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GIS-Based Land Suitability Classification for Wheat Cultivation Using Fuzzy Set Model

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Abstract

In terms of food safety, it is important to use the lands correctly in agricultural production. In this study, potential crop suitability classes for wheat cultivation were created by using the fuzzy model and GIS together. Spatial and spectral factors considered as model inputs were separated four main groups, such as soil (drainage, depth, texture, CaCO3, stoniness, pH, organic matter, salinity, ESP), topography (slope), water availability (irrigation) and vegetation indices (NDVI). Criterion maps were standardized with the fuzzy membership model. Analytical Hierarchy Process was used to determine the weights of the factors. The vegetation change between years in the study area was determined by using NDVI values obtained from Landsat satellite images. In addition, the effect of temporal difference on land use and land suitability was evaluated. Land suitability index was created in GIS environment by weighted linear combination method and divided into four main suitability classes. The results with the Fuzzy method showed 9.7% (805 ha) of the study area as highly suitable for wheat, 46.5% (3868 ha) as medium suitable, 27.6% (2297 ha) as marginally suitable and 16.2% (1350 ha) as unsuitable. According to these classes, highly suitable and medium suitable classes are the areas that should be evaluated primarily in agricultural production. The Fuzzy model and GIS integration can be effectively used to identify priority areas for crop cultivation and sustainable land use management.

Keywords: Fuzzy set model, Analytical Hierarchy Process, Land suitability analysis, Geographic Information Systems, Wheat

Introduction

Today, there are restrictive threats to the conservation and sustainability of natural resources. Climate change is an important problem for today and for the future due to its negative effects on agricultural productivity and food safety in many regions of the world (IPCC, 2014). However, population growth adversely affects agricultural lands and natural resources. Accurate land use is critical for effective land use and agricultural sustainability. Identification of the physical and socio-economical potential of the land is necessary for sustainable planning and reducing negative effects. It is essential to determine and plan the potential crop pattern of the lands for agricultural planning. This evaluation process is related to spatial and temporal factors (Al Taani et al., 2021).

Land suitability analysis plays a fundamental role for the rational planning and use of lands. The assessment of the suitability of the land for the growth of a particular crop involves a process. According to this process, firstly, the ecological requirements of the product and the physical conditions of the land are compared (FAO, 1985; 1976). Land suitability analysis is performed to determine which area is suitable for a particular area in the correct management of natural resources (Bodaghabadi et al., 2015). In addition, a crop planning system can be created to increase land productivity for decision makers (Chen, 2014). In land suitability analysis, determining the limiting factors affecting the cultivation of a particular crop is a priority (Halder, 2013). The main feature of the land suitability assessment is that the land requirements are compared with land features such as soil, water availability, vegetation cover, climate and landforms (Dent and Young, 1981).

Land suitability analysis is defined as the Multi Criteria Evaluaition (MCE) approach since there are many criteria at the decision-making stage in the solution of a problem (Malczewski, 2006). Since transition values are available for most of the factors in the MCE process, it is difficult to express with an absolute value (Reshmidevi 2009). In nature, some

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objects can be defined as a homogeneous feature in terms of geographic area, while ecological characteristics such as soil and topography show continuity and variability. Therefore, boundaries between ecological features should be gradual rather than sharp boundaries (Van Ranst and Tang 1999; Burrough 1989). In addition, these properties can be expressed as different units and sizes. Standardizing and combining these characteristics on a common scale is important for land suitability assessment (Voogd, 1982).

Standardization and aggregation of criteria and modeling of vogue concepts are possible with the fuzzy sets approach (Jiang and Eastman, 2000). The fuzzy set theory facilitates the analysis of continuous structures and the membership degree is defined as an object class (Zadeh, 1965). Wang et al. (1990) proposed land suitability assessment with membership grading in fuzzy set theory instead of sharp boundaries such as true or false for suitable and unsuitable classes. The traditional approach tends to represent land features as discrete parts. However, there is a continuous structure in nature, except that a few elements are discrete. Fuzzy modeling is a suitable approach for defining continuous or uncertain structures (Burrough and Frank, 1996). Fuzzy logic-based land evaluation methods are widely used to determine agricultural land suitability (Garofalo, 2020; Zhang, 2015; Nurmiaty and Baja, 2014; Sicat et al., 2005; Baja, et al., 2002).

Analytical Hierarchy Process (AHP) is one of the most widely used multi-criteria assessment methods for land suitability analysis (Everest et al., 2020). AHP is widely used in agriculture as a decision support tool used to solve complex decision problems (Cengiz and Akbulak, 2009). In this case, AHP is a suitable method for determining weights by using pair-wise comparison (Saaty, 1980). In this process, the criteria in a hierarchical structure can be divided into groups and each group can have sub-criteria within itself. However, all criteria have not equal weight. Therefore, each criterion is weighted according to its importance. For this reason, a weight is assigned to the criteria for each level of the hierarchical structure. Criterion maps were created with the Geographical Information System (GIS) based fuzzy model (Yalew et al., 2016; Zabihi et al., 2015; Feizizadeh and Blaschke, 2013). Criteria maps were combined in GIS environment by using weighted linear combination (WLC) method for land suitability analysis. The total land suitability score is calculated by weighting the standardized criteria maps with the WLC approach (Tugac and Sefer, 2021; Tercan and Dereli, 2020; Tashayo, 2020; Herzberg, 2019; Malczewski, 2004).

In this study, land suitability classification was made by integrating GIS and fuzzy method in a multi-criteria evaluation approach according to land characteristics for wheat cultivation.

Material and Methods

Study area

The present study was performed at Bala Agricultural Enterprise. Bala is a district of Ankara Province in the Central Anatolia region of Turkey. It is geographically located between 33º 14' 45'' - 33º 21' 20'' E longitude and 39º 19' 39'' - 39º 30' 58'' N latitude. The elevation of the study area ranges from 750 to 980 m.a.s.l. The surface area covers approximately 8320 ha (Figure 1). This area has a semi-arid climate with cold and snowy winters and hot dry summers. In the region, the hottest month of the year is July, while the coldest month of the year is January. The mean annual total precipitation is 330 mm. The annual average, average minimum and average maximum temperatures are 11,7ºC, -4ºC, and 30ºC, respectively.

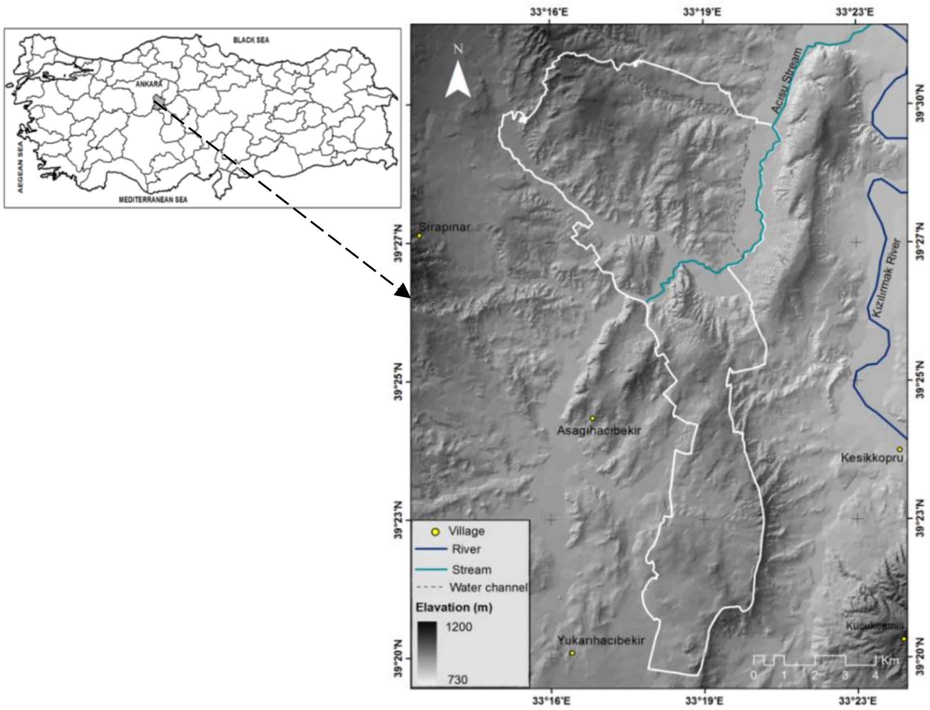

Figure 1. Study area

The area consists of four different physiographic structures: alluvial plain, undulating, sloping and hilly. The parent materials in the study area are limestone, alluvium, marl, gypsum and gravel. The study area includes entisols, aridisols soil orders and 23 different soil series (Soil Survey Staff, 1987). The alluvial soils formed by the river are the most productive soils occupying the middle of the study area. The existing land use in the study area consists of rain-fed agriculture, irrigated agriculture, pasture, degraded land and natural vegetation. Bala agricultural enterprise, which continues its activities under the General Directorate of Agricultural Enterprises, was leased to a private sector subsidiary in 2008.

Data Sources

In this study, different databases including maps and images such as soil, topography, land use, vegetation development were used for land suitability analysis. In determining the soil structure of the area, physical and chemical soil properties obtained from the detailed soil study map with a scale of 1: 16.000 were used (Arcak, 1992). Soil physical features (soil depth, texture, surface stoniness, drainage, erosion), which were digitized in vector-based databases, were converted into the raster-based features. Thematic maps of soil chemical properties such as pH, salinity, lime, organic matter, ESP were created using the Inverse Distance Weighted (IDW) interpolation method in ArcGIS software. Climate data was obtained from meteorological station, which belong to Turkish State Meteorological Service. Topographic criteria, slope produced from digital elevation model (DEM) which was obtained 1 / 5.000 scale topographic maps.

Land use maps provide information on land use types, irrigation areas, parcel borders, water bodies, roads, rocky places, service areas. These maps were defined and digitized from the ariel photograph and Sentinel-2A image. Landsat 5, 7 and 8 satellite images were used to obtain Normalized Difference Vegetation Index (NDVI) data. In order to determine the vegetation activity in the field during the year, 16-day and cloudless NDVI data were transformed into maximum composite data. NDVI is derived from the red and near infrared band reflectance values (Tucker, 1979).

Model input maps were prepared in raster data format using the ArcGIS 10.4 (ESRI, 2015) program in the Geographic Information System (GIS) environment. The crop suitability map was created at 10 m cellular resolution.

With this study is to generate wheat (*Triticum aestivum L*) suitability classes using the GIS-based fuzzy set model and AHP (Fig.3). The general evaluation procedure followed in this study can be divided into four main parts: (1) Selection of criteria and definition of hierarchical structure.: (1) Selection of criteria and definition of hierarchical structure. (2) Determining membership function and applications of fuzzy model. (3) Obtaining weight for the criteria by using the AHP method (4) Creation of agricultural land suitability classes and map. The flowchart of the land suitability analysis for wheat is shown in Figure 2.

Hierarchical structure

The hierarchical structure of the model can be separated into three main parts. The first level is the definition of the goal that implies land suitability index for wheat. The second level, the agricultural land suitability assessment is to determine the relevant ecological variables. The criteria selected for the assessment of land suitability are divided into four main groups: (1) soil, (2) topography, (3) vegetation indices, and (4) water availability factors. The third level is the determination of sub-criteria related to the main group. At this stage, thirteen factors such as soil depth, texture, surface stoniness, drainage, erosion, organic matter, $CaCO_3$, pH, ESP, salinity, slope, NDVI and irrigation zone were selected. Depending on the purpose of the project, the systematic classification of components reveals a relative hierarchy and a model tree structure is created (Figure 3).

Fuzzy membership model

Fuzzy set theory creates a system for defining uncertain data and assigning membership degrees (Mendel, 1995). The fuzzy set is widely used in nature to classify continuous ecological data where class values are not sharp. For a class with permanent membership, each object is assigned a value ranging from zero to one, and the higher the membership value, the higher the suitability class value (Zadeh, 1965).

In traditional set theory, the membership value of a set is expressed as 1 (full membership) or 0 (non-full membership) (Tang et al., 1997). Fuzzy set models are used to classify membership features whose attributes are uncertain (McBratney and Odeh, 1997). A fuzzy set X is a supposed finite set of attributes. A fuzzy set (A) can be expressed as follows (Burrough and McDonnell, 1998).

$$A = \{x, \mu_A(x)\} \text{ for each } x \in X$$

Where, $x \in X$ is a finite set of points and $\mu A(x)$ is a membership model, which describes the degree of membership of x in A. For all A, $\mu A(x)$ a value in the unit interval [0, 1]. In this context, $\mu A = 0$ indicates that the value of x does not belong to A and $\mu A = 1$ indicates that the value belongs entirely to A. On the other hand, if, $0 < \mu A(x) < 1$, it is defined as A for a certain degree.

There are some models to create the fuzzy membership (FM) function. The FM model functions applied in grading the land features are based on the Semantic Import (SI) model (Elaalem et al., 2011; Braimoh et al., 2004; Baja, et al., 2007; Burrough and Frank 1996; Davidson et al., 1994; Burrough 1989). This application consists of two basic functions: symmetrical and asymmetrical (Figure 4). The first model, also referred optimum interval, is divided into two parts: one uses a single ideal point (Model 1), the other uses an interval of ideal points (Model 2). The second model, an asymmetric model, is used when only the upper and lower boundary of a feature is important. This model can be divided into two parts: asymmetric left (Model 3) and asymmetric right (Model 4) (Burrough and McDonnell, 1998). Membership functions are given below.

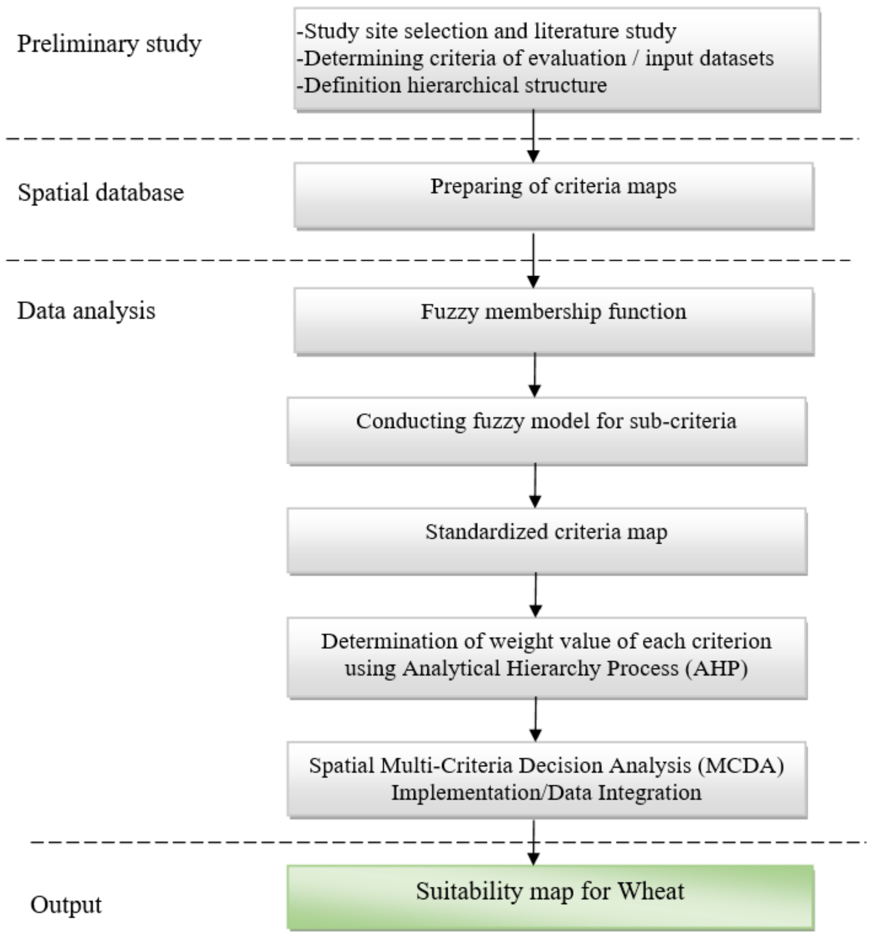

Figure 2. Schematic diagram of suitability assessment for wheat

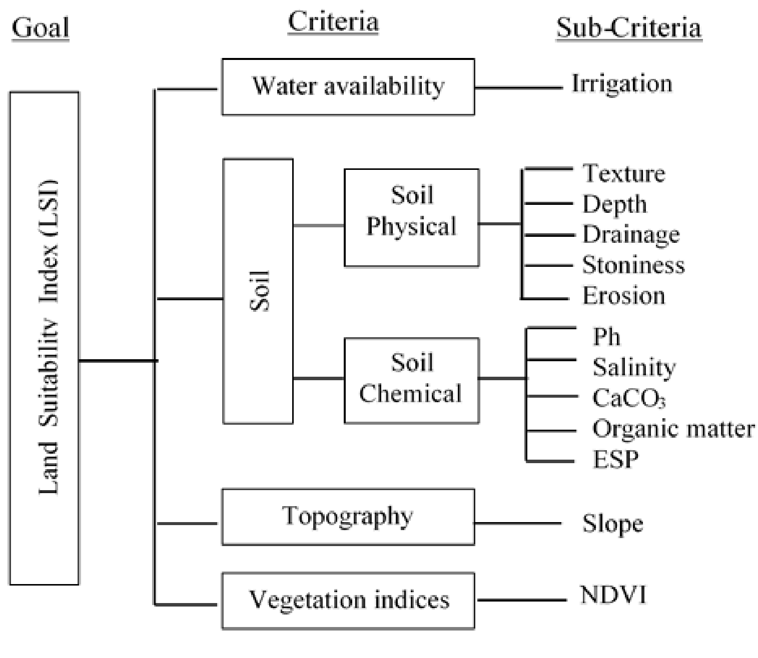

Figure 3. The hierarchical structure for the suitability assesment

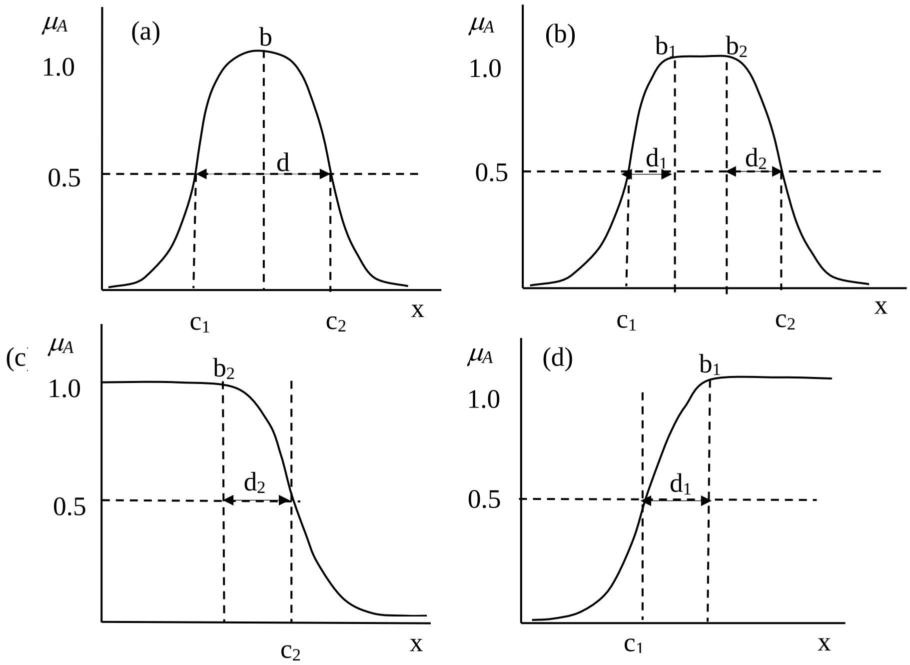

Figure 4. symmetric model (a,b), asymmetric right (c), asymmetric left (d)

$\mu_A(x_i) = [\,1/(1 + \{(x_i - b)/d\}^2)]$ if $0 \leq xi \leq 1$ (Model 1)

$\mu_A(x_i) = 1$ if $(c_1 + d_1) \leq xi \leq (c_2 - d_2)$ (Model 2):

$\mu_A(x_i) = [1/(1 + \{(x_i - c_1 - d_1)/d_1\}^2)]$ if $xi < (c_1 + d_1)$ (Model 3):

$\mu_A(x_i) = [1/(1 + \{(xi - c_2 + d_2)/d_2\}^2)]$ if $xi > (c_2 - d_2)$ (Model 4):

Where $\mu_A\ (x_i)$ shows MF values for cell *i* of land characteristic *x* in a raster layer, b is the value of land attribute *x* at the ideal point, d is the width of the transition zone, c_1 and c_2 are LCP and UCP respectively.

The crossover point can be defined as the lower crossover point (LCP) or the upper crossover point (UCP) according to the criteria. Asymmetric models only have LCP or UCP values while both LCP and UCP are available in symmetric models. In this study, asymmetric right decreasing (ARFM) and asymmetric left (ALFM) increasing membership functions were applied. Increasing values such as slope, CaCO3, salinity and ESP indicates a decreasing suitability value. On the other hand, increasing soil organic matter and NDVI values indicates increasing suitability value. Therefore, ARFM and ALFM models were applied for this factors, respectively. Also, a symmetric membership function (SFM) was used for soil pH for the model. The class values of land features such as soil texture, drainage, surface stoniness and irrigation have been converted into fuzzy numbers. While assigning membership values to classes for discrete structures, layer class values are normalized as follows (Voogd, 1982):

$\mu_A(x_i) =\ x_i - x_{min} / x_{max} - x_{min}$

where $\mu_A\ (x_i)$ is the membership value for cell *i* of land characteristic *x* in a raster layer; x_i is the raw rank value; x_{min} is the minimum value of the criteria; and x_{max} is the maximum value of the criteria.

The FM was used to create the factor maps. In this context, the lowest and highest suitability level values were determined. The threshold values for wheat suitability analysis were determined according to literature information (Nwer, 2005; Sys et al., 1993; Van Diepen et al. 1991; FAO, 1985) and expert opinions. (Table 1).

Land suitability analysis

The land suitability index (LSI) was calculated using the ArcGIS program, taking into account the factor scores and weights. AHP technique was used to weigh the criteria according to their importance. Factor priorities are determined according to expert opinion. In a multi-criteria analysis, factor weights were applied to a pairwise comparison approach to determine the relative preference between factors (Saaty, 1980). The suitability score was obtained by integrating the standardized layers with the 'weighted overlay analysis' technique (Eastman, 2012). This model combines multiple variables on a linear basis for the main purpose. Weighted criterion maps are combined to obtain the land suitability score. LSI is calculated using the WLC method with the equation given below:

$$LSI = \sum_{i=1}^{k} w_{i*}\,\mu_A(x_i) \quad (i = 1, 2, 3, ..., k;\ \sum w_i = 1;\ w_i > 0\ )$$

Where LSI is the Land Suitability Index of overall suitability for all variables,
$A_1,..., A_k$ are fuzzy subclasses of the defined universe of objects X,
$\mu_A(x_i)$ is the membership value for land characteristic x_i,
$w_1,..., w_k$ are the weights of the membership values.

The total suitability index of the land for wheat was created according to the fuzzy classification approach. Both, weight and membership grade values are between 0 and 1. The index value of the suitability map produced using the fuzzy model varies between 0 and 1. Where a value of 0 indicates completely unsuitable, and a value of 1 indicates completely suitable. The Suitability Index map is divided into four classes according to the FAO framework approach (FAO, 1976). In this classification, LSI values were classified as highly suitable (1–0.85), moderately suitable (0.85–0.6), marginally suitable (0.6–0.4), and unsuitable (0.4–0).

Table.1. Fuzzy membership limit degrees of criteria for wheat

Sub-Criteria	Complete membership (suitable)	Nonmembership (unsuitable)	Data type	Fuzzy membership function
Slope (%)	<2	>12	Continuous	ARFM,$[r_{(0.5,R)},d_{(R)}]=$ [7,5]
Soil Depth (cm)	>90	<25	Thematic	[deep(1),medium(0.65),shallow (0.40),very shallow(0)]
Textur (class)	L,ZL,Z,CL, ZCL, SCL	S, LS	Thematic	[L, SiL, SiCL, CL (1), SCL, C<%45 (0.75), SiC, SC, C>%45 (0.6), SL (0.4), LS (0.3)]
Soil stoniness (class)	Absent	Severe	Thematic	[absent (1), low(0.75), medium(0.45), severe(0)]
Drainage (class)	Well drained	poorly	Thematic	[well drained (1),moderately (0.70),imperfectly (0.4),poorly (0.1)]
Erosion (class)	Absent	Severe	Thematic	[absent (1), low(0.85), medium(0.55), severe(0.1)]
Organic matter (%)	> 3	< 0.5	Continuous	ALFM,$[r_{(0.5,L)},d_{(L)}]=$ [1, 2]
$CaCO_3$ (%)	< 10	> 30	Continuous	ARFM,$[r_{(0.5,R)},d_{(R)}]=$ [20,10]
pH	6.5-7.5	>8.5 , <5.5	Continuous	SFM,$[r_{(0.5,R)},d_{(R)}, r_{(0.5,L)},d_{(L)}]=$ [8.2,0.7,5.8,0.7]
ESP (%)	< 10	> 25	Continuous	ARFM,$[r_{(0.5,R)},d_{(R)}]=$ [18, 8]
Salinity($dS\ m^{-1}$)	< 2	> 16	Continuous	ARFM,$[r_{(0.5,R)},d_{(R)}]=$ [9,7]
NDVI	>0.65	< 0.3	Continuous	ALFM,$[r_{(0.5,L)},d_{(L)}]=$ [0.45,0.2]
Irrigation (class)	irrigated	non irrigated	Thematic	[irrigated area(1), rainfed area (0.65)]

C: Clay, CL: Clay loam, L: Loam, LS: Loamy sand, S: Sand, SC: Sandy clay, SCL: Sandy clay, L: loam, Si: Silt, SiC: Silty clay, SiCL: Silty clay loam, SiL: Silt loam

Results and Discussions

The main goal of the case study is to determine the priority areas of the land for wheat cultivation by using the GIS based fuzzy set model. In this context, determining the ecological criteria that affect the cultivation of the crop is a priority. In agricultural areas, topographic structure, soil and irrigation facilities are determining factors due to the soil fertility of the land and the sensitivity of the soil to degradation. Although rainfed agriculture is common in the region, the existence of irrigated lands was also important for constructing the model and selection of the criteria. The factors that affect the determination of the suitability of agricultural areas have different levels of importance. Factors taken into consideration; water availability (irrigation), soil (texture, depth, drainage, surface stoniness, pH, salinity, $CaCO_3$, organic matter), topography (slope) and vegetation index (NDVI). Soil and irrigation are the highest weighted factors in terms of wheat cultivation and productivity. The weights of these factors were determined as 0.374 and 0.324, respectively. Soil properties include soil nutrients and water availability for plant growth. The soil factor was evaluated physically and chemically. Among the physical factors, texture (0.332) and soil depth (0.290) are the most important factors. However, among the chemical factors, pH (0.383) and salinity (0.242) were the determining factors. The topographical factor, with a weight of 0.201, is another factor. The slope is related to the movement of soil particles and soil erosion; consequently, it

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affects the soil quality. NDVI with a weight value of 0.101 has a lower importance than other main factors (Table 2).

In the multi-criteria approach, as the number of criteria increases, it becomes difficult to determine the weight values. While it is important to determine the relative priorities of the criteria with respect to each other, it also requires experience (Keshavarzi and Sarmadian, 2009). Criterion weight values may vary according to land conditions and ecological requirements of the crops.

Table 2. Main criterion and sub criterion weight values

Goal	Criteria	Weight	Sub-Criteria	Weight
Land Suitability Index (LSI)	Soil	0.374	Soil Physical	
			Texture	0.332
			Depth	0.290
			Erosion	0.166
			Drainage	0.131
			Soil stoniness	0.081
			Soil Chemical	
			Ph	0.383
			Salinity	0.242
			$CaCO_3$	0.194
			Organic matter	0.118
			ESP	0.064
	Irrigation	0.324		
	Topography	0.201		
	NDVI	0.101		

The main land uses in the area are rainfed agriculture (5100 ha), irrigated agriculture (1053 ha), pasture (1022 ha), degraded land (918 ha), orchard (95 ha), natural vegetation (92 ha) and service area (40 ha). The proportions of these areas in the total area are 61.3%, 12.7%, 12.3%, 11.0%, 1.14%, 1.11% and 0.48%, respectively. In dry and irrigated farming areas; wheat, barley, sainfoin, vetch, sunflower, chickpea, corn and alfalfa are grown. Rangeland includes both natural meadowlands and artificial lands. Natural vegetation land is characterized by shrub, pine, wooded. Most of the pasture and natural plant areas are within marginal suitable areas. Degraded areas contain rock and eroded lands. The service area consists of accommodation, livestock facilities and stores.

Bala agricultural enterprise, which continues its activities under the General Directorate of Agricultural Enterprises, was leased to a private sector subsidiary in 2008. With the investments made in the enterprise such as irrigation and facilities, there have been changes in the field use related to crop production, fruit orchard and animal husbandry. Irrigated agricultural areas were increased as a result of irrigation investments in 2012.

Satellite images are used extensively to detect temporal and spatial changes and determine crop yields in agricultural production areas. NDVI data is the most widely used plant growth index for monitoring vegetation in remote sensing technology (Basso et al., 2013). NDVI defines the chlorophyll concentration of plants and varies between -1 and +1 values. Increasing positive values of the index indicate healthy and high plant density. The temporal variation of precipitation has a great effect on crop development, biomass and yield. The correlation between NDVI and vegetation increases during the growing period (Labus et al., 2002). In this study, the differences in vegetation were determined from the long-term averages of the maximum composite data obtained for each year with Landsat 5, 7 and 8 images. NDVI data was taken as a criterion to determine the change in vegetation density between years in dry and irrigated areas. In particular, the change in irrigated farming areas was clearly observed after the irrigation investments. In this context, NDVI data between 2001-2011 and 2012-2020 were evaluated. While the rate of areas with high vegetation density (NDVI > 0.65) was 3% (211 ha) until 2011, it was observed that this rate increased to 11% (932 ha) with the increase in irrigated areas (Figure 5).

The parcel map of the area was digitized and the obtained parcel database was updated over the satellite image data, and land use classes belonging to two different periods were created. Land-use changes in two different periods for 2011 and 2020 were determined in the area (Table 3). The highest change was in rainfed agricultural areas with a decrease of 7.2%, while the highest increase was 6.0% and 1.1% in irrigated agriculture and fruit orchard, respectively. The effects of these changes over the years on land suitability have also been determined.

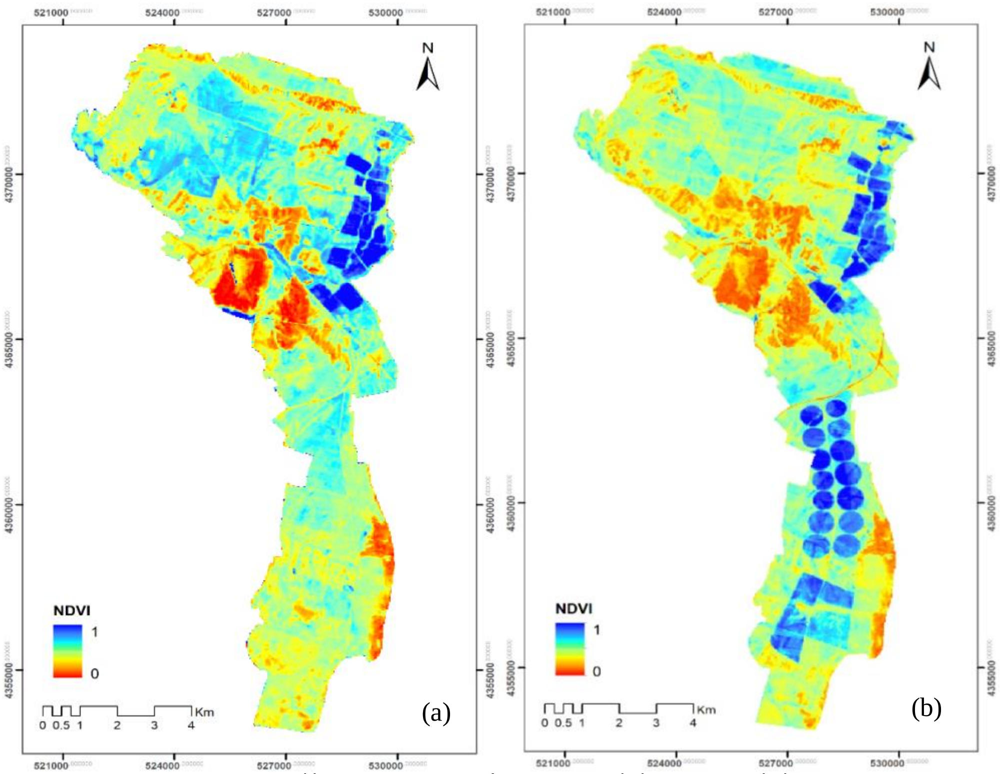

Figure 5. NDVI maps for 2011 (a) and 2020 (b)

Table 3. Distribution of land use classes for 2011 and 2020

Landuse classes	2011		2020		Difference	
	Area (ha)	%	Area (ha)	%	Area (ha)	%
Rainfed agriculture	5702	68.50	5100	61.30	-602	-7.2
Irrigated agriculture	556	6.70	1053	12.70	497	+6.0
Rangeland	1015	12.2	1022	12.30	7	+0.1
Dagraded areas	918	11.0	918	11.0	-	-
Fruit orchard	6	0.07	95	1.14	89	+1.07
Natural vegetation	89	1.10	92	1.11	3	+0.01
Service area	34	0.42	40	0.48	6	+0.06

The effect of the investments made on the land was investigated for two different periods, as the study area was rented out with a private partnership (Figure 6). While the highly suitable area was 4.8% (403 ha) in 2011, 9.7 % (805 ha) of the total area was found as highly suitable for wheat in 2020. Irrigated agricultural areas have great potential in terms of productivity. With the increase in irrigated agricultural lands, the areas with suitable land class increased by 4.9% (403 ha). Between the years, the moderately suitable areas with the majority of dry farming areas decreased by 3.7% (310 ha). According to the current land use, 46.5% (3868 ha) of the area is in the medium suitable class, while 27.6% (2297 ha) is in the less suitable class. However, 16.2% (1350 ha) of the total area is unsuitable for agriculture (Table 4). As expected, rainfed farming and irrigated farming areas are among the highly suitable and moderately suitable areas within the current land use. In the study area, the highly suitable areas for wheat cultivation can be generally characterized by flat, deep soil, soil pH level between 7.7 and 7.9, lime content of 10-20%, high water-holding capacities and humidity. In these areas, there are partially low salinity and drainage problems. In moderately suitable lands, medium depth soils are common and some areas have stoniness, liminess and erosion problems. On the other hand, there are drainage and salinity problems in irrigated lands. In irrigated agricultural lands, there are negative impacts on a part of the land due to the low quality of irrigation water and salinity. Salinity negatively affects product development, nutrient intake and yield (Munns and Gilliham, 2015). For this reason, some areas in irrigated agricultural lands are in a lower class. In marginally suitable areas, low soil depth, rugged areas, low water-holding capacities and erosion are limiting factors. In addition, there are problems with high salinity and liminess in some areas. Areas that are not suitable for agriculture are especially rocky areas with steep slopes and very shallow soil depth. There is a very severe erosion problem for these areas.

Spatial matching was made by comparing the crop suitability classes with the existing land use map. 76.4% (805 ha) of irrigated agricultural lands are very suitable for wheat production. In irrigated agricultural lands, 23.6 % (248) ha is in the middle class due to restrictive land features such as drainage and salinity. In rainfed areas, 68 % (3471 ha) is in the medium suitable class, while 31.5 % (1606 ha) is in the marginally suitable class. On the other hand, 96.1% of the medium suitable class was found in rain-fed agriculture and irrigated agriculture. For the medium suitable class, 1.8% of the class was found in the rangeland. 69.9% of the marginally suitable class is rain-fed areas, and in these areas, land deficiencies are sighted. In addition, 21.3% of this class is rangeland (Table 5).

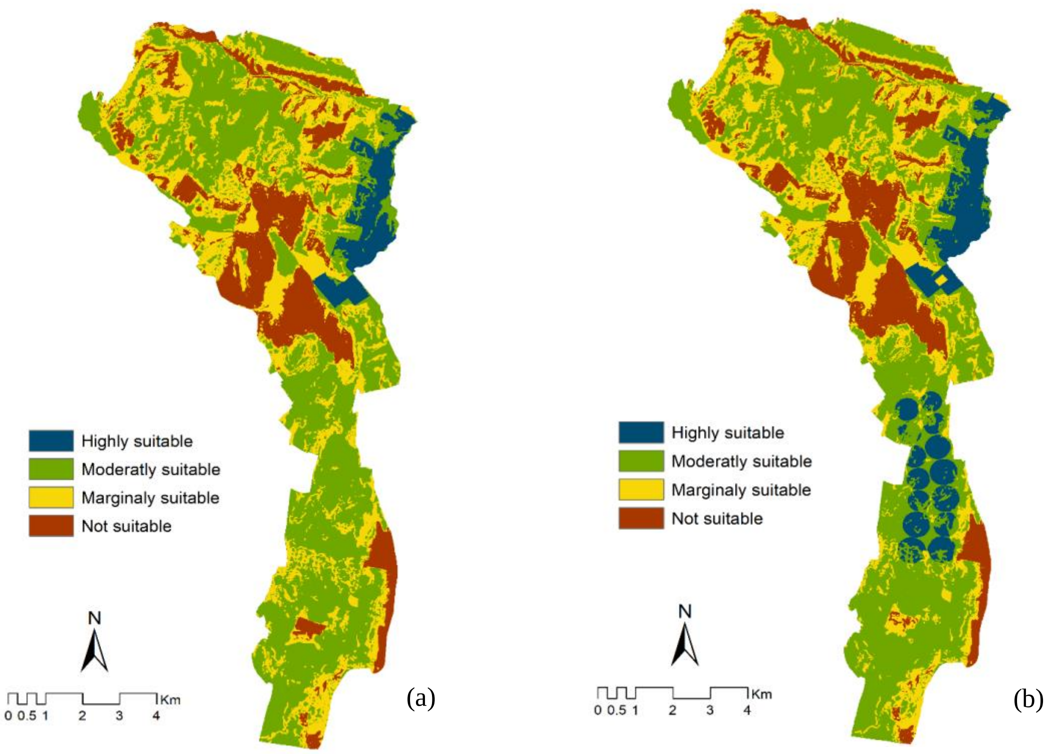

Figure 6. Land suitability maps of wheat for 2012 (a) and 2020 (b)

Table 4. Distribution of suitability classes for 2011 and 2020

Suitability level	2011		2020		Difference	
	Area (ha)	%	Area (ha)	%	Area (ha)	%
Highly suitable	402	4.8	805	9.7	+403	+4.9
Moderately suitable	4178	50.2	3868	46.5	-310	-3.7
Marginally suitable	2390	28.8	2297	27.6	-93	-1.2
Unsuitable	1350	16.2	1350	16.2	-	-

Table 5. Comparison of land use and suitability classes in the study area

Land use	Suitability level							
	Highly suitable		Moderately suitable		Marginally suitable		Unsuitable	
	ha	%	ha	%	ha	%	ha	%
Rainfed farming			3471	89.7	1606	69.9	23	1.7
Irrigated farming	805	100	248	6.4				
Rangeland			70	1.8	490	21.3	462	34.2
Natural vegetation					62	2.7	30	2.2
Degraded areas					90	3.9	828	61.4
Fruit orchard			67	1.7	28	1.2		
Service area			12	0.3	21	0.9	7	0.5

In this study, the potential suitability of dry and irrigated agricultural lands for wheat cultivation was determined. In the land suitability analysis, the Fuzzy model, AHP and GIS were used together. There are critical stages in the modeling process. By applying the fuzzy set model, the criterion values were transformed into membership degrees. Thus, different land features were converted into a standard index. Model inputs were determined and their weights were calculated. With the applied model approach, it is aimed to create a sustainable land management.

Conclusion

In this study, fuzzy set model, GIS and MCE techniques were applied in land evaluation analysis for wheat cultivation. Thirteen factors were selected, including soil, topographic and water availability and their grade of membership functions were calculated by the fuzzy set model. Suitability analysis was performed by integrating GIS-based spatial data with MCE. AHP technique is used in the relative weighting of the criteria. Although a large number of model inputs, the field was evaluated quickly and accurately with the hierarchical structure of the model.

Most of the model inputs include continuous data structures such as slope (0-20 %). Sometimes, in cases where there are data structures of different sizes, it may be difficult to correlate these data with land suitability. In this case, the Fuzzy set is standardized in the 0-1 range by converting all data into membership functions. A value of 1 indicates that the land is suitable for 100 % wheat cultivation. While integration of MCE and GIS is very useful for land assessment, the selection of assessment factors, factor boundary values, and weight ratios have a direct effect on outcomes.

A comprehensive definition of the land characteristics within the natural and continuous structure of the land was made by applying the FM approach. Therefore, the suitability map shows a more accurate result (Burrough 1989). The Fuzzy method is useful in grading the criteria in which the land characteristics show continuity and variation. Moreover, the FM model was effective to create standardized criteria maps. Therefore, the final map provides a more realistic result as the ecological conditions are taken into consideration. The accuracy of the results mainly depends on the weight assignments by selecting the correct land features. The critical point of the fuzzy methodology in crop suitability analysis is the determination of the class centers, transition values and weight values of membership functions. The weakest part of the fuzzy set method used for land suitability classification is the determination of the membership functions and the crossover point value. On the other hand, in the assignment of criterion weights, attention should be paid to determining the effective and restrictive criteria according to the crop growing requirements.

Remote sensing data were useful in spatial analysis between potential suitability areas and the existing land use type, and in determining the land use changes among the years. This information ensures optimum use of the land and the correct future land use preferences. The land suitability index map provides basic data to decision-makers by revealing the physical analysis of the area. In this study, vegetation change between 2001-2011 and 2012-2020 was determined with NDVI values obtained from Landsat satellite images. In addition, the effect of temporal difference on land use and land suitability has been evaluated.

The quality of the investment in the land, such as irrigation investments, necessary financial support and facilities, will also have a positive impact on the increase in land suitability potential. In this context, irrigation availability is very important in semi-arid climatic conditions, it should be evaluated with soil and topographic conditions.

The land suitability index is useful for revealing the variability in yield of the crop depending on the land characteristics (Dedeoglu and Dengiz 2019; Sharififar et al. 2016; Braimoh et al. 2004). With this approach, it can be ensured that optimal land use planning is made by determining the places where the land is advantageous to reach the highest yield. However, the high correlation between crop yield and Fuzzy method (Tang et al., 1992; Van Ranst and

Tang, 1999; Braimoh et al., 2004; Meleki et al., 2010; Keshavarzi and Sarmadian, 2009, Mohammadrezae et al. 2014) will provide a more accurate estimation of yield in the field.

With the model approach in this study, it is possible to grade the land characteristics in a way that reflects the land conditions more accurately and to reduce the uncertainties. The obtained suitability index map can serve a basis for the decision support tool in the sustainability, optimum use and planning of the land.

Compliance with Ethical Standards

Conflict of interest

The authors declared that for this research article, they have no actual, potential or perceived conflict of interest.

Author contribution

The author read and approved the final manuscript. The author verifies that the Text, Figures, and Tables are original and that they have not been published before.

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