Identification of erosion-prone areas using different multi-criteria decision-making techniques and GIS

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ABSTRACT
The awareness of erosion risk in watersheds provides the possibility of identifying critical areas and prioritising protective and management plans. Soil erosion is one of the major natural hazards in the rainy mountainous regions of the Neka Roud Watershed in Mazandaran Province, Iran. This research assesses soil erosion susceptibility through morphometric parameters and the land use/land cover (LU/LC) factor based on multiple-criteria decision-making (MCDM) techniques, remote sensing and GIS. A set of 17 linear, relief and shape morphometric parameters and 5 LU/LC classes are used in the analysis. The aforementioned factors are selected as indicators of soil erosion in the study area. Then, four MCDM models, namely, the new additive ratio assessment (ARAS), complex proportional assessment (COPRAS), multi-objective optimisation by ratio analysis and compromise programming, are applied to the prioritisation of the Neka Roud sub-watersheds. The Spearman’s correlation coefficient test and Kendall’s tau correlation coefficient test indices are used to select the best models. The validation of the models indicates that the ARAS and COPRAS models based on morphometric parameters and LU/LC classes, respectively, achieve the best performance. The results of this research can be used by planners and decision makers in soil conservation and in reducing soil erosion.

1. Introduction
Soil and water are two vital elements not only for the livelihood of humankind, but also for the economic and social advancement of different countries worldwide (Debelo et al. 2017). Soil erosion has always been one of the most critical problems of watersheds in the world; it can be considered one of the largest obstacles to achieving sustainable development in agriculture and natural resource use (Molla and Sisheber 2017;...
Singh and Panda 2017; Subhatu et al. 2017; Tadesse et al. 2017; Tamene et al. 2017; Vulević and Dragović 2017). Knowledge of the extent of erosion risk in watersheds provides the possibility of identifying critical areas and prioritising protective and management plans. The sensitivity or potential of different areas of a watershed frequently require estimation in terms of the severity of soil erosion or the zonation of the soil erosion potential because no correct and acceptable information about the quantitative rate of erosion in watersheds is available (Samanta et al. 2016). Most watersheds in Iran are vast; thus, conservation projects cannot be implemented in the entire watershed. Consequently, the critical areas of a watershed should be identified and prioritised from the perspective of soil erosion potential to improve the performance of watershed plans (Pakhmode et al. 2003). The prioritisation of watersheds can be defined as the procedure for identifying enforced sub-watersheds to perform soil protection actions on the basis of priority and various criteria for sediment yield, soil loss and morphological factors (Jaiswal et al. 2015; Farhan et al. 2017; Singh and Singh 2017). The morphometric analysis of a drainage network is essential for realising the geomorphological and geological reactions of a drainage basin for soil and water conservation and river basin evolution (Kottagoda and Abeysingha 2017). Land use/land cover (LULC) change is a major issue in soil erosion. Land use is another dimension of the natural environment, including rocks, biodiversity, soil and man-made structures, such as infrastructure (Iqbal and Sajjad 2014). Soil erosion and soil loss depend on several geo-environmental factors; hence, the detection of areas that are susceptible to erosion is possible using a set of geo-environmental parameters under multiple-criteria decision-making (MCDM) techniques to acquire appropriate weights that can finally represent watershed areas that are susceptible to erosion (Jaiswal et al. 2015). MCDM models have become important components of operation research on designing mathematical and computational tools for supporting the intellectual evaluation of criteria and alternatives by decision makers (Mardani et al. 2015).

MCDM approaches are important for solving complex problems because of their intrinsic capability to examine various alternatives based on different criteria to select the best alternatives (Ardielli 2016). At present, geographic information system (GIS) and remote sensing (RS) techniques have become crucial because they help decision makers and planners make effective decisions (Meshram and Sharma 2017; Singh and Singh 2017). In recent years, several studies have been conducted on the prioritisation of watersheds and sub-watersheds using morphometric and LU/LC parameters from MCDM models (Altaf et al. 2014; Iqbal and Sajjad 2014; Azarnivand et al. 2015; Jaiswal et al. 2015; Al-Saady et al. 2016; Arabameri et al. 2017; Vulević and Dragović 2017). In the Neka Roud Watershed in Mazandran Province, north of Iran, human pressure from population growth coupled with strong precipitation events, land use change, deforestation and a hilly landscape have led to serious soil erosion and related problems. This research aims to combine morphometric parameters and LU/LC classes to identify soil erosion-prone areas using four MCDM models, namely, additive ratio assessment (ARAS), complex proportional assessment (COPRAS), multi-objective optimisation by ratio analysis (MOORA) and compromise programming (CP). No report/article that compares the aforementioned techniques in prioritising watersheds and sub-watersheds worldwide is yet available.
2. Material and methods

2.1. Study area

The Neka Roud Watershed is located between longitudes 53° 04' 08" to 54° 08' 53" E and latitudes 35° 58' 34" to 36° 28' 34" N. It is in Mazandran Province in the north of Iran (Figure 1). This watershed has 42 sub-watersheds. The total drainage area of the Neka Roud Watershed is 3768 km². Sub-watershed 32 is the largest, with an area of 227 km², and Sub-watershed 30 is the smallest, with an area of 5.94 km². The perimeter of the total study area is 1929.79 km. The basin length of the watershed is 141.95 km. On the basis of GIS analysis, Sub-watershed 40, with a basin length of 28.28 km, and Sub-watershed 30, with 3.63 km, have the maximum and minimum stream lengths among the 42 sub-watersheds, respectively. Neka Roud is a sixth-order watershed according to Strahler's scheme (Strahler 1957, 1964). The total number

Figure 1. The study area.
(Nu) and total length (Lu) of streams in the study area are 4336 and 35219.76 km, respectively. First-order streams account for 50.75% (2168) of the total number of streams and 5.09% (1796.06 km) of the total length of streams. By contrast, sixth-order streams account for 0.7% of the total number of streams and 21.57% of the length of streams. The stream specifications of the Neka Roud Watershed authenticate Horton’s first and second laws (Figures 2(a, b)), which state that the average number and length of streams of different orders in a drainage basin tend to have an inverse and direct geometric ratio, respectively. The maximum and minimum elevations of the watershed are between 95 m.a.s.l and 3711 m.a.s.l. Subwatershed 1 in the south sector of the study area has the highest mean elevation (2691 m), whereas Subwatershed 39 in north sector of study area has the lowest mean elevation (204 m).

2.2. Methodology

The main objectives of this research are as follows: (1) extraction of linear, shape and relief morphometric parameters using a digital elevation model (DEM) from the Advanced Spaceborne Thermal Emission Reflection Radiometer (ASTER);
(2) preparation of an LU/LC map in the study area using RS data from the Linear Imaging Self-scanning Sensor (LISS) III of the Indian Remote Sensing Satellite (IRS); (3) application of four MCDM models, namely, ARAS, COPRAS, MOORA and CP, to the prioritisation of sub-watersheds according to soil erosion susceptibility; (4) comparison of different methods and selection of the best model using Spearman’s correlation coefficient test (SCCT) and Kendall’s tau correlation coefficient test (KTCCT) indices; (5) combination of maps of prioritisation of sub-watersheds using morphometric and LU/LC factors and (6) determination of soil erosion-prone sub-watersheds and their classification into five susceptibility classes, namely, very high, high, moderate, low and very low. The flowchart of the methodology of the current study is shown in Figure 3.

Figure 3. Methodological flowchart applied in this research.
ASTER DEM, with a resolution of 30 m × 30 m, and IRS LISS III data, with a resolution of 23.5 m, were used to generate the land cover information of the study area. In this research, the LU/LC map was prepared using IRS satellite images, but the morphometric parameters were extracted from drainage networks and the DEM generated by ASTER (Ahmad Rather et al. 2017). Arc Hydro extension was used in drainage network extraction (Altaf et al. 2014). The generation of the drainage network (Figure 4) using Arc Hydro was explained by Ahmad Rather et al. (2017). In this research, the stream networks in the sub-watershed were defined according to the cumulative number of upstream cells that drain in each cell. In addition, a threshold higher than 300 was used to extract the drainage basin. The area and perimeters of the sub-watersheds were computed using ArcGIS 10.5 software. Strahler’s method was used in ordering the streams of the watershed (Strahler 1952). The equations used for computing the linear, relief and shape morphometric parameters can be found in previous studies (Rakesh et al. 2000; Horton 1945; Langbein 1947; Miller 1953; Schumm 1956; Faniran 1968; Moore et al. 1991; Nautiyal 1994; Nooka Ratnam et al. 2005; Altaf et al. 2014; Ahmad Rather et al. 2017; Arabameri et al. 2017). The basic morphometric factors are listed in Table 1, and the linear, relief and shape parameters are provided in Table 2. The maximum likelihood supervised classification algorithm was used to generate the LU/LC of the study area (Altaf et al. 2014). In general, five LU/LC classes were observed in the study area, namely, agriculture, forest, pasture, plantation and wasteland (Figure 5). The produced LU/LC was verified in the field using 345 ground control points (GCPs). Equation 1 is used to calculate the kappa coefficient (Lo and Yeung 2002).

![Sub-watersheds of study area.](image)
The kappa coefficient of the generated LC/LU was 97.65%.

### 2.3. MCDM techniques

#### 2.3.1. CP

In accordance with the CP model, the shorter the distance from the ideal solution, the higher the rank of an alternative, and the longer the distance from the ideal solution, the lower the rank of an alternative (Raju et al. 2000).

#### Table 1. Basin network characteristics of Neka Roud sub-watersheds.

| WSs | Area (km²) | Perimeter (km) | Total No. of Streams | Stream Length (km) | Basin Length (km) | Elevation (m) |
|-----|-------------|----------------|----------------------|--------------------|------------------|--------------|
|     |             |                |                      |                    |                  | Max | Min | Mean |
| W51 | 117.31      | 48.23          | 134                  | 98.47              | 19.78            | 3711 | 1833| 2691 |
| W52 | 148.17      | 68.25          | 198                  | 135.96             | 22.59            | 2994 | 1588| 2328 |
| W53 | 39.19       | 27.29          | 38                   | 32.86              | 10.61            | 2930 | 1622| 2307 |
| W54 | 63.92       | 52.76          | 64                   | 63.48              | 14.01            | 2954 | 1557| 2189 |
| W55 | 63.66       | 41.30          | 80                   | 53.32              | 13.98            | 2859 | 1213| 2062 |
| W56 | 101.66      | 42.83          | 105                  | 87.45              | 18.24            | 2833 | 790 | 1663 |
| W57 | 169.78      | 59.15          | 198                  | 150.31             | 24.40            | 2861 | 949 | 1838 |
| W58 | 41.96       | 29.09          | 45                   | 34.89              | 11.03            | 1771 | 812 | 1191 |
| W59 | 83.67       | 61.97          | 100                  | 78.46              | 16.33            | 3160 | 625 | 1392 |
| W60 | 32.33       | 24.98          | 32                   | 32.31              | 9.51             | 1826 | 614 | 918  |
| W61 | 80.22       | 50.65          | 104                  | 81.58              | 15.94            | 2780 | 867 | 1685 |
| W62 | 46.92       | 40.24          | 37                   | 36.97              | 11.76            | 1527 | 401 | 935  |
| W63 | 104.74      | 51.78          | 132                  | 99.49              | 18.55            | 2780 | 867 | 1685 |
| W64 | 25.84       | 21.17          | 30                   | 20.85              | 8.38             | 1663 | 452 | 1087 |
| W65 | 116.52      | 70.84          | 141                  | 102.26             | 19.71            | 2305 | 399 | 1065 |
| W66 | 23.92       | 23.40          | 27                   | 19.281             | 8.02             | 1385 | 331 | 754  |
| W67 | 80.70       | 38.10          | 103                  | 76.06              | 16.00            | 1792 | 784 | 1191 |
| W68 | 167.42      | 75.54          | 201                  | 176.14             | 24.21            | 2755 | 1459| 2024 |
| W69 | 129.01      | 60.90          | 125                  | 117.89             | 20.88            | 2006 | 927 | 1405 |
| W70 | 13.25       | 18.78          | 17                   | 13                 | 5.73             | 1203 | 298 | 648  |
| W71 | 31.69       | 24.24          | 37                   | 30.24              | 9.41             | 1100 | 333 | 764  |
| W72 | 42.78       | 34.68          | 46                   | 37.99              | 11.16            | 1619 | 236 | 703  |
| W73 | 120.69      | 54.59          | 134                  | 110.14             | 20.10            | 2704 | 923 | 1652 |
| W74 | 141.30      | 71.47          | 160                  | 121.8              | 21.99            | 1667 | 237 | 864  |
| W75 | 23.39       | 22.76          | 28                   | 21.63              | 7.92             | 962  | 180 | 468  |
| W76 | 215.16      | 87.17          | 235                  | 185.83             | 27.92            | 2602 | 513 | 1351 |
| W77 | 56.15       | 30.89          | 63                   | 52.88              | 13.02            | 1031 | 225 | 599  |
| W78 | 5.94        | 10.44          | 9                    | 7.2                | 3.63             | 759  | 158 | 315  |
| W79 | 31.84       | 23.42          | 42                   | 27.12              | 9.43             | 875  | 161 | 511  |
| W80 | 227.61      | 81.43          | 287                  | 283.27             | 28.83            | 3154 | 1355| 1926 |
| W81 | 200.83      | 62.36          | 230                  | 164.52             | 26.85            | 1433 | 334 | 847  |
| W82 | 36.83       | 29.63          | 28                   | 28.59              | 10.24            | 1030 | 184 | 601  |
| W83 | 12.11       | 14.97          | 20                   | 12.52              | 5.45             | 515  | 128 | 269  |
| W84 | 124.87      | 67.91          | 149                  | 116.26             | 20.50            | 2697 | 953 | 1694 |
| W85 | 65.08       | 41.59          | 70                   | 53.66              | 14.16            | 1668 | 587 | 1135 |
| W86 | 67.14       | 39.02          | 75                   | 60.15              | 14.41            | 882  | 96 | 384  |
| W87 | 14.22       | 17.59          | 19                   | 14                 | 5.97             | 434  | 95 | 204  |
| W88 | 220.13      | 90.40          | 264                  | 197.98             | 28.28            | 1436 | 127 | 630  |
| W89 | 147.65      | 64.19          | 168                  | 130.12             | 22.54            | 2083 | 587 | 1175 |
| W90 | 149.70      | 53.05          | 173                  | 138.27             | 22.72            | 2596 | 993 | 1722 |
| W91 | 75.72       | 41.56          | 81                   | 60.43              | 15.43            | 2926 | 1355| 2006 |
| W92 | 107.27      | 59.20          | 107                  | 85.59              | 18.80            | 2183 | 1588| 2286 |

\[
K = \left\{ \frac{N \sum_{i=1}^{N} (X_{ii}) - N \sum_{i=1}^{N} (X_{ii} \cdot X_{ii})}{N^2} \right\} \div \sqrt{\sum_{i=1}^{N} (X_{ii} \cdot X_{ii})}
\]

(1)

The kappa coefficient of the generated LC/LU was 97.65%.
To maximise criteria, the ideal solution is given as $x^+_i = \max x_{ij}$; to minimise criteria, the ideal solution is given as $x^-_j = \min x_{ij}$ (Zeleny and Cochrane 1973). The CP model can be calculated using Equation (2) (Chitsaz and Banihabib 2015).

$$L_{p,i} = \left\{ \sum_{j=1}^{n} \frac{w^+_j \left( \frac{x^+_i - x_{ij}}{x^+_i - x^-_j} \right)}{p^+_j} \right\}^{\frac{1}{p^+_i}}$$

where $L_{p,i}$ is the alternative ideal solution, and $w^+_j$ is the criterion weight (Chitsaz and Banihabib 2015).
2.3.2. COPRAS

COPRAS is an MCDM method presented by Zavadskas and Kaklauskas in 1996 (Podvezko 2011; Popovic et al. 2012; Organ & Yalcın 2016). The COPRAS method assumes the direct and commensurate affiliation of the level of magnitude and usefulness of alternatives in the presence of conflicting criteria (Chatterjee 2013).

The COPRAS procedure consists of the following steps (Organ and Yalcın 2016):

Step 1: Preparation of the primary matrix
Step 2: Normalisation of the primary matrix using Equation 3:

\[
x_{ij}^{\text{norm}} = \frac{x_{ij}}{\sum_{i=1}^{m} x_{ij}},
\]

where \( x_{ij} \) is the normalised quantity of the \( j \)-th criterion, \( x_{ij} \) is the \( i \)-th alternative performance of the \( j \)-th criterion and \( m \) denotes the alternative numbers.

Step 3: Determination of the normalised weighted decision-making matrix using Equation 4:

\[
d_{ij} = w_j \times \overline{x}_{ij},
\]

where \( \overline{x}_{ij} \) is the efficiency of the \( i \)-th alternative, and \( w_j \) is the criterion weight.

Step 4: Computation of the maximum and minimum indices for alternatives. In this step, alternatives are classified as maximising and minimising indices using Equations 5 and 6:
\[ S_j^+ = \sum_{j=1}^{n} y_{+ij} \quad j = 1, 2, 3..., n; \]  
\[ S_j^- = \sum_{j=1}^{n} y_{-ij} \quad j = k + 1, \; k + 2, \; ..., n; \]

where \( y_{+ij} \) and \( y_{-ij} \) are the weighted normalised qualities for advantageous and non-advantageous adjectives, respectively.

Step 5: Calculation of the relative weights of each alternative using Equation 7:

\[ Q_i = \frac{S_{\min} \sum_{j=1}^{n} S_j^-}{S_j^- \sum_{j=1}^{n} S_{\min}} = S_j^+ + \frac{\sum_{j=1}^{n} S_j^-}{S_j^- \sum_{j=1}^{n} S_{\min}}, \]

where \( S_{\min} \) is the minimum value of \( S_j^- \). \( S_j^+ \) and \( S_j^- \) are maximum and minimum indices, respectively.

2.3.3. New ARAS

The ARAS method (Zavadskas and Turskis 2010) is based on the logic that complex relations can be realised using simplex comparative comparisons.

The ARAS model consists of the following steps (Zavadskas and Turskis 2010):

Step 1: Preparation of the decision-making matrix

Step 2: Normalisation of the criteria. The criteria whose superior amounts are maximum are normalised using Equation 9, whereas the criteria whose superior amounts are minimum are normalised using Equation 10 (Zavadskas and Turskis 2010):

\[ x_{ij} = \frac{\sum_{i=1}^{m} x_{ij}}{m}, \]

\[ x_{ij} = \frac{1}{\sum_{i=0}^{m} x_{ij}}, \]

where \( x_{ij} \) is the normalised amount of the \( j \)th criterion, \( x_{ij} \) is the \( i \)th alternative performance of the \( j \)th criterion and \( m \) is the number of alternatives.

Step 2: Computation of the normalised-weighted matrix as Equation 11:

\[ \hat{x}_{ij} = x_{ij} \times w_j, \]

where \( w_j \) is the criterion weight of \( j \), and \( x_{ij} \) is the normalised ranking of the \( j \)th criterion.
Step 3: Calculation of the values of the optimality function as Equation 12:

\[ S_i = \sum_{j=1}^{n} \hat{x}_{ij}; \quad i = 0, m; \]  

where \( S_i \) is the value of the optimality function of alternative \( i \).

Step 4: Selection of the most acceptable alternative based on the values of efficiency that can be computed using Equation 13:

\[ K_i = \frac{S_i}{S_0}; \quad i = 0, m; \]  

where \( S_i \) and \( S_0 \) are the optimality criterion amounts.

The values of \( K_i \) vary from 0 to 1; the higher the value, the better the alternative rank (Karabasevic et al. 2015).

2.3.4. MOORA

The MOORA method was introduced by Brauers (2003). It is based on the ratio system and dimensionless measurement (Brauers et al. 2010).

The MOORA method consists of the following steps (El-Santawy and Ahmed 2012):

Step 1: Production of the decision matrix

Step 2: Normalisation of the decision matrix using Equation 14:

\[ x_{ij}^* = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}} \quad (j = 1, 2, ... n), \]  

where \( x_{ij}^* \) is a dimensionless number that demonstrates the normalised performance of the \( i \)th alternative on the \( j \)th criteria.

Step 3: Assessment of positive and negative effects using Equation 15:

\[ y_i = \sum_{j=1}^{g} x_{ij}^* - \sum_{j=g+1}^{n} x_{ij}^* \]  

where \( y_i \) is the normalised evaluation value of the \( i \)th alternative when all the criteria are considered, \( g \) is the number of criteria to be maximised and \( (n - g) \) is the number of criteria to be minimised.

Step 4: Computation of the weighted evaluation amounts using Equation 16:

\[ y_i^* = \sum_{j=1}^{g} w_j \times x_{ij}^* - \sum_{j=g+1}^{n} w_j \times x_{ij}^* \quad (j = 1, 2, ... n), \]  

where \( w_j \) is the weight of the \( j \)th criteria, which can be obtained using different MCDM methods.

Step 5: Ranking of alternatives in ascending order
2.4. Assigning weights to criteria using AHP model

Different methods are used to characterise the weights of criteria. In this study, the Analytical Hierarchy Process (AHP) was used to estimate the weights of criteria. The AHP was calculated according to a pair-wise comparison matrix. The data for this method were obtained from experts’ votes. For this purpose, the AHP questionnaires were designed (Table 5) and answered by 18 experts of geomorphology and 15 experts of hydrology. Initially, due to the incompatibility of some of the paired comparison matrices from the experts’ votes, the questionnaires were redistributed to confirm the matrix compatibility and validity of the questionnaires. Judgments that are applied in paired comparisons by experts are a mixture of rational thinking and experience (Chitsaz and Banihabib 2015). On the basis of the AHP method, Saaty’s linguistic scales (Table 3) of pair-wise comparisons should be converted to quantitative values (Saaty 1980). Then, the weights of criteria were determined using Equations 17 and 18 (Chitsaz and Banihabib 2015):

\[
n_{ij} = \frac{a_{ij}}{\sum_{i=1}^{n} a_{ij}} \quad (17)
\]

\[
W_j = \frac{\sum_{i=1}^{n} a_{ij}}{n} \quad (18)
\]

where \(W_j\) is the weight of criteria by AHP, \(n_{ij}\) is normalized of pair-wise comparison matrix and \(a_{ij}\) is matrix element in row \(i\) and column \(j\).

The consistency ratio is the mechanism by which the validity of the expert response is measured by pair-wise comparison matrix (Chitsaz and Banihabib 2015). In AHP method, the consistency ratio less than 0.1 is acceptable. Equations 19–23 were used to calculate the consistency ratio (Saaty 1980):

\[
CR = \frac{CI}{RI} \quad (19)
\]

\[
CI = \frac{\hat{\lambda}_{\text{max}} - n}{n - 1} \quad (20)
\]

\[
\hat{\lambda}_{\text{max}} = \frac{\sum_{i}^{n} \hat{\lambda}}{n} \quad (21)
\]

| Preference factor | Degree of preference |
|-------------------|----------------------|
| 1                 | Equally              |
| 3                 | Moderately           |
| 5                 | Strongly             |
| 7                 | Very strongly        |
| 9                 | Extremely            |
| 2, 4, 6, and 8    | Intermediate         |
where, CR is consistency ratio, CI is consistency index, RI is a random index whose values are extracted from Table 4, n is number of criteria, $k_{\text{max}}$ is the largest special matrix value, $k$ is consistency vector, WSV is weighted sum vector, A is pair-wise comparison matrix, and W is weight of criteria vector. Questionnaires of AHP for calculation of the weights of criteria are shown in Table 5.

### 2.5. Nonparametric correlation tests for comparing the four MCDM techniques

MCDM models have diverse outcomes; thus, a correlation test should be performed among the ranks of MCDM models to select the best model.

Nonparametric correlation tests, such as KTCCT and SCCT, are the most popular methods for distinguishing the best models. These nonparametric correlation tests are based on ranks (Szmidt and Kacprzyk 2011; Chitsaz and Banihabib 2015). KTCCT was calculated using Equation 24, when the two compared models did not have any similar ranks. By contrast, Equation 25 was used when one of the compared models had the same ranks (Athawale and Chakraborty 2011):

\[
\lambda = \frac{\text{WSV}}{w}
\]

(22)

\[
\text{WSV} = A \times W
\]

(23)

where, CR is consistency ratio, CI is consistency index, RI is a random index whose values are extracted from Table 4, n is number of criteria, $k_{\text{max}}$ is the largest special matrix value, $k$ is consistency vector, WSV is weighted sum vector, A is pair-wise comparison matrix, and W is weight of criteria vector. Questionnaires of AHP for calculation of the weights of criteria are shown in Table 5.

| n  | 1  | 2  | 3  | 4  | 5  | 6  | 7  | 8  | 9  | 10 | 11 | 12 | 13 | 14 | 15 |
|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|
| RI | 0.00 | 0.00 | 0.58 | 0.9 | 1.12 | 1.24 | 1.32 | 1.41 | 1.45 | 1.49 | 1.51 | 1.53 | 1.56 | 1.59 | 1.67 |

### Table 5. Questionnaires of AHP for calculation of the weights of criteria.

| Dd | T | Fu | If | Rn | C | Re | Cc | Rc | Sa | Hi | Rbm | Rr | Lo | Rh | Bs | Rf |
|----|---|----|----|----|---|----|----|----|----|----|----|----|----|----|----|----|
| 1  |   | 1  |    |    |   |    |    |    |    |    |    |    |    |    |    |    |
| 1  |   |    | 1  |    |   |    |    |    |    |    |    |    |    |    |    |    |
| 1  |   |    |   | 1  |   |    |    |    |    |    |    |    |    |    |    |    |
| 1  |   |    |   |    | 1 |    |    |    |    |    |    |    |    |    |    |    |
| 1  |   |    |   |    |   | 1  |    |    |    |    |    |    |    |    |    |    |
| 1  |   |    |   |    |   |    | 1  |    |    |    |    |    |    |    |    |    |
| 1  |   |    |   |    |   |    |   | 1  |    |    |    |    |    |    |    |    |
| 1  |   |    |   |    |   |    |   |   | 1  |    |    |    |    |    |    |    |
| 1  |   |    |   |    |   |    |   |   |   | 1  |    |    |    |    |    |    |
| 1  |   |    |   |    |   |    |   |   |   |   | 1  |    |    |    |    |    |
| 1  |   |    |   |    |   |    |   |   |   |   |   | 1  |    |    |    |    |
| 1  |   |    |   |    |   |    |   |   |   |   |   |   | 1  |    |    |    |
| 1  |   |    |   |    |   |    |   |   |   |   |   |   |   | 1  |    |    |
| 1  |   |    |   |    |   |    |   |   |   |   |   |   |   |   | 1  |    |

$\lambda = \frac{\text{WSV}}{w}$

(22)

$\text{WSV} = A \times W$

(23)

$T = \frac{C-D}{n(n-1)/2},$

(24)

$T = \frac{C-D}{\sqrt{(n(n-1)/2 - T) \times (n(n-1)/2 - U)}},$

(25)
where $C$ and $D$ are the numbers of agreeing and disagreeing pairs, respectively. $T$ and $U$ are the numbers of pairs with similarities in each pair of compared models.

In the nonparametric SCCT test, Equation 26 is used if two compared models have no similar ranks, and Equation 27 is applied if one of the compared models has similar ranks (Raju et al. 2000):

$$r_s = 1 - \frac{6 \sum_{i=1}^{n} d_i^2}{n(n^2-1)},$$

$$r_s = \frac{\sqrt{\sum_{i=1}^{n} (x_i - \bar{x}) \times (y_i - \bar{y})}}{\sqrt{\sum_{i=1}^{n} (x_i - \bar{x})^2} \times \sqrt{\sum_{i=1}^{n} (y_i - \bar{y})^2}},$$

where $d_i$ is the difference between the ranks of models for each alternative; and $\bar{x}$ and $\bar{y}$ are the mean of the $x$ and $y$ models, respectively.

3. Results and Discussion

3.1. Prioritisation of soil erosion-prone sub-watersheds using morphometric parameters and MCDM models

Morphometric parameters play an important role in understanding the lithology type and characteristics of hydrological behaviour, soil properties and erosion characteristics (Al-Saady et al. 2016; Ahmad Rather et al. 2017). In this research, based on extensive literature review (Farhan et al. 2015; Farhan et al. 2017; Ahmad Rather et al. 2017; Arabameri et al. 2017; Meshram and Sharma 2017) and environmental features of study area, 17 morphometric parameters selected for priority of sub-watersheds in soil erosion and soil erosion susceptibility mapping.

The linear, shape and relief morphometric parameters derived for the sub-watersheds of the Neka Roud Watershed are provided in Table 2. The linear parameters, namely, stream density ($D_d$), stream frequency ($F_u$), mean bifurcation ratio ($R_{bm}$), length of overland flow ($L_o$), texture ratio ($T$), infiltration number ($I_f$), constant of channel maintenance ($C$), relief ratio ($R_h$), relative relief ($R_r$), ruggedness number ($R_n$), average slope ($S_a$) and hypsometric integral ($H_I$), exhibit a direct relationship with erodibility. Accordingly, the higher the values of these parameters, the greater the degree of erosion in a sub-watershed and vice versa. Meanwhile, the shape parameters, namely, elongation ratio ($R_e$), compactness coefficient ($C_c$), circularity ratio ($R_c$), form factor ($R_f$) and shape factor ($B_s$), exhibit an inverse relation to erodibility. Therefore, the higher the values of these parameters, the lower the degree of erosion in a sub-watershed and vice versa (Farhan et al. 2015, 2017; Arabameri et al. 2017; Meshram and Sharma 2017).

The analysis of morphometric parameters indicates that based on the $T$ factor, Sub-watersheds (WSs) 31, 30 and 7 obtained the highest values (3.68, 3.52 and 3.34,
respectively) because of low infiltration capacity, and thus, they have high susceptibility to soil erosion. Meanwhile, WSs 12, 20 and 28, which have the lowest values (0.919, 0.905 and 0.861, respectively) are not prone to erosion. In terms of If, WSs 28 (0.927), 33 (0.743) and 37 (0.560) have the highest values and are the most susceptible to erosion due to high runoff, whereas WSs 38 (0.154), 31 (0.153) and 26 (0.141) are resistant to erosion because of low runoff. In accordance with the C factor, WSs 13 (1.28), 12 (1.26) and 42 (1.25) have the highest values and are prone to soil erosion, whereas WSs 18, 28 and 30 have the lowest values (0.950, 0.824 and 0.803, respectively) and are more resistant to soil erosion.

The highest value of Dd was observed in WSs 28 (0.611 km), 33 (0.449 km) and 20 (0.432 km), which indicates that these WSs have the least permeability and the highest erosion susceptibility among the WSs. WSs 26 (0.129 km), 38 (0.128 km) and 30 (0.126 km) with the lowest Dd have the lowest erosion susceptibility. In the case of Rbm, WS 2 has the highest value (41.26), and thus, has high susceptibility to erosion. WS 2 is followed by WSs 42 (39.78), 40 (26.4), 24 (26.17), 18 (22.51), 6 (22.37), 23 (22.27), 7 (21.6), 30 (19.97), 39 (19.92), 26 (18.82), 8 (17.75), 34 (17.73), 17 (16.5), 11 (15.9), 31 (15.39), 38 (15.08), 5 (14.86), 6 (14.86), 13 (14.25), 1 (14.007), 41 (14.005), 12 (14), 21 (13.27), 19 (12.52), 9 (12.18), 27 (11.27), 15 (10.67), 4 (10.66), 36 (10.48), 35 (10.47), 25 (9.85), 32 (9.5), 29 (9.41), 10 (8.20), 33 (8.1), 14 (8.1), 28 (8), 16 (7.7), 20 (7.66), 37 (7) and 3 (3.52). Among the 42 WSs, WSs 33, 28 and 2 have the highest Fu (1.652, 1.515 and 1.336 km²) and high potential for erosion, whereas WSs 19 (0.968 km²), 12 (0.788 km²) and 32 (0.760 km²) have the lowest Fu, the highest permeability and a tendency to withstand erosion.

The highest values of Lo (0.305, 0.224, and 0.216) were obtained by WSs 28, 33 and 20. Therefore, these WSs have the highest erosion potential among the 42 WSs. By contrast, WSs 26, 33 and 30 have the lowest Lo (0.0648, 0.0642 and 0.0633) and are more resistant to erosion. The highest Cc was obtained by WS 27 (1.154), which indicates that it has the lowest infiltration capacity and the highest susceptibility to erosion, whereas WS 9 (1.897) has the highest infiltration capacity. On the basis of the Re factor, WSs 30 (0.590), 38 (0.592) and 26 (0.592) obtained the lowest values and have the highest susceptibility to erosion, whereas WSs 20 (0.716), 33 (0.721) and 28 (0.756) got the highest Re and have the lowest susceptibility to erosion. With regard to Rc, WSs 9 (0.273), 4 (0.288) and 15 (0.291) presented the lowest values because of their extremely low infiltration capacity. Therefore, these WSs are more susceptible to erosion. Similarly, WSs 14 (0.729), 29 (0.728) and 27 (0.738) demonstrated the highest Rc because of their low relief and high infiltration capacity. Consequently, these WSs have the lowest susceptibility to soil erosion. In the case of RF, WSs 28 (2.22), 33 (2.44) and 20 (2.47) achieved the lowest values and are the most susceptible to erosion among the 42 WSs, whereas WSs 26 (3.62), 38 (3.63) and 30 (3.65), which have the highest Rf, have low soil erosion susceptibility. In terms of the Rf factor, WSs 30 (0.273), 38 (0.275) and 26 (0.276) have low values and the highest contribution to erosion. The highest basin shapes were observed in WSs 20 (0.403), 33 (0.408) and 28 (0.449). Therefore, these WSs are less prone to erosion. The values of Rr for the 42 WSs vary from 0.10 to 0.015, and WSs 3 (0.107), 14 (0.078) and 1 (0.076) have the highest values. In accordance with the Rh factor, WSs 28 (0.165), 20
(0.157) and 9 (0.155) have the highest values and are the most sensitive to soil erosion, whereas WSs 38 (0.046), 31 (0.04) and 42 (0.031) are the least sensitive.

Among all the WSs of the Neka Roud Watershed, the highest slope percentages were observed in WSs 9 (27.71), 20 (24.86) and 28 (24.66), whereas the lowest were recorded in WSs 42 (5.74), 31 (7.75) and 42 (5.74). In terms of the Rn factor, WSs 9 (0.494), 14 (0.392) and 20 (0.391) exhibited the highest Rn, and thus, the highest sensitivity to erosion. By contrast, WSs 31 (0.146), 37 (0.142) and 42 (0.104) achieved the lowest Rn and are the least susceptible to soil erosion. On the basis of HI, WSs 42 (1.17), 21 (0.561) and 2 (0.526) have the highest values and are the most sensitive to erosion.

The decision matrix (Table 3) was created after extracting the linear, relief and shape morphometric values for the 42 sub-watersheds. For the linear and relief parameters that exhibit direct relationships with soil erosion, the highest values were considered the maximising criteria. For the shape parameters that demonstrate an inverse relation with soil erosion, the lowest values were considered the maximising criteria and vice versa in the COPRAS, ARAS, CP and MOORA models. The weight of each criterion was calculated before the implementation of the models (Figure 6).

The computation results of criterion weights (linear relief, and shape parameters) (Table 6 and Figure 6) according to the AHP technique using Equations 17 and 18 indicate that parameters Dd, Sa and T, which have the highest weights (0.18, 0.14 and 0.12, respectively), exert the greatest impact on soil erosion. This result is consistent with those of Farhan and Anaba (2016) and Arabameri et al. (2017). Meanwhile, parameters Cc, Rf and Rc, which have the lowest weights (0.013, 0.011 and 0.009, respectively) exert less effect on soil erosion than the other parameters. This result is consistent with that of Arabameri et al. (2017). Parameters T, HI, Fu, Rbm, If, Rr, Rn, Lo, C, Rh, Re and Bs account for the subsequent rank.

According to Table 6, the consistency rate obtained was 0.054. Because this value is less than 0.1, then it is acceptable and there is no need to resolve the incompatibility. Thus, it can be said that the matrix has the consistency. The results of sub-watersheds prioritisation using the CP (Equation 2), COPRAS (Equations 3–8), ARAS
MCDM models are presented in Table 6 and Table 7 and Figure 7a. As shown in Table 7, WSs 28 (0.415), 20 (0.510) and 14 (0.535), which have the lowest scores, are the most susceptible to soil erosion in the CP model. On the basis of the COPRAS, ARAS and MOORA models, WSs 28 (0.370, 928 and 0.204), 20 (0.305, 762 and 0.166), and 33 (0.289, 725 and 0.156), which have the highest scores, exhibit more potential for soil erosion than the other sub-watersheds. The results of the model comparison based on morphometric parameters using the SCCT and KTCCT techniques are provided in Table 7 and Table 8. The results indicate that the ARAS model exhibits the highest correlation in the SCCT and KTCCT techniques compared with the other MCDM methods, whereas the CP model presents the lowest correlation with the others.

### 3.2. Prioritisation of soil erosion prone-sub-watersheds to the LU/LC parameters and MCDM models

In general, LU/LC exerts a considerable influence on the drainage network patterns of a watershed and significantly affects the erosion susceptibility of the sub-watersheds (Altaf et al. 2014, Ahmad Rather et al. 2017). In addition, infiltration, soil moisture, evapo-transpiration and the interception process of watersheds strongly depend on the diversity of vegetation (Romshoo et al. 2012). Impervious lands, such as infrastructure and human settlements, strongly contribute to runoff because of the blockage of the infiltration process (Dams et al. 2013). Large amounts of root biomass and a high percentage of vegetation are significant in decreasing the rates of soil erosion (Badar et al. 2013). The LU/LC classes generated in the study area are agriculture, forest, pasture, orchard and wasteland (Table 9). The identified classes in the study area strongly affect soil erosion.

Agriculture: This class covers approximately 17.1% of the total watershed (Table 9). In agricultural lands, the upper soil layer is strongly protected by the root biomass
Figure 7. Soil erosion susceptibility maps based on: (a) morphometric parameters, (b) LU/LC classes, and (c) combined model.
### Table 7. Prioritization of sub-watersheds using morphometric parameters and MCDM models.

| WSs | COPRAS | ARAS | CP | MOORA |
|-----|--------|------|----|-------|
| Qj  | Ki     | Lpi  | yj | Rank  |
| WS1 | 0.237  | 0.593| 0.612| 9    |
| WS2 | 0.249  | 0.622| 0.618| 12   |
| WS3 | 0.239  | 0.596| 0.626| 14   |
| WS4 | 0.217  | 0.545| 0.704| 38   |
| WS5 | 0.253  | 0.632| 0.578| 7    |
| WS6 | 0.247  | 0.619| 0.599| 8    |
| WS7 | 0.241  | 0.603| 0.616| 11   |
| WS8 | 0.233  | 0.581| 0.651| 22   |
| WS9 | 0.258  | 0.647| 0.573| 5    |
| WS10| 0.241  | 0.602| 0.649| 20   |
| WS11| 0.218  | 0.543| 0.699| 35   |
| WS12| 0.217  | 0.541| 0.686| 33   |
| WS13| 0.242  | 0.605| 0.615| 10   |
| WS14| 0.275  | 0.689| 0.535| 3    |
| WS15| 0.225  | 0.564| 0.650| 21   |
| WS16| 0.264  | 0.659| 0.568| 4    |
| WS17| 0.224  | 0.561| 0.672| 28   |
| WS18| 0.217  | 0.543| 0.711| 40   |
| WS19| 0.193  | 0.481| 0.754| 42   |
| WS20| 0.305  | 0.762| 0.511| 2    |
| WS21| 0.239  | 0.597| 0.661| 26   |
| WS22| 0.241  | 0.602| 0.626| 15   |
| WS23| 0.234  | 0.584| 0.643| 19   |
| WS24| 0.221  | 0.553| 0.675| 30   |
| WS25| 0.250  | 0.625| 0.630| 16   |
| WS26| 0.226  | 0.566| 0.655| 23   |
| WS27| 0.213  | 0.533| 0.711| 39   |
| WS28| 0.371  | 0.928| 0.415| 1    |
| WS29| 0.242  | 0.604| 0.631| 17   |
| WS30| 0.235  | 0.588| 0.679| 31   |
| WS31| 0.215  | 0.538| 0.671| 27   |
| WS32| 0.210  | 0.525| 0.704| 36   |
| WS33| 0.290  | 0.725| 0.573| 6    |
| WS34| 0.227  | 0.568| 0.661| 25   |
| WS35| 0.215  | 0.537| 0.682| 32   |
| WS36| 0.202  | 0.503| 0.728| 41   |
| WS37| 0.252  | 0.631| 0.657| 24   |
| WS38| 0.209  | 0.523| 0.704| 37   |
| WS39| 0.220  | 0.549| 0.673| 29   |
| WS40| 0.238  | 0.595| 0.636| 18   |
| WS41| 0.232  | 0.580| 0.625| 13   |
| WS42| 0.222  | 0.555| 0.694| 34   |

### Table 8. Comparison of models based on morphometric parameters and LU/LC classes.

| Morphometric parameters | COPRAS | ERAS | CP | MOORA | KTCCT  | LU/LC classes | COPRAS | ERAS | CP | MOORA |
|-------------------------|--------|------|----|-------|--------|---------------|--------|------|----|-------|
| KTCCT                   | 1      | 0.886| 0.749| 0.702| 1      | 0.992         | 1      | 0.894| 0.821|
| ERAS                    | 1      | 0.725| 0.751| 0.786| 1      | 0.825         | 1      | 0.814| 0.901|
| MOORA                   | 1      | 0.786| 0.821| 1    | 1      | 0.786         | 1      | 0.821| 0.901|
| SCCT                    | 1      | 0.295| 0.037| 0.179| 1      | 0.457         | 1      | 0.175| 0.265|
| ERAS                    | 1      | 0.037| 0.179| 0.173| 1      | 0.111         | 1      | 0.111| 0.198|
| MOORA                   | 1      | 0.037| 0.179| 0.173| 1      | 0.111         | 1      | 0.111| 0.198|
|                        |        |      |      |       | 1      |               |        | 1    | 0.108|
|                        |        |      |      |       | 1      |               |        | 1    | 0.108|
|                        |        |      |      |       |        |               |        |      |    |
of crops. Therefore, these lands are less susceptible to erosion (Iqbal and Sajjad 2014). Among the 42 sub-watersheds, the maximum area under agricultural land was observed in WSs 33 (86.98%), 37 (60.19%) and 19 (55.09%). Therefore, these WSs are less susceptible to erosion. By contrast, WSs 3, 14 and 42 have the minimum area of agricultural land, and thus, are more susceptible to erosion.

Forest: Forests exhibit a significant capability to control soil erosion; they comprise dense and moderately dense forests and plantations (Altaf et al. 2014). In this research, 61% of the study area is covered by the forest class (Table 9). This class present an inverse relation to soil erosion. Therefore, WSs 4 (2.55%), 3 (0.539%) and 1 (0.367%), with the lowest percentage of forest, are susceptible to soil erosion.

### Table 9. Area and area percentage under different LU/LC classes for the sub-watersheds of the present study.

| WSs | Agriculture | Plantation | Forest | Pasture | Wasteland |
|-----|-------------|------------|--------|---------|-----------|
| WS1 | 22.48 0.13  | 0.72 0.06  | 3.01 0.50 | 90.84 0.26 | 0 0 |
| WS2 | 0.07 19.20  | 3.79 0.61  | 0.79 2.57  | 143.09 77.61 | 0 0 |
| WS3 | 0.00 0.05  | 0 2.56    | 1.00 0.53  | 38.30 96.85 | 0 0 |
| WS4 | 26.41 0.00  | 1.65 0    | 16.32 2.55 | 19.47 97.45 | 0 0 |
| WS5 | 7.73 41.37  | 0 2.57    | 24.05 25.56 | 31.78 30.49 | 0 0 |
| WS6 | 1.57 12.16  | 0 0       | 100.28 37.84 | 0.00 50.00 | 0 0 |
| WS7 | 50.25 1.55  | 0 0       | 99.28 98.45 | 20.69 0 | 0 0 |
| WS8 | 9.81 29.52  | 0 0       | 32.50 58.33 | 0.00 12.15 | 0 0 |
| WS9 | 14.10 23.18 | 0 0       | 67.57 76.82 | 2.15 0.00 | 0 0 |
| WS10| 7.01 16.82  | 0 0       | 25.34 80.61 | 0.00 2.56 | 0 0 |
| WS11| 27.77 21.68 | 0 0       | 52.47 78.32 | 0.00 0 | 0 0 |
| WS12| 7.30 34.61  | 0 0       | 38.72 65.39 | 0.00 1 2.13 | 0 0 |
| WS13| 17.61 15.53 | 0 0       | 77.95 82.34 | 8.73 0 | 0.00 |
| WS14| 0.00 16.88  | 0 0       | 25.41 74.74 | 0 8.37 0.21 | 0.84 |
| WS15| 26.27 0.00  | 0 0       | 87.97 99.16 | 0 0 1.86 | 1.60 |
| WS16| 1.79 22.63  | 0 0       | 21.98 75.77 | 0 0 0.29 | 1.19 |
| WS17| 25.12 7.44  | 0 0       | 55.62 91.37 | 0 0 0 | 0 0 |
| WS18| 27.56 31.12 | 1.29 0    | 7.59 68.88 | 130.92 0 | 0 0 |
| WS19| 71.22 16.47 | 0.72 0.76 | 54.76 4.53 | 2.57 78.23 | 0 0 |
| WS20| 5.08 55.09  | 0 0.55    | 8.30 42.36 | 0 1.99 0 | 0 0 |
| WS21| 10.88 37.97 | 0 0       | 20.54 62.03 | 0 0 0 | 0 0 |
| WS22| 3.72 34.62  | 0 0       | 39.01 65.38 | 0 0 0 | 0 0 |
| WS23| 3.01 8.71   | 4 0       | 72.08 91.29 | 41.87 0 | 0 0 |
| WS24| 16.68 2.49  | 0 3.31    | 124.12 59.59 | 0.00 34.62 | 0 0 |
| WS25| 7.87 11.85  | 0 0       | 15.46 88.15 | 0 0 0 | 0 0 |
| WS26| 14.39 33.74 | 0.14 0    | 197.56 66.26 | 3.87 0 | 0 0 |
| WS27| 5.77 6.66   | 0 0.06   | 51.11 91.48 | 0.00 1.79 | 0 0 |
| WS28| 3.22 9.51   | 0 0       | 2.79 90.49 | 0.00 0 | 0 0 |
| WS29| 8.88 53.57  | 0 0       | 23.05 46.43 | 0.00 0 | 0 0 |
| WS30| 16.82 27.80 | 3.50 0    | 22.05 72.20 | 184.75 0 | 0 0 |
| WS31| 30.64 7.41  | 0 1.54    | 170.00 9.71 | 0 81.34 0 | 0 0 |
| WS32| 1.22 15.27  | 0 0       | 35.58 84.73 | 0 0 0 | 0 0 |
| WS33| 10.52 3.31  | 0 0       | 1.57 96.69 | 0 0 0 | 0 0 |
| WS34| 15.03 86.98 | 0 0 109.66 | 13.02 0 | 0 0 | 0 0 |
| WS35| 11.60 12.06 | 0 0 53.40 87.94 | 0 0 0 | 0 0 |
| WS36| 11.88 17.84 | 0 0 55.26 82.16 | 0 0 0 | 0 0 |
| WS37| 8.66 17.70  | 0 0 5.73 82.30 | 0 0 0 | 0 0 |
| WS38| 26.77 60.20 | 0 0 193.48 39.80 | 0 0 0 | 0 0 |
| WS39| 26.91 12.15 | 0 0 114.24 87.85 | 6.30 0 | 0 0 | 0 0 |
| WS40| 44.38 18.25 | 0 0 105.37 77.48 | 0 4.27 0 | 0 0 |
| WS41| 16.54 29.64 | 0 0 50.03 70.36 | 8.88 0 | 0 0 | 0 0 |
| WS42| 0 21.92    | 0 0 36.00 66.32 | 72.01 11.76 | 0 0 | 0 0 |
whereas WSs 15 (99.16%), 7 (98.45%) and 33 (96.96%) have the least susceptibility to erosion.

Pasture: Pasture is important for keeping the soil particles together because of the dense root structure of grass. Pasture also decreases the rate of runoff on land surface, thereby providing sufficient time for infiltration (Altaf et al. 2014). This class covers 21.39% of the total study area (Table 9) and demonstrates an inverse relation to soil erosion similar to forest and agriculture. Thus, WSs 3 (97.44%), 2 (96.85%) and 30 (81.34%) have the highest percentage of pasture, and consequently, the least susceptibility to erosion. By contrast, WSs 37, 38 and 40 have the lowest percentage and are more susceptible to erosion.

Plantation: This class includes orchards, gardens of fruits, ornamental shrubs and trees and vegetable farms. Nearly 0.41% of the study area is covered by plantations (Table 9). WSs 24 (3.31%), 5 (2.57%) and 3 (2.56%) have the highest percentages of plantation and are resistant to soil erosion.

Wasteland: Wasteland is any unused land surface area. This area is prone to wind and water erosion (Ahmad Rather et al. 2017). Unlike the other classes, this class exhibits a direct relation to soil erosion. Thus, WSs 12 (2.13%), 15 (1.6%) and 16 (1.19%), which have the highest percentage, are more susceptible to erosion.

In this research, prioritisation ranking of sub-watersheds was performed using the COPRAS, ARAS, CP and MOORA MCDM models according to the response of LU/LC to soil erosion. The percentage areas of the classes (Table 9) in each subwatershed were used as the index for prioritisation (Altaf et al. 2014, Ahmad Rather et al. 2017). Similar to morphometric parameters, the highest percentages of classes that directly cause soil erosion, such as wasteland, were considered the maximising criteria, whereas the highest percentages of classes that restrict erosion, such as forest, were considered the minimising criteria. The results of the calculation of criterion weights using AHP model showed that among the five LU/LC classes, forest class, with the highest score (0.502), exerts the greatest effect on the erodibility of sub-watersheds, whereas plantation, with lowest score (0.034), exerts the least impact. Agriculture, pasture, and wasteland are in the subsequent rank. The CR of LU/LC parameters matrices obtained was 0.034 and because this value is less than 0.1, then it is acceptable. The results of the prioritisation of the sub-watersheds by LU/LC classes and MCDM models are presented in Table 10 and Figure 7(b).

As indicated in Table 10, WSs 2 (0.392 and 0.530), 23 (0.363 and 0.442), and 30 (0.328 and 0.439), which obtained the highest scores, are the most sensitive sub-watersheds to soil erosion in the COPRAS and ARAS models. In the MOORA model, WSs 23 (0.153), 2 (0.150) and 30 (0.134), which achieved high scores, are more susceptible to erosion, whereas WSs 15 (0.083), 12 (0.0794) 33 (0.0792), which have the lowest scores, are less susceptible to erosion among the 42 WSs. In accordance with the CP model, WSs 33 (0.233), 1 (0.295) and 18 (0.305), which obtained the lowest scores, exhibit the highest susceptibility to erosion. The results of the model comparison based on the LU/LC parameters using the SCCT and KTCCT techniques are provided in Table 7 and Table 8. The results indicate that the COPRAS model in the SCCT and KTCCT techniques exhibited the highest correlation, whereas the CP model exhibited the lowest correlation among the four MCDM methods.
3.3. Evaluation of the level of soil erosion susceptibility using the combination of morphometric parameters and LU/LC classes

To obtain the collective contribution of the morphometric parameters and the LU/LC classes towards soil erosion susceptibility, the values of the morphometric parameters and LU/LC classes were combined and their average was calculated to identify the sub-watersheds that are most susceptible to erosion. For this purpose, the best models were selected among the four MCDM models. ARAS and COPRAS exhibit the best performance in the morphometric parameters and LU/LC classes, respectively. The results of the combined methods are presented in Table 11 and Figure 7(c).

Table 10. Prioritization of sub-watersheds using LU/LC classes and MCDM models.

| WSs | COPRAS Q_j Rank | ARAS K_i Rank | CP L_{p,i} Rank | MOORA y_j' Rank |
|-----|-----------------|---------------|----------------|----------------|
| WS1 | 0.281           | 7             | 0.376          | 7              |
| WS2 | 0.392           | 1             | 0.530          | 7              |
| WS3 | 0.306           | 4             | 0.391          | 4              |
| WS4 | 0.286           | 6             | 0.377          | 6              |
| WS5 | 0.269           | 9             | 0.289          | 10             |
| WS6 | 0.261           | 16            | 0.190          | 20             |
| WS7 | 0.269           | 11            | 0.204          | 15             |
| WS8 | 0.247           | 28            | 0.182          | 32             |
| WS9 | 0.259           | 18            | 0.189          | 22             |
| WS10| 0.250           | 27            | 0.182          | 31             |
| WS11| 0.231           | 33            | 0.177          | 37             |
| WS12| 0.090           | 42            | 0.309          | 9              |
| WS13| 0.266           | 13            | 0.201          | 17             |
| WS14| 0.123           | 38            | 0.240          | 13             |
| WS15| 0.108           | 41            | 0.276          | 11             |
| WS16| 0.108           | 40            | 0.258          | 12             |
| WS17| 0.235           | 31            | 0.178          | 35             |
| WS18| 0.302           | 5             | 0.387          | 5              |
| WS19| 0.267           | 12            | 0.203          | 16             |
| WS20| 0.145           | 35            | 0.176          | 39             |
| WS21| 0.165           | 34            | 0.177          | 38             |
| WS22| 0.258           | 19            | 0.188          | 23             |
| WS23| 0.363           | 2             | 0.442          | 2              |
| WS24| 0.256           | 21            | 0.186          | 25             |
| WS25| 0.233           | 32            | 0.177          | 36             |
| WS26| 0.265           | 14            | 0.196          | 18             |
| WS27| 0.256           | 20            | 0.187          | 24             |
| WS28| 0.127           | 36            | 0.169          | 40             |
| WS29| 0.243           | 29            | 0.180          | 33             |
| WS30| 0.328           | 3             | 0.439          | 3              |
| WS31| 0.254           | 24            | 0.185          | 28             |
| WS32| 0.259           | 17            | 0.190          | 21             |
| WS33| 0.122           | 39            | 0.155          | 42             |
| WS34| 0.256           | 22            | 0.186          | 26             |
| WS35| 0.251           | 26            | 0.184          | 30             |
| WS36| 0.251           | 25            | 0.184          | 29             |
| WS37| 0.126           | 37            | 0.166          | 41             |
| WS38| 0.254           | 23            | 0.186          | 27             |
| WS39| 0.262           | 15            | 0.192          | 19             |
| WS40| 0.236           | 30            | 0.179          | 34             |
| WS41| 0.269           | 10            | 0.206          | 14             |
| WS42| 0.271           | 8             | 0.328          | 8              |
The results indicate that among the 42 sub-watersheds, WSs 28 (0.604), 20 (0.516) and 33 (0.515), with the highest combined values, are prone to soil erosion. By contrast, WSs 23 (0.345), 4 (0.335) and 18 (0.332), with the lowest combined values, have low sensitivity to soil erosion. The sub-watersheds were categorised into two priority classes, namely, moderate (0.25–0.5) and high (0.5–0.75) susceptibility, according to the combined values. The results showed that among the 42 sub-watersheds, 38 are in the moderate susceptibility area, whereas 4 are in the high susceptibility area. That is, 98.36% (3737.04 km²) of the total study area is moderately susceptible to soil erosion.

Real-world decision-making problems are typically too complex and unstructured to be evaluated by examining only one criterion. To solve these problems, several criteria should be considered (Angilella and Mazziu 2015). MCDM is one of the most popular decision methodologies in science and is defined as a complex decision-making tool that involves quantitative and qualitative factors and can help improve the quality of decisions by making the decision-making process more rational, explicit and efficient. In recent years, several MCDM techniques and approaches have been suggested for selecting optimal probable options. The wide range of MCDM problem solution techniques vary in complexity and possible solutions, and each method has its own strengths, weaknesses and potentials (Şengül et al. 2015). In this research, the MOORA, ARAS, COPRAS and CP MCDM models were selected because of their advantages, such as rational and understandable logic, low computational time, simple mathematical form for the selection of the best alternatives for each criterion, straightforward computation processes, simplicity, transparent mathematical calculations without the use of additional parameters, such as $v$ in the VIKOR method, and high possibility of graphical interpretation over other MCDM methods, such as ELECTER, TOPSIS, AHP and PROMETHEE. These models have been successfully
used to solve various problems in various fields of research (de Almeida et al. 2015; Chitsaz and Banihabib 2015; Büyüközkan and Karabulut 2017; Debnath et al. 2017; Valipour et al. 2017).

4. Conclusion

The most important conclusion of this research is that the utilisation of satellite-based RS datasets with MCDM models in an ArcGIS environment for evaluating the influence of morphometric parameters and LU/LC classes in soil erosion susceptibility is a more suitable and accurate framework than the conventional approach.

On the basis of the morphometric parameters, the ARAS model exhibited the best accuracy in the prioritisation of sub-watersheds among the four MCDM models. The study area was categorised into three priority classes according to the ARAS model. Among the 42 sub-watersheds, 2 fit the very high susceptibility class, 39 are in the high susceptibility class, and 1 falls in the moderate susceptibility class. On the basis of the LC/LU-based watershed prioritisation for erosion susceptibility of the Neka Roud sub-watersheds, the COPRAS model exhibited the highest correlation among the four MCDM methods according to the SCCT and KTCCT indices. The results of this model indicate that the total study area falls in low and moderate susceptibility classes. The prioritisation result based on the combined model of morphometric and LU/LC analysis indicates that WSs 14, 20, 28 and 33 are highly susceptible to erosion and require instant measures for decreasing soil erosion in prone areas. Recognising areas that are susceptible to soil erosion is necessary to develop and implement the best management measures for soil conservation in the mountainous study area. Significant soil conservation measures that can help decrease soil erosion in the study area include strip farming, rotation of crops, change in land use patterns, afforestation and reforestation, plantation of soil-protecting crops, construction of check dams, flood control measures and control of animal grazing.

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