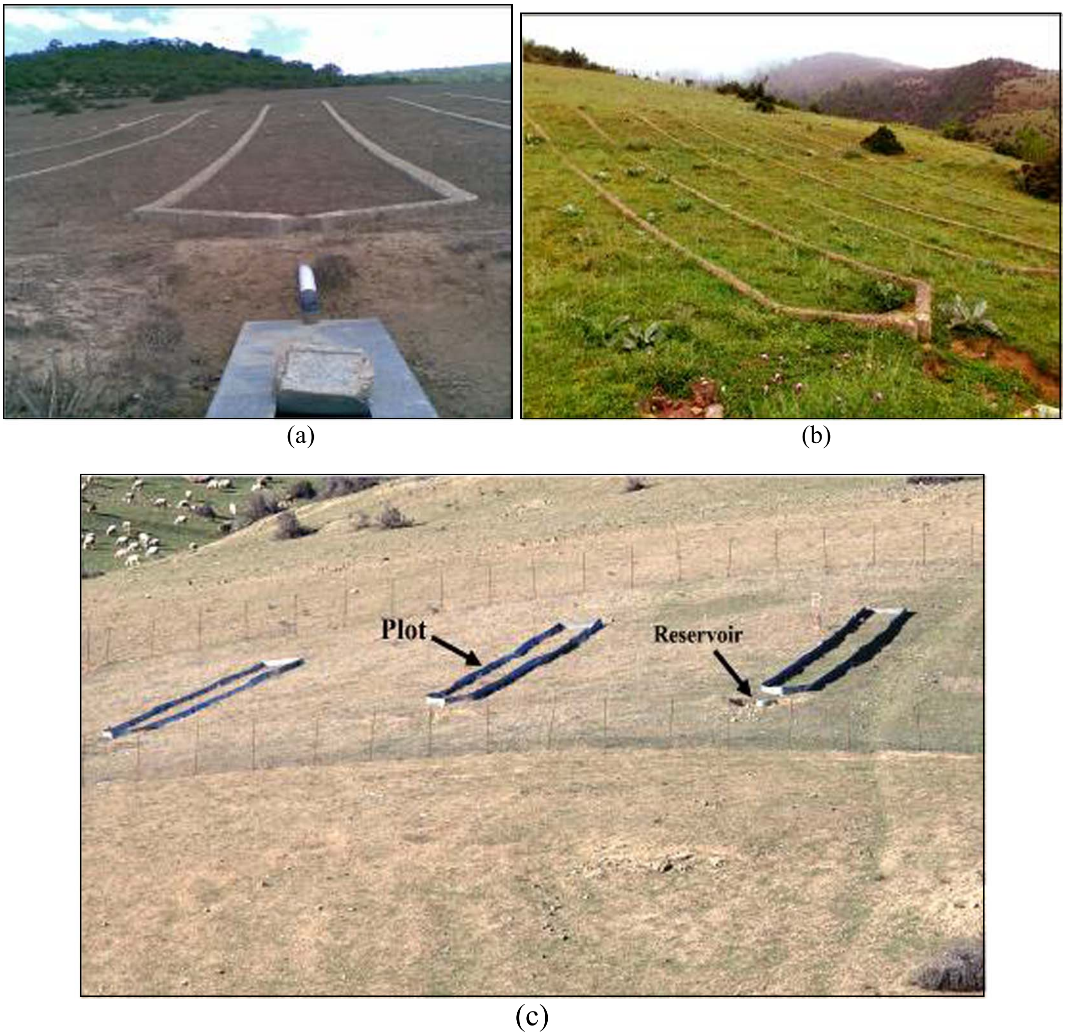


Fig. 2. A view of the plots for soil erosion measurement: (a) winter season (b) spring season (c) metal plots.

$$MSE = \frac{\sum \left(Ei - \hat{Ei}\right)}{n} \tag{1}$$

$$Rsqr = \left[\frac{\sum_{i=1}^{n} (Ei - \overline{E}i).\,(\widehat{E}\mathrm{i} - \widetilde{E}\mathrm{i})}{\sqrt{\sum_{i=1}^{n} (Ei - \overline{Ei})^2.\ \sum_{i=1}^{n} (\widehat{E}\mathrm{i} - \widetilde{E}\mathrm{i})^2}}\right]^2 \tag{2}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n} /Ei - \widehat{E}i/ \tag{3}$$

where E_i is the observed value, $\hat{Ei}$ is the simulated value, $\overline{Ei}$ is the mean of the observed data, $\widetilde{E}i$ is the mean of the simulated data, and n is the number of data points. These criteria were used to evaluate the ANN performance in soil erosion modeling because the inputs and output data were parametric (quantitative) variables, since these criteria are common in model performance evaluation (Krause et al., 2005).

We can use the simulation of erosion rates as a tool for soil erosion mapping and classification and also for estimating daily and annual erosion rates.

2.5. Mapping of soil erosion by coupling ANN and GIS

The verified network was applied to simulate soil erosion rates for days without erosion records. We simulated the daily and annual soil erosion rates by using the verified network and its inputs for the study hillslopes during 2013 (the year without soil erosion measurements). The modeling process of the year 2013 is an example of how to apply the model for an annual simulation. For this purpose, the ANN and GIS were coupled to simulate and map soil erosion rates. The ANN was used for simulating soil erosion values using field plot data and the affecting factors of soil erosion. The geographic information system (GIS) was used for data processing and mapping. The applied data include a digital elevation model (DEM, 10 m), slope values, rainfall amount, rainfall intensity, vegetation cover and air temperature for 15 February 2014 (the rainfall event studied). The rainfall of 15 February 2014 was selected for soil erosion modeling and mapping, since this event was not used in the network modeling and test process. We can estimate and map annual soil erosion or daily soil erosion with coupling ANN and GIS on the hillslopes.

One of the goals of our study was to couple an ANN and GIS to simulate soil erosion rates for hillslopes without erosion rate data. Therefore, raster layers of the five input variables were combined using overlay analysis with a pixel size of 10 m × 10 m and hence the study area was divided into more than 40,000 geo-referenced pixels. Pixel data were transferred from GIS to NeuroSolutions software for erosion rate simulation. The soil erosion rates on the hillslopes were simulated using the verified network for all pixels. Next, the simulated erosion rates were transferred from the ANN back to GIS. A soil erosion rate map was generated using the estimated erosion values and GIS

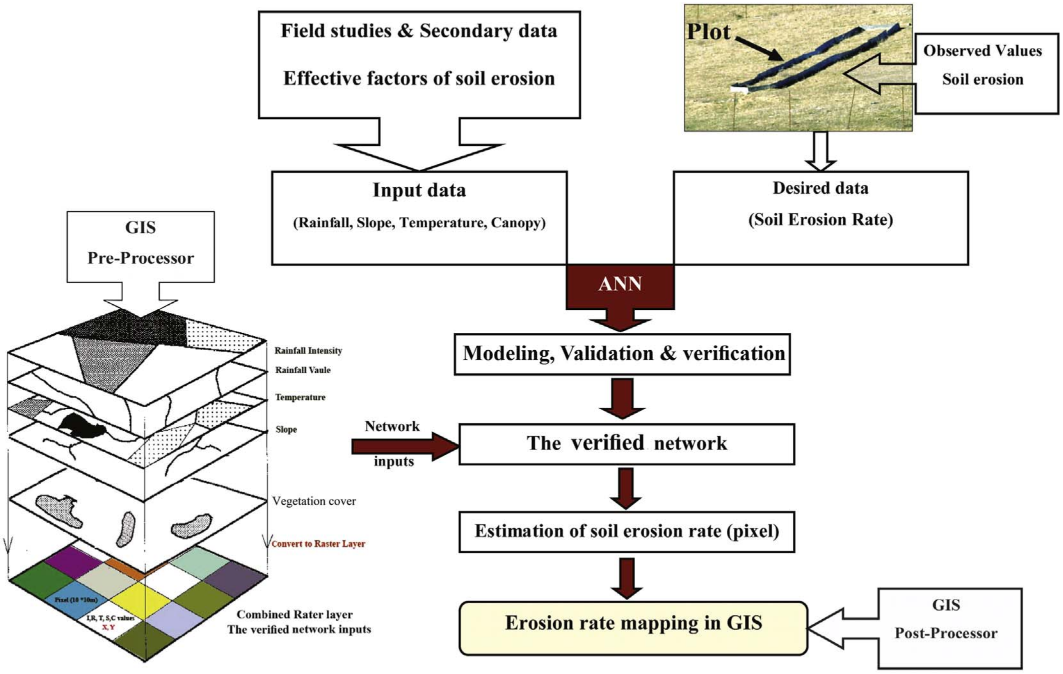


Fig. 3. The flowchart of the methodology stages used for erosion rate estimation and mapping based on the plots observed data, ANN and GIS.

capabilities. Finally, erosion mapping was done after having the ANN classified results in GIS. The different methodological steps are shown in Fig. 3. The ANN performance in soil erosion modeling was evaluated via the stage. The performance of the coupled ANN and GIS was evaluated via overlaying the observed soil erosion values (plot data) on the generated soil erosion map.

3. Results

3.1. Measurement of soil erosion

Soil erosion rates were measured using field plots on the three study hillslopes. A summary of the soil erosion rates and the affecting factors for soil erosion (input and output values of the ANN) is given in Table 1. Table 1 shows the erosion rates in an area 1 m^2 for some studied rainfall events during 2014–2015. We analyzed the relation between soil erosion and the affecting factors by estimating Pearson correlation coefficients between soil erosion rate and the affecting factors. The results in Table 2 show that rainfall intensity and amount, air and soil temperature, soil moisture and vegetation cover are the most important factors for the soil erosion process on the study hillslopes. Rainfall intensity, rainfall amount, and soil temperature have a positive relation with erosion rate and vegetation cover and soil moisture have negative relations. According to the results, the water erosion rates during the study period range from 0 (without rainfall) to 5 g (most severe rainfall) per 1 m^2 for the study plots. The slopes range from 10° to 20° and vegetation cover varies from 10 to 70% on the study hillslopes during the growing season. Also, vegetation can vary a lot during a year (0 to 70%).

3.2. Simulation of soil erosion rates using ANN

The inputs and output data were used to simulate soil erosion rate with the ANN. Rainfall intensity and amount, vegetation cover, slope and air temperature were selected as the optimal inputs for simulating soil erosion rates (based on network optimization results).The soil temperature can be used as an efficient input in simulating soil erosion, but a network with soil temperature as input could not be used when coupling the network to a GIS since we did not have soil temperature data for the complete study area for all days. The training network gave good results (Rsqr = 0.95), and the error values (MSE) in the training stage were less than 0.004 (g). According to these results, acceptable outcomes during the training stage were obtained (see Table 3).

Moreover, a sensitivity analysis was carried out for evaluating the suitability of the inputs. The results of the sensitivity analysis in Fig. 4 and statistical analysis show that rainfall intensity is the most important input for soil erosion rate simulation. Moreover, the trial-and-error method results showed that vegetation cover, slope and air and soil temperature are suitable inputs for simulating soil erosion using an ANN as well.

After network training and optimization, we carried out the verification (test) stage for the optimized network. This was conducted through the comparison between the measured values (plots) and the simulated soil erosion rates, and the results are shown in Fig. 5 and Table 4. Fig. 5 shows the comparison between the soil erosion rates in an area of 1 m^2 and the simulated soil erosion rates using the verified network. According to the results (Fig. 5), the simulated values of soil erosion are close to observed values (Rsqr = 0.88). Therefore, according to the error values in Tables 3 and 4, the verified network can be used for simulating soil erosion rates. Past studies confirm the efficiency of ANNs in simulating soil erosion and other environmental variables (Samani et al., 2007). Moreover, Fig. 6 shows the relation between soil erosion rates and rainfall intensity for (a) observed and (b) simulated soil erosion rates. It is observed that these relations are similar for the observed data and simulated data. Then, the verified optimum network was used to estimate soil erosion values for days or events without erosion data (during 2013, a year with a minimum amount of snowfall). In fact, this simulation is an example of how to apply the model for soil erosion simulation (daily, monthly or annual).

3.3. Coupling ANN and GIS

The MLP network estimated soil erosion rates for each pixel and the GIS was used to process the input data and map the soil erosion rate such as in Fig. 7. The optimized network performance was confirmed in soil erosion modeling in the test stage. According to the results, the presented network can estimate soil erosion with an acceptable level. Further, coupling ANN and GIS performance were evaluated via

Table 1
Network inputs and outputs for simulating soil erosion rates for some of the ninety studied rainfall events.

Soil erosion (g/m^2)	T_{air} (C°)	T_{soil} (C°) (depth 50 cm)	Soil moisture (%)	Rainfall (mm)	AMC (mm)	Rainfall intensity (mm/h)	Slope°	Vegetation cover (%)
0.088	13.67	10.01	33.07	1.2	0	1.2	10	15
2.32	2.4	14.1	32.1	18	53.7	1.22	20	15
4.625	− 0.6	5.1	29.7	10.5	25.2	11.5	20	10
4.438	12.16	17.12	28.36	10.2	39.5	7	20	15
3.13	8.91	17.04	28.12	46.3	15.5	6.61	10	15
0.86	1.1	12.4	31	1.1	48	1	10	15
0.075	1.2	11.8	31	1.5	23.2	1	10	10
0.021	18.2	18.7	23.4	0.5	109.8	1.1	10	50
2.063	4.96	15.78	31.32	12.8	70.7	4	20	15
3.645	8.91	17.04	28.12	46.3	15.5	6.41	20	15
2.04	11.44	17.8	25.92	11.6	61	8	10	15
4.23	− 0.6	5.1	29.7	11.3	32.8	13.1	10	10
0.03	8.44	13.5	37	18.3	27.5	3.2	10	70
0.86	1.1	12.4	31	1.1	48	1	20	15
1.23	2.4	14.1	32.1	18	53.7	1.22	10	15
3.291	8.91	17.04	28.12	45.3	15.5	6.61	10	15
4.333	14.63	17.97	24.45	35.1	0	5.83	20	15
0.22	10.3	7.4	32.9	0.5	5	1	20	40
0	1.5	9.9	30.1	0	24.8	0	10	10
0.333	1.2	11.8	31	1.5	23.2	1	20	10
0.059	13.67	10.01	33.07	1.2	0	1.2	20	15
1.36	4.8	14.4	30.6	14.5	39.2	4.5	10	15
0.76	10.3	7.4	32.9	0.5	5	1	10	40
4.452	− 0.6	5.1	29.7	9.6	34.8	10.5	10	10
2.407	11.44	17.8	25.92	8.3	61	8	10	15
4.28	11.44	17.8	25.92	8.3	66	10	20	15
2.74	4.8	14.4	30.6	16	41	4.8	20	15
5.176	− 0.6	5.1	29.7	9	30.4	13.5	20	10
1.871	4.96	15.78	31.32	13.9	70.7	3.8	20	15
1.36	12.16	17.12	28.36	10.2	39.5	7	10	15
1.76	14.63	17.97	24.45	35.1	0	5.83	10	15
0	1.9	9.1	30.7	0	56.3	0	20	10
4.417	12.16	17.12	28.36	12	36.4	6.6	20	15
0	12.9	3.5	36.2	0	43.8	0	20	25
2.862	8.91	17.04	28.12	45.6	15.5	6.61	20	15
2.163	2.4	14.1	32.1	16.8	45.7	1.36	20	15
0.52	17.1	18.6	21	1.2	61.3	2.4	10	60
4.046	11.44	17.8	25.92	8.3	61	8	20	15
2.229	4.8	14.4	30.6	14.5	39.2	4.5	20	15
1.25	4.8	14.4	30.6	13.5	29.6	4.4	10	15
1.09	4.96	15.78	31.32	13.9	70.7	4	10	15

overlying the observed values (filed plot data) on the generated soil erosion map in Fig. 7. As can be seen in Fig. 7, the presented methodology could provide an acceptable simulation (via the comparison between observed and simulated values at the plots sites) for estimating and classifying the soil erosion rate. Coupling of ANN and GIS can estimate soil erosion within a short time and with low costs. Moreover, the method can be applied again where plot data embracing major factor variability are available.

4. Discussion

We evaluated the relationships between soil erosion rate and the affecting factors in soil erosion. In erosion and sediment studies, it is important to select the most important inputs for modeling. Statistical analysis and network optimization showed that rainfall intensity, rainfall amount, slope, air temperature and vegetation cover are the best inputs for soil erosion rate modeling. Previous studies similarly

Table 3
Results of network training for simulating soil erosion rates.

Criteria $N = 63$	Soil erosion estimation (g)
MSE	0.004
MAE (mean absolute error)	2.2
Min abs error	0.07
Max abs error	6.7
Rsqr	0.95

Table 2
The Pearson correlation matrix between soil erosion and the factors affecting soil erosion.

	Soil erosion	Rainfall intensity	Rainfall amount	Soil temperature	Soil moisture	Air temperature	AMC	Vegetation cover	Slope
Rainfall intensity	0.91	x	0.58	0.04	0.41	− 0.15	0.12	− 0.3	0.02
Rainfall amount	0.64	0.58	x	0.16	0.29	− 0.04	− 0.05	− 0.21	0.02
Soil temperature	0.3	0.28	0.46	x	− 0.68	0.48	0.43	0.3	0.03
Soil moisture	− 0.39	0.41	0.29	− 0.45	x	− 0.37	0.28	− 0.07	− 0.00
Air temperature	− 0.3	− 0.15	− 0.04	0.79	− 0.37	x	0.11	0.6	− 0.01
AMC	0.09	0.12	− 0.06	− 0.05	0.28	0.11	x	0.22	0.02
Vegetation cover	− 0.37	− 0.3	− 0.2	0.32	− 0.07	0.6	0.22	x	− 0.02
Slope	0.15	0.02	0.02	− 0.003	− 0.005	− 0.01	0.02	− 0.02	x

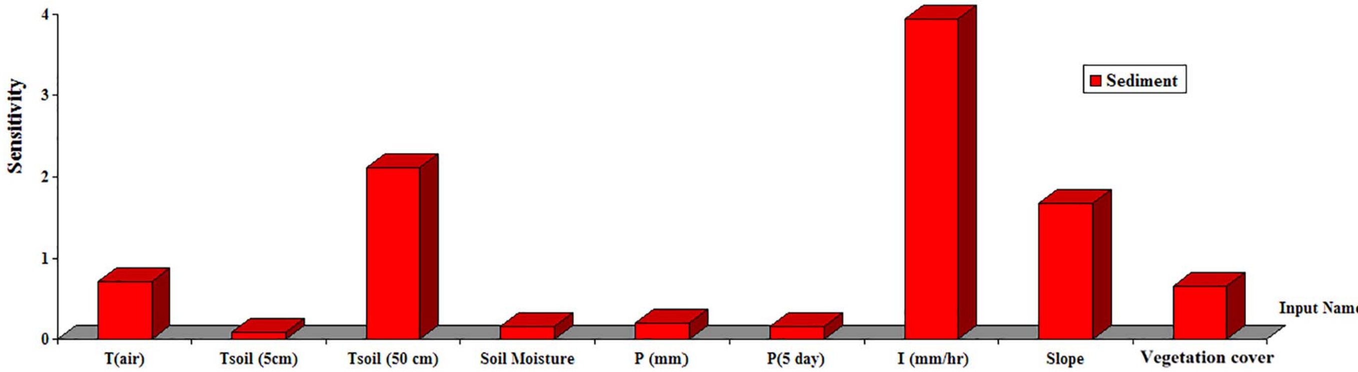


Fig. 4. Results of the sensitivity analysis using the tested network for soil erosion estimating and mapping.

showed that water erosion was affected by rainfall characteristics, vegetation, slope and soil moisture conditions (Keim et al., 2006; Yanosek et al., 2006; Cattan et al., 2009; Davies et al., 2011). According to the statistical analysis the factors rainfall intensity, rainfall amount and slope have a positive relation with soil erosion rates and air temperature and vegetation have a negative relation with soil erosion (Table 2). The most important factor for soil erosion on the hillslope is rainfall intensity ($R = 0.91$). Rainfall values cannot be used as an alternative for rainfall intensity in the modeling process, because rainfall intensity is the most effective factor in soil erosion (splash erosion).

Furthermore, slope and vegetation changes are determinative factors for soil erosion on the hillslopes, but vegetation changes are notable especially during a year (Sun et al., 2016). Therefore, vegetation has a higher correlation and a more dominant influence on soil erosion in the study area (Table 2). Vegetation cover has an inverse relation with soil erosion rate. A high Slope changes are not observed in the study area. Therefore, its correlation with soil erosion is low. According to Table 2, the most important factors for soil erosion are rainfall intensity and rainfall amount. Soil moisture is an effective factor for runoff generation and hence for soil erosion as well (Table 2). The results showed that soil erosion rates (splash erosion) will be higher for a dry soil than for a wet soil. The soil temperature is dependent on the air temperature and, therefore, the air temperature is the determining factor for the soil temperature as well as the antecedent soil moisture conditions and runoff generation potential. The results (Pearson correlation coefficients) showed that air temperature has a significant relation with erosion rates in the study area. We had better data on air temperature in comparison to soil moisture. Soil moisture was not a suitable input for soil erosion modeling and mapping, because we had limitations in providing a soil moisture map in the study area. Instead, we could easily simulate the spatial variation of temperature based on climatological station data using an interpolation technique in the study area.

Table 4
Results of the optimized network for simulating soil erosion rates in the testing phase.

Criteria $N = 27$	Soil erosion estimation (g)
MSE	0.04
MAE	2.90
Min abs error	0.08
Max abs error	8.42
Rsqr	0.88

In the modeling process, an ANN was used to simulate soil erosion rates using the affecting factors in the soil erosion process as inputs. The results of the training and testing showed that an ANN can be used as an

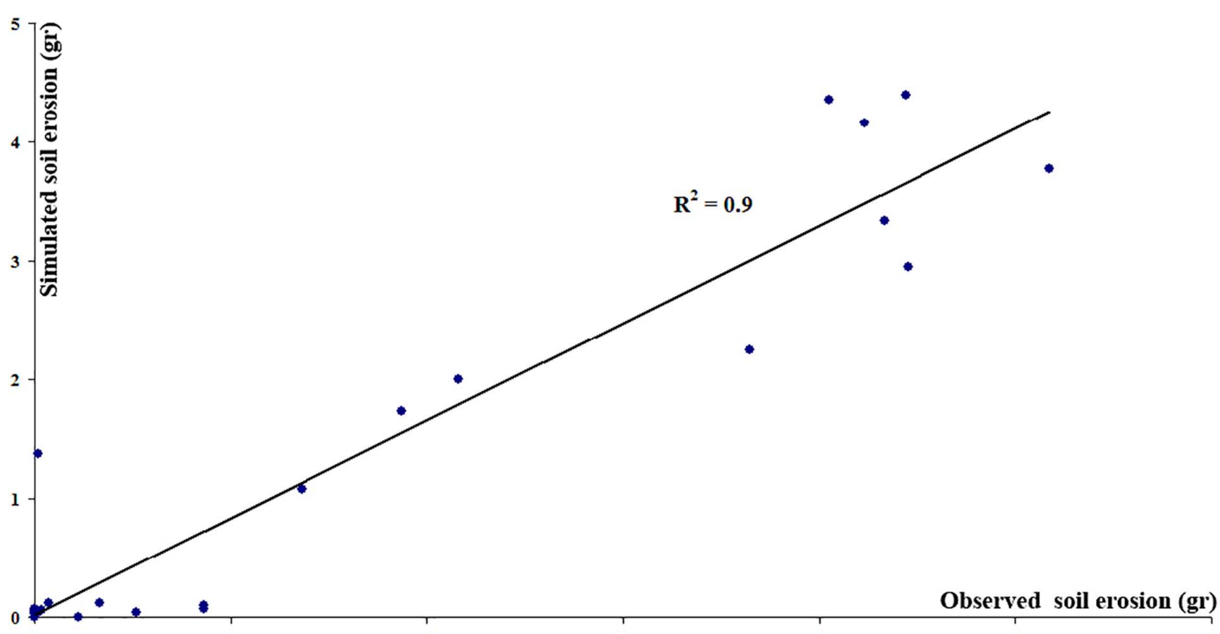
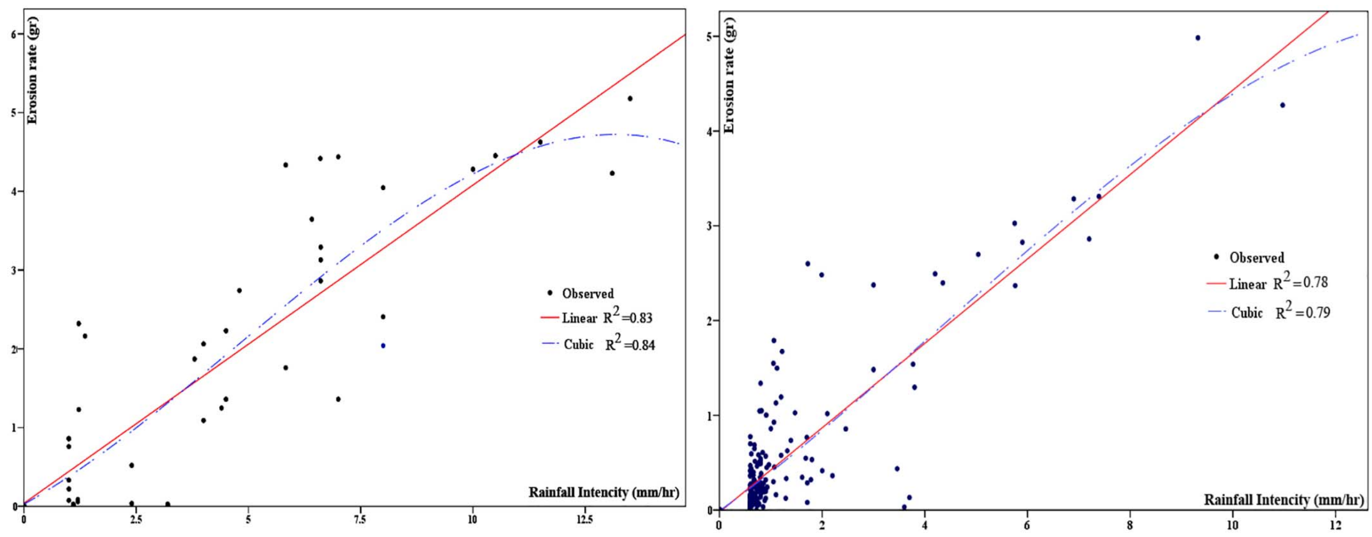


Fig. 5. Comparison between observed and simulated soil erosion (gram per m^2) in the test stage (sample or rainfall events = 27).



(a) (b)

Fig. 6. The relation between rainfall intensity and soil erosion (in an area 10 m^2) based on observed soil erosion (a) and simulated soil erosion (b) for the year 2013 using the tested network.

efficient tool in simulating erosion and sediment processes. We also used the tested network for simulating the soil erosion during 2013 (a year without field measurements). The modeling results can be used for mapping erosion rates for locations without data. An ANN can simulate soil erosion rate with a high accuracy, but cannot be used to estimate the inputs or map spatial patterns of inputs. Hence, we also used a GIS to map the spatial distribution of the verified network outputs. The erosion rate map shows the spatial erosion intensity in the studied area. Moreover, the resulting map can be used to classify soil erosion intensity for planning and managing soil and land use and conservation. The accuracy and efficiency of the coupling of an ANN and GIS are dependent on the accuracy of the input data and the selection of appropriate input factors for the network. Moreover, we will not have any limitation in defining the study area or in selecting pixel sizes, but these selections should be evaluated according to the study conditions (the changes of inputs and output data) and the accuracy and correctness of data (Gholami et al., 2016). Coupling an ANN and GIS in soil erosion modeling has different advantages for researchers such as (a) a decrease of the estimation costs (b) a decrease of the estimation time (c) estimation of soil erosion at ungauged (Gholami et al., 2016) locations (d) presentation of the modeling results to all users (e) creation of overlying and combining capabilities with the other data.

5. Conclusions

The results of this study show that coupling of an ANN and GIS can

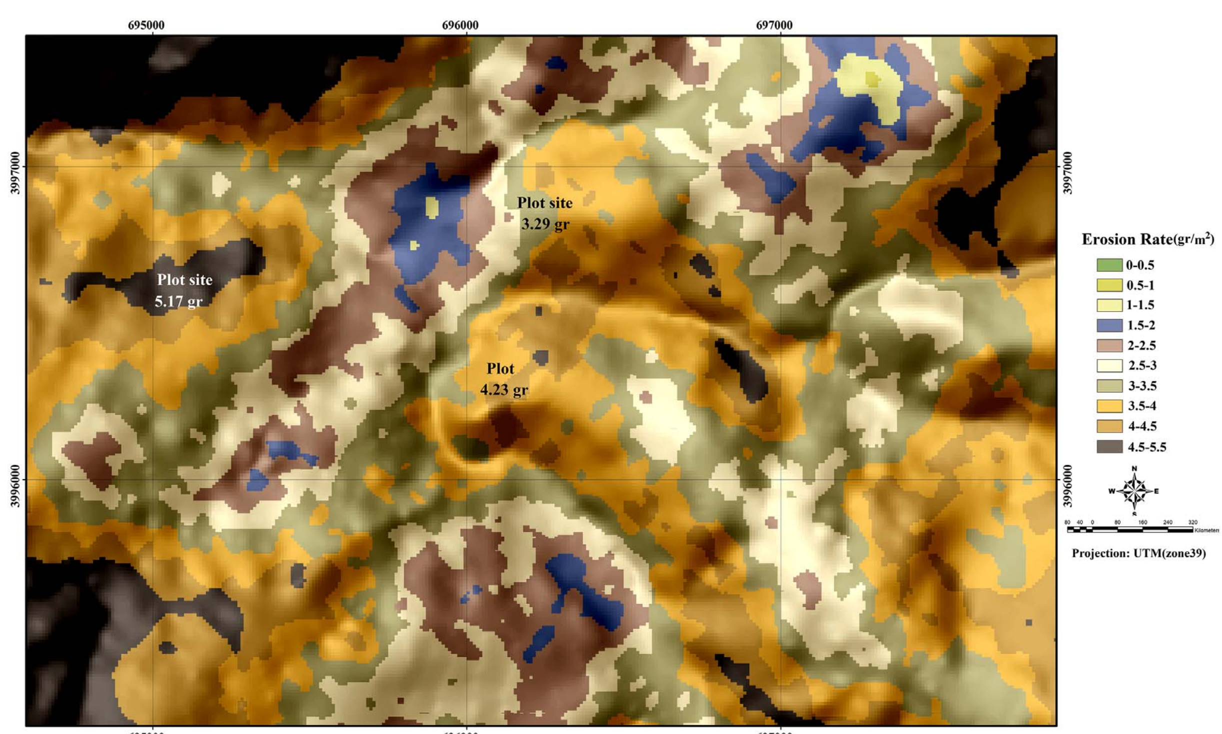


Fig. 7. Map of soil erosion rate (g/m^2) for the rainfall event of 15 February 2014.

be applied for modeling and mapping soil erosion at different time scales (daily and annual soil erosion). Rainfall intensity is the most important factor for soil erosion on the hillslopes. Moreover, slope, vegetation cover, soil moisture and temperature are other important factors as well. An ANN is a black box model, where the user has not any knowledge about its internal functioning. Soil erosion rates can be estimated for other hillslopes using the optimized ANN network and observed soil erosion data. The most important advantage of ANN in soil erosion estimation is the high accuracy and high calculation speed. It is clear that coupling of an ANN and GIS can be used to estimate soil erosion during rainfall storms, but we need plots to monitor surface and rill erosion (Las Heras et al., 2010). The accuracy of the input and output data are the most important determinative factors for the modeling accuracy and efficiency. A GIS can help us to map the spatial distribution of the input parameters and the simulated soil erosion rates. The coupled ANN and GIS can be used for zoning soil erosion hazard and as a tool for planning in soil conservation practices. We suggest that future studies should be done using a larger number of plots with different slope gradients and land use types and more intense rainfall events.

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