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An evaluation of land-use capability using the LESA method coupled with geostatistics in a GIS environment

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ABSTRACT: Land-use effectiveness can be ensured by utilizing GIS and geostatistical tools in conjunction with land assessment methods to prevent soil erosion and salinization. This study employs a GIS-based LESA methodology, combined with geostatistics, to evaluate the land's capacity to produce agricultural crops on calcareous soils. Land Evaluation for Agricultural Uses (LESA) key components are site assessment and land evaluation, with the former being non-soil-dependent and the latter being soil-dependent. Geostatical kriging was used to interpolate and generalize a GIS map of land capability. The study found that 27.88, 47.94, 18.76, and 5.41 % of the study area were unsuitable for crop farming, marginally suitable, moderately suitable, and highly suitable, respectively. Our research demonstrates that a flexible GIS framework can assist decision-makers in more accurately assessing land resources, including unsuitable, marginally-suitable, and reforested lands.

Keywords: agriculture activities, land capability evaluation, site assessment.

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INTRODUCTION

Land evaluation is the first step to provide suitability and limitations of the land resources. Farming systems have increased economic productivity due to advances in agricultural technologies, such as fertilizers, irrigation systems, and pest control. However, soil resources in large parts of Iran have high carbonate contents (Ostovari et al., 2020). Crop farming is complex with carbonate materials. Land management is negatively affected by soil salinization (Khajehzadeh et al., 2022) and land degradation (Mirzaee et al., 2017; Mirzaee and Ghorbani-Dashtaki, 2021) in many parts of Iran. Additionally, carbonates affect soil structure, potentially leading to hard layers and reduced water movement. While providing essential calcium and magnesium, their associated high pH poses challenges for crops favoring slightly acidic conditions. Thus, in a semi-arid climate, such as Iran, accurate methods are needed for identifying and determining the land potential for agricultural production.

Land capability has a significant impact on yield potential. Several models have been proposed to assess and determine land capability classes, including the FAO framework (FAO, 1976), ALES (Rossiter and Van Wambeke, 1994), LESA (LESA Handbook, 2011), and ALC (MAFF, 1988). For evaluating land capability using ALES, ALC or FAO methods, soil quality parameters are the most important variables. However, both soil-dependent and non-soil-dependent factors will be important to agricultural decision-makers. In addition to soil capability classes and yield potential, there are economic and social factors that play a role. As a result of considering both soil-dependent and soil-independent factors, the USDA NRCS developed the LESA method. The method consists of two components or subsystems: (1) LE (land evaluation) and (2) SA (site assessment), which consider non-soil-dependent factors impacting the classification type for farming activities (Hoobler et al., 2003).

One important advantage of the LESA method is it can be adapted to the local context, which means it is an effective method for assessing land capability because it can be tailored to local conditions (Dung and Sugumaran, 2005; Mathews and Rex, 2011). Because of urban development, road construction, natural disasters, and development pressures, non-soil-dependent factors tend to be unstable and dynamic in the SA component, while soil-dependent factors tend to be more stable and permanent in the LE component (LESA Handbook, 2011).

Integrating spatial analysis techniques with the Land Evaluation for Agricultural Uses - LESA method - within a GIS framework is pivotal for a nuanced comprehension of land capability characteristics, providing essential insights for informed agricultural decision-making. The amalgamation of land suitability analysis and GIS technology has been substantiated by prior research (Ostovari et al., 2019; Zhu et al., 2022). Notably, Hoobler et al. (2003) conducted a study in East Park County, Wyoming, illustrating enhanced accuracy in decision-making related to yield potential through the synergistic application of the LESA procedure and GIS. Furthermore, Dung and Sugumaran (2005) reported time-saving benefits when employing GIS and the LESA method to delineate land capability classes at the field scale. It is imperative to underscore the LESA method requires meticulous calibration to local conditions, exemplified in this study's focus on calcareous soils and non-soil-dependent factors specific to Iran. Even on a national scale across Iran, Akbari et al. (2022) and Esmaeili et al. (2021) demonstrated variations in local conditions, emphasizing the significance of localized calibration for accurate and context-specific land capability assessments.

This study aims to evaluate the applicability of the Land Evaluation for Agricultural Uses (LESA) method in a semi-arid region. It begins with a thorough calibration of the LESA method, scrutinizing its performance considering the region unique environmental conditions. The focus then shifts to integrating the refined LESA method into a framework. This integration allows for the generation of detailed maps illustrating land capability classes. These maps, supported by the calibrated LESA method and GIS technology can offer valuable insights for decision-making in land-use planning and sustainable agricultural development in a semi-arid context.

MATERIALS AND METHODS

Studied region

The studied area (Figure 1) cover approximately 3,235 km^2 and is located in the Khuzestan province, Iran (30° 30' 0" N – 31° 25' 0" N and 48° 10' 0" E - 49° 0' 0" E). The elevation in this area varied between 1562 to 3099 m a.s.l. (Figure 1). Taxonomically, soil types in this area fall under Inceptisols, Mollisols, and Entisols according to Soil Survey Staff (2010) and carbonates are the most abundant parent material in this region. This area mostly is agricultural lands under cereal productions. Irrigated and rainfed winter wheat are the dominant agricultural productions. The native vegetation was replaced by farming crops. However, it persists and grows in steep, high-altitude areas.

Climate

Climate in the region is semi-arid, and the average annual rainfall and annual air temperature are 291.7 mm and 17.5 °C, respectively. Most rainfall is typically the result of irregular, but heavy, rainfall events during spring (Figure 2).

Sampling and analyzing in the laboratory

Soil samples were collected from 72 profiles employing a random sampling approach and were analyzed for the following soil properties: SOC (Soil Organic Carbon) contents were measured by applying wet-oxidation method (Nelson, 1983); EC (Electrical Conductivity) and pH were measured in the extraction of saturated soil; ESP (Exchangeable Sodium Percentages) contents were measured by applying ammonium acetate following the

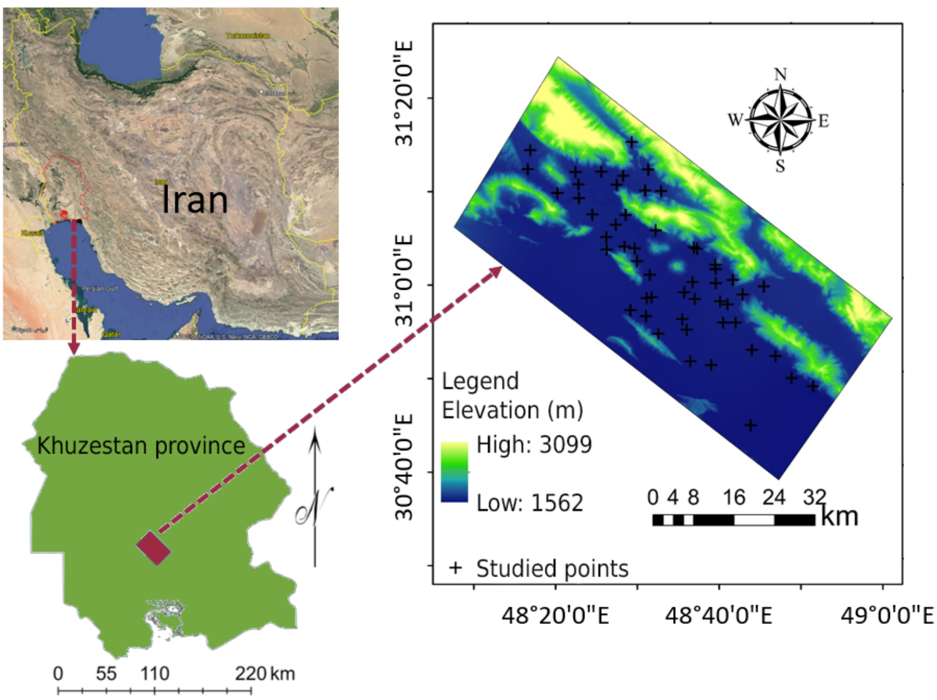

Figure 1. Sample point locations in Khuzestan province, Iran.

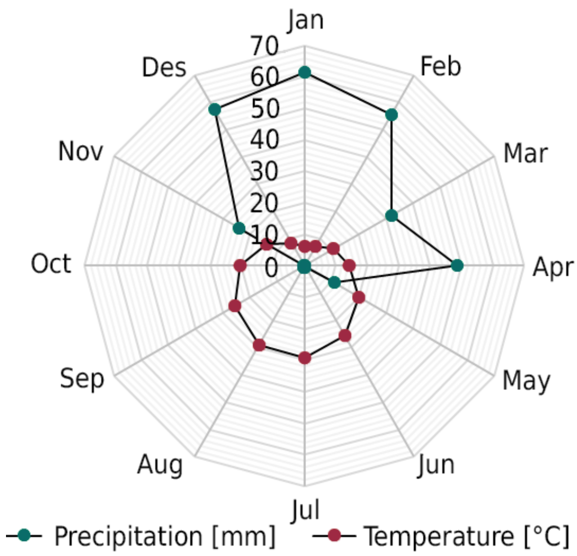

Figure 2. Monthly precipitation and average temperature from 2001 to 2022.

Lavkulich (1981) method; CCE (Calcium Carbonate Equivalent) contents were measured following the back-titration method (Nelson and Sommers, 1983); sand, silt and clay contents were measured following the hydrometer method (Gee and Bauder, 1986). Table 1 shows descriptive statistics for the determined soil properties.

Spatial analysis

Kriging is a family of methods for predicting a random variable based on the observed structure of spatial variability and can be used to generate unbiased interpolated maps for soil properties. In this study, we use Ordinary Kriging (OK), which assumes an unknown constant trend (Triantafilis et al., 2001; Mirzaee et al., 2016). Kriging is a two-step process: first, the covariance structure is characterized, and then the prediction is made with the estimated parameters of a semi-variogram function. Covariance structure, or experimental semi-variogram as it is termed, was calculated using equation 1 (Triantafilis et al., 2001; Mirzaee et al., 2016).

$$\gamma(h) = \frac{1}{2N(h)} \sum_{i=1}^{n} \left[Z(x_i) - Z(x_i + h) \right]^2 \qquad \text{Eq. 1}$$

in which: Y(h) is the semi-variance for a given lag separation h; and $Z(x_i)$ is the real value at sample location x_i. Given a parameterized semi-variogram function, the next step is to apply OK to estimate soil properties at unsampled point locations. As shown in

Table 1. Descriptive statistics of the studied soils (n = 72)

Properties	Min	Max	Mean	Std. dev
Clay (g kg^{-1})	17.9	40.0	26.5	4.53
Silt (g kg^{-1})	24.0	40.0	31.7	3.20
Sand (g kg^{-1})	30.1	55.0	41.8	4.94
SOM (%)	1.74	3.56	2.79	0.43
CCE (%)	11.5	66.3	43.5	12.05
pH(H_2O)	7.0	7.8	7.6	0.21
EC (dS m^{-1})	0.04	12.7	2.4	2.24
ESP (%)	1.0	110.5	14.4	13.6
Soil depth (m)	0.553	1.981	1.458	0.330

ESP: Exchangeable Sodium Percent; EC: Electrical Conductivity; SOM: Soil Organic Matter; CCE: Calcium Carbonate Equivalent.

equation 2, OK calculates a weighted sum of the available data (Triantafilis et al., 2001; Mirzaee et al., 2016):

$$\hat{Z}(x_0) = \sum_{i=1}^{n} W_i(x_0) Z(x_i) \qquad \text{Eq. 2}$$

in which: W_i represents the OK weights, $Z(x_i)$ is the real value at sample point location x_i, and $\hat{Z}(x_o)$ indicates the model prediction at location x_0. ArcGIS v10.3 was used to perform the geostatistical analysis.

LESA model

The LESA method, a numerical model for predicting land capability classification, can quantify land resources accurately to improve agricultural productivity (LESA, 2011). This method for assessing land capability classes was designed to include an understanding of local conditions based on local committee knowledge and experiences (LESA, 2011). The knowledge and experiences of 22 local experts were employed to form a local committee that would characterize local conditions. These local agricultural experts were best placed to help characterize the LESA method because they had been involved in local agriculture production for several years. These local experts informed the selection, weighting, and scaling of all the factors considered in the LESA method.

The LESA approach is composed of two distinct and important components, LE and SA, which are now discussed in greater depth (LESA, 2011).

Land evaluation component

The LE component is further subdivided into subcomponents or factors. These subcategories include land capability, prime farmland classification, and soil productivity index classification (LESA, 2011). These subcategories are now outlined in more detail.

(1) Land capability classification

A land capability classification system has previously been developed in 1970 for Iran (Mahler, 1979) by an expert from the FAO, P.J. Mahler, along with a team of experienced staff. Iranian capability classification system is still widely used for soil surveys and related projects in Iran. This Iranian system continues to be extensively employed for soil surveys and associated projects within the country. It has been well used during the past 40 years since being published and is considered a reliable source for classifying land capability and will be used in this study. The LC (land capability), classified by Mahler (1979), defines and describes six distinct classes and are designated by numbers I–VI. In class I, the soil resource is excellent for agricultural activities. In class II, soil resource creates some limitations for agricultural activities by diminishing the plant selection for farming and requiring some conservation practices for cultivation. In class III, soil resources are too limited for farming some specific plant which decreases the plant selection, requires some special conservation practice, or both for cultivation. In class IV, soil resource has very high limitation, restricts plant selection, and requires special management methods or both for agricultural activities. In class V, soil resources have high limitations and, in the current situation, are unsuitable for farming activities. In class VI, soil resources have severe limitations and, for permanent times, are unsuitable for agriculture.

(2) Soil Productivity Index (SPI)

As the name suggests, the SPI is a rating or measure of farmland productivity. Generally speaking, the higher the SPI, the better the productivity of an area, although it is important to understand how the SPI is calculated for a particular location. In the Khuzestan region, the main crops that are farmed are corn, wheat, and alfalfa, which are used as the basis of the SPI calculation. The SPI calculation is outlined in equation 3 and the potential yields are assumed based on the best crop management conditions for corn, wheat, and alfalfa are calibrated by the long-term mean yield for alfalfa (4.5 Mg ha^{-1}), wheat (5.5 Mg ha^{-1}), and forage corn (62 Mg ha^{-1}), as determined by a local committee of experts (Esmaeili et al., 2021). The SPI values at the sample point locations were in the range 0-100.

$$SPI = [(Corn\ yield/62) + (Wheat\ yield/5.5) + (Alfalfa\ yield/4.5)] \times 100 \quad \text{Eq. 3}$$

(3) Prime Farmland Classification

Prime Farmland Classification attribute described here is used to identify prime farmland, or farmland of regional importance. Conditional farmland is also considered, which takes into account drainage, flooding and irrigation conditions. This classification system considers a combination of physical and chemical soil properties necessary for high agricultural productivity (Gould et al., 2017). In this study, the sample point are located in six groups: P1 – prime farmland, P2 – important farmland, P3 – prime farmland if it has drainage network, P4 – prime farmland if it is protected against flood or flood not-occurred in this location, P5 – prime farmland if it has drainage network and either it is protected against flood or flood not-occurred in this location, especially in the season that plants are at the field, and P6 – not-prime farmland.

A local committee of experts prioritized the prime farmland classification as P1 > P2 > P3 > P4 > P5 > P6 by considering a number of factors, including economic conditions, crop yields, and energy requirements.

Site Assessment Component

The SA component was further subdivided into some factors that were selected based on the local expert committee's knowledge and experiences. Factors in this section of the LESA method are non-soil characteristics that influence crop farming site application (LESA, 2011). Following the methodology of Akbari et al. (2022), the SA factors were divided into three groups, denoted as: SA-1, SA-2 and SA-3:

SA-1 factors: Crop farming influences

The first set of factors describes crop farming influences. Local expert committee selected measures of area and surrounding land-use. These measures were divided into five categories and a score was assigned to each (Table 2). These factors include: adjacent land-use compatibility, access to farming support services, and agricultural area within 1.5 miles.

SA-2 factors: Development pressures on crop farming

The SA-2 factors were composed of factors that influence crop farming in the study area through networks such as drainage, irrigation, and road. Local expert committee determined four important distance factors such as public roads, water, drainage systems, and urban feeder highway. These data for these factors were divided into six categories and assigned scores (Table 3).

Table 2. Scoring of SA-1 factors: crop farming influences

Adjacent land use compatibility	Score	Area in agriculture applying within 1.5 miles	Score	Accessing farming support services	Score
4 sides in agriculture use	100	80-100 %	100	<0.8 km	100
3 sides in agriculture use	80	60-80 %	75	0.8-1.6 km	80
2 sides in agriculture use	60	40-60 %	50	1.6-2.4 km	60
1 side in agriculture use	40	20-40 %	25	2.4-3.2 km	40
4 sides in non- agriculture applying	0	<20 %	0	>3.2 km	0

Table 3. Scoring of SA-2 factors: development pressures on crop farming

Distance of urban feeder highway	Score	Distance of public water	Score	Distance of public road	Score	Distance of public drainage systems	Score
<1.6 km	100	<60 m	100	<360 m	100	<60 m	100
1.6-3.2 km	80	60-360 m	80	360-1200 m	80	60-360 m	80
3.2-4.8 km	60	360-784 m	60	1200-1900 m	60	360-784 m	60
4.8-6.4 km	40	784-1200 m	40	1900-2700 m	40	784-1200 m	40
6.4-8.0 km	20	1200-2400 m	20	2700-3600 m	20	1200-2400 m	20
>8.0 km	0	>2400 m	0	>3600 m	0	>2400 m	0

SA-3 factors: Qualitative public values on crop farming

SA-3 factors include a number of qualitative factors related to public values, such as: environmentally sensitive zones, proximity of wetland and riparian zones, and proximity of historic buildings. Different subfactors were split into six categories and assigned scores as determined by the local expert committee, which are summarized in table 4.

Weight of factors in the LESA procedure

Based on local expert committee (22 local agriculture experts), weights were assigned to each factor, both LE and SA, to represent each factor's relative importance in the LESA method. The LE component with a weight of 0.4 (i.e., 0.1, 0.06, and 0.24 for the soil productivity index, classification of prime farmland, and land capability, respectively) contains most soil features that indirectly characterize the environment costs and crop farming economy. As a result, according to the local expert committee opinion, the land capability classification got the highest relative importance in the LE component (0.24). Additionally, the committee characterized weights of 0.3, 0.2 and 0.1 for the SA 1, SA 2 and SA 3 subcomponents, respectively.

To calculate the final LESA score, a weighted sum of all of the factors was done using equation 4.

$$LESA\ score = \sum_{i=1}^{n} W_i \mu_i (x) \qquad \text{Eq. 4}$$

in which: n is the number of components used; W_i and μ_i (x) are weight and factor score, respectively, for a particular factor i, at a location x. The factor weights are constrained by $W_i \in [0,1]$, $\sum_{i=1}^{n} W_i = 1$ and hence must sum to 1. Calculated final LESA score will be in the range 0 (not suitable for crop farming) to 100 (high capability for crop farming). To generate a final land capability map for crop farming, the Weighted Overlay tool, available in ArcGIS v10.3, was used (Basharat et al., 2016) according to figure 3.

Table 4. Scoring of SA-3 factors: qualitative public values on crop farming

Proximity of historic buildings	Score	Proximity of wetland and riparian	Score	Environmentally sensitive area	Score
>2400 m	100	>800 m	100	>2400 m	100
2400-1200 m	80	800-400 m	80	2400-1200 m	80
1200-784 m	60	400-200 m	60	1200-784 m	60
784-360 m	40	200-100 m	40	784-360 m	40
360-60 m	20	100-300 m	20	360-60 m	20
<60 m	0	<30 m	0	<60 m	0

Model performance

Standard summary statistics were used to quantify the performance of the derived models. Assuming N is the number of data sets, Y_i is the measured data sets, and $\hat{Y}_i$ is the estimated data sets, then the mean error (ME) is given by equation 5 and provides an indication of the bias in the model.

$$ME = \frac{1}{N}\sum_{i=1}^{N}\left(\hat{Y}_i - Y_i\right) \qquad \text{Eq. 5}$$

The root mean square error (RMSE) is defined by equation 6 and gives an indication of the magnitude of the error in the model.

$$RMSE = \sqrt{\left[\sum_{i=1}^{N}\frac{\left(\hat{Y}_i - Y_i\right)^2}{N}\right]} \qquad \text{Eq. 6}$$

Finally, the coefficient of determination (R^2) is defined by equation 7 and provides insight into the goodness of fit of the model:

$$R^2 = 1 - \left[\sum_{i=1}^{N}\left(Y_i - \hat{Y}_i\right)^2 / \left(\sum_{i=1}^{N}\left(Y_i\right)^2 - \frac{\left(\sum_{i=1}^{N}Y_i\right)^2}{N}\right)\right] \qquad \text{Eq. 7}$$

RESULTS AND DISCUSSION

Soil attribute maps

The estimated variogram model and best-fit parameters for each soil property are shown in table 5. Using these estimated variogram model and best-fit parameters, OK interpolated maps for each of the soil properties were generated and are shown in figure 4. Table 5 indicates that three different variogram models (spherical, Gaussian,

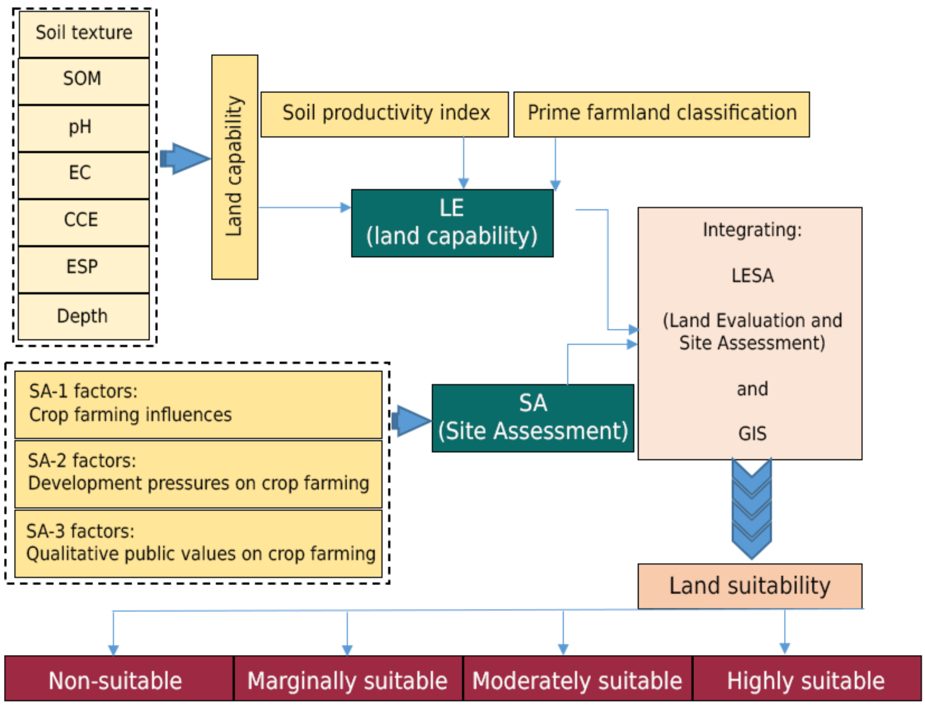

Figure 3. The flowchart for this study.

Table 5. Estimated semi-variogram models and parameters of soil property data sets

Soil property	Model	Range (km)		k*	Direction	Nugget	Sill	Nugget/Sill
		minor	major		(degrees)			
pH	Gaussian	28.9	79.40	2.74	165.1	0.02	0.07	0.28
EC	Spherical	21.2	31.4	1.48	58.8	1.71	4.61	0.37
CCE	Gaussian	11.00	33.04	3.00	53.6	50.14	147.51	0.34
ESP	Gaussian	22.7	31.6	1.39	55.7	39.02	300.78	0.13
SOM	Spherical	5.40	16.31	3.02	117.1	0.06	0.18	0.33
Clay	Gaussian	52.02	71.86	1.38	67.8	11.34	35.22	0.32
Silt	Spherical	5.75	12.81	2.23	16.8	2.04	8.34	0.25
Sand	Spherical	5.71	8.97	1.57	26.1	7.39	20.11	0.37
Soil depth	Gaussian	10.80	32.34	2.99	85.7	871.31	2337.11	0.37

*: k is the ratio of the average major range to the average minor range.

and exponential) were found to best describe variability in these soil properties datasets. The C_0/sill (Nugget/Sill) ratio was calculated to indicate the spatial dependence and variability for each soil property data (Mirzaee et al., 2016). Spatial dependence refers to the degree to which the values or characteristics of observations at one location in space are related to the values or characteristics of observations at nearby locations. Using the system for spatial dependence by Cambardella et al (1994), the soil properties such as EC, silt, CCE, sand, pH, clay, soil depth and SOM presented a moderate spatial dependence (C_0/sill = 0.25 - 0.75) (Table 5). However, the ESP factor showed a high dependency (C_0/sill ≤ 0.25) (Table 5). The major to minor ranges (k parameter) ratio (Table 5) was calculated according to Mirzaee et al. (2016) for investigating anisotropy in the soil attribute data. The k parameter column shows that this value was calculated as a value of more than one for all soil features considered in this study (Table 5). This implies and demonstrates that anisotropy in the semi-variogram was observed for all soil features. Anisotropy indicates that the dependency values of the soil features is not the same in all geography directions.

Summary statistics were calculated (Table 6) for the OK interpolation prediction error for each soil property using the estimated variogram model parameters described in table 5. Significant evidence in soil science research indicates that OK interpolation is an extremely reliable method for generating maps of soil properties (Li, 2010; Pilevar et al., 2020). Figure 4 shows the OK interpolated maps for all measured soil properties within the study region.

Land capability evaluation

Land evaluation components

Figure 5 shows the interpolated maps generated for the soil-dependent factors (LE component). Soil features such as texture, organic matter, among other properties, are highly relevant variables for estimating the expected yield. Land capability classification component includes all attributes that directly impact soil for agricultural production. This study used the Iranian classification system of land capability formulated by Mahler (1979). Table 7 shows the classification yields of the land capability and indicates that 27.88, 47.94, 18.76 and 5.41 % of this part of Iran were included in different classes such as I, II, III, and IV land capability classes of crop farming, respectively. By inspecting figure 5, most of the studied soils in the central and west parts are located in class I. Therefore, when only soil-dependent factors are considered, these areas of the study have the fewest constraints and the greatest potential for agricultural production. Evidently, the soil textures class in the western and central parts of this area are clay loam and loam classes that can the well area for crop farming. According to Kazemi et al. (2016), Ostovari et al. (2019) and, in agreement with local expert committee opinion, the soil texture has a great soil factor at crop farming.

Table 6. Yield of Ordinary Kriging (OK) method at predicting soil factors

Parameters	R^2	RMSE	ME
pH	0.64	0.151	0.001
EC	0.71	0.694	0.012
CCE	0.52	12.78	0.165
ESP	0.61	15.98	0.961
SOM	0.73	0.46	-0.025
Clay	0.56	4.24	-0.044
Silt	0.55	3.40	-0.198
Sand	0.67	4.87	-0.063
Soil depth	0.51	39.24	0.741

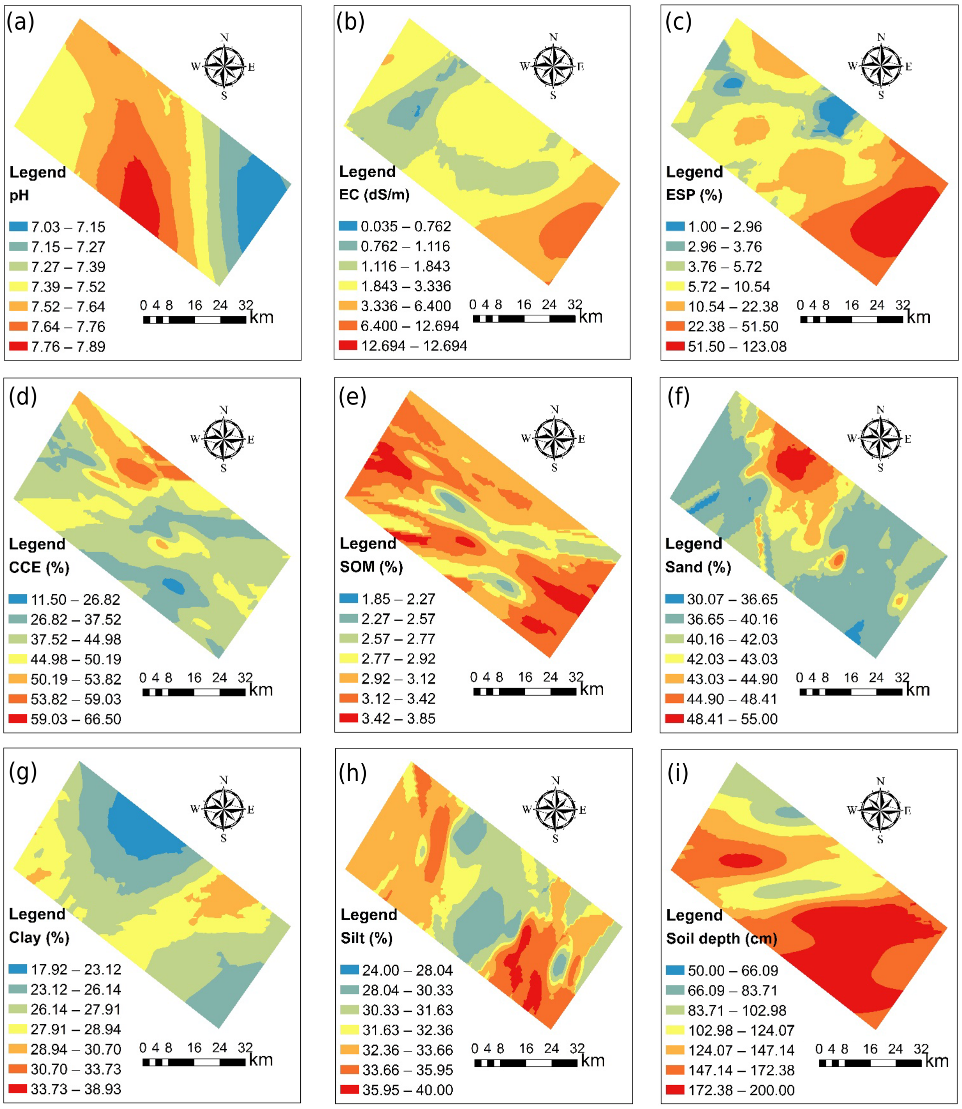

Figure 4. Generated maps for pH (a), salinity (EC) (b), exchangeable sodium percentage (ESP) (c), calcium carbonate equivalent (CCE) (d), soil organic matter (SOM) (e), sand (f), clay (g), silt (h) and soil depth (i).

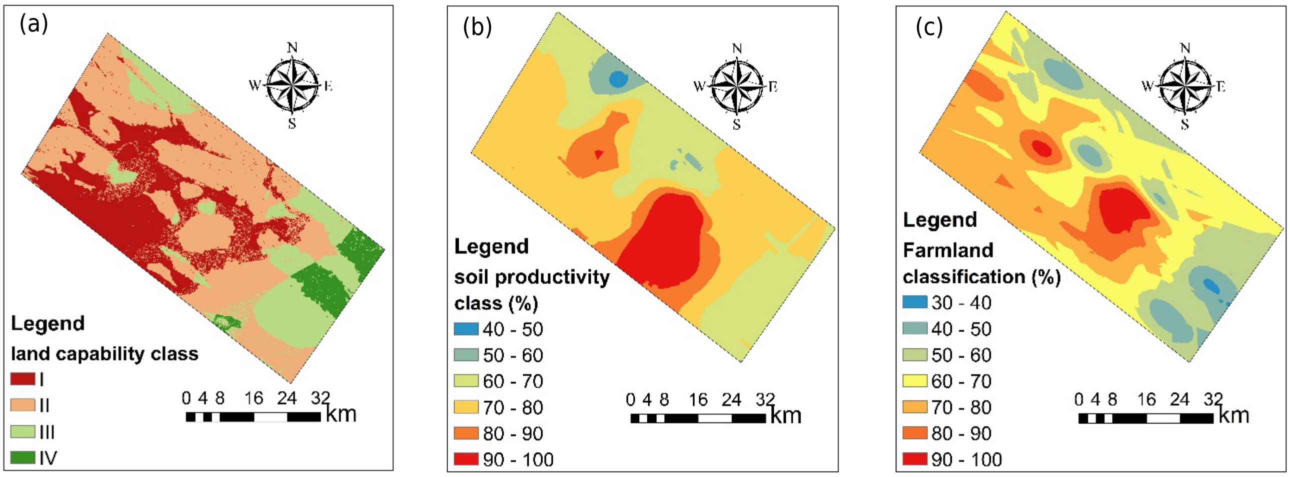

Figure 5. LE components map for different prime farmland (c), soil productivity index (b) and classifications of: land capability (a).

Other remaining soil-dependent factors in the LESA method are prime farmland classification and SPI. In table 7, the scoring of the SPI and prime farmland factors are shown. Maps of these individual factors are shown in figure 5. Based on the prime farmland classification and SPI maps in figures 5b and 5c, there seems to be evident good soil management in some parts of this region, such as the southwest.

Site assessment components

Components of SA part are the three individual non-soil-dependent factors. The generated maps of SA factors such as SA-3, SA-2 and SA-1 are shown in figure 6. Classification and scoring for each SA factor are summarized in table 8. As stated earlier, according to the local expert committee opinion, the SA-1 factor is composed of three sub-factors. The main reason for embedding these sub-factors is to capture information about commercial agricultural activities such as the agricultural support services and land area. Factor SA-2 shows pressures of development on crop productions. The SA-2 factor encompasses subfactors including networks like irrigation systems, roads, and drainage channels. These sub-factors have been taken into account when establishing the basis for creating a sustainable cropping system. The SA-3 factor incorporates subfactors such as existing historic infrastructure, wetlands, and other environmentally sensitive areas, which were included based on the recommendations of the local expert committee.

Table 7. Areas with different types of land evaluation components

Prime farmland classification score	Area		Soil productivity class	Area		Land capability class	Area	
	ha	%	%	ha	%		ha	%
0-10	-	-	0-10	-	-	I	90,207	27.88
10-20	-	-	10-20	-	-	II	155,116	47.94
20-30	-	-	20-30	-	-	III	60,702	18.76
30-40	2,940	0.91	30-40	-	-	IV	17,511	5.41
40-50	11,310	3.50	40-50	813	0.25	-	-	-
50-60	100,513	31.07	50-60	9,231	2.85	-	-	-
60-70	98,068	30.31	60-70	110,741	34.23	-	-	-
70-80	90,810	28.07	70-80	153,001	47.29	-	-	-
80-90	15,052	4.65	80-90	33,693	10.41	-	-	-
90-100	4,845	1.50	90-100	16,058	4.96	-	-	-

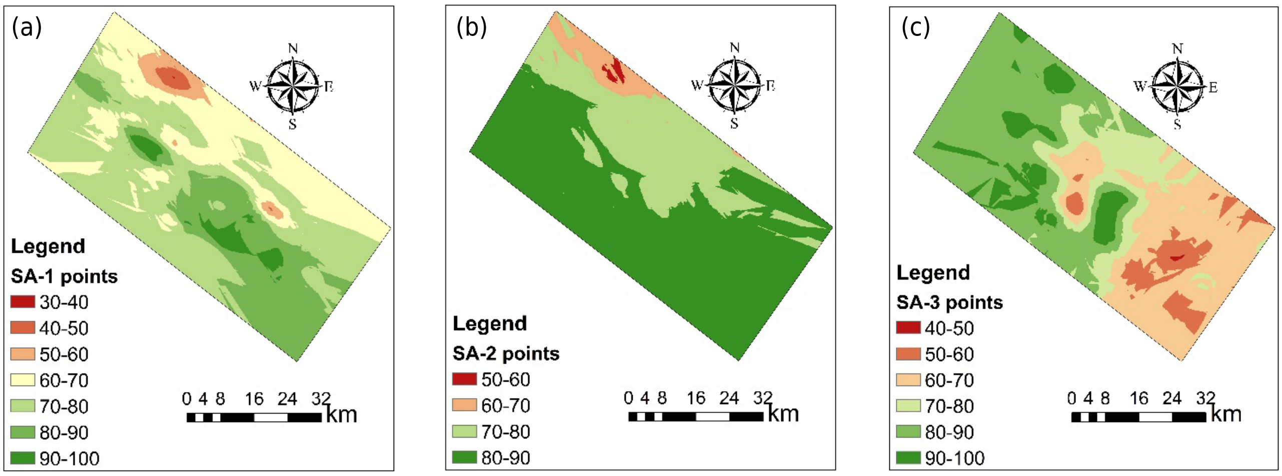

Figure 6. Maps of site assessment factors SA-2 (b), SA-3 (c) and SA-1 (a).

These sub-factors have the potential to diminish significantly, and threats crop farming. Wetlands, for example, may be the best habitat for various pests, which ultimately could threaten crop production.

In support of these findings, Dung and Sugumaran (2005) employed some SA factors, such as farm and development potential, to assess land capability by employing LESA method. In Hoobler et al. (2003), the study of SA included sewer lines, major roads, and distance from the city for predicting land capability by LESA method.

Employing LESA system

The scores of LESA were calculated by employing the linear additive weighted (Equation 4). The map of land capability generated by applying LESA method for the studied region is indicated in figure 7. In the basis of the recommendations of the local committee, LESA scores were divided into four land capabilities for crop production categories: highly-suitable (LESA score >80), moderately-suitable (LESA score 60-80), marginally-suitable (LESA score = 40-60) and not-suitable (LESA score <40). Table 9 shows the area of land capability in the study region for the different LESA score classes. These results show that, based on the LESA score classes, 52.24 and 47.75 % of this region were classified as marginally-suitable and moderately-suitable for crop production,

Table 8. Scores of all SA-components including SA-1, SA-2, and SA-3

SA-1 score	Area		SA-2 score	Area		SA-3 score	Area	
	ha	%		ha	%		ha	%
0-10	-	-	0-10	-	-	0-10	-	-
10-20	-	-	10-20	-	-	-10-20	-	-
20-30	-	-	20-30	-	-	20-30	-	-
30-40	11,000	0.00	30-40	-	-	30-40	-	-
40-50	1,495	0.46	40-50	-	-	40-50	127,000	0.04
50-60	12,693	3.92	50-60	687,000	0.21	50-60	14,279	4.41
60-70	92,030	28.44	60-70	22,746	7.03	60-70	98,728	30.52
70-80	154,222	47.67	70-80	89,652	27.71	70-80	30,595	9.46
80-90	56,035	17.32	80-90	210,452	65.05	80-90	157,953	48.82
90-100	7,052	2.18	90-100	-	-	90-100	21,854	6.75

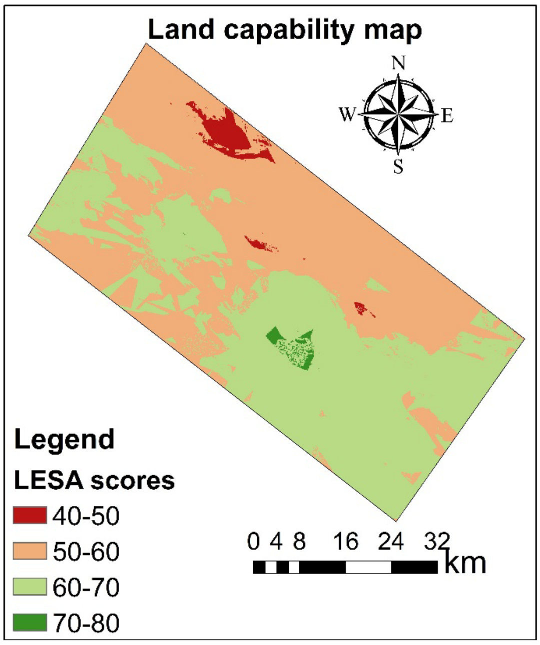

Figure 7. Map of land capability produced by LESA procedure.

respectively. Higher LESA score represents a better land capability for crop production. A land capability map was generated using the LESA method (Figure 7), which shows lower LESA scores along the north-east edge of the study area. Higher LESA scores are more apparent in the south and, to a lesser degree, in the west.

Previous studies emphasize the need for land capability evaluation methods for crop production. However, it is crucial to calibrate these methods to account for the unique characteristics of local conditions. This calibration ensures the accuracy and relevance of land capability assessments, considering the intricate interplay of soil characteristics, climate, and other region-specific factors (Kazemi et al., 2016; Zhang et al., 2015; Mohamed et al., 2018; Ostovari et al., 2019; Abdel Rahman and Arafat, 2020, 2022; Zakarya et al., 2021; Akbari et al., 2022; Wu et al., 2022; Zhu et al., 2022). Optionally, integrated with GIS technology, the system provides spatial insights, aiding in decision-making for land-use planning. By regularly monitoring and adapting the LESA system, stakeholders can make decisions to optimize agricultural practices, ensuring sustainable land utilization aligned with its inherent capabilities. This integration facilitates a streamlined and responsive procedure, enabling rapid assessments of land suitability for various agricultural purposes. By utilizing GIS technology, decision-makers are provided with a powerful tool that not only accelerates the analysis of spatial data but also enhances the quality of planning and management decisions through informed insights. The synergy between the LESA method and GIS expedites the evaluation process and empowers decision-makers with valuable insights, fostering more effective and strategic approaches to land-use planning and agricultural management.

Table 9. LESA score and associated area of cropland

LESA score	LESA score class	Area	
		ha	%
40-50	Marginally-suitable	11,271	3.48
50-60	Marginally-suitable	157,759	48.76
60-70	Moderately-suitable	152,848	47.24
70-80	Moderately-suitable	1,659	0.51

CONCLUSION

This study used a GIS-based approach for applying the LESA method to predict land capability for calcareous soils in the Khuzestan province, Iran. Land evaluation (LE) component, comprising soil-dependent factors that typically depend on soil measurements—which are both costly and time-consuming to collect—can be effectively generalized across extensive geographic areas using GIS technology. The site assessment (SA) subcomponents utilized in this study were derived from support services for agricultural production and area, development pressures, and qualitative public values. This approach will enable agricultural managers to efficiently inventory extensive areas of farmland using straightforward, proven methodologies such as LESA and GIS. The GIS techniques in this project currently rely on applying geostatistics to a relatively sparse and small dataset (72 sample locations). In the future, using remotely sensed data (typically densely sampled data) as a covariate should be investigated as a potential approach for improving the accuracy of the generated kriged maps. Furthermore, we intentionally do not utilize the uncertainty estimates generated by the kriging models in this study. Future opportunities lie in improving GIS accuracy by incorporating remotely sensed data, potentially enhancing the precision and reliability of land capability predictions. This method helps decision-makers better interpret the generated maps.

DATA AVAILABILITY

All data generated or analyzed during this study are included in this published article.

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