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Assessment the soil fertility classes for common bean (*Phaseolus Vulgaris* L.) production using fuzzy-analytic hierarchy process (AHP) method

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Abstract

This study was carried out to evaluate the capability of a combined fuzzy-analytic hierarchy process (AHP) method for soil fertility evaluation of common bean in Shiraz, Iran. A set of membership functions was constructed to represent the soil fertility classes, which were derived from 50 field samples collected through a purposive sampling approach. Seven soil parameters including phosphorus (P), potassium (K), iron (Fe), zinc (Zn), manganese (Mn) copper (Cu) and organic content (OC), of the soil were chosen for soil fertility analysis using inverse distance weighting (IDW) method and then fuzzy and AHP method were employed. The IDW showed that the south of the study area had the more P amount compared to the other area (Fig. a). In contrast, the Fe value was between 1.40 to 14.98 (mg/kg) where only some parts of northwest and southwest had the medium Fe value (about 8 mg/kg). The OC value of the study area was between 0.18 to 1.64% which all of the study area with OC more than 1% was suitable for bean production except the some parts of north and south. Fuzzy map showed that except the parts of northwest, all of the area was suitable for K that had the value close to 1. AHP model showed that the most important factor in soil fertility were P and OC of the soil with weights of 0.39 and 0.37, respectively. Fuzzy-AHP model showed that 52.38% of the study area had medium fertility for bean production and this method was a useful tool for prediction of soil fertility status in each case study.

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Keywords: fertility map, fuzzy-AHP model, inverse distance weighting, organic content.
Abbreviations: AHP_analytic hierarchy process; Cu_copper, Fe_iron; IDW_inverse distance weighting; K_potassium; Mn_manganese; OC_organic content: P_ phosphorus; Zn_zinc.

Introduction

Common bean (*Phaseolus Vulgaris* L.) is one of the most important legume and represents a suitable protein source (20-24%) due to easy adaptability to many climate conditions in Iran (Akbari and Seifi, 2013). The area of common bean in Iran was 113865 hectares with total grain production of 221318 ton in 2014 (Mahalati, 2015). Common bean yield, quality, and quantity are highly dependent on fertilization management. The common bean productivity is considered low in Iran as compared to the potential of the varieties recommended by researchers. The explanation for this low productivity could be several factors, such as, inadequate farming management, poor soil and lack of using of improved breed varieties, and lake of information about soil nutrients status (Da Silva et al., 2015, Naderan et al., 2010; Malakoti, 2003).

Management of soils nutrients is needed to feed the billions people on the world. Soil data and the use of nutrient application rates based on scientific principles and research are critical components of nutrient management (Mahler, 2011). So, study of soil fertility and determine situation of soil characteristics for cultivation of different crops in very importance. Several methods were sued in the field for determination of soil fertility. For example, Ghosh and Koley (2014) used machine learning for soil fertility. Li et al. (2012) used data mining for studying soil fertility.

One of the famous methods for determination of soil characteristics is fuzzy method. Fuzzy set theory has been widely used in soil science for soil fertility classification and mapping and land evaluation (McBratney et al., 2003; Zhang et al., 2004; Lagacherie, 2005; Sanchez Moreno, 2007). In fuzzy logic approaches, soil spatial parameters are expressed as spatial parameters of membership in soil classes (Mc Bratney et al., 2003), 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, alkalinity, soil texture, fertility slope, soil depth, $CaCO_3$, water 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). In order to predict soil map, Zhu et al. (2001) used membership functions under fuzzy logic. Davatgar et al., (2012) used fuzzy method for determination of nutrient management. Also, Mawale, and Chavan (2014) used fuzzy logic for productivity and fertility of soil. The results of the studies show that fuzzy method is a suitable method for determination of soil fertility and other soil characteristics. Soil fertility degradation has become a problem for agricultural management in Fars Province, Iran (Mahalati, 2015). So, the main aim of this research is the use of fuzzy-AHP model to evaluate the soil fertility maps for bean production in Shiraz, southern Iran.

Results

Preparing raster map using inverse distance weighting (IDW)

IDW interpolation explicitly implements the assumption that things that are close to one another are more alike than those that are farther apart. In the study area for preparing raster map for each parameter IDW method was used. For this purpose, 50 surface soil samples were taken. Then, raster maps for seven parameters consisted of P, K, Fe, Zn, Mn, Cu, and OC of the soil were prepared using IDW model for bean production in ArcGIS software (Fig. 1). Results showed that the south of the study area had the more P amount compared to the other area (Fig. 1a). According to Fig. 1, yellow, red, and blue colors showed minimum, medium, and maximum value for each parameter, respectively. The range of K value was between 147.17 (yellow color) to 664.12 (blue color) (mg/kg) and large parts of the study area was suitable from K value (Fig. 1b). In contrast, the Fe value was between 1.40 (yellow color) to 14.98 (blue color) (mg/kg) where only some parts of northwest and southwest had the medium Fe value (about 8 mg/kg; Fig 1c). The Zn value in the soil area was low especially in the north and west of study area (Fig. 1d). The Mn value was between 3.20 (yellow color) to 52.17 (blue color) (mg/kg) where except the some parts of the west and southeast, the other parts of the area had the minimum Mn value (Fig. 1e). Based on Fig 1f, most of surface soil in the study area had Cu between 0.21 (yellow color) to 1.99 (blue color) (mg/kg) where the lowest Cu value was observed in north and northwest of the study area. The OC value of the study area was between 0.18 (yellow color) to (blue color) 1.64% which all of the study area with OC% more than 1% was suitable for bean production except the some parts of north and south (Fig. 1g).

Fuzzy model

Classification the soil fertility of the study area is given between 0 and 1, which values close to one showed high fertility and values close to zero showed not fertility in fuzzy model. Based on Fig. 2, it is possible to find low and high fertility areas for bean with membership values between 0 (red color) and 1 (blue color). Results showed that, southern half of the region was suitable for P (Fig. 2a). Also, fuzzy map showed that except the parts of northwest, all of the area was suitable for K that had the value close to 1 (Fig. 2b). The some parts of northeast and southwest was not suitable for Fe that had the value close to zero (Fig. 2c). The entire region except the some parts of southeast had not high Zn value for bean production (Fig. 2d). Overall, almost all of the study area except the parts of northwest and southwest was suitable for Mn and Cu values (Figs. 2e and 2f). For bean production, the most of the study area except some parts of north and south of the study area had not good status of OC (Fig. 2g).

Analytic hierarchy process (AHP)

The AHP method was applied on the fuzzy parameter maps and the pairwise comparison matrix which was used for preparation of the weights for each parameter was given in Table 1. Results showed that the most important factor in soil fertility were P and OC of the soil with weights of 0.39 and 0.37, respectively. In contrast, for bean production in southern Iran, the least important soil parameters were Mn and Cu with weights of 0.04 and 0.05, respectively (Table 1).

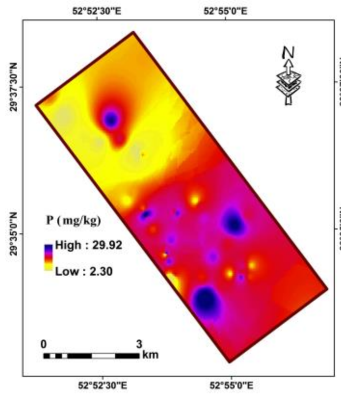
Combination of Fuzzy and AHP methods

Based on the fuzzy maps for each parameters (Fig. 2) and weight of each parameter that was calculated using AHP method (Table 1), the final fuzzy map was determined (Fig. 3). The value of final fuzzy map was between 0 (pink color) to 1 (dark brown color) where showed the some parts of the study area had high fertility [for value more than 0.75(dark blue color)], medium fertility [for value between 0.5 to 0.75 (light blue color)], low fertility [for value between 0.25 to 0.5 (yellow color)] and very low fertility [(for value between 0 to 0.25 (red color)] for bean production and only some parts of south had good soil fertility with value close to 1 (Fig. 4). Then, the fuzzy map reclassified in four classes consisted of very low (0.12 km^2), low (3.38 km^2), medium (20.18 km^2) and high (14.84 km^2) (Fig. 4 and Table 2). Likewise, the area (%) for each of the classes in the study area showed in Fig. 5. The results of the Fuzzy-AHP combination method in this study showed that 38.52% of the lands had high fertility (green color), 52.38% medium fertility (blue color), 8.78% low fertility (yellow color) and 0.31% very low fertility (red color). After reclassifying the fuzzy map prepared in the four classes that consist of very low, low, medium and high (Fig. 5).

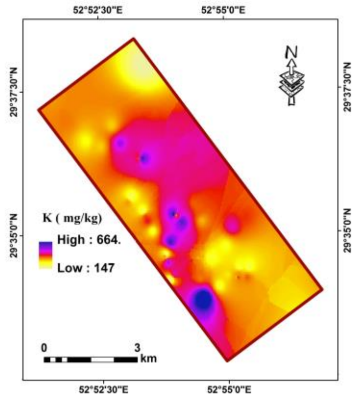
According to Fig. 6, for determination of precision and accuracy of fuzzy and AHP method, 38 sample points were used randomly where number of points from 1 to 38 were shown in Fig. 6. For 38 sample points, 7 parameters including, phosphorus (P), potassium (K), iron (Fe), zinc (Zn), manganese (Mn), copper (Cu), and organic content (OC) of the soil were evaluated. Also, the class of soil fertility was predicted by fuzzy-AHP model for each point. Then for determination of precision and accuracy of fuzzy and AHP method, the class of soil fertility were compared with 7 parameters values which showed in Table 3.The classes of low soil fertility (such as number of 1 and 3) had the low P, K, Fe, Zn, Mn, Cu and OC (Table 3). In contrast, the high value of P, K, Fe, Zn, Mn, Cu and OC was in high class of soil fertility that showed high accuracy of fuzzy-AHP combination model for prediction of soil fertility. For example in sample 3 (low fertility), the value of P, K, Fe, Zn, Mn, Cu and OC were 10.33 mg/kg, 265.96 mg/kg, 5.46 mg/kg, 0.50 mg/kg, 13.84 mg/kg, 0.74 mg/kg, and 0.81%, respectively. While for sample of 38 (high fertility), the value of P, K, Fe, Zn, Mn, Cu and OC were 22.83 mg/kg, 513.13 mg/kg, 6.00 mg/kg, 1.47 mg/kg, 32.34 mg/kg, 1.40 mg/kg, and 1.36%, respectively. According to Table 5 the critical level of the value of P, K, Fe, Zn, Mn, Cu and OC were 10 mg/kg, 200 mg/kg, 4.25 mg/kg, 0.95 mg/kg, 2.9 mg/kg, 0.38 mg/kg, and 1%, respectively. The model of fuzzy-AHP showed that the samples of 3 and 38 predicted in classes of low and high fertility, respectively. On the other hand, for very low class, such as sample 2, values of soil properties

Table 1. Pairwise comparison matrix for soil fertility for common bean.

Parameters	P	K	Fe	Zn	Mn	Cu	OC	Weight
P	1	2	4	3	6	5	1/2	0.39
K	1/2	1	3	2	5	4	1/3	0.16
Fe	1/4	1/3	1	1/2	3	2	1/5	0.06
Zn	1/3	1/2	2	1	4	3	1/4	0.11
Mn	1/6	1/5	1/3	1/4	1	1/2	1/7	0.04
Cu	1/5	1/4	1/2	1/3	2	1	1/6	0.05
OC	2	3	5	4	7	6	1	0.37



(a)



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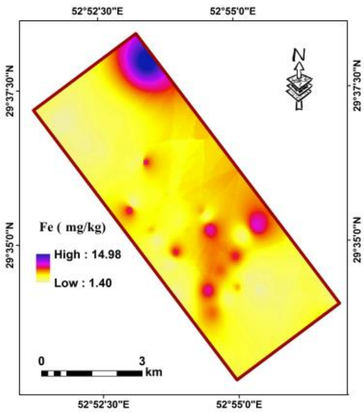

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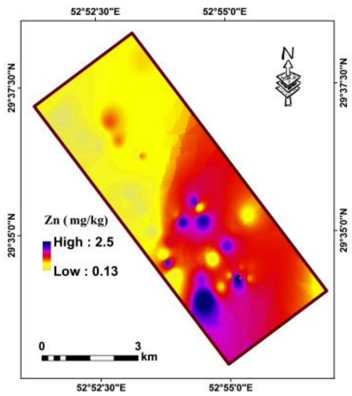

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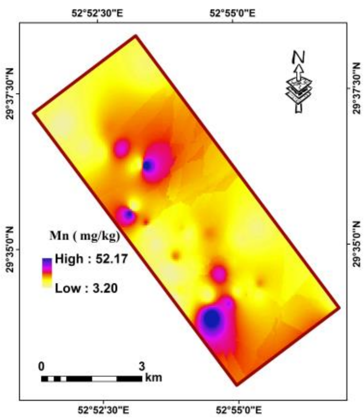

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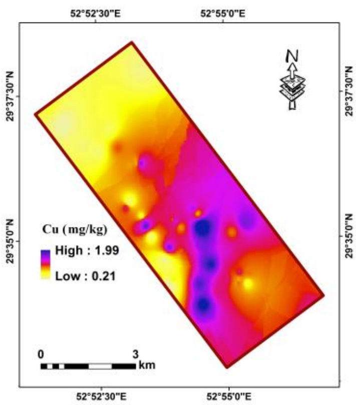
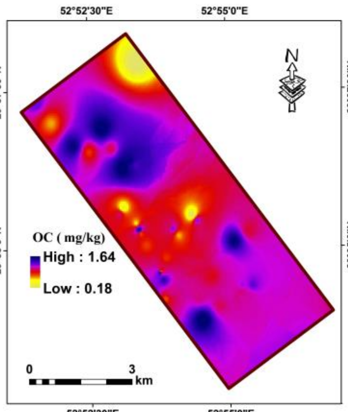


(f)

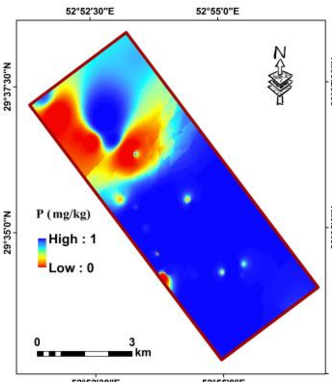


(g)

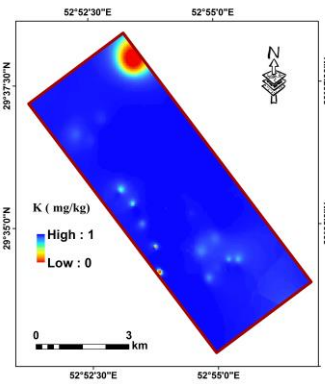
Fig 1. Preparing the raster maps for each of the soil parameters included P (a), K (b), Fe (c), Zn (d), Mn (e), Cu (f), and OC (g) using inverse distance weighting (IDW) model in the study area for bean, Shiraz, Southern Iran. Yellow, red, and blue colors showed minimum, medium, and maximum value for each parameter, respectively.

Table 2. The area (%) for each of the classes for soil fertility.

Class	Area (km^2)
Very low	0.12
Low	3.38
Medium	20.18
High	14.84



(a)



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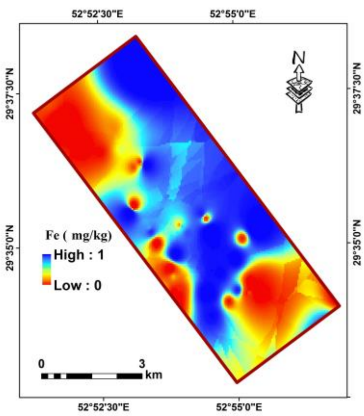

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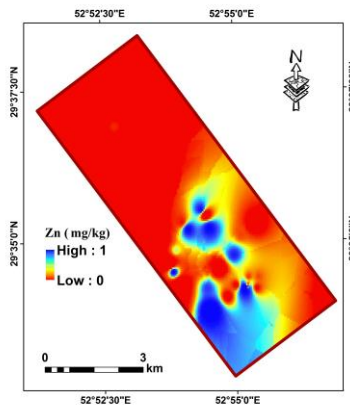

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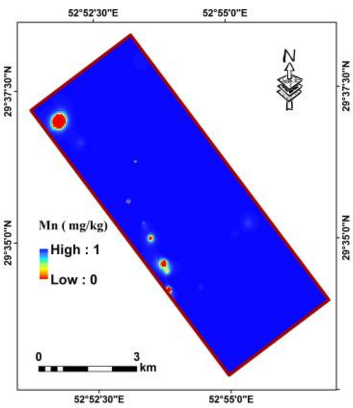

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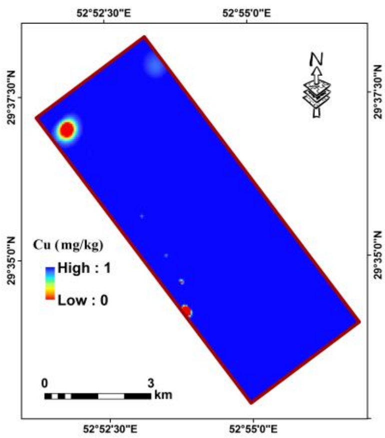
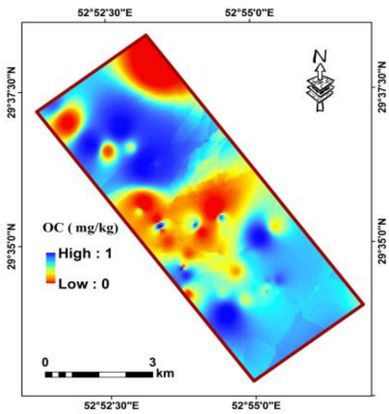


(f)



(g)

Fig 2. Preparing the fuzzy maps for each parameter for determining the soil fertility for bean in the study area, Shiraz, Southern Iran. P (a), K (b), Fe (c), Zn (d), Mn (e), Cu(f), and OC (g). Low and high fertility areas for bean with membership values was between 0 (red color) and 1 (blue color).

were lower than low class such as sample 1. Overall, according to Table 3, the model of Fuzzy-AHP was a suitable tool for prediction of soil fertility status in each point of the study area.

Discussion

All of the soil fertility maps in different methods were interpreted according to the critical level of nutrients for common bean (Table 5). Critical level of nutrients defined as the narrow range of concentration at which grain yield begins to decline in comparison to plants at a higher nutrient level (Malakoti, 2003). IDW and Fuzzy models showed that southern half of the region was suitable for P (Figs. 1a and 2a**)**. Westermann et al. (2011) declared that P and OC amount in the soil had main effect on common bean grain yield compared to the other nutrients. Rezvani et al. (2007), declared that the excess of P can cause deficiency of heavy metals such as Fe, Cu, Zn and Mn, thus the higher level of this nutrient increase the necessity of the other. Lynch et al. (1991) reported that the effect of low P is primarily reduced leaf area development of common bean rather than reduced photosynthetic capacity of the leaves that develop. Overall, soil maps showed that K is seldom low enough to limit bean production in southern Iran (Figs. 1b and 2b). Mahalati (2015) found that more than 50% of soils in western and southern Iran were rich in available K, and that farmers often did not apply K fertilizer in these areas.

For Fe, only some parts of northwest and southwest had the medium Fe value (about 8 mg/kg) and the other parts need Fe fertilizer (Fig. 1c). Ahmadi et al. (2014) declared that common bean varieties developed on high organic matter soils might be more susceptible to Fe, B, Cu, and Mn. Rezvani et al. (2007) showed that using Fe fertilizers more than critical level of Fe increased common bean grain yield 22-35%.

Fuzzy model showed that all of the study area except the some parts of southeast had not high Zn (Fig. 2d). Akbari and Seifi (2013) declared that Zn deficiencies typically occurred in similar landscape positions as where P shortages occurred and using Zn more than critical level (0.95 mg/kg) increased biological yield and grain yield of common bean 18 and 21%, respectively. All of the models showed that for bean production in southern Iran, the least important soil parameters were Mn and Cu. Da Silva et al. (2015) in a study on common bean in Brazil repoted that the most limiting nutrients were N, OC and P. Also, Cu, Mg and Mn had not any results in terms of limitation in any situation. IDW and Fuzzy models showed that all of the study area with OC% more than 1% was suitable for bean production except the north and south of the study area (Fig. 1g and 2g). Westermann et al. (2011) reported that the OC% higher than critical level had main effect on availability of some nutrients

Table 3. The characteristic of sample points of the study area.

Number	P (mg/kg)	K (mg/kg)	Fe (mg/kg)	Zn (mg/kg)	Mn (mg/kg)	Cu (mg/kg)	OC (%)	classes of fuzzy
1	10.89	186.80	12.56	0.54	9.35	0.60	0.40	Low fertility
2	4.27	141.73	1.49	0.14	3.56	0.46	0.22	Very low fertility
3	10.33	265.96	5.46	0.50	13.84	0.74	0.81	low fertility
4	11.11	261.52	8.19	0.51	12.58	0.70	0.83	medium fertility
5	14.45	360.88	5.58	0.90	15.07	1.19	0.83	medium fertility
6	16.54	417.91	5.35	1.11	11.29	1.07	0.81	medium fertility
7	13.40	365.88	4.76	0.64	14.87	1.07	0.94	medium fertility
8	17.11	297.79	4.94	0.34	12.06	1.07	0.92	medium fertility
9	10.20	300.17	4.85	0.33	18.09	0.90	0.94	medium fertility
10	16.10	355.50	6.13	0.89	14.69	1.25	0.91	medium fertility
11	15.90	317.67	3.67	0.58	7.35	0.78	1.00	medium fertility
12	10.10	343.26	5.61	0.55	16.88	0.90	1.05	medium fertility
13	11.98	379.96	5.39	0.76	16.68	1.15	1.05	medium fertility
14	17.44	319.15	7.14	1.11	15.06	1.51	0.99	high fertility
15	10.78	296.94	4.98	0.45	11.81	0.69	1.04	medium fertility
16	12.84	346.71	2.89	0.37	10.57	0.70	0.99	medium fertility
17	9.01	306.12	2.92	0.34	8.67	0.64	1.03	medium fertility
18	16.53	288.94	6.17	0.81	18.43	1.33	1.01	medium fertility
19	8.18	305.26	3.37	0.33	13.56	0.73	1.09	medium fertility
20	16.41	334.68	9.13	0.51	7.38	1.35	0.97	medium fertility
21	15.47	323.13	3.05	0.30	14.99	0.89	1.16	high fertility
22	15.34	251.99	7.44	1.20	13.23	1.18	1.07	high fertility
23	13.86	309.03	2.06	0.75	11.33	0.77	1.06	medium fertility
24	9.54	301.53	3.03	0.35	10.53	0.65	1.12	medium fertility
25	13.79	279.60	3.89	0.66	12.84	1.03	1.07	medium fertility
26	9.55	346.60	5.06	0.48	18.75	0.90	1.20	medium fertility
27	16.53	309.73	3.99	1.04	17.76	1.08	1.09	high fertility
28	13.77	268.17	3.96	0.82	16.25	1.00	1.09	high fertility
29	16.25	330.88	4.26	1.07	19.37	1.13	1.09	high fertility
30	15.54	286.94	4.10	0.83	11.85	1.03	1.09	high fertility
31	16.18	284.41	4.43	0.86	12.61	1.06	1.11	high fertility
32	15.71	299.27	3.85	1.00	17.85	1.05	1.11	high fertility
33	7.46	275.25	2.54	0.25	8.51	0.63	1.27	medium fertility
34	17.75	380.53	4.71	1.14	22.48	1.20	1.14	high fertility
35	8.02	400.52	5.45	0.50	24.67	1.06	1.30	medium fertility
36	14.52	325.27	4.13	0.56	17.61	0.79	1.29	high fertility
37	7.19	366.22	4.14	0.46	15.72	0.95	1.39	medium fertility
38	22.83	513.13	6.00	1.47	32.34	1.40	1.36	high fertility

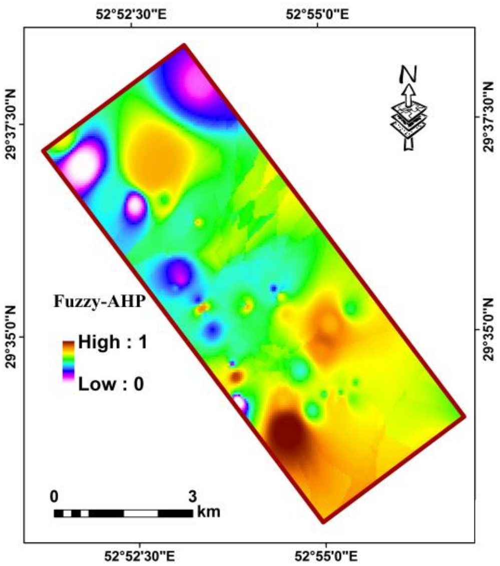


Fig 3. Preparing the fuzzy-AHP combination map for soil fertility classes in bean. The value of final fuzzy map was between 0 (pink color) for low fertility to 1 (dark brown color) for high fertility.

Table 4. Minimum, Maximum and average of effective parameters for soil fertility of the study area.

Parameters	Minimum	Maximum	STDEV	Average
P(mg/kg)	2	30	6.62	13.57
K(mg/kg)	137	666	102.82	312.09
Fe(mg/kg)	1	19	3.34	4.66
Zn(mg/kg)	0.1	3	0.5	0.63
Mn(mg/kg)	2.7	52.5	11.31	14.8
Cu(mg/kg)	0.2	2	0.37	0.95
OC (%)	0.18	1.65	0.35	1

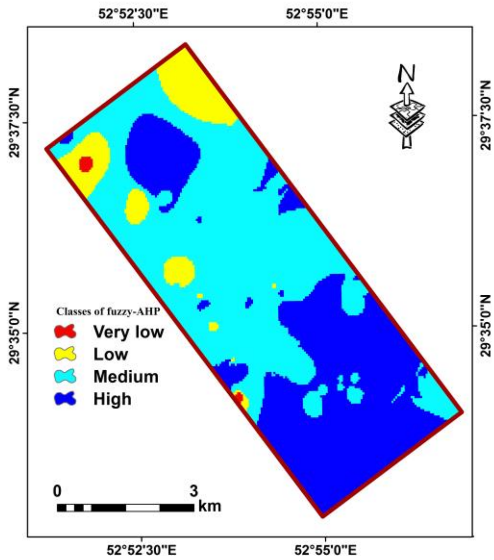


Fig 4. Map of the fuzzy classification. Some parts of the study area had high fertility [for value more than 0.75(dark blue color)], medium fertility [for value between 0.5 to 0.75 (light blue color)], low fertility [for value between 0.25 to 0.5 (yellow color)] and very low fertility [(for value between 0 to 0.25 (red color)].

Table 5. Soil nutrients critical level for bean production extracted from some references.

Parameters	Critical level	References
P	10 (mg/kg)	Rezvani et al. (2007)
K	200 (mg/kg)	Mahalati et al. (2015)
Fe	4.25 (mg/kg)	Ahmadi et al. (2014)
Zn	0.95 (mg/kg)	Akbari and Seifi, (2013)
Mn	2.9 (mg/kg)	Naderan et al. (2010)
Cu	0.38 (mg/kg)	Rezvani et al. (2007)
OC	1 (%)	Malakoti, (2003)

P: phosphorus; K: potassium, Fe: iron; Zn: zinc; Mn: manganese; Cu; copper, OC: organic content

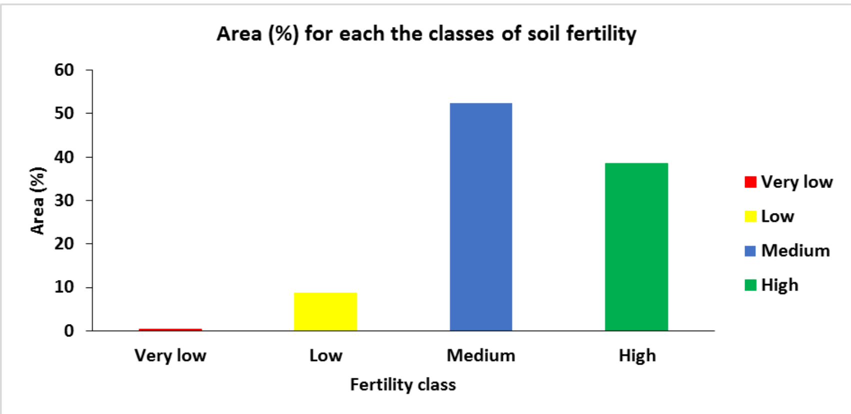


Fig 5. Percentage of the stydy area for each of the soil fertility classes. 38.52% of the lands had high fertility (green color), 52.38% medium fertility (blue color), 8.78% low fertility (yellow color) and 0.31% very low fertility (red color).

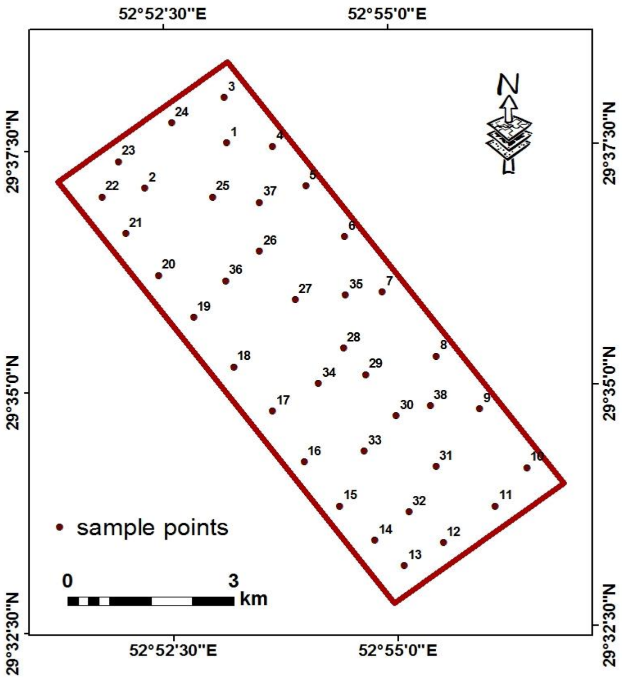


Fig 6. Sample points of the study area for determination of precision and accuracy of fuzzy and AHP method.

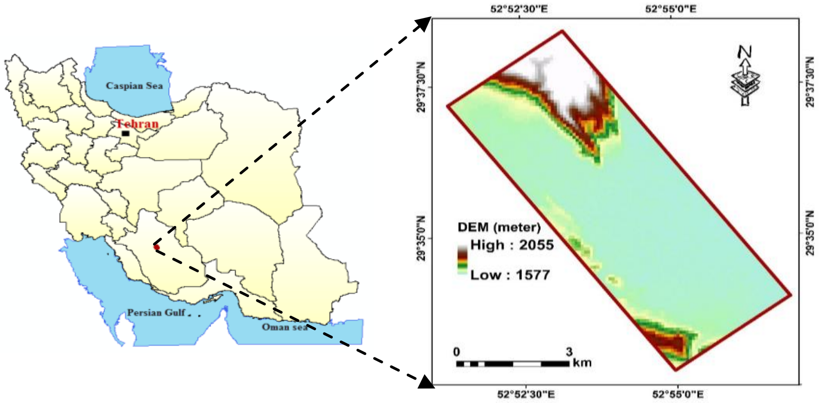


Fig 7. Position of the study area in Shiraz, Fars province, southern Iran.

such as P, K and Fe for bean due to increase the water capacity of soil. Masnadi and Samadi (2000) reported that in southern Iran a shortage of organic matter and P is generally associated with increasing land leveling or erosion**.** Interestingly, AHP model showed that, the most important nutrients were P and OC, and the least important were Cu and Mn (Table 1). This finding was in agreement with results of Mahalati.et al., (2015) Turuko et al., (2014) and Naderan et al. (2010) for common bean.

Material and Methods

Case study

The study area is located in the Fars province in the south of Iran, between latitudes 29° 33' 24" N-29° 38' 24" N and longitudes 52° 51' 00" E- 52° 58′ 12"E with an area 38.532 km^2 (Fig. 7); elevation 1577 m above mean sea level. The dataset is extracted from a land classification study done by the Fars Soil and Water Research Institute in the year 2012 and consists of phosphorus (P), potassium (K), iron (Fe), zinc (Zn), manganese (Mn), copper (Cu), and organic content (OC) of the soil (Table 4).

Inverse Distance Weighted (IDW)

To predict a value for any unmeasured location, IDW will use the measured values surrounding the prediction location. Assumes value of an attribute *z* at any unsampled point is 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):

$$\mu_A(X) = f(x) = \left\{\begin{matrix} 0 & x \le a \\ x - a/b - a & a < x < b \\ 1 & x \ge b \end{matrix}\right\} \quad (1)$$

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

Fuzzy set theory

The fuzzy set theory includes fuzzy mathematics, fuzzy measures, fuzzy integrals, etc. One of the aspects of the field of fuzzy mathematics is Fuzzy logic. In classical set theory, the membership of a set is defined as true or false, 1 or 0.
Membership of a fuzzy set, however, is expressed on a continuous scale from 1 to 0 that μ_A =0 means that the value of x does not belong to A and μ_A=1 means that it belongs completely to A. A fuzzy set A, defined in the total space X, is a function defined in X which assumes values in the range [0, 1]. A fuzzy set A is written as a set of pairs {X, A (x)} as A = {{x, A (x)}}, x in the set X where x is an element of the total space X, and A (x) is the value of the function A for this element. The value A (x) is the membership grade of the element x in a fuzzy set A (Lagacheri et al., 2005).

A fuzzy membership function is described by a membership function μ_A (X) of A. Each element x $_\sigma$ ∈ X a number as μ $_A$ (X $_\sigma$) in the closed unit interval [0, 1] associates for membership function. The number μ $_A$ (X $_\sigma$) shows the degree of membership of x σ in A. The attention used for membership function μ $_A$ (X) of a fuzzy set A is A: X→ [0, 1] (Lagacheri et al., 2005).
The following function was used for nitrogen (N), phosphorus (P), potassium (K), Mn, Fe, Cu and organic content of the soil (Sanchez Moreno, 2007; Sys, 1993).

$$X) = f(x) = \begin{cases} 0 & x \le a \\ x - a / b - a & a < x < b \\ 1 & x \ge b \end{cases} \qquad (2)$$

Where, x is the input data and a, b are the limit values. In order to define the fuzzy rules, the critical level of each soil parameter for bean production was extracted using some references in the study area (Table 5).

Analytic Hierarchy Process (AHP) method

AHP is based on pairwise comparison matrices which are matrices relating different components and assigning values according to their relative importance (Saaty, 1980). When there are a limited number of choices, the AHP facilitates the selection of weighting criteria and admits the decision making. These weighting criteria are given by a scale from 1 to 9, where 1 means that the two elements being compared have the same importance and 9 indicates that of the two elements one is extremely more important than the other.

Combination of Fuzzy and AHP methods

Finally, to make 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 which 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 3 and 4 show the convex combination (Burrough, 1989).

$$\mu_A = \sum_{j=1}^{k} W_j \times \mu_{A(x)} \qquad x \varepsilon X \qquad (3)$$

$$\sum_{j=1}^{k} W_j = 1 \qquad W_j > 0 \qquad (4)$$

Conclusion

It was concluded that for suitable bean production, the fuzzy and AHP method had a higher accuracy for predictive soil fertility. According to AHP model, the most important factors in soil fertility were P and OC the least important soil parameters were Mn and Cu for bean production in southern Iran. The class of soil fertility was predicted by fuzzy-AHP model for each point which showed that 38.52% of the lands had high fertility, 52.38% medium fertility, 8.78% low fertility and 0.31% very low fertility. Overall, more than half of the study area had suitable status for bean production.

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