Australian Journal of Crop Science

AJCS

AJCS 7(11):1699-1706 (2013) ISSN:1835-2707

Case Study

The use of fuzzy- AHP methods to assess fertility classes for wheat and its relationship with soil salinity: east of Shiraz, Iran : A case study

Ehsan Bijanzadeh* **and Marzieh Mokarram**

Department of Plant Production, Agriculture College and Natural Resources of Darab, Shiraz University, Iran

***Corresponding author: ebijanzadeh@gmail.com**

Abstract

Fuzzy membership function is an effective tool to reveal the relationship between soil and environment to predict soil fertility mapping. This research was conducted to evaluate the capability of a combined Fuzzy- AHP method for soil fertility evaluation of wheat in the east of Shiraz, Fars Province, Iran. A set of membership functions was conducted to reveal the soil fertility classes, which were derived from 64 field samples collected through a purposive sampling approach. Seven soil parameters [soil texture, potential of hydrogen (pH), cation exchange capacity (CEC), nitrogen (N), phosphorus (P), potassium (K) and organic content (OC) of the soil] were chosen for the soil fertility analysis and thematic maps were developed for each of these parameters with kriging method. Different fuzzy membership functions obtained from the literature were employed. Finally, in order to finalize soil fertility map and weight of the layers, AHP method was used. With the fuzzy approach, it is possible to find lowly fertility areas for wheat with valueso between 0.25 and 0.5. The results of the Fuzzy-AHP method in this study showed that 15% of the lands had highly fertility, 23% medium fertility, 45% low fertility and 16% very low fertility. In the study area, in regions with less fertility, CEC was a major factor. The comparison of wheat yield and CEC on 20 points of the study area showed that soil salinity had a high correlation (R^2=0.82) with wheat yield. Also, significant relationship was observed between soil salinity and fertility. Generally, in Fars Province, saline areas had low fertility compared to non saline areas.

Keywords: Fuzzy-AHP method, kriging method, salinity, soil fertility, wheat yield.
Abbreviations: CEC_cation exchange capacity, AHP_Analytic Hierarchy Process, N_nitrogen, P_phosphorus, K_potassium, OC_ organic content, pH_potential of hydrogen.

Introduction

Fuzzy set theory has been used in soil science for soil classification and fuzzy soil geostatistics, soil quality indices (Burrough, 1989; Zhu et al., 1996; McBratney and Odeh, 1997; McBratney et al., 2003; Zhang et al., 2004; Lagacherie, 2005). The development of fuzzy logic-based digital soil mapping techniques is due to its ability to represent the continuous nature of soil spatial variation (Zhu, 1997; Zhu et al., 2001; Yang et al., 2007). Fuzzy set theory has been widely used in soil science for soil fertility classification, 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 (McBratney et al., 2000), which is then used to produce conventional soil class maps and to forecast spatial parameters of specific soil properties (Zhu et al., 1996). Lagacherie (2005) proposed a procedure based on fuzzy pattern matching to translate soil class description in soil database into a set of membership functions. Qi et al. (2006) developed a prototype-based fuzzy soil mapping approach to represent soil-environment knowledge as fuzzy membership functions. Qi et al. (2008) developed a data mining method using the Expectation Maximization (EM) algorithm to define membership functions based on the information extracted from conventional soil class maps. Liu and Zhu (2009) developed a mapping with words approach based on computational theory of perceptions to define membership functions. 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) suggest 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; Mokarram et al., 2010). 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 (H2O) and gypsum should be assessed and measured (Sys et al. 1993). In 2006, soil mapping was developed with a fuzzy approach which were also constructed based on the knowledge obtained from soil experts (Qi et al, 2006). In order to predict soil map, Liu and Zhu (2009) and Zhu et al., (2010) used membership functions under fuzzy logic. Dobermann and Oberthür (1997) used fuzzy method for mapping of soil fertility. The method has been successful in mapping spatial variation of discrete soil classes. However, to be able to map spatial continuity of soils using the soacquired descriptive knowledge under fuzzy logic. This paper presents a method to construct fuzzy membership function from descriptive knowledge (Bui et al., 1999; Qi and Zhu, 2003) for predictive soil mapping. Soil

Table 1. Pairwise comparison matrix for soil fertility of wheat field.

Parameters	CEC	N	P	K	OC	PH	Texture	Weight
CEC	1	2	3	4	5	6	7	0.35
N	0.5	1	2	3	4	5	6	0.24
P	0.33	0.5	1	2	3	4	5	0.16
K	0.25	0.33	0.5	1	2	3	4	0.11
OC	0.2	0.25	0.33	0.5	1	2	3	0.07
PH	0.16	0.2	0.25	0.33	0.5	1	2	0.05
Texture	0.14	0.16	0.2	0.25	0.33	0.5	1	0.03

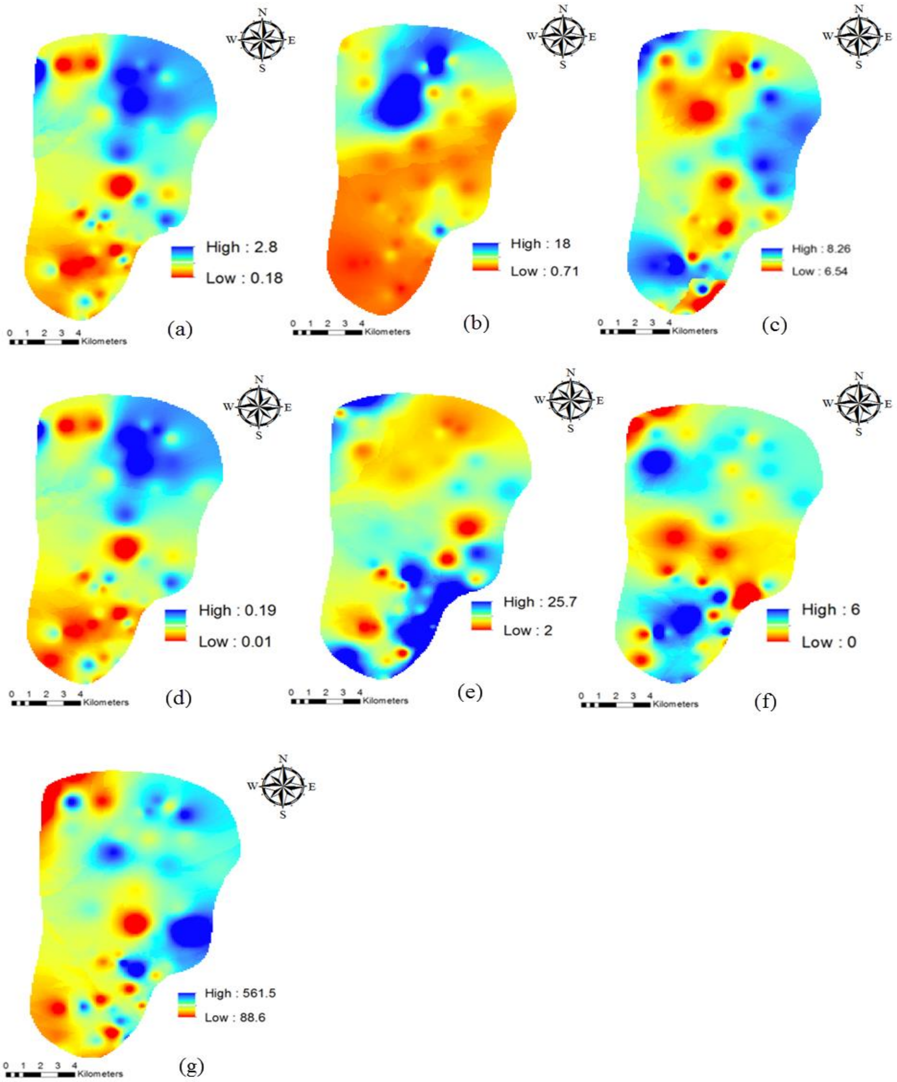

Fig 1. Kriging method was used in order to prepare Raster maps for each of the parameters. a: Organic Content (OC), b: Cation-Exchange Capacity (CEC), c: potential of hydrogen (pH), d: Nitrogen (N), e: Phosphorus (P), f: Soil texture, g: Potassium (K).

fertility degradation has become a problem for agricultural management in Fars Province, Iran. So the main purpose of the study is the use of fuzzy membership for predictive soil fertility map.

Results and Discussion

In order to make soil fertility map soil texture, soil pH, CEC (dS/m), nitrogen, phosphorus and potassium applied to the soil (ppm) and organic content of the soil (%) were used (Fig 1). Based on Fig 1, most of surface soil in the study area had medium texture (from silt to loam). Most of case study soil had CEC lower than 10 dS/m. Soil pH in the study area was medium acid (pH is between 5 to 6). Because of light texture, the soil was quite porous in the surface horizon, and had strong mineralization, consequently soil was poor in organic matter. Most of soils contained organic carbon lower than 1%. The soil in the study area was poor in nitrogen (N<0.19). Degraded soil in the study was phosphorous poor. Potential potassium of degraded soil in the study area was low. In general, most of the soil had total K_2O lower than 400 (ppm) (0.4%) (Fig 1).To evaluate of soil fertility status from Sangamner area in India pH, EC, organic matter, available Nitrogen, Phosphorus and potassium were applied by Deshmukh (2012). Neppel et al. (2004) used pH, EC, phosphorus, organic carbon, potassium, and total nitrogen for

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

Class	Area (km^2)
Very low	25.2
Low	72.85
Medium	38.36
High	24.51

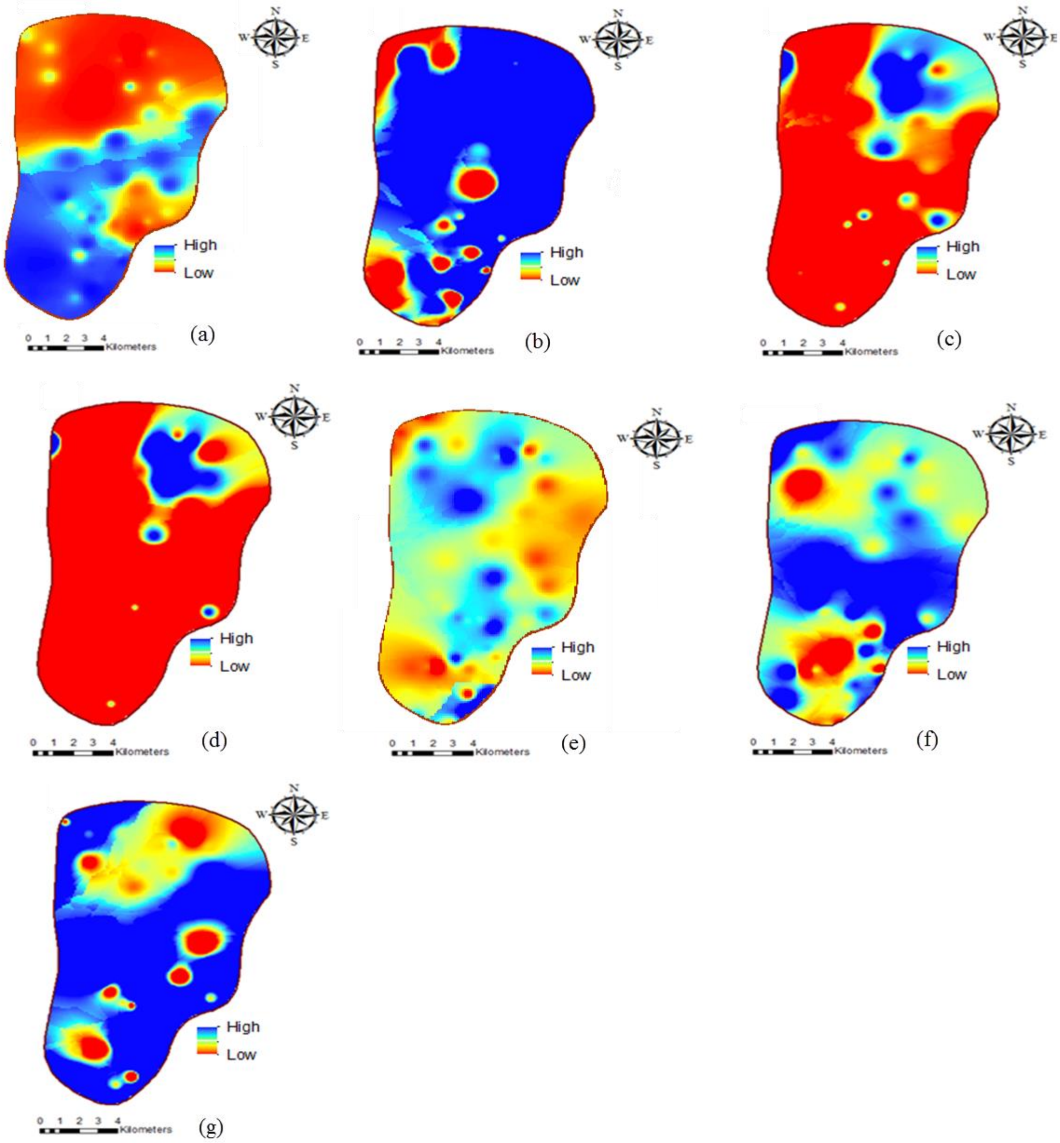

Fig 2. Fuzzy maps were used for each parameter for determining the soil fertility for wheat that assumes values in the range [0, 1]. a: Organic Content (OC), b: Cation-Exchange Capacity (CEC), c: potential of hydrogen (pH), d: Nitrogen (N), e: Phosphorus (P), f: Soil texture, g: Potassium (K).

assessing soil fertility in the South Fork Watershed of the Iowa River and results showed that nitrogen and potassium amount of soil had key elements in yield improvement. In total 64 surface soil samples were taken in the study area. In ArcGIS software raster maps using Kriging model were prepared (Fig 1). In the fuzzy classification the fertility was given between 0 and 1, being 1 a highery fertility area and 0 a not fertility area (Equations 1 and 2). In the study area with the fuzzy approach it was possible to find lowly fertility areas both for wheat with membership values between 0.25 and 0.5. The fuzzy model for each of the parameters was shown in Fig 2. In the study area, deficient N and organic materials and in terms of salinity were a critical condition (Fig 2). Next, the AHP method was applied on the fuzzy parameter maps. The pairwise comparison matrix used for preparation of the weights for each parameter in the AHP method (Table 1). As was shown in Table 1, the most important factor in soil fertility was soil salinity and the least important factor was soil texture in the study area while in Lao PDR area in China, the most important factor was soil salinity (EC) and the least important factor was available potassium (Sanchez Moreno, 2007). Soil fertility maps based on the Fuzzy-AHP were shown in Fig 3. After reclassifying the fuzzy map prepared in the four classes that consist of very low, low, medium and high (Fig 4). Area for each of the classes was shown in Table 2 . The results of the Fuzzy-AHP method showed that 15% of the lands had highly fertility, 23% medium fertility, 45% low fertility and 16% very low fertility. Soil fertility in the study area was influenced by soil salinity (Sears et al., 2005; Kravchenko et al 2003). After

Table 3. Total wheat yields in response to different degree of salinity.

EC (Salinity dS/m)	Wheat yield (kg/m^2)
1	0.6
3	0.587
3	0.587
4.6	0.563
4.5	0.550
4.3	0.567
4	0.572
6	0.542
6.3	0.537
6.5	0.534
7	0.527
7.8	0.515
8	0.512
8.4	0.5
9	0.497
9.5	0.489
10	0.482
13	0.437
14	0.422

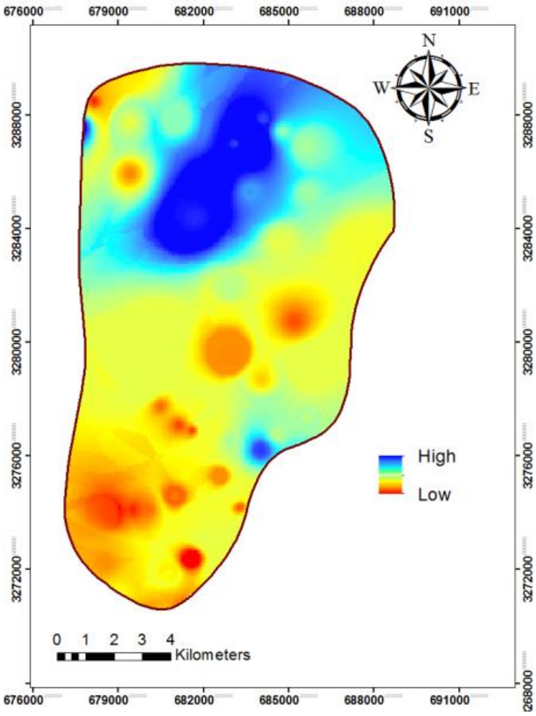

Fig 3. Fuzzy-AHP map was used for soil fertility in wheat. High fertility and low fertility were shown with blue and red colors, respectively

that, According to Equation 1 relative yield and final wheat yield (kg/m^2) was calculated (Maas and Hoffman 1977).

$$Y/Y_m = 100\text{-}b\ (EC_e\text{-}a) \qquad \text{Eq.1}$$

Where, Y/Y_m is the relative yield (%)
Y_m is maximum yield obtained with good water
EC_e is the electrical conductivity of a saturated soil paste extract (dS/m)
a= Salinity threshold value
b= Yield loss per unit increase in salinity

Results showed that a and b parameters were 2.1 and 2.5, respectively. Wheat yield response to different degree of salinity was given in Table 3. Wheat yield was reduced with higher salinity. The reduction was high beyond EC value 4. Fig 5 indicates that there was a high correlation between soil salinity and wheat yield. The relationship between soil salinity and wheat yield resulted the following significant (R^2= 0.98) mathematical yield model. The equation could be applied to estimate wheat yield in the study area. Also the results achieved by Yadav (2005) showed that a significant relationship exists between crop yield and soil salinity (R^2 = 0.8). Francois et al., (1986) gained a positive relationship between crop yield and soil salinity (R^2 = 0.86). The result in Fig 5 showed that suitable areas for the production of wheat crops were under different degree of salinity. Therefore, it could be applied in managing salinity for the wheat crops in the study area. Wheat yield collected from the measured samples were closely related to estimated yield (R^2=0. 82)(Fig 6). Generally, yield from measured 20 point varied from 3.5 to 6 ton/ha which correlate well to yield map obtained from the simulation. So measured yield in average that could be used to validate the results.

Materials and methods

Case study

The study area was located in the Fars Province in the southwest of Iran, between latitudes 29° 33' 00" N-29° 43' 11" N and longitudes 52° 49' 12" E- 52° 57′ 00"E with an area 161 km^2 (Fig 7); elevation 1810 m above mean sea level. The dataset was extracted from a land classification study done by the Fars Soil and Water Research Institute in the year 2010 and soil pH (0 – 8.27), CEC (0.11 – 18.4) (dS/m), N (0.01- 0.19), P (2 - 30) and K applied to the soil (147 - 666) (ppm), OC (0.18 – 2.04) (%) and consists of soil texture (0 – 6) that values of soil texture were reclassified between 0 to medium texture to 6 for best texture for wheat [(Table 4), Department of Natural Resources and Watershed of Fars Province, 2009)]. In the current study fuzzy-AHP procedure was used for determination of soil fertility map (Fig 8):

Fuzzy set theory

The fuzzy set theory originated by Lotfi Zadeh (1965). According to Lotfi Zadeh "The theory of fuzzy sets is, in effect, a step toward a rapprochement between the precision of classical mathematics and the pervasive imprecision of the real world - a rapprochement born of the incessant human quest for a better understanding of mental processes and cognition". Fuzzy set theory is a mathematical method used in data and functional relationships to characterize uncertainty and imprecision. To characterize uncertainty using standard statistical measures using fuzzy set is useful (e.g., Mean, standard deviation, and distribution type). The fuzzy set theory includes fuzzy mathematics, fuzzy measures, fuzzy integrals, etc. One of the aspect 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) may be defined as follows (Burrough et al., 1992): (Eq. 1)

For each $A = \{ x , \mu A(x)\} \quad x \in X$

Table 4. Summaries of effective parameters for land suitability of the study area.

ROW	Parameter	STDEV	AVERAGE	MAX	MIN
1	CEC(dS/m)	2.88	2.86	18.40	0.11
2	PH	1.00	7.60	8.27	0.00
3	OC (%)	0.38	1.04	2.04	0.18
4	N (%)	0.03	0.10	0.19	0.01
5	P (ppm)	6.57	13.03	30.00	2.00
6	K (ppm)	99.87	321.10	666.00	147.0
7	Soil texture*	1.35	3.68	6.00	0.00

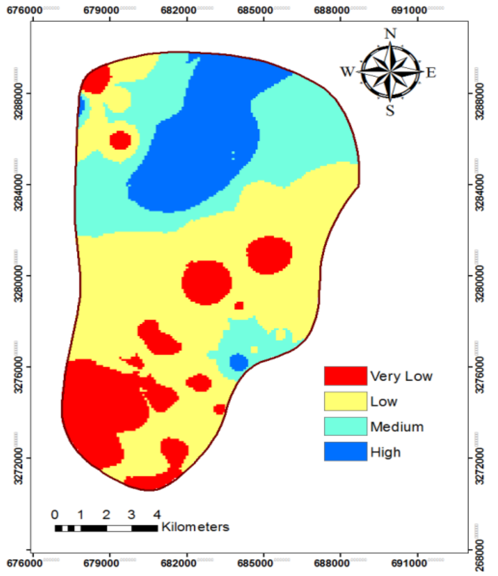

Fig 4. Map of the fuzzy classification. High fertility is in the north area with blue color and very low fertility located in the south area with red color.

Table 5. Reclassified probability values for soil texture (Sanchez Moreno, 2007).

Soil texture	New value
Loam	8
Silty Loam	6
Silty clay loam	9
Clay Loam	9

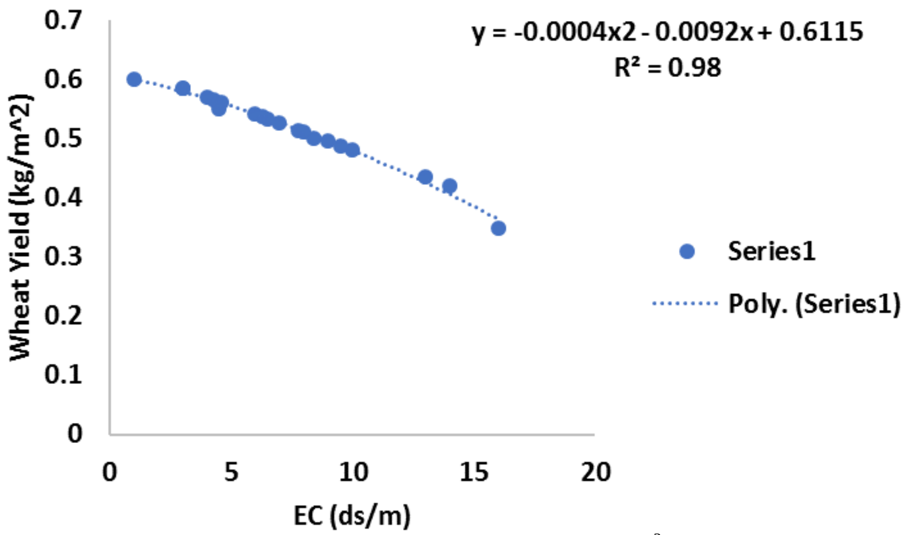

Fig 5. Relationship between EC (ds/m) and wheat yield (kg/m^2) in the study area.

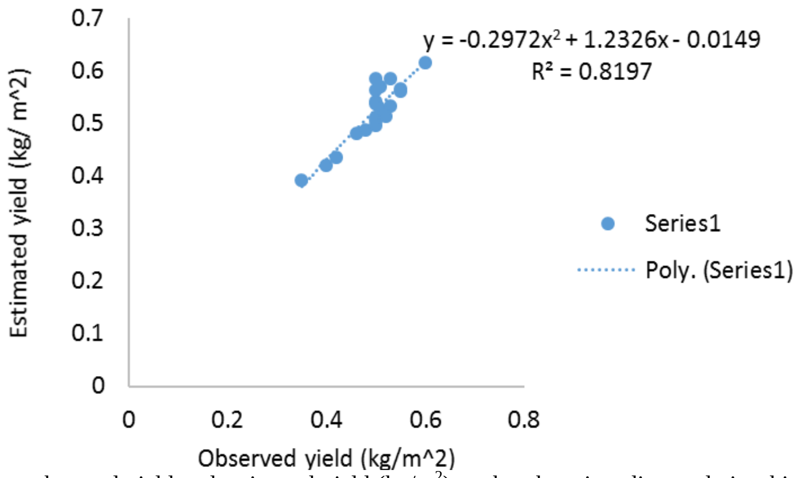

Fig 6. Relationship between observed yield and estimated yield (kg/m^2) so that there is a direct relationship between observed yield and estimated yield.

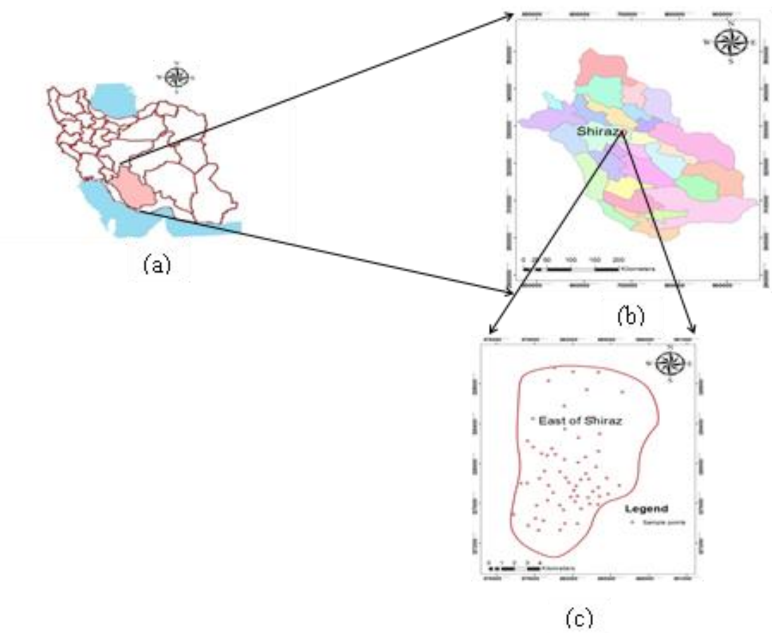

Fig 7. Location of the study area in the Iran. (a): Iran country, (b): Fras county, (c): Watershed study and Position of the profiles in the area.

where X = {x} is a finite set of points and μA(x) is a membership function of x in A.

The membership function describes the variable's membership assigned to A and, therefore, it may quantify the influence of the variable x on the predicted phenomenon, as it is grasped by the developer (Burrough and McDonnell, 2000). There are several fuzzy membership function that in the paper was used Linear membership function. The Fuzzy Linear transformation function applies a linear function between the user-specified minimum and maximum values. Anything below the minimum will be assigned a 0 (definitely not a member) and anything above the maximum a 1 (definitely a member). fuzzy membership function variables are divided into two fuzzy values based on categories and ranges that are shown in Equations1 and 2. For potassium (K_2O), soil texture, soil organic matter (OC), Nitrogen (N), Phosphorus (P_2O_5) considered only two fuzzy values: For example, used two fuzzy values for organic matter: low organic matter and high organic matter that in fuzzy set, μ_A =0 is value of x does not belong to A and μ_A=1 is belongs completely to A (Sanchez Moreno, 2007; Sys et al., 1993) : (Eq. 2)

Where x is

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

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

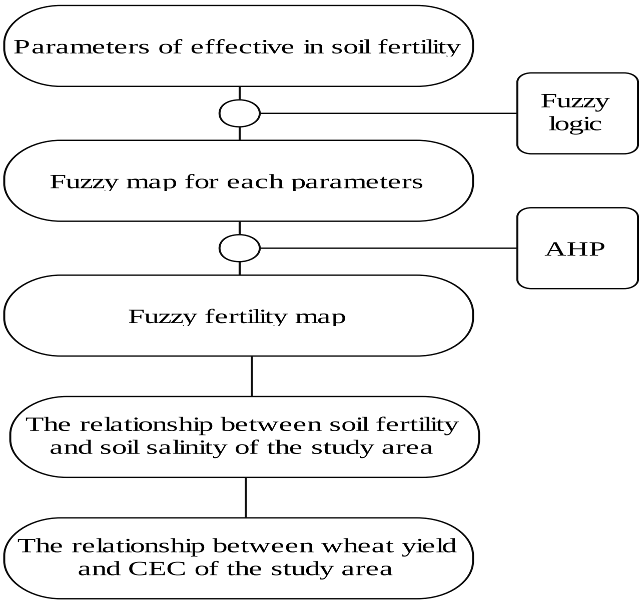

Fig 8. Flowchart of the Fuzzy AHP procedure was used for soil fertility of wheat. In this method, after the determination of the parameters of effective soil fertility in the area, fuzzy map was prepared for each parameters. Then the relationship between soil fertility and soil salinity was determined.

the input data and a, b are the limit values. For cation exchange capacity (CEC), and pH values, the following function was used. So that in fuzzy set, μ_A =1 is value of *x* does not belong to A and μ_A=0 is belongs completely to A. (Sanchez Moreno, 2007; Sys et al., 1993) : (Eq. 3)

AHP method

In order to prepare the soil fertility map, it was necessary to calculate the convex combination of the raster values containing the different fuzzy parameters. $A_1, \ldots A_k$ was fuzzy subclasses of the defined universe of objects X**,** and $W_1, \ldots W_k$ is non-negative weights summing up to unity. The convex combination of $A_1, \ldots A_k$ is a fuzzy class *A* (Burrough, 1989), and the weights $W_1, \ldots W_k$ were calculated using AHP and fuzzy method parameters had been calculated in ArcGIS. Analytic Hierarchy Process (AHP) was developed by Thomas Saaty in the 1980. When there are a limited number of choices, the AHP facilitates the selection of weighting criteria and admits the decision making.

Conclusion

Given the non-discrete characteristics of soils, fuzzy theory suits well to the analysis of soil fertility. With fuzzy representation the boundaries between suitability classes were not so strict and map units that were more or less suitable can be described properly. With fuzzy theory, the spatial entities were associated with membership grades that indicate to which extent the entities belong to a class. In this study fuzzy-AHP were used for soil fertility. Using fuzzy-AHP method was defined membership function for each parameter. In this study area, results showed that fuzzy-AHP method is useful for determining soil fertility. Using fuzzy-AHP method, fertility classes was given between 0 and 1, being 1 a highery fertility area and 0 a not fertility where soil fertility was low or soil salinity was high. On the other hand total and marketable wheat yields decrease with the increase of EC rates. The correlation between soil salinity and wheat yield resulted the following significances. It is well known that salinity has adverse effect on crop yield (wheat) through affecting the osmotic potential balance between soil and plant. The simulation result showed that the crop yield decreases with increasing salinity. So crop yield with different degree of salinity in relation to soil fertility can be predicted by crop yield model This results is integrated in GIS environment for further manipulations. Also using different methods such as leaching should reduce the amount of salt and also using different manure should be increased soil fertility. Finally, it was concluded that the Fuzzy-AHP method has a higher accuracy for predictive soil fertility maps and it is recommended that fuzzy-AHP method use in soil fertility modeling.

Acknowledgements

The authors would like to acknowledge the Fars Soil and Water Research Institute for their assistance during the study and providing dataset.

References

Bui EN, Loughhead A, Corner R (1999) Extracting soil–landscape rules from previous soil surveys. Aust J Soil Res. 37, 495–508.

Burrough PA (1989) Fuzzy mathematical methods for soil survey and land suitability. J Soil Sci. 40: 477-492.

Burrough PA, McDonnell RA (2000) Principles of Geographical Information Systems. Oxford University Press, New York.

Deshmukh KK (2012) Evaluation of soil fertility status from Sangamner area, ahmednagar district, maharashtra, India. Chem 5: 398-406.

Dobermann A, Oberthür T (1997) Fuzzy mapping of soil fertility — a case study on irrigated rice land in the Philippines. Fuzzy Sets in Soil Science. Volume 77, Issues 2–4, June 1997, Pages 317–339

Francois LE, Maas EV, Donovan TJ, Youngs VL (1986) Effect of salinity on grain yield and quality, vegetative growth, and germination of semi-dwarf and durum wheat. Agron J. 78: 1053-1058.

Kravchenko AN, Thelen, KD, Bullock, DG., Miller, NR (2003) Relationship among crop grain yield, topography, and soil electrical conductivity studied with cross-correlograms. Agron J. 95:1132-1139.

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

Liu J, Zhu AX (2009) Mapping with words: a new approach to automated digital soil survey. Int J Intell Syst. 24: 293–311.

Lotfi Zadeh LH (1965) Fuzzy sets. Infor Control. 8: 338–353.

Maas EV, Hoffman GJ (1977) Crop salt tolerance, current assessment. J Irrig Drain E-ASCE. 103: 115-134.

McBratney AB, Mendonca Santos ML, Minasny B (2003) On digital soil mapping. Geoderma. 117: 3–52.

McBratney AB, Odeh IOA (1997) Application of fuzzy sets in soil science: fuzzy logic, fuzzy measurements and fuzzy decisions. Geoderma. 77: 85–113.

McBratney AB, Odeh IOA, Bishop TFA, Dunbar MS, Shatar TM (2000) An overview of pedometric techniques for use in soil survey. Geoderma. 97: 293–327.

Mokarram M, Rangzan K, Moezzi A, Baninemehc J (2010). Land suitability evaluation for wheat cultivation by fuzzy theory approach as compared with parametric method. The international archives of the photogrametry. Rem Aen Spa Inf Sci. 38: 1440-145.

Neppel J, Tomer M, Karlen D (2004) Assessing soil fertility in the south fork watershed of the iowa river. Soil W Con Soc. 34:131-144.

Qi F, Zhu AX (2003) Knowledge discovery from soil maps using inductive learning. Int J Geogr Inf Sys. 17: 771–795.

Qi F, Zhu AX, Harrower M, Burt JE (2006) Fuzzy soil mapping based on prototype category theory. Geoderma. 136: 774–787.

Qi F, Zhu AX, Pei T, Qin C, Burt JE (2008) Knowledge discovery from are-class resource maps: capturing prototype effects. Int J Geogr Inf Sys. 35: 223–237.

Saaty, T (1980) The Analytic Hierarchy Process, McGraw-Hill, Inc., New York.

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

Sears BG, Mijatovic B, Mueller TG, Barnhisel RI (2005) Interpreting Yield Variability with Electrical Conductivity and Terrain Attributes across a Central Kentucky Landscape. Crop Management. doi:10.1094/CM-2005-0928-01-RV.

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

Yadav RD (2005) Modeling saliniity affects in relation to soil fertility and crop yield; A Case Study of Nakhon Ratchasima, Nong Suang District, Thailand. International Institute For Geo-Information Science And Earth Observation Enschede, The Netherlands. 165 pp.

Yang L, Zhu AX, Li BL, Qin CZ, Pei T, Liu BY, Li RK, Cai QG (2007) Extraction of knowledge about soil-environment relationship for soilmapping using fuzzy c-means (FCM) clustering. Acta Ped Sin. 44: 16–23.

Zhang B, Zhang Y, Chen D, White RE, Li Y (2004) A quantitative evaluation system of soil productivity for intensive agriculture in China. Geoderma. 123: 319–331.

Zhu AX, Band LE, Dutton B, Nimlos T (1996) Automated soil inference under fuzzy logic. Ecol Model. 90: 123–145.

Zhu AX, Band LE, Vertessy R, Dutton B (1997) Derivation of soil properties using a soil land inference model (SOLIM). Soil Sci Soc Am J. 61: 523–533.

Zhu AX, Hudson B, Burt JE, Lubich K, Simonson D (2001) Soil mapping using GIS, expert knowledge, and fuzzy logic. Soil Sci Soc Am J. 65: 1463–1472.

Zhu AX, Mackay DS (2001) Effects of spatial detail of soil information on watershed modeling. J Hydrol. 248, 54–77.

Zhu AX, 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.