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Original article

Combination of fuzzy-AHP and GIS techniques in land suitability assessment for wheat (*Triticum aestivum*) cultivation

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ABSTRACT

Land suitability classification is a useful management practice to ensure planned and sustainable use of agricultural lands according to their potentials. The main purposes of this study were to analyze land suitability for bread wheat (*Triticum aestivum*) cultivation and generate a land suitability map for wheat by integrating the analytical hierarchy (AHP)-fuzzy algorithm with the Geographical Information System (GIS) in the Tozanlı sub-basin located in the upper part of Yeşilırmak Basin, Turkey. Topographic (elevation, slope, aspect) characteristics of the basin and some of physical and chemical properties of soils (texture, pH, electrical conductivity, lime, organic matter, and soil depth) were used as criteria in determining the suitability classes. Ninety-two disturbed soil samples were collected from 0 to 20 cm depth in October 2017 using random sampling method. Weighted overlay spatial analysis in GIS was used to combine different thematic layers to identify areas suitable for wheat production. The fuzzy-AHP suitability assessment model was adapted to determine the weights for topographic and soil properties. The highest specific weights were obtained for soil depth (0.232) and elevation (0.218), while the lowest weight was calculated for aspect (0.042). Highly, moderately, and marginally suitable lands for wheat cultivation cover 2.63, 9.85 and 32.59% of the study area, respectively. In addition, the results indicated that 54.92% of the total area is permanently unsuitable for wheat cultivation. The results revealed that integration of AHP-fuzzy algorithm and GIS techniques is a useful method for accurate evaluation of land suitability in planning for specific crop production and decreasing the negative environmental impacts of agricultural practices.

1. Introduction

The need for natural resources has increased in the 21st century to meet the increasing food and fiber demand of rapidly increasing world population. Global climate change, inappropriate land uses and pressure to meet the increasing food and fiber demands are significantly threatening the global agricultural production and food security (IPCC, 2013; Kilic and Gunal, 2021). Many developed and developing countries have recently realized the importance of the problems and modified their agricultural policies to conserve and appropriate use of their agricultural lands (Ramamurthy et al., 2020). Therefore, the main goal of new policies is to ensure the sustainability in agricultural production (Dengiz, 2013; Zhang et al., 2015). The accurate assessment of land suitability for various uses is vital in transferring the productive lands to future generations for their food and fiber productions (Sharma et al., 1994).

A prerequisite for land use plans is the assessment of land suitability, which allows to determine the most appropriate uses of lands (Akinci et al., 2013). Land suitability analyses are carried out to determine the potential of a land for different uses based on specific requirements and preferences of a land use type (Akbulak, 2010). Land use planning is necessary not only for agricultural lands, but also for many socio-economic alternative pur-

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poses such as the selection of settlements, road construction, national parks, recreation areas and factory construction areas (Al-shalabi et al., 2006). Land planning, which is the reorganization of resources in the environment to create more efficient land use patterns (FAO, 1976), has two important issues. The first one is to use the natural resources in the most beneficial mean to people, and the second one is to conserve the resources for the future generations (Cengiz and Akbulak, 2009). Therefore, a thorough understanding of the natural environment and the contemplated land use patterns are essential in planning. Otherwise, natural resources may be degraded or land use attempts may fail due to the ignorance of interrelationship between land suitability and land use pattern. One function of land suitability assessment is to compare the most promising land use types, and present them to planners (Dedeoğlu and Dengiz, 2019; Tashayo et al., 2020). In this process, main soil, climate, vegetation, and other land characteristics are evaluated in terms of suitability to different land use patterns. The suitability of land use patterns to physical, economic, and social structure of the land is compared in land use planning. In addition, economic suitability of the land use patterns is also taken into account in land use planning (Duc, 2006; Fao, 1976). In this context; land suitability assessment should naturally be treated as a multi-criteria process (Dengiz and Sarioğlu, 2013).

Evaluation of more than one criterion, which includes different qualitative and quantitative information, for an aim is expressed as the "Multi-Criteria Decision Making (MCDM)" process (Timor, 2011). The MCDM helps to determine the most logical choice in evaluating many parameters and analyze the relationships between these parameters. Because, every criterion is not of equal importance, and the contribution of each criterion to suitability is at different levels (Prakash, 2003). Land suitability evaluation contains more than one environmental component, and these components have complex relationships among them, therefore, the MCDM approach was preferred in this study. The Analytical Hierarchy Process (AHP), which uses pairwise comparison technique, is one of the MCDM methods developed by Saaty (1980), and have been widely used in different parts of the world (Akinci et al., 2013; Dengiz and Usul, 2018; Mandal and Mondal, 2018; Mandal et al., 2020; Pramanik, 2016; Yalew et al., 2016). Each criterion is compared by assigning a degree of importance between 1 and 9 (Saaty, 1988). The comparisons expressed with a single value may not be sufficient in uncertain cases (Kuo et al., 2006). Land suitability assessments also require integrating various levels of expert knowledge at the decision stage. However, an expert at the decision stage may not always be sure, and uncertainties in case of no definite judgments can be handled better by using fuzzy logic (Prakash, 2003). Fuzzy logic, introduced by Zadeh (1965), is a proposed method to overcome uncertainties and imprecise issues in judgment (Elaalem et al., 2011). In this context, fuzzy logic theory is combined with AHP to ensure a more accurate decision-making process (Huang et al., 2008; Ustaoglu et al., 2021; Zhang et al., 2021). Spatial evaluations can also be carried out by using multi-criteria decision analysis (MCDA) with geographic information systems (GIS). The MCDA integration with GIS is an excellent spatial analysis tool that allows the preparation of a comprehensive spatial database to be used by multi-criteria methodologies in land evaluation and suitability analysis and allows the user to evaluate different alternatives on the basis of multiple and conflicting objectives (Orhan, 2021; Saha et al., 2021). Appropriate decisions in disaster management (Ofluoğlu et al., 2017), solid waste storage area (Çeliker et al., 2019), and wind-solar energy installation land (Mevlüt, 2017), and assessment of conservation areas (Görmüş, 2012) were taken by using MCDA and GIS methods. In addition to aforementioned advantages, suitable areas to agricultural production can also be determined using the combination of MCDA and GIS methods (Dengiz et al., 2015; Mohammed et al., 2020; Özkan et al., 2020; Pilevar et al., 2020; Saha et al., 2021; Ustaoglu et al., 2021).

Wheat is the field crop with the largest cultivation area (217 million hectares), the largest production after corn and rice (776 million tons), and also the most traded crop (189 million tons) in the world (FAOSTAT, 2021). Wheat, which meets >20% of daily calorie needs of people, has the highest carbohydrate and protein content among the cereals (Peng et al., 2011). Wheat is used in nutrition as the basic food item in Turkey as well as in the whole world. The wheat is also used as a raw material in other agricultural industries, and creates added value for the economy (Atak, 2017). The latest data indicated that wheat is the field crop with the largest cultivation area (6.8 million ha) and production (19 million tons) in Turkey (FAOSTAT, 2021). By the middle of the 21st century, the production of annual 642 million tons of wheat should be increased to 840 million tons to meet the need of increasing world population (Sharma et al., 2015). In this respect, land suitability analyzes are needed to ensure efficient and sustainable wheat supply from agricultural lands, which are the limited natural resources (Bodaghabadi et al., 2015; El Baroudy, 2016; Mohammed et al., 2020). The most comprehensive study that spatially mapped the production capacities of lands in Turkey was prepared by the General Directorate of Soil-Water between 1966 and 1972 (Doğan et al., 2013). These maps with 1/25000 scale were prepared in paper format with great soil group levels and their important phases classified according to 1938 American soil classification system. The inclusion of only land capability classes on the productivity of lands in these maps is not sufficient for evaluating land capacity for land use alternatives. Therefore, alternative land evaluation methods are needed to increase the production of agricultural crops, especially wheat production in Turkey (Dedeoğlu and Dengiz, 2019). In this context, this study focused on analyzing land suitability to wheat cultivation, and generate a land suitability map for wheat by integrating the AHP-Fuzzy algorithm with GIS in the Tozanlı sub-basin located in the upper part of the Yeşilırmak Basin, Turkey.

2. Material and methods

2.1. Study area

Tozanlı basin is located between 36̊40′- 37̊50′ East latitudes and 40̊10′ – 40̊20′ North longitudes in Tokat and Sivas provinces of Turkey (Fig. 1). The total surface area of the basin is 2364 km^2, and the altitude varies between 774 and 2703 m, while the average altitude is 1488 m. The annual average temperature and precipitation are 10.7 °C and 481 mm, respectively. Paleozoic aged schist, marble, crystallized limestone and metabasite rocks, which are called Tokat metamorphic, compose the majority of geological formation. Haydaroglu formation, which includes Lutetian conglomerate, sandstone, mudstone, limestone and volcanic rocks are the other common geological formations in the study area. In addition, the Artova ophiolite complex formed by basic, ultrabasic, volcanic and sedimentary rocks; Almus formation consisting of conglomerate, sandstone, mudstone, marine limestone; Doğanşar formation consisting of sandstone, conglomerate, clayey-sandy limestone and tuffite, agglomerate, andesite, basalt rocks and Boztepe formation consisting of conglomerate, sandstone, shale pelagic and neritic limestone are found in the area. Common soil types in the basin are Eutric Cambisols, Calcic Cambisols, Lithosols, Calcaric Regosols and Calcic Xerosols (FAO, 1990).

2.2. Methodology

Most of the mathematical methods used in determining the suitability of lands use different evaluation criteria when deciding

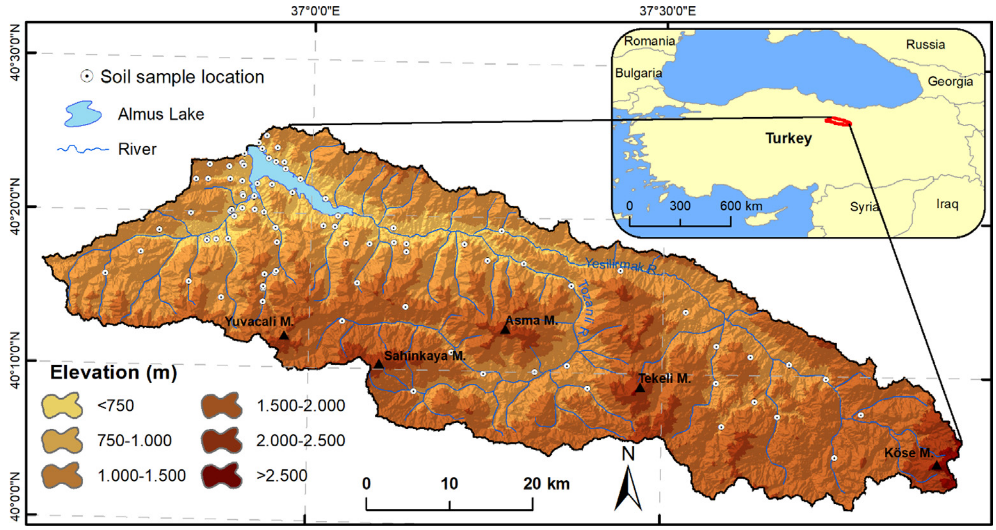

Fig. 1. Location of the Tozanlı basin.

the suitability of a land. In this study, GIS-based analysis was adapted to determine suitable areas for wheat production in the Tozanlı Basin. The integration of GIS and MCDA methods provides powerful spatial analysis functions for suitability analysis due to the ability to process and analyze different layers of spatial data (Kumar and Jhariya, 2015). The weights for topographic and soil properties were determined using the fuzzy-AHP suitability assessment model proposed by Tashayo et al. (2020). Different thematic layers were combined using weighted overlay spatial analysis in GIS to identify areas suitable for wheat production. The flowchart of the process used in the study is shown in Fig. 2.

Nine different parameters consisting of topographic (slope, elevation, aspect, soil depth) and physical and chemical soil properties (electrical conductivity (EC), pH, organic matter, soil texture, and calcium carbonate) were used to determine the suitability of lands for wheat cultivation. These thematic parameters were divided into subclasses considering the land requirements of wheat production (Table 1). The weights for subclasses were determined accordance to local field conditions and expert opinions. The parameters used, the creation of databases and the determination of weights for main parameters using the fuzzy-AHP process were explained in the relevant section.

2.3. Preparation of topographic parameters

Topography of the Tozanlı basin is an important limiting factor for agricultural production, as lands have a fractured and sloppy structure. Many environmental factors such as soil water content, precipitation, radiation, evaporation, and temperature which vary with altitude and aspect, are important factors in crop yield, growth and distribution. Therefore, topographic parameters were included in the analysis to determine the suitable areas for agricultural production. Data sets of topographic parameters were obtained from ALOS Global Digital Elevation Model (DEM) with 10×10 m resolution. Slope and aspect maps were also produced from the DEM data. Slope is an important topographic factor in soil formation, and the increase in slope causes problems in irrigation and mechanization facilities (FAO, 1976). In addition, high slope causes soil erosion, removal of fertile topsoil and land degradation; therefore, is considered as a limiting parameter in the suitability assessment.

Plants need sunlight to sustain development of root and vegetative parts, flowering and photosynthesis and to produce the highest yield (Bajracharya et al., 2013). In this regard, most cultivars optimally grow in south- and west-facing lands. Since the aspect of a land has a significant impact on plant growth, the aspect was used as a parameter in determining suitable lands for wheat production. Slope and aspect parameters were classified considering the conditions of the study area and the requirement of wheat plants (Table 1).

2.4. Soil parameters

Soil depth is one of the most important criteria for hydrological dynamics of soils and plant growth (Hirzel and Matus, 2013; Rhoton and Lindbo, 1997), and thus soil depth was used as a land

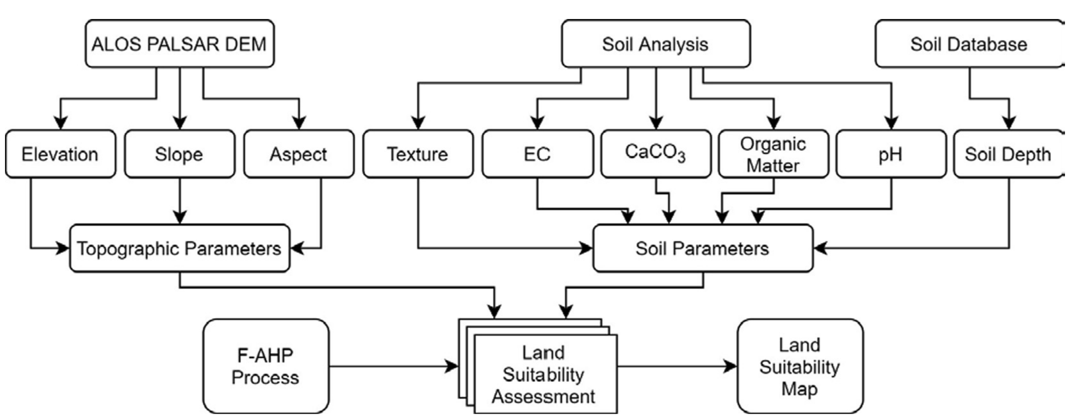

Fig. 2. Process diagram of the methods used in the study.

Table 1
Subclasses and weight scores of parameters.

Criteria	Sub-criteria	Sub-criteria Weight	Criteria	Sub-criteria	Sub-criteria Weight
Depth	Deep	10	**Slope (°)**	0–2	10
	Moderately Deep	7		2–5	8
	Shallow	3		5–10	5
	Very shallow	1		10–40	2
	Wetland and Stoniness surface	0		> 40	0
Elevation (m)	774–1000	7	**Organic Matter**	0–1	2
	1000–1250	5		1–2	4
	1250–1500	3		2–4	6
	> 1500	1		> 4	8
Texture	Clay	4	**$CaCO_3$**	0–5	6
	Sandy Clay Loam	9		5–15	9
	Clay Loam	6		15–25	7
	Silt Loam	7		> 25	2
	Loam	7	**pH**	6 – 7.5	9
	Sand	1		7.5 – 8.2	6
	Loamy Sand	2		> 8.2	1
	Sandy Loam	2	**Aspect**	S, SE, SW	9
	Gravel, massive clay, pit	0		W, E	7
EC	0–250	9		NE, NW	4
	250–500	9		N	2
	>500	8			

suitability indicator for wheat production. The soil depth information of the study area was obtained from the soil database produced by Turkey Village Services (Anonymous, 1970). Ninety-two soil samples were collected in October 2017 to determine physical and chemical soil criteria used in land suitability assessment. Random sampling method was used to collect soil samples, and geographical coordinate of each location was recorded. Particle size distribution, pH, EC, organic matter, and calcium carbonate content of soil samples were determined for land suitability assessment.

Soil texture is considered an important basic soil property due to the effect on structure, water holding capacity, infiltration, aeration etc. (Abdelrahman et al., 2016; Elsheikh et al., 2013). Therefore, soil texture classes were evaluated as the criteria in land suitability classification. The optimum soil texture class for wheat production is specified as loam (Ahmed et al., 2016). The texture was determined by the Bouyoucos hydrometer method (Bouyoucos, 1951). Soil reaction (pH) is defined as the negative logarithm of H^+ ions in soil solution, and greatly influences nutrient uptake, crop production and soil chemistry. The soil pH is an important measure in assessing the potential availability of nutrients and toxic elements to plants. The optimum pH value for wheat production is 6.8 and wheat grows appropriately in the pH range of 6 and 7.5. Therefore, soil pH was also considered as the basic soil criterion in the land suitability analysis. The pH of soil samples was measured with a glass electrode Neel pH meter in a 1:2.5 soil–water solution (Jackson, 1958). The EC indicates the amount of total soluble ions in soil solution, and is used as the indicator of salinity (Richards, 1954). Soil salinity is a limiting factor for plant growth especially in arid and semi-arid climatic regions. Therefore, the EC is considered an important soil quality indicator and was used in the land suitability analysis. The EC of soil samples was determined by a conductivity meter in 1:2.5 soil–water solutions (Richards, 1954).

Soil organic matter is an important factor that regulates many physical, chemical and biological processes in soils. Soil organic matter enhances formation of soil aggregates, and therefore, regulates infiltration rates and water holding capacity. Soil organic matter supplies nutrients and energy to microorganisms, and also acts as a nutrient storage for plants (Zdruli et al., 2004). Therefore, organic matter content of soils was used as a land suitability criterion. The organic matter content was determined as percent (%) by the modified Walkley–Black method (Nelson and Sommers, 1983). Calcium carbonate (lime) content of soils was also used as a land suitability criterion. The availability of phosphorus, which is an essential nutrient for plants, especially in soils with high lime content, decreases due to the formation of calcium phosphates (Margenot et al., 2018). Soils in the study area are calcareous and very calcareous, therefore, lime content was used as an important criterion for wheat production. Lime content of soils was determined as percentage (%) by Scheibler calcimeter (Allison and Moodie, 1965).

Empirical semivariograms were constructed for each of indicator, and model variograms of indicators were constructed using the GS + 7.0 software. The abnormal distribution of a parameter negatively affects the accuracy of prediction. Therefore, normality of parameters was checked before analyzing the spatial variability. The parameters with abnormal distribution were subjected to square root and logarithmic transformations to normalize the distribution. Kriging was used to express the spatial variation and to minimize the errors of predicted values. The empirical semivariogram was calculated using Eq. (1) (Webster and Oliver, 2001).

$$\Upsilon(h) = \frac{1}{2N(h)}\sum_{i=1}^{N(h)}[Z(x_i) - Z(x_i + h)]^2 \quad (1)$$

where; Z(xi) is the value of soil properties at the location of xi, ϒ(h) is the variogram for a lag distance h between Z(xi) and Z(xi + h), and N(h) is the number of data pairs separated by h distance, respectively.

The best fit model was selected based the R^2 of the model and the Residual Sum of Squares (RSS) value, which is the indicator of measurement errors. The models with a R^2 value close to 1.0 and RSS value close to zero were selected as the best fit models (Budak and Acir, 2019). Spatial distribution maps of parameters were produced by ordinary kriging method using ArcGIS 10.3.1.

2.5. Weight for criteria maps

Different fuzzy numbers can be used depending on the nature of study. Triangular fuzzy numbers were preferred in this study because of their simplicity in the calculation and their usefulness in expressing and processing fuzzy logic (Ertuğrul and Karakaşoğlu, 2008). Triangular fuzzy numbers are a special class of fuzzy numbers defined by three real numbers, usually *l, m, and u*. In a defined triangular fuzzy number, *l* represents the lower limit, *u* represents the upper limit, and *m* is the possible value (Deng, 1999; van Laarhoven and Pedrycz, 1983). Basic fuzzy arithmetic should be used in arithmetic calculations where evaluations are expressed with fuzzy numbers. Basic arithmetic calculations for triangular fuzzy number were done as stated in Deng (1999).

Different methods have been proposed to integrate fuzzy logic and AHP (Buckley, 1985; Chang, 1996; Deng, 1999). In this study, geometric mean method introduced by Buckley (1985) was used to combine both methods. This method was applied considering the process steps explained by Hsieh et al. (2004):

Step 1: A comparison matrix was created with linguistic expressions based on the importance among the criteria. Triangular fuzzy numbers were created during comparisons by considering the table introduced by Gumus (2009) (Table 1).

$$A = \begin{bmatrix} 1 & a_{12} & \cdots & a_{1n} \\ a_{21} & 1 & \cdots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{n1} & a_{n2} & \cdots & 1 \end{bmatrix} = \begin{bmatrix} 1 & a_{12} & \cdots & a_{1n} \\ 1/a_{12} & 1 & \cdots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ 1/a_{1n} & 1/a_{2n} & \cdots & 1 \end{bmatrix}$$

where;

$$a_{ij} = \begin{cases} 1,2,3,4,5,6,7,8,9 \\ 1 \\ 1^{-1},2^{-1},3^{-1},4^{-1},5^{-1},6^{-1},7^{-1},8^{-1},9^{-1} \end{cases}$$

criterion i is relative importance to criterion j
i = j
criterian i relative less importance to criterion j

Step 2: Geometric mean is used to determine the fuzzy geometric mean and fuzzy weights of each criterion.

$$r_i = (a_{i1} \otimes a_{i2} \otimes \cdots \otimes a_{in})^{1/n} \quad (2)$$

$$w_i = r_i \otimes (r_1 \oplus \cdots \oplus r_n)^{-1} \quad (3)$$

where a_{in}, is the fuzzy value of the i criterion when compared to the n criterion. In this case, r_i, represents the geometric mean of the fuzzy values produced by comparing the criterion i with each other criterion. w_i indicates the fuzzy weight of the i criterion. This w_i value consists of triangular fuzzy numbers ($w_i = (lw_i, mw_i, uw_i)$).

Step 3: The weight values obtained for each criterion consist of triangular fuzzy numbers as explained in the second step. These fuzzy numbers are defuzzified and a single value (crisp) was obtained for each criterion. Thus, the Best Non-Fuzzy Performance Value (BNP) was obtained. This value represents the weight of the criterion. For this purpose, the center of area (COA) method was used. Compared to other methods (mean of maximal (MOM) and α-cut used for clarification), the COA is a simple and practical method (Chen et al., 2008), therefore, preferred in this study. The equation used to calculate the BNP with COA is given below (Opricovic and Tzeng, 2003):

$$BNP_i = lw_i + \frac{(uw_i - lw_i) + (mw_i - lw_i)}{3} \quad (4)$$

2.6. Land suitability assessment

Suitable areas for wheat production in the Tozanlı Basin were determined using thematic maps produced and classified for the parameters and the weights determined by the fuzzy-AHP method. The following equation was used in the production of wheat suitability map (Eq. (5)).

$$LSI = \sum_{i=1}^{n} (Wi.Xi) \quad (5)$$

where LSI expresses the land suitability value. Wi is the weight of a parameter; Xi represents the weight of the subclasses within a parameter (Cengiz and Akbulak, 2009; Pramanik, 2016). The Eq. (5) was adapted to the thematic maps in GIS, which allows the integration of different spatial parameters, and suitable areas for wheat production were determined in the study area. Land suitability for wheat production was assessed based on the methodology given in the FAO land assessment framework (FAO, 1976). Each land was assessed as suitable or unsuitable for the land use type. The suitable class was classified as highly suitable (S1), moderately suitable (S2), and marginally suitable (S3). Not suitable class was divided into two classes as not suitable for economic reasons (N1) and not suitable for physical reasons (N2). The process of assessing land suitability for wheat production involves matching the wheat plants requirements with the characteristics of the particular land unit. The LSI values obtained in the MCDA and GIS processes were divided into 4 classes: areas with land suitability values between 6 and 9 are highly suitable (S1), areas between 5 and 6 are moderately suitable (S2), areas between 4 and 5 are marginally suitable (S3), and the areas between 3 and 4 are unsuitable (N) classes (see Table 2).

3. Results

3.1. Evaluation of topographic parameters

Spatial distribution maps (Fig. 3) of topographic parameters (elevation, slope, aspect) used to evaluate land suitability were produced and coverage area of their spatial distributions were calculated (Table 3). Mountainous areas and hilly lands are dominant in the Tozanlı basin where the altitude varies between 774 m and 2703 m. The areas where the elevation is higher than 1500 m cover approximately 50% of the study area.

The classes with low elevations do not occupy large areas in the basin. The areas with the lowest elevation, which was between 774 and 1000 m, cover only 9.92% (231.85 km^2) of the basin. Areas with low elevation in the basin correspond to valley bottoms and slopes developed due to gully erosion by streams. Fluvial processes also control the slope in the study area. Flat areas (slope between 0 and 5%) correspond to only 20.85% of the basin (487.49 km^2). The slope in the remaining lands which covers approximately 80% of the basin is >5%. Steep slopes with a slope between 10 and 40% constitute the most widespread slope class, covering 61.95% of the basin (1448.37 km^2). Approximately 5% of the basin consists of steep slopes (>40%). The classes for slope aspects formed by the deformation of topography by external factors are given in Table 3. South facing slopes (S, SE, SW), and flat (F) areas cover 38.77% (906.55 km^2) of the basin, and followed by east and west facing (692.34 km^2 – 29.61%), north facing (386.95 km^2 – 16.55%) and northwest-northeast facing (352.23 km^2 – 15.07%) slopes.

Table 2
Fuzzy comparison measures.

Linguistic terms	Fuzzy number	Triangular fuzzy numbers
Perfect	9	(8,9,10)
Absolute	8	(7,8,9)
Very good	7	(6,7,8)
Fairly good	6	(5,6,7)
Good	5	(4,5,6)
Preferable	4	(3,4,5)
Not bad	3	(2,3,4)
Weak advantage	2	(1,2,3)
Equal	1	(1,1,1)

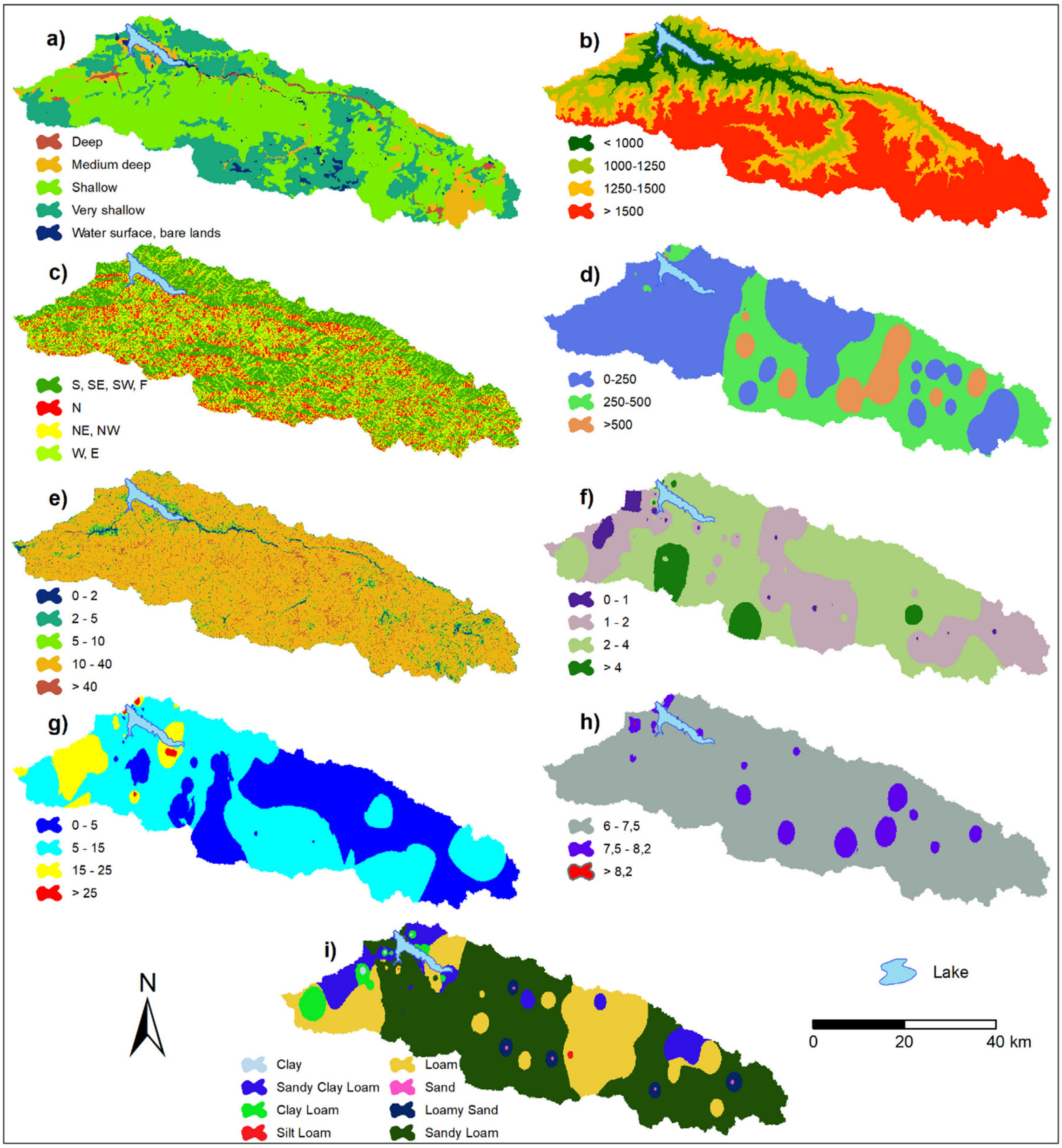

Fig. 3. Soil and topography parameters used in the suitability analysis for wheat production in the Tozanlı basin. a) soil depth, b) elevation, c) aspect, d) EC, e) slope, f) organic matter, e) $CaCO_3$, f) pH, i) texture.

3.2. Soil characteristics in the study area

Descriptive statistics of soil properties are given in Table 4. The clay content of soils varied between 1.25 and 46.25%, with an average of 18.62%. The silt content varied between 7.50 and 55%, with an average of 26.76%. The sand content varied between 23 and 88% with and average value of 54.63. The pH values ranged between 6.40 (slightly acidic) and 8.30 (slightly alkaline), with an average pH value of 7.26 (neutral). Soil pH is generally optimum for wheat production. The EC values varied between 70 and 1000 mmhos, which indicate that the soluble salt content in the basin is very low. Organic matter content of soils varied between 0.07 and 7.94%, with an average value of 2.40. The lime content ranged from 1.66% (low) to 41.06 (very calcareous), with an average of 10.81%.

The variability of soil properties within a field or a larger area is classified based on CV values Wilding (1985). The variability of a soil property is considered high, moderate or low when the CV is higher than 35%, between 15% and 35%, and <15%, respectively. Soil pH vales are the only soil property with low variability, while silt and sand contents had moderate variability and clay, EC, organic matter and lime contents had high variability. The differences in parent materials, high variability of the topography, as well as the differences in land uses caused high variability in soil properties.

Table 4 reveals that clay, sand, and pH (0.61,-0.13, 0.45) had normal distribution; however, silt, EC and lime had non-normal distribution (1.35, 3.89, 1.05, 1.52). Silt, organic matter and lime were transformed by square root transformation, whereas EC was transformed by log transformation technique. Table 5 reveals that different soil properties has significant correlations $p < 0.05$ *ve* $p < 0.01$. The individual soil properties were highly correlated as expected and sand and clay exhibitd the strongest correlation ($p < 0.01$; r:-0.81). Budak et al. (2018) reported positive correlation among pH and $CaCO_3$. The correlation among pH and $CaCO_3$

Table 3
Spatial Data of Parameters Used in Land Suitability Assessment for Wheat Production.

Sub-criteria classes	Area		Sub-criteria classes	Area	
	km^2	%		km^2	%
Depth			**Slope**		
Deep	30.33	1.30	0–2	326.73	13.97
Medium Deep	147.58	6.31	2–5	160.76	6.88
Shallow	1338.49	57.25	5–10	284.95	12.19
Very shallow	748.73	32.02	10–40	1448.37	61.95
Water and Bare	72.95	3.12	> 40	117.27	5.02
Elevation			**Organic Matter**		
774–1000	231.85	9.92	0–1	43.04	1.84
1000–1250	417.12	17.84	1–2	815.12	34.86
1250–1500	525.18	22.46	2–4	1344.50	57.50
> 1500	1163.92	49.78	>4	135.41	5.79
Texture			**CaCO3**		
Clay	2.53	0.11	0–5	892.14	38.16
Sandy Cl.	192.46	8.23	5–15	1273.82	54.48
Clay Loam	60.00	2.57	15–25	165.96	7.10
Silt Loam	1.83	0.08	> 25	6.14	0.26
Loam	619.89	26.51	**pH**		
Sand	2.11	0.09	6–7.5	2194.91	93.88
Loamy Sand	41.97	1.79	7.5–8.2	142.91	6.11
Sandy Loam	1417.28	60.62	> 8.2	0.25	0.01
Aspect			**EC**		
S. SE. SW. Flat	906.55	38.77	0–250	1255.86	53.71
W. E	692.34	29.61	250–500	871.35	37.27
NE. NW.	352.23	15.07	>500	210.85	9.02
N	386.95	16.55			

Table 4
Descriptive statistics of soils.

Properties	Unit	Min	Max	Mean	Std. dev.	CV	Skewness
Clay	%	1.25	46.25	18.62	10.65	57.21	0.61
Silt		7.50	55.00	26.76	7.48	27.93	1.35
Sand		23.00	88.00	54.63	12.82	23.47	−0.13
pH		6.40	8.30	7.26	0.35	4.77	0.45
EC	mmhos cm^{-1}	70.00	1000.00	190.00	156.01	82.11	3.89
Organic matter	%	0.07	7.94	2.40	1.60	66.73	1.05
Lime		1.66	41.06	10.81	8.82	81.64	1.52

($p < 0.01$) was parallel to earlier reports. The significant positive/negative correlations at $p < 0.05$ were noted among $CaCO_3$ and clay (0.287) pH and sand (0.288), organic matter and sand (-0.263) and organic matter and clay (0.268). Similarly, EC and pH (0.319) were also had significant positive correlation.

3.3. Geostatistical analysis of soil properties

The parameters of the geostatistical models for soil properties are given in Table 6. All soil properties had an anisotropic semivariogram. Exponential model was the best to predict clay content and pH values, and linear model was the best for organic matter and lime contents. The sand and silt content and EC values semivariograms were well-described by spherical model. Spatial dependency, which is the ratio of nugget (Co) semivariance to sill (Co + C), was used to express the extent of the spatial changes within the study area. The spatial dependence value of ≤25% indicates a strong degree of dependence, a value between 25 and 75% indicates a moderate degree of dependence, and a value of >75% indicates a weak degree of spatial dependence (Cambardella et al., 1994). Organic matter (13.12%) content had strong spatial dependence, and lime (30.81%) and silt (50.10%) contents showed moderate spatial dependence, while other soil properties had a weak spatial dependence. Strong spatial dependence indicates a continued similarity between samples even over long distances.

Range values of clay, silt, pH, organic matter and lime were 3022, 4648, 5907, 5824, 9302 m, respectively. After semivariogram models were created for soil properties, spatial distribution maps were prepared using the ordinary kriging method. The soil maps prepared were reclassified for suitability analysis using the classes

Table 5
Correlation coefficients between soil properties.

	Clay	Silt	Sand	pH	EC	OM
Clay	1					
Silt	−0.031	1				
Sand	−0.813**	−0.557**	1			
pH	0.045	0.034	−0.057	1		
EC	0.086	0.061	−0.107	0.319*	1	
OM	0.268*	0.070	−0.263*	−0.181	,041	1
$CaCO_3$	0.287*	0.085	−0.288*	0.329**	−0.168	−0.034

* : significant at p < 0.05, **: significant at p < 0.01

Table 6
Parameters of semivariogram models calculated for soil properties.

Soil Prop.	Model	Nugget (Co)	Sill (Co + C)	Spatial Dependence	Range (m)	R^2	RSS	Dispersion pretreatment
Clay	Exponential	0.0130	1.626	99.20	3022	0.826	0.51	Normal
Silt	Gaussian	0.400	0.801	50.10	4648	0.277	0.194	Square root
Sand	Spherical	76.00	562.9	86.50	9321	0.732	1.512	Normal
pH	Exponential	0.093	0.483	80.71	5907	0.931	4.687E-04	Normal
EC	Spherical	0.195	1.045	81.30	1953	0.874	0.012	Log.
OM	Linear	0.105	0.106	13.12	5824	0.941	4,479E-03	Square root
$CaCO_3$	Linear	0.518	0.748	30.81	9302	0.631	0.068	Square root

in Table 1, considering wheat growth requirements (Fig. 3). The range values in a semivariogram model represents the maximum distance of autocorrelation, and beyond this distance the autocorrelation is not exist among variables. The distance with the highest autocorrelation (9321 m) was calculated for sand content. The range value of sand content can be attributed to the widespread distribution of sandstone, conglomerate, clayey sandy limestone parent materials in the basin and also the high sand content of agricultural lands found over large alluvial terraces located on the edges of stream beds. The EC values had the shortest range value (1953 m). Similarly, Emadi et al. (2008) also reported that the range value of EC values was shorter compared to the range values of other soil properties. The short range value of EC is related to the low salt content of parent materials and similar climatic characteristics throughout the study area (Budak et al., 2018).

3.4. Effects of parameters used in land suitability

The weights expressed with the quantitative values were obtained by using the MCDA process over the topography and soil parameters to calculate the suitable places for wheat cultivation in the basin. The fuzzy-AHP method was used to determine the weights of nine environmental components determined in the study area. The pairwise comparison matrix contains the opinions of experts. In this decision-making process, the comparison matrix, which is the first step of fuzzy-AHP, was created by considering Table 2 (Table 7).

The r_i values were calculated following the comparison matrix table. Eq. (2) was used for this calculation. For example, the calculation of r_i for the slope parameter is as follows:

$$r_i = \left(1 \times \frac{1}{4} \times \frac{1}{3} \times \frac{1}{4} \times 2 \times 2 \times 1 \times 3 \times 2\right)^{\frac{1}{9}},$$
$$\left(1 \times \frac{1}{3} \times \frac{1}{2} \times \frac{1}{3} \times 3 \times 3 \times 1 \times 4 \times 3\right)^{\frac{1}{9}},$$
$$(1 \times 1/2 \times 1 \times 1/2 \times 4 \times 4 \times 1 \times 5 \times 4)^{1/9}$$
$$= (0.93, 1.22, 1.63)$$

The w_i values were calculated by the r_i values using Eq. (3). For example, the value of w_i for the slope parameter was calculated as follows:

$$w_i = (0.93, 1.22, 1.63) \times \Big(\frac{1}{1.63 + 3.23 + 3.45 + 1.61 + 0.77 + 0.86 + 1.90 + 0.90 + 0.67},$$
$$\frac{1}{1.22 + 2.46 + 2.65 + 1.17 + 0.54 + 0.59 + 1.49 + 0.59 + 0.42},$$
$$\frac{1}{0.93 + 1.79 + 1.79 + 0.79 + 0.39 + 0.43 + 1.13 + 0.41 + 0.32}\Big)$$

The w_i for slope parameters was calculated as w_i=(0.062, 0.110, 0.204). This value is a triangular fuzzy number. At this stage, the BNP value was calculated by performing the defuzzification process using the COA method given in Eq. (4):

$$BNP_i = 0.062 + \frac{(0.204 - 0.062) + (0.110 - 0.062)}{3}$$

Since the weight sum of the criteria should be 1, the BNP values for the parameters used were calculated and defuzzification was carried out normalize the values. The weights calculated were given in Table 8. The weight values indicated that depth (0.232) is the parameter of highest importance.

The second most important parameter is the altitude (0.218) that is one of the topographic factors. Especially in the mountains, 0.5 °C decrease in air temperature with every 100 m elevation causes a delay of up to six days in vegetation period and flowering (Atalay, 2006). Thus, areas with lower altitudes received higher weight scores, which played an important role in determining suitable lands. Since the increase in slope with the altitude causes erosion and consequently formation of shallow soils, the altitude parameter has been considered as an important limiting factor for wheat production. The effects of slope on erosion is similar to the altitude; thus, the slope has a high weight score (0.110). The weights of other properties in determining suitable areas for wheat production were calculated as 0.056 for organic matter and lime, 0.050 for pH and 0.042 for aspect, respectively (Table 8).

Table 7
Binary comparison matrix.

	Slope	Elevation	Depth	EC	pH	Org Mat	Texture	Lime	Aspect
Slope	1	3^{-1}	2^{-1}	3^{-1}	3	3	1	4	3
Elevation	3	1	2^{-1}	3	4	4	3	5	3
Depth	2	2	1	3	3	3	3	5	4
Electrical Conductivity	3	3^{-1}	3^{-1}	1	3	3	3^{-1}	2	2
pH	3^{-1}	4^{-1}	3^{-1}	3^{-1}	1	3^{-1}	3^{-1}	2	2
Organic Matter	3^{-1}	4^{-1}	3^{-1}	3^{-1}	3	1	3^{-1}	2^{-1}	2
Texture	1	1/3	3^{-1}	3	3	3	1	3	4
Lime	4^{-1}	5^{-1}	5^{-1}	2^{-1}	2^{-1}	2	3^{-1}	1	2
Aspect	3^{-1}	1/3	4^{-1}	2^{-1}	2^{-1}	2^{-1}	4^{-1}	2^{-1}	1

Table 8
Weights of criteria obtained with fuzzy AHP.

Criteria	Weight
Depth	0.232
Elevation	0.218
Texture	0.131
Slope	0.110
Electrical Conductivity	0.105
Organic Matter	0.056
Lime	0.056
pH	0.050
Aspect	0.042

3.5. Land suitability assessment for wheat production

A land suitability map for wheat production was obtained by analyzing and classifying the weights determined using Fuzzy-AHP methods and the thematic maps produced in GIS environment (Fig. 4). The results revealed that highly suitable (S1) areas for wheat production covers 2.63% (61.59 km^2) of Tozanlı Basin. (Table 9). These areas are generally located around the Dam Lake, in the alluvial lands of the mountain plain and on the valley bottoms formed by the Yeşilırmak and Tozanlı rivers. The soils in highly suitable areas are deep and the slope of the land is almost flat. Moderately suitable (S2) areas (230.41 km^2 – 9.85%) generally are located around highly suitable areas. Marginally suitable (S3) lands are distributed in 32.59% (761.94 km^2) of the basin and are generally located in hillside lands. Majority of study area (54.92%, 1284.13 km^2) was classified as unsuitable (N) for wheat production due to the high elevation, slope and insufficient soil depth.

4. Discussion

Fuzzy-AHP and GIS integrated-based approach was successfully used in the current study to evaluate land suitability for wheat cultivation. Nine parameters, including topographic (elevation, slope and aspect) and pedological (soil depth, texture, $CaCO_3$, pH, EC, OM) were selected and the weights of each parameter were calculated using the multi-criteria fuzzy-AHP model effectively. A land suitability map was then created for wheat production. According to the map created, S1 (61.59 km^2), S2 (230.41 km^2), S3 (761.94 km^2) and N (1284.13 km^2) classes were determined for wheat production in the study area.

Table 9
Spatial distribution of classes in the suitability map.

Suitability	Area (km^2)	Ratio (%)
S1	61.59	2.63
S2	230.41	9.85
S3	761.94	32.59
N	1284.13	54.92

High degree of slope due to the relief conditions throughout the basin prevents the formation of soil depth that will provide the effective root depth in plant production. Depth parameter was considered as the most important criterion for wheat production due to the importance in providing sufficient moisture and plant nutrients. Similarly, Dedeoğlu and Dengiz (2019) who carried out a suitability analysis conducted in a similar basin in Turkey, reported that soil depth is the most important parameter for wheat production. The result indicates that the depth criterion is an important parameter for suitability analyzes in areas with high elevation and shaped by fluvial processes.

The weight obtained for slope is consistent with the weight reported by researchers who performed suitability analysis in different regions such as Tashayo et al. (2020) and Akıncı et al. (2013). Soil texture is an important parameter affecting the suitability of wheat; therefore, the weight of texture was calculated as 0.131. Mandal et al. (2020) also pointed out that soil texture is the most important parameter in determining suitable land for wheat production in calcareous soils. Contrary to the researchers, texture was the third important limiting factor since topographic conditions in the study area were more important limiting factors in terms of agricultural production compared to texture. Soil salinity is an important limiting factor for crop production, therefore, EC factor has the highest weight value (0.105) among chemical soil properties (Miransari and Smith, 2007). Since salinity was not a problem in the study area, the EC effect on wheat suitability was equal throughout the study area.

The suitability of lands in the region for wheat production is mostly determined by soil depth and elevation factors. In addition to the parameters used, the use of topographic position index (TPI) (De Reu et al., 2013), which indicates the topographic positions of the lands calculated with the DEM data, and the topographic wetness indices (TWI) (Ma et al., 2010), which gives information about the soil moisture content, will add more details to the results of similar studies. The TPI and TWI will also provide more detailed information for the suitability analysis. In particular, the flat lands can be easily determined spatially by the landform classification to

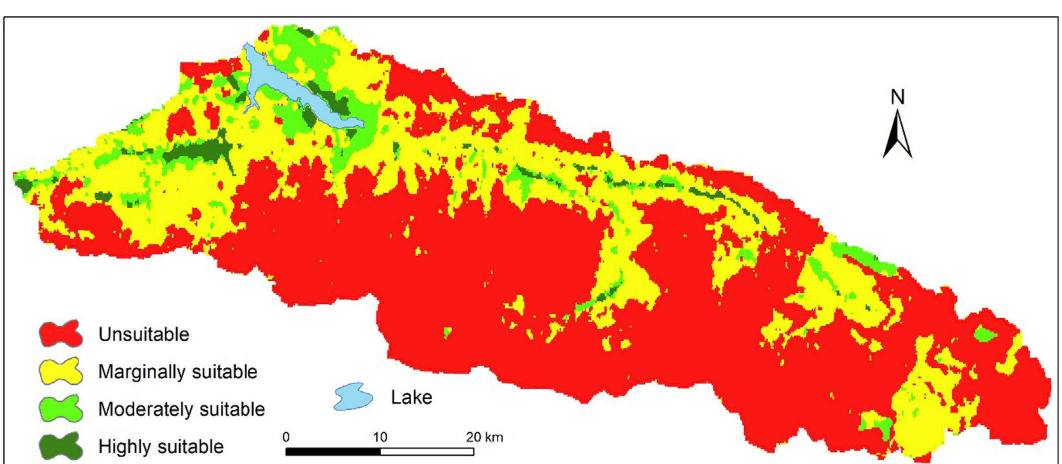

Fig. 4. Land suitability map for wheat production.

be obtained using the TPI index. The areas with irrigation facilities can be easily determined by evaluating the soil moisture conditions in the basins using TWI. In future studies, the inclusion of these indices in multi-criteria decision-making analyzes and their impacts on land suitability studies should be investigated.

5. Conclusion

The aim of this study was to determine land suitability assessment for wheat production in Tozanlı Basin using geostatistics, Fuzzy-AHP approach and geographic information system techniques. The suitability analysis showed that highly suitable (S1) lands for wheat production cover 2.63% (61.59 km^2), moderately suitable (S2) lands 9.85% (230.41 km^2), and marginally suitable (S3) lands was 32.59% (761.94 km^2). Unsuitable lands (N) to wheat production covers 54.92% (1284.13 km^2) due to the geomorphological features (elevation and slope) of the study area. Majority of the lands in the study area were classified as not suitable for wheat production due to the high elevation, insufficient soil depth and severe erosion problems in the high sloping areas. The findings may serve as a guide for future land use management planning to explore the impact of soil and topography on crop yields in similar watersheds. The results revealed that combining of fuzzy-AHP and GIS methods is an applicable and effective approach to take more effective decisions in agricultural land use plannings.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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