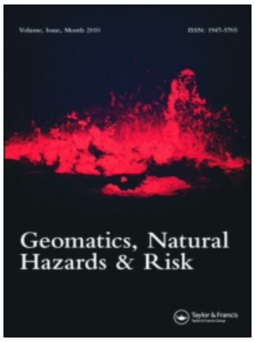

Geomatics, Natural Hazards and Risk

ISSN: 1947-5705 (Print) 1947-5713 (Online) Journal homepage: http://www.tandfonline.com/loi/tgnh20

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To cite this article: Alireza Arabameri, Biswajeet Pradhan, Hamid Reza Pourghasemi & Khalil Rezaei (2018) Identification of erosion-prone areas using different multi-criteria decision-making techniques and GIS, Geomatics, Natural Hazards and Risk, 9:1, 1129-1155, DOI: 10.1080/19475705.2018.1513084

To link to this article: https://doi.org/10.1080/19475705.2018.1513084

Published online: 30 Oct 2018.

GEOMATICS, NATURAL HAZARDS AND RISK
2018, VOL. 9, NO. 1, 1129–1155
https://doi.org/10.1080/19475705.2018.1513084

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.

ARTICLE HISTORY
Received 4 June 2018
Accepted 10 August 2018

KEYWORDS
Soil erosion; morphometric parameters; remote sensing; land use/land cover; GIS

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;

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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 geomorphical 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 km^2. Sub-watershed 32 is the largest, with an area of 227 km^2, and Sub-watershed 30 is the smallest, with an area of 5.94 km^2. 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

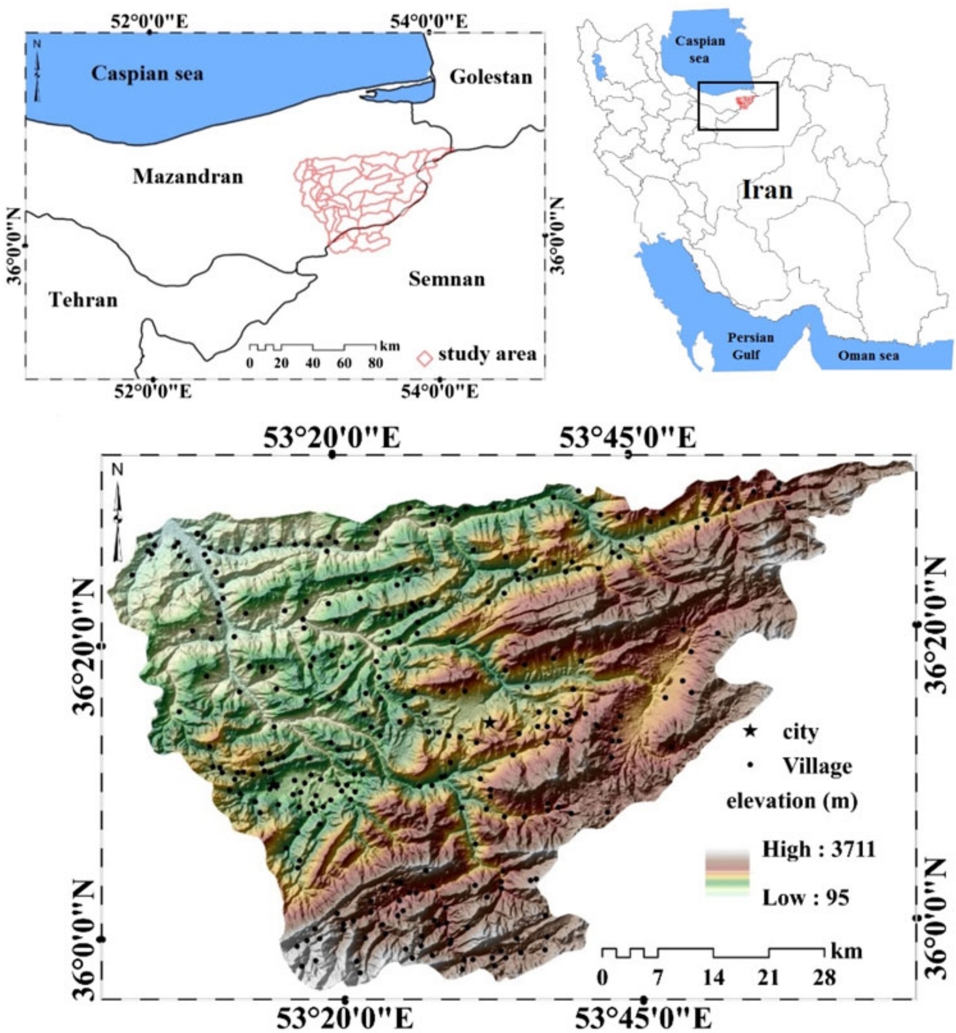

Figure 1. The study area.

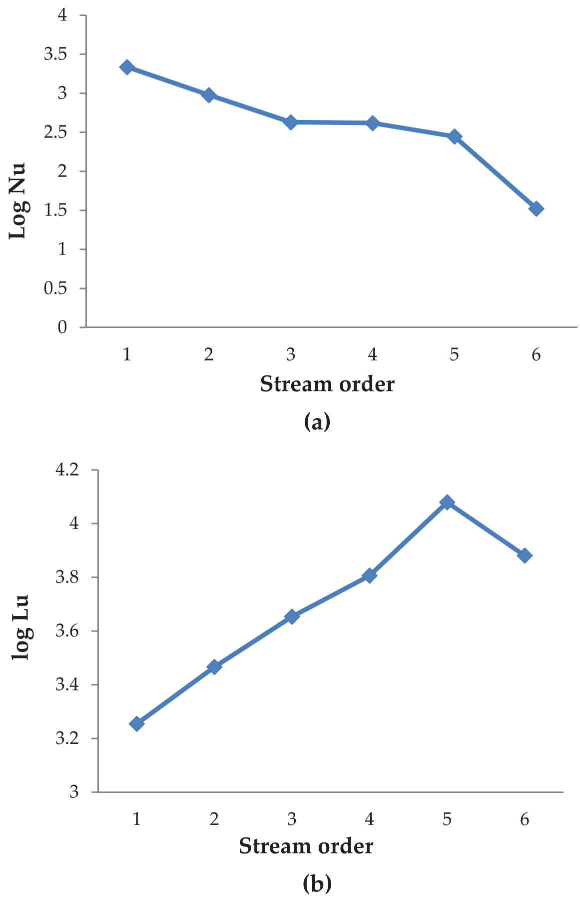

Figure 2. (a) Horton's first law, and (b) Horton's second law in Neka Roud Watershed.

(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);

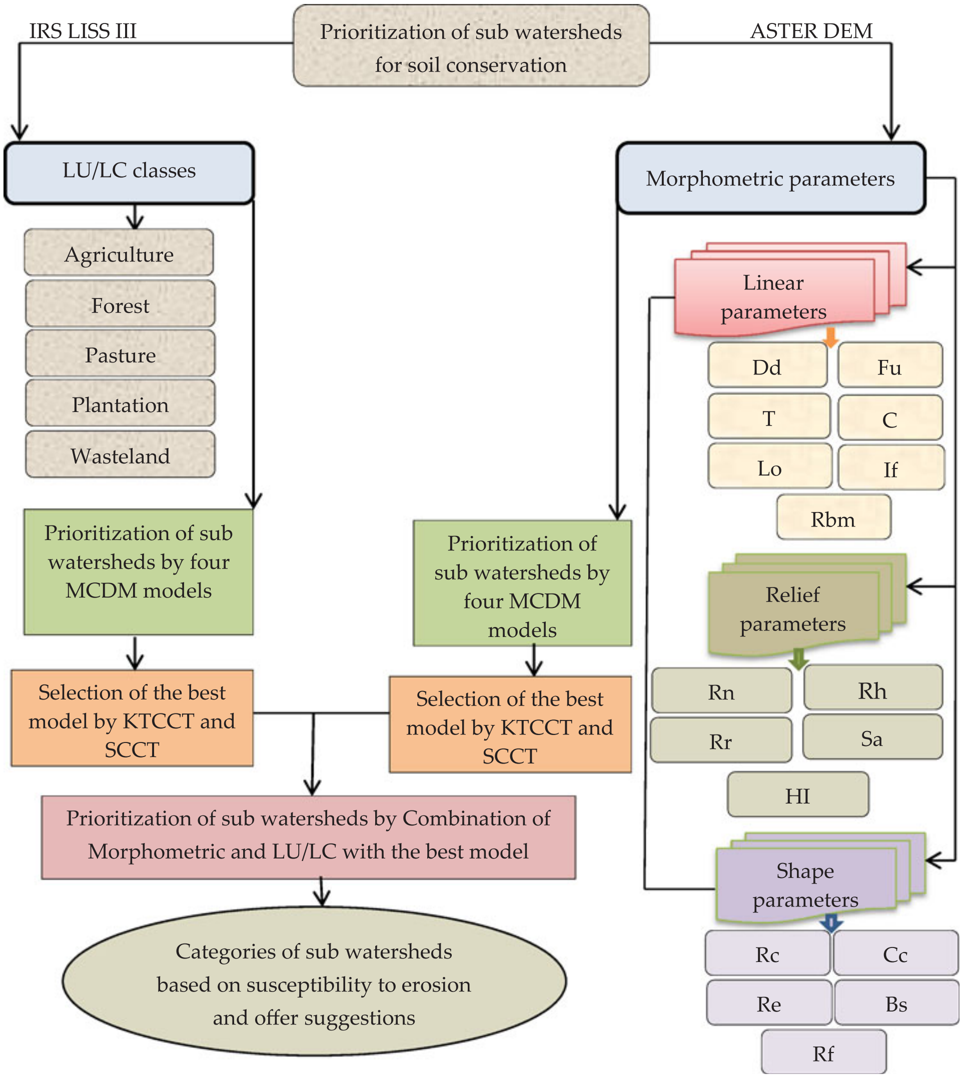

Figure 3. Methodological flowchart applied in this research.

(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.

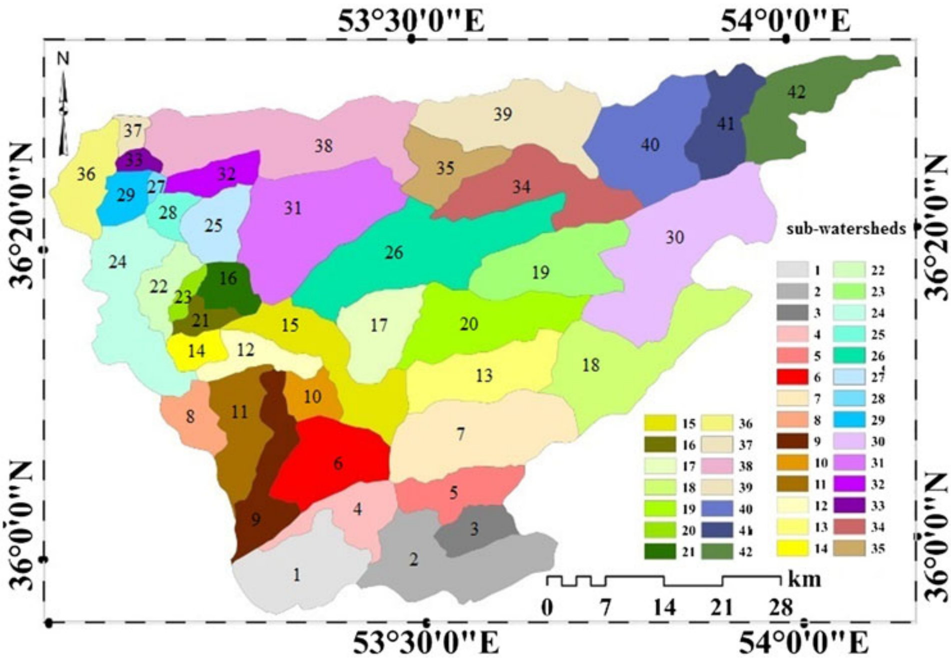

Figure 4. Sub-watersheds of study area.

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).

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

WSs	Area (km^2)	Perimeter (km)	Total No. of Streams	Stream Length (km)	Basin Length (km)	Elevation (m)		
						Max	Min	Mean
WS1	117.31	48.23	134	98.47	19.78	3711	1833	2691
WS2	148.17	68.25	198	135.96	22.59	2994	1588	2328
WS3	39.19	27.29	38	32.86	10.61	2930	1622	2307
WS4	63.92	52.76	64	63.48	14.01	2954	1557	2189
WS5	63.66	41.30	80	53.32	13.98	2859	1213	2062
WS6	101.66	42.83	105	87.45	18.24	2833	790	1663
WS7	169.78	59.15	198	150.31	24.40	2861	949	1838
WS8	41.96	29.09	45	34.89	11.03	1771	812	1191
WS9	83.67	61.97	100	78.46	16.33	3160	625	1392
WS10	32.33	24.98	32	32.31	9.51	1826	614	918
WS11	80.22	50.65	104	81.58	15.94	1753	659	1010
WS12	46.92	40.24	37	36.97	11.76	1527	401	935
WS13	104.74	51.78	132	99.49	18.55	2780	867	1685
WS14	25.84	21.17	30	20.85	8.38	1663	452	1087
WS15	116.52	70.84	141	102.26	19.71	2305	399	1065
WS16	23.92	23.40	27	19.281	8.02	1385	331	754
WS17	80.70	38.10	103	76.06	16.00	1792	784	1191
WS18	167.42	75.54	201	176.14	24.21	2755	1459	2024
WS19	129.01	60.90	125	117.89	20.88	2006	927	1405
WS20	13.25	18.78	17	13	5.73	1203	298	648
WS21	31.69	24.24	37	30.24	9.41	1100	333	764
WS22	42.78	34.68	46	37.99	11.16	1619	236	703
WS23	120.69	54.59	134	110.14	20.10	2704	923	1652
WS24	141.30	71.47	160	121.8	21.99	1667	237	864
WS25	23.39	22.76	28	21.63	7.92	962	180	468
WS26	215.16	87.17	235	185.83	27.92	2602	513	1351
WS27	56.15	30.89	63	52.88	13.02	1031	225	599
WS28	5.94	10.44	9	7.2	3.63	759	158	315
WS29	31.84	23.42	42	27.12	9.43	875	161	511
WS30	227.61	81.43	287	283.27	28.83	3154	1355	1926
WS31	200.83	62.36	230	164.52	26.85	1433	334	847
WS32	36.83	29.63	28	28.59	10.24	1030	184	601
WS33	12.11	14.97	20	12.52	5.45	515	128	269
WS34	124.87	67.91	149	116.26	20.50	2697	953	1694
WS35	65.08	41.59	70	53.66	14.16	1668	587	1135
WS36	67.14	39.02	75	60.15	14.41	882	96	384
WS37	14.22	17.59	19	14	5.97	434	95	204
WS38	220.13	90.40	264	197.98	28.28	1436	127	630
WS39	147.65	64.19	168	130.12	22.54	2083	587	1175
WS40	149.70	53.05	173	138.27	22.72	2596	993	1722
WS41	75.72	41.56	81	60.43	15.43	2926	1355	2006
WS42	107.27	59.20	107	85.59	18.80	2183	1588	2286

$$K = \left\{ N\sum_{i=1}^{r}(X_{ii}) - N\sum_{i=1}^{r}(X_{i+}.X_{+i}) \right\} \Big/ {}_{N^2} - \sum_{i=1}^{r}(X_{i+}.X_{+i}) \quad (1)$$

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 2. Linear, relief, and shape morphometric parameters.

	Linear parameters							Relief parameters					Shape parameters				
WSs	Dd	Fu	T	C	Lo	If	Rbm	Rh	Rn	Rr	HI	Sa	Cc	Rc	Bs	Re	Rf
WS1	0.17	1.14	2.78	1.19	0.08	0.19	14.01	0.09	0.32	0.08	0.46	17.34	1.25	0.63	3.34	0.62	0.30
WS2	0.15	1.34	2.90	1.09	0.08	0.20	41.27	0.06	0.21	0.04	0.53	11.55	1.57	0.40	3.44	0.61	0.29
WS3	0.27	0.97	1.39	1.19	0.14	0.26	3.53	0.12	0.35	0.11	0.52	20.89	1.22	0.66	2.87	0.67	0.35
WS4	0.22	1.00	1.21	1.01	0.11	0.22	10.67	0.10	0.31	0.06	0.45	17.47	1.85	0.29	3.07	0.64	0.33
WS5	0.22	1.26	1.94	1.19	0.11	0.28	14.87	0.12	0.36	0.07	0.52	20.63	1.45	0.47	3.07	0.64	0.33
WS6	0.18	1.03	2.45	1.16	0.09	0.19	22.37	0.11	0.37	0.07	0.43	20.26	1.19	0.70	3.27	0.62	0.31
WS7	0.14	1.17	3.35	1.13	0.07	0.17	21.60	0.08	0.27	0.05	0.46	14.67	1.27	0.61	3.51	0.60	0.29
WS8	0.26	1.07	1.55	1.20	0.13	0.28	17.75	0.09	0.25	0.06	0.40	14.80	1.26	0.62	2.90	0.66	0.34
WS9	0.20	1.20	1.61	1.07	0.10	0.23	12.19	0.16	0.49	0.05	0.30	27.71	1.90	0.27	3.19	0.63	0.31
WS10	0.29	0.99	1.28	1.00	0.15	0.29	8.20	0.13	0.36	0.07	0.25	21.32	1.23	0.65	2.80	0.67	0.36
WS11	0.20	1.30	2.05	0.98	0.10	0.26	15.90	0.07	0.22	0.03	0.32	12.21	1.58	0.39	3.17	0.63	0.32
WS12	0.25	0.79	0.92	1.27	0.13	0.20	14.00	0.10	0.28	0.04	0.47	16.44	1.65	0.36	2.95	0.66	0.34
WS13	0.18	1.26	2.55	1.05	0.09	0.22	14.25	0.10	0.34	0.05	0.43	18.69	1.42	0.49	3.29	0.62	0.30
WS14	0.32	1.16	1.42	1.24	0.16	0.38	8.00	0.14	0.39	0.08	0.52	23.82	1.17	0.72	2.72	0.68	0.37
WS15	0.17	1.21	1.99	1.14	0.08	0.20	10.67	0.10	0.32	0.03	0.35	17.66	1.84	0.29	3.33	0.62	0.30
WS16	0.34	1.13	1.15	1.24	0.17	0.38	7.70	0.13	0.35	0.06	0.40	21.55	1.34	0.55	2.69	0.69	0.37
WS17	0.20	1.28	2.70	1.06	0.10	0.25	16.50	0.06	0.20	0.05	0.40	11.22	1.19	0.70	3.17	0.63	0.32
WS18	0.14	1.20	2.66	0.95	0.07	0.17	22.51	0.05	0.19	0.04	0.44	10.02	1.63	0.37	3.50	0.60	0.29
WS19	0.16	0.97	2.05	1.09	0.08	0.16	12.53	0.05	0.17	0.03	0.44	9.50	1.50	0.44	3.38	0.61	0.30
WS20	0.43	1.28	0.91	1.02	0.22	0.56	7.67	0.16	0.39	0.06	0.39	24.86	1.44	0.47	2.48	0.72	0.40
WS21	0.30	1.17	1.53	1.05	0.15	0.35	13.27	0.08	0.23	0.05	0.56	13.62	1.21	0.68	2.79	0.68	0.36
WS22	0.26	1.08	1.33	1.13	0.13	0.28	9.43	0.12	0.36	0.05	0.34	21.14	1.48	0.45	2.91	0.66	0.34
WS23	0.17	1.11	2.45	1.10	0.08	0.18	22.27	0.09	0.30	0.05	0.41	16.21	1.39	0.51	3.35	0.62	0.30
WS24	0.16	1.13	2.24	1.16	0.08	0.18	26.17	0.07	0.22	0.02	0.44	12.03	1.68	0.35	3.42	0.61	0.29
WS25	0.34	1.20	1.23	1.08	0.17	0.41	9.86	0.10	0.26	0.04	0.37	16.17	1.32	0.57	2.68	0.69	0.37
WS26	0.13	1.09	2.70	1.16	0.06	0.14	18.82	0.07	0.27	0.03	0.40	14.24	1.66	0.36	3.62	0.59	0.28
WS27	0.23	1.12	2.04	1.06	0.12	0.26	11.28	0.06	0.19	0.03	0.46	10.76	1.15	0.74	3.02	0.65	0.33
WS28	0.61	1.52	0.86	0.82	0.31	0.93	8.00	0.17	0.37	0.07	0.26	24.66	1.20	0.68	2.22	0.76	0.45
WS29	0.30	1.32	1.79	1.17	0.15	0.39	9.42	0.08	0.21	0.04	0.49	12.65	1.16	0.73	2.79	0.68	0.36
WS30	0.13	1.26	3.52	0.80	0.06	0.16	19.97	0.06	0.23	0.04	0.32	11.92	1.51	0.43	3.65	0.59	0.27
WS31	0.13	1.15	3.69	1.22	0.07	0.15	15.39	0.04	0.15	0.02	0.47	7.75	1.23	0.65	3.59	0.60	0.28
WS32	0.28	0.76	0.94	1.29	0.14	0.21	9.50	0.08	0.24	0.03	0.49	13.94	1.37	0.53	2.85	0.67	0.35
WS33	0.45	1.65	1.34	0.97	0.22	0.74	8.17	0.07	0.17	0.03	0.36	11.12	1.20	0.68	2.45	0.72	0.41
WS34	0.16	1.19	2.19	1.07	0.08	0.20	17.74	0.09	0.29	0.04	0.42	15.61	1.70	0.34	3.36	0.62	0.30
WS35	0.22	1.08	1.68	1.21	0.11	0.23	10.48	0.08	0.24	0.04	0.51	13.40	1.44	0.47	3.08	0.64	0.32
WS36	0.21	1.12	1.92	1.12	0.11	0.24	10.48	0.05	0.17	0.02	0.37	9.59	1.33	0.55	3.09	0.64	0.32
WS37	0.42	1.34	1.08	1.02	0.21	0.56	7.00	0.06	0.14	0.02	0.32	8.99	1.31	0.58	2.50	0.71	0.40
WS38	0.13	1.20	2.92	1.11	0.06	0.15	15.09	0.05	0.17	0.02	0.38	8.82	1.71	0.34	3.63	0.59	0.28
WS39	0.15	1.14	2.62	1.13	0.08	0.17	19.92	0.07	0.23	0.03	0.39	12.31	1.48	0.45	3.44	0.61	0.29
WS40	0.15	1.16	3.26	1.08	0.08	0.18	26.41	0.07	0.24	0.05	0.45	13.10	1.21	0.67	3.45	0.61	0.29
WS41	0.20	1.07	1.95	1.25	0.10	0.22	14.01	0.10	0.32	0.07	0.41	18.05	1.34	0.55	3.14	0.64	0.32
WS42	0.18	1.00	1.81	1.25	0.09	0.17	39.79	0.03	0.10	0.04	1.17	5.74	1.60	0.38	3.30	0.62	0.30

To maximise criteria, the ideal solution is given as $x_j^* = \max x_{ij}$; 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).

$$L_{p,i} = \left\{ \sum_{j=1}^{n} w_j^p \left[\frac{x_j^* - x_{ij}}{x_j^* - x_j^-} \right] \right\}^{p\frac{1}{p}}, \tag{2}$$

where $L_{p,i}$ is the alternative ideal solution, and w_j^p is the criterion weight (Chitsaz and Banihabib 2015).

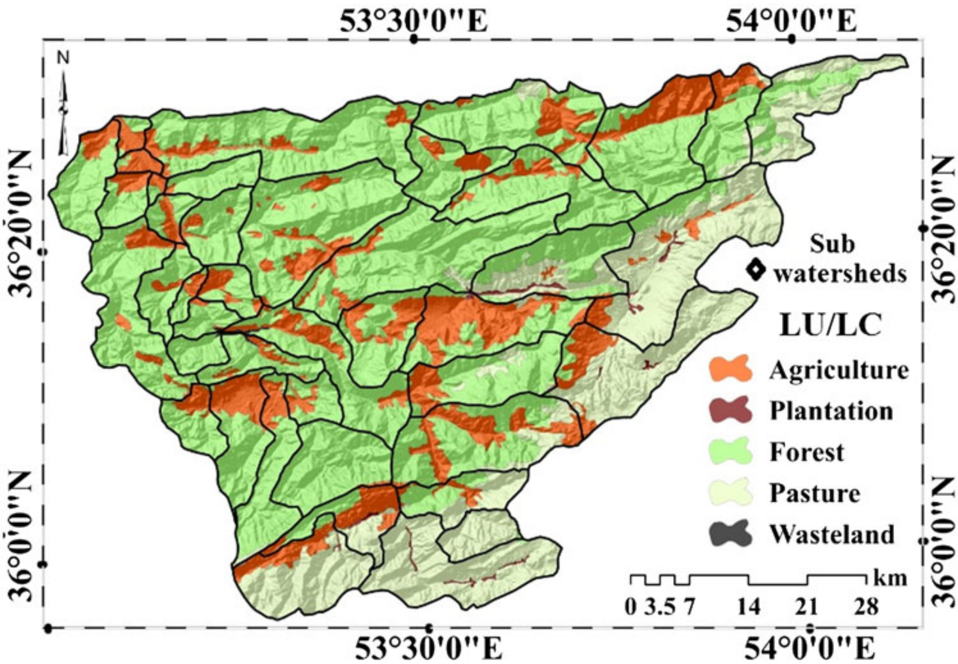

Figure 5. LU/LC map of study area.

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:

$$\overline{x_{ij}} = \frac{x_{ij}}{\sum_{i=1}^{m} x_{ij}}, \tag{3}$$

where $\overline{x_{ij}}$ is the normalised quantity of the j-th criterion, x_{ij} is the ith alternative performance of the jth criterion and m denotes the alternative numbers.

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

$$d_{ij} = w_j \times \overline{x_{ij}}, \tag{4}$$

where $\overline{x_{ij}}$ is the efficiency of the ith 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:

$$S_j^+ = \sum_{j=1}^{n} y_{+ij} \quad j = 1, 2, 3..., n; \tag{5}$$

$$S_j^- = \sum_{j=1}^{n} y_{-ij} \quad j = k+1, \ k+2, \ ..., n; \tag{6}$$

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:

$$Q_i = S_j^+ + \frac{S_{\min}^- \sum_{j=1}^{n} S_j^-}{S_j^- \sum_{j=1}^{n} \frac{S_{\min}^-}{S_j^-}} = S_j^+ + \frac{\sum_{i=1}^{n} S_j^-}{S_j^- \sum_{i=1}^{n} \frac{1}{S_j^-}}, \tag{7}$$

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):

$$\overline{x_{ij}} = \frac{x_{ij}}{\sum_{i=1}^{m} x_{ij}}, \tag{9}$$

$$x_{ij} = \frac{1}{x_{ij}^*}; \ \overline{x_{ij}} = \frac{x_{ij}}{\sum_{i=0}^{m} x_{ij}}, \tag{10}$$

where $\overline{x_{ij}}$ is the normalised amount of the jth criterion, x_{ij} is the ith alternative performance of the jth criterion and m is the number of alternatives.

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

$$\hat{\hat{x}}_{ij} = \overline{x_{ij}} \times w_j, \tag{11}$$

where w_j is the criterion weight of j, and $\overline{x_{ij}}$ is the normalised ranking of the jth criterion.

Step 3: Calculation of the values of the optimality function as Equation 12:

$$S_i = \sum_{j=1}^{n} \widehat{x_{ij}};\quad i = \overline{0, m}; \tag{12}$$

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:

$$K_i = \frac{S_i}{S_0};\quad i = \overline{0, m}; \tag{13}$$

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:

$$x_{ij}^{*} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^{2}}}\quad (j = 1, 2, \ldots n), \tag{14}$$

where x_{ij}^{*} is a dimensionless number that demonstrates the normalised performance of the ith alternative on the jth criteria.

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

$$y_i = \sum_{j=1}^{g} x_{ij}^{*} - \sum_{j=g+1}^{n} x_{ij}^{*}, \tag{15}$$

where y_i is the normalised evaluation value of the ith 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:

$$y_i^{*} = \sum_{j=1}^{g} w_j \times x_{ij}^{*} - \sum_{j=g+1}^{n} w_j \times x_{ij}^{*}\qquad (j = 1, 2, \ldots n), \tag{16}$$

where w_j is the weight of the jth 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):

$$n_{ij} = \frac{a_{ij}}{\sum_{i=1}^{n} a_{ij}} \tag{17}$$

$$W_j = \frac{\sum_{i=1}^{n} a_{ij}}{n} \tag{18}$$

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)

$$\mathrm{CR} = \frac{\mathrm{CI}}{\mathrm{RI}} \tag{19}$$

$$\mathrm{CI} = \frac{\lambda_{\max} - n}{n - 1} \tag{20}$$

$$\lambda_{\max} = \frac{\sum \lambda}{n} \tag{21}$$

Table 3. Saaty's linguistic scales in AHP (Saaty 1980).

Preference factor	Degree of preference
1	Equally
3	Moderately
5	Strongly
7	Very strongly
9	Extremely
2, 4, 6, and 8	Intermediate

Table 4. Values of random index (RI).

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

$$\lambda = \frac{\text{wsv}}{w} \tag{22}$$

$$WSV = A \times W \tag{23}$$

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, $\lambda_{\max}$ is the largest special matrix value, λ 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):

$$t = \frac{C-D}{n\ {(n-1)}/{2}}, \tag{24}$$

$$T = \frac{C-D}{\sqrt[2]{\left(\frac{n(n-1)}{2} - T\right) \times \left(\frac{n(n-1)}{2} - U\right)}}, \tag{25}$$

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):

$$r_s = 1 - \frac{6\sum_{i=1}^{n} d_i^2}{n(n^2-1)}, \tag{26}$$

$$r_s = \frac{\sum_{i=1}^{n} (x_i-\overline{x}) \times (y_i-\overline{y})}{\sqrt[2]{\sum_{i=1}^{n} (x_i-\overline{x})^2 \times \sum_{i=1}^{n} (y_i-\overline{y})^2}}, \tag{27}$$

where d_i is the difference between the ranks of models for each alternative; and $\overline{x}$ and $\overline{y}$ 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 (Dd), stream frequency (Fu), mean bifurcation ratio (Rbm), length of overland flow (Lo), texture ratio (T), infiltration number (If), constant of channel maintenance (C), relief ratio (Rh), relative relief (Rr), ruggedness number (Rn), average slope (Sa) and hypsometric integral (HI), 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 (Re), compactness coefficient (Cc), circularity ratio (Rc), form factor (Rf) and shape factor (Bs), 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), 5 (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 km^2) and high potential for erosion, whereas WSs 19 (0.968 km^2), 12 (0.788 km^2) and 32 (0.760 km^2) 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

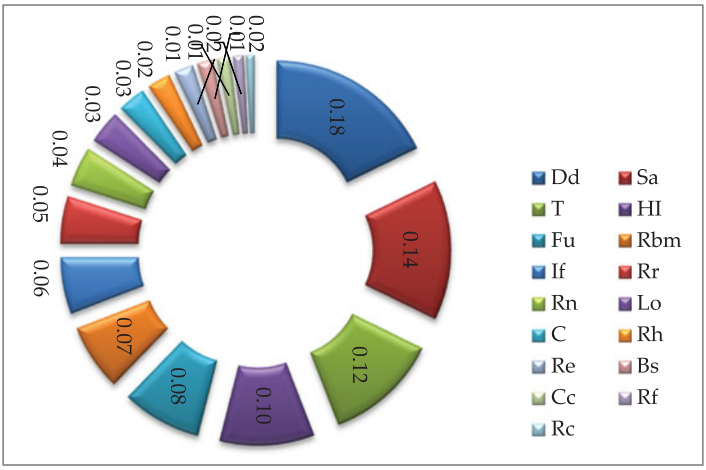

Figure 6. Weight of morphometric criteria by AHP.

(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

Table 6. Pair-wise comparison matrix.

	Dd	Sa	T	Hl	Fu	Rbm	If	Rr	Rn	Lo	C	Rh	Re	Bs	Cc	Rf	Rc
Dd	1																
Sa	0.43	1															
T	0.31	0.46	1														
Hl	0.21	0.33	0.41	1													
Fu	0.25	0.23	0.35	0.47	1												
Rbm	0.21	0.24	0.26	0.31	0.39	1											
If	0.21	0.19	0.22	0.29	0.38	0.40	1										
Rr	0.22	0.22	0.18	0.23	0.26	0.37	0.42	1									
Rn	0.19	0.19	0.22	0.19	0.25	0.27	0.39	0.45	1								
Lo	0.15	0.18	0.18	0.19	0.21	0.24	0.23	0.35	0.43	1							
C	0.18	0.14	0.15	0.19	0.23	0.22	0.23	0.2	0.33	0.4	1						
Rh	0.13	0.17	0.16	0.17	0.21	0.21	0.18	0.24	0.23	0.36	0.49	1					
Re	0.16	0.16	0.12	0.18	0.16	0.23	0.20	0.19	0.22	0.28	0.32	0.5	1				
Bs	0.11	0.12	0.18	0.17	0.15	0.18	0.22	0.18	0.21	0.24	0.25	0.37	0.43	1			
Cc	0.13	0.12	0.11	0.12	0.14	0.16	0.19	0.21	0.22	0.22	0.22	0.29	0.38	0.47	1		
Rf	0.12	0.12	0.14	0.15	0.17	0.15	0.18	0.19	0.20	0.21	0.21	0.23	0.24	0.32	0.46	1	
Rc	0.11	0.12	0.11	0.13	0.12	0.13	0.13	0.15	0.17	0.19	0.20	0.20	0.24	0.22	0.31	0.41	1

consistency ratio = 0.054

(Equations 9–13) and MOORA (Equations 14–16) 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 exhibit 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

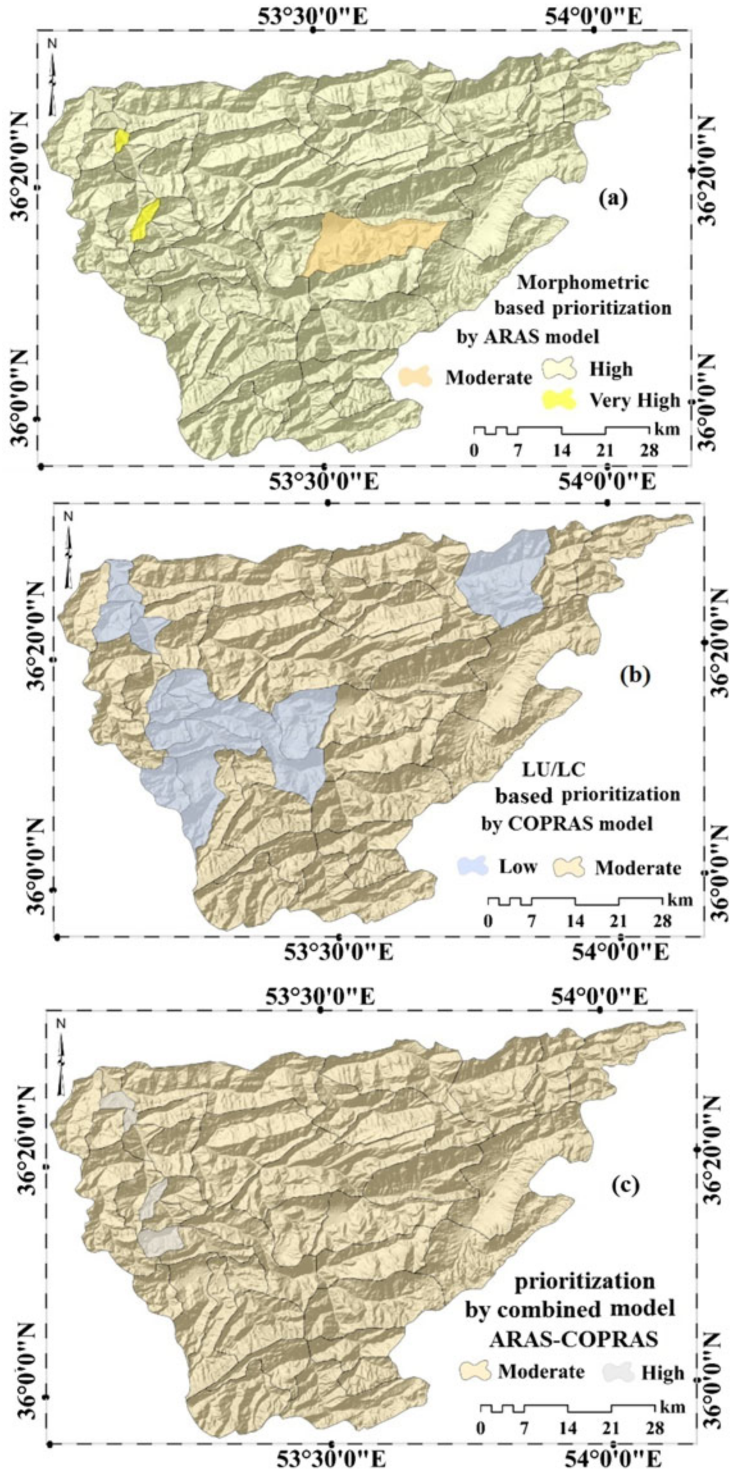

Figure 7. Soil erosion susceptibility maps based on: (a) morphometric parameters, (b) LU/LC classes, and (c) combined model.

Table 7. Prioritization of sub-watersheds using morphometric parameters and MCDM models.

	COPRAS		ARAS		CP		MOORA	
WSs	Q_j	Rank	K_i	Rank	$L_{p,i}$	Rank	y_i^*	Rank
WS1	0.237	20	0.593	20	0.612	9	0.126	19
WS2	0.249	10	0.622	10	0.618	12	0.133	11
WS3	0.239	18	0.596	18	0.626	14	0.128	17
WS4	0.217	33	0.545	32	0.704	38	0.114	32
WS5	0.253	7	0.632	7	0.578	7	0.136	7
WS6	0.247	11	0.619	11	0.599	8	0.133	10
WS7	0.241	14	0.603	14	0.616	11	0.128	16
WS8	0.233	23	0.581	23	0.651	22	0.123	24
WS9	0.258	6	0.647	6	0.573	5	0.139	6
WS10	0.241	16	0.602	16	0.649	20	0.128	15
WS11	0.218	32	0.543	33	0.699	35	0.114	34
WS12	0.217	35	0.541	35	0.686	33	0.114	33
WS13	0.242	12	0.605	12	0.615	10	0.129	12
WS14	0.275	4	0.689	4	0.535	3	0.149	4
WS15	0.225	27	0.564	27	0.650	21	0.119	27
WS16	0.264	5	0.659	5	0.568	4	0.143	5
WS17	0.224	28	0.561	28	0.672	28	0.118	28
WS18	0.217	34	0.543	34	0.711	40	0.113	36
WS19	0.193	42	0.481	42	0.754	42	0.099	42
WS20	0.305	2	0.762	2	0.511	2	0.166	2
WS21	0.239	17	0.597	17	0.661	26	0.127	18
WS22	0.241	15	0.602	15	0.626	15	0.129	13
WS23	0.234	22	0.584	22	0.643	19	0.124	21
WS24	0.221	30	0.553	30	0.675	30	0.116	30
WS25	0.250	9	0.625	9	0.630	16	0.134	9
WS26	0.226	26	0.566	26	0.655	23	0.119	26
WS27	0.213	38	0.533	38	0.711	39	0.111	38
WS28	0.371	1	0.928	1	0.415	1	0.204	1
WS29	0.242	13	0.604	13	0.631	17	0.129	14
WS30	0.235	21	0.588	21	0.679	31	0.123	23
WS31	0.215	36	0.538	36	0.671	27	0.113	37
WS32	0.210	39	0.525	39	0.704	36	0.110	39
WS33	0.290	3	0.725	3	0.573	6	0.156	3
WS34	0.227	25	0.568	25	0.661	25	0.120	25
WS35	0.215	37	0.537	37	0.682	32	0.113	35
WS36	0.202	41	0.503	41	0.728	41	0.105	41
WS37	0.252	8	0.631	8	0.657	24	0.134	8
WS38	0.209	40	0.523	40	0.704	37	0.108	40
WS39	0.220	31	0.549	31	0.673	29	0.116	31
WS40	0.238	19	0.595	19	0.636	18	0.126	20
WS41	0.232	24	0.580	24	0.625	13	0.124	22
WS42	0.222	29	0.555	29	0.694	34	0.117	29

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

	Morphometric parameters	COPRAS	ERAS	CP	MOORA	LU/LC classes	COPRAS	ERAS	CP	MOORA
KTCCT	COPRAS	1	0.886	0.749	0.702	KTCCT	1	0.992	0.894	0.821
	ERAS		1	0.725	0.751			1	0.825	0.901
	CP			1	0.786				1	0.786
	MOORA				1					1
SCCT	COPRAS	1	0.295	0.036	0.179	SCCT	1	0.457	0.175	0.265
	ERAS		1	0.036	0.179			1	0.111	0.198
	CP			1	0.03				1	0.108
	MOORA				1					1

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

	Agriculture		Plantation		Forest		Pasture		Wasteland	
WSs	Area	%	Area	%	Area	%	Area	%	Area	%
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	0	1	2.13
WS13	17.61	15.53	0	0	77.95	82.34	8.73	0	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
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
WS21	10.88	37.97	0	0	20.54	62.03	0	0	0	0
WS22	3.72	34.62	0	0	39.01	65.38	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	0.00	0	0	0
WS26	14.39	33.74	0.14	0	197.56	66.26	3.87	0	0	0
WS27	5.37	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
WS32	1.22	15.27	0	0	35.58	84.73	0	0	0	0
WS33	10.52	3.31	0	0	1.57	96.69	0	0	0	0
WS34	15.03	86.98	0	0	109.66	13.02	0	0	0	0
WS35	11.60	12.06	0	0	53.40	87.94	0	0	0	0
WS36	11.88	17.84	0	0	55.26	82.16	0	0	0	0
WS37	8.66	17.70	0	0	5.73	82.30	0	0	0	0
WS38	26.77	60.20	0	0	193.48	39.80	0	0	0	0
WS39	26.91	12.15	0	0	114.24	87.85	6.30	0	0	0
WS40	44.38	18.25	0	0	105.37	77.48	0	4.27	0	0
WS41	16.54	29.64	0	0	50.03	70.36	8.88	0	0	0
WS42	0	21.92	0	0	36.00	66.32	72.01	11.76	0	0

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, 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.

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

	COPRAS		ARAS		CP		MOORA	
WSs	Q_j	Rank	K_i	Rank	$L_{p,i}$	Rank	y_i^*	Rank
WS1	0.281	7	0.376	7	0.295	2	0.118	7
WS2	0.392	1	0.530	1	0.346	7	0.150	2
WS3	0.306	4	0.391	4	0.305	4	0.120	6
WS4	0.286	6	0.377	6	0.360	10	0.129	4
WS5	0.269	9	0.289	10	0.377	11	0.111	10
WS6	0.261	16	0.190	20	0.536	42	0.112	9
WS7	0.269	11	0.204	15	0.408	14	0.102	27
WS8	0.247	28	0.182	32	0.460	24	0.103	26
WS9	0.259	18	0.189	22	0.476	28	0.106	20
WS10	0.250	27	0.182	31	0.465	26	0.104	25
WS11	0.231	33	0.177	37	0.419	16	0.099	33
WS12	0.090	42	0.309	9	0.441	22	0.079	41
WS13	0.266	13	0.201	17	0.462	25	0.106	18
WS14	0.123	38	0.240	13	0.524	40	0.102	28
WS15	0.108	41	0.276	11	0.427	18	0.083	40
WS16	0.108	40	0.258	12	0.490	32	0.094	37
WS17	0.235	31	0.178	35	0.431	19	0.100	31
WS18	0.302	5	0.387	5	0.305	3	0.121	5
WS19	0.267	12	0.203	16	0.350	8	0.098	35
WS20	0.145	35	0.176	39	0.407	13	0.098	36
WS21	0.165	34	0.177	38	0.419	15	0.099	34
WS22	0.258	19	0.188	23	0.511	38	0.109	13
WS23	0.363	2	0.442	2	0.500	36	0.153	1
WS24	0.256	21	0.186	25	0.500	35	0.108	15
WS25	0.233	32	0.177	36	0.422	17	0.099	32
WS26	0.265	14	0.196	18	0.515	39	0.111	12
WS27	0.256	20	0.187	24	0.508	37	0.109	14
WS28	0.127	36	0.169	40	0.352	9	0.092	38
WS29	0.243	29	0.180	33	0.443	23	0.102	29
WS30	0.328	3	0.439	3	0.342	6	0.134	3
WS31	0.254	24	0.185	28	0.488	31	0.106	19
WS32	0.259	17	0.190	21	0.530	41	0.111	11
WS33	0.122	39	0.155	42	0.233	1	0.079	42
WS34	0.256	22	0.186	26	0.499	34	0.108	16
WS35	0.251	26	0.184	30	0.479	29	0.105	23
WS36	0.251	25	0.184	29	0.479	30	0.105	22
WS37	0.126	37	0.166	41	0.328	5	0.089	39
WS38	0.254	23	0.186	27	0.499	33	0.108	17
WS39	0.262	15	0.192	19	0.467	27	0.106	21
WS40	0.236	30	0.179	34	0.437	21	0.101	30
WS41	0.269	10	0.206	14	0.435	20	0.105	24
WS42	0.271	8	0.328	8	0.380	12	0.117	8

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 11. Prioritization of sub-watersheds using combined model.

		Combined model					
WSs	weight	Rank	priority	WSs	weight	Rank	priority
WS1	0.3597	34	Moderate	WS22	0.4277	16	Moderate
WS2	0.3561	37	Moderate	WS23	0.3458	40	Moderate
WS3	0.3589	35	Moderate	WS24	0.4045	25	Moderate
WS4	0.3358	41	Moderate	WS25	0.4467	10	Moderate
WS5	0.3986	26	Moderate	WS26	0.4048	24	Moderate
WS6	0.4344	12	Moderate	WS27	0.3934	30	Moderate
WS7	0.4180	19	Moderate	WS28	0.6049	1	High
WS8	0.4217	17	Moderate	WS29	0.4347	11	Moderate
WS9	0.4489	9	Moderate	WS30	0.3482	39	Moderate
WS10	0.4314	14	Moderate	WS31	0.3978	29	Moderate
WS11	0.4062	22	Moderate	WS32	0.3880	32	Moderate
WS12	0.4668	6	Moderate	WS33	0.5158	3	High
WS13	0.4208	18	Moderate	WS34	0.4120	21	Moderate
WS14	0.4953	4	High	WS35	0.3980	28	Moderate
WS15	0.4638	7	Moderate	WS36	0.3810	33	Moderate
WS16	0.4938	5	Moderate	WS37	0.4583	8	Moderate
WS17	0.4137	20	Moderate	WS38	0.3895	31	Moderate
WS18	0.3328	42	Moderate	WS39	0.3984	27	Moderate
WS19	0.3579	36	Moderate	WS40	0.4307	15	Moderate
WS20	0.5167	2	High	WS41	0.4056	23	Moderate
WS21	0.4331	13	Moderate	WS42	0.3499	38	Moderate

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 km^2) 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 Mazzù 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.

Conflict of Interest: Authors declare that there is no conflict of interest in regarding the publication of this paper.

Funding

This research is supported by the UTS under grant number 321740.2232335 and 321740.2232357.

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