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Agricultural land suitability assessment with GIS-based multi-criteria decision analysis and geostatistical approach in semi-arid regions

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Abstract

For sustainable land use planning, evaluating land characteristics and making suitable land use decisions is a priority and critical step. In order to make these evaluations safely, spatial analyzes of many criteria should be made. In this study, the suitability of the land for wheat production was evaluated by Geographical Information Systems (GIS) based Multiple Criteria Decision Analysis (MCDA) in semi-arid conditions. In obtaining the land suitability map; fuzzy set model, Analytical Hierarchy Process (AHP) and GIS are integrated. Ecological criteria weights for agricultural land suitability were determined by AHP. In the suitability analysis, a total of criteria including soil and topographic features were evaluated. Geostatistical analysis approach was applied to determine the spatial variability of soil properties (sand, clay, silt, pH, OM, CEC, ESP, $CaCO_3$, EC). The lowest variation among soil properties was observed in pH (3.8%), while the largest variation was observed in ESP content (107.5%). The nugget/sill ratio is poor for EC and pH, while other soil properties are moderately spatially dependent. According to the results of the analysis, 25.7% (3.226 km^2) of the area is highly suitable, while 27.6% (3.457 km^2) is moderately suitable and 19.5% (2.440 km^2) is marginally suitable for wheat cultivation. In addition, 27.2% (3.415 km^2) of the area is not suitable for agricultural production. The use of geostatistical modeling, MCDA and GIS together is very beneficial in making agricultural land management decisions.

Introduction

In the face of the rapidly increasing world population, the sustainability of agricultural production is one of the most important problems for the future. According to the projection of the United Nations organization, the world population is estimated to be between 8.3 and 10.9 billion by 2050. In this case, the increase in food demand will require an increase in agricultural production by 50 to 75% (Prosekov & Ivanova, 2018). On the other hand; climate change, natural disasters, land constraints make it difficult to achieve optimal production and agricultural sustainability (FAO, 2017; Tóth et al., 2018; Arora, 2019). Increasing environmental constraints gradually increasing the pressure on agricultural lands, which is a

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limited natural resource. In order to reduce the impact of these difficulties, it is necessary to create rational agricultural plans and strategies and to use agricultural lands effectively.

Land suitability assessment is a fundamental data for the sustainable development of agriculture and for accurate land use planning. Therefore, sustainable land use planning and management is important for increasing production and protecting land resources (Baroudy, 2016). Land suitability assessment is a preliminary step in land use planning (FAO, 1993). In agricultural production, it is necessary to determine the land conditions in order to obtain maximum benefit per unit area at the economic level. In agricultural production, it is necessary to determine the land conditions in order to obtain maximum benefit per unit area at the economic level. The suitability of the land for a crop includes the evaluation of many different criteria such as climate, soil, topography, water resources (FAO, 1976; Sys, 1985). Identifying effective land features and obtaining accurate data is a priority to determine the suitability of an area for a particular land use.

Important factors affecting crop production are soil and topographic features apart from climate. Soil features have a heterogeneous structure in the land and show a spatial distribution where variation is seen depending on distance (Zhan et al., 2020). This distribution can be affected by soil management, fertilization, crop rotation, land characteristics and geomorphological structures (Cambardella & Karlen, 1999). Spatial distribution maps of soil properties are one of the basic inputs of agricultural land suitability and sustainable agricultural planning (Aggag & Alharbi, 2022). Spatial variation maps of soil properties can better correlate soil properties with ecological conditions (Goovaerts, 1998). There is spatial dependence for soil variables (Webster, 1985). The spatial dependence of the variables is determined by variogram analysis (Mcbratney & Pringle, 1999). The relationships with the distance between the samples are characterized by the variogram (Trangmar et al., 1985). Kriging is an interestimation technique that can make spatially linear estimation with variogram models (Khan et al., 2019). In the geostatistical approach, spatial variability of soil properties for different land uses is characterized by spatial modeling (variogram) and spatial interpolation (kriging) (Kariuki et al., 2009; Liu et al., 2014; Reza et al., 2016; AbdelRahman et al., 2020). Spatial distribution maps are produced by integrating geostatistics and GIS techniques (Tashayo et al., 2020; Yeneneh et al., 2022).

Crop production is under the influence of different ecological characteristics. In the MCDA approach, spatial decisions can be made by evaluating many criteria according to the determined purpose (Malczewski, 2006). In eliminating the uncertainty, the values belonging to the objects are assigned to the set membership with functions and converted into a standard scale (Zhang et al., 2015; Nguyen et al., 2015, Tuğaç, 2021). AHP is a decision-making method in which hierarchical structure and criterion weights are determined. AHP is based on pairwise comparisons of factors according to their importance using a comparison scale on the decision hierarchy (Ramamurthy et al., 2020; Everest et al., 2021). In the evaluation of different ecological characteristics in land suitability analysis, the integration of GIS and AHP provides spatial analysis of the data and rational results according to the preferences of the decision maker (Pilevar et al., 2020; Şenol et al., 2020; Shaloo et al., 2022).

Turkey has large production areas of wheat, barley, corn, sunflower, cotton and sugar beet crops. Approximately, 11 million hectares of these areas are cereal fields (TUIK, 2021). One of the main centers of agricultural production in Turkey is the Central Anatolian Region. While this region accounts for 35.8% of the total grain production, wheat (53.2%) and barley (36.7%) are widely produced in the region (TUIK, 2021). Due to the fact that the Central Anatolia Region is in a semi-arid climate regime, it is under the limiting effect of drought and precipitation distribution irregularities. For this reason, it is important to ensure the effective and sustainable use of lands in semi-arid areas. In this context, spatial variability of some soil properties was determined by geostatistical analysis in the study area. Agricultural land suitability for wheat was evaluated with the GIS-based Fuzzy-AHP approach, taking into account soil and topographic characteristics.

Materials and Methods

Study area

The study area is between 31° 49' 10" and 33° 46' 40" east longitudes and 38° 40' 21" and 39° 53' 05" north latitudes. The study area is between 31° 49' 10" and 33° 46' 40" east longitudes and 38° 40' 21" and 39° 53' 05" north latitudes. The area is located between Sakarya river in the west, Kızılırmak river in the east, and Lake Tuz in the south and has a surface area of approximately 12,537 km^2 (Figure 1). The study area consists of Polatlı, Haymana, Gölbaşı and Bala districts of the Ankara province and Kulu districts of the Konya province. The study area has a semi-arid climate regime that typically characterizes the Central Anatolia Region. The average annual temperature is 11.3°C. The monthly average 98 temperature ranges from -2 to 24°C. The coldest month is January with a minimum temperature of -14°C. The hottest months are July and August, when the maximum temperature exceeds 37°C. The average annual precipitation of the area is 378 mm. Steppe vegetation characterizes the region (Öner et al., 2016). The elevation of the study area is between 620 m and 1,865 m and the average elevation is 1010 m above sea level.

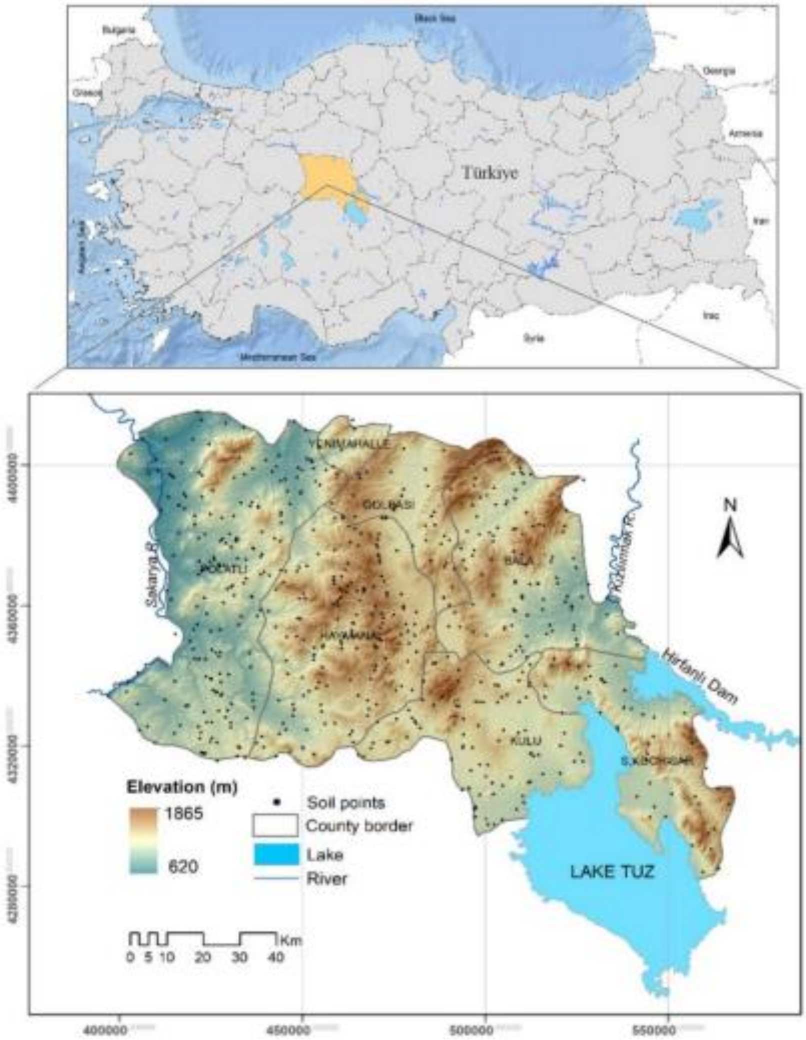

Figure 1. Study Area.

Sandstone, conglomerate and limestone are common in the area as geological formations (Ünalan et al., 1976). Wheat and barley are the main crops in the region, which mainly consists of rainfed agricultural areas. Except for cereals; chickpeas, beans, lentils, sunflowers, safflower, sugar beet and corn are produced throughout the region.

Data sources

The agricultural suitability of the area was evaluated by considering the soil and topographic characteristics. Digital Elevation Model (DEM) was created by combining 1/25,000 scale topographic maps and then slope parameter was obtained. Soil data includes 1/25,000 scaled digital soil database and land evaluation survey data produced by the Ministry of Agriculture and Forestry, and soil samples collected from field studies. Physical and chemical parameters obtained from 640 soil samples were used to determine the spatial changes of the study area. Spatial distribution maps of soil parameters were prepared using Ordinary Kriging (OK) interpolation technique. Geostatistical analysis, parameter maps and land suitability model were produced using ArcGIS 10.4 program.

Geostatistical analysis

Geostatistical analysis provides spatial models of samples taken from the field to make estimations at unsampled locations and evaluate the uncertainty associated with these estimations (Goovaerts, 1998). In the geostatistical approach, mostly variogram functions are used to determine the relationship based on distance (Mousavi et al., 2017). The variogram function is the variance of the difference between two random variables separated by the distance (h) from each other. The variogram function equation (Equation 1) characterizing the spatial variability of a variable is given below (Trangmar et al., 1985).

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

Where, $Z(x_i)$ is the soil properties measured at the x_i location, Y(h) represents the variogram for the lag distance h between $Z(x_i)$ and $Z(x_i + h)$, and N(h) is the number of data pairs. In the variogram graph, the y-axis is the variance, and the x-axis is the lag distances, in other words, the distance between the pairs of points. One of the kriging methods, OK, is based on taking the weighted average of the points containing the measured value in an area. The estimation equation (Equation 2) for OK is given below (Webster & Oliver, 2001).

Eq. (2) $$\hat{Z}(x_o) = \sum_{i=1}^{N} \lambda_i \, z(x_i)$$

Where, Ẑ(x0) is the predicted value, N is the number of observations, λi, z (x_i) is the weight assigned to the measured values. One of the frequently used methods for the determination of variogram model parameters is the cross validation technique. In this method, the difference between the actual values and the estimated value is calculated and the statistics of the estimation errors are checked. The variogram model and parameters that meet the desired criteria for these statistics are determined. The mean error (ME), root mean square error (RMSE) and root mean square standardized error (RMSSE) equations (Equation 3-5) applied in cross validation are given below.

Eq. (3) $$\mathrm{ME}=\frac{1}{n}\sum_{i=1}^{n}(P_i - O_i)$$

Eq. (4) $$\mathrm{RMSE}=\sqrt{\frac{1}{n}\sum_{i=1}^{n}(P_i - O_i)^2}$$

Eq. (5) $$\mathrm{RMSSE}=\sqrt{\frac{1}{n}\sum_{i=1}^{n}[(P_i - O_i)/\sigma_i]^2}$$

Where; P is the estimate, O is the observed value, and n is the number of samples. Low MAE and RMSE represent higher prediction accuracy, while RMSSE is desired to be close to 1.

Land suitability assessment

Land suitability assessment includes criteria standardization, criterion weighting and land suitability map creation in the MCDA approach.

Fuzzy set modelling

Fuzzy set approach was used to define different criteria with a common criterion in agricultural land suitability assessment. In the fuzzy set approach, a function is created to define continuous data and assign membership degrees. With a scale between 0 and 1, objects with high-value membership classes are assigned to a better suitability class (Zadeh, 1965). A fuzzy set (A) can be expressed as follows (Burrough, 1996).

$$A= \{x, MF(x)\}, x \in X$$

Here, x ϵ X belongs to a finite set of points. MF is membership function of x in A. Therefore, a fuzzy subset is defined by the MF, which describes the membership degrees of the objects. The MF of a fuzzy subset determines the degree of membership of x in A. For all A, MF(x) is a value in the range 0 -1. In this context, MF = 0 indicates that the value x does not belong to A and MF = 1 indicates that the value completely belongs to A. On the other hand, if 0 < MF(x) < 1, it is defined as partial A.

There are different models for constructing the MF function. In this study, the Semantic Import (SI) model was applied to grade land features (Burrough & McDonnel, 1998). The attribute values, which are evaluated depending on the phenological development of the product and the land requirements, are converted into common membership degrees (0-1) according to the threshold values determined by taking into account the expert opinions (Zhang et al., 2015; Bagherzadeh & Gholizadeh, 2018; Arab & Ahamed, 2022). In the cellular data structure, 1 indicates full membership or suitability, while 0 indicates unsuitability. For each criterion, a function definition is made in accordance with the data structure. These functions can be defined as linear model, symmetric optimum range model-SFM (Equation 6), left asymmetrical model-ALFM (Equation 7) and right asymmetric model-ARFM (Equation 8) (Figure 2).

$$MF(x_i) = \begin{cases} 1 & (c_1 + d_1) \le x_i \le (c_2 - d_2) \quad \text{Eq. (6)} \\ 1/(1 + ((x_i - c_1 - d_1)/d_1)^2) & x_i < (c_1 + d_1) \quad \text{Eq. (7)} \\ 1/(1 + ((x_i - c_2 + d_2)/d_2)^2) & x_i > (c_2 - d_2) \quad \text{Eq. (8)} \end{cases}$$

Where, $MF(x_i)$ represents the membership function value, x_i is the land feature, c_1 and c_2 are the center point value where the MF is 0.5, d_1 and d_2 are the width of the transition region (distance from the center).

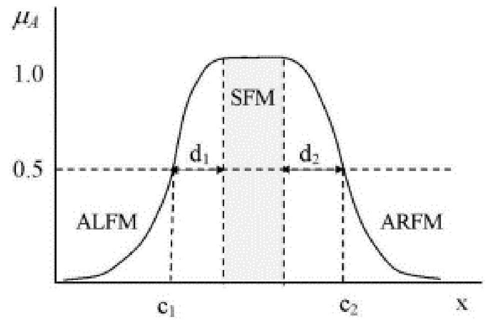

Figure 2. Fuzzy membership functions

According to the variables, an increase in the values of slope, $CaCO_3$, EC and ESP parameters indicates a decreasing suitability value, while a high soil organic matter value indicates an increased suitability value.

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Table 1. Fuzzy membership function thresholds of land suitability criteria for wheat

Criteria	Model	Suitable (Complate membership)	Unsuitable (non membership)	Weight
Slope (%)	ARFM	<3	>15	0.182
Elevation (m)	ARFM	<1100	>1500	0.029
pH	SFM	6.5-7.5	>8.5, <5	0.063
EC (dS/m)	ARFM	< 2	>16	0.042
OM (%)	ALFM	> 3	< 0.5	0.077
$CaCO_3$ (%)	ARFM	< 15	> 40	0.052
CEC (cmol/kg)	ALFM	> 24	< 16	0.022
ESP (%)	ARFM	<15	>45	0.013
Depth (cm)	Linear	deep	very shallow	0.237
Texture (class)	Linear	medium	very coarse	0.103
Erosion (class)	Linear	none	severe	0.129
Drainage (class)	Linear	good	poor	0.035
Stoniness (class)	Linear	none	high	0.017

ARFM: Right asymmetric model, ALFM: Left asymmetrical model, SFM: Symmetric model, OM: organicmatter, CEC: cation exchange capacity, ESP: exchangeable sodium percentage, EC: electrical conductivity

Therefore, ARFM and ALFM models were applied for these factors, respectively. In addition, symmetric membership function (SFM) was used for soil pH. Among the soil properties, the data with vector data structure are divided into suitability classes. In this context; depth (deep (>90), moderate (90-50), shallow (50-20), very shallow (<20)), erosion (none, light, medium, severe), drainage (good, moderate, insufficient, poor), texture (fine(Sandy clay, Clay>%45, Silty clay), medium (Silt, Silt loam, Loam, Clay loam, Silty clay loam, Sandy clay loam, Clay<%45), coarse (Sandy loam), very coarse (Loamy sand, sand)) and stoniness (none, light, medium, high) layers were created. The suitability classes of soil physical properties are graded between 1 and 9 according to their importance levels. The threshold values of the parameters for the wheat suitability analysis were developed based on the literature (Sys et al., 1993) and expert opinions (Table 1).

Analytical hierarchy process

A decision problem can be divided into four main parts in the AHP approach. (i) the decision problem is defined, (ii) the comparison matrix between factors is created, (iii) factors weights are determined, (iv) the consistency of the comparison matrix is measured.

In defining the decision problem, the factors affecting the determination of the agricultural suitability of the land are determined. In particular, the correct determination of the effective factors is important in terms of making pairwise comparisons consistent.

The Original Matrix (A) was created, comparing the priorities of all criteria with each other. The comparison matrix is an m x n square matrix (Figure 3). It takes the value 1 when the components on the diagonal of this matrix are i=j. Factors are compared with each other according to their relative importance. A scale of 1 to 9 is used to compare variables. In this scale, one factor takes the value 3 if it is more important than the other, and 9 if it is extremely important. If the opposite is true, it is expressed as $x_{ij}=1/x_{ji}$.

$$A = \begin{bmatrix} 1 & x_{12} & x_{1i} & x_{1j} & x_{1n} \\ x_{21} & 1 & x_{2i} & x_{2j} & x_{2n} \\ x_{i1} & x_{i2} & 1 & x_{ij} & x_{in} \\ x_{j1} & x_{j2} & x_{ji} & 1 & x_{jn} \\ x_{m1} & x_{m2} & x_{mi} & x_{mj} & 1 \end{bmatrix}$$

Figure 3. Comparison matrix

Matrix values are normalized. Here, matrix C is formed by dividing the pairwise comparison values of matrix A by the column sum (Figure 4).

$$k_{ij} = \frac{x_{ij}}{\sum_{i=1}^{n} x_{ij}}$$

$$C = \begin{bmatrix} k_{11} & k_{12} & \dots & k_{1n} \\ k_{21} & k_{22} & \dots & k_{2n} \\ \vdots & \vdots & \dots & \vdots \\ k_{m1} & k_{m2} & \dots & k_{mn} \end{bmatrix}$$

Figure 4. Normalized pairwise matrix

By using the C matrix, the percent importance values of the factors relative to each other are obtained. For this, the arithmetic average of the sum of the row components forming the C matrix is taken and the priority vector (w) is obtained (Figure 5).

$$w_i = \frac{\sum_{i=1}^{n} kij}{n} = \begin{bmatrix} w_1 \\ w_2 \\ \vdots \\ w_n \end{bmatrix}$$

Figure 5. Weighted criteria matrix

The consistency of the pairwise comparison matrix is measured. The Consistency Ratio (CR) is calculated with the equation (Equation 9) given below. In the equation, CI is the consistency index and RI is the random index. The following formula (Equation 10) is used to calculate the consistency index (CI):

Eq. (9) $CR = CI/RI$
Eq. (10) $CI = (\lambda mak - n)/(n-1)$

Where, λmax is the largest eigenvector of the preference matrix and n is the number of criteria. RI values according to the number of parameters are given in Table 2. If the calculated CR value is less than 0.10, it shows that the comparisons made by the decision maker are consistent. A CR value greater than 0.10 indicates either a calculation error in the AHP or inconsistency in the decision maker's comparisons (Saaty, 1980).

Table 2. Random index (RI) values (Saaty, 1980)

n	1	2	3	4	5	6	7	8	9	10	11	12	13
RI	0	0	0.58	0.90	1.12	1.24	1.32	1.41	1.45	1.49	1.51	1.48	1.56

Land suitability map

In the suitability model, the standardized cellular data values of the variables are weighted according to the importance of the parameters. In the GIS environment, an agricultural land suitability index (ALS) map is generated using the weighted linear combination method (Malczewski, 2011). The linear combination equation (Equation 11) is given below.

Eq. (11) $ALS = \sum_{i=1}^{n} w_i x_i$

Where, ALS is the land suitability index value, wi is the weight of the criterion, x_i is the standardized criterion value, n is the number of criteria. ALS is divided into suitability classes as suitable (S1), medium (S2), low (S3) and unsuitable (N) areas (FAO, 1985).

Results and Discussion

Soil characteristics

Soil physical properties, depth, erosion, drainage and stoniness maps were obtained from the soil database. Geostatistical analysis was applied to create spatial maps of soil properties (sand, silt, clay, pH, EC, $CaCO_3$, OM, ESP, CEC). Geostatistical modeling and

Table 3. Descriptive statistics of soil parameters

Soil Criteria	Minimum	Maximum	Mean	CV	SD	Skewness	Kurtosis
Sand (%)	9.9	92.5	39.0	34.7	13.6	0.72	3.9
Clay (%)	0.4	72.7	34.5	34.8	12.0	-0.05	2.8
Silt (%)	1.8	56.7	26.5	27.6	7.3	0.28	4.1
CEC (cmol kg^{-1})	10.8	54.7	29.2	26.2	7.7	0.37	3.0
pH	6.6	8.7	7.7	3.8	0.3	-0.33	3.4
$CaCO_3$ (%)	0.8	68.7	18.3	57.2	10.4	1.29	5.9
OM (%)	0.3	5.6	1.3	40.7	0.54	1.88	12.3
ESP (%)	0.1	15.3	1.8	107.5	1.9	2.74	12.6
EC (ds m^{-1})	0.2	8.8	1.0	76.9	0.73	6.18	56.7

CV: coefficient of variation; SD: standard deviation, OM: organic matter; CEC: cation exchange capacity, ESP: exchangeable sodium percentage, EC: electrical conductivity creation of parameter maps are completed in two parts. (i) Descriptive statistics were determined to describe the trends and distributions of soil properties. (ii) Ordinary Kriging (OK) technique was used to determine the spatial dependence and variability of soil parameters.

Descriptive statistics for soil properties are given in Table 3. While the sand, clay and silt values of the soils vary between 9.9-92.5%, 0.4-72.7% and 1.8-56.7%, the averages are 38.9%, 34.5% and 26.5%, respectively. $CaCO_3$ content varies between 0.8% and 68.7%, with an average of 18.3%. Organic matter content varies between 0.3% and 5.6%, with an average of 1.3%. While the pH level in the area ranged from 6.50 (slightly acidic) to 8.70 (strongly alkaline), it was characterized as slightly alkaline with an average value of 7.70. It can be said that the area is suitable for agricultural production in terms of average value. The CEC content varies between 10.8% and 54.7%, with an average of 29.2%. While the EC level varies between 0.2 and 8.8 ds m^{-1}, its average value is 1.0 ds m^{-1}, and it is not at a level that will adversely affect the wheat in the whole area. On the other hand, there is moderate salinity in some areas as irrigated agriculture is intense. The ESP value varies between 0.1% and 15.3%, with an average value of 1.8%.

The normal distribution of the data sets was evaluated according to the skewness values of the variables. Webster & Oliver (2001) stated that if the skewness value is greater than 1, transform can be done. In this context; While Clay, Silt, CEC and pH showed normal distribution, Sand, OM, $CaCO_3$, ESP and EC did not show normal distribution and positive skewness was determined and log-transform was applied. This need for transformation has been consistent with similar studies (Di Virgilio et al., 2007; Liu et al., 2014; Mousavifard et al., 2013; Bogunovic et al., 2017; Sharma & Sood, 2020).

The variability of the datasets is evaluated with the coefficient of variation (CV). A CV value of less than 15% indicates a weak variation, a moderate variation of 16-35%, and a high variation above 36% (Wilding, 1985). Among the variables, pH showed a weak change with the lowest (3.8%) value, while ESP showed the highest change (107.5%). While pH, the parameter with the lowest CV value, is the least affected by the land structure and agricultural practices, OM (40.7%), $CaCO_3$ (57.2%), EC (76.9%) and ESP (107.5%) with a CV value > 35 are the most affected soil properties. On the other hand, there is moderate variability (26.4-34.8 % CV) for CEC, Silt, Sand and Clay. Soil pH value showed a homogeneous distribution with a low CV value (3.8%) and showed similarity with other studies (Emadi et al., 2008; Jiang et al., 2012; Mousavifard et al., 2013; Bogunovic et al., 2014).

Spatial variation of soil properties

The geostatistical analysis showed different spatial distribution patterns and nugget/sill relationships explaining the spatial relationships for the selected soil features. Spatial distributions of soil properties are described by Ordinary Kriging technique and isotropic variogram models. Spatial distribution models and spatial dependence degrees were determined for the variables by geostatistical analysis. The spatial variability of sand, clay, silt, OM, $CaCO_3$, CEC and pH were described by the exponential model, while the ESP and EC variables were best characterized by the spherical model (Table 4). Model type and parameters are given in Table 4, and experimental and model variograms are given in Figure 6.

The nugget-to-sill ratio gives a measure of the short-range variability of the variable. It can be said that if this ratio is below 0.25, a large part of the variance is spatially included and there is a strong spatial dependence, if it is between 0.25 and 0.75, it is medium level, and if it is above 0.75, there is a weak spatial dependence due to a high short-distance variability (Cambardella et al., 1994). In this context, there is generally a moderate short-range variability for the study area soils, while there is a weak spatial dependence for EC and pH. Cambardella et al. (1994)

Table 4. Geostatistical model and model parameters of soil parameters

Soil Criteria	Model	Nugget	Sill	Nugget/ Sill	Spatial Dependence	Range (km)	Cross Validation		
							ME	RMSE	RMSSE
Sand (%)	Exponential	90	160	0.56	Moderate	18	-0.15	12.2	1.05
Clay (%)	Exponential	66	140	0.47	Moderate	16	0.014	11.1	1.05
Silt (%)	Exponential	26	50	0.52	Moderate	15	0.012	6.64	1.02
$CaCO_3$ (%)	Exponential	0.12	0.43	0.28	Moderate	23	0.54	8.49	0.91
CEC (cmol kg^{-1})	Exponential	34	63	0.54	Moderate	50	-0.015	6.73	1.03
OM (%)	Exponential	0.07	0.16	0.43	Moderate	13	0.001	0.51	1.06
ESP (%)	Spherical	0.45	0.75	0.60	Moderate	4	0.007	1.79	0.96
EC (ds m^{-1})	Spherical	0.17	0.20	0.85	Weak	4	-0.032	0.73	1.50
pH	Exponential	0.072	0.086	0.84	Weak	16	0.002	0.29	1.01

ME: Mean error, RMSE: root mean square, RMSSE: root mean square standardized error

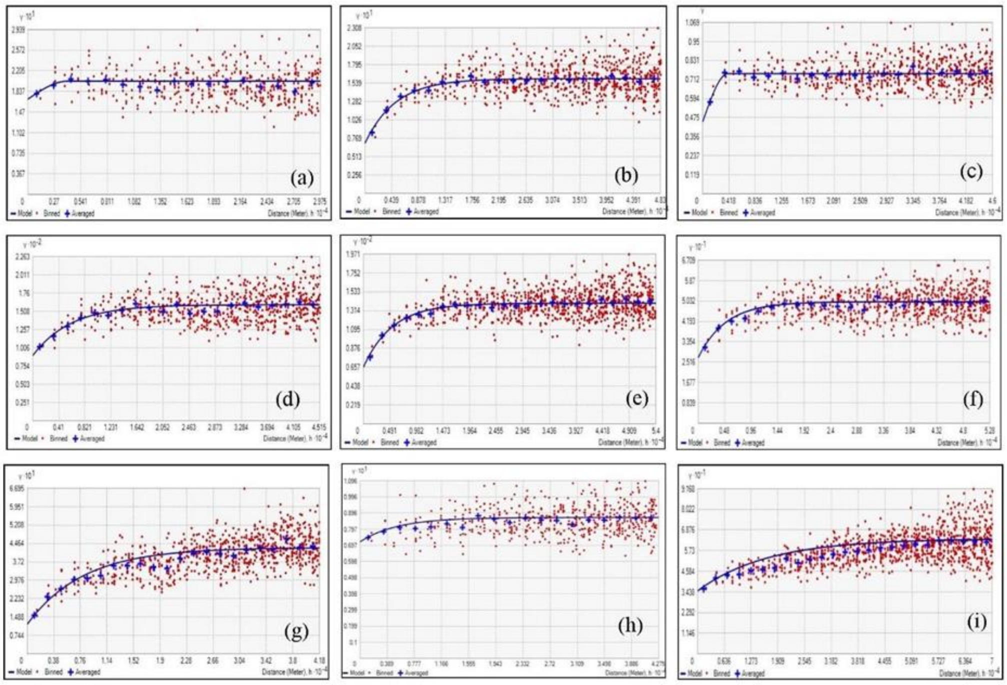

Figure 6. Experimental variogram models of soil properties (a) EC, (b) OM, (c) ESP, (d) 396 sand, (e) clay, (f) silt, (g) $CaCO_3$, (h) pH, (i) CEC

stated that the dependence of soil properties is closely related to topography, climate, parent material and land use. In the variogram model, the structural distance (range) value represents the maximum distance of the relationship depending on the distance, and beyond that, there is no autocorrelation between the variables (Behera et al., 2018). The highest range value was observed in the CEC (50 km) content, while the lowest was determined at 4 km in the EC and ESP variables.

Distribution maps of soil and topographic features are given in Figure 7. In terms of soil texture characteristics, while the clay content in the area varies between 30-40%, the areas with higher clay content are mostly located in the middle part of the area. It was observed that the clay content decreased to 25-30% around Lake Tuz and along the river, which also constitutes the boundaries of the area in the west and east. In the areas where the clay content is low, the sand content rises to 45%. While the clay content drops below 30% around Lake Tuz, the sand content rises above 50%. In a general approach, it can be said that the sand content is low in areas with high clay content. The negative relationship between the clay and sand contents of the soils is seen in the distribution maps (Figure 6). This situation was similar to previous studies (Tesfahunegn et al., 2011; Selmy et al., 2022). The widespread distribution of conglomerate and limestone materials can be attributed to the high sand content found in alluvial lands.

Although the EC varies between 0.2 and 8.8 dS m^{-1}, the average salinity in the area is not sufficient to restrict crop growth. Lake Tuz, located in the southeast of the study area, is the second largest lake in Turkey. Lake Tuz is important as a salt source and has a high value both as a natural structure and as a habitat. Lake Tuz and its surroundings are covered with Oligocene aged formations with gypsum and salt layers. Although the lake is closed, it is fed by underground and surface waters (Dengiz & Baskan, 2009). In addition, the Hirfanlı Dam is located on the Kızılırmak river in the east of the study area. It has been observed that moderate saline soils are present in the irrigated agriculture areas around Lake Tuz and Hirfanlı Dam. EC is one of the soil properties with the shortest distance range. Similar studies have also stated that EC has the shortest range compared to other soil properties (Emadi et al., 2008; Kılıç et al., 2022). The OM content ranges from 0.3% to 5.6%, while the coefficient of variation value has a high variation of 40.7%. It was observed that the OM content was higher than the average (1.3%) in the southwestern and central parts compared to other areas. The $CaCO_3$ content in the study area increases from east to west. While the $CaCO_3$ rate varies between 15-30% throughout the area, moderately calcareous areas are common. Depending on the parent material, the $CaCO_3$ has moderate short-range variability in the area. While the CEC is 25-28 cmol/kg in the western and eastern part of the area, it decreases to 20 cmol/kg in the southern part. In the central part of the area, as in the clay distribution, it increases and exceeds 35 cmol/kg. The pH content showed a weak spatial dependence, ranging from 7.4 to 7.8 (slightly alkaline) over a wide area (Figure 7).

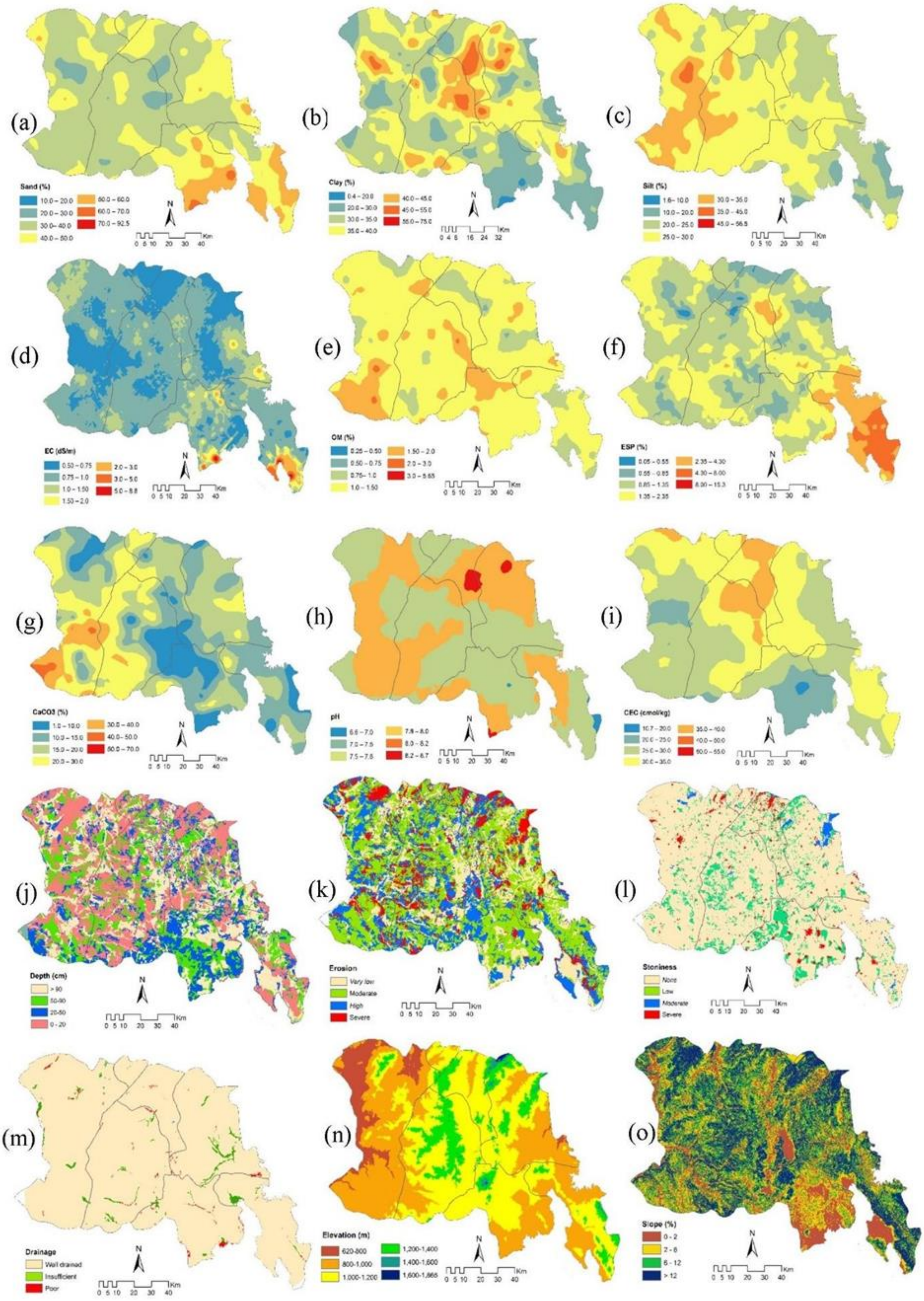

Figure 7. Soil and topographic parameter distribution maps (a) Sand, (b) Clay, (c) Silt, (d) EC, (e) OM, (f) ESP, (g) $CaCO_3$, (h) pH, (i) CEC, (j) depth, (k) erosion, (l) stoniness, (m) drainage, (n) elevation, (o) slope

Table 5. The correlation coefficients matrix of the studied soil attributes

	Clay	Silt	Sand	OM	ESP	CEC	$CaCO_3$	pH
Silt	-0.077*							
Sand	-0.843**	-0.471**						
OM	-0.008	0.200**	-0.101**					
ESP	0.009	-0.110**	0.052	-0.204**				
CEC	0.406**	0.052	-0.388**	-0.037	0.023			
$CaCO_3$	0.067	0.165**	-0.148**	0.131**	-0.100*	-0.140**		
pH	0.225**	-0.126**	-0.131**	-0.114**	0.066	0.008	0.007	
EC	-0.019	0.034	-0.002	-0.014	0.236**	-0.005	-0.020	-0.034

∗ $P < 0.05$, ∗∗ $P < 0.01$

The interpolation method used in spreading soil samples over the area is important. Soil properties values in unsampled areas were produced by kriging according to spherical and exponential variogram models. Spatial variation maps of soil parameters were produced using the OK method based on variogram models. It has been reported that the OK method performs well in mapping different soil properties (Tesfahunegn et al., 2011; Piccini et al., 2014; Pham et al., 2019; Dengiz, 2020). The cross-validation results of the prediction maps produced with OK are given in Table 4. The OK method produced lower RMSE errors to predict pH, EC and OM, while the highest RMSE errors were observed to predict sand and clay.

In the study area, the relations of soil properties with each other were evaluated. A strong negative relationship was observed between clay and sand (r = -0.843**), while a significant positive relationship was found between clay and CEC (r =0.406**) and pH (r = 0.225**). A significant negative relationship was found between sand and CEC (r = - 0.388**), OM (r = -0.101**), $CaCO_3$ (r = -0.148**), and pH (r = -0.131**). In the correlation analysis, a negative significant relationship was observed between OM and ESP (r = - 0.204**) and pH (r = -0.114**). In addition, there was a negative significant relationship between $CaCO_3$ and CEC (r = -0.140**), while a positive significant relationship was found between ESP and EC (r =0.236**) (Table 5).

In the findings obtained in similar studies; the relationships between clay and sand (Mustavifard et al., 2013; Kılıc et al., 2022), clay and CEC (Selenay et al., 2022; Usowicz & Lipiec, 2021) and ESP and EC (Selenay et al., 2022) variables consistent with the results of the study. The spatial variation of soil parameters and their interrelationships can affect soil management, fertilization, crop rotation, land characteristics and geomorphological structures (Cambardella & Karlen, 1999). In this context, the relationships between some soil properties in the literature could not be observed in the study area. In these studies, a positive relationship was determined between OM and clay and CEC (Saidian et al., 2016; Azadi & Baninemeh, 2022; Mishra et al., 2022). Soil organic matter content can be affected by climate, topography and land use (Durdevic et al., 2019), intensive tillage (Lopez-Fando & Pardo, 2011), and crop residue removal (Raffa et al., 2015). The low biomass of the steppe vegetation in the semi-arid climatic conditions in the Central Anatolian Region caused the soil organic matter to become poor (Öner et al., 2016). The study area is also under the influence of the steppe ecosystem and intensive agricultural activities for many years.

Land suitability evaluation

Multiple criteria analysis was applied to determine the suitability of agricultural land. In the suitability model, criterion weights were determined by the AHP approach (Table 6). Depth, which is among the soil physical parameters, has the highest weight with a value of 0.237. This criterion was followed by slope (0.182), erosion (0.129) and texture (0.103). Among the soil chemical properties, OM (0.077) has the highest weight. OM was followed by pH (0.063), Lime (0.052) and EC (0.042) parameters. The CR values of the criteria matrix were calculated as 0.059.

In the study area, the depth is the most effective factor with the highest weight value (0.237). Depth is an important criterion for moisture and plant nutrient intake (Dedeoğlu & Dengiz, 2019). Soil depth has different depth levels throughout the field. This situation creates a limiting effect for crop growth. Slope is the second most influential and weighted (0.182) factor in the study area. In areas where the slope is high, plant growth is limited with the decrease of plant root depth and the effect of erosion increases. In addition, these areas may have indirect negative effects on agricultural practices, mechanization and yield. In the Central Anatolian Region, depth and topographic parameters have significant weight in suitability studies for large areas (Özkan et al., 2020; Kılıc et al., 2022). In the field-specific evaluations, depth and slope factor were determined as the most important factors and showed similarities with other studies.

The steppe ecosystem is dominant in the Central Anatolia Region and it is a region with a high risk of land degradation and erosion due to topographic and anthropogenic conditions in semi-arid climate conditions (FAO-TOB, 2020). In the study area, there is erosion effect throughout the area due to the high sloping lands. In this respect, the weight value of erosion was determined as 0.129. The weight of the soil texture was calculated as 0.103. It has good and medium class soil structure throughout the Central Anatolian Region (Özkan et al., 2020). In the study area, there is a medium and clay loam texture, which is mostly suitable for wheat cultivation. Among the soil chemical parameters, OM has the highest weight (0.077). OM has an important effect on soil fertility in terms of both soil structure and plant nutrients (Obalum et al., 2017). A calcareous soil structure is common in the area and the pH value is between 7 and 8. These soils are in the slightly alkaline class due to their lime content and insufficient rainfall. pH, which is the basic soil criterion in land suitability analysis, plays an important role in the availability of plant nutrients. Therefore, pH has the highest weight value (0.066) after OM among the soil chemical properties. EC is not at a level that will adversely affect wheat production in the whole area, except around Lake Tuz and local areas where irrigated agriculture is made. In large areas, more sampling of areas with extreme soil properties or evaluation with sub-zoning can provide more accurate results for the area.

The land suitability class map was obtained by classifying the agricultural land suitability index (ALS) (Figure 8). According to the suitability map, 25.7% (3,226 km^2) of the area is highly suitable, 27.6% (3,457 km^2) is moderately suitable, 19.5% (2,440 km^2) is marginally suitable and 27.2% (3,415 km^2) is not suitable for wheat cultivation (Table 6).

Table 6. Spatial distribution of wheat suitability classes

Suitability classes	Area (km^2)	(%)
Highly suitable	3,226	25.7
Moderately suitable	3,457	27.6
Marginally suitable	2,440	19.5
Not suitable	3,415	27.2

Suitable class (S1) lands do not have a significant barrier to agricultural production. These lands are flat and nearly flat alluvial areas with 0-3% slope. These areas have deep soil structure and medium texture. Moderately suitable (S2) lands is important for

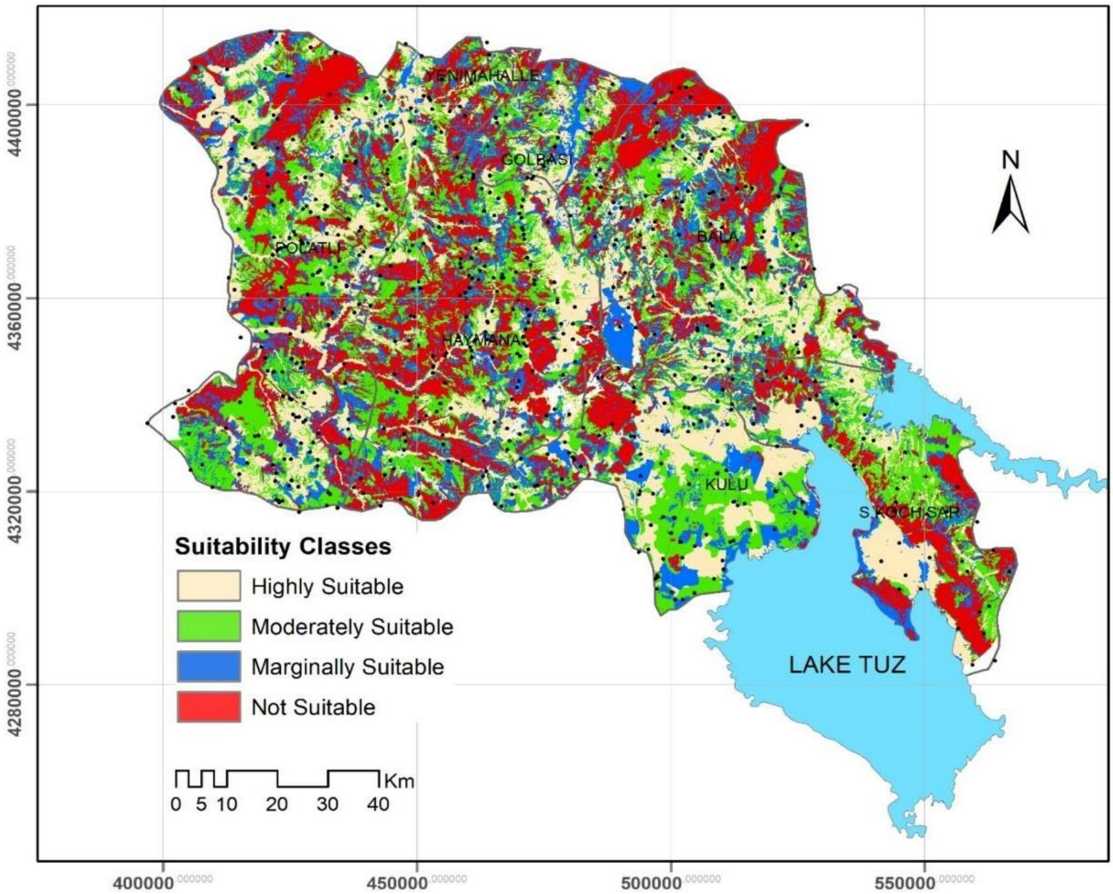

Figure 8. Land suitability classes for wheat

agricultural production, although it has several limitations for land use. This class covers 27.6% of the study area. Intensive agricultural activities are carried out on the soils in this class. The slope in these lands varies between 0-6% and they are medium deep soils. The less suitable (S3) lands, covering 19.5% of the area, have serious limitations. These lands have low agricultural potential due to negative features such as shallow soil depth, erosion risk, stoniness, low organic matter and protection measures are required. 27.2% of the area is not suitable for agriculture. These lands have very serious limitations due to insufficient soil depth, steep slope and severe erosion.

Conclusion

For semi-arid regions, wheat production is mainly preferred in dry agricultural areas. Due to the limited rainfall in these areas, the effects of soil and topographic conditions on production are high. Identifying effective land features among many variables is a priority for suitability analysis. Geostatistical modeling was applied to determine the spatial changes of soil parameters. Fuzzy-AHP and GIS integrated approach were applied in land suitability assessment. Potential areas for wheat production were determined by land suitability analysis. As a result of the study, 25.7% (3,226 km^2) of the area for wheat production is highly suitable (S1), While 27.6% (3,457 km^2) is mederately suitable (S2), 19.5% (2,440 km^2) is marginally suitable (S3) and 27.2% (3,415 km^2) is not suitable (N). In the preliminary stage of land use planning, it is important to evaluate land characteristics and develop land use alternatives. Since ecological needs differ in land use decisions, it is necessary to compare land characteristics with ecological demands and select the most optimum area. The relative importance of different parameters for land suitability was defined with AHP and integrated into the decision-making process with GIS techniques. MCDA has played an active role in evaluating many criteria and making the right choices. In the MCDA process, it is necessary to determine the relative importance or weight of the factors. At this stage, determining the effective criteria by evaluating the field conditions and expert opinions increases the accuracy of the result map. In the study area, it has been observed that the spatial variability of soil properties is high, but this variability is also effective in climate and topographic structure, as well as land use and agricultural practices. The results of the study can be an example for land planning studies in relation to the impact of ecological data on crop development in semi-arid and large areas. The land suitability maps produced in this context can be used as base data in current and future planning studies. In land use preferences, sustainability should be ensured by taking into account the balance of protection and use of the land, as well as the increase in production.

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Conflict of Interest

The authors declare that they have no known competing financial or non-financial, professional, or personal conflicts that might apper to influence the work reported in this paper.

Author Contribution

MGT: Conceptualization, investigation, methodology, validation, software, carried out the field study, collected the soil samples, resources, data curation, writing (original draft preparation), writing (review and editing), visualization, supervision, statistical analysis, project administration; **AET:** Conceptualization, investigation, geostatistical analysis, writing (review and editing); **HT:** Carried out the field study, collected the soil samples, software, validation, investigation, data curation; **EK:** Carried out the field study, collected the soil samples, validation, investigation, data curation; **MU:** Investigation, validation, soil analysis, data curation. All authors have read and agreed to the published version of the manuscript.

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