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Variation of USLE-K Soil Erodibility Factor and Its Estimation with Artificial Neural Network Approach in Semi-humid Environmental Condition

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HIGHLIGHTS

- Neural network technique uses extensively in soil science.
- The K-factor, which has a direct effect on the erosion susceptibility of soils, was calculated.

Abstract: Soil erosion is the most important soil degradation process threatening arid, semi-arid and semi-humid areas. In this current study, in order to determine the susceptibility of micro basin soils in Çorum province with semi-humid ecological conditions to erosion, some physico-chemical soil properties such as organic matter, sand, silt, clay, bulk density and hydraulic conductivity factors that closely affect soil erosion (USLE-K factor) were determined. For that aim, soil erodibility values were determined for soil samples taken from surface depth (0-20 cm) of the micro basin. In addition, ANN approach was used to estimate the availability of this parameter in similar ecological conditions and spatial distribution of erosion susceptibility maps for the current micro basin were produced with the results obtained. The neural network's input parameters included organic matter, bulk density, hydraulic conductivity, sand, silt, and clay. The output parameter chosen was erodibility. R2 values of 0.81509 for the test, 0.99 for the training, 0.95 for the validation value, and 0.99 for all values were achieved when taking into account the results of the artificial neural network study.

Keywords: Artificial Neural Network; Erodibility; Soil; K-Factor.

INTRODUCTION

Soils are losing their sustainability daily due to the increase in urbanization, excessive agricultural practices to get more efficiency from the unit area, the effect of global warming, and the rise in desertification and erosion. Soil, considered only a production material by many people in the world, is defined by scientists as a living, dynamic entity that lives and keeps it alive [1]. However, it is gradually disappearing due to not taking the necessary precautions, excessive misuse, and not being effectively protected against natural factors [2]. Soil erosion was defined by Ellison (1947) [3] as the process of erosion and transport of soil-forming materials by factors that cause erosion. Turkey's geographical location, topography, climate, and soil conditions increase the effect of erosion. Apart from these, one of the causes of erosion comes to the forefront as human activities. Especially the destruction of natural vegetation, industrialization, urbanization, inappropriate land use, and overuse of pastures are the main factors that increase erosion [4]. When human activities accelerate natural processes that cause soil erosion, soil erosion threatens the sustainability of natural resources [5-7].

Soil erosion is one of the most important ecological problems and is one of the most critical factors that destroy natural resources. Kanar and Dengiz (2015) [2] emphasized that vegetative soil protection methods should be noted to reduce the sensitivity of soils to erosion, increase the value of stable aggregates, and decrease the K factor value, which expresses sensitivity to erosion. This is because vegetative soil protection methods support the microbiological structure and improve the soil structure, making the soil more resistant to erosion. Accordingly, Jiang and coauthors (2020) [8] reported that the volume weight measured in shrub and forest areas is due to vegetation and organic matter density. At the same time, they reported that it is higher than terracing agricultural lands and slope agricultural lands. On the other hand, Wang and coauthors, (2014) [9] stated that the clay, sand, and silt contents of soils are very effective on hydraulic conductivity. This situation significantly affects soil erosion because there is a significant relationship between the water content of soils and erosion. The higher the silt and sand ratio in the soil, the higher the potential erodibility. This situation reveals how effective the soil texture's effectiveness on erodibility [10]. Soil texture affects permeability significantly, and soils with low permeability cannot sufficiently absorb the incoming water and cause surface runoff by dragging soil particles along with them.

Recently, ANN has been widely used in agriculture as well as in many fields (health field, defense industry, communication, fault analysis and detection, automation and control, control of robot systems, nonlinear system modeling and control) [11]. An artificial Neural Network (ANN) is designed with the principle of simulating biological neural networks [12-13]. The neural network can use different numbers of hidden layers, neurons, and other transfer functions between layers [14-15]. Artificial neural networks can be defined as “a computer program created for a mathematical formula that will adapt the parameters with the help of a set of examples.” [16]. While all neurons in neural networks can receive one or more input data, they produce only one output data [17]. This output can be used as an output or input in another artificial neuron [18]. D'Emilio and coauthors (2018) [19], in their study, aimed to evaluate the accuracy of the ANN by applying the van Genuchten model parameters with a large and variable soil properties data set and to reveal the ANN structure that shows the best prediction performance for the soil water retention curve by using the evaluation parameters; Clay, sand, silt and organic carbon from soil properties were used as input data. According to the results from the study conducted to simulate the water retention of soils, the high predictive performance was estimated with MAE=0.026 and RMSE=0.069 accuracy. The AIC efficiency criterion revealed that the ANN model with the highest accuracy was trained with fewer input nodes than the others. In another study, the soil quality status was calculated with the Analytical Hierarchy Method; the soil quality status was found that when the soil parameters pH, EC, lime, texture, phosphorus, potassium, and nitrogen are estimated by ANN as input data, it can be estimated with an accuracy of R2=0.99 [20].

In this study, the K factor, which has a direct effect on the erosion susceptibility of soils, was calculated with the results obtained from the analysis. Then, it is aimed to simulate the K factor by using these results (clay, silt, sand, organic matter, bulk weight, hydraulic conductivity) as input parameters in the artificial neural network. Recently, predictive engineering has reached a fundamental level in agriculture, as in many other fields, and in this context, the use of artificial neural networks has become widespread [21]. Despite the increasing number of studies using ANN in agriculture, the studies carried out to evaluate the sensitivity of soil erosion are insufficient. This study on the high-accuracy estimation of erodibility with the help of artificial neural networks will make an important contribution to the literature.

MATERIAL AND METHODS

Field Description

The present research was conducted at the micro catchment in the Çorum province located in the north of Turkey and in the central part of the Black Sea region (Figure 1). This micro catchment is coordinated between 645000–663000E and 44850000–4510000N (WGS84, Zone36N, Universal Transverse Mercator-UTM). The total study area is about 21001.7 ha.

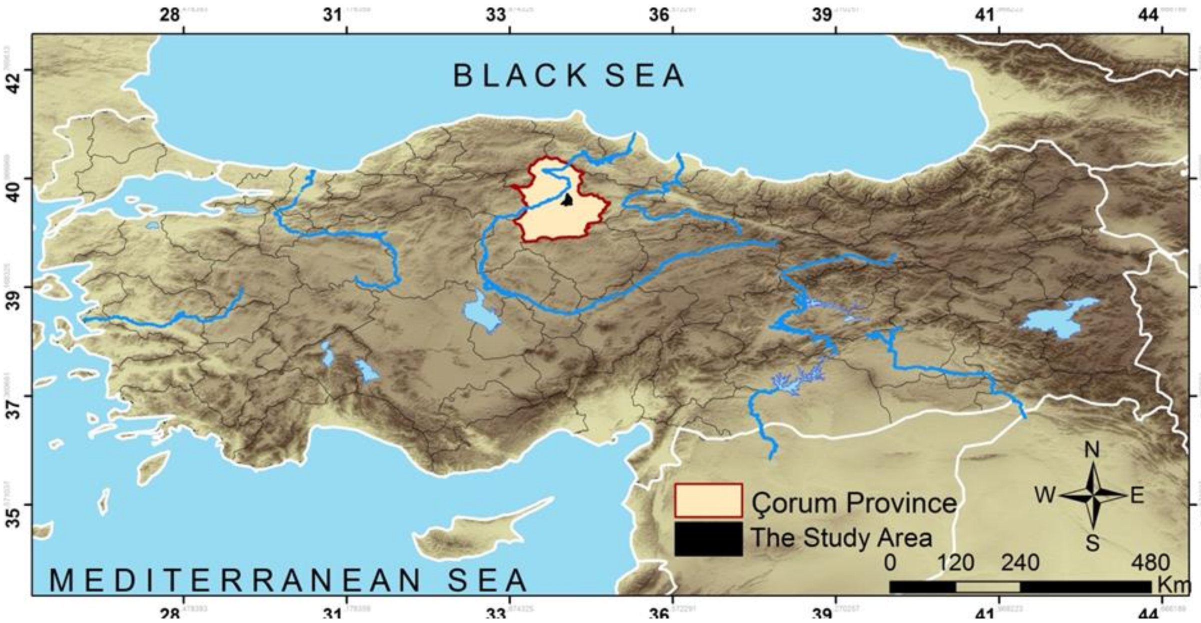

Figure 1. Location map of the study area

The lowest and the highest elevations of the stud area are 746 m and 1781 m (a.s.m.l). In mountainous areas in the north west sides, the elevation rises above 1600 meters with steep slope (>45%), whereas southeast part of the study area has low and gently slopes (0%-6%). In addition, most of the study area has south east and southwest aspects while some of the southern regions have north and northwest aspects (Figure 2).

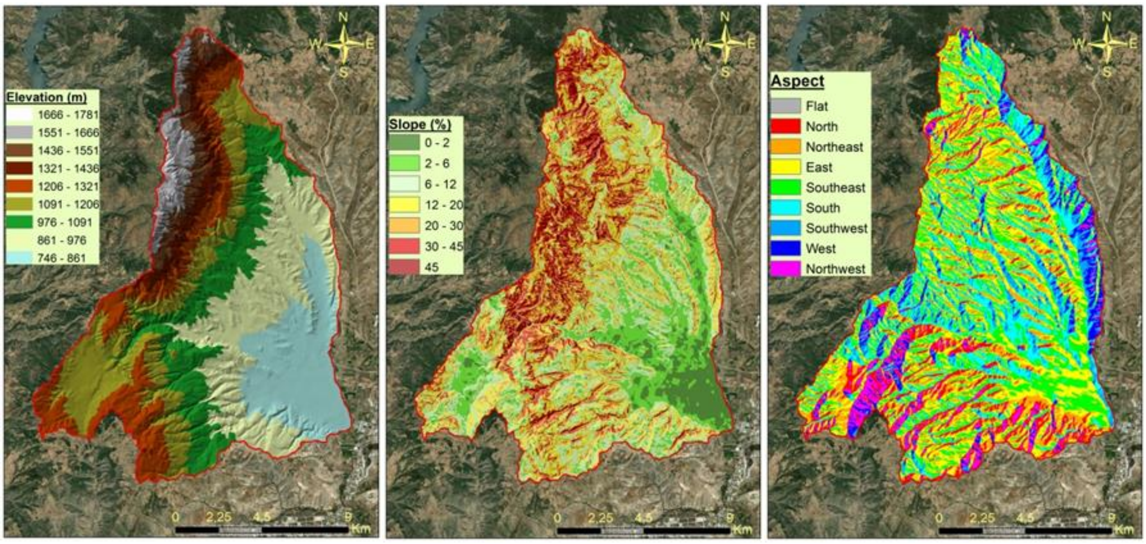

Figure 2. Elevation, slope and aspect maps of the study area

According to Corum meteorology station (long term data between 1981 and 2021) located in the research area, the average annual precipitation and heat are 443.7 mm and 10.7°C. According to Boluk (2016) [22], the study area falls into the sub-humid class with 25.21 score of precipitation activity index based on Erinc's macro climatic regions in Turkey. In addition, with respect to the Newhall simulation model, the soil moisture and temperature regimes of the study area were found as Xeric and Mesic [23].

Soil Sampling and Analysis

To determine the physical and chemical properties of the soils taken from each point where the study was carried out, 33 soil samples were taken from 0-20 cm depth (Figure 3). Soil samples were dried in the laboratory. These dried samples were prepared for analysis by passing through a 2 mm sieve.

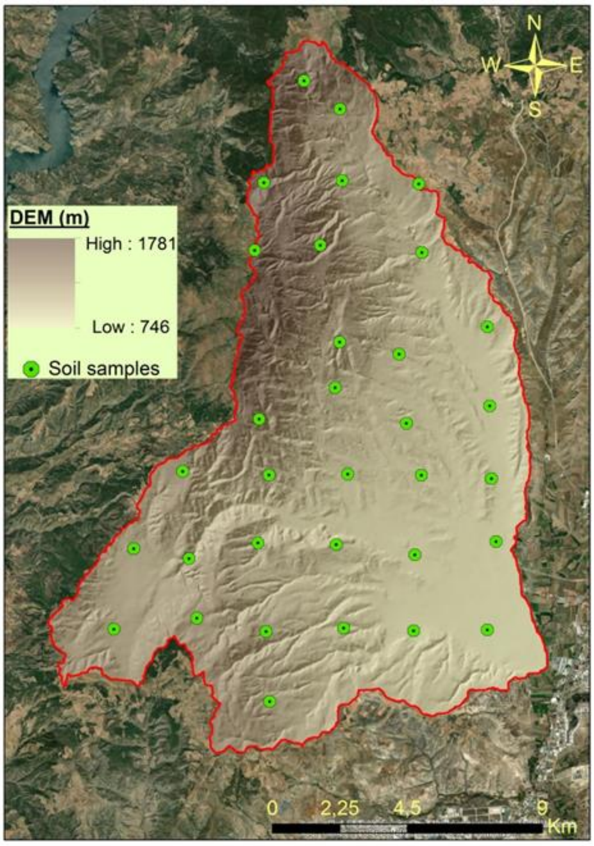

Figure 3. Soil sample pattern (DEM: Digital Elevation Model)

The soil samples determined particle size distribution (clay, silt, sand) according to Bouyoucos Method [24]. The bulk density was determined according to the cylinder method [25]. Organic matter content was determined by the Walkley-Black method [26]. The hydraulic conductivity value is determined in accordance with the Klute and Dirksen method [27].

Soil Erodibility Factor (K)

The USLE (Universal Soil Loss Equation) method is based on finding a result by multiplying the relations between various factors such as precipitation, soil erosion feature, slope status, vegetation cover, and soil protection that affect erosion [28]. The Equation (1) given below calculates the Soil Erodibility Factor (K)

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$$K = \frac{1}{100}\{2.1x10^{-4}x(12 - OM)x[SIx(SA + SI)]^{1.14} + 2.5x(PE - 3).25x(ST - 2)\}$$

Where; K: ta h ha-1 MJ MM-1, OM: Organic Matter, SI: Silt content, SA: Sand content, PE: permeability, ST: Structure.

Statistical Analysis

In each of the 33 soil samples taken from the study area, 6 different soil properties were examined and descriptive statistical analyses of these properties were made with SPSS program (SPSS 23).

Data set and Artificial Neural Network

Artificial neural networks mimic the biological neural structure of the human brain in general; It is a system that uses previously learned or classified information with the support of neural sensors and can create new knowledge in line with this information and make decisions [29]. The task of an artificial neural network is to produce an output in response to the information given to it as input (Figure 4 and Figure 5).

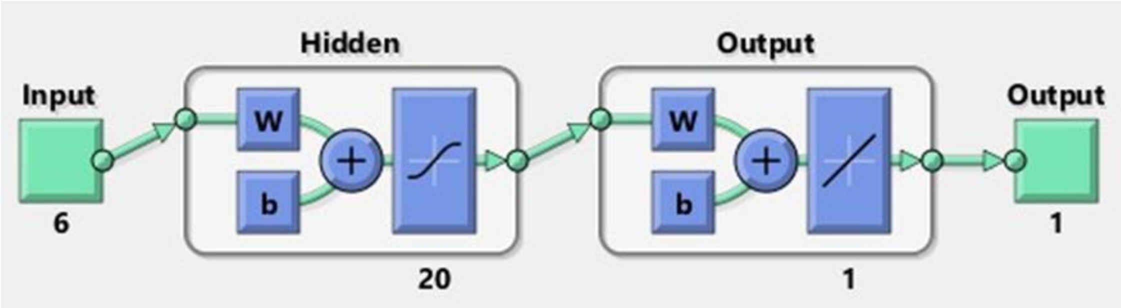

Figure 4. Single hidden layer network model

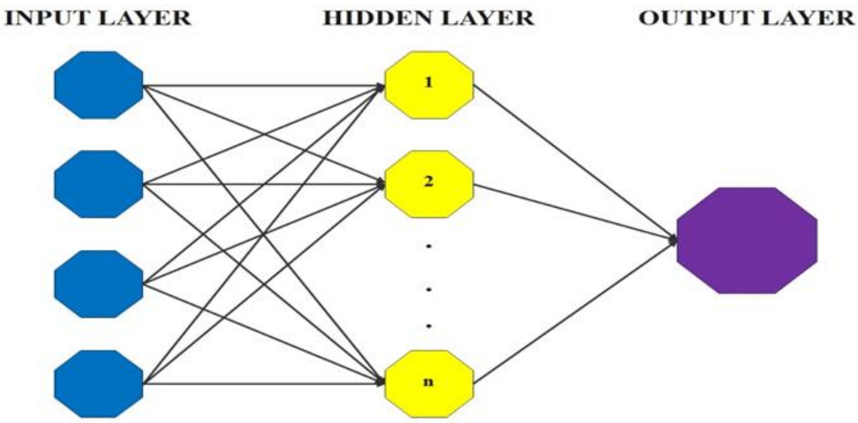

Figure 5. The typical structure of ANN.

The network is first trained with specific examples. Then the network reaches the level of generalization and decision-making. Then, it determines the outputs with this acquired ability. ANN uses data and results related to real-life problems in its learning and prediction processes. The variable factors associated with the real-life problem space constitute the input series of the ANN, and the real-life results obtained with these variables include the target output series that the ANN should reach [20]. The artificial neural network model used the organic matter content, clay, silt, sand, volume weight, and hydraulic conductivity values of soil samples taken from 33 different places as input parameters. The Levenberg-Marquardt function was used to estimate the erodibility (output parameter). The best results were found in 2 hidden layers and 20 neurons.

Following model training and testing, the ANN has been shown to be an effective model for complicated data computation. The network appears to produce highly accurate predictions based on the R values. The mean-squared-error (MSE), the coefficient of determination, and other statistical measures (R2) are defined as follows equations.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(Y^{i.mod} - Y^{i.exp})^2$$

$$R^2 = 1 - \frac{\frac{1}{n}\sum_{i=1}^{n}(Y^{i.mod} - Y^{i.exp})^2}{\sum_{i=1}^{n}(Y^{i.mod} - Y)^2}$$

Generating spatial maps

Based on cross-validation statistics [30, 31], the two methods of interpolation, inverse distance weighting (IDW), Radial Base Function (RBF) and kriging, were compared by taking into consideration of the lowest root mean square error (RMSE) values and the best interpolation method was used to map the calculated values in Current-K and ANN-K in each scenario using ArcGIS software 10.5v.

RESULTS AND DISCUSSION

According to statistical analysis, soil samples contain 28.42% - 79.43% sand, 12.62% - 54.88% silt and 3.88% - 54.18% clay (Table 1). The hydraulic conductivity value, which is significantly affected by the soil texture, varies between 0.05 cm h-1 and 10.60 cm h-1, with an mean of 1.80 cm h-1. The water content of the soil is one of the main factors affecting the transport of soil particles by water and wind [32]. According to a large amount of literature information, the water content is higher in soils with higher clay content than sand and silt contents [33, 34]. This depends on the relationship between the pores and the water molecules. Clay soils can hold more water than sandy soils because their micropores have a greater electrical charge [35]. The organic matter content of the soils varies between 0.96% and 5.31%, with an average of 2.52%. In arid climates, the high temperature and low precipitation increase the decomposition of organic matter in the soil, disrupt the aggregate structure, disperse the soil particles and cause the soil structure to deteriorate. The bulk density values of the soils vary between 1.34 g cm-3 and 1.57 g cm-3 depending on the ratio of organic matter, sand, and clay content.

According to the results, all values show a right-skewed (+) distribution, away from the normal distribution. The feature with the highest skewness coefficient and the furthest distribution from the normal was determined as silt with 1.68. The data show that organic matter, silt, and hydraulic conductivity curves have a steeper (+) distribution than the normal distribution, in contrast to soil properties' clay, sand, and volume weight curves. The coefficient of variability (CV) is an essential factor when defining the instability of soil properties in the region [36]. Coefficient of variation; It is divided into three classes as low (< 15%), medium (15-35%), and high (> 35%). In this direction, bulk density coefficient of variation from soil properties of the study area is low while the organic matter, clay, silt, and sand have medium variation. On the other hand, hydraulic conductivity coefficient of variation has the highest coefficient of variation (Table 1).

Table 1. Descriptive statistics of some properties of soil sample.

Parameters	**Mean**	**SD**	**CV**	**Variance**	**Min.**	**Max.**	**Skewness**	**Kurtosis**
OM (%)	2.52	1.00	39.68	1.01	0.96	5.31	0.77	0.40
Clay (%)	27.16	13.39	49.30	179.55	3.88	54.18	0.01	-0.82
Silt (%)	25.92	8.79	33.91	77.32	12.62	54.88	1.68	4.37
Sand (%)	46.91	14.11	30.07	199.33	28.42	79.43	0.75	-0.20
BD (g cm^{-3})	1.44	0.06	4.16	0.004	1.34	1.57	0.04	-0.78
HC (cm h^{-1})	1.80	2.21	122.77	4.90	0.05	10.60	2.26	6.72

OM: Organic Matter, BD: Bulk Density, HC: Hydraulic onductivity, SD: Standard Deviation, CV: Coefficient of Variation, Min: Minimum, Max: Maximum.

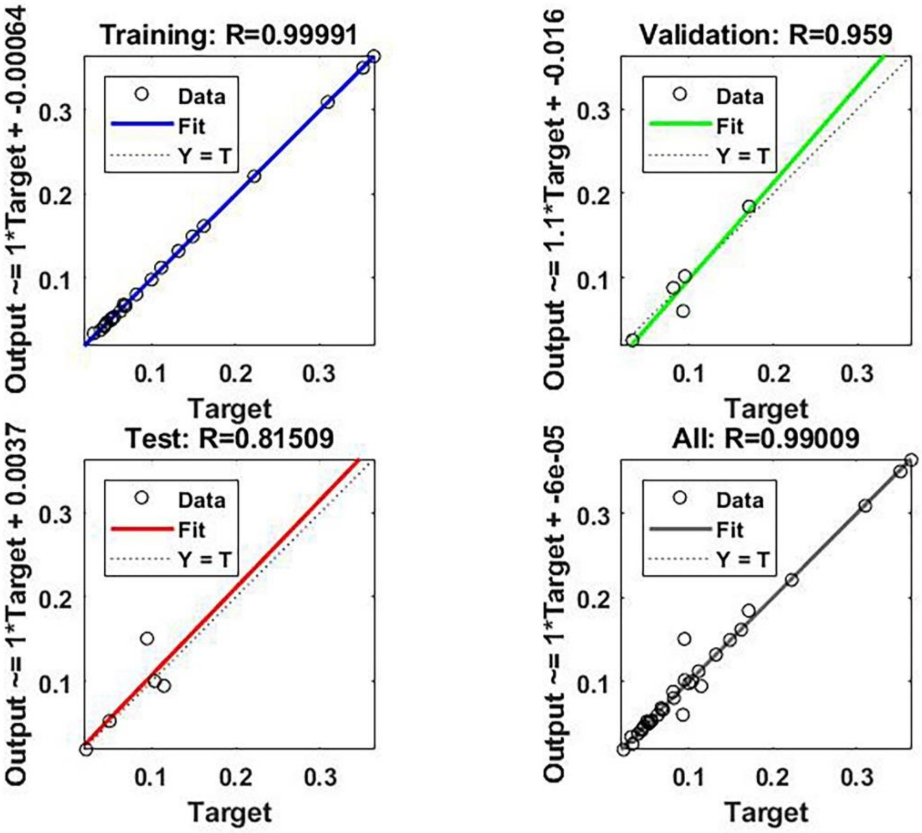

Figure 6. Results of regression between output data and targets for the Levenberg-Marquardt approach.

Organic matter, bulk density, hydraulic conductivity, sand, silt, and clay were used as input parameters in the neural network. On the other hand, erodibility was used as an output parameter. Considering the R^2 values obtained from the artificial neural network analysis, values of 0.81509 for the test, 0.99 for the training, 0.95 for the validation value, and 0.99 for all values were obtained. Considering these values, the artificial neural network model predicts erodibility as an output parameter with 99% accuracy (Figure 6).

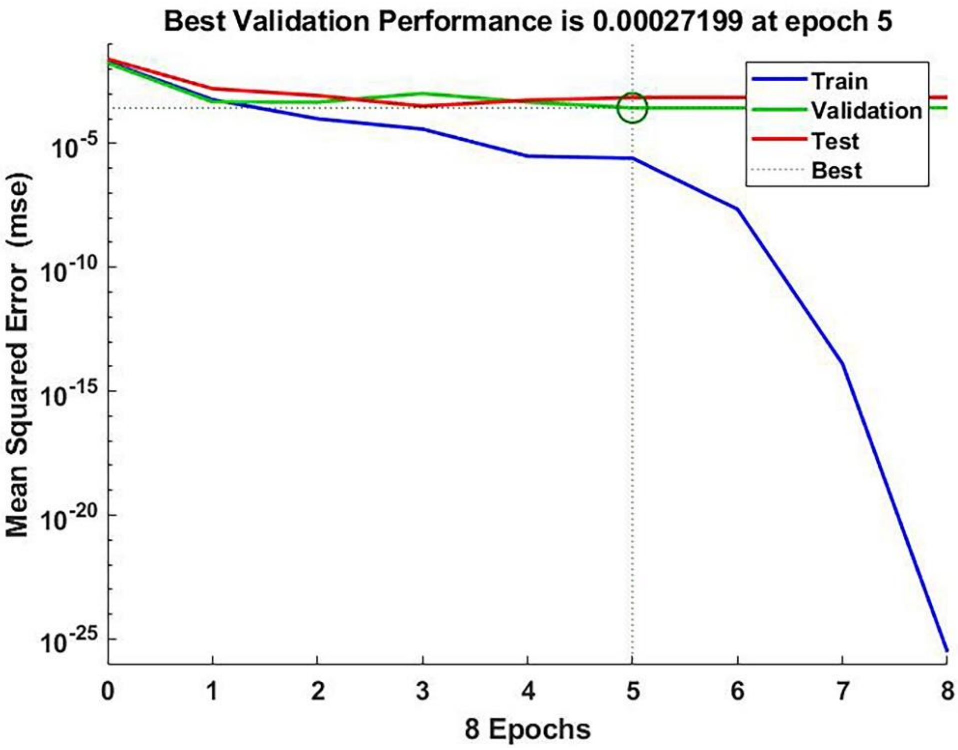

Figure 7. Graph of Levenberg-Marquardt combination performance.

The ANN used eight epochs during the data estimation process and showed the best validation performance with the lowest mean square error in the 5th epoch with 0.00027199 (Figure 7). The value of the performance function in relation to the number of iterations is displayed on the performance plot. Epochs are used to describe each repetition of the entire training set. Every epoch, the network modifies the weights in a way that minimizes the error. Before training is finished, often many epochs are needed. A rise in the MSE (Mean Square Error) of the validation samples indicates that generalization has come to an end, and training has therefore automatically stopped. While 0 indicates no error, lower numbers are preferable. To determine the correlation between outputs and targets, regression analysis was used. The network outputs and the targets would be exactly equal if the training were flawless, but in reality, the relationship is rarely ideal (Figure 5).

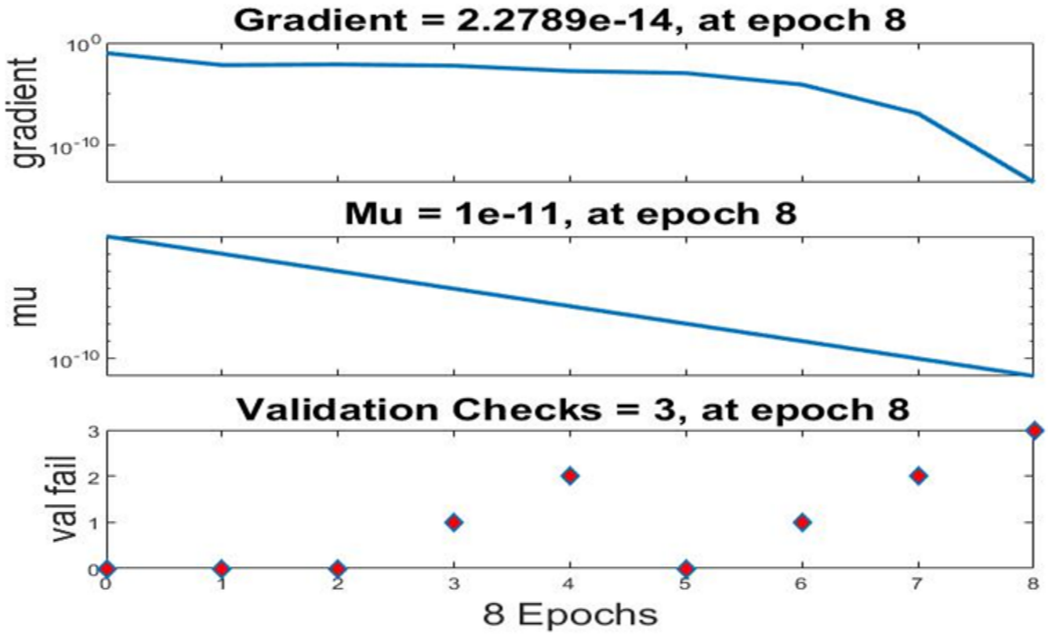

Figure 8. Graph of educational status parameters of erodobility factors.

When Figure 8 is examined, each iteration sees the gradient values of the estimated network values. Depending on the inverse proportion between the gradient value and the epoch number, as the epoch number increases, the gradient value decreases. Artificial Neural Networks have the feature of completing their training early according to the mean square error of the validation data or the gradient value of the training data, without completing the number of iterations. The generated code was run in MATLAB to determine the best model for the outcome, and Figure 8 shows the plot of the best resulting network based on the average performance of training and test errors with the number of training epochs. It can be seen that as the network is trained, the large values for the network decrease to a smaller value.

When the results obtained are examined, it is seen that the Validation checks value is 3. When the validation checks graph is examined, it is seen that the K-factor values calculated using soil parameters and the K-factor values estimated by the network overlap with 99% accuracy. This situation reveals that the Artificial Neural Network makes predictions with very high accuracy.

Table 2. Calculated K-factor value and estimated K-factor values with ANN.

Sample No	Current_K	ANN_K	Sample No	Current_K	ANN_K	Sample No	K	ANN_K
1	0.031	0.034	12	0.040	0.038	23	0.095	0.151
2	0.047	0.047	13	0.063	0.060	24	0.132	0.132
3	0.033	0.026	14	0.069	0.067	25	0.365	0.364
4	0.050	0.053	15	0.082	0.081	26	0.162	0.162
5	0.056	0.054	16	0.095	0.102	27	0.171	0.185
6	0.055	0.054	17	0.068	0.066	28	0.081	0.088
7	0.093	0.061	18	0.044	0.044	29	0.222	0.221
8	0.067	0.069	19	0.104	0.100	30	0.112	0.112
9	0.052	0.050	20	0.022	0.019	31	0.352	0.350
10	0.100	0.098	21	0.115	0.095	32	0.149	0.150
11	0.044	0.042	22	0.052	0.052	33	0.310	0.309

We identified the best appropriate distribution models for the USLE-K values at each point using various interpolation techniques in order to create a spatial distribution map for Current-K and ANN-K in the micro catchment. The RMSE values for interpolation models are shown in Table 2. Accordingly, the lowest RMSE values were observed for the spherical model of Simple Kriging model in both Current-K and ANN-K (Table 3).

Table 3. Interpolation models and RMSE values of Current-K and ANN-K

Interpolation	Semivariogram model		Current-K	ANN-K
IDW	IDW-1		0,0951	0,0957
	IDW-2		0,0937	0,0941
	IDW-3		0,0942	0,0943
RBF	TPS		0,1142	0,1138
	CRS		0,0933	0,0931
	SWT		0,0933	0,0931
Kriging	Ordinary	Gaussian	0,0902	0,0901
		Exponential	0,0906	0,0900
		Spherical	0,0898	0,0904
	Simple	Gaussian	0,0857	0,0859
		Exponential	0,0866	0,0872
		Spherical	**0,0850**	**0,0851**
	Universal	Gaussian	0,0902	0,0901
		Exponential	0,0906	0,0900
		Spherical	0,0898	0,0904

TPS: Thin Plate Spline, CRS: Completely Regularized Spline, SWT: Spline with Tension

Spatial distribution maps are given in Figure 9. Accordingly, the spatial distributions were quite similar between the Current-K and ANN K values. It can be seen that north part of the study area has low erodobility values whereas K value is decreasing in the south and southeast regions of the micro basin especially due to high silt and poor organic matter content.

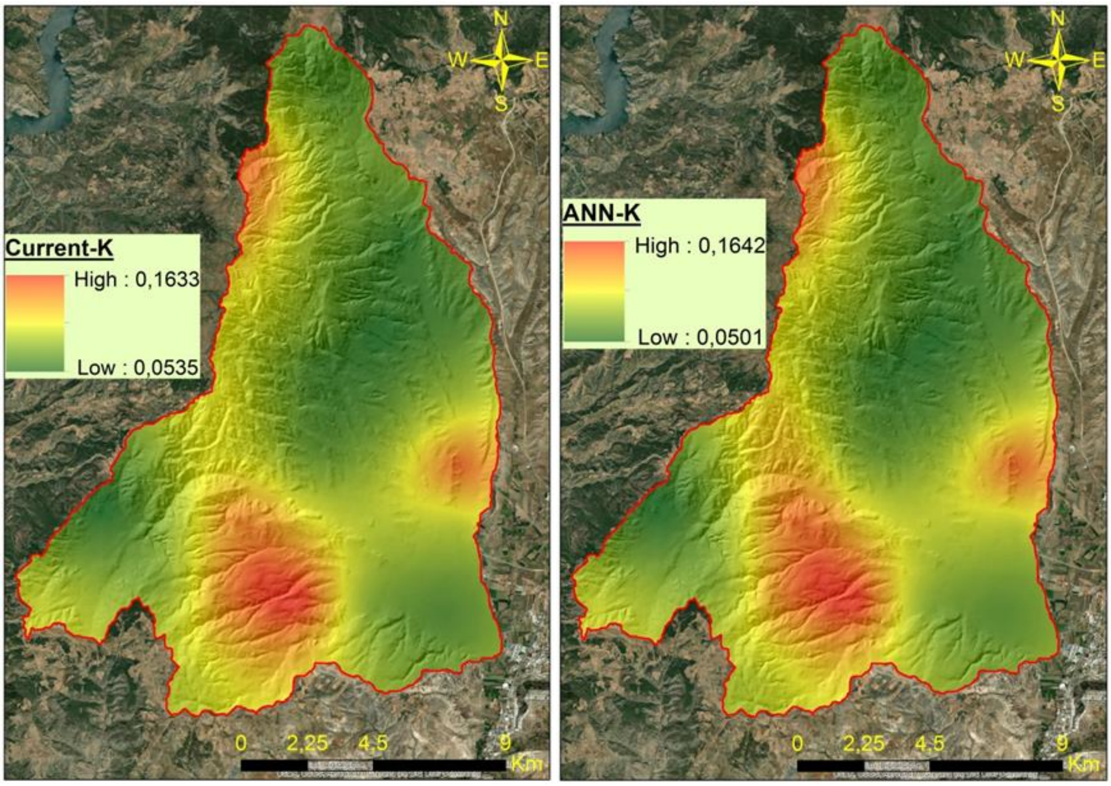

Figure 9. Spatial distribution maps of Current-K and ANN- K

CONCLUSION

In this current study, in order to determine the susceptibility of micro basin soils in Çorum province with semi-humid ecological conditions to erosion, some physico-chemical soil properties such as organic matter, sand, silt, clay, bulk density and hydraulic conductivity factors that closely affect soil erosion (USLE-K factor) were determined. In addition, ANN approach was used to estimate the availability of this parameter in similar ecological conditions and spatial distribution maps of the current micro basin were produced with the results obtained. In the results obtained, both current and ANN K values and the map available in the numerical data and the spatial distribution pattern, as well as the ANN data and the map showed that they were quite close to each other.

Although most of the investigated soils are in the sandy class, a significant part is in the clay class. Since the amount of organic matter in the study area is also variable, the volume weights of the soils also differ. The decrease in crust formation at the points with high organic matter content in the soil and the decrease in sensitivity to erosion by increasing aggregation cause the K-factor to be lower than at the other points. Similarly, the K-factor was found to be low at the points where the amount of clay is high. In the artificial neural network, organic matter, sand, silt, clay, bulk weight, and hydraulic conductivity values were used as input, and the calculated K-factor was used as the target. According to the result obtained from the model, a very high estimation rate was determined, with the ANN-K-factor being 99%. In addition, it is thought that the findings obtained in this study will make significant scientific contributions to the studies on erosion.

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Conflicts of Interest: “The authors declare no conflict of interest.”

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