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Evaluation the Soil Fertility Mapping for Corn Production (*Zea mays* L.) using Fuzzy and Analytic Hierarchy Process Methods

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ABSTRACT: Fuzzy membership function and analytic hierarchy process (AHP) are effective tools to evaluate the soil fertility mapping of corn. To investigate the soil fertility maps using fuzzy and analytic hierarchy process (AHP) models a case study was conducted in Shiraz plain, southern Iran. In the study area from 34 field samples, seven soil parameters including organic content (OC), phosphorus (P), potassium (K), iron (Fe), zinc (Zn), manganese (Mn) and copper (Cu) of the soil were selected for soil fertility maps using inverse distance weighting (IDW) method and then fuzzy and AHP method were employed. Results of IDW showed that OC of soil was between 0.37 to 1.51% and only northwest and south of study area had suitable OC more than critical level. Also, Fuzzy model showed that most of the study area had low OC and need fertilization. All of the models showed that P content for most of the study area was lower than the critical level. Fuzzy map showed that most of the study areas except the parts of east and center had unsuitable value for Fe and Zn. In contrast, except the northwest, the other areas had suitable K and Mn values using fuzzy map. For Zn and Mn, only the small parts of study area were more than critical level for corn production. AHP model showed that the most and least important factor in soil fertility were OC (with weight of 0.35) and Mn (with weight of 0.04), respectively. Fuzzy-AHP combination method showed that only 0.96% of the lands (located in northeast) had high fertility and most of the study area had low soil fertility and needed fertilizer for corn production.

Keywords: Fuzzy map, critical level, inverse distance weighting, organic content.

Abbreviations: AHP: analytic hierarchy process; IDW: inverse distance weighting; OC: organic content; P: phosphorus; K: potassium, Fe: iron; Zn: zinc; Mn: manganese; Cu; copper.

INTRODUCTION

Corn (*Zea mays* L.) is a major crop in Iran and ranks third, behind wheat and rice in hectares grown. Also, corn has important role linkages within the agricultural sector among various crops and between crops and live stocks. Because of corn's role and its proportion of 65-70% in commixture of food ration for birds, implant of corn in Iran has outspread day by day and necessity of increasing in its production is clearer than before in these days as corn's acreage has increased from 10 thousand hectares to 205 thousand hectares during 1980-2005 (Yazdani *et al*. 2008).

One of the most important factors in corn grain yield improvement is soil fertility and different methods such as geographic information system (GIS), fuzzy membership functions, analytic hierarchy process (AHP) and their combinations have been applied to assess soil fertility status of crops (Zhu *et al.* 1996; Mc Bratney *et al.* 2000; Zhu *et al.* 2001; Zhu *et al.* 2010). Combining GIS with fuzzy logic approach provides a relatively new land evaluation (Badenko *et al*. 2004). Combining these two methods is more flexible and reflects human ingenuity and intelligence more and more in making decisions. Fuzzy inference is considered as a deduction for mathematical modeling in imprecise and ambiguous processes, uncertainty about data and imprecision associated with the awareness of decision makers in assigning precise criteria, and thus provides a context for modeling uncertainly (Kurtener *et al*. 2005).

Fuzzy set theory has been widely used in soil science for soil fertility classification and mapping and land evaluation (Mc Bratney *et al.* 2003; Zhang *et al*. 2004; Lagacherie 2005; Sanchez Moreno 2007; Zhu *et al*. 2010). The development of fuzzy logic in the soil mapping community due to its ability to represent the continuous nature of soil spatial variability (Zhu *et al*. 2001; Yang *et al*. 2007).

In fuzzy logic approaches, soil spatial parameters are expressed as spatial parameters of membership in soil classes (McBratney *et al*. 2000; Qi *et al*. 2006), which is then used to produce conventional soil class maps and to forecast spatial parameters of specific soil properties (Zhu *et al*. 1996).

Membership functions in soil fertility classes were established based on FAO and expert knowledge (Sanchez Moreno 2007). The topic principal in this knowledge-based method to the fuzzy membership function definition is the determination of class limits and membership gradation within these class limits (Zhu *et al*. 2010). Lagacherie (2005) suggested a fuzzy pattern matching to soil class description in soil database into a set of membership functions. In 2007, it became clear that the fuzzy AHP method in the land suitability is one of the best methods (Sanchez Moreno 2007). Nevertheless in this method, a lot of factors such as primary slope, secondary slop, micro-relief, Wetness, Salinity (EC), Alkalinity (ESP), soil texture, fertility slope, Soil depth, CaCO3, pH and gypsum should be assessed and measured (Sys *et al*. 1993). In 2006, soil mapping was developed with a fuzzy approach which was also constructed based on the knowledge obtained from soil experts (Qi *et al*. 2006). Finally, in order to predict soil map, Zhu *et al*. (2010) used membership functions under fuzzy logic. The methodology employed in this study is summarized in Fig. 1.

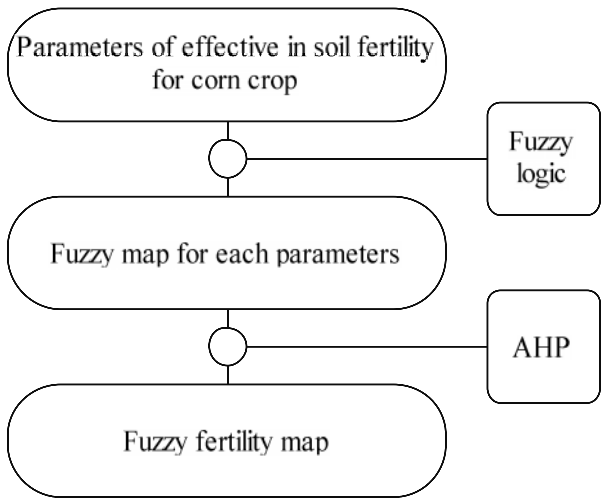


Fig. 1. Fuzzy-AHP procedure for soil fertility of corn.

The assessment of soil fertility for agricultural production in the field is vital, which should be considered soil elements and critical level of nutrients. Also, soil fertility degradation has become a problem for agricultural management, in Shiraz, Fars Province, Iran (Malakoti 2003; Soufi 2004). So, the main aim of the study is evaluation the soil fertility maps using fuzzy-AHP combination method for corn production in southern Iran.

MATERIAL AND METHODS

Case study: The study area is located in the Fars province in the south of Iran, between latitudes 29° 33' 00" N to 29° 36' 36" N and longitudes 52° 51' 36" E to 52° 58? 12"E with an area 36.25 km^2 (Fig. 2); elevation 1571 m above mean sea level. The dataset is extracted from a land classification study done by the Fars Soil and Water Research Institute in 2012.

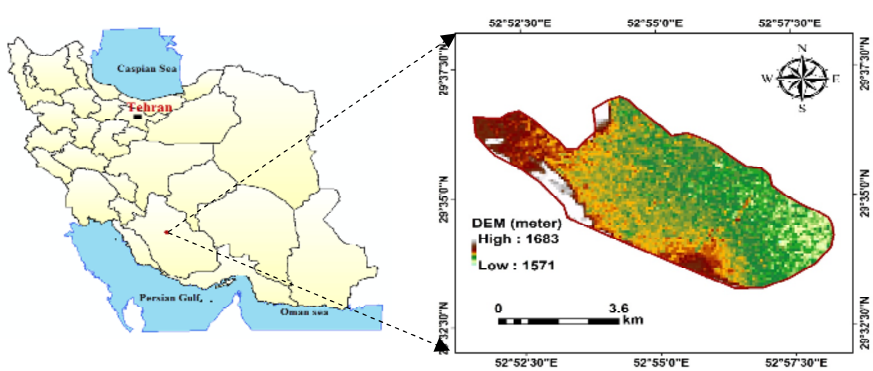


Fig. 2. Location of the study area in Shiraz, Fars province, Iran.

Input data for determination of soil fertility were derived from 34 field samples collected through a purposive sampling approach. In order to predict the soil fertility of corn seven parameters of 34 soil sample that including organic content (OC), phosphorus (P), potassium (K), iron (Fe), zinc (Zn), manganese (Mn) and copper (Cu) were measured (Table 1).

Table 1: Summaries of effective parameters for soil fertility of the study area.

Parameters	Maximum	Minimum	Average	STDEV
OC (%)	1.48	0.37	1.01	0.25
P (mg/kg)	25	5	15.33	4.67
K_PPM	539	167	310.9	81.99
Fe (mg/kg)	12.3	1	4.82	3.33
Zn (mg/kg)	1.5	0.13	0.69	0.36
Mn (mg/kg)	28	2.8	13.04	7.83
Cu (mg/kg)	1.8	0.55	1.08	0.36

Method

Inverse Distance Weighting (IDW). The prediction of soil properties was prepared using IDW method in the study area. IDW interpolation explicitly implements the assumption that things that are close to one another are more alike than those that were farther apart. To predict a value for any unmeasured location, IDW will be used to measure neighborhood values in the predicted location. Assumes value of an attribute z at any unsampled point was a distance-weighted average of sampled points lying within a defined neighborhood around that unsampled point. Essentially it is a weighted moving average (Burrough, *et al*. 1998):

$$\hat{z}(x_0)=\frac{\sum_{i=1}^{n} z(x_i)d_{ij}^{-r}}{\sum_{i=1}^{n} d_{ij}^{-r}} \quad (1)$$

Where $\hat{z}(x_0)$ is the value of estimation point and $\hat{z}(x_i)$ are the value of data points within a chosen neighborhood. The weights (r) are related to distance by d_{ij}.

Fuzzy set theory. Fuzzy logic was initially developed by Lotfi Zadeh (1965) as a generalization of classic logic. Lotfi Zadeh (1965) defined a fuzzy set by memberships function from properties of objects. A membership function assigns to each object a grade ranging between 0 and 1. The value 0 means that x is not a member of the fuzzy set, while the value 1 means that x is a full member of the fuzzy set. Traditionally, thematic maps represent discrete attributes based on Boolean memberships, such as polygons, lines and points. Mathematically, a fuzzy set can be defined as following (Mc Bratney *et al*. 2000):

$$A=\{x,\mu_A(x)\} \quad for \ each \quad x\varepsilon X \quad (2)$$

where μ_A is the membership function (MF) that defines the grade of membership of x in fuzzy set A. MF takes values between and including 1 and 0 for all A, with μ_A =0 meaning that x does not belong to A and μ_A =1 meaning that it belongs completely to A. Alternatively, 0< μ_A (x) <1 implies that x belongs in a certain degree to A. If X={x1,x2,….,xn} the previous equation can be written as following (Mc Bratney *et al*. 2000):

$$A=\{[x_1,\mu_A(x_1)]+[x_2,\mu_A(x_2)]+......+[x_n,\mu_A(x_n)]\} \quad (3)$$

In simple terms, Equations (2) and (3) mean that for every x that belongs to the set X, there is a membership function that describes the degree of ownership of x in A.

The development of GIS has contributed to facilitate the mapping of soil fertility with both Boolean and fuzzy methods. For each of parameters, the following function was used (Shobha *et al*. 2013).

$$X)=f(x)=\begin{Bmatrix} 0 & x\le a \\ x-a/b-a & a<x<b \\ 1 & x\ge b \end{Bmatrix} \quad (4)$$

In order to define the fuzzy rules and fuzzy-AHP models, the critical level of each parameter for corn production was extracted using some references in the study area (Table 2).

Table 2: Critical level of soil nutrients for corn production.

Parameters	Critical level	References
OC	<1 (%)	Sobhani and Sadat, 2010
P	<18.5 (mg/kg)	Malakoti, 2003
K	<260 (mg/kg)	Ghiabi *et al.*, 2015
Fe	<6. 5 (mg/kg)	Khademi *et al.*, 2011
Zn	<1.4 (mg/kg)	Malakoti, 2003
Mn	<10 (mg/kg)	Ghiabi *et al.*, 2015
Cu	<1 (mg/kg)	Sianaki *et al.*, 2010

Analytic hierarchy process (AHP). AHP is a structured technique for organizing and analysing complex decisions. This method is based on a pair-wise comparison matrix. The matrix is called consistent if the transitivity Equation (5) and reciprocity (Equation (6) rules are respected (Mokarram *et al*. 2010).

$$a_{ij} = a_{ik} \cdot a_{kj} \qquad (5)$$

$$a_{ij} = 1/ a_{ji} \qquad (6)$$

where i, j and k are any alternatives of the matrix.

In a consistent matrix (Equation (7)), all the comparisons a_{ij} obey the equality a_{ij}= pi/pj , where pi is the priority of the alternative i. When the matrix contains inconsistencies, two approaches can be applied:

$$\begin{vmatrix} P_1/P_1 & \ldots & P_1/P_j & \ldots & P_1/P_n \\ \ldots & 1 & \ldots & \ldots & \ldots \\ P_i/P_1 & \ldots & 1 & \ldots & P_i/P_n \\ \ldots & \ldots & \ldots & 1 & \ldots \\ P_n/P_1 & \ldots & P_n/P_j & \ldots & P_n/P_n \end{vmatrix} \qquad (7)$$

In this method, pair-wise comparisons are considered as input, while relative weights are considered as outputs. The average of each row of the pair-wise comparison matrix is calculated and these average values indicate relative weights of compared criteria.

Combination of Fuzzy and AHP methods. Finally, in order to prepare the soil fertility map, it is necessary to calculate the convex combination of the raster values containing the different fuzzy parameters. A_1, … A_k are fuzzy subclasses of the defined universe of objects X, and W_1, … W_k are non-negative weights summing up to unity. The convex combination of A_1, … A_k is a fuzzy class A, and the weights W_1, … W_k are calculated using AHP and fuzzy method parameters have been calculated in ArcGIS. Equations 8 and 9 show the convex combination (Burrough 1989).

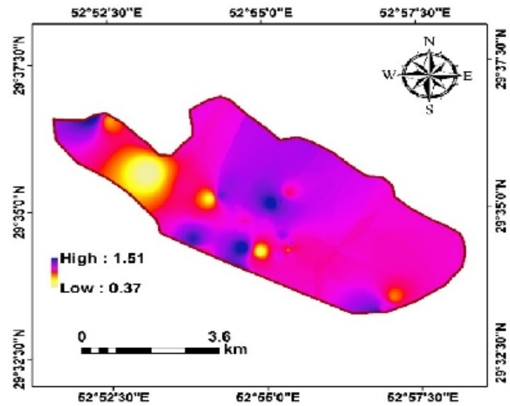
$$\mu_A = \sum_{j=1}^{k} W_j \times \mu_{A(x)} \qquad x \varepsilon X \quad (8)$$

$$\sum_{j=1}^{k} W_j = 1 \qquad W_j > 0 \quad (9)$$

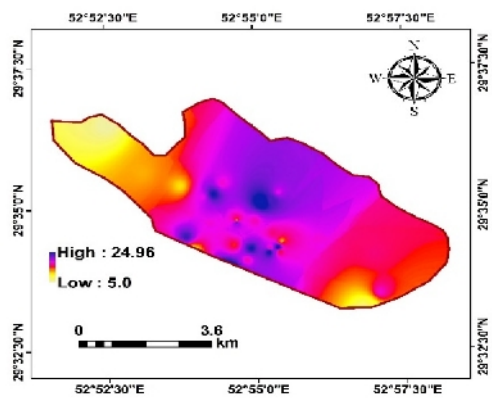
RESULTS

Inverse Distance Weighting (IDW). In order to make soil fertility maps, 34 soil samples were taken in the study area. In ArcGIS software raster maps for each parameter including organic content (OC), phosphorus (P), potassium (K), iron (Fe), zinc (Zn), manganese (Mn) and copper (Cu) of the soil were prepared using IDW model that was shown in Figure 3. Based on Figure 3 (a) the OC of soil was between 0.37 to 1.51% and only northwest and south of study area had suitable OC more than critical level (OC<1%; see Table 1).

The P content for most of the study area was lower than the critical level (P <18.5mg/kg) except in the center of study area (P=24.96mg/kg) (Fig. 3b). Overall, the K value of soil had appropriate amount (139.62 to 538.54 mg/kg) in soil of the study area (Fig. 3 c). The Fe value of the soil was between 1 to 12.24 (mg/kg) which all of the study area with Fe value more than 6.5 mg/kg was suitable for corn production except the parts of south and east (Fig. 3d).



(a)



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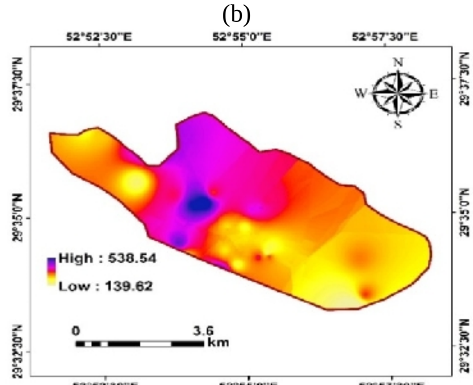

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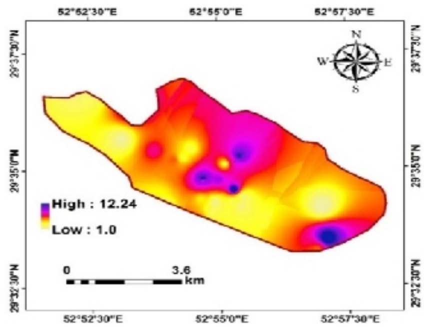

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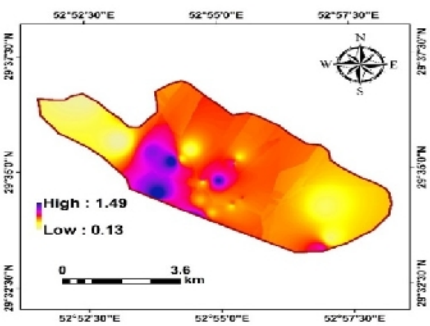

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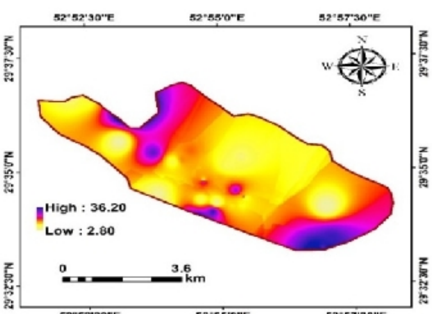

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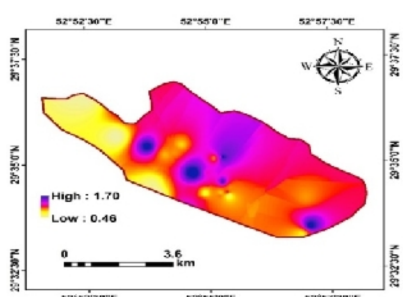
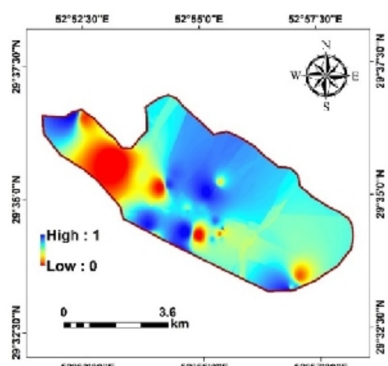


(g)

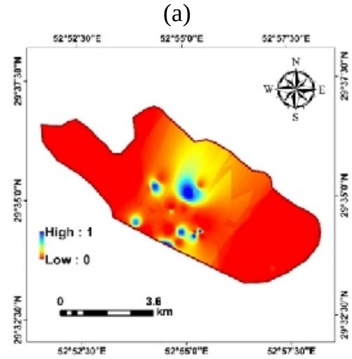
Fig. 3. Raster maps for each of the parameters using inverse distance weighting (IDW). OC (a), P (b), K (c), Fe (d), Zn (e), Mn (f), Cu(g).

The Zn value was between 0.13 to 1.49 mg/kg for the study area and only the small parts of west were suitable for Zn. (Fig. 3e). The Mn value of soil in the study area was low, so that the only parts of southeast and northwest with value more than the critical level (Mn> 10 mg/kg) was suitable for corn (Fig. 3f). Finally, the results of IDW method showed that surface soil in the study area had the Cu value between 0.46 to 1.70 (mg/kg) and according to Table1 , the Cu value of soil (Cu<1mg/kg) was enough for corn production and only the parts of northwest and west was not suitable for Cu (Fig. 3g).

Fuzzy model. In the fuzzy classification the fertility is given between 0 and 1 which values close to one showed high fertility and values close to zero showed not fertility (Equation 1 and 2). The result of fuzzy model for each of the parameters was shown in Figure 4. Most of the study area, except the parts of northwest and south had low OC content and need fertilization (Fig. 4a). Almost in all of the study area, P and Zn values were unsuitable, so that had the value close to zero (Fig. 4b and 4e). In contrast, most of study area except the northwest had K and Mn values close to 1 using fuzzy map (Figure 4c and 4f). Also, fuzzy map showed that most of the study area except the parts of east and center had unsuitable value for Fe (Fig. 4d). Finally, except the parts of northwest and southwest the other areas had suitable Cu values for corn production (Fig. 4g).



(a)



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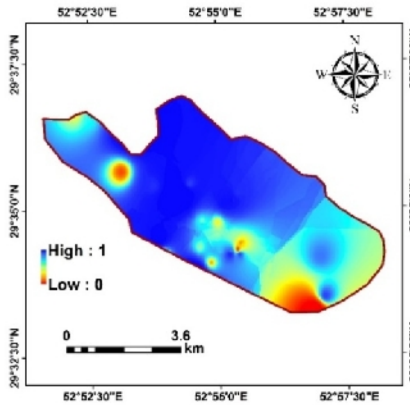

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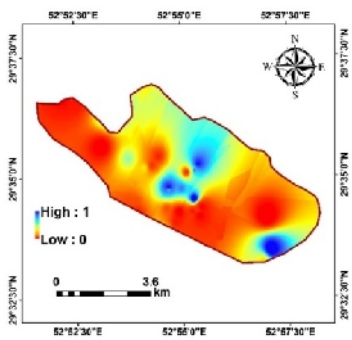

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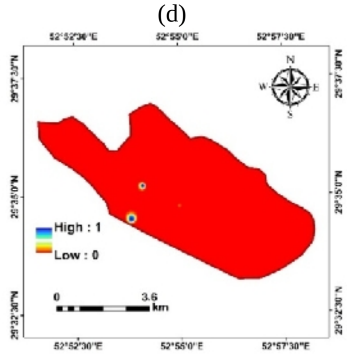

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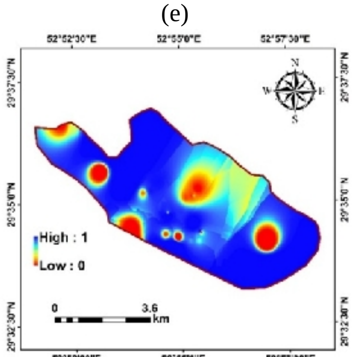

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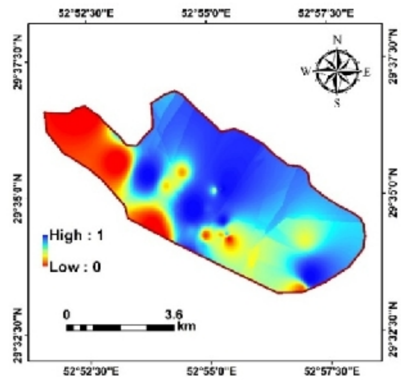

(g)

Fig. 4. Fuzzy maps for each parameter for determining the soil fertility for corn. OC (a), P (b), K (c), Fe (d), Zn (e), Mn (f), Cu(g).

Analytic hierarchy process (AHP)

The AHP method was applied on the fuzzy parameter maps and the pairwise comparison matrix used for preparation of the weights of each parameter. As shown in Table 3, the most important factor in soil fertility was OC soil (with weight of 0.35) and the least important factor was Mn (with weight of 0.04) in the study area.

Combination of Fuzzy and AHP methods

Based on the fuzzy maps for each parameters (Fig. 4) and weight of each parameter that was calculated using AHP method (Table 3), the final fuzzy map was determined (Fig. 5).

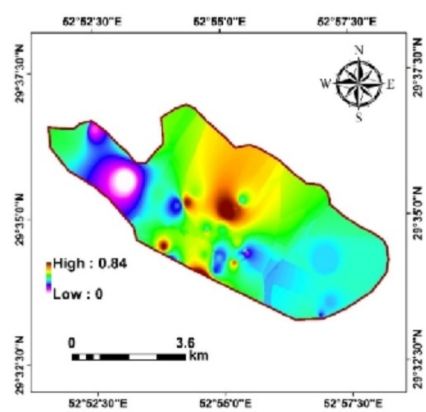

Fig. 5. Fuzzy-AHP combination map for soil fertility for corn.

According to Figure 5, the value of final fuzzy map was between 0 to 0.84 where showed the some parts of the study area had high fertility (for value more than 0.75), medium fertility (for value between 0.5 to 0.75), low fertility (for value between 0.25 to 0.5) and very low fertility (for value between 0 to 0.25) for corn production. Interestingly, only some parts of northeast had good soil fertility.

Table 3: Pairwise comparison matrix for soil fertility of corn production using analytic hierarchy process.

Parameters	OC	P	K	Fe	Zn	Mn	Cu	Weight
OC	1	2	3	5	4	7	6	0.35
P	1/2	1	2	4	3	6	5	0.24
K	1/3	1/2	1	3	2	5	4	0.16
Fe	1/5	1/4	1/3	1	1/2	3	2	0.06
Zn	1/4	1/3	1/2	2	1	4	3	0.11
Mn	1/7	1/6	1/5	1/3	1/4	1	1/2	0.04
Cu	1/6	1/5	1/4	1/2	1/3	2	1	0.05

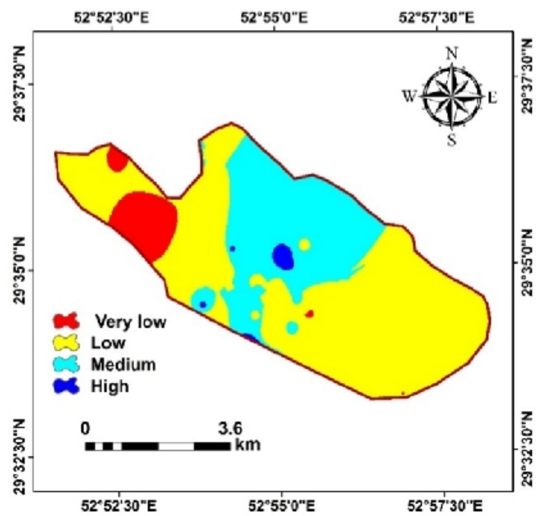

Fig. 6. Map of the fuzzy classification.

Table 4. The area (%) for each of the classes for soil fertility.

Class	Area (km^2)
Very low	2.30
Low	22.76
Medium	10.85
High	0.35

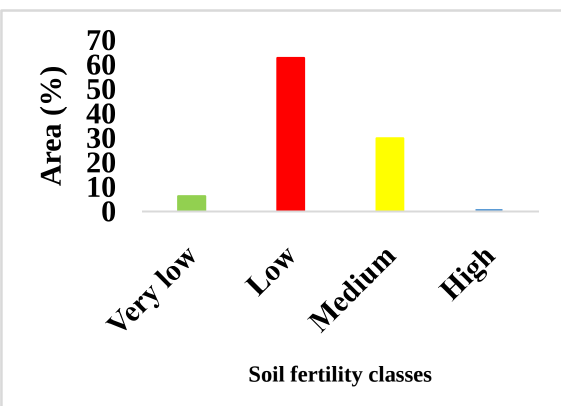

Fig. 7. The area (%) for each of the classes using fuzzy-AHP combination model.

Then, the fuzzy map reclassified in four classes consisted of very low (2.3 km^2), low (22.76 km^2), medium (10.85 km^2) and high (0.35 km^2) (Fig. 6 and Table 4). Likewise, the area (%) for each of the classes in the study area showed in Fig. 7.

The results of the fuzzy and AHP method in this study show that only 0.96% of the lands (locateted in northeast) had high fertility, 29.92% medium fertility, 62.75% low fertility and 6.34% very low fertility (Fig. 7) and most of the study area had low soil fertility and need fertilizer for suitable corn production. As was shown in Figure 8, for determination of precision and accuracy of fuzzy and AHP method 26 sample points were used randomly and 7 parameters including organic content (OC), phosphorus (P), potassium (K), iron (Fe), zinc (Zn), manganese (Mn) and copper (Cu) of the soil evaluated. Also, the class of soil fertility was predicted by fuzzy-AHP model for each points showed in Table 5.

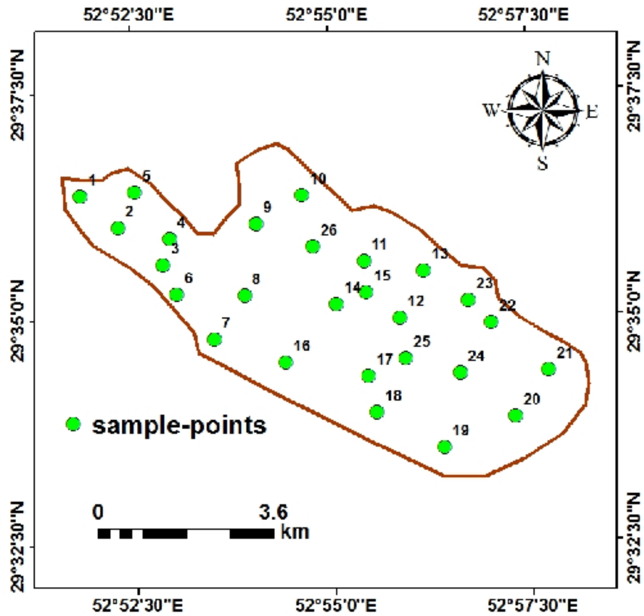

Fig. 8. Sample points of the study area for fuzzy-AHP combination model.

Table 5: The characteristics of the sample points in the study area.

Sample number	**OC (%)**	**P (mg/kg)**	**K (mg/kg)**	**Fe (mg/kg)**	**Zn (mg/kg)**	**MN (mg/kg)**	**Cu (mg/kg)**	**Class of Fuzzy-AHP**
1	1.09	11.8	229.22	5.4	0.65	22.58	1	low
2	0.95	14.67	243.14	2.5	0.66	10.31	0.98	very low
3	0.59	11.15	261.5	2.77	0.31	9.1	0.71	very low
4	1.03	13.39	268.2	4.73	0.52	15.27	1.07	low
5	1	13.24	272.39	5.84	0.47	17.91	1.15	low
6	1.03	13.93	275.4	3.63	0.5	11.57	1.03	low
7	0.85	5.54	277.82	2.81	0.22	10.26	0.62	very low
8	1.04	14.25	280.31	4.71	0.55	12.46	1.11	low
9	1.17	7.88	281.99	3.07	0.31	10.54	0.7	low
10	1.05	15.98	282.44	4.51	0.69	11.72	1.08	low
11	0.67	10.96	284.9	3.36	0.35	12.85	0.77	very low
12	1.01	16.35	285.74	3.43	0.66	12.91	0.96	low
13	0.99	8.57	297.69	3.47	0.36	12.75	0.75	low
14	0.73	11.84	297.75	3.59	0.51	11.62	0.84	very low
15	1.06	16.27	306.15	5.07	0.59	10.48	1.15	low
16	1.14	15.68	310.67	5.35	0.78	13.12	1.18	medium
17	1.09	17.15	311.55	5.95	0.7	10.69	1.2	medium
18	1.1	17.05	315.05	5.96	0.69	9.91	1.21	medium
19	0.97	16.44	340.25	9.57	0.5	6.86	1.4	low
20	1.12	17.85	344.19	7.37	0.65	9.42	1.32	medium
21	1.12	17.38	363.7	5.8	0.67	12.63	1.19	medium
22	1.05	15	366.71	4.46	1.01	11.14	0.91	low
23	1.39	23	375.73	4.12	0.75	10.58	1.07	high
24	1.11	16.69	382.08	6.19	0.73	16.05	1.23	medium
25	1.03	15.08	390.95	5.68	0.71	19.34	1.18	low
26	0.9	13.76	399.34	5.52	1.08	16.88	1.21	low

According to Table 5, the low soil fertility class such as number of 1, 4, 5 and so on, had the low P, K, Fe, Zn and Cu while the high value of OC, P, K, Fe, Zn, Mn, and Cu was observed in high class of soil fertility in sample 23 which this method showed high accuracy of fuzzy-AHP combination model for prediction of soil fertility in corn field. For example, OC, P, K, Fe, Zn, Mn, and Cu values for sample 1 (low fertility) were 1.09, 11.8, 229.22, 5.4, 0.65, 22.58 and 1 respectively. According to critical level of nutrients (see table 1), in sample 1, the values of all of the parameters except of OC and Mn, were lower than critical level. In contrast, in sample 23 (high fertility), the values of all of the parameters except of Zn (0.75mg/kg) and Fe(4.12 mg/kg) were more than criteria level Overall, for very low class, such as sample 11, values of soil parameters were lower than low class such as sample 12 (Table 5).

DISCUSSION

Critical level of nutrients defined as the narrow range of concentration at which growth rate or yield begins to decline in comparison to plants at a higher nutrient level (Malakoti 2003). In our study, all of the soil fertility maps in different methods were interpreted according to the critical level of soil nutrients for corn production (Table 2). According to IDW results, OC of soil was between 0.37 to 1.51% and only northwest and south of study area had suitable OC more than critical level (Figure 3a). Also, Fuzzy model showed that most of the study area had low OC and need fertilization (Fig. 4a). Sobhani and Sadat (2010) reported that the OC more than critical level had main effect on availability of some nutrients such as P, K and Mn for corn due to increase the water capacity of soil especially in dry areas.

All of the models showed that the P content for most of the study area was lower than the critical level (Figures 3b and 34). Tchuenteu (2007) reported critical levels of available P were 12 mg/kg for Olsen, 11 mg/kg for Brayl, 12 mg/kg for Bray2, 5-14 mg/kg for Mehlich1, and 29 mg/kg for Truog methods in Cameron. Ghiabi *et al*., (2015) showed that critical level for P and K were 16 and 260 mg/kg when the OC% was more than 1%. Also, weak in K, and Zn and Mn decreased corn grain yield 22-26%. Sianaki *et al*. (2010) declared that OC, P, K, Fe, and Cu had main effect on corn grain yield improvement compared to the other parameters. Overall, our results showed that, the K value of soil had appropriate amount (139.62 to 538.54 mg/kg) in soils of the study area (Figures 4 and 5). Mahalati (2013) found that more than 50% of soils in western and southern Iran were rich in available potassium ions, and that farmers often did not apply potassium fertilizer in these areas.

Generally, results of IDW showed that the Fe value was suitable for corn production except the parts of south and east (Figure 3d). Fuzzy map also, showed that most of the study areas except the parts of east and center had unsuitable value for Fe and Zn so that had the value close to zero (Fig. 4d and 4e). In contrast, except the northwest the other areas had K and Mn values close to 1 using fuzzy map (Fig. 4c and 4f). In a study in southern Iran, Khademi *et al*. (2011) showed that applying Fe more than critical level of Fe increased biological yield of corn, significantly.

For Zn, only the small parts of west were suitable (Figure 3e). Also, the Mn value of soil in the study area was low, so that the only parts of southeast and northwest with value more than (10 mg/kg) was suitable for corn production (Figure 3f). Malakoti (2003) declared the most of the soils in southern Iran had Zn and Mn value less then critical level where Zn amount in alkaline soils is very important factor for cereals grain yield improvement. Finally, the results of IDW method showed that surface soil in the study area had the Cu value between 0.46 to 1.70 (mg/kg) and according to Table1 , the Cu value of soil (Cu<1mg/kg) was enough for corn production and only the parts of northwest and west was not suitable for Cu (Fig. 3g).

Adeoye and Agboola (1995) declared that available P, K, and Zn had positive relationship with corn yield in Nigeria. Also, similar to our results, most of the soils in Nigeria were low in available P with a wide variability. The average P in soil was 12.8 mg/kg which falls within the critical range. In soil of Nigeria the available Zn, and Mn could be considered adequate while Fe and Cu were generally low in the soils. They concluded that critical ranges for optimize corn production for P, K, Zn and Mn were 10-16mg/kg160-180mg/kg, 5-10 mg/kg, and 25-30 mg/kg, respectively. Kayode and Agboola (1993) studied ten soil series in South western Nigeria and declared that Egbeda, Iwo, Gamberi, Balogun and Jago soil series had available Zn higher than 3 mg/kg which is the critical soil Zn recommended in corn field of Nigeria. Also, P critical level of these soils was 25 mg/kg. Six areas in the South western Nigeria had K contents higher than the critical level of K (160 mg/kg) and Optimum biological yield was obtained within the 25 to 100 mg/kg range. Also, 5 to 20 mg/kg Fe and 2.5 to 5 mg/kg Cu, 5 to 10 mg/kg appeared to be sufficient for maximum corn biological yield depended on soil series. Finally, in our study area, AHP methods showed that the most important factor in soil fertility was OC and the least important factor was Mn (Table 3) and these results are in agreement with results of Sianaki *et al*. (2010) and Ghiabi *et al*. (2015).

CONCLUSIONS

The aim of this study was to determination of soil fertility in the east of Shiraz, southern Iran. Seven major soil properties were selected to soil fertility evaluation including organic content (OC), phosphorus (P), potassium (K), iron (Fe), zinc (Zn), manganese (Mn) and copper (Cu) of the soil were evaluated.

Then, raster map was prepared in ArcGIS for each of the parameters using IDW method. Also, the fuzzy and AHP method used for predictive soil fertility map. The results of the fuzzy and AHP method in this study show that only 0.96% of the lands had highly fertility, 29.92% medium fertility, 62.75% low fertility and 6.34% had very low fertility. Finally it was concluded that for suitable corn production, the fuzzy and AHP method has a higher accuracy for predictive soil fertility and the most important factor in soil fertility was OC and the least important factor was Mn in the study area.

REFERENCES

Adeoye, G. O., & Agboola, A. A., (1995). Critical level for soil pH, available P, K, Zn and Mn and maize ear-leaf content of P, Cu and Mn in sedimentary soils of south-western Nigeria. *Fertilizer Research*, **16**, 5-71.

Badenko, V., & Kurtener D., (2004). Fuzzy modeling in GIS environment to support sustainable land use planning. The AGIL Econference on geographic information science. 29 April-1may. Heralion, Greece, parallel session a.1-"geographic knowledge discovery.

Burrough, P. A., Goodchild, M. F., McDonnell R.A., Switzer, P., & Worboys M. (1998). Principles of Geographic Information Systems. Oxford University Press, Oxford, Uk.

Burrough, P. A., (1989). Fuzzy Mathematical Methods for Soil Survey and Land Suitability, *Journal of Soil Science*, **40**, 477-492.

Ghiabi, H., Rezaii, M., & Talebzadeh, S., (2015). Considering the critical level of soil nutrient in corn field. *Water and soil*. **18**, 91-98. (In Persian)

Kayode, G., & Agboola, A.A., (1993). Investigation on the use of macro and micro nutrients to improve maize yield in south western Nigeria. *Liming research*, **14**, 211-221.

Khademi, S. B., Rezvan, D., Asghari, G., & Nekodar, F., (2011). Effect of some nutrients on yield and yield components of corn in Sothern Iran. *Iranian Journal of soil Science*, **11**, 113-121. (In Persian)

Kurtener D., Green T. R., Krueger-Shvetsova E., &Erskine RH., (2005). Exploring relationships between geomorphic factors and wheat yield using fuzzy. *Inference System, Hydrology*, **11**, 121-130

Lagacherie, P., (2005). An algorithm for fuzzy pattern matching to allocate soil individuals to pre-existing soil classes. *Geoderma*, **128**, 274-288.

Lotfi Zadeh, L H., (1965). Fuzzy sets. *Information and Control*, **8**, 338-353.

Mahalati, K. S., (2013). Critical Level of Nutrients in Crop Production. Amir Kabir Pub. Tehran, Iran. 311 pp.

Malakoti, M. J., (2003). Recommendations and applications of chemical fertilizers in fields of Iran. Tarbiat Modarres University Press.318 pp.

Mc Bratney, A.B., Mendonca Santos, M.L., & Minasny, B., (2003). On digital soil mapping. Geoderma, 117, 3-52.

McBratney, A.B., Odeh, I.O.A., Bishop, T.F.A., Dunbar, M.S., & Shatar, T.M., (2000). An overview of pedometric techniques for use in soil survey. *Geoderma*, **97**, 293-327.

Mokarram, M., Rangzan, K., Moezzi, A., & Baninemeh, J. (2010). Land suitability evaluation for wheat cultivation by fuzzy theory approach as compared with parametric method. Proceedings of the international archives of the photogrametry, remote sensing and spatial information sciences, Isfahan University, Iran.

Organization of Agriculture Jahad Fars. (2012). (http://fajo.ir/index.php/).

Qi, F., Zhu, A. X., Harrower, M., Burt, J.E., (2006) Fuzzy soil mapping based on prototype category theory. *Geoderma*, **136,** 774-787.

Sanchez Moreno, J.F., (2007). Applicability of knowledge-based and Fuzzy theory-oriented approache to land suitability for upland rice and rubber, as compared to the farmers' perception. International Institute fo Geo-Information Science and Earth Observation, Enschede, the Netherlands. 133 pp.

Shobha, G., Gubbi, J., Raghavan, K.S., Kaushik, K., &Palaniswami. M., (2013). A novel fuzzy rule based system for assessment of ground water portability: A case study in south India. *IOSR Journal of Computer Engineering*, **15**, 35-41.

Sianaki, L., Sadat Hasani, S., Zamani, M., & Afshar, B. (2010). Evaluation the most important nutrient in corn grain yield improvement in alkaline soils. *Agricultural soil management*, **23**, 33-45. (In Persian)

Sobhani L., & Sadat, B., (2010). Effects of organic content in corn grain yield in dry land areas. *Water and Soil*, **13**, 51-59. (In Persian)

Soufi, M., (2004). Morpho-climatic classification of gullies in fars province, southwest of Iran. International Soil Conservation Organisation Conference - Brisbane.

Sys, C., Van Ranst, E., Debaveye, J.. (1993). Land Suitability, part ?: crop requirements, International Training Center for post graduate soil scientists. Chent university, Ghent, 199 pp.

Tchuenteu, F., (2007). Critical levels of available P in acid soils of Cameroon. *Plant Nutrition for Sustainable Food Production*, **23**, 371-373.

Yazdani, S., Shahbazi, H., Haghsheno, M., & Sadat Barikani, S.H., (2008). Corn import demand model in Iran; Political Factors Application. *American-Eurasian journal of Agriculture and Environtal Science,* **4**, 633-639.

Zhang, B., Zhang, Y., Chen, D., White, R.E., & Li, Y., (2004). A quantitative evaluation system of soil productivity for intensive agriculture in China. *Geoderma*, **123**, 319-331.

Zhu, A. X., Yang, L., Li, B., Qin, C., Pei, T., Liu, B., (2010) Construction of membership functions for predictive soil mapping under fuzzy logic. *Geoderma*, **155**, 164-174.

Zhu, A.X., Band, L.E., Dutton, B., & Nimlos, T., (1996). Automated soil inference under fuzzy logic. *Ecological Modelling*, **90**, 123-145.

Zhu, A.X., Hudson, B., Burt, J.E., Lubich, K., & Simonson, D., (2001). Soil mapping using GIS, expert knowledge, and fuzzy logic. *Soil Science Society of America Journal*, **65**, 1463-1472.