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Soil erodibility and its prediction in semi-arid regions

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**ABSTRACT**

Pedotransfer functions (PTFs) have been used to save time and cost in predicting certain soil properties, such as soil erodibility (\(K\)-factor). The main objectives of this study were to develop appropriate PTFs to predict the \(K\)-factor, and then compare new PTFs with Universal Soil Loss Equation (USLE) and the Revised Universal Soil Loss Equation (RUSLE) \(K\)-factor models. The \(K\)-factor was measured using 40 erosion plots under natural rainfall in Simakan Watershed, an area of 350 km\(^2\) in central Iran. The Regression Tree (RT) and Multiple Linear Regression (MLR) were used to develop PTFs for predicting the \(K\)-factor. The result showed that the mean of measured \(K\) was 0.01 t h MJ\(^{-1}\) mm\(^{-1}\). The mean \(K\) value predicted by USLE and RUSLE was 2.08 and 2.84 times more than the measured \(K\), respectively. Although calcium carbonate was not considered in the original USLE and RUSLE \(K\)-factors, it appeared in the advanced PTFs due to its strong positive significant impact on aggregate stability and soil infiltration rate, resulting in decreased \(K\)-factor. The results also showed that the RT with \(R^2 = 0.84\) had higher performance than developed MLR, USLE and RUSLE for the \(K\) estimation.

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**KEYWORDS**

Dorudzan; data mining; erosivity; stepwise regression; regression tree

**Introduction**

The Universal Soil Loss Equation (USLE) (Wischmeier and Smith 1978) and its successor, the Revised Universal Soil Loss Equation (RUSLE) (Renard et al. 1997), have been extensively used for soil loss predictions, especially when data of erosional processes are limited. The USLE and revised USLE are simple, easy and quick water erosion empirical models with six factors: soil erodibility (\(K\)), soil erosivity (\(R\)), slope length (\(L\)), slope steepness (\(S\)), land cover (\(C\)) and practice (\(P\)) (Ostovari et al. 2016). The performance of USLE and RUSLE models are dependent on all six factors. \(L\) and \(S\) factors may not be significantly changed unless soil conservation plans are performed. \(R\)-factor is directly related to erosive precipitation events (Renard et al. 1997; Ostovari et al. 2018). \(P\) and \(C\) factors are dependent on human activities (Shabani et al. 2014). Soil erodibility is reflected in the \(K\)-factor of USLE and its successors and is highly affected by physical, hydrological, chemical, mineralogical and biological properties (Perez-Rodriguez et al. 2007).

The \(K\) measurement methods are categorized into various types: soil physicochemical properties, rainfall simulation, wind tunnel experiments and erosion plot experiments (Breshears et al. 2003). Measuring \(K\) using erosion standard plots is the best way to predict this parameter and eventually achieve high accuracy of soil loss estimation. Direct measurement of \(K\) in the field, using
erosion plots under natural erosive rainfall, requires long-term erosion monitoring, which is tedious, time-consuming, labor-intensive and costly. However, it can be estimated by pedotransfer functions (PTFs) using available soil properties.

Regression techniques have been widely applied for the development of PTFs to predict the K-factor. Of particular application to our study are the Wischmeier and Smith (1978) and Römkins et al. (1977) designed PTFs for K prediction under different climate and soil conditions. In the USLE model, K-factor was predicted using the nomograph, based on soil properties as follows:

$$K = 2.8 \times M^{1.14} \times 10^{-7} \times (12 - \% \text{ OM}) + 4.3 \times 10^{-3} \times (S - 2) + 3.3 \times 10^{-3} \times (P - 3) \quad (1)$$

where $K$ is the soil erodibility factor in t h MJ$^{-1}$ mm$^{-1}$, $M$ is $(100 - \% \text{ clay}) \times (\% \text{ very fine sand} + \% \text{ silt})$, OM is organic matter (%), $S$ is soil structure and $P$ is profile permeability class (Vaezi et al. 2010). Auerswald et al. (2014) highlighted that K-factor nomograph is the main factor in soil erosion modelling for evaluating the soil erodibility. In the RUSLE model, K-factor was estimated using the mean geometric diameter of soil particles ($D_g$) as follows:

$$K = 0.0034 + 0.0405 \exp \left[ -\frac{1}{2} \left( \frac{\log(D_g) + 1.659}{0.710} \right)^2 \right]$$  

$$D_g = \exp \left[ 0.01 \left( P_{\text{sand}} \cdot \ln 1 + P_{\text{silt}} \cdot \ln 0.025 + P_{\text{clay}} \cdot \ln 0.001 \right) \right] \quad (2)$$

where $D_g$ is mean geometric diameter of soil particles (mm), $P_{\text{sand}}$, $P_{\text{silt}}$ and $P_{\text{clay}}$ are sand, silt and clay percentages, respectively. The USLE and RUSLE K-factors have been continuously used to estimate $K$ in many studies worldwide (Vaezi et al. 2010; Shabani et al. 2014).

However, the equations are not applicable in regions with certain soils and climate conditions, such as in calcareous soils and semi-arid regions (Vaezi et al. 2008; Ostovari et al. 2016), in that the USLE and RUSLE K-factors were developed from areas in the United States, where soils have no calcium carbonate content due to rainfall intensity greater than 63 mm h$^{-1}$ and rock fragments less than 10% (Renard et al. 1997). This creates huge variations in using the USLE and RUSLE K-factors, compared with $K$ in other regions. Hence, it seems that utilization of the USLE and RUSLE K-factors in calcareous soils may lead to inaccurate assessment of $K$ (Vaezi et al. 2008), which limits the application of these models for soil loss estimation.

Soils are mainly calcareous in semi-arid regions and have plenty of carbonates. In calcareous soils, carbonates increase soil resistance to erosion due to significant effects in aggregate stability and consequently soil permeability, resulting in decreased $K$ (Shabani et al. 2014). Therefore, calibration of the USLE and RUSLE K-factors for calcareous soils is necessary to achieve a high accuracy of soil loss prediction using these models. A few studies have been conducted (Vaezi et al. 2008, 2016; Vaezi and Sadeghi 2011; Shabani et al. 2014; Ostovari et al. 2016) to calibrate the soil erodibility factor of USLE and RUSLE in Iran, where soils are calcareous and water erosion is a major cause of land degradation (Vaezi and Sadeghi 2011).

Recently, Ostovari et al. (2016) predicted soil erodibility ($K$) in calcareous soil in Iran using the Mamdani fuzzy inference system (MFIS) and artificial neural networks (ANN). The results showed that the ANN had a higher performance that MFIS and the USLE equation to predict K-factor. Vaezi et al. (2016) developed an erodibility triangle for soils in the north of Iran using simulated rainfall and regression method. A K-factor triangle was designed using the Kriging method. The results showed that triangle soil erodibility had a 5.4% error in the prediction of K-factor in calcareous soil. Vaezi et al. (2018) investigated the relationship between aggregate-size classes and inter-rill erodibility ($K_i$) and the factors controlling this relationship in the semi-arid region of Iran. Five aggregate-size classes were separated from soil samples and the $K_i$ of each aggregate-size was determined using the inter-rill sediment delivery and estimated using the Water Erosion Prediction
Project (WEPP) model. Significant decreases in $K_i$ were observed with increasing aggregate-size associated with increasing clay and saturated hydraulic conductivity.

Ostovari et al. (2018) predicted soil erodibility ($K$-factor) using the pedotransfer function (PTF) and spectrotransfer function (STF) using spectral reflectance information in the Vis-NIR range. The $K$-factor was measured in 40 erosion plots under natural rainfall and the spectral reflectance of soil samples was analysed in the laboratory. Results showed that the developed PTF had the highest performance ($R^2 = 0.74$, RMSE = 0 and ME = 0 t h MJ$^{-1}$ mm$^{-1}$) compared with the USLE equation and STF.

Bagarello et al. (2018) investigated the plot scale effects on event run-off per unit area, sediment concentration, and soil loss per unit area. The measurements were fulfilled for 31 events occurring in bare ploughed plots ranging from 1 to 48 m$^2$. Results showed that for 48% of the events, a statistically significant scale effect was detected for all tested variables. Moreover, they highlighted that while both run-off and soil loss always decreased, sediment concentration always increased in the passage from the reference plot (1 m$^2$) to the largest one (48 m$^2$).

In this study, we focused on measuring, predicting and evaluating soil erodibility factor in areas with calcareous soils located in semi-arid regions. Here we (i) measured the soil erodibility factor in calcareous soils in different soil types, (ii) developed new PTFs to predict the $K$-factor using MLR and RT models, and (iii) compared advanced PTFs with USLE and RUSLE $K$-factor models.

Methods and materials

Description of the study site

The study site, with an area around 350 km$^2$, is located in Pasargad County in central Fars Province, Iran (Figure 1). The altitude varies from 1827 to 2205 m above sea level. The climate is semi-arid with 308 mm mean annual precipitation. Soils are calcareous with more than 45% calcium carbonate, in most parts thin and classified as Aridisols (Soil Survey Staff, Keys to soil taxonomy) or Calcisols (Pocketbook FFS 2016), Inceptisols (Soil Survey Staff, Keys to soil taxonomy) or Calcisols (Pocketbook FFS 2016) and Entisol (Soil Survey Staff, Keys to soil taxonomy) or Cambisols (Pocketbook FFS 2016). Normal rainfall intensity is below 25 mm h$^{-1}$, with the most precipitation occurring from November to March. The annual mean temperature is 11.8 °C, and differences in mean temperature between winter and summer are generally about 25 °C (Ostovari et al. 2016, 2018). Total annual evaporation in the study site exceeds 1500 mm, with more than 50% occurring during June, July and September. The major geomorphologic features of the site include structural hills, buried pediments and small valley fills.

Soil sampling

Three soil samples were randomly collected from a 0 to 30 cm depth in each erosion plot (; yellow bullets) and mixed together. The mixed samples were air-dried and sieved through 2-mm mesh for physicochemical analyses. The distribution of particle size which comprised sand content (0.05–2 mm), silt content (0.05–2 mm), clay content (< 2 mm) and %very fine sand (0.05–0.1 mm) was determined using the hydrometer method (Nelson and Sommers 1996). OM content was measured using the Walkly-Black method (Nelson and Sommers 1982); calcium carbonate equivalent as total neutralizing value (TNV) was obtained based on the neutralizing rate of carbonates with hydrochloric acid (Nelson and Sommers 1982) and stability of soil aggregates (MWD) was determined using the wet-sieving method. The permeability (PE) was measured using a double-ring (Turner and Sumner 1978) at three replicates in the three points of the plots (in first, end and middle of the each plot). The measurements of PE were carried out in the June 2015 (in the dry season), in order to eliminate the impact of the residual humidity during the rainy season (Ostovari et al. 2016, 2018).
Soil erodibility (K-factor)

The K-factor was determined as the annual soil loss from a standard erosion plot divided by rainfall erosivity factor:

\[ K = \frac{A}{R} \]  \hspace{1cm} (4)

where annual soil loss A is in t h\(^{-1}\) y\(^{-1}\); rainfall erosivity factor R is expressed in MJ mm ha\(^{-1}\) h\(^{-1}\) and therefore soil erodibility K is in t h MJ\(^{-1}\) mm\(^{-1}\). Madar-Soleyman is the only rain-gauge station in the centre of our study site. Due to a lack of equipment in the Madar-Soleyman rain-gauge station, it was not possible to record the intensity and duration of rainfalls. For regions with no detailed climate data, the modified Fournier index can be used to estimate the R factor (Hui et al. 2010) as follows:

\[ MFI = \sum_{i=1}^{12} \frac{p_i^2}{p_i} \]  \hspace{1cm} (5)

Arnoldus (1977) developed a model between MFI and R-factor to generate an erosion map for Morocco as follows:

\[ R = 0.264 \ MFI^{1.5} \]  \hspace{1cm} (6)
where MFI is modified Fournier index, \( R \) is the rainfall erosivity factor (MJ mm\(^{-1}\) h\(^{-1}\) y\(^{-1}\)), \( p \) is the monthly rainfall (mm) and \( p \) is the annual rainfall (mm). Zhang and Fu (2003) modelled the equation \( R = 0.34 \text{MFI}^{1.95} \) for Jiangxi Province in China. Hui et al. (2010) used the Zhang equation to compute the \( R \)-factor due to the climate similarity between the two study areas. Due to similar climate conditions to our study site, the \( R \)-factor was computed by the Arnoldus equation (Arnoldus 1977) using monthly rainfall data of 15 years (1999–2014). The mean \( R \)-factor varied from 19.30 to 723 with a mean of 255.70 MJ mm ha\(^{-1}\) h\(^{-1}\) y\(^{-1}\) (For further details of \( R \)-factor, refer to Ostovari et al. (2016)).

The Iranian natural resources organization provided a digital elevation model (DEM), with a resolution of 10 m, was used to extract the slope surface layer. The slope layer was then reclassified to define slopes of 9%. In order to measure \( K \), 40 standard plots (The standard plot is \( 22.1 \times 1.83 \text{m} \)) with a uniform ploughed slope of 9% in the upslope/downslope direction (Wischmeier and Smith 1978) were installed in pasture and agricultural lands with a uniform. To exclude the effect of crop cover on the \( K \)-factor, the plots were installed on fallow lands (Hussein et al. 2007) and were treated in bare condition with herbicide (Vaezi et al. 2008; Ostovari et al. 2016). To prevent water movements, both inwards and outwards, the plots were surrounded by earth berms and 30 cm galvanized sheets. The run-off collection system comprised a flow concentrator, a pipe, and a 100-l tank, installed at the lowest part of each plot (For further information and details of plots, refer to Ostovari et al. 2016).

This study was fulfilled during two rainy seasons (2013–2014) due to time, cost and equipment limitations. Similar to the present study, Vaezi et al. (2008) modelled the USLE \( K \)-factor using two years data. Soil loss from each plot was collected for only four erosive rainfall events because of drought during the study, resulting in soil erosion. The mean soil loss was 3.68 t ha\(^{-1}\) y\(^{-1}\) with the range from 1.44 to 6.38 t ha\(^{-1}\) y\(^{-1}\).

**Developing and validating MLR and RT models**

Available soil properties were tested for normality using the Kolmogorov–Smirnov test prior to model development. Forty erosion plots, which contain information on soil properties and \( K \), were randomly divided into two sets: 30 samples for PTF development and 10 samples for PTF validation. The forward stepwise multiple linear regressions (MLR) were used to develop the PTF point as follows:

\[
K = a_0 + a_1 \text{Cl} + a_2 \text{Si} + a_3 \text{Sa} + a_4 \text{Dg} + a_5 \text{VFS} + a_6 \text{MWD} + a_7 \text{PE} + a_8 \text{CaCO}_3
\]  

(7)

where Cl, Si, Sa, Dg and VFS are clay, silt, sand, mean geometric diameter and very fine sand (%), respectively. MWD represents mean weight aggregate diameter (mm), PE permeability (cm h\(^{-1}\)), CaCO\(_3\) calcium carbonate (%) and \( a_0 \) to \( a_8 \) regression coefficients. Multicollinearity, where two or more predictor variables in regressions are linearly correlated, among predictor variables was evaluated by the Variance Inflation Factor (VIF) as follows:

\[
\text{VIF} = \frac{1}{1 - R_j^2}
\]  

(8)

where \( R_j^2 \) is adjusted \( R^2 \). A VIF exceeding 5 indicates that there is collinearity among predictor variables. In this situation, the coefficient of determination (\( R^2 \)) of the regression models may change unpredictably with small changes in data or model.

In addition to the MLR method, the regression tree (RT) has been used to develop PTFs (Pachepsky and Schaap 2004). RT is a data mining technique that obtains the data structure and uses qualitative and quantitative variables as inputs (Ostovari et al. 2015). For better comparison between RT and MLR methods to estimate \( K \), the same predictor variables used in MLR were used as input variables in the RT method. RT model was developed using RT modules from STATISTICA 8.0 with special conditions. The maximum sample size per node was set at 20 to avoid excessive
enlargement of the tree structure. The performance of MLR and RT was evaluated using 1:1 lines, determination coefficient \( R^2 \), mean geometric mean error (GME).

\[
R^2 = \frac{\sum_{i=1}^{n} (O_i - \bar{O})^2 1/mu \sum_{i=1}^{n} (P_i - \bar{P})^2}{\sum_{i=1}^{n} (O_i - \bar{O})^2 1/mu \sum_{i=1}^{n} (P_i - \bar{P})^2}
\]

\[
RMSE = \sqrt{\frac{\sum_{i=1}^{n} (P_i - O_i)^2}{n}}
\]

\[
ME = \frac{\sum_{i=1}^{n} (P_i - O_i)}{n}
\]

\[
GME = \exp \left[ \frac{1}{n} \sum_{i=1}^{j} \ln \left( \frac{P_i}{O_i} \right) \right]
\]

where \( n \) is the number of observations, \( O \) and \( P \) are the observed and predicted values, respectively, and \( i \) is the number of samples (Abbasi et al. 2011).

**Results**

Figure 2 shows the USDA textural triangle for soil samples. According to the diagram, soil samples were mainly present in loamy, clay loam and sand-clay loam categories. Table 1 presents the descriptive statistics of easily measurable soil properties. The \( t \)-test showed that there was no significant difference between the mean values of the two datasets (\( p < 0.05 \)). Clay content varied from 17.90\% to 41.9\% with a mean value of 26.7\%. Similarly, sand content varied from 24.10\% to 56\% with a mean of 41.10\%. \( D_g \) mean was 0.05 with a range from 0.02 to 0.10 mm. The OM mean was 3.13\%. Soil permeability (PE) was found to be between 0.80 and 3.4 cm h\(^{-1}\) and its classification based on the final infiltration was classes 3 and 4. The soils were limey with good stability of soil aggregate sand moderate soil permeability.

**K-factor determination**

The \( K \) values were determined to take into account the mean of \( R \)-factor. The \( K \) value varied from 0.01 to 0.02 t h MJ\(^{-1}\) mm\(^{-1}\) with a mean of 0.01 t h MJ\(^{-1}\) mm\(^{-1}\). The \( K \) values estimated by the USLE varied from 0.02 to 0.05 t h MJ\(^{-1}\) mm\(^{-1}\) with a mean 0.03 t h MJ\(^{-1}\) mm\(^{-1}\). The \( K \) values predicted by RUSLE varied from 0.02 to 0.04 t h MJ\(^{-1}\) mm\(^{-1}\) with a mean 0.04 t h MJ\(^{-1}\) mm\(^{-1}\).

**PTFs development and validation**

Figure 3(a,b) show the relationship between the measured \( K \) and estimated \( K \) in USLE and RUSLE. The USLE and RUSLE have an overestimation of 0.01 and 0.02 t h MJ\(^{-1}\) mm\(^{-1}\) (intercepts of the regression equation) for \( K \) prediction, respectively. The measured \( K \) versus predicted \( K \) by USLE and RUSLE for different soil classes are given in Figure 3(c). Figure 4(a) shows the mean of soil loss and OM content for different soil classes. The mean \( K \) value predicted by the USLE, RUSLE and the measured \( K \) values for different soil types are shown in Figure 4(b).
Table 2 illustrates the relationships between the measured \( K \) and the properties of soil considered in this study. Five of the most promising estimators were identified for \( K \), namely PE, OM, CaCO\(_3\), \( D_g \) and MWD. For \( K \) estimation using MLR, multivariate analysis and stepwise multiple linear regressions were used to select significantly correlated parameters with \( K \). According to statistical analysis, the PE, \( D_g \), VFS and CaCO\(_3\) are highly related to \( K \). Newly advanced regression PTFs using the USLE parameters and calcium carbonate are given as follows:

\[
K = 0.0271 - 0.0024 \text{PE} - 0.00423 \text{D}_g - 7.8 \times 10^{-5} \text{CaCO}_3 + 1.6 \times 10^{-4} \text{VFS} R^2 = 0.84, p < 0.01 \tag{13}
\]

where VFS is very fine sand (%), PE is Permeability (cm h\(^{-1}\)), \( D_g \) is mean geometric diameter (mm) and CaCO\(_3\) (%) is calcium carbonate. Table 3 shows the regression coefficients, standard error and significance levels of the MLR between soil erodibility and four main soil properties. The regression tree (RT) diagram to estimate the \( K \)-factor from the soil significant properties is shown in Figure 5. Figure 6 illustrates the comparison of the RT, MLR, the USLE and the RUSLE to predicate the \( K \)-factor using 1:1 line in the development (Figure 6(a)) and validation (Figure 6(b)) datasets. Table 4 shows the statistical indices for the MLR, RT, USLE and RUSLE for the \( K \) estimation. For model development, the \( R^2 \) values were 0.91, 0.84, 0.21 and 0.19 for RT, MLR, USLE and RUSLE, respectively.

**Discussion**

Most precipitation events occurred in December, January and February when the site had no suitable vegetation cover and soils were bare. Data from the Madar-soleyman rain gauge station, as the only in the study site, hence, data from this gauge station was used to compute the \( R \)-values, in order to obtain the mean \( R \)-value for subsequent calculation. According to Kouli et al. (2009) and Alexakis et al. (2013), the MFI agrees well with the rainfall erosivity factor. The measured \( K \) values

![Figure 2. USDA soil textural classes. Filled and empty circle are the development and validation data.](image-url)
Table 1. Descriptive statistics of the \( K \)-factor and soils physicochemical properties for different soil types (Entisols (n = 20), Inceptisols (n = 11), and Aridisols (n = 9)).

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Unit</th>
<th>Entisols</th>
<th>Aridisols</th>
<th>Inceptisols</th>
<th>Entisols</th>
<th>Aridisols</th>
<th>Inceptisols</th>
<th>Entisols</th>
<th>Aridisols</th>
<th>Inceptisols</th>
<th>Entisols</th>
<th>Aridisols</th>
<th>Inceptisols</th>
</tr>
</thead>
<tbody>
<tr>
<td>S</td>
<td>%</td>
<td>40.2(^n)</td>
<td>39.9(^n)</td>
<td>42.1(^n)</td>
<td>24.5</td>
<td>26.5</td>
<td>25.2</td>
<td>53.6</td>
<td>55.2</td>
<td>56.0</td>
<td>7.3</td>
<td>6.5</td>
<td>7.8</td>
</tr>
<tr>
<td>Si</td>
<td>%</td>
<td>33.6(^n)</td>
<td>31.5(^n)</td>
<td>32.2(^n)</td>
<td>19.2</td>
<td>18</td>
<td>19.01</td>
<td>44.5</td>
<td>46</td>
<td>45.2</td>
<td>5.9</td>
<td>6.2</td>
<td>7.1</td>
</tr>
<tr>
<td>C</td>
<td>%</td>
<td>25.9(^n)</td>
<td>26.7(^n)</td>
<td>26.4(^n)</td>
<td>17.9</td>
<td>18.5</td>
<td>20.3</td>
<td>40.5</td>
<td>41.9</td>
<td>39.8</td>
<td>5.6</td>
<td>6.8</td>
<td>7</td>
</tr>
<tr>
<td>SOM</td>
<td>%</td>
<td>2.99(^n)</td>
<td>3.09(^n)</td>
<td>3.55(^n)</td>
<td>1.8</td>
<td>1.94</td>
<td>1.88</td>
<td>3.41</td>
<td>3.15</td>
<td>3.84</td>
<td>0.3</td>
<td>0.2</td>
<td>0.31</td>
</tr>
<tr>
<td>CaCO(_3)</td>
<td>%</td>
<td>45.6(^n)</td>
<td>44.1(^n)</td>
<td>46.51(^n)</td>
<td>25</td>
<td>32.1</td>
<td>33.2</td>
<td>62.5</td>
<td>61.3</td>
<td>66.7</td>
<td>10.7</td>
<td>11.6</td>
<td>12.31</td>
</tr>
<tr>
<td>MWD</td>
<td>mm</td>
<td>1.24(^n)</td>
<td>1.15(^n)</td>
<td>1.52(^n)</td>
<td>0.85</td>
<td>1.1</td>
<td>1.05</td>
<td>1.95</td>
<td>2.3</td>
<td>2.5</td>
<td>0.2</td>
<td>0.5</td>
<td>0.47</td>
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<tr>
<td>PE</td>
<td>cm h(^{-1})</td>
<td>1.76(^n)</td>
<td>1.64(^n)</td>
<td>2.256(^n)</td>
<td>0.8</td>
<td>0.95</td>
<td>1.01</td>
<td>2.45</td>
<td>2.3</td>
<td>2.5</td>
<td>0.4</td>
<td>0.6</td>
<td>0.51</td>
</tr>
<tr>
<td>K</td>
<td>t h MU(^{-1}) mm(^{-1})</td>
<td>0.02(^n)</td>
<td>0.02(^n)</td>
<td>0.01(^n)</td>
<td>0.01</td>
<td>0.01</td>
<td>0.01</td>
<td>0.02</td>
<td>0.02</td>
<td>0.02</td>
<td>0.01</td>
<td>0.01</td>
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</tr>
<tr>
<td>Soil loss</td>
<td>t ha(^{-1}) y(^{-1})</td>
<td>3.7(^n)</td>
<td>3.65(^n)</td>
<td>3.15(^n)</td>
<td>1.42</td>
<td>1.52</td>
<td>1.38</td>
<td>5.6</td>
<td>6.75</td>
<td>5.2</td>
<td>0.85</td>
<td>1.1</td>
<td>0.84</td>
</tr>
</tbody>
</table>

S: Sand; Si: Silt; C: Clay; SOM: Soil organic matter content; PE: Permeability; MWD: Water aggregate stability; CaCO\(_3\): Calcium carbonate content; \( K \): soil erodibility factor. Superscripts \(^n\) and \(^*\) represent no significant and significant difference (\( p < 0.05 \)), respectively, among the soil types.
were in the range of 1.08 to 3.57 with a mean of 2.08, and 1.79 to 5.70 with a mean 2.84 times less than estimated $K$ values using USLE and RUSLE $K$-factors, respectively. According to Vaezi et al. (2010), the estimated $K$ values by the USLE were from 4.40 to 17.64 times higher than the measured $K$ values using standard erosion plots.

The $t$-test showed a significant difference ($n = 40; p < 0.01$) between the measured $K$ driven from unit plots and the predicted values derived from the USLE and RUSLE. The $K$ value estimated using USLE confirms the values of 0.03 and 0.04 t h MJ$^{-1}$ mm$^{-1}$ obtained by Addis and Klik (2015) and Bonilla and Johnson (2012), respectively. The $K$ value estimated in RUSLE concurs with the result of Vaezi and Sadeghi (2011). The results indicated that the correlation between measured $K$ and predicted $K$ by the USLE and the RUSLE was significant with $R^2 = 0.26$ and $R^2 = 0.29$, respectively. Although the $t$-test indicates significant difference ($p < 0.05; n = 40$) between the
mean values of $K$ estimated by USLE and RUSLE, there is no significant correlation ($p < 0.05; n = 40$) between the predicted $K$ by USLE and RUSLE (Figure 3(c)).

There is a negative significant correlation ($r = -0.46; p < 0.05; n = 40$) between soil loss (A) and OM content. Soil loss and OM content in Inceptisols are significantly higher and lower than that in Entisols and Aridisols, respectively; however, no significant differences were observed between

Figure 4. Variation of the measured and estimated $K$ by the USLE and RUSLE for different soil types ($p < 0.05, n = 40$) (a) and variation of soil loss and % OM for different soil types. ($n = 20, 11$ and $9$ for Entisols, Inceptisols and Aridisols, respectively).
Table 2. Correlation matrix of soil properties and soil erodibility (K).

<table>
<thead>
<tr>
<th></th>
<th>VFS</th>
<th>PE</th>
<th>MWD</th>
<th>FS</th>
<th>CaCO$_3$</th>
<th>OM</th>
<th>Dg</th>
<th>Sa</th>
<th>Si</th>
<th>Cl</th>
</tr>
</thead>
<tbody>
<tr>
<td>VFS</td>
<td>1</td>
<td>-0.29</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>PE</td>
<td>1</td>
<td>-0.52**</td>
<td>-0.67**</td>
<td></td>
<td>Sa</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>MWD</td>
<td></td>
<td>1</td>
<td>0.75</td>
<td>0.26</td>
<td>-0.62**</td>
<td>Dg</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>FS</td>
<td></td>
<td></td>
<td>1</td>
<td>0.25</td>
<td>0.23</td>
<td>-0.21</td>
<td>-0.08</td>
<td>OM</td>
<td></td>
<td></td>
</tr>
<tr>
<td>CaCO$_3$</td>
<td></td>
<td></td>
<td></td>
<td>1</td>
<td>0.51**</td>
<td>0.44*</td>
<td>0.56**</td>
<td>-0.49*</td>
<td>-0.21</td>
<td>CaCO$_3$</td>
</tr>
<tr>
<td>OM</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>1</td>
<td>-0.23</td>
<td>-0.14</td>
<td>-0.29</td>
<td>-0.18</td>
<td>0.2</td>
</tr>
<tr>
<td>Dg</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>1</td>
<td>-0.45**</td>
<td>0.36*</td>
<td>0.58**</td>
<td>0.21</td>
</tr>
<tr>
<td>Si</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>1</td>
<td>-0.24</td>
<td>0.51**</td>
<td>0.47**</td>
</tr>
<tr>
<td>Cl</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>1</td>
<td>-0.28</td>
<td>-0.31</td>
</tr>
<tr>
<td>K</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.43*</td>
<td>-0.77**</td>
</tr>
</tbody>
</table>

Sa: Sand; Si: Silt; Cl: Clay; FS: Fine sand; Dg: mean geometric diameter of soil particles; OM: Organic matter; VFS: Very fine sand; PE: Permeability; MWD: Water aggregate stability; CaCO$_3$: Calcium carbonate; **: Correlation significant at p < 0.01; *: Correlation significant at p < 0.05

Table 3. Regression coefficients, standard error and significance levels of the multiple regression between soil erodibility and four main soil properties.

<table>
<thead>
<tr>
<th>Model</th>
<th>Unstandardized Coefficients</th>
<th>Standardized T coefficients</th>
<th>Significance level (p)</th>
<th>VIF</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>B</td>
<td>Std. Err</td>
<td>Beta</td>
<td></td>
</tr>
<tr>
<td>Constant</td>
<td>0.02</td>
<td>0.03</td>
<td>-0.34</td>
<td>0.01</td>
</tr>
<tr>
<td>PE</td>
<td>-0.01</td>
<td>0</td>
<td>-0.27</td>
<td>0.03</td>
</tr>
<tr>
<td>Dg</td>
<td>-0.04</td>
<td>0.02</td>
<td>-0.27</td>
<td>0.03</td>
</tr>
<tr>
<td>CaCO$_3$</td>
<td>$-7.8 \times 10^{-5}$</td>
<td>0</td>
<td>-0.27</td>
<td>1.45</td>
</tr>
<tr>
<td>VFS</td>
<td>$1.6 \times 10^{-4}$</td>
<td>0</td>
<td>0.32</td>
<td>0.01</td>
</tr>
</tbody>
</table>

VFS: Very fine sand; PE: Permeability; Dg: mean geometric diameter of soil particles; CaCO$_3$: Calcium carbonate

Figure 5. RT diagram to estimate K-factor from soil easily measurable properties. Mu: mean of soil erodibility, Si: Silt; OM: Organic matter; VFS: Very fine sand; PE: Permeability; MWD: Water aggregate stability.
Entisols and Aridisols for soil loss and OM content, which is in agreement with Shabani et al. (2014). Water erosion could be the reason for this difference due to the loss of silt, very fine sand and organic matter for areas with Aridisols and Entisols that have sensitive compounds of dolomite.

Table 4. Statistical indices for the RT and MLR (suggested function and the USLE equation) methods for predicting K-factor in the development (N = 30) and validation dataset (N = 10).

<table>
<thead>
<tr>
<th>Method</th>
<th>Development dataset</th>
<th>Validation dataset</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$R^2$</td>
<td>ME</td>
</tr>
<tr>
<td>RT</td>
<td>0.91</td>
<td>0</td>
</tr>
<tr>
<td>MLR</td>
<td>0.84</td>
<td>0</td>
</tr>
<tr>
<td>The USLE</td>
<td>0.21</td>
<td>0.02</td>
</tr>
<tr>
<td>The RUSLE</td>
<td>0.19</td>
<td>0.02</td>
</tr>
</tbody>
</table>

Figure 6. Predicted K-factor using RT and MLR (suggested and the USLE equation) versus measured K-factor. (a) and (b) developing (N = 30) and validating dataset, respectively.
limestone and fine clay carbonate with marl and shale. Due to the minimal vegetation in Aridisols, it is far easier for run-off and rainfall to wash soils compared with Inceptisols distributions. Vaezi et al. (2017) reported that slope, vegetation, and soil organic matter described about 44%, 23% and 20% of the total variance in sediment yield of the Zanjanroud Watershed, Iran, respectively. Cerdà et al. (2018) studied the long-term impact of rained agricultural land abandonment on soil erosion in the Western Mediterranean basin. Their results showed an increase in sediment-yield in fallow agricultural land during the two years after abandonment. The results also proved, inversely, that two years of recovery of vegetation significantly reduced soil losses.

The K values driven from unit plots and natural rainfall and estimated K from the USLE and RUSLE were significantly different (p < 0.05) in varied soil classes. The measured and estimated values with both USLE and RULE in Inceptisols with 3.55% OM were noticeably lower than that in Entisols with 2.99% OM and Aridisols with 3.09% OM. OM content changes with soil classes, therefore soil classes can play an important role in determining K-factor and subsequently soil loss. Although there was no significant difference (p > 0.05) between values of measured K in Entisols and Aridisols, the mean K value predicted by RUSLE is markedly (p < 0.05) higher than that predicted by USLE in Inceptisols.

**Development of PTFs**

PE had the most significant correlation (r = −0.77, p < 0.01, n = 40) with K, which is supported by the results of (Vaezi and Sadeghi 2011). Silt and -VFS contents, due to their high susceptibility to soil detachment and transport by raindrops and run-off, were positively correlated with K, which is in agreement with Vaezi and Sadeghi (2011), Bonilla and Johnson (2012), while sand content and Dg were negatively correlated. As expected, K-factor was negatively correlated with %OM (r = −0.60, p < 0.01, n = 40), CaCO3 (r = −0.52, p < 0.05, n = 40), and MWD (r = −0.58, p < 0.05, n = 40).

High aggregate stability, due to increasing soil resistance to raindrop detachment, can reduce the soil erodibility factor (Charman and Murphy 2007). Vaezi et al. (2017) indicated that aggregate stability was the most important indicator describing the influence of aggregate-size on the inter-rill erodibility in semi-arid soils. Significant correlation was also found between OM content (r = 0.58, p < 0.05, n = 40) and CaCO3 (r = 0.36, p < 0.05, n = 40) with MDW. According to Vaezi and Sadeghi (2011), OM and Ca2+ act as binding agents to flocculate minerals colloid and increase the stability of soil aggregation, sequentially decreasing the K-factor. The influences of MWD and PE on K were also pointed out by Hoyos (2005). Conversely, sand decreases the MWD, which is corroborated with Veihle (2002).

The VIF values lower than 2 for all predictor variables indicate that there is no Multicollinearity among these (Table 3). Table 3 shows that soil permeability with Beta = −0.386 is the most important parameter to estimate K, which is supported by Vaezi et al. (2008). Table 2 indicates that although PE measurement is difficult and time-consuming, the contents of silt, sand, OM or calcium carbonate can predict PE with explanation variance of 42%, 49%, 54% and 51%, respectively.

In the first node (parent node), the classification was based on permeability (PE). As mentioned previously, among the predictors of soil properties, PE had the highest correlation with the K-factor (Table 2). In this node, PE was divided into parts at 2.15 cm h\(^{-1}\). The second node (first child node) on the right side (PE > 2.15 cm h\(^{-1}\)) was separated using VFS (very fine sand) as the only separator, whereas left child node (PE < 2.15 cm h\(^{-1}\)) was divided into PE, Dg, VFS and SI (silt). Silt appeared in the lowest node (after MWD and VFS), which was in accordance with its correlation with the K-factor. Figure 6 shows that although sand had a significant correlation with the K-factor (Table 2), it did not appear in the tree diagram (Figure 5).
Validation of PTFs

Overall, RT and the MLR function had better accuracy than USLE and RUSLE to predict the K-factor. The latter two displayed overestimation of the K-factor, especially at higher K values, which is in agreement with Vaezi et al. (2010). Although the CaCO$_3$ was not considered in the original USLE and RUSLE, it significantly decreased the K-factor due to significant effects on the stability of soil aggregate sand soil permeability (Shabani et al. 2014). According to Renard et al. (1997), the USLE is well suited for less aggregated soil because it was developed in regions that had an aggregation stability index lower than 0.30 and little calcium carbonate in soils.

In our study, soils are calcareous and have plenty of lime (CaCO$_3$). In calcareous soils, calcium has a significant impact on increasing aggregate stability and consequently infiltration rates that have a negative significant effect on the soil erodibility factor, which is supported by Orts et al. (2000), Charman and Murphy (2007). Some studies have pointed out that polyvalent cations (especially Ca$^{2+}$) significantly increase the flocculation of mineral colloids and reduce sensitivity to erosion. Vaezi et al. (2008) showed a high negative influence of %CaCO$_3$ on the soil erodibility factor in Iran. In both studies, %CaCO$_3$ was accounted as an input variable to develop PTFs for K estimation. As pointed out, the RUSLE K-factor was designed in the Midwest of the United States with less than 10% rock fragments in soils. In some portions of our study site, soils have considerably more than 10% rock fragments, and more than 25% in the pastures located close to the mountains.

ME values for RT and MLR showed no skew to estimate K (good match between predicted and measured soil erodibility factor). However, according to GME values, there is negligible overestimation between predicted and measured K for RT (GME = 1.01) and MLR (GME = 1.01). Regarding RT and MLR, ME values for RUSLE and USLE were 0.015 and 0.01, respectively, which indicate a very weak match (very high overestimation) between estimated and measured K. In addition, RMSE values were 0, 0.02 and 0.02 t h MJ$^{-1}$ mm$^{-1}$ for RT, MLR, USLE and RUSLE, respectively (Table 4). Therefore, based on the criteria indices, RT is the best method for K prediction in the development of a dataset.

For model validation, RT had the highest $R^2$ ($R^2 = 0.84$). Moreover, according to ME, GME and RMSE values, RT had the lowest skew (ME = 0 t h MJ$^{-1}$ mm$^{-1}$ and GME = 1) and error (RMSE = 0 t h MJ$^{-1}$ mm$^{-1}$), in agreement with the results of model development. As shown in Table 4, RT had higher performance than MLR, ULSE and RUSLE in the prediction of the K-factor. Although there is no study for K prediction with RT, the high performance of this method for estimation of FC was reported by Pachepsky et al. (2006). Dehghani et al. (2012) also highlighted that the RT method had better performance than the MLR method in predicting pH and hydraulic conductivity, respectively. Furthermore, MLR had higher efficiency than USLE and RUSLE to estimate K. Vaezi and Sadeghi (2011) reported that the developed linear PTF in their study had higher performance than USLE to predict K. Overall, according to statistical indices, the USLE showed greater efficiency than RUSLE in predicting K because it considered more variables having an important effect on K.

Conclusion

The results showed that soil permeability is the soil properties affecting most on K-factor. We found a highly negative significant correlation between CaCO$_3$ with K ($r = -0.52; p < 0.01$) due to its (Ca$^{2+}$) strong effects on the stability of soil aggregates. The mean of the estimated K by USLE and RUSLE is about two and three times greater than the measured K, respectively. Results also showed that the RT method displayed higher performance ($R^2 = 0.91$ and $R^2 = 0.84$) in developing and validating the dataset, respectively, than MLR, USLE and RUSLE to estimate K. Moreover, the developed MLR PTFs was the second most efficient method in predicting K and had a higher performance than
USLE and RUSLE. There are some reasons why the USLE and RUSLE did not have high performance in the estimation of $K$-factor in this study. Firstly, the soil variables, which relate to soil erodibility, varied in both space and time. Secondly, the USLE equation was derived from soils with specific geographic and climatic conditions.

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**Disclosure statement**

No potential conflict of interest was reported by the authors.

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**References**


