



Calibrating the WEPP model to predict soil loss for some calcareous soils

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Abstract

Accurate soil loss prediction at the regional scale is necessary for a better understanding of the soil erosion processes and conservation practices. This study aimed to calibrate the WEPP model for predicting soil loss under semi-arid region conditions in the northwest of Iran. Inter-rill and rill erosion were simulated at 59 points with three replications. Therefore, the ability of the regression equation in WEPP model and the derived regression and artificial neural network (ANN) models by Mirzaee et al. (2017) for predicting baseline soil erodibility parameters were evaluated to estimate soil loss. The results of the present study showed that the WEPP model that applied soil baseline erodibility predicted data by the regression equation in the WEPP model performed poorly in comparison to the derived aspatial models by Mirzaee et al. (2017). Additionally, the WEPP model that used soil baseline erodibility predicted data by the developed ANNs by Mirzaee et al. (2017) yielded the best results with the highest R^2 (0.681) and the lowest RMSE (5.1 Mg ha⁻¹) values for predicting soil loss rate. In general, the prediction map of soil erosion showed that soil erosion varied from 1.0 to 26.5 Mg ha⁻¹.

Keywords Artificial neural networks · Regression · Soil erosion

Introduction

One of the main paths for land degradation is water erosion on croplands. Water erosion leads to loss of fertile topsoil and creates sediment and pollution in water bodies (Brown and Wolf 1984). Water erosion is a critical environmental problem in the arid and semi-arid zones of the world especially in northwestern of Iran where it threatens to impair sustainable programs on agriculture lands. In this part of Iran, large amounts of agriculture land are abandoned every year because of natural and human-induced soil erosion (Mirzaee et al. 2017). Since soil erosion could adversely influence ecosystems on-site as well as off-site, the prediction of soil loss at a watershed scale has become vital issue in order to guarantee food security and maintain

environmental health. Therefore, it is necessary to focus on the prediction and monitoring of soil erosion in croplands where water erosion is at the highest rate (Zhang et al. 2008; Wang et al. 2014).

Several models have been developed for predicting soil loss, including ANSWERS (areal non-point source watershed environment response simulation) (Beasley et al. 1980), GUEST (Griffith University Erosion System Template) (Rose et al. 1983a, 1983b; Hairsine and Rose 1992a, 1992b), WEPP (Water Erosion Prediction Project) (Lafren et al. 1997), and EUROSEM (European Soil Erosion Model) (Morgan et al. 1998). All of those models used the main components of factors that could influence soil erosion such as rainfall erosivity, soil erodibility, slope length and degree, soil cover, and conservation practice. The accuracy of soil erosion models that are used for predicting soil loss depends on a large number of soil and environmental parameters including climate, soil, management, vegetation, and topography factors based on scientific theory (Amore et al. 2004).

The WEPP model, a physically based erosion prediction model developed by the US Department of Agriculture (USDA), was developed for predicting soil loss along a slope and sediment yield at the end of a hillslope (Flanagan and Nearing 1995). This physically based model is capable

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of (i) distinguishing zones of soil particles detachment and deposition within channels; (ii) calculating the influences of backwater on soil particle detachment, transport, and deposition within channels; and (iii) predicting the spatial and temporal distributions in soil loss and sediment deposition for both hill slope and watershed on an event or a continuous time basis (Ascough II et al. 1995; Flanagan and Nearing 1995). The WEPP has been applied successfully for predicting water erosion and sediment yield in different conditions in the USA (Huang et al. 1996; Lafen et al. 2004; Maalim et al. 2013; Brooks et al. 2016; Srivastava et al. 2020), in the UK (Brazier et al. 2000), in Australia (Rosewell 2001), in Italy (Pieri et al. 2007), and in India (Pandey et al. 2008).

A calcareous soil contains high calcium carbonate equivalent and pH ($\text{pH} > 7.5$). The existence of a high amount of calcium carbonate equivalent could be influenced the soil erosion process. However, only a few studies have calibrated and applied the WEPP model for properly predicting soil loss under calcareous conditions. The main aims of the present study were to calibrate and apply the WEPP model for predicting and monitoring soil loss under calcareous conditions in a semi-arid region in the northwest of Iran.

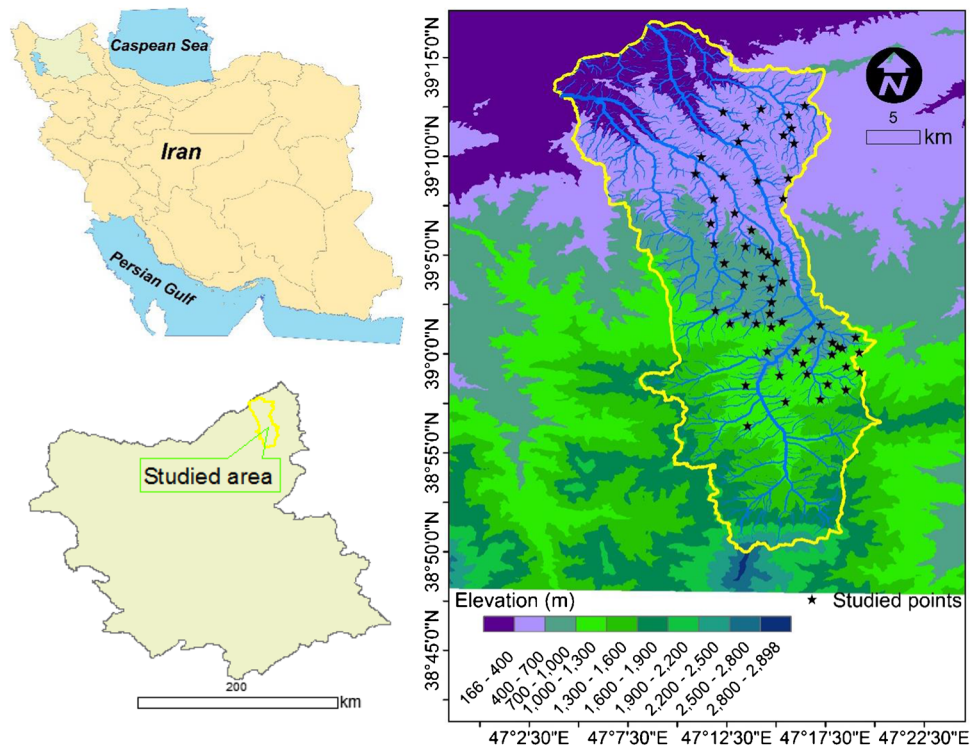
Material and methods

Study site

The study sites, with an area 619.5 km^2 , were located in Kaleybar, in the East-Azerbaijan province, northwestern of Iran (Fig. 1). Typically, this region was ploughed to a depth of 15–20 cm by using a moldboard plow. The rain-fed winter wheat and winter barley are the main agronomy crops in this region. The soil types in the study sites are Inceptisols, Entisols, and Mollisols (USDA 2010) with the soil parent materials enriched by carbonate material.

According to the measured daily data from 2001 to 2019 acquired in the Iran Meteorological Service, the mean monthly temperature ranged from 4.45 to 24.69 °C with an average annual of 14.2 °C. The minimum and maximum temperatures occur in January and August months, respectively. In addition, the mean annual precipitation for the studied region is 383.5 mm. The mean lowest and highest precipitations occur in August (5.9 mm) and May (82.3 mm), respectively. Moreover, the mean daily precipitations for Jan, Feb, Mar, Apr, May, Jun, Jul, Aug, Sep, Oct, Nov, and Dec are 1.06, 1.04, 1.42, 0.66, 2.77, 1.93, 0.97, 0.25, 0.70, 0.06, 1.05, and 0.89 mm, respectively. More than 50% of rainfall falls in the early spring in short rainstorms and irregular heavy rainfalls events that lead to a serious soil erosion in this area (Mirzaee et al. 2017).

Fig. 1 Location of study area in northwest Iran and distribution of the 57 studied points



Soil sampling and analysis

The soil samples (at 59 points) were taken from a depth of 0–15 cm using a stratified random method at various slope classes (0–5, 5–10, 10–15, 15–20, and > 20%) (Fig. 1). For laboratory analysis, the sampled soils were air-dried and sieved by a 2-mm sieve. SOM (soil organic matter) was measured by wet-oxidation approach (Nelson 1982). The CCE (calcium carbonate equivalent) content was determined using back-titration approach (Nelson & Sommers 1986). The particle size including sand-sized particles (0.05–2 mm) classes was measured by sieving method. Silt-sized particles (0.05–0.002 mm) and clay-sized particles (< 0.002 mm) contents were determined by the hydrometer approach (Gee & Bauder 1986).

Measurement of inter-rill and rill erosion at field scale

Inter-rill and rill erosion processes are considered in the WEPP model as important soil erosion components. Inter-rill erosion is explained as a soil detachment process created by rain-drop influence and transport by shallow sheet flow. Rill erosion is explained as a process of the concentrated flowability to detach and transport sediment (Flanagan and Nearing 1995).

A portable field rainfall capillary-type simulator (Fig. 2a) applied raindrops to simulate inter-rill erosion at 59 points. This rainfall simulator had the runoff plot which covered an area of 0.25 m². Additionally, the falling distance of rainfall capillary-type simulator was 40 cm with 2.3 mm min⁻¹ intensity. This type of rainfall simulator was used to measure inter-rill erosion in several studies such as Kamphorst (1987), Romero et al. (2007), and Nzeyiman et al. (2017). In addition, rill erosion was simulated in a rill with a width of 0.2 m and length of 4 m in cultivated soil (Fig. 2b, c). Concentrated flows were added at rates of 4, 12, 20, and 30 l min⁻¹ at the top of each plot through an energy dissipater. Each outflow rate was measured when observing a steady-state condition which was typically observed after 10 min. In this study, a steady-state condition duration was selected as 15 min to ensure that these situations were established for all of the inflow rates.

Application of WEPP model

Inter-rill and rill erosion

The WEPP model divides soil loss into two important components including (1) inter-rill erosion and (2) rill erosion (Flanagan and Nearing 1995). The erosion

components were applied in this model are described as follows:

$$\frac{dG}{dx} = D_i + D_r \quad (1)$$

where G is the sediment load (kg s⁻¹ m⁻¹), x is the distance down the slope (m), D_i is the inter-rill erosion (kg s⁻¹ m⁻²), and D_r is the rill erosion (kg s⁻¹ m⁻²) (Lafren et al. 1991). In the WEPP model, D_i and D_r components are accounted by the following equations (Lafren et al. 1991):

$$D_i = K_{ib} I q S_f \quad (2)$$

$$D_r = D_c \left(1 - \frac{G}{T_c} \right) \quad (3)$$

$$D_c = k_{rb} (\tau - \tau_{cb}) \quad (4)$$

where K_{ib} , K_{rb} , and τ_{cb} are the baseline inter-rill erodibility (kg s m⁻⁴), rill erodibility (s m⁻¹), and baseline critical shear stress (Pa), respectively. I and q are the rainfall intensity (m s⁻¹) and runoff rate (m s⁻¹), respectively. S_f is the slope adjustment factor. D_c and T_c are the detachment capacity of the flow (kg s⁻¹ m⁻²) and transport capacity of the flow (kg s⁻¹ m⁻²), respectively. τ is the shear stress acting on the soil (Pa). Net soil particle detachment in a rill occurs when flow hydraulic shear stress exceeds on the soil critical shear stress. Moreover, net soil particle deposition in a rill occurs when the sediment load in the rill flow exceeds on the sediment transport capacity.

The baseline inter-rill erodibility (K_{ib}), baseline rill erodibility (K_{rb}), and critical shear stress (τ_{cb}) were estimated in this region for cropland soils containing at least 30% sand or more sand (Flanagan and Livingston 1995):

$$K_{ib} = 272800 + 19210000VFS \quad (5)$$

$$K_{rb} = 0.00197 + 0.03VFS + 0.03863e^{-1840M} \quad (6)$$

$$\tau_c = 2.67 + 6.5\text{clay} + 5.8VFS \quad (7)$$

For soils containing < 30% sand, predicted by the following equations:

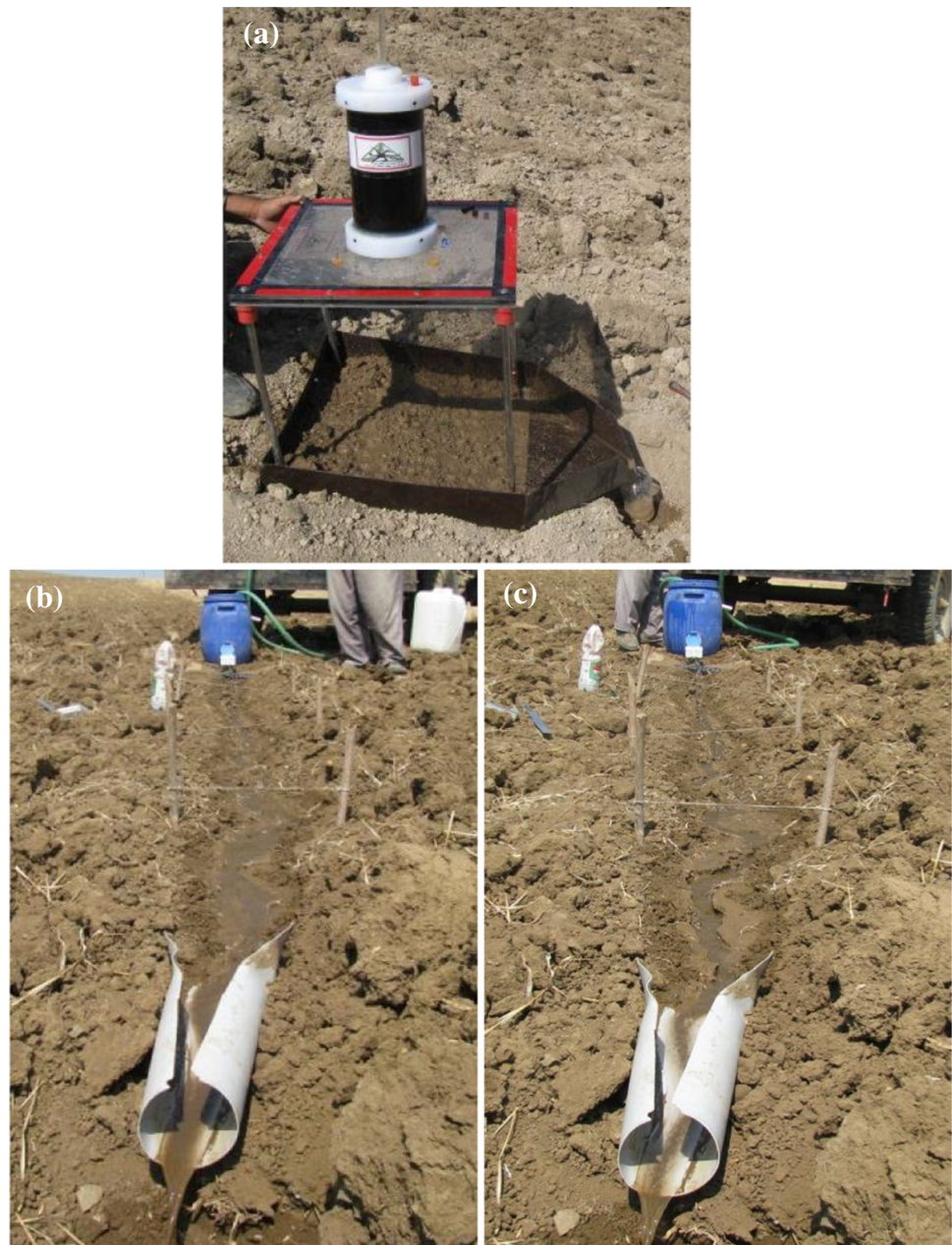
$$K_{ib} = 6054000 - 5513000\text{clay} \quad (8)$$

$$K_{rb} = 0.0069 + 0.134e^{-20\text{Clay}} \quad (9)$$

$$\tau_c = 3.5 \quad (10)$$

where VFS is the very fine sand fraction. Moreover, aspatial models including regression and artificial neural network (ANN)-based models (Mirzaee et al. 2017) were

Fig. 2 **a** Rainfall capillary-type simulator. **b** Rill experiment in unsteady-state conditions. **c** Rill experiment in steady-state conditions



used to predict baseline soil erodibility values from the observed field data. The descriptive statistics for the baseline soil erodibility parameters i.e., the K_{ib} , K_{rb} , and τ_{cb} by using the best different models are presented in Table 1.

WEPP application

The WEPP model needs four input files including climate, topography, soil, and management files for predicting soil erosion.

Climate file The climate file as single-storm climate was generated in CLIGEN (Nicks et al. 1995) by using the amount, duration, and intensity of simulated rainfall data.

Topography file The WEPP model applies topography data for estimating soil loss. Slope degree data derived from DEMs (digital elevation models) with a spatial resolution of 30 m are processed in this study. The distribution of slope classes is summarized in Table 2.

Table 1 Summary statistics for baseline soil erodibility parameters

Soil erodibility parameters	Min	Max	Mean	Median	St.D	CV (%)
<i>Measured data</i>						
K_{ib} (kg s m ⁻⁴)	4.1×10^5	5.0×10^6	2.1×10^6	1.9×10^6	9.3×10^5	42.81
K_{rb} (s m ⁻¹)	1.1×10^{-4}	2.15×10^{-3}	8.1×10^{-4}	7.9×10^{-4}	4.49×10^{-4}	55.43
τ_{cb} (Pa)	0.00	9.32	3.49	3.26	2.54	72.78
<i>Predicted by regression equations in WEPP model (Flanagan and Livingston 1995)</i>						
K_{ib} (kg s m ⁻⁴)	3.9×10^5	5.8×10^6	3.3×10^6	3.4×10^6	1.1×10^6	33.62
K_{rb} (s m ⁻¹)	5.1×10^{-3}	4.05×10^{-2}	1.1×10^{-2}	1.0×10^{-2}	4.66×10^{-3}	42.36
τ_{cb} (Pa)	1.32	5.12	3.22	3.18	0.78	24.22
<i>Predicted data by developed regression equations in Mirzaee et al. (2017)</i>						
K_{ib} (kg s m ⁻⁴)	1.1×10^6	3.0×10^6	2.0×10^6	2.0×10^6	4.2×10^5	20.72
K_{rb} (s m ⁻¹)	3.9×10^{-4}	1.7×10^{-3}	7.8×10^{-4}	7.7×10^{-4}	2.1×10^{-4}	26.92
τ_{cb} (Pa)	1.29	7.43	3.08	3.03	0.96	31.17
<i>Predicted data by developed ANNs in Mirzaee et al. (2017)</i>						
K_{ib} (kg s m ⁻⁴)	7.7×10^5	3.1×10^6	2.0×10^6	2.1×10^6	5.6×10^5	27.48
K_{rb} (s m ⁻¹)	3.6×10^{-5}	1.8×10^{-3}	7.7×10^{-4}	7.4×10^{-4}	2.3×10^{-4}	29.87
τ_{cb} (Pa)	0.01	7.74	3.38	3.26	1.52	44.97

K_{ib} inter-rill erodibility, K_{rb} rill erodibility, τ_{cb} critical shear stress

Table 2 The distribution of studied area in different slope classes

Slope class (%)	Area (ha)	Area (%)
0–2	961.6	1.55
2–6	4118.8	6.65
6–12	11,606.2	18.73
12–16	9021.5	14.56
16–25	17,074.2	27.56
> 25	19,168.0	30.94
Total	61,950.3	100

Soil file The soil input data for the WEPP model were based on the laboratory measurement such as soil organic matter, calcium carbonate equivalent, sand-, silt-, and clay-sized particles contents as described in Table 3. The SOM map by ordinary Kriging method is presented in Fig. 3. Indeed, the baseline inter-rill erodibility (K_{ib}), baseline rill erodibility (K_{rb}), and critical shear stress (τ_{cb}) predicted data by using

regression equation in WEPP model Flanagan and Livingston (1995), and the best regression- and artificial neural network (ANN)-derived models by Mirzaee et al. (2017) were entered as soil input data. In addition, to quantify the saturated hydraulic conductivity parameter (i.e., K_s), the Green and Ampt (1911) model (Eq. (11)) was applied, as follows:

$$I = K_s t + G \ln \left(1 + \frac{I}{G} \right) \tag{11}$$

where I is the cumulative infiltration (cm), K_s (cm min⁻¹) is the saturated hydraulic conductivity, and G is a constant parameter. Finally, the K_s values were obtained by fitting processes during parameterization of the K_s and G parameters in Eq. 11.

Management file In the present study, the management input file in WEPP model contains all data related to plant type and parameters, tillage type and parameters, residue management, and crop rotations. Tillage and crop management

Table 3 Descriptive statistics of studied soil

Properties	Min	Max	Mean	Median	Std. dev	CV
Clay (%)	10.0	54.0	31.3	32.0	9.10	29.1
Silt (%)	22.0	70.0	36.9	36.0	7.70	20.9
Sand (%)	8.00	50.0	31.7	34.0	10.1	31.9
VFS (%)	0.66	28.7	17.90	18.37	4.93	27.5
CCE (%)	0.50	42.0	16.4	16.1	7.93	48.2
SOM (%)	0.17	3.02	1.72	1.81	0.59	34.3
K_s (cm min ⁻¹)	0.002	0.465	0.107	0.097	0.085	79.4

CCE calcium carbonate equivalent, SOM soil organic matter

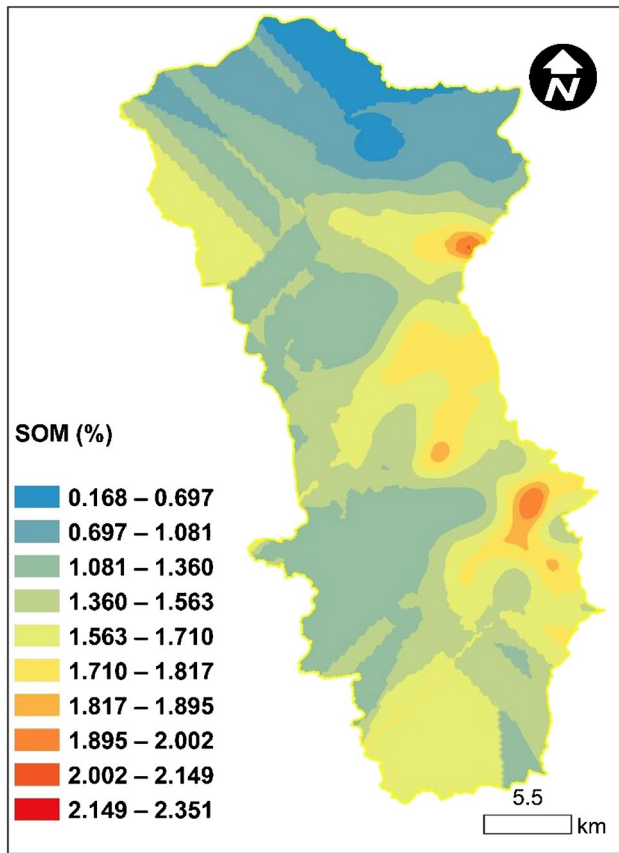


Fig. 3 Soil organic map for studied area

data including tillage equipment type and date of applying, type of crop, planting date, harvest date, residue management, and crop rotations were entered into the management files. In addition, the study area includes agricultural lands (25,253.2 ha; 40.8%), rangelands (20,126.8 ha; 32.5%), forest lands (4893.9 ha; 7.9%), rocks (5564.8 ha; 9.0%), urban areas (5886.6 ha; 9.5%), and water body (149.0 ha; 0.24%) (Fig. 4). The main agricultural crops in this region include cereal productions such as wheat and barley.

Evaluation of models

GeoWEPP model was applied to estimate soil erosion at the hillslope scale. WEPP model version 2008.907 and ArcGIS 9.3 (ESRI, Redlands, CA). The 59-soil sample points were used as randomly as a training-data set, (80%) and test-data set (20%). The accuracy of WEPP model for estimating soil loss in this study was evaluated by applying the ME (mean error), RMSE (root mean square error), and R^2 (coefficient of determination) criteria and were described as follows:

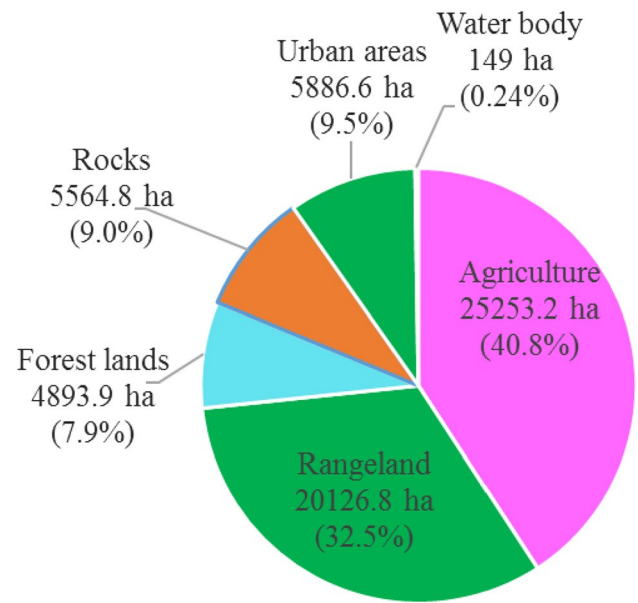


Fig. 4 The main land use classes area in studied area

$$ME = \frac{1}{N} \sum_{i=1}^N (\hat{Y}_i - Y_i) \tag{12}$$

$$RMSE = \left[\frac{\sum_{i=1}^N (\hat{Y}_i - Y_i)^2}{N} \right]^{0.5} \tag{13}$$

$$R^2 = 1 - \frac{\sum_{i=1}^N (Y_i - \hat{Y}_i)^2}{\sum_{i=1}^N (Y_i - \bar{Y}_i)^2} \tag{14}$$

where Y_i and \hat{Y}_i are the measured and estimated data of soil loss, respectively. \bar{Y}_i is the mean of the measured data of soil loss, and N is the number of observations (i.e., 59).

Results and discussion

Prediction of soil loss by using WEPP model

Input of soil baseline erodibility predicted data by regression equations in the WEPP model

The prediction of soil loss by using WEPP model with input of soil baseline erodibility predicted data by regression equations in WEPP model (Flanagan and Livingston 1995) yielded the $R^2=0.089$, $RMSE=107.3 \text{ Mg ha}^{-1}$, and $ME=92.8 \text{ Mg ha}^{-1}$ with the test-data set (Table 4). In addition, the scatter plots of the measured against the estimated data of soil erosion

Table 4 Prediction of soil erosion with input of soil baseline erodibility data predicted by different methods in WEPP model

Models	Train			Test		
	ME	RMSE	R^2	ME	RMSE	R^2
Regression equations in WEPP model	110.3	130.6	0.125	92.8	107.3	0.089
Regression equation (Mirzaee et al. 2017)	3.5	5.7	0.424	3.3	5.2	0.562
ANN model (Mirzaee et al. 2017)	3.4	5.4	0.519	3.5	5.1	0.681

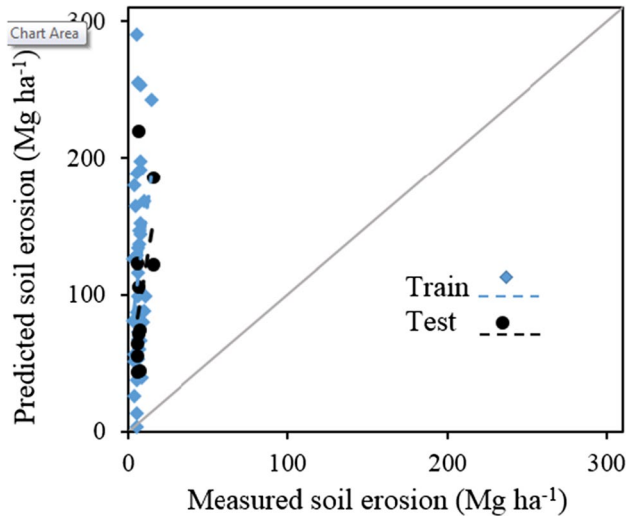


Fig. 5 Relationships between measured and predicted soil erosion with input of soil baseline erodibility data predicted by regression equations in WEPP model

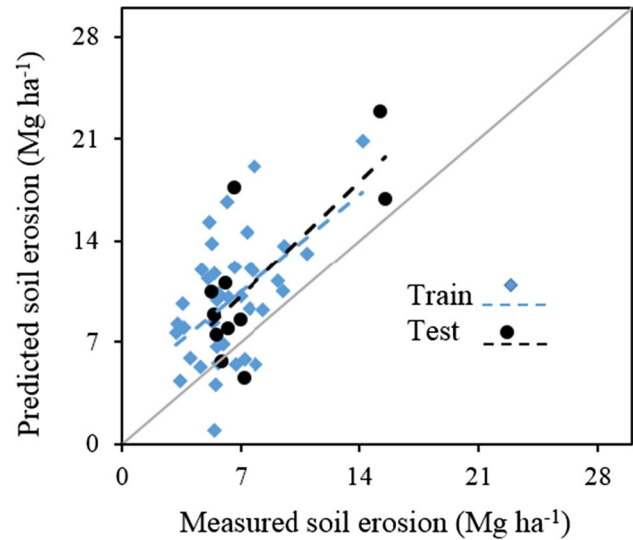


Fig. 6 Relationships between measured and predicted soil erosion with input of soil baseline erodibility data predicted by the best regression equations in Mirzaee et al. (2017)

around 1:1 line for the train-data and test-data sets are present in Fig. 5. Based on Fig. 5, WEPP model had consistent over-estimated soil erosion at all points. This could be described by the fact that soil erosion processes are highly complex. Interactions of several factors such as soil texture and structure, runoff, rainfall, slope degree, and land use can be influenced soil erosion processes. Another possible reason for the over-estimated by the WEPP equations was that those equations were developed from soils that had been tilled for only 100 to 300 years, whereas northwestern of Iran soils have likely been tilled for several thousand years. The extended time of tillage may have resulted in historic erosion removing more erodible topsoil while leaving less erodible calcareous subsoils behind. This suggests that the WEPP model needs to be calibrated for different field conditions in different areas of the world such as Iran and other semi-arid areas due to the influence of calcareous materials on erosion processes (Ostovari et al. 2016).

Input of soil baseline erodibility predicted data by the best-developed regression model in Mirzaee et al. (2017)

Table 4 presents the statistical results of using WEPP model for prediction of soil loss with input of soil baseline

erodibility predicted data by the best-developed regression model in Mirzaee et al. (2017). Applying the best regression-derived model for predicting soil baseline erodibility data from more easily available soil properties in Mirzaee et al. (2017) yielded the $R^2=0.562$, $RMSE=5.2 \text{ Mg ha}^{-1}$, and $ME=3.3 \text{ Mg ha}^{-1}$ with the test-data set (Table 4). The ME values in test-data set showed that the soil erosion predicted by using WEPP model had consistent over-estimated soil erosion (Table 4). This could be observed in the scatter plots illustrated in Fig. 6.

Input of soil baseline erodibility predicted data by the best-developed ANNs in Mirzaee et al. (2017)

The ME, RMSE, and R^2 values for the test-dataset presented for soil loss prediction with input of soil baseline erodibility predicted data by developed ANNs in Mirzaee et al. (2017) in Table 4. This method explained for up to 68.1% of the variation in soil loss prediction by using WEPP model (Table 4). Moreover, the scatter plots of the measured and predicted soil loss data for the train-data and test-data sets are given in Fig. 7.

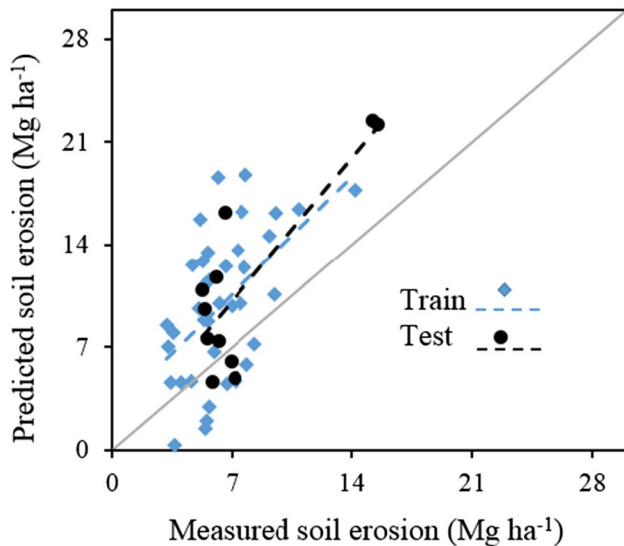


Fig. 7 Relationships between measured and predicted soil erosion with input of soil baseline erodibility data predicted by the best ANN model in Mirzaee et al. (2017)

Comparison of soil erosion prediction accuracy at different soil baseline erodibility predicted data inputs to the WEPP model

As can be seen from Table 4, the highest R^2 value (0.681) and the smallest RMSE value (5.1 Mg ha^{-1}) at the test-data set were obtained by WEPP model that applied soil baseline erodibility predicted data by the best-developed ANNs in Mirzaee et al. (2017). Comparison the accuracy of WEPP model with different input soil baseline erodibility predicted data by different methods in Table 4 showed the smallest R^2 (0.089) and highest RMSE (107.3 Mg ha^{-1}) at the test-data set were from to the WEPP model that applied soil baseline erodibility predicted data by regression equations in WEPP model (Flanagan and Livingston 1995). However, results in Table 4 indicated that the lowest ME value (3.3 Mg ha^{-1}) was produced in WEPP model that used soil baseline erodibility predicted data by the best-developed regression equations in Mirzaee et al. (2017).

Overall, the results showed that the WEPP model that applied soil baseline erodibility predicted data by the best-developed ANNs in Mirzaee et al. (2017) was the best method for predicting soil loss at this region. Recent studies by Pachepsky et al. (1996), Khalilmoghadam et al. (2009), Havaee et al. (2015), and Mirzaee et al. (2017) have found that ANN methods outperform regression models for predicting different soil hydraulic attributes. One of the reasons for the higher accuracy when applying ANNs for predicting soil baseline erodibility parameters as an important input data for soil loss prediction is non-linear relationship between target and more easily measurable basic

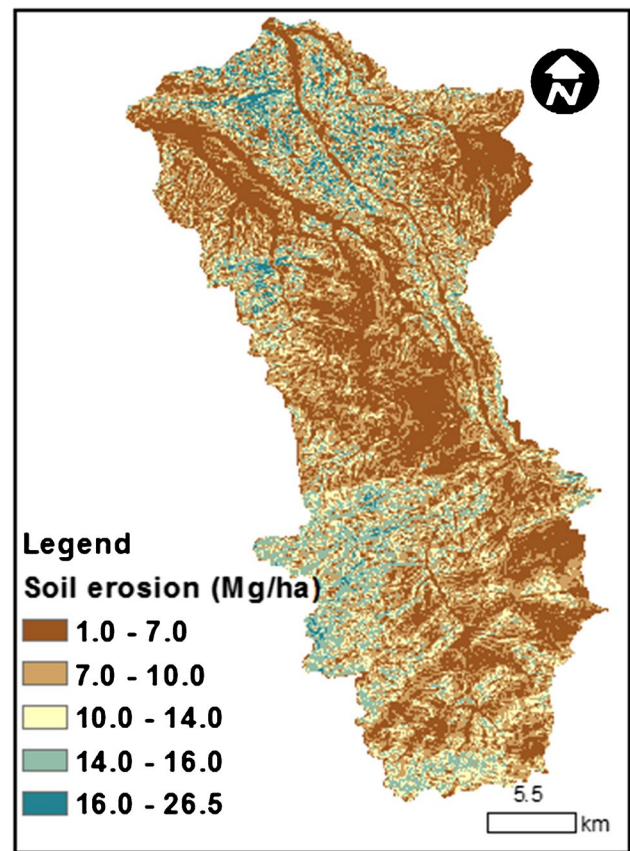


Fig. 8 Soil erosion map for studied area

soil attributes (Izenman 2008; Parchami-Araghi et al. 2013; Mirzaee et al. 2020). In addition, recently, increased applications of ANNs methods have been developed for modeling different types of soil hydrological properties. This could be related to their ability of this method to capture complex non-linear relationships between target and more easily measurable basic soil attributes (Maier & Dandy 2000; Parchami-Araghi et al. 2013) that have an incomplete understanding of the physical processes involving.

Soil erosion map by the GeoWEPP

Figure 8 indicates the regions susceptible to soil erosion. The map accuracy in this study was the $R^2=0.623$, $\text{RMSE}=5.4 \text{ Mg ha}^{-1}$, and $\text{ME}=3.8 \text{ Mg ha}^{-1}$ with the test-data set. As the results from Fig. 8, 25,875 ha (41.8%), 23,302 ha (37.6%), 9439 ha (15.2%), 1283 ha (2.1%), and 2051 ha (3.3%) were in soil erosion classes including 1.0–7.0, 7.0–10, 10.0–14.0, 14.0–16.0, and 16.0–26.5 Mg ha^{-1} , respectively. The lowest soil erosion i.e., 1.0–7.0 Mg ha^{-1} class is in the flattest part of the watershed. These parts of the studied area were used for horticultural productions because of the availability of water. In some

parts of this area, where most of the rain-fed cereals farming occurs, crop rotation is rain-fed cereals-fallow, and slope steepness is high, so soil erosion values are high. Moreover, as can be seen from Fig. 8, the higher rates of soil erosion occur mainly in the north and southwest parts of the studied area. In contrast, the lower rates of soil erosion observe mainly in central and east parts of the studied area (Fig. 8).

Several studies have focused on determining soil loss tolerance (T -value) in calcareous soils of semi-arid regions in Iran (Ostovari et al. 2020; Gohardust et al. 2011). Gohardust et al. (2011) reported that about 43.7% of the studied region had a T -value of 5.37 Mg ha^{-1} in the Chehel-Chay Watershed of Golestan Province, Iran. In addition, Ostovari et al. (2020) showed that T -values ranged from 3.5 to 22.5 Mg ha^{-1} . In the present study, soil erosion prediction data by the best method ranged from 1.0 to 26.5 Mg ha^{-1} for in a single event (Fig. 8). This is an important characteristic to note for calibrating WEPP model for the different field conditions.

Conclusions

Inter-rill and rill soil erosion were measured in a semi-arid region on some calcareous soils in northwestern of Iran. The results of this research indicated that the best regression- and ANN-derived models in Mirzaee et al (2017) performed better than the regression model in the WEPP model in Flanagan and Livingston (1995) for predicting soil loss. It can be a result that the WEPP model needs to be calibrated for different field condition especially in calcareous soils under the impairing of calcareous materials. In this way, the best ANN-derived models for predicting soil erodibility parameters data in Mirzaee et al (2017) provided more accurate estimations of soil loss by using WEPP model than the best regression-derived models for soil erodibility parameters in Mirzaee et al (2017) as input data in WEPP model. The WEPP model that applied soil baseline erodibility predicted data by the best-developed ANNs in Mirzaee et al. (2017) was able to explain for up to 68.1% of the variation in soil loss prediction. Moreover, soil erosion prediction map showed that soil erosion at the studied area varied from 1.0 to 26.5 Mg ha^{-1} for a single event. In general, it is necessary to calibrate the WEPP model for an accurate prediction of soil loss rate for local soils.

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Declarations

Conflict of interest The authors declare that they have no competing interests.

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