Investigation of the relationship between electrical conductivity (EC) of water and soil, and landform classification in the northern part of Meharloo watershed, Fars province, Iran using fuzzy model and GIS

Marzieh Mokarram[1] and Dinesh Sathyamoorthy[2]

[1]Marzieh Mokarram(Department of Range and Watershed Management, College of Agriculture and Natural Resources of Darab, Shiraz University, Iran, Email: m.mokarram@shirazu.ac.ir)

[2]Dinesh Sathyamoorthy (Science & Technology Research Institute for Defence (STRIDE), Ministry of Defence, Malaysia (E-mail: dinesh.sathyamoorthy@stride.gov.my)

Corresponding author: *Marzieh Mokarram, Tel.: +98-917-8020115; Fax: +987153546476 , Address: Darab, Shiraz university, Iran, Postal Code: 71946-84471, Email: m.mokarram@shirazu.ac.ir*

Investigation of the relationship between electrical conductivity (EC) of water and soil, and landform classification in the northern part of Meharloo watershed, Fars province, Iran using fuzzy model and GIS

Abstract

In this research, the relationship between landform classification and electrical conductivity (EC) of soil and water in the in the northern part of Meharloo watershed, Fars province, Iran was investigated using a combination of geographical information system (GIS) and fuzzy model. The results of the fuzzy method for water EC showed that 36.6% of the land to be moderately land suitable for agriculture; high, 31.69%; and very high, 31.65%. In comparison, the results of the fuzzy method for soil EC showed that 24.31% of the land to be as not suitable for agriculture (low class); moderate, 11.78%; high, 25.74%; and very high, 38.16 %. In the total, the land suitable for agriculture with low EC is located in the north and northeast of the study area. The relationship between landform and EC shows that EC of water is high for the valley classes, while the EC of soil is high in the upland drainage class. In addition, the lowest EC for soil and water are in the plain small class.

Keywords: Meharloo watershed, Groundwater quality, landform, electrical conductivity (EC), fuzzy model.

1. Introduction

Soil features are largely controlled by the landforms on which they are developed. The physiographic penetration on soil properties is recognized based on the progress of the soil–landform relationship (Ali and Moghanm, 2013). The landforms formed by the same geomorphic processes is the main key feature because they can easily be identified, and were responsible for making the undercoat material of the soils (Park and Burt, 2002; Henderson et al., 2005; Mini et al. 2007; Poelking et al., 2015). Previous studies have shown that there is a clear relationship between landform and soils, in that landforms and soil both control hydrological erosional, biological, and geochemical cycles. Based on the type of landform, other parameters of watersheds can be predicted, such as soil, erosion, biological and so on (Berendse et al., 2015; Brevik et al., 2015; Decock et al., 2015; Keesstra et al., 2012; Smith et al., 2015)

Geographical information systems(GIS) GIS, with features such as the ability to acquire and exchange many different sources, organization, retrieval and display of data, analysis of numerous data, and possibility to provide multiple services, has been introduced as an efficient tool in the planning. Combining GIS with fuzzy logic provides a comparatively new land evaluation method (Badenki and Kurtener, 2004; Oinam et al, 2014; Wang et al., 2015). Incorporating both of these methods is more flexible, and reflects human creativeness and understanding to make decisions. Fuzzy inference is considered as a deduction for mathematical modeling in imprecise and vague processes, uncertainty about data and thus makes a context for modeling uncertainly (Kurtener, 2005).

Ali and Moghanm (2013) studied the variation of soil properties over the landforms around Idku Lake, Egypt, with tthe spatial distribution of $CaCO_3$, EC, organic matter (OM), pH, nitrogen (N), phosphor (P), potassium (K), iron (Fe), manganese (Mn), copper (Cu) and zinc (Zn) over the various landforms discussed in detail. The results showed that the changes of $CaCO_3$, EC and OM are minimal in the landforms of sand sheets, hammocks, sabkhas, clay flats and former lake-bed.

Aliabadi and Soltanifard (2014) apply GIS and fuzzy inference for determination of the impact of water and soil EC, and calcium carbonate on wheat crop. Regarding the results of the fuzzy inference system, 76% was achieved using the of Mamdani and 52% of accuracy for the Sugeno technique was achieved.

In addition, El-Keblawy et al (2015) investigated relationships between landforms, soil characteristics and dominant xerophytes in the northern United Arab Emirates. Soil texture, electrical conductivity (EC) and pH were determined in each stand. The results showed that soil and landforms also control the geomorphological and hydrological processes (Cerdà and García-Fayos, 1997, Cerdà, 1998, Dai et al, 2015, Nadal-Romero et al., 2015).

One of the largest wheat producing regions in Iran is located in the Shiraz Plain, Fars province (Bijanzadeh et al., 2014). The aim of this study is to investigate of the relationship between landform classes and EC of water and soil in this area using a combination of GIS and fuzzy models. The methodology employed in this study is summarized in Figure 1.

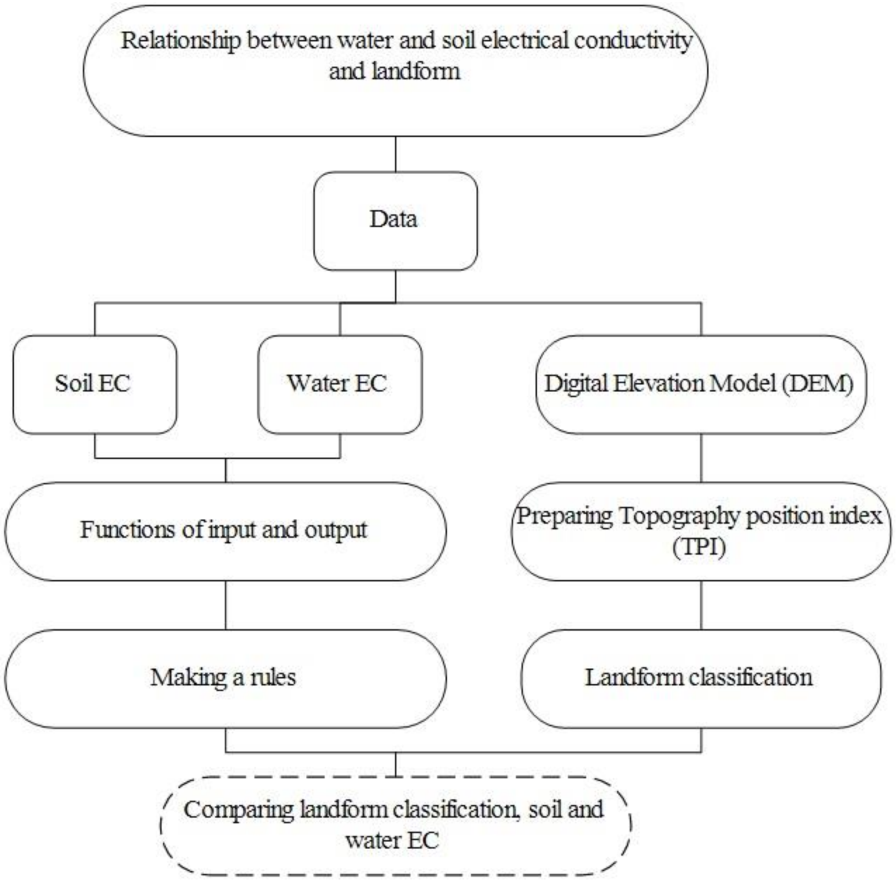


Figure 1. Flowchart of the methodology employed to investigate the relationship between landform classification, and soil and water EC.

2. Case study

The study area has an area of 3,909 km^2 and is located at longitude of N 29° 06´- 29° 43´and latitude of E 52° 18´ to 53° 28´ (Figure 2). The altitude of the study area ranges from the lowest of 1,433 m to the highest of 3,083 m. The region is located in the north of the Fars province, which has cold winters with hot summers. The average temperature for the area is 16.8 °C, ranging between 4.7 and 29.2 °C (Soufi, 2004). The research area is a biodiversity of mountains, relief and lithology, and geological characteristics such as for instance sedimentary basin and elevated reliefs (Soufi, 2004). The main land use types of the region are agriculture, range land, farming and forests.

In terms of geology the Precambrian Hormoz series and the Quaternary units are the oldest and youngest rocks in the basin, respectively. Spans of outcropped rocks, covering from the Cretaceous to Quaternary, are carbonate sediments of deep to shallow marine facies. These sedimentary sequences include large and small stratigraphic gaps in the form of disconformity and sometimes nonconformity (Khaksar et al., 2006).

The area is situated in an arid and semi-arid region. Rainfall varies from 150mm on the plains to 650mm on the high mountains, with an average of 350 mm. The rainfall is concentrated in cold seasons, while the precipitation is very low from June to October (Sigaroodi et al., 2014).

During winter, several migratory bird species from north of Caspian Sea, flamingos (Phoenicopterus roseus), common shelducks (Tadorna tadorna) and mallards (Anas platyrhynchos), spend 4 months in the area feeding on brine shrimp (Artemia franciscana). Thus, the lake has important ecological value (Sigaroodi et al., 2014).

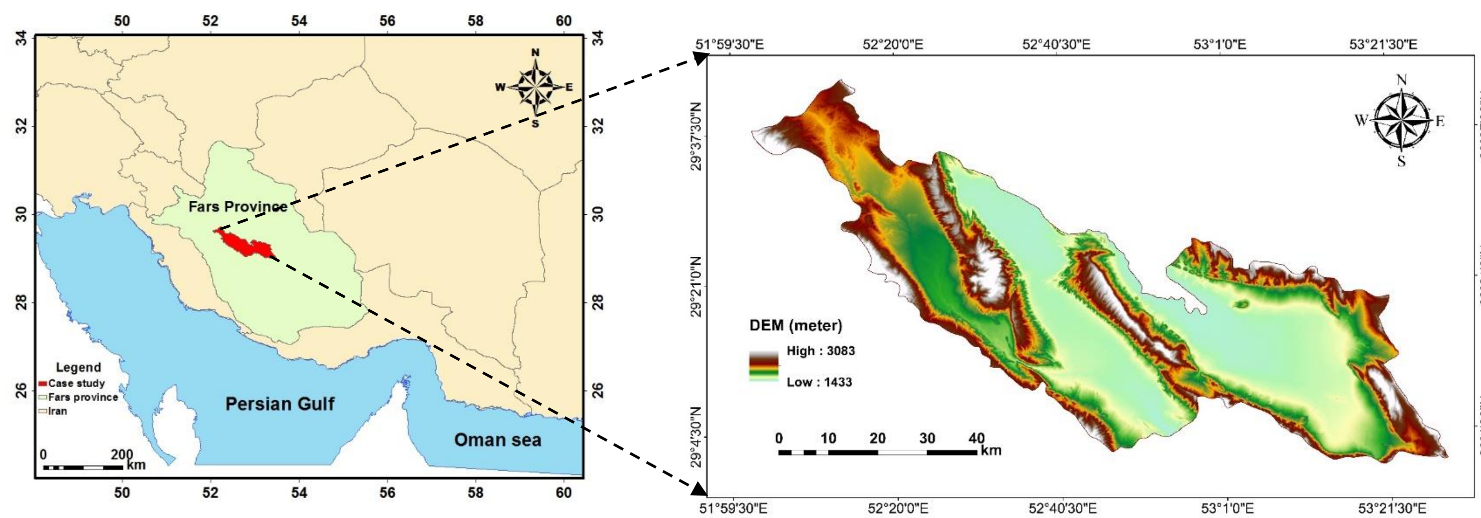


Figure 2. Location of the study area (DEM with spatial resolution of 30 m) (Source: http://earthexplorer.usgs.gov).

3. Materials and methods

3.1. Inverse Distance Weighted (IDW)

IDW model was used for interpolating the EC properties. IDW interpolation explicitly implements the assumption that things that are close to one another are more alike than those that are farther apart. To predict a value for any unmeasured location, IDW will be used that measures neighborhood values in the predicted location. Assumed value of an attribute f at any unsampled point is an average of distance-weighted of sampled points lying within a defined neighborhood around that unsampled point. Basically it is a weighted moving average (Burrough, et al., 1998):

$$\hat{f}(x_0) = \frac{\sum_{i=1}^{n} \mathrm{f}(x_i)\,\mathrm{d}_{ij}^{-r}}{\sum_{i=1}^{n} \mathrm{d}_{ij}^{-r}} \qquad (1)$$

Where x_0 is the estimation point and x_i are the data points within a chosen surrounding. The weights (r) are related to distance by d_{ij}.

3.2. Fuzzy method

In the research, model functions are accustomed to compute membership function (MF), as described in Figure 3 (Burrough and McDonnell, 1998). In such status, an asymmetric function needs to be applied (Models 1 and 2) (Figure 3). If $MF(x_i)$ shows individual membership value for i^{th} land property x, then in the computation process these model functions (Models 1 to 2) show the following form:

For *asymmetric left* (Model 1):

$$MF(x_i) = [1/(1 + \{(x_i - a_i - b_1)/b_1\}^2)]\ if\ x_i < (a_1 + b_1) \quad (2)$$

For asymmetric right (Model 2):

$$MF(x_i) = [1/(1 + \{(x_i - a_2 + b_2)/b_2\}^2)]\ if\ x_i > (a_2 - b_2) \quad (3)$$

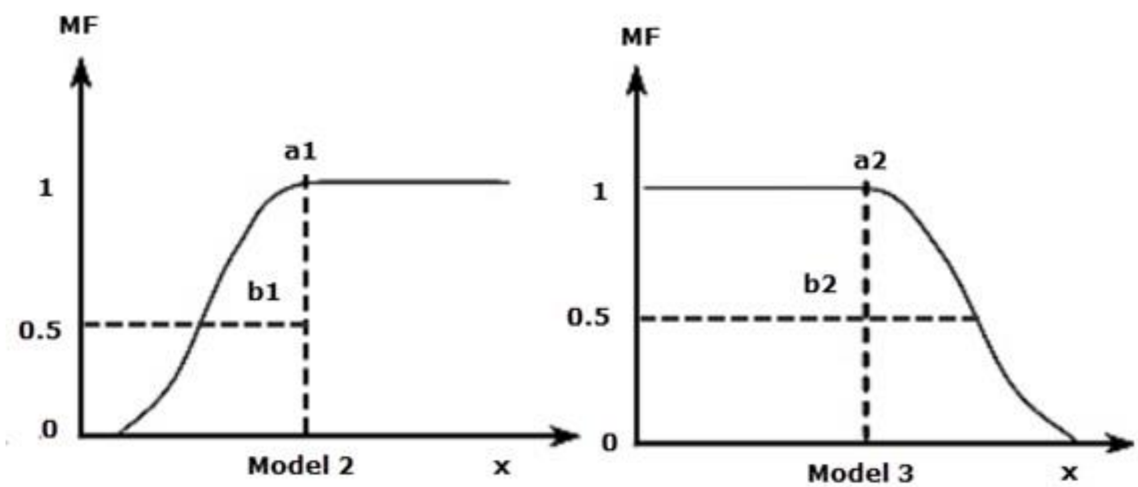


Figure 3. Membership functions.

In this study, in order to define fuzzy rule based membership functions, the categories shown in Tables 1 and 2 are used.

Table 1. Classification of water EC values (Kumar et al., 2003).

Class	EC (ds/m)
Low	< 0.25
Moderate	0.25 – 0.75

High	0.75 – 2.25
Very high	> 2.25

Table 2. Classification of soil EC values (Mokarram et al., 2010).

Class	EC (ds/m)
Low	< 8
Moderate	8-12
High	12-16
Very high	> 16

3.3. Landform classification

TPI (Weiss, 2001) compares the elevation of each cell in a DEM to the mean elevation of a specified neighborhood around that cell. Positive

TPI (Eq. (4)) compares the elevation of each cell in a DEM to the mean elevation of a defined neighborhood around that cell. Mean elevation is subtracted from the elevation value at center (Weiss 2001):

$$TPI_i = Z_0 - {\sum_{n-1} Z_n}/{n} \tag{4}$$

where;

Z_0= elevation of the model point under evaluation

Z_n= elevation of grid

n = the total number of surrounding points employed in the evaluation

Incorporating TPI at small and large scales permit a number of nested landforms to be distinguished (Table 3). The actual breakpoints among classes can be selected to optimize the classification for a specific landscape. As in slope position classifications, additional topographic metrics, such as for example differences of elevation, slope, or aspect within the neighborhoods, can help delineate landforms more accurately (Weiss 2001).

Table 3.Topographic Position Index (TPI) thresholds for small and large neighborhoods used to define landscape feature classes

Landform	TPI	
Landform	Small Neighborhood	Large Neighborhood
Plains	-1 < TPI < 1	-1<TPI<1*
Open slopes	-1 < TPI < 1	-1<TPI<1**
U-shaped valleys	-1 < TPI < 1	TPI < -1
Mountain tops/High ridges	TPI > 1	TPI > 1
Upper slopes/Mesas	-1 < TPI < 1	TPI > 1
Midslope drainages/Shallow valleys	TPI < -1	-1 < TPI < 1
Canyons/Deeply incised streams	TPI < -1	TPI < -1
Midslope ridges/Small hills in plains	TPI > 1	-1 < TPI < 1
Upland drainages/Headwaters	TPI < -1	TPI > 1
Local ridges/Hills in valleys	TPI > 1	TPI < -1

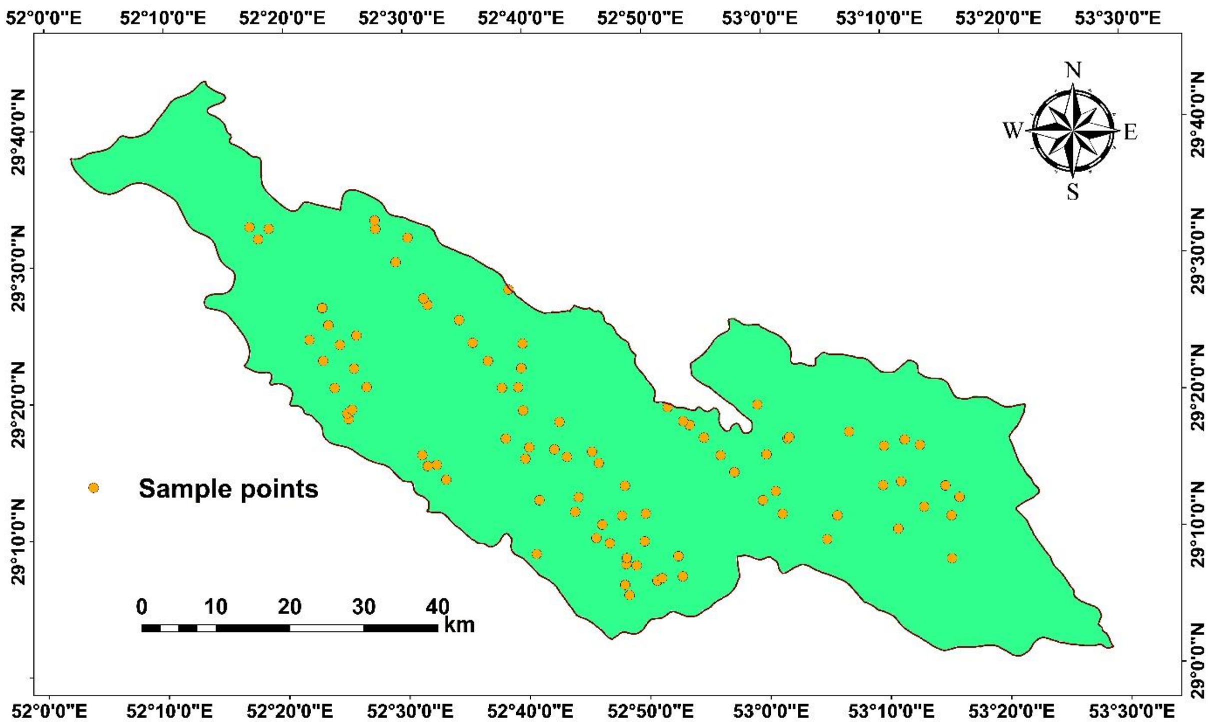
*Plain landform class required a slope of < 0.5
**Open slopes landform class required a slope of > 0.5

Also the classes of canyons, deeply incised streams, midslope and upland drainages, shallow valleys, and tend to have strongly negative plane form curvature values. On the other hand, local ridges / hills in valleys, midslope ridges, small hills in plains and mountain tops, and high ridges have strongly positive plane form curvature values.

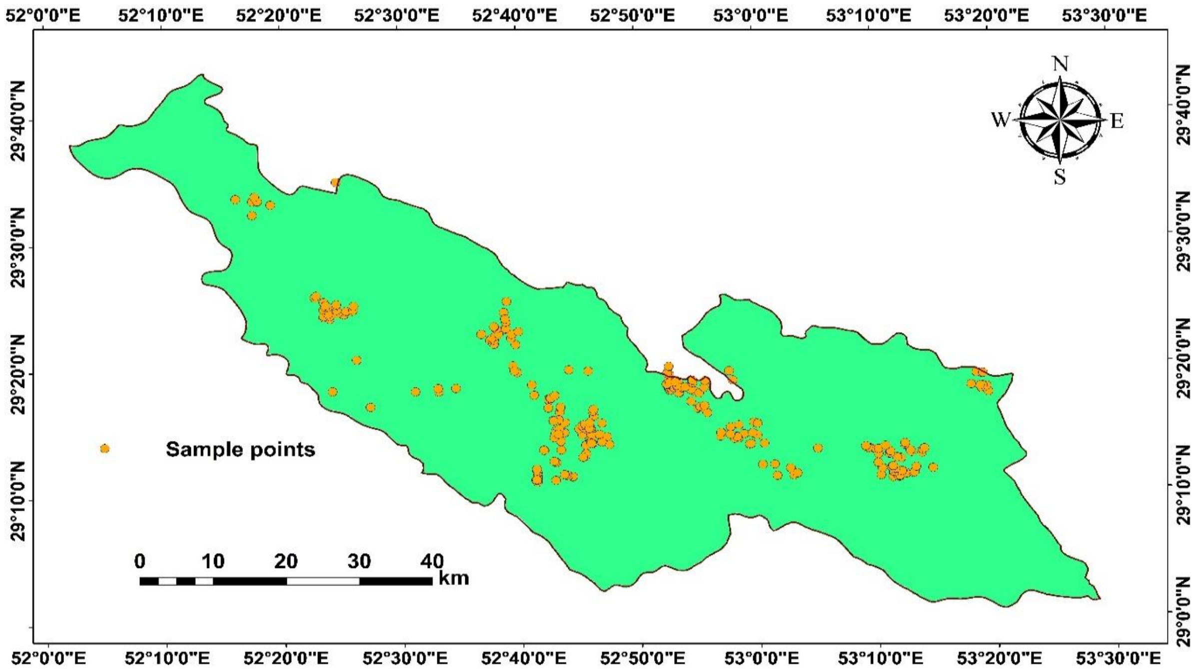
4. Results and Discussion

4.1. Inverse Distance Weighted (IDW)

IDW interpolation was used to produce the prediction of soil and water EC, as shown in Figure 4. The lowest and highest output for IDW were 0.016 and 14.48 respectively for water EC, while the lowest and highest soil EC were 0 and 34.5 respectively. The interpolation maps for soil and water EC are shown in Figure 5. The statistical properties of the interpolated soil and water EC are shown in Table 4.



(a)

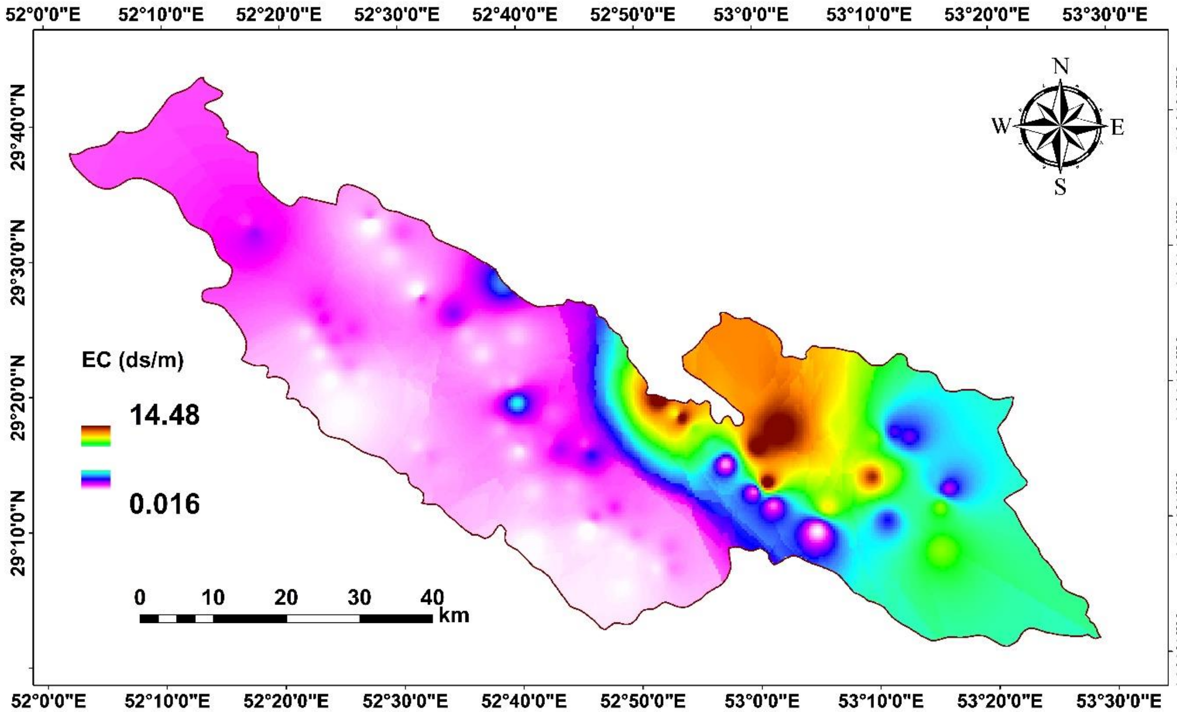


(b)

Figure 4. Position of sample points for (a) water and (b) soil EC.

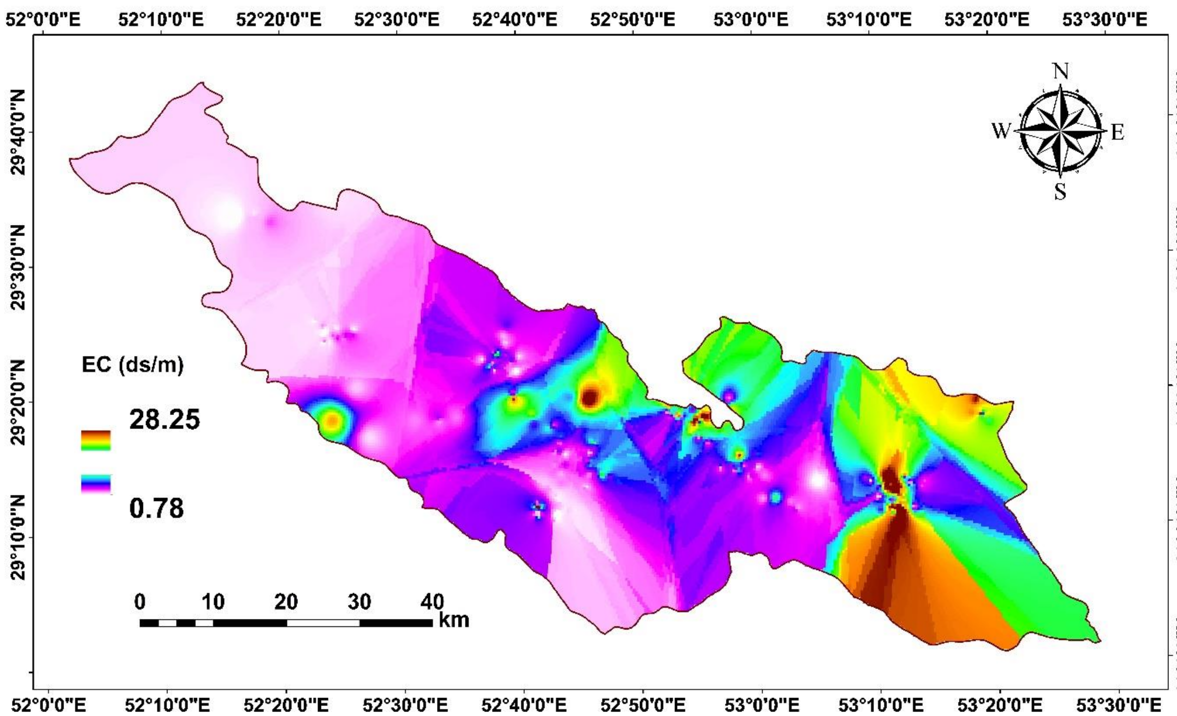
Table 4. Descriptive statistics of the water and soil EC.

Statistic parameter	Water EC (ds/m)	Soil EC (ds/m)
Maximum	14.48	28.25
Minimum	0.016	0.78
Average	3.80	3.91
STDEV	6.13	3.82
Skewness	6.54	3.09
Kurtosis	62.97	15.46



52°0'0"E
52°10'0"E
52°20'0"E
52°30'0"E
52°40'0"E
52°50'0"E
53°0'0"E
53°10'0"E
53°20'0"E
53°30'0"E
29°40'0"N
29°30'0"N
29°20'0"N
29°10'0"N
29°0'0"N
N
W
E
S
EC (ds/m)
14.48
0.016
0
10
20
30
40
km

(a)



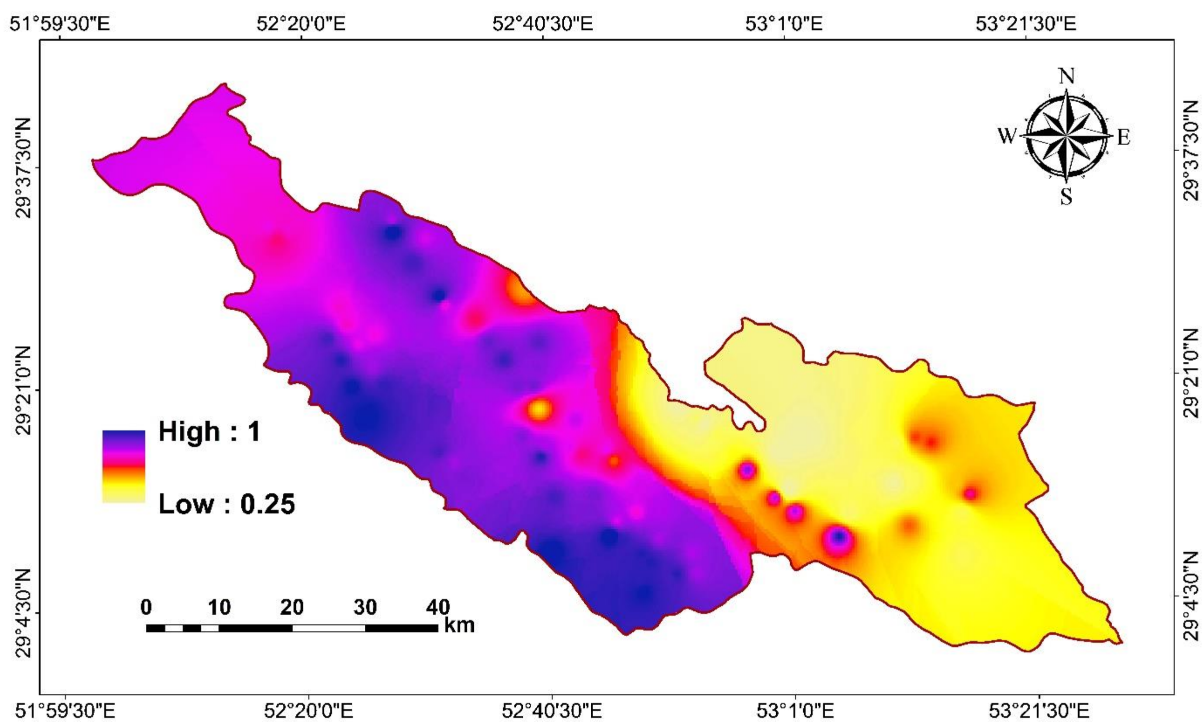
52°0'0"E
52°10'0"E
52°20'0"E
52°30'0"E
52°40'0"E
52°50'0"E
53°0'0"E
53°10'0"E
53°20'0"E
53°30'0"E
29°40'0"N
29°30'0"N
29°20'0"N
29°10'0"N
29°0'0"N
N
W
E
S
EC (ds/m)
28.25
0.78
0
10
20
30
40
km

(a)

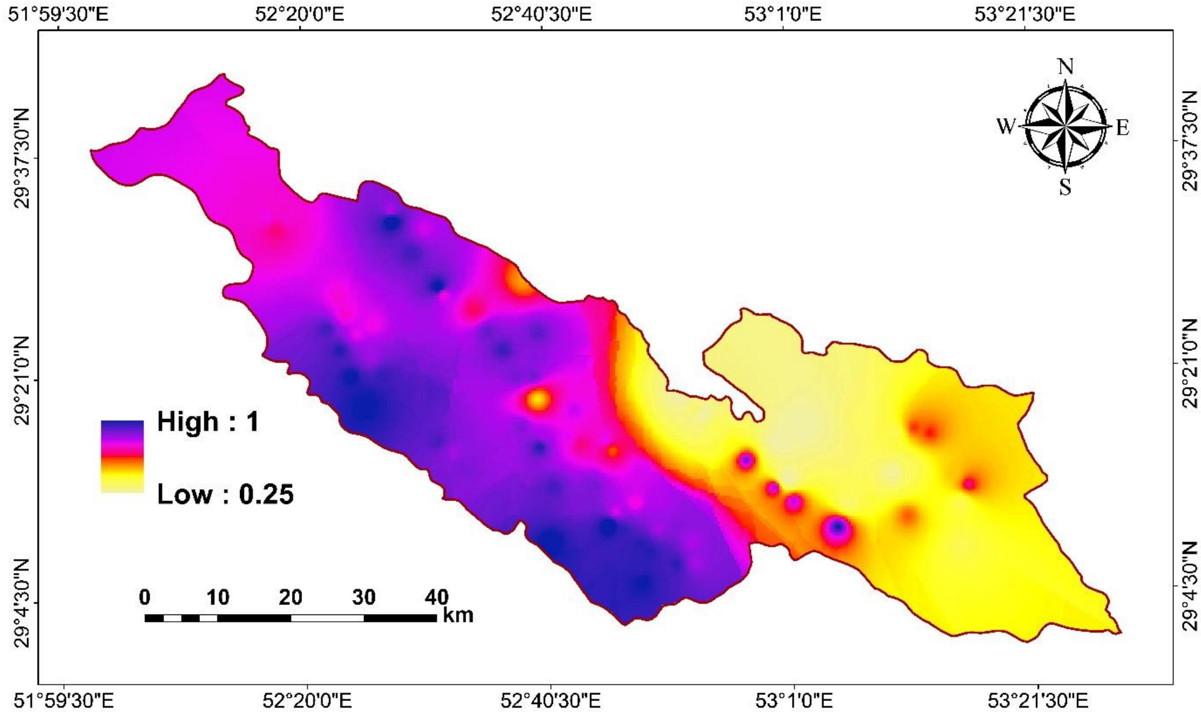
Figure 5**.** Interpolated maps of study area for (a) water and (b) soil EC.

4.2. Fuzzy method

Fuzzy maps were prepared for soil and water EC, as shown in Figure 6. The fuzzy values were classified into four classes. EC < 0.25, EC between 0.25-0.5, EC between 0. 5-0.75 and EC > 0.75 are in the classes of low, moderate, high and very high respectively (Shobha et al., 2014). The areas of the classes for soil and water EC are shown in Table 5.



(a)



(b)

Figure 6. Fuzzy maps of the study area for (a) soil and (b) water EC.

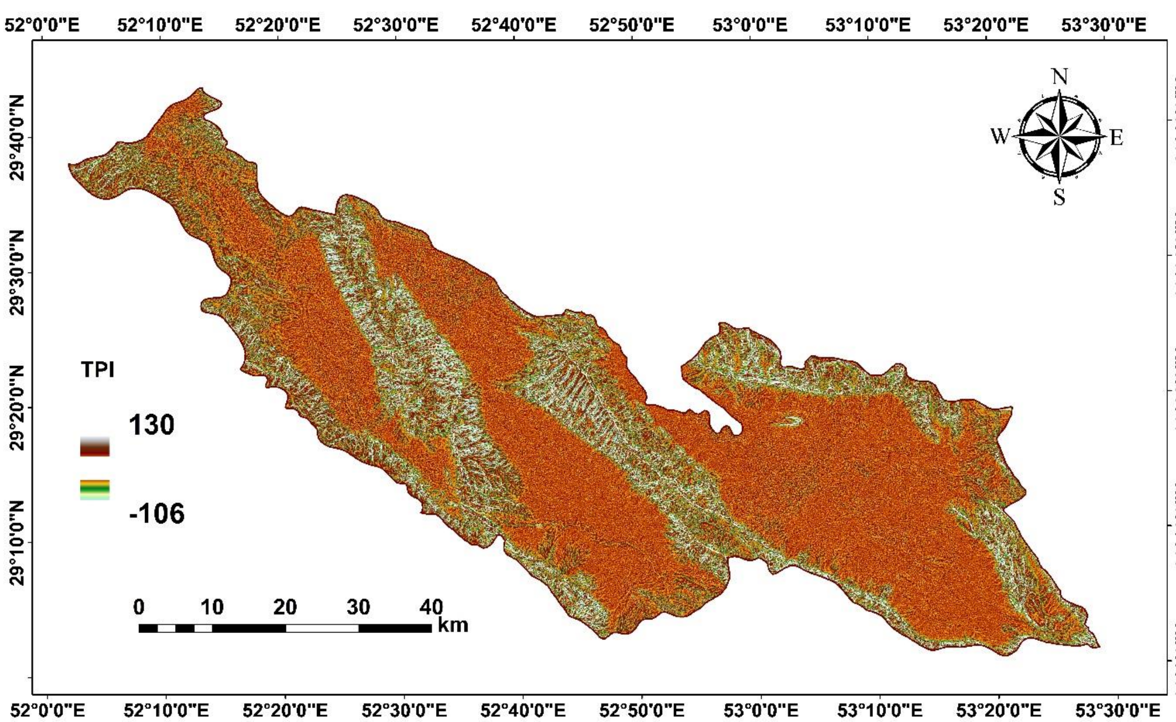
Table 5. Areas of the classes for water and soil EC.

Class	Area (%)		Area (km^2)	
	Water EC	Soil EC	Water EC	Soil EC
Low	0.00	24.31	0.11	950.23
Moderate	36.60	11.78	1430.87	460.63
High	31.69	25.74	1238.91	1006.27
Very high	31.65	38.16	1237.10	1491.86

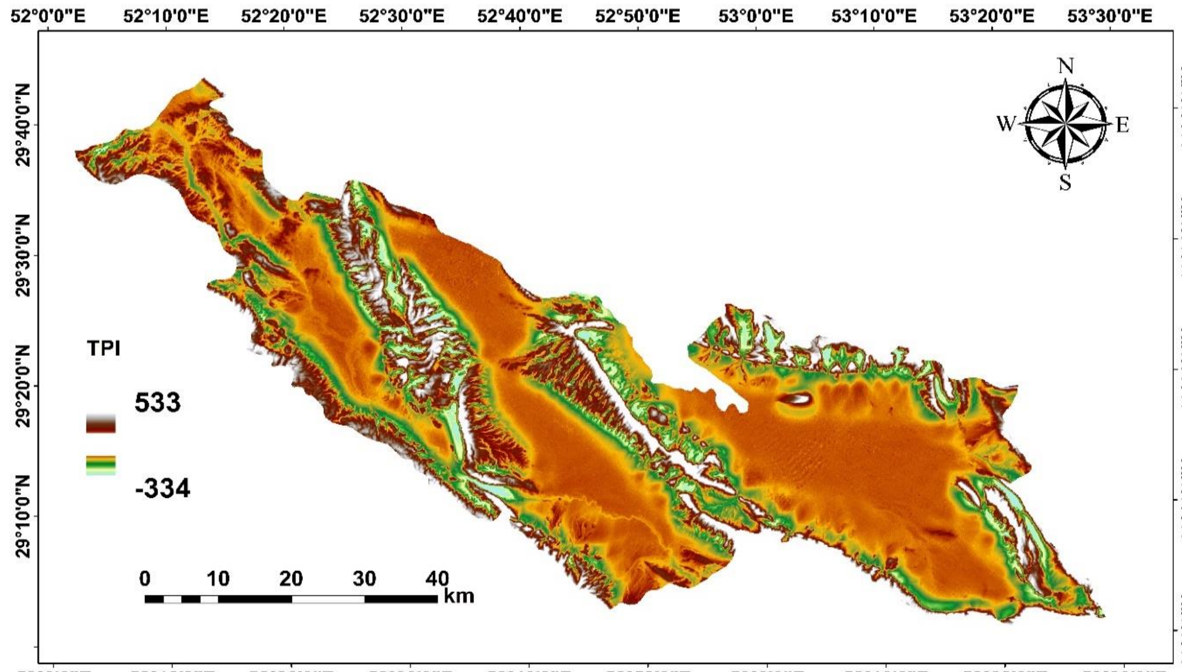
For water EC, the fuzzy model showed that 36.6% of the land was in the moderate class; high, 31.69%; and very high, 31.65%. In comparison, the results of the fuzzy model for soil EC showed that 24.31% of the land was in the low class; moderate, 11.78%; high, 25.74%; and very high, 38.16 %. Based on the results obtained, the land suitable for wheat agriculture is located in the north and northeast in the study area.

4.3. Landform classification

In order to determine of relationship between landform classification, and soil and water EC, the landform map of the study area was prepared. Using TPI, the landform classification map of the study area was generated. The TPI maps generated using small and large neighborhoods are shown in Figures 7. TPI is between -106 to 130 and -334 to 533 for 3 and 45 cells for small and large neighborhoods respectively (Figure 8). The landform maps generated based on the TPI values are shown in Figure 8. The classification has ten classes; high ridges, midslope ridges, upland drainage, upper slopes, open slopes, plains, valleys, local ridges, midslope drainage and streams. The areas of the landform classes are shown in Figure 9. It is observed that the largest landform is streams, while the smallest is plains.



(a)



(b)

Figure 7. TPI maps generated using (a) small (3 cells) and (b) large (45 cells) neighborhood.

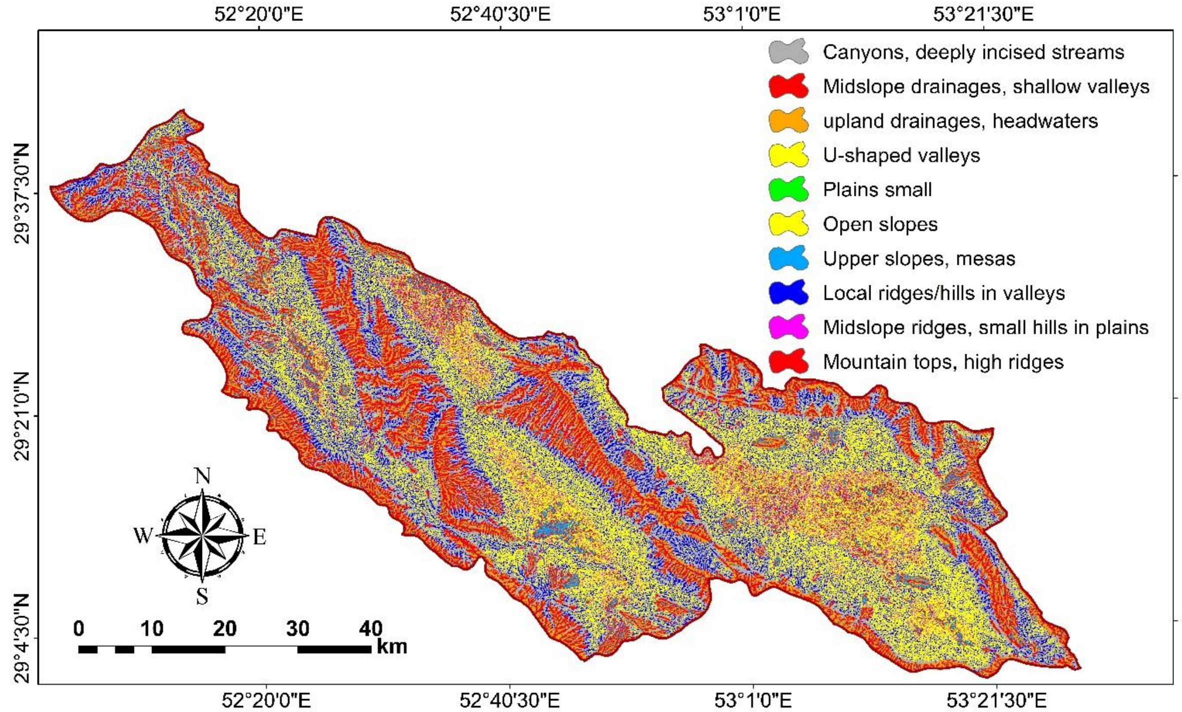


Figure 8. Landform classification using the TPI method.

The average EC for each landform class was determined, and the relationship between EC and landform was prepared. According to Figure 9, the EC of water is high for the valley class while high EC of soil is in upland drainage class. The lowest EC for soil and water are in the plain small class.

Figure 9. Relationship between landform classes.

Ali and Moghanm (2013), who investigated the relationship between soil properties and landform classes in Idku Lake, Egypt, also found that the lowest EC was in plain class. In fact, there is a relationship between soil parameters and land use (Wasak and Drewnik, 2015; Debasish-Saha et al., 2014). Yu et al. (2012) showed that there is relationship between soil parameters (such as soil organic carbon (SOC), soil total nitrogen (STN)) and types of land cover (grassland, farmland, swampland). Niu et al. (2015) and Yu et al. (2015) investigated the relationship between land use and soil moisture. The results provided an insight into the significances for land use and farming water management in this area. Saha and Kukal (2015) found that there is a relationship between soil structural stability and land use. The results indicated the degradation of soil physical attributes due to the conversion of natural ecosystems to farming system and increased erosion hazards. In fact, for landforms that are located in high elevation such as mountains, the leaching process is high, while for landforms that are located in low elevation such as plain, there is the accumulation process. Hence, in the study area and similar researches EC value was recorded high in the lower topographical position (Walia and

Chamuah, 1994; Singh and Rathore, 2015). Based on this, without measuring salinity in a laboratory, EC and other soil properties can be estimated using satellite data such as DEMs, which can save time and money.

5. Conclusion

In this study, the relationship between classes of landform, and electrical conductivity (EC) of soil and water was in the Shiraz Plain was investigated using a combination of geographical information system (GIS) and fuzzy model. The results of the fuzzy method for water EC showed that 36.6% of the land to be moderately land suitable for agriculture; high, 31.69%; and very high, 31.65%. In comparison, the results of the fuzzy method for soil EC showed that 24.31% of the land to be as not suitable for agriculture (low class); moderate, 11.78%; high, 25.74%; and very high, 38.16 %. In the total, the land suitable for agriculture with low EC is located in the north and northeast of the study area. The relationship between landform and EC shows that EC of water is high for the valley classes, while EC of soil is high in the upland drainage class. In addition, the lowest EC for soil and water are in the plain small class.

References

1. Ali R. R. and Moghanm, F. S: Variation of soil properties over the landforms around Idku lake, Egypt. The Egyptian Journal of Remote Sensing and Space Sciences (2013) 16, 91–101, 2013.

2. Ali, R. R., Ageeb, G. w. and Wahab, M. A.: Assessment of soil capability for agricultural use in some areas West of the Nile Delta,Egypt: an application study using spatial analyses. J. Appl. Sci.Res. 3-11, 1622–1629, 2007.
3. Aliabadi, K. and Soltanifard, H.: The Impact Of Water And Soil Electrical Conductivity And Calcium Carbonate On Wheat Crop Using A Combination Of Fuzzy Inference System And GIS. International journal of scientific & technology research volume 3, ISSUE 9, 118-124, 2014.
4. Badenko, v. and kurtener, D.: Fuzzy modeling in GISenvironment to support sustainable land use planning. The AGILEconference on geographic information science. 29 April-1may. Heralion, Greece, parallel session a.1-geographic knowledge discovery, 2004.
5. Berendse, F., van Ruijven, J., Jongejans, E. and Keesstra, S.: Loss of plant species diversity reduces soil erosion resistance Ecosystems, 18 (5), 881-888, 2015.
6. Bijanzadeh, E., Mokarram, M. and Naderi, R.: Applying Spatial Geostatistical Analysis Models for Evaluating Variability of Soil Properties in Eastern Shiraz, Iran. Iran Agricultural Research, Vol. 33, No. 2, 2014.
7. Brevik, E. C., Cerdà, A., Mataix-Solera, J., Pereg, L., Quinton, J. N., Six, J. and Van Oost, K.: The interdisciplinary nature of Soil, Soil, 1, 117-129, DOI:10.5194/soil-1-117-2015.
8. Burrough, P. A. and McDonnell, R. A.: Principles of geographical information systems. Spatial Information System and Geostatistics. Oxford University Press, New York, 1998.

9. Cerdà, A.: The influence of geomorphological position and vegetation cover on the erosional and hydrological processes on a Mediterranean hillslope (1998) Hydrological Processes, 12 (4), pp. 661-671, 1998.

10. Cerdà, A. and García-Fayos, P.: The influence of slope angle on sediment, water and seed losses on badland landscapes. Geomorphology. 18(2), pp.77–90, 1997.

11. Dai, Q., Liu, Z., Shao, H. and Yang, Z.: Karst bare slope soil erosion and soil quality: A simulation case study. Solid Earth, 6 (3), pp. 985-995, DOI: 10. 5194/se-6-985-2015.

12. Debasish-Saha, Kukal, S. S. and Bawa, S. S.: Soil organic carbon stock and fractions in relation to land use and soil depth in the degraded Shiwaliks hills of lower Himalayas. Land Degradation and Development, 25 (5), pp. 407-416, 2014.

13. Decock, C., Lee, J., Necpalova, M., Pereira, E. I. P., Tendall, D. M. and Six J.: Mitigating N2O emissions from soil: from patching leaks to transformative action Soil, 1, 687-694, 2015.

14. El-Keblawy, A., Abdelfattah, M. A. and Khedr, A.: Relationships between landforms, soil characteristics and dominant xerophytes in the hyper-arid northern United Arab Emirates. Journal of Arid Environments 117 (2015) 28e36, 2015.

15. Henderson, B. L., Bui, E. N., Moran, C. J. and Simon, D. A. P.: Australia-wide predictions of soil properties using decision trees.Geoderma 124, 383–398, 2005.

16. Keesstra, S. D., Geissen, V., van Schaik, L., Mosse, K. and Piiranen, S.: Soil as a filter for groundwater quality. Current Opinions in Environmental Sustainability 4, 507-516, DOI:10.1016/j.cosust.2012.10.007.

17. Khaksar, K. Goodarzi, M. Gharibreza M. and Rahmati, M.: A Study on the Sensivity of Geological Formations to Erosion in __the Maharlou Basin. Journal of Earth Sciences, No. 62. 14 pp. 2006.
18. Kumar, A., Bohra, C. and Singh, L. K.: Environment, Pollution and Management. APH Publishing, 2003 - Environmental management - 604 pages. ISBN: 81- 7648-419-9, 2003.
19. Kurtener, D., Green, T. R., Krueger–Shvetsova, E. and Erskine, R. H.: Exploring Relationships Between Geomorphic Factors and Weaht Yield Using Fuzzing Inference System, Hydrology Days, 121-130, 2005.
20. Mini, V., Patil, P. L. and Dasog, G. S.: A remote sensing approach for establishing the soil physiographic relationship in the Coastal agro eco system of North Karnataka. Karnataka J. Agric. Sci. 20–3, 524–530, 2007.
21. Mokarram, M., Rangzan, K., Moezzi, A. and Baninemeh, J.: Land suitability evaluation for wheat cultivation by fuzzy theory approache as compared with parametric method. The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, Vol. 38, Part II, 2010.
22. Nadal-Romero, E., Revuelto, J., Errea, P. and López-Moreno, J. I.: The application of terrestrial laser scanner and SfM photogrammetry in measuring erosion and deposition processes in two opposite slopes in a humid badlands area (central Spanish Pyrenees). Soil 1, 561-573, DOI:10.5194/soil-1-561-2015.
23. Niu C. Y., Musa A. and Liu Y.: Analysis of soil moisture condition under different land uses in the arid region of Horqin sandy land, northern China. Solid Earth, 6 (4), pp. 1157-1167, 2015.

24. Oinam B. C., Marx W., Scholten T. and Wieprecht S.: A fuzzy rule base approach for developing a soil protection index map: A case study in the upper awash basin, Ethiopian highlands. Land Degradation and Development, 25 (5), pp. 483-500, DOI: 10. 1002/ldr. 2166, 2014.
25. Park, S. J. and Burt, T. P.: Identification and characterization of pedo-geomorphological processes on a hillslope. Soil Sci. Soc. Am.J. 66, 1897–1910, 2002.
26. Poelking E. L., Schaefer C. E. R., Fernandes Filho E. I., De Andrade A. M., Spielmann A. A. Soil-landform-plant-community relationships of a periglacial landscape on Potter Peninsula, maritime Antarctica. (2015) Solid Earth, 6 (2), pp. 583-594. DOI: 10. 5194/se-6-583-2015
27. Saha, D. and Kukal, S. S.: Soil structural stability and water retention characteristics under different land uses of degraded lower himalayas of North-West India. Land Degradation and Development, 26 (3), pp. 263-271, 2015.
28. Shobha, G. Gubbi, J., Raghavan, K. S., Kaushik, L. K. and Palaniswami, M.: A novel fuzzy rule based system for assessment of ground water potability: A case study in South India. IOSR Journal of Computer Engineering (IOSR-JCE). Volume 15, Issue 2 (Nov. - Dec. 2013), PP 35-41, 2014.
29. Sigaroodi, S. K. Chen, Q. Ebrahimi, S. Nazari, A. and Choobin B.: Long-term precipitation forecast for drought relief using atmospheric circulation factors: a study on the Maharloo Basin in Iran. Hydrol. Earth Syst. Sci., 18, 1995–2006.2014.
30. Singh, D.P., and Rathore, M.S.: Morphological, physical and chemical properties of soils associated in top sequence for establishing taxonomy classes in Pratapgarh

District of Rajasthan, India. African Journal of Agricultural Research. Vol. 10(25), pp. 2516-2531, 18 June, 2015

31. Smith, P., Cotrufo, M. F., Rumpel, C., Paustian, K., Kuikman, P. J., Elliott, J. A., McDowell, R., Griffiths, R. I., Asakawa, S., Bustamante, M., House, J. I., Sobocká, J., Harper, R., Pan, G., West, P. C., Gerber, J. S., Clark, J.M., Adhya, T., Scholes, R.J. and Scholes, M.C.: Biogeochemical cycles and biodiversity as key drivers of ecosystem services provided by soils. Soil 1, 665-685, DOI:10.5194/soil-1-665-2015.
32. Soufi, M.: Morpho-climatic classification of gullies in fars province, southwest of i.r. iran . International Soil Conservation Organisation Conference – Brisbane, 2004.
33. Walia, C.S. and Chamuah, G.S.: Soils of riverine plain in Arunachal plain and their suitability for some agricultural crops. J. Indian Soc. Soil Sci. 42:425-429. 1994.
34. Wang, J., Ge, A., Hu, Y., Li, C. and Wang, L.: A fuzzy intelligent system for land consolidation - A case study in Shunde, China Solid Earth, 6 (3), pp. 997-1006, DOI: 10.5194/se-6-997-2015.
35. Wasak, K. and Drewnik, M.: Land use effects on soil organic carbon sequestration in calcareous Leptosols in former pastureland-a case study from the Tatra Mountains (Poland). Solid Earth, 6 (4), pp. 1103-1115, 2015.
36. Weiss, A.: Topographic Positions and Landforms Analysis (Conference Poster). ESRI, 2001.
37. Yu, B., Stott, P., Di, X.Y. and Yu, H. X.: Assessment of land cover changes and their effect on soil organic carbon and soil total nitrogen in daqing prefecture, China. Land Degradation and Development, 25 (6), pp. 520-531, 2014.

38. Yu,Y., Wei, W., Chen, L. D., Jia, F. Y., Yang, L., Zhang, H. D. and Feng, T. J.: Responses of vertical soil moisture to rainfall pulses and land uses in a typical loess hilly area, China. Solid Earth, 6 (2), pp. 595-608. Cited 1 time, 2015.