

USING ORDERED WEIGHT AVERAGING (OWA) FOR MULTICRITERIA SOIL FERTILITY EVALUATION BY GIS (CASE STUDY: SOUTHEAST IRAN)

Marzieh Mokarram^{1*}, Majid Hojati²

5

^{1*}Department of Range and Watershed Management, College of Agriculture and Natural Resources of Darab, Shiraz University, Iran, Email: m.mokarram@shirazu.ac.ir

²Department of GIS and RS, University of Tehran, Faculty of Geography, Dep. of RS & GIS

Corresponding author: Marzieh Mokarram, Tel.: +98-917-8020115; Fax: +987153546476 , Address:

10

Darab, Shiraz university, Iran, Postal Code: 71946-84471, Email: m.mokarram@shirazu.ac.ir

Abstract

The Multicriteria Decision Analysis (MCDA) and Geographical Information Systems (GIS) are used to provide more accurate decisions to the decision makers in order to evaluate the effective factors in the natural science. One of the popular algorithm of multicriteria analysis is Ordered Weighted Averaging (OWA). The OWA procedure depends on some parameters, which can be specified by means of fuzzy. The aim of this study is to take the advantage of the incorporation of fuzzy into GIS-based soil fertility analysis by OWA in west Shiraz, Fars province, Iran. For the determination of soil fertility maps, OWA parameters such as potassium (K), phosphor (P), copper (Cu), iron (Fe), manganese (Mn), organic carbon (OC) and zinc (Zn) were used. After generated interpolation maps with Inverse Distance Weighted (IDW), fuzzy maps for each parameters were generated by the membership functions. Finally with OWA six maps for fertility with different risk level were made. The results show that with decreasing risk (no trade-off), almost all of the parts of the study area were not suitable for soil fertility. While increasing risk, more area was suitable in terms of soil fertility in the study area. So using OWA can generate many maps with different risk levels that lead to different management due to the different financial conditions of farmers.

25

Key words: Multicriteria Decision Analysis (MCDA); Ordered weighted averaging (OWA); fuzzy; Soil fertility, west Shiraz, Fars province.

30 **1. Introduction**

Spatial planning involves decision-making techniques that are associated with techniques such as Multi Criteria Decision Analysis (MCDA) and multicriteria Evaluation (MCE). Combining GIS with MCDA methods creates a powerful tool for spatial planning (Malczewski, 1999; Shumilov et al., 2011; Kanokporn & Iamaram, 2011; Belkhiri et al., 2011; Salehi et al., 2012; Feng et al., 35 2012; Ashrafi et al., 2012). Multicriteria evaluation may be used to develop and evaluate alternative plans that may facilitate compromise among interested parties (Malczewski, 1996). In general, the GIS-based soil fertility analysis assumes that a given study area is subdivided into a set of basic units of observation such as polygons or rasters. Then, the soil fertility problem involves evaluation and classification of the areal units according to their fertility for a 40 particular activity. There are two fundamental classes of multicriteria evaluation methods in GIS: the Boolean overlay operations (noncompensatory combination rules) and the weighted linear combination (WLC) methods (compensatory combination rules). These approaches can be generalized within the framework of the ordered weighted averaging (OWA) (Asproth et al., 1999; Jiang and Eastman, 2000; Makropoulos et al., 2003; Malczewski et al., 2003; Malczewski 45 & Rinner, 2005; Malczewski .,2006). OWA is a family of multicriteria combination procedures (Yager, 1988). Conventional OWA can utilizes the qualitative statements in the form of fuzzy quantifiers (Yager, 1988, 1996). The main goal of this paper is to produce the land suitability maps according to OWA operators for GIS-based multicriteria evaluation procedures.

OWA has been developed as a popularization of multicriteria combination by Yager (1988). The 50 OWA concept has been extended to the GIS applications by Eastman (1997) as a part of decision support module in GIS-IDRISI. Subsequently, Jiang and Eastman (2000) demonstrate the utility of the GIS-OWA for land use/suitability problems. The implementation of the OWA concept in IDRISI15.01 resulted in several applications of OWA to environmental and urban planning problems (Asproth et al., 1999; Mendes & Motizuki, 2001).

55 Mokarram and Aminzadeh (2010) used OWA for land suitability in Shavur plain, Iran. The results showed that OWA is a multicriteria evaluation procedure (or combination operator). The quantifier-guided OWA procedure is illustrated using land-use suitability analysis in Shavur plain, Iran.

Liu and Malczewski (2013) used GIS-Based Local Ordered Weighted Averaging in London,
60 Ontario. In the study area, the aim was to implement local form of OWA. The local model was
based on the range sensitivity principle. The results showed that there were substantial
differences between the spatial patterns generated by the global and local OWA methods.

Accordingly, the study area is one of the most important centers of agriculture in Iran, and the
aim of the study is the determination of produce the soil fertility maps according to OWA
65 operators for GIS-based multicriteria evaluation procedures in southeast Iran using OWA. In the
study, we expected that the selected OWA method is the best method for the determination
of multicriteria soil fertility. According to OWA method the amount of soil fertility with
different risk levels was determined that is useful for farmers with different financial
conditions.

70 **2. Study Area**

This study was carried out in west Shiraz, Fars province, Iran. It is an area of about 100.02 km²,
and is located at longitude of N 29° 31' - 29° 38' and latitude of E 52° 49' to 52° 57' (Figure 1).
The altitude of the study area ranges from the lowest of 1,571 m to the highest of 2,203 m. The
main agricultural produce consists of grain, fruit, and vegetables, while the partly wooded
75 mountains are used for 120 pasture. It has a moderate climate and has been a regional trade
center for over a thousand years. Shiraz's climate has distinct seasons, and is overall classed as a
hot semi-arid climate, though it is only a little short of a hot-summer Mediterranean climate
(Csa). Summers are hot, with a July average high of 38.8 °C (101.8 °F). Winters are cool, with
average low temperatures below freezing in December and January. Around 300 mm (12 in) of
80 rain falls each year, almost entirely in the winter months, though in some cases as much as this
has fallen in a single month (as in January 1965 and December 2004). As of 2011, Shiraz has a
population of 2,353,696 the majority of whom are Persian.

Geomorphology of the study area is affected by physical specification of different geological
formations. Also because of its location is in Zagros Mountains, this region impressed by
85 geological structures and related fractures. The constructor rocks of this region are defined in 2
parts:

- 1- Rocks older than Quaternary that are hard and to some extent compacted.

2- Quaternary and Recent sediments that are loose and construct surface alluvium.

Quaternary and Recent Sediments are mainly in plains between mountains, coastal flats, and
90 so on. These two zones are similar to some extent but highest mountains of Zagros, resistant
carbonate rocks, high cliffs, crags and highest crests with more than 2500m difference in
elevation are located in High Zagros Zone.

Fars area includes western border of Kazeroon Fault, Eastern margin of imaginary line that
separates Bandar-Abbas Hinterland from Fars province, thrust belt in the north and Persian Gulf
95 coastline in the south. Anticlines in this area have different orientations in northwest-southeast
directions, as well as east west and northeast-southwest orientations (Motiei, 1993).

According to the isobaric contours and potentiometric maps, there is a general hydrodynamic
flow from Zagros Mountains to the Persian Gulf. This hydrodynamic flow varies with
topography, anticline geometry, faults and fracture intensity, porosity and permeability. The
100 isosaline contours follow hydrodynamic flow (Motiei, 1995).

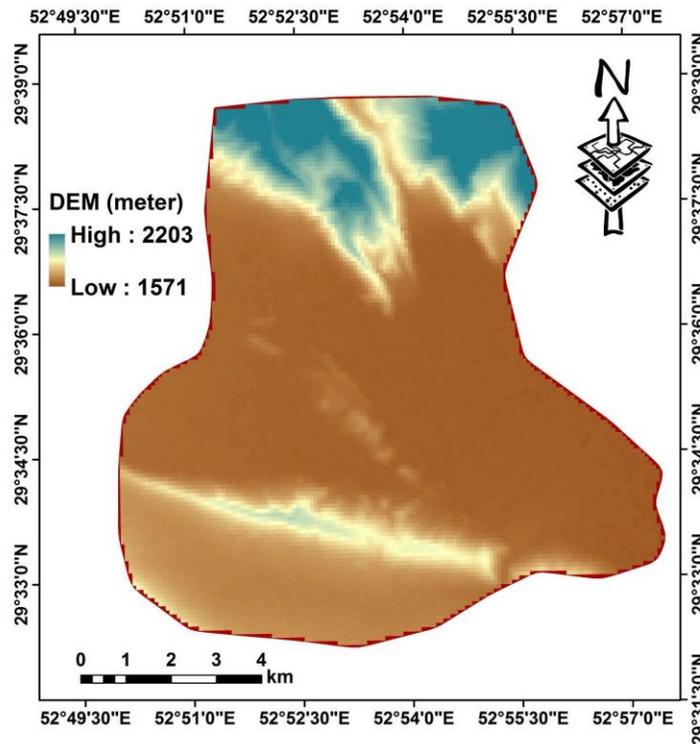


Figure 1. Location of the study area (digital elevation model (DEM) with spatial resolution of 30 m) (Source: <http://earthexplorer.usgs.gov>).

The assessment of soil fertility for agricultural production in the region is vital, which should consider environmental factors and human conditions (Soufi, 2004). In order to predict the variability of soil fertility, P, K, Cu, Fe, Mn, OC and Zn maps were prepared (Table 2) (Organization of Agriculture Jahad Fars province).

Table 2. Descriptive statistics of the data for soil fertility (Organization of Agriculture Jahad Fars province)

Statistic parameters	OC (mg/kg)	P (mg/kg)	K (mg/kg)	Fe (mg/kg)	Zn (mg/kg)	Mn (mg/kg)	Cu (mg/kg)
maximum	1.65	30.00	666.00	15.00	3.00	52.50	2.00
minimum	0.18	2.00	137.00	1.00	0.10	2.80	0.20
average	1.01	13.94	313.73	4.54	0.65	14.77	0.97
STDEV	0.35	6.49	104.28	2.84	0.50	10.71	0.36

3. Materials and methods

In order to prepare soil fertility maps using OWA method, 45 sample soils were used that after the creation of the interpolation maps for each parameters using Inverse Distance Weighted (IDW) and the creation of a fuzzy parameter map for each parameter, in order to make different risk levels OWA was used. The description of each method is in the following:

3.1. Inverse Distance Weighted (IDW)

IDW model was used for interpolating Effective data in determining of soil fertility such as potassium (K), phosphor (P), copper (Cu), iron (Fe), manganese (Mn), organic carbon (OC) and zinc (Zn). 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 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):

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

Where 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} .

130

3.2. Ordered Weight Average (OWA)

OWA is a multicriteria evaluation procedure. The nature of the OWA procedure depends on some parameters, which can be specified by fuzzy quantifiers. The GIS-based multicriteria evaluation procedures involve a set of spatially defined alternatives and a set of evaluation criteria represented as map layers. According to the input data (criterion weights and criterion map layers), the OWA combination operator associates with the i -th location (e.g., raster or point) a set of order weights $v = v_1, v_2, \dots, v_n$ such that $v_j \in [0, 1], j=1,2,\dots,n, \sum_{j=1}^n v_j = 1$, and is defined as follows (see Yager, 1988; Malczewski et al., 2003):

135

$$OWA_i = \sum_{j=1}^n \left(\frac{u_j v_j}{\sum_{j=1}^n u_j v_j} \right) z_{ij} \quad (2)$$

140

where $z_{i1} \geq z_{i2} \geq \dots \geq z_{in}$ is the sequence obtained by reordering the attribute values $a_{i1}, a_{i2}, \dots, a_{in}$, and u_j is the criterion weight reordered according to the attribute value, z_{ij} . It is important to point to the difference between the two types of weights (the criterion weights and the order weights). The criterion weights are assigned to evaluation criteria to indicate their relative importance. All locations on the j -th criterion map are assigned the same weight of w_j . The order weights are associated with the criterion values on the location-by-location basis. They are assigned to the i -th location's attribute value in decreasing order without considering from which criterion map the value comes. With different sets of order weights, one can generate a wide range of OWA operators including the most often used GIS- base map combination procedures: the weighted linear combination (WLC) and Boolean overlay operations, such as intersection (AND) and union (OR) (Yager, 1988; Malczewski et al., 2003). The AND and OR operators represent the extreme cases of OWA and they correspond to the MIN and MAX operators, respectively. The order weights associated with the MIN operator are: $v_n = 1$, and $v_j = 0$ for all other weights. Given the order weights, OWA_i (MIN) = $\text{MIN}_j (a_{i1}, a_{i2}, \dots, a_{in})$. The following

145

150

weights are associated with the MAX operator: $v_1 = 1$, and $v_j = 0$ for all other weights, and consequently $OWA_i(\text{MAX}) = \text{MAX}_j(a_{i1}, a_{i2}, \dots, a_{in})$. Assigning equal order weights (that is, $v_j = 1/n$ for $j = 1, 2, \dots, n$) results in the conventional WLC, which is situated at the mid-point on the continuum ranging from the MIN to MAX operators (Table 1) (Malczewski, 2006).

Table 1. Properties of Regular Increasing Monotone (RIM) quantifiers with selected values of Parameter (source: Malczewski, 2006).

α	Quantifier (Q)	Order Weights(v_{ik})	GIS Combination Procedure	<i>ORness</i>	<i>rade-off</i>
$\alpha \rightarrow =$	<i>At least one</i>	$V_{i1}=1; v_{ik}=0, (1 < k \leq n)$	OWA (OR)	1.0	0
$\alpha=0.1$	<i>At least a few</i>	a	OWA	a	a
$\alpha=0.5$	<i>A few</i>	a	OWA	a	a
$\alpha=1$	<i>Half (identity)</i>	$v_{ik}=1/n, 1 \leq k \leq n$	OWA (WLC)	0.5	1
$\alpha=2$	<i>Most</i>	a	OWA	a	a
$\alpha=10$	<i>Almost all</i>	a	OWA	a	a
$\alpha \rightarrow \infty$	All	$V_{in}=1; v_{ik}=0, (1 \leq k < n)$	OWA (AND)	0	0.0

^a The set of order weights depends on values of sorted criterion weights and parameter.

160

4. Results

4.1. Inverse Distance Weighted (IDW)

In the study area for the determination of soil fertility 45 sample points were used. This data was prepared by the Organization of Agriculture Jahad Fars province in 2012. This points was collected using a random sampling method that only was prepared from wheat fields. Because of the legal authority of some agriculture land owners in some parts of the study area the points are not scattered well. In the study spline, inverse distance weighted (IDW) and simple kringing method (gaussian, circular, spherical, exponential model) were used for the production of raster maps for each soil parameter in ArcGIS 10.2. The results of root-mean-square deviation (RMSE) for three models showed that IDW method (circular model) with lowest RMSE is the best model for the prediction of soil parameters. According to Figure 2 sample points was selected randomly in the study area.

170

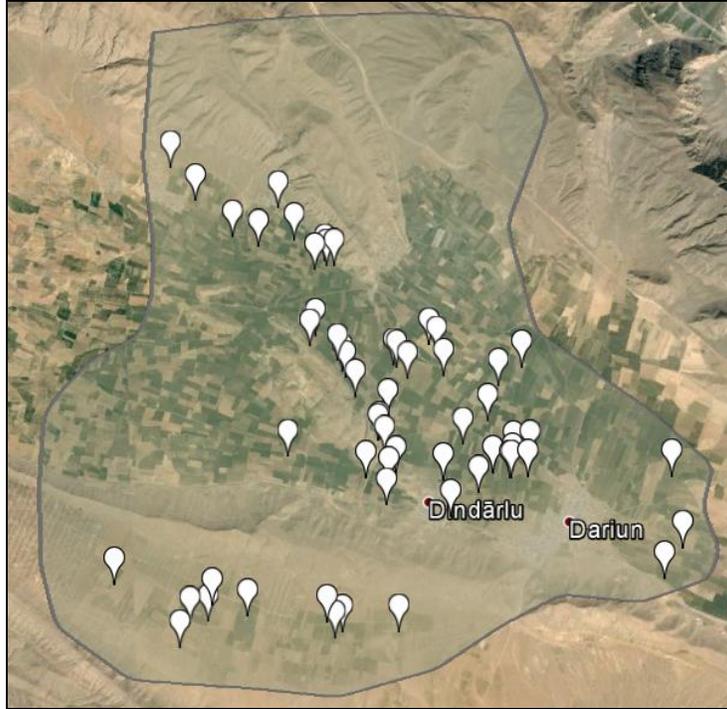
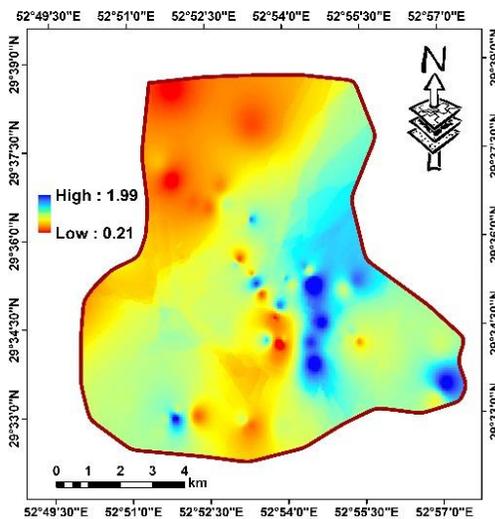
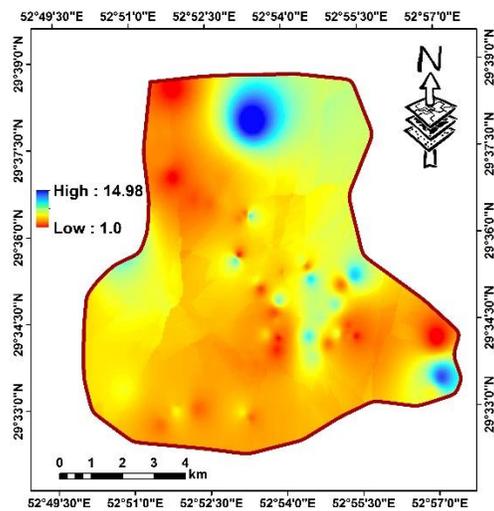


Figure 2. Position of sample points for the study area.

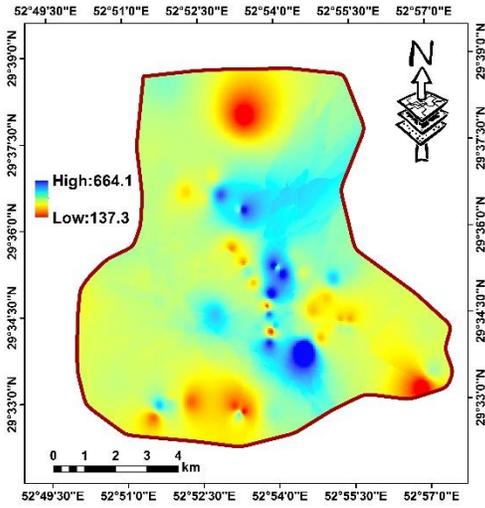
175 In the study area the IDW interpolation was used for produces in order to predict of K, P, Cu, Fe, Mn, OC and Zn that are shown in Figure 3. According to Figure 3, most elements in the north and parts of south of the study area were determined to have lower amounts than the other regions.



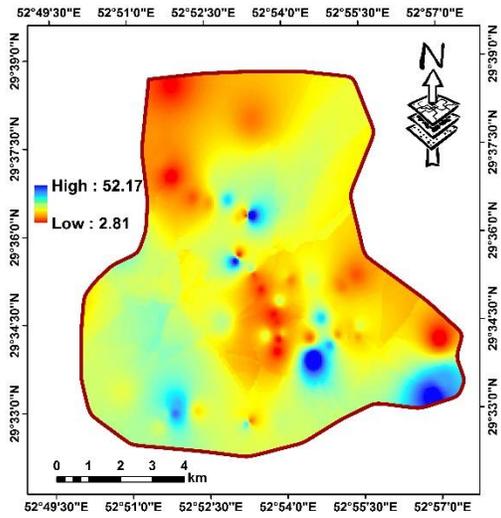
Potassium (K) IDW Map(a)



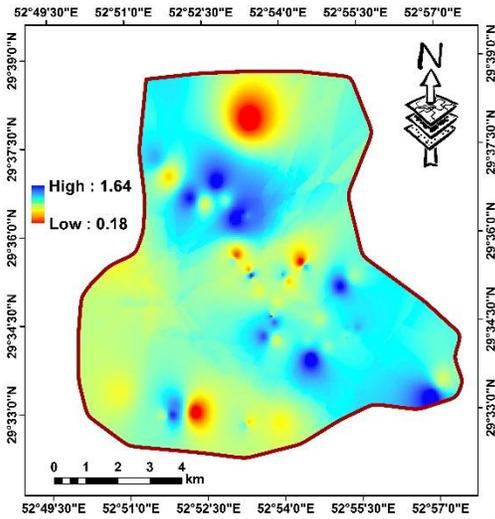
Phosphor (P) IDW Map(b)



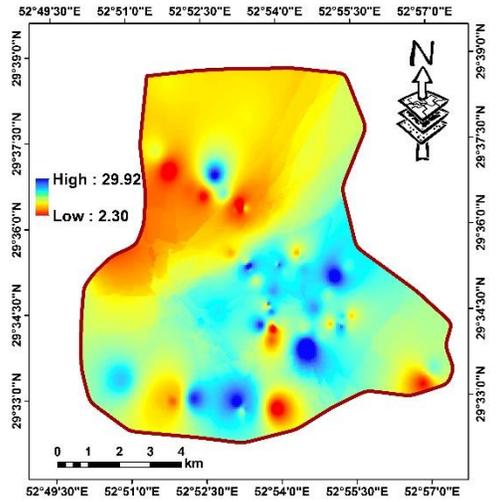
Cu IDW Map (c)



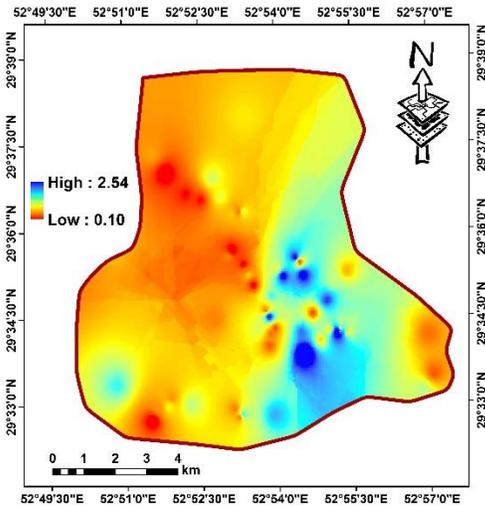
Fe IDW Map (d)



Mn IDW MAP (e)



OC IDW MAP (f)

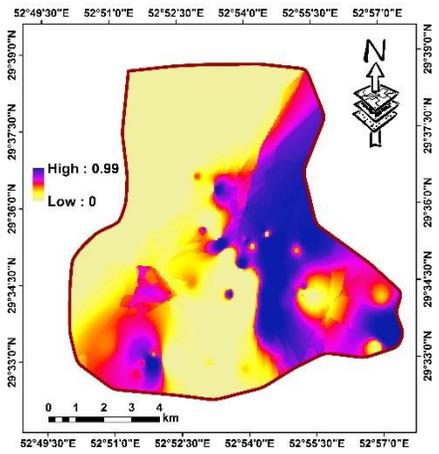


Zn IDW MAP(g)

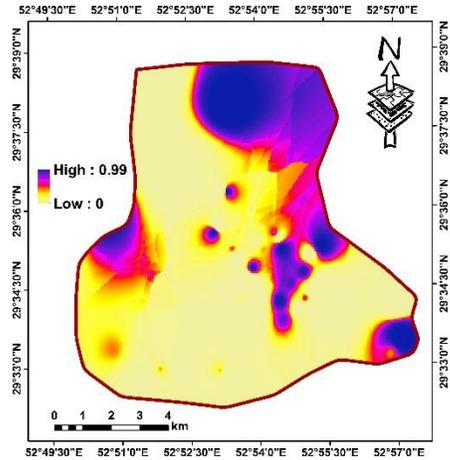
Figure 3. Interpolation map using IDW method. (a):K; (b):P (c):CU, (d):Fe; (e):Mn; (f):OC; (g):
 180 Zn.

4.2. Fuzzy method

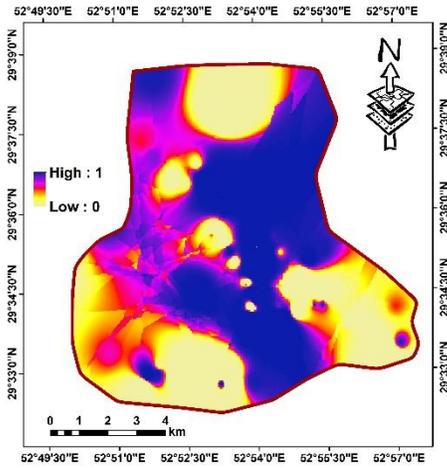
In this study, P, K, Cu, Fe, Mn, OC and Zn maps from IDW were used as input to fuzzy inference system. In order to homogenize each parameter for weightedness by OWA method for preparing the final soil fertility fuzzy method was used. According to FAO (1983) membership function for each parameter was defined (K, P, Cu, Fe, Mn, OC and Zn) and each of fuzzy map was created for each elements between 0 to 1. The prepared fuzzy maps for the soil fertility parameters are shown in Figure 4, where MF is closer to 0 with decreasing soil fertility, while MF is closer to 1 with increasing soil fertility (Soroush et al., 2011).
 185



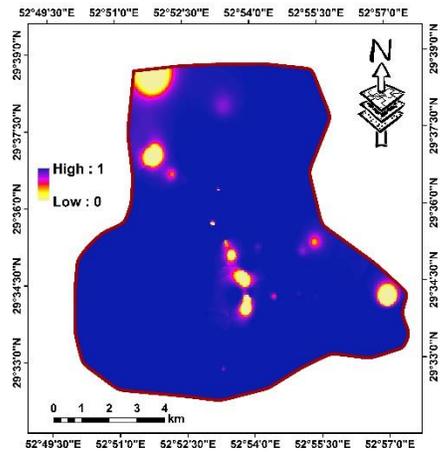
Potassium (K) Fuzzy Map(a)



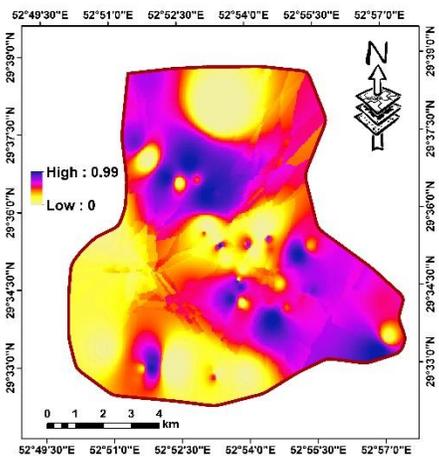
Phosphor (P) Fuzzy Map(b)



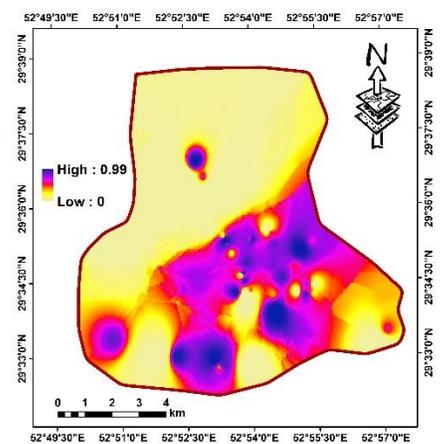
Cu Fuzzy Map (c)



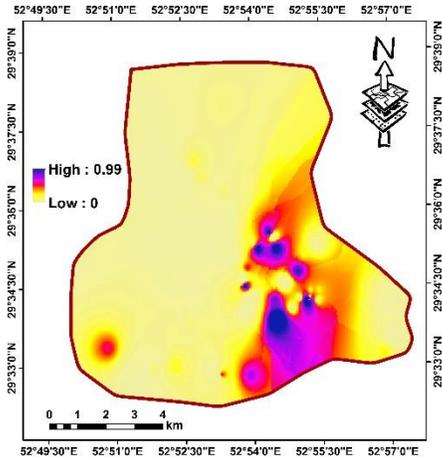
Fe Fuzzy Map(d)



Mn Fuzzy MAP (e)



OC Fuzzy MAP (f)



Zn Fuzzy MAP (g)

190 Figure 4. Fuzzy map of studied area for each soil fertility parameter. (a):K; (b):P (c):CU, (d):Fe; (e):Mn; (f):OC; (g): Zn.

195 According to Figure 4 most of the study area did not have a suitable value for Mn parameter that in the fuzzy map had the value close to zero (critical limit =10 (mg/kg)). While the results of fuzzy method showed that most of the study area (the parts of east, southeast and the small parts of south west of the study area) had suitable values for P and Zn parameters that had the value close to 1 in fuzzy map (critical limit= and for P and Zn respectively). Parts of north, south west and south of the study area were not suitable for fertility (critical limit=). According to the fuzzy map of K parts of north, southeast and west were not suitable (critical limit=). Also parts of north, northwest and south of the study area were not suitable for Cu. Finally it was determined
 200 that only parts of northeast, southeast and the small parts of west and east were suitable for soil fertility.

205 Finally to overt each parameter and to prepare the soil fertility OWA method was used. OWA offers a wealth of possible solutions for our residential developmental problems. In our application, seven order weights were applied corresponding to the seven factors that were rank-ordered for each parameter after the modified factor weights were applied. Table 3, gives six typical sets of order weights for the seven factors: (1) average level of risk and full trade-off, (2) low level of risk and no trade-off, (3) high level of risk and no trade- off, (4) low level of risk and average trade-off, (5) high level of risk and average trade-off, (6) average level of risk and

210 no trade-off. Figure 5 shows the locations of typical sets of order weights in the decision-support space (Figure 5).

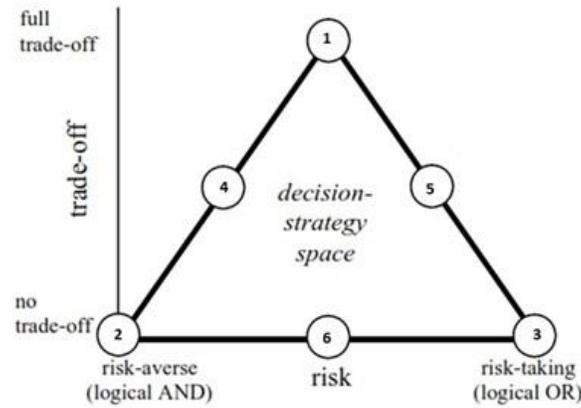


Figure 5. Decision-strategy space and typical sets of order weights (see Table 3)

Table 3: Typical sets of order weights for seven factors.

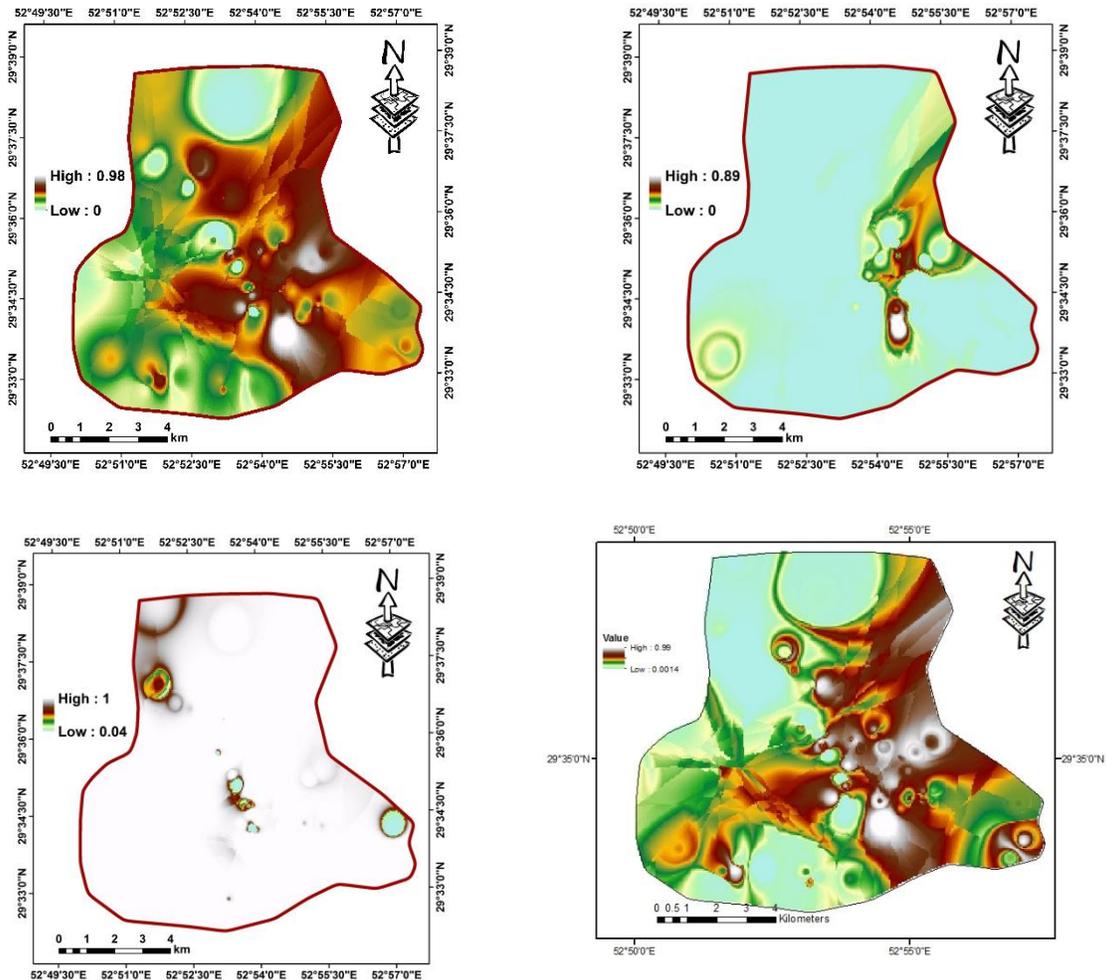
	(1) Average level of risk and full trade-off						
order weight	0.1428	0.1428	0.1428	0.1428	0.1428	0.1428	0.1428
rank	1 st	2 nd	3 rd	4 th	5 th	6 th	7 th
	(2) Low level of risk and no trade-off						
order weight	1	0	0	0	0	0	0
rank	1 st	2 nd	3 rd	4 th	5 th	6 th	7 th
	(3) High level of risk and no trade-off						
order weight	0	0	0	0	0	0	1
rank	1 st	2 nd	3 rd	4 th	5 th	6 th	7 th
	(4) Low level of risk and average trade-off						
order weight	0.4455	0.2772	0.1579	0.0789	0.0320	0.0085	0
rank	1 st	2 nd	3 rd	4 th	5 th	6 th	7 th
	(5) High level of risk and average trade-off						
order weight	0	0.0085	0.032	0.0789	0.1579	0.2772	0.4455
rank	1 st	2 nd	3 rd	4 th	5 th	6 th	7 th

(6) Average level of risk and no trade-off							
order weight	0	0	0	1	0	0	0
rank	1 st	2 nd	3 rd	4 th	5 th	6 th	7 th

215

Given the standardized criterion maps and corresponding criterion weights, we apply the OWA operator using Eq. (2) for selected values of fuzzy quantifiers: at least one, at least a few, a few, identity, most, almost all, and all are used. Each quantifier is associated with a set of order weights that are calculated according to Eq. (2). Figure 6 shows the six alternative soil fertility patterns.

220



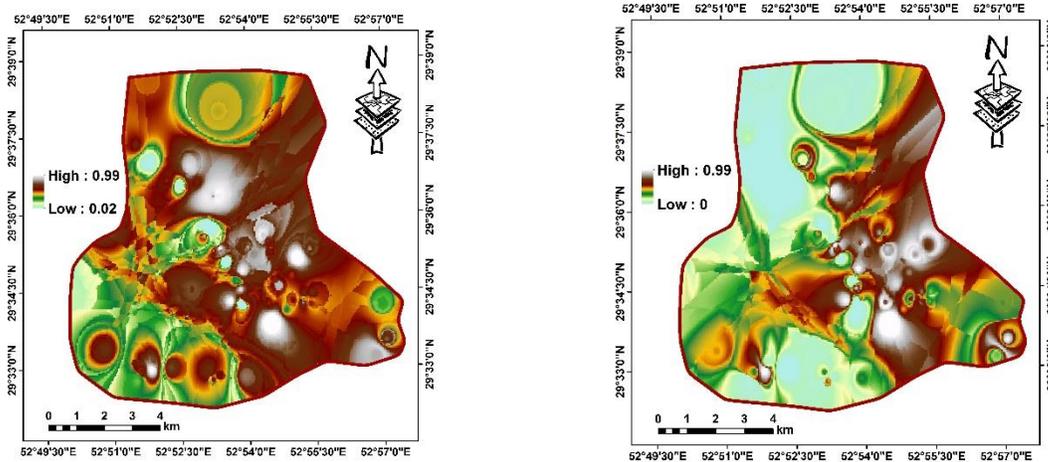


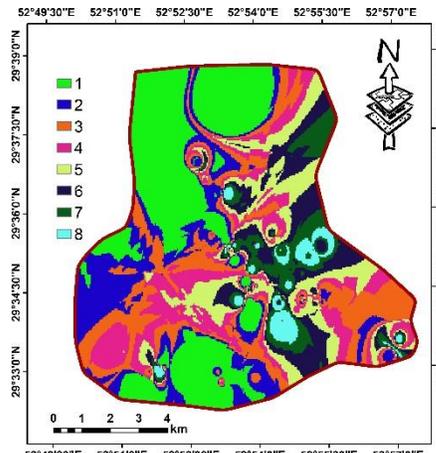
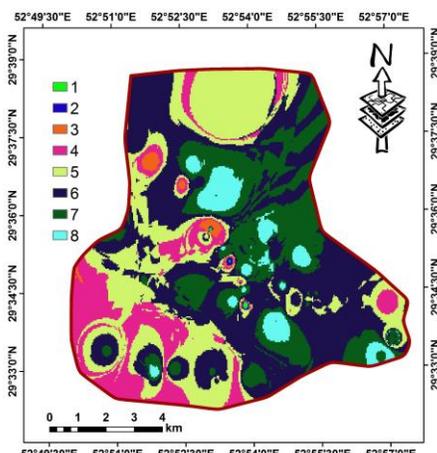
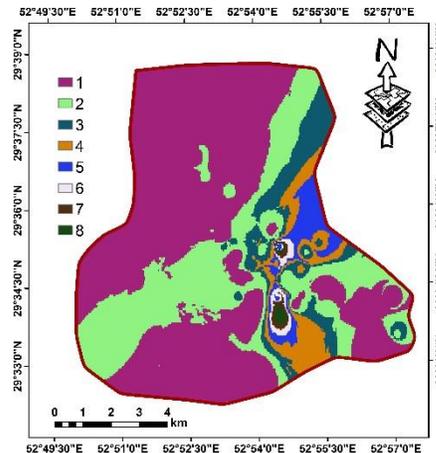
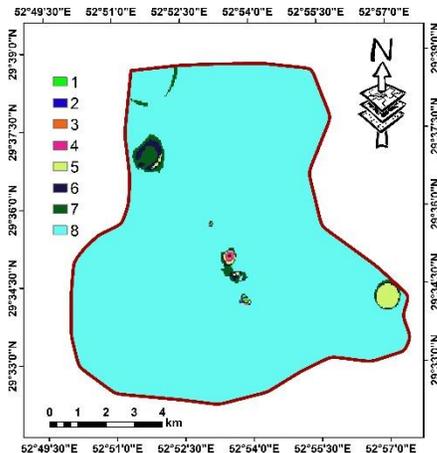
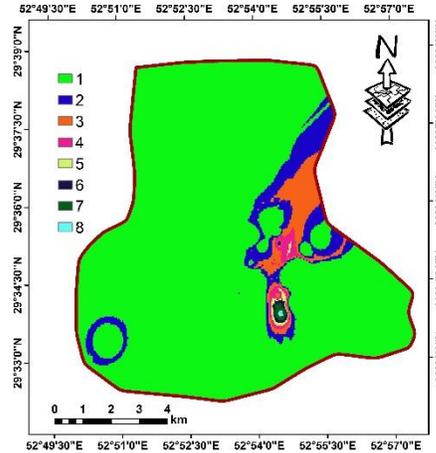
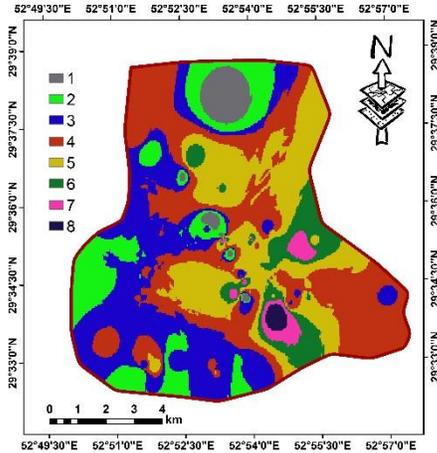
Figure 6. Soil fertility maps of OWA results for selected fuzzy linguistic quantifiers

According to Figure 6 (1) the parts of the study area had high value for soil fertility (high risk level for farmers with good financial conditions). According to Figure 6 (2), with decreasing risk (no trade-off), the area with high soil fertility was determined. So, only the parts of west and southwest of the study area were suitable for soil fertility. While almost all of the parts were not suitable for soil fertility. According to Figure 6 (3) almost all of the study area had low soil fertility. The Figure 6 (4) showed low risk with average trade-off that in comparison of Figure 6 (2) had more risk. The Figure 6 (5) showed high risk with average trade-off that in comparison of Figure 6 (3) had lower risk for the determination of soil fertility. Figure 6 (6) showed average risk with no trade-off that in comparison of Figure 6 (3) had more risk.

5. Discussion

Based on Table 4, the OWA map was classified in eight classes that is shown in Figure 7, figure 8 and Table 5. According to Figure 7 shows the six alternative soil fertility patterns. According to Figure 7 with average risk (full trade-off) (Figure 7 (1)) all of effective parameters of soil fertility received some weight (0.33). According to Figure 7 (1) the parts of the study area had high value (southeast and east of the study area), and low value (north the study area). According to Figure 7 (2), with decreasing risk (no trade-off), the area with high soil fertility was determined. So, just the parts of east of the study area were suitable for soil fertility. While almost all of the parts were not suitable for soil fertility. Also with increasing risk (no trade-off) (Figure 7 (3)) almost all of the study area had good soil fertility. The Figure 7 (4) showed low risk with average trade-off that in comparison of Figure 7 (2) had more risk.

The Figure 7 (5) showed high risk with average trade-off that in comparison of Figure 7 (3) had lower risk for determination of soil fertility. Figure 7 (6) showed average risk with no trade-off that in comparison of Figure 7 (3) had more risk (0-1).



245 **Fig 7.** OWA map were classified in eight classes

Table 4. Description of each classes for soil fertility

	Range	Description
1	0 – 0.125	Very low
2	0.125 – 0.25	
3	0.25 – 0.375	Low
4	0.375 – 0.5	
5	0.5 – 0.625	Medium
6	0.625 – 0.75	
7	0.75 – 0.875	Very high
8	0.875 - 1	

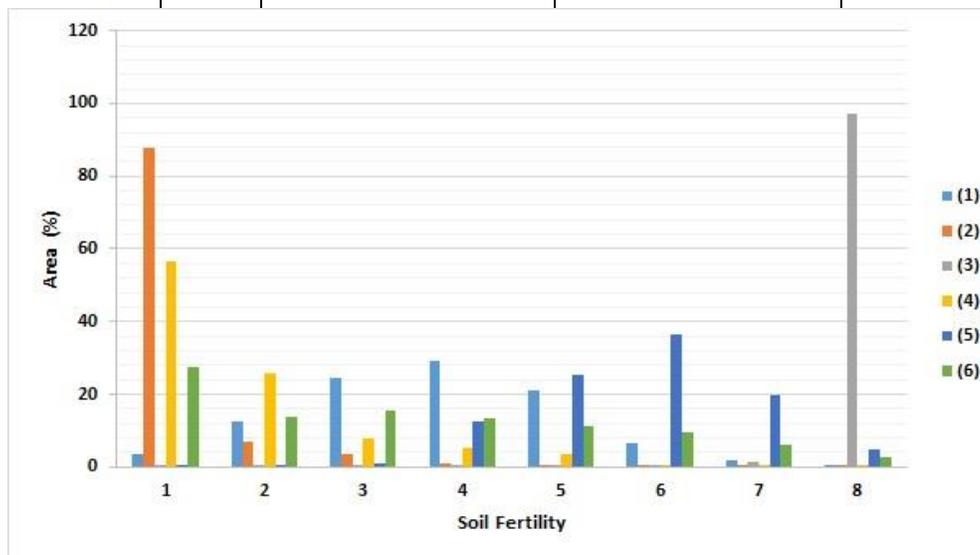


Figure 8. Area of each classes using OWA method.

250 Based on Table 5, the OWA map was classified in eight classes that are shown in Figure 8. The results in the study are similar to the results of another research by Mokarram and Aminzadeh (2010). They was used seven order weights for land suitability. They were applied corresponding to the ten factors (EC, pH, ESP, CaCO₃, Gypsum, wetness, texture, slope, depth and topography) that were rank-ordered for each parameter. Drobne and Lisec (2009) for the

255 determination of six designs with different risk level used OWA for seven factors for soil
 fertility analysis. In fact using OWA can produce an almost infinite range of possibilities for
 different designs. The newest research for different agricultural issues such as soil fertility is by
 Khaki et al. (2015), Bijanzadeh and Mokarram (2013) and Mokarram, Bardideh (2012) in
 order to determine soil fertility used fuzzy algorithm. In this research only medium risk (AHP)
 260 was used and the researchers did not check different risk levels. In the total, it is stated that
 using OWA method with difference risk levels can create several maps that can help a user (for
 example farmer) to make different decisions, according to different financial situations and
 different risk levels. For example with low risk, the farmer can select an area that has more soil
 fertility to yield maximum produce. So OWA can be applied for fields of natural science to
 265 make accurate decisions.

Table 5. Area (km²) of each classes using OWA method for soil fertility.

class	(1)	(2)	(3)	(4)	(5)	(6)
1	3.39	87.98	0.03	56.48	0.05	27.70
2	12.68	6.97	0.04	25.82	0.10	13.89
3	24.45	3.62	0.04	7.82	0.84	15.69
4	29.23	0.87	0.06	5.09	12.55	13.20
5	21.26	0.25	0.69	3.41	25.17	11.20
6	6.60	0.16	0.59	0.73	36.69	9.38
7	1.83	0.15	1.34	0.44	19.76	6.25
8	0.59	0.03	97.23	0.24	4.86	2.70

6. Conclusions

The soil fertility problem involves evaluation and classification of the areal units according to
 270 their fertility for a particular activity. So the aim of the study was the determination of produce
 the soil fertility maps according to OWA operators for GIS-based multicriteria evaluation
 procedures in southeast Iran using OWA. The OWA approach provides a mechanism for
 guiding the decision maker/analyst through the multicriteria combination procedures. OWA
 method is an important tool in the management sciences and operational researches. Types of
 275 decision rules with definitions in OWA method lead to solve semi-structured decision problems.

In order to preparing the soil fertility using OWA, first of all using IDW model was determined interpolation maps for input data such as potassium (K), phosphor (P), copper (Cu), iron (Fe), manganese (Mn), organic carbon (OC) and zinc (Zn). Then were used P, K, Cu, Fe, Mn, OC and Zn maps from IDW as input to fuzzy inference system. In order to homogenize each parameter for weightedness by OWA method for preparing the final soil fertility fuzzy method was used. The results showed that with decreasing risk (no trade-off), the area with high soil fertility was determined. So, just the parts of east and southeast of the study area were suitable for soil fertility. Also with increasing risk (no trade-off) almost all of the study area had good soil fertility. So with OWA method can prepared high maps of soil fertility with different managements.

Acknowledgements

The authors would like to acknowledge the Organization of Agriculture Jahad Fars for their assistance during the study and for providing the dataset.

References

1. Ashrafi, Kh., Shafiepour, M. Ghasemi, L. and B. NajjarAraabi. 2012. Prediction of Climate Change Induced Temperature Rise in Regional Scale Using Neural Network, *International Journal of Environmental Research* 6 (3), 677-688.
2. Asproth , V. , Holm berg, S. C. and A. Håka nsson. 1999. Decision support for spatial planning and management of human settlements', in Lasker, G.E. (Ed.): Advances in Support Systems Research, Vol. 5, *International Institute for Advanced Studies in Systems Research and Cybernetics*, Windsor, Ontario, Canada, pp.30–39.
3. Basso, B., De Simone, L., Cammarano, D., Martin, E.C., Margiotta, S., Grace, P.R., Yeh, M.L. and T.Y. Chou. 2012. Evaluating Responses to Land Degradation Mitigation Measures in Southern Italy, *International Journal of Environmental Research* 6 (2), 367-380.
4. Beedasy, J., and D. Whyatt. 1999. Diverting the tourists: aspatial decisionsupport system for tourism planning on a developing island. *Journal of Apply Earth Observ. Geoinformation*. 3/4, 163–174.

- 305 5. Belkhir, L., Boudoukha, A., and L. Mouni. 2011. A multivariate Statistical Analysis of Groundwater Chemistry Data, *International Journal of Environmental Research* 5 (2), 537-544.
6. Burrough, P.A., and R.A. McDonnell. 1998. Principles of geographical information systems. Spatial Information System and Geostatistics. Oxford University Press, New York.
- 310 7. Eastman, J. R. 1997. IDRISI for Windows, Version 2.0: Tutorial Exercises, Graduate School of Geography, Clark University, Worcester.
8. Feng, X.Y., and Luo, G.P., Li, C.F., Dai, L. and L. Lu. 2012. Dynamics of Ecosystem Service Value Caused by Land use Changes in Manas River of Xinjiang, China, *International Journal of Environmental Research* 6 (2), 499-508.
- 315 9. Fumagalli, N. and A. Toccolini. 2012. Relationship Between Greenways and Ecological Network: A Case Study in Italy, *International Journal of Environmental Research* 6 (4), 903-916.
10. Organization of Agriculture Jahad Fars province (<http://www.fajo.ir>).
- 320 11. Jiang, H., and J.R. Eastman. 2000. Application of fuzzy measures in multi-criteria evaluation in GIS. *International Journal of Geography Information System* 14, 173–184.
12. Kanokporn, K. and V. Iamaram. 2011. Ecological Impact Assessment; Conceptual Approach for Better Outcomes, *Int. J. Environ. Res.*, 5 (2), 435-446.
- 325 13. Kim, D.K., Jeong, K.S., McKay, R.I.B., Chon, T. S. and G. J. Joo . 2012. Machine Learning for Predictive Management: Short and Long term Prediction of Phytoplankton Biomass using Genetic Algorithm Based Recurrent Neural Networks, *International Journal of Environmental Research* 6 (1), 95-108.
14. Liu, X., J. Malczewski. 2013. GIS-Based Local Ordered Weighted Averaging: A Case Study in London, Ontario. Electronic Thesis and Dissertation Repository. Paper 1227.
- 330 15. Makropoulos, C., Butler, D., and C. Maksimovic. 2003. A fuzzy logic spatial decision support system for urban water management. *J. Water Resour. Plann. Manage.* 129 (1),69–77.
- 335 16. Malczewski, J. 2006. Ordered weighted averaging with fuzzy quantifiers: GIS-based multicriteria evaluation for land-use suitability analysis. *International Journal of Applied Earth Observation and Geoinformation*. 8: 270–277.

17. Malczewski, J. 1996. A GIS-based approach to multicriteria group decision making. *International Journal of Geographical Information Systems* 10(8), 955-971.
18. Malczewski, J. 1999. GIS and Multicriteria Decision Analysis. *John Wiley & Sons Inc.*, New York.
- 340 19. Malczewski, J. 2004. GIS-based land-use suitability analysis: a critical overview. *Progr. Plann.* 62 (1), 3–65.
20. Malczewski, J., Chapman, T., Flegel, C., Walters, D., Shrubsole, D., and M.A. Healy. 2003. GIS-multicriteria evaluation with ordered weighted averaging (OWA): case study of developing watershed management strategies. *Environ. Plann. A* 35 (10), 1769–1784.
- 345 21. Malczewski, J., and C. Rinner. 2005. Exploring multicriteria decision strategies in GIS with linguistic quantifiers: a case study of residential quality evaluation. *Journal of Geography System* 7 (2), 249–268.
22. Mendes, J.F.G. and W.S. Motizuki. 2001. Urban quality of life evaluation scenarios the case of são carlos in Brazil. *CTBUH Review*, 1 (2), 1–10.
- 350 23. Mokarram M., and F. Aminzadeh. 2010. GIS-based multicriteria land suitability evaluation using ordered weight averaging with fuzzy quantifier: a case study in Shavur plain, Iran. *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, Vol. 38, Part II.
- 355 24. Motiei, H., (1995). Petroleum geology of Zagros. Geological Survey of Iran., (in Farsi), Vol(1).
25. Motiei, H., (1993). Stratigraphy of Zagros. Treatise on the geology of Iran., (in Farsi), Vol(1)
- 360 26. Nejadi, A., Jafari, H.R., Makhdom, M. F. and M. Mahmoudi. 2012. Modeling Plausible Impacts of land use change on wildlife habitats, Application and validation : Lisar protected area, Iran, *International Journal of Environmental Research* 6 (4), 883-892.
- 365 27. Rasouli, S., Makhdom Farkhondeh, M., Jafari, H.R., Suffling, R., Kiabi, B. and A. R. Yavari. 2012. Assessment of Ecological integrity in a landscape context using the Miankale peninsula of Northern Iran, *Int. J. Environ. Res.*, 6 (2), 443-450.

28. Salehi, E., Zebardast, L. and A. R. Yavri. 2012. Detecting Forest Fragmentation with Morphological Image Processing in Golestan National Park in northeast of Iran, *International Journal of Environmental Research* 6 (2), 531-536.
29. Sanaee., M. FallahShamsi, S. R. and H. FerdowsiAsemanjerdi. 2010. Multi-criteria land evaluation, using WLC and OWA strategies to select suitable site of forage plantation (Case study; Zakherd, Fars). *Rangeland*, 4 (2), 216-227.
30. Shumilov, O.I., Kasatkina, E.A., Mielikainen, K., Timonen, M. and A.G. Kanatjev. 2011. Palaeovolcanos, Solar activity and pine tree-rings from the Kola Peninsula (northwestern Russia) over the last 560 years, *International Journal of Environmental Research* 5 (4),855-864.
31. Soufi M. 2004. Morpho-climatic classification of gullies in fars province, southwest of i.r. iran . International Soil Conservation Organisation Conference – Brisbane.
32. Yager, R.R. 1988. On ordered weighted averaging aggregation operators in multi-criteria decision making. *IEEE Trans. Syst. Man Cybernet.* 18 (1), 183–190.
33. Yager, R.R. 1996. Quantifier guided aggregation using OWA operators. *Int. J. Intell. Syst.* 11, 49–73.
34. Drobne, S., Lisec A. 2009. Multi-attribute Decision Analysis in GIS: Weighted Linear Combination and Ordered Weighted Averaging. *Informatica* 33 (2009) 459–474.
35. B. Delsouz Khaki, N. Honarjoo, N. Davatgar, A.Jalalian, H. Torab. 2015. Soil Fertility Evaluation Using Fuzzy Membership Function (Case Study: Southern Half of Foumanat Plain in North of Iran). *Allgemeine forst undjagdzeitung.* 53-64P.
36. Mokarram M, Bardideh M. 2012. Soil fertility evaluation for wheat cultivation by fuzzy theory approache and compared with boolean method and soil test method in gis area. *Agronomy journal (pajouhesh & sazanegi).* Volume 25 , number 3 (96); page(s) 111 - 123.
37. Bijanzadeh E, Mokarram, M. 2013. 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. *AUSTORALIUN journal of crop science.* 7(11):1699-1706

395

Figure captions

Figure 1. Location of the study area (digital elevation model (DEM) with spatial resolution of 30 m) (Source: <http://earthexplorer.usgs.gov>).

Figure 2. Position of sample points for the study area.

Figure 3. Interpolation map using IDW method. (a):Cu; (b):Fe; (c):K; (d):Mn; (e):OC; (f):P; (g): Zn.

Figure 4. Fuzzy map of studied area for each soil fertility parameter. (a):Cu; (b):Fe; (c):K; (d):Mn; (e):OC; (f):P; (g): Zn.

Figure 5. Decision-strategy space and typical sets of order weights (see Table 3)

Figure 6. Soil fertility maps of OWA results for selected fuzzy linguistic quantifiers

Figure 7. Classification of OWA map for soil fertility.

Figure 8. Area of each classes using OWA method.