ALEXANDRIA
SCIENCE EXCHANGE JOURNAL

VOL. 41 OCTOBER- DECEMBER 2020

Land Evaluation for Alternative Crops of Alfalfa Using GIS in south Hail, Saudi Arabia

Abdulaziz B. Alharbi [1], and Ahmed. M. Aggag[1,2]

ABSTRACT

The assessment of soil suitability for sustainable intensive agriculture is important for the selection of land suitable for agricultural production with the least economic and environmental costs. This study was directed to evaluate agricultural soil suitability in the south of Hail province, Saudi Arabia to suggest alternative crops of alfalfa using the Agricultural Land Evaluation System for arid regions (ALES-Arid) model and Geographic Information System (GIS). The study area covers about 77558 ha and 111 soil samples were collected from 37 profiles and 37 groundwater samples were analyzed for physical, chemical and fertility properties. To evaluate land suitability for selected crops, the FAO guideline was used and also to analyze and map soils within the study area, the GIS was employed. The main research goals were to characterize the soil and water resources of the study area, in order to plan the best alternative crops of alfalfa using land evaluation facilities for different purposes (capability and suitability). The results indicated that the soils of the area are characterized by sandy loam texture, low fertility, low total carbonate and most of the area have moderate to high salinity soil. Capability classes of the area are C3 and C4 which covers about 89.19% and 10.81% of the total area, respectively. The most fertile classes were situated in C2 and C3 which covers 37.84 and 40.54% of the area with phosphorus and potassium limitation. The land suitability results show that 99.68, 97.18 and 85.37% of the area is classified as S1 (highly suitable) for wheat, barley and alfalfa, respectively; while 98.91% of the area is classified as S3 (marginally suitable) for maize. From the obtained data, growers are advised to cultivate barley or wheat in winter and maize in summer instead of alfalfa, in order to save irrigation water. This is also because the expected productivity of either wheat or barley is high. It is important for decision makers to determine the best way of using land for agricultural purposes, since it serves as a decision and planning support.

Key words: GIS, land capability, land suitability, Hail-Saudi Arabia.

INTRODUCTION

Importance of agricultural soils include supporting of crop production, maintaining clean air and water, reducing emissions of greenhouse gas, certifying food quality and preserving natural biodiversity (Bremer and Ellert, 2004). With the growing demand for crop production in relation to the increasing global population, assessing soil suitability has become a serious challenge to understanding the dynamics and distribution of the soil characteristics that are important for predicting future sustainable land use (Bastida et al., 2008; Filep et al., 2016; Barakat et al., 2017; Ennaji et al., 2018).

The spatial variability of soil properties is assessed by various estimators in order to quantitatively predict or estimate soil property values at a non-sampled location within a certain area, and continuous thematic maps are prepared. Kazemi et al. (2016) stated that, the spatial variability of land suitability for specific uses can be assessed by arranging these thematic maps and categorizing the organized derived map according to the requirements of the imagined land use categories, since suitability, as a secondary attribute of soils, can be created by soil properties (Rossiter, 1996; Safari et al., 2013).

In order to confirm sustainable land management, we must check the land degradation through cost effective techniques to predict the best upcoming use, and for observing and mapping land use changes (Bodaghabadi et al., 2015; Jimoh et al., 2016). Assessment of agricultural land suitability is characterized as the method of assessing land performance when used for alternative types of agriculture (He et al., 2011). The nature of the assessment of agricultural land suitability is to predict the capacity and restriction of land for crop production (Pan and Pan, 2011; Halder, 2013).

DOI: 10.21608/ASEJAIQJSAE.2020.120560
[1] Plant Production and Protection Department, College of Agriculture & Veterinary Medicine, Qassim University, Buraydah, KSA, aabanialharby@hotmail.com.
[2] Nat. Res. & Agric. Eng., Faculty of Agriculture - Damanhour University.
Received September 29, 2020, Accepted October 27, 2020

Land potential is determined by various land features, such as the type of soil that is important for productivity, geology, topography, hydrology, etc. Those features restrict the extent of land available for different purposes (Bizuwerk et al., 2005). The ultimate objective of classification of land capacity is to estimate the agricultural capacity of land development units on the benefit of land resources (SYS et al., 1991). The fitness of a given section of land for particular purposes is land suitability. Consequently, land assessment is often carried out to establish the suitability of a land use for a given location and to determine the limiting factors for a specific crop production (AbdelRahman et al., 2016). Land suitability assessment is based on land capability and other variables such as land quality, proximity to various accesses, land ownership, consumer demand and economic values (Girmay et al., 2018).

To spatially define and determine physical land capability and suitability, Geographic Information Systems (GIS) techniques have been used. GIS approaches have proven to be valuable and effective tools for researching, mapping, processing and introducing certain problems (Aggag and Yehia, 2006). For this purpose, it is important to assess the present land characteristics, as well as the potential capability and suitability of crop production (El Baroudy, 2016).

One of the most important applications for spatial planning and management is land suitability mapping, based on GIS (Malczewski, 2006). GIS can be described in conjunction with the ALES-Arid model as a process that integrates with the preferences and reservations of decision makers to obtain an overall assessment for choosing between alternative activities and locations (Boroushaki and Malczewski, 2008; Romano et al., 2015). It also stimulates a system of crop management to increase land productivity (Chen, 2014).

The Hail Province is one of the Kingdom of Saudi Arabia's most important areas for crop production. The region has a large percentage of wheat and maize production (Alharbi et al., 2017 and Alharbi, 2020). Therefore, the main objective of this study was to compare the precision of the classification of qualitative land suitability based on soil properties estimated. Other objectives include: 1) Using geostatistical analysis for soil properties estimation, in order to minimize the sample numbers and characterize the soil and water resources of the study area.2) Planning the suitability of wheat, barley, alfalfa and maize pattern using land evaluation facilities and 3) To prepare land capability and land suitability maps using a GIS for selected crops.

MATERIALS AND METHODS

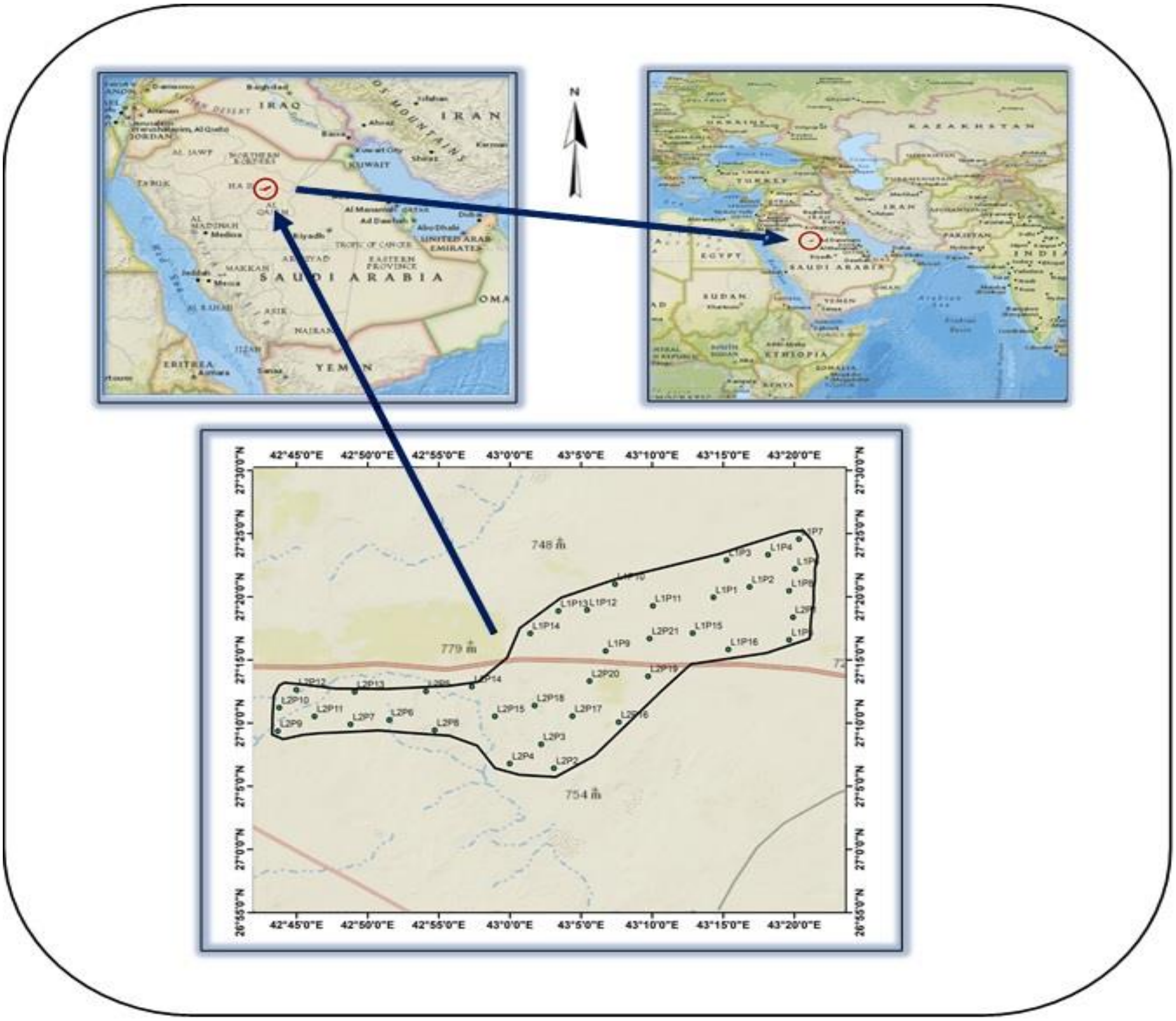
Study Area:

The study area is situated at Hail province in the north-west of Saudi Arabia. The study area is about 775.58 km^2 and is located between latitudes 27° 8′ 23.101″and 27° 8′ 35.837″ N and longitudes 42° 43′ 48.522″ and 43° 20′ 39.453″ E, (Map 1). Generally, the soils are characterized by sandy to sandy loam texture with a deep profile. Ground water is the main irrigation source in the area with good to moderate water quality. As a result of the use of new irrigation techniques, there is no drainage network (Drip and Sprinkler irrigation). The climate in Hail is mild during summer with air temperature ranging between 30 to 40 ºC but it is cold during winter and accompanied by rain and precipitation with air temperature between 5 to 15 ºC and can drop to even 0 ºC. Date palm, barley, alfalfa, wheat, maize and a few vegetables are cultivated in some of the areas under investigation.

Fieldwork and laboratory analyses:

The fieldwork aimed to characterize soil properties by selecting sites according to the surface soil characteristics. The total number of soil profiles having a depth of more than 150 cm was 37. The soil profiles were geo-located to the UTM coordinate system by the GPS. The 111 soil samples and 37 water samples were prepared and analyzed for chemical, physical and fertility characterization as follows:

Physical properties: Munssel Color Charts was used to determine the soil color in wet and dry samples, C.U.S.D.A. The hydrometer method was used to measure the particle size distribution of soil samples according to (Gee and Bauder, 1986). Soil bulk density was determined from the volume–mass relationship for each core sample according to Blake and Hartge (1986). Saturated soil hydraulic conductivity was determined under a constant head method (Klute and Dirksen, 1986). Saturation percentage, field capacity, wilting point, and plant available water were determined using the method of Cassel and Nielsen (1986).



Map 1. General location of the study area

Chemical properties: Soil samples which collected from each horizon of the soil profile were air dried and less than 2 mm particles were used for chemical analyses. Electrical conductivity (EC) was measured in the saturated soil paste extract, soil reaction (pH) was measured in (1: 2.5) soil water suspension according to Page et al. (1982). Collin's calcimeter was used to determine volumetrically total calcium carbonate using (Loeppert and Suarez, 1996). Available soil nitrogen was extracted using 2.0 M KCl and determined using the micro-Kjeldahl apparatus. Available phosphorus was extracted using 0.5 N $NaHCO_3$ solution (pH 8.5) and determined colorimetrically using a spectrophotometer. Available potassium was extracted by the 1.0 N ammonium acetate solution (pH 7) and measured using a flame photometer. Available N, P and K were determined according to Page et al. (1982). Available Fe, Zn, Mn and Cu were extracted by using DTPA and assayed using an Inductively Coupled Plasma Atomic Emission Spectrometer (ICP-AES) (Thermo 7000).

Terrain Analysis was conducted using the Arc-GIS 10.4.1 software. Digital Elevation Model (DEM), slope and aspect were derived using a spatial analyst extension (ESRI, 2015).

Land Evaluation

ALES-Arid is a methodology for land capability and suitability evaluation (Abdel Kawy, 2004). ALES-Arid is described as a land use decision support system, which is associated with integrated databases and GIS. Through the ALES-Arid program, land evaluation algorithms were expressed in notation forms that can be understood by a calculating device. Optimization tools based on land evaluation models are considered very important for the creation of decision alternatives. According to Storie (1964); six productivity classes were identified as shown in Table 1.

The ALES-Arid model evaluates the suitability of utilizing crops (field crops, vegetables, forage crops, and fruit trees) for the identification of optimal land use. Land suitability classes were identified using the correlation between standard crop requirements (Sys, 1975; FAO, 1985; SYS et al., 1993) and land characteristics.

Statistical analysis

Descriptive statistical analysis

Statistical analysis was carried out using the Excel spreadsheet. The following classical statistical parameters were calculated: minimum, maximum, mean, standard deviation and coefficient of variation (Webster, 1977; Khiddir et al., 1986).

Geostatistical analysis

The geostatistical and interpolation methods such as Ordinary Kriging was used to evaluate spatial distribution of soil characteristics (Eq. (1)). Kriging is regarded as an optimal method of spatial prediction. It is a hypothetical weighted moving average:

$$\hat{z}(x_0) = \sum_{i=1}^{n} \lambda_i \, z(x_i) \qquad (1)$$

where $\hat{z}(x_0)$ is the estimated value at the location of x_0, $z(x_i)$ is the known value at the sampling site x_i and (n) is the number of sites surrounded by the search neighborhood used for the estimation.

The Semi-Variogram

The most important tool in geostatistical applications for soil is semi-variogram. It represents the average rate of soil property variation with distance. It is the basis for the data set modeling and for contour maps drawing (Burgess and Webster, 1980).

The semi-variogram γ (h) is defined as:

$$\gamma(\mathrm{h}) = \frac{1}{2} Var[Z(x) - Z(x+h)] \qquad (2)$$

An estimate of the semi-variance function is given by:

$$\gamma^{*}(\mathrm{h}) = \frac{1}{2n(h)} \sum_{i=1}^{n(h)} [Z(xi+h) - Z(xi)]^2 \qquad (3)$$

With n(h) number of pairs spirited by a distance h.

The accomplished semi-variogram values for each lag were fitted to one of the semi-variogram functions using Arc GIS 10.4.1.

A spherical semi-variogram model is given by:

$$\gamma(\mathrm{h}) = C_o + C[1.5\frac{h}{A_o} - 0.5(\frac{h}{A_o})^3], \text{ for } h \le A_o$$

$$\gamma(\mathrm{h}) = C_o + C \qquad (4)$$

The Gaussian model:

$$\gamma(\mathrm{h}) = C_o + C[1 - \exp(\frac{3h^2}{A_o{}^2})] \qquad (5)$$

The exponential model:

$$\gamma(\mathrm{h}) = C_o + C[1 - \exp(\frac{-h}{A_o})] \qquad (6)$$

Where γ is the semi-variogram, C_o is the nugget variance, (C_o+C) is the sill variance, A_o is the range distance, and h is the lag distance. The nugget (C_o) represents semi-variogram values due to short scale or inherited variability, the range (A_o) is the distance at which each semi-variogram reaches its maximum, after which there is no spatial dependence among the samples, and within it interpolation is worthwhile; and the sill (C+ C_o) is the plateau (constant value) which the semi-variogram reaches (Warrick et al., 1986; Isaaks and Srivastava, 1989).

Based on the results obtained, thematic maps of all analysed parameters were prepared using inverse distance weighting (IWD) interpolation techniques. Slope map was prepared using a digital elevation model (DEM) with a 38 × 38 m cell size of the study area. All thematic maps were generated using the ArcGIS software (version 10.41).

Table 1. Productivity classes and ratings according to Storie. 1964

Class	Description	Rating (%)	Class	Description	Rating (%)
C1	Excellent	80 – 100	C2	Good	60 – 80
C3	Fair	40 – 60	C4	Poor	20 – 40
C5	Very poor	10 – 20	C6	Non-agriculture	< 10

RESULTS AND DISCUSSION

Terrain analysis

Analysis of the Digital Elevation Model (DEM) indicated that the elevations varied from 698.6 to 813.7 m A.S.L. The lowest elevation was located in the eastern part of the study area. The dominant elevation which ranged from 700 to 760 m A.S.L. comprised 83.36% of the total area as shown in map (2). The slope of the soil is particularly important in terms of the effect on erosion. It was found that soil depth decreased with increasing slope rate and increased with decreasing slope (Ennaji et al., 2018). The GIS software was used to obtained the slope information from the Digital Elevation Model. The slope ranged from 0 to 71.79% and the main slope class was from 0 to 10.70% which covered about 84.01% (65156.84 ha) of the total area. This slope was classified as slightly inclined as shown in Table (2). Indirectly, the slope restricts agricultural production by adversely influencing soil resources. It can be noticed that the north facing directions (NE, E, SE) are the dominant aspect classes representing 38.25% (29666.10 ha) of the total area, followed by the south facing directions (S, SE, SW) with 37.24% of the total area as shown in Table 3.

Descriptive statistical parameters and soil classification

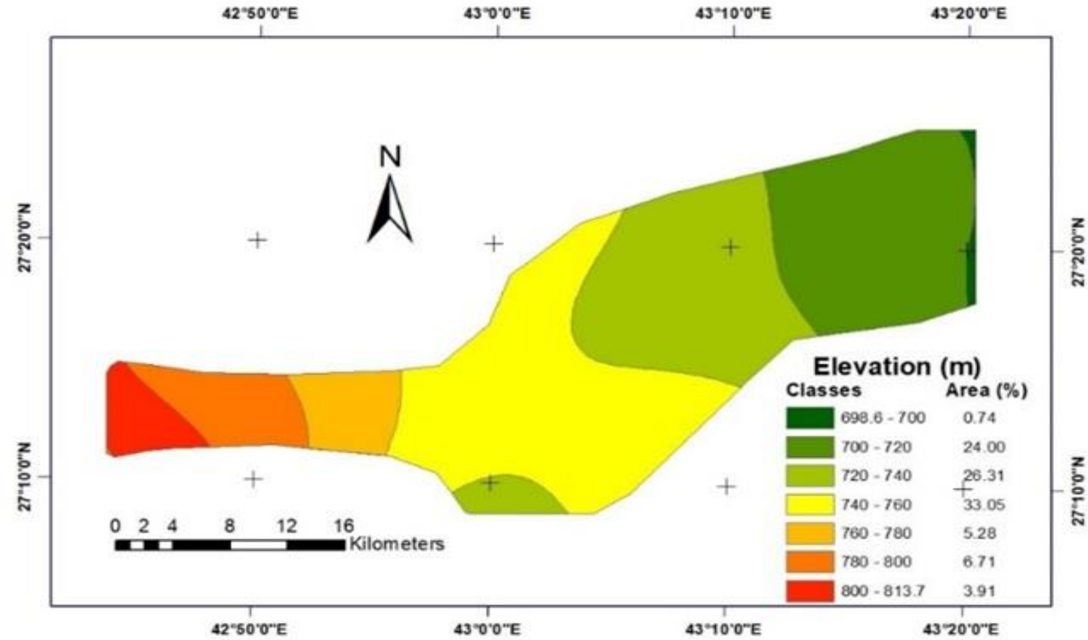
The soil was characterized as sandy loam deep soil with low fertility content. Table 4 shows the descriptive statistical analysis which indicated that the sand content ranged from 47.0 to 80.0%, soil salinity varied from 1.0 to 19.6 dSm^{-1} and calcium carbonate content from 0.26 to 19.8%. Available Fe showed the highest variance followed by Mn, Zn, Cu and N, respectively.

Table 2. DEM, slope classes and area percentage of the study area

Digital Elevation Model (DEM)		Slope Classes	
Elevation range, m	**Area, %**	**Slope Class, %**	**Area, %**
699 - 700	0.74	0 – 3.94	28.41
700 - 720	24.00	3.94 – 7.04	32.79
720 - 740	26.31	7.04 – 10.70	22.81
740 - 760	33.05	10.70 – 15.20	10.79
760 - 780	5.28	15.20 – 22.24	4.28
780 - 800	6.71	22.24 – 71.79	0.92
800 - 814	3.91		

Table 3. Direction and area percentage of the soil aspect

Direction Class	Area, %	Direction Class	Area, %
Flat	0.16	South	12.59
North	12.42	South West	12.27
North East	12.79	West	12.46
East	13.08	North West	11.84
South East	12.38		



Map 2. Digital Elevation Model for the area under investigation

Table 4. Statistical characterization of soil properties

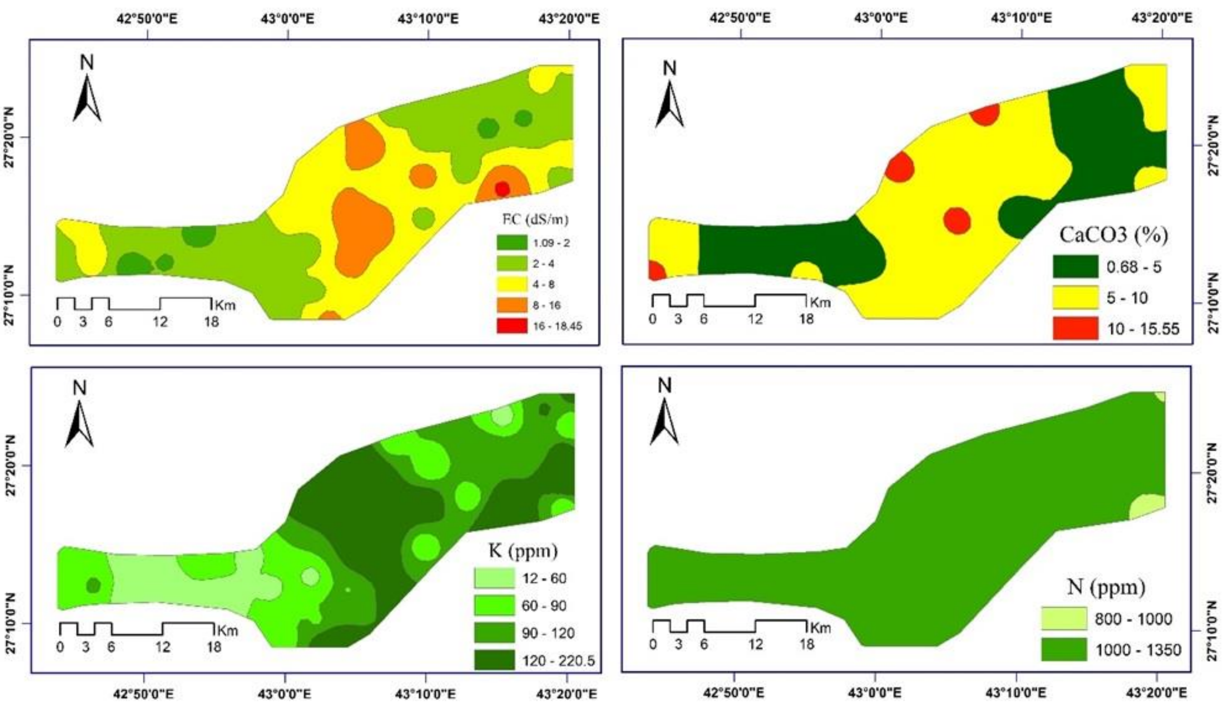
Soil Property	Statistical parameters					
	Min	Max	Mean	Variance	St. Dev.	C.V.
pH	7.4	8.3	7.9	0.05	0.22	2.7
EC (dS/m)	1.0	19.6	4.7	22.44	4.74	100.7
N (ppm)	800	1500	1135.1	29433.54	171.6	15.1
P (ppm)	2.5	48.8	23.0	138.80	11.78	51.3
K (ppm)	9.0	309.0	100.7	4437.82	66.62	66.2
Fe (µg/kg)	38.2	9982.0	809.8	1464461.76	1210.15	149.4
Zn (µg/kg)	13.5	1012.0	315.3	68379.54	261.49	82.9
Mn (µg/kg)	111.0	3304.0	610.8	234997.47	484.77	79.4
Cu (µg/kg)	13.3	821.0	196.6	38929.54	197.31	100.3
Cd (µg/kg)	0.01	47.9	7.5	76.46	8.74	115.9
Ni (µg/kg)	0.01	488.0	53.3	8615.67	92.82	174.1
Pb (µg/kg)	28.9	297.0	88.0	2505.71	50.06	56.9
$CaCO_3$, %	0.26	19.75	5.99	15.17	3.89	0.65
Sand (%)	47.0	80.0	67.7	91.94	9.59	14.2
Silt (%)	4.0	42.5	14.4	56.59	7.52	52.4
Clay (%)	10.0	37.0	17.4	25.85	5.08	29.3
B.D. (Mg/m^3)	1.3	1.6	1.5	0.003	0.05	3.5
Ks (cm/hr)	0.3	2.8	1.1	0.378	0.62	55.2
S.P.(cm^3/cm^3)	0.4	1.4	0.5	0.014	0.12	25.9
F.C.(cm^3/cm^3)	0.2	0.4	0.2	0.001	0.03	13.0
PWP(cm^3/cm^3)	0.1	0.2	0.1	0.0005	0.02	17.8
A.W.(cm/cm)	0.1	0.1	0.1	0.0002	0.01	13.8

(BD) Bulk density, (Ks) Saturated hydraulic conductivity, (S.P.) Saturation Percentage, (F.C.) Field Capacity, (PWP) Permanent wilting point, (A.W.) Available water.

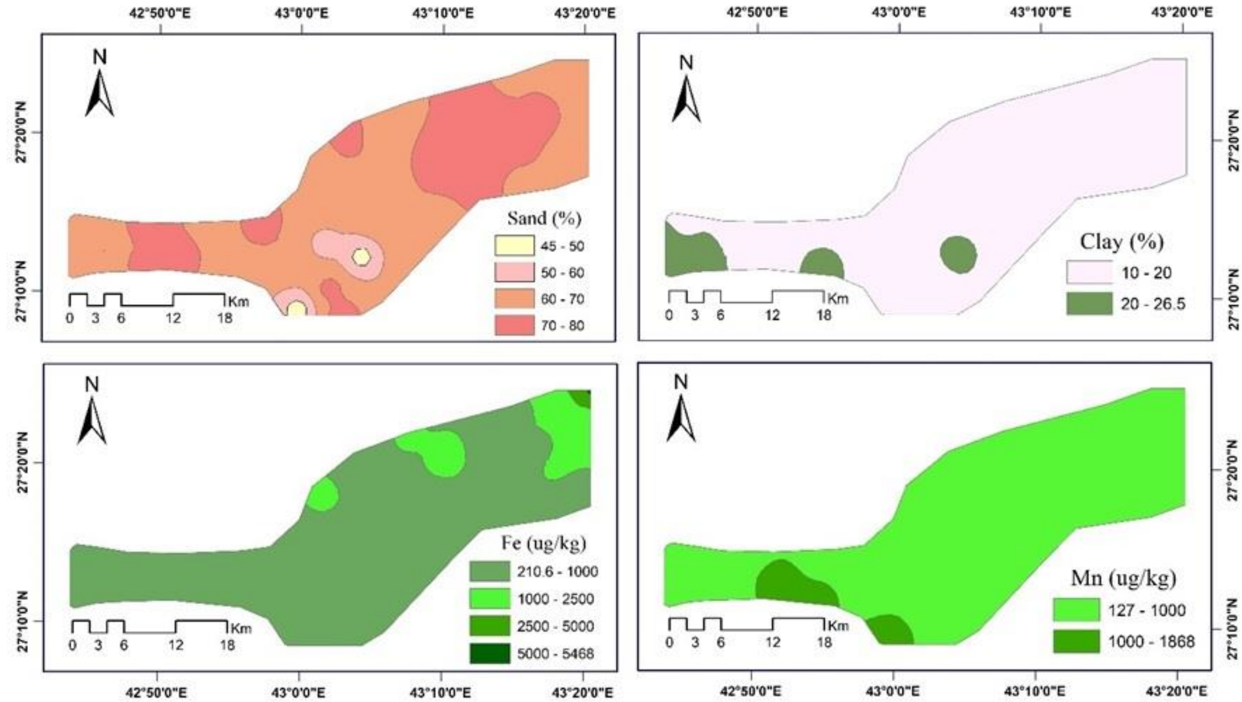
Distribution of soil properties:

The contents of the clay fraction measured in the study area ranged from 10 to 26%. The clay fraction range was classified as low with less than 20% clay and the coverage was 92.49% (71736.47 ha) of the study area while medium categories ranged from 20 to 26% clay and covered 7.51% (5821.95 ha) of the study area (Map 4). On the other hand, the sand fraction ranged from 47 to 80% and was classified as medium with 70 to 80% sand which covered 31.85% (24701.95 ha) and high category with 50 to 70% sand, covering 68.15% (52856.48 ha) of the study area.

The measured salinity value ranged from 1.09 to 18.45 dS/m, indicating low, as well as medium to high soil salinity. It was found that about 3.65% (2830.93 ha) of the study area recorded low salinity and was suitable for agriculture, 43.51% (33744.09 ha) of the area showed medium salinity and 39.50% (30633.67 ha) of the area showed high salinity (Map3). The percentage of $CaCO_3$ in the study area ranged between 0.26 and 19.75% and was classified into low (less than 10%) about 96.52% of the area (74859.77 ha) and medium (10 to 20%) 3.48% (2698.66 ha)(Map 3). Most of the area was classified as having medium nitrogen content (1000-1350 ppm) which covers 98.73% of the area (76576.14 ha) and 1.27% of the area (982.29 ha) classified as having low N content (less than 1000 ppm). While 53.43% of the area (41437.79 ha) was classified as having medium potassium concentration (60-120 ppm K), 33.04% of the area (25627.79 ha) was classified as having high K-concentration (greater than 120 ppm) and 13.53% of the area (10492.85 ha) recorded low K-concentration (less than 60 ppm). Most of the area recorded low Fe and Mn concentrations (less than 1000 µg/kg) which covers 87.52% (67886.25 ha) and 93.97% (72879.96 ha) of the area for Fe and Mn, respectively (Map 4).



Map 3. Distribution of soil salinity, total carbonate, available nitrogen and potassium classes of the study area



Map 4. Distribution of sand, clay, Fe and Mn classes in the study area

Semi-Variogram of soil properties:

Three semi-variograms were mainly fitted to individual soil properties. EC, N and K were fitted to the Gaussian model, sand was fitted to the Exponential model, while Clay%, $CaCO_3$%, Fe and Mn were fitted to the Spherical model as shown in Figure 1. The parameters of these models for different soil properties indicators are shown in Table 5. It is clear that Fe has the highest nugget variance followed by N and K; which indicates their strong spatial dependence and high inherited variability (Warrick et al., 1986). Maps 3 and 4 show the distribution of some soil properties in the study area.

Table 5. The best-fitted models for interpolation of some soil properties in the area under investigation

Soil quality indicator	Model	Nugget (C_o)	Sill (C1)	Range (a)	Lag (m)
EC, dSm^{-1}	Gaussian	19.281	3.843	23366	2920
$CaCO_3$, %	Spherical	7.468	4.506	9812	1226
Sand, %	Exponential	50.409	12.431	27431	3428
Clay, %	Spherical	5.434	8.247	7119	889
N, ppm	Gaussian	12937.1	0	15761	1970
K, ppm	Gaussian	2805.19	1130.56	23366	2920
Fe, $\mu g\ kg^{-1}$	Spherical	569792	0	8237	1029
Mn, $\mu g\ kg^{-1}$	Spherical	0	115897	6965	870

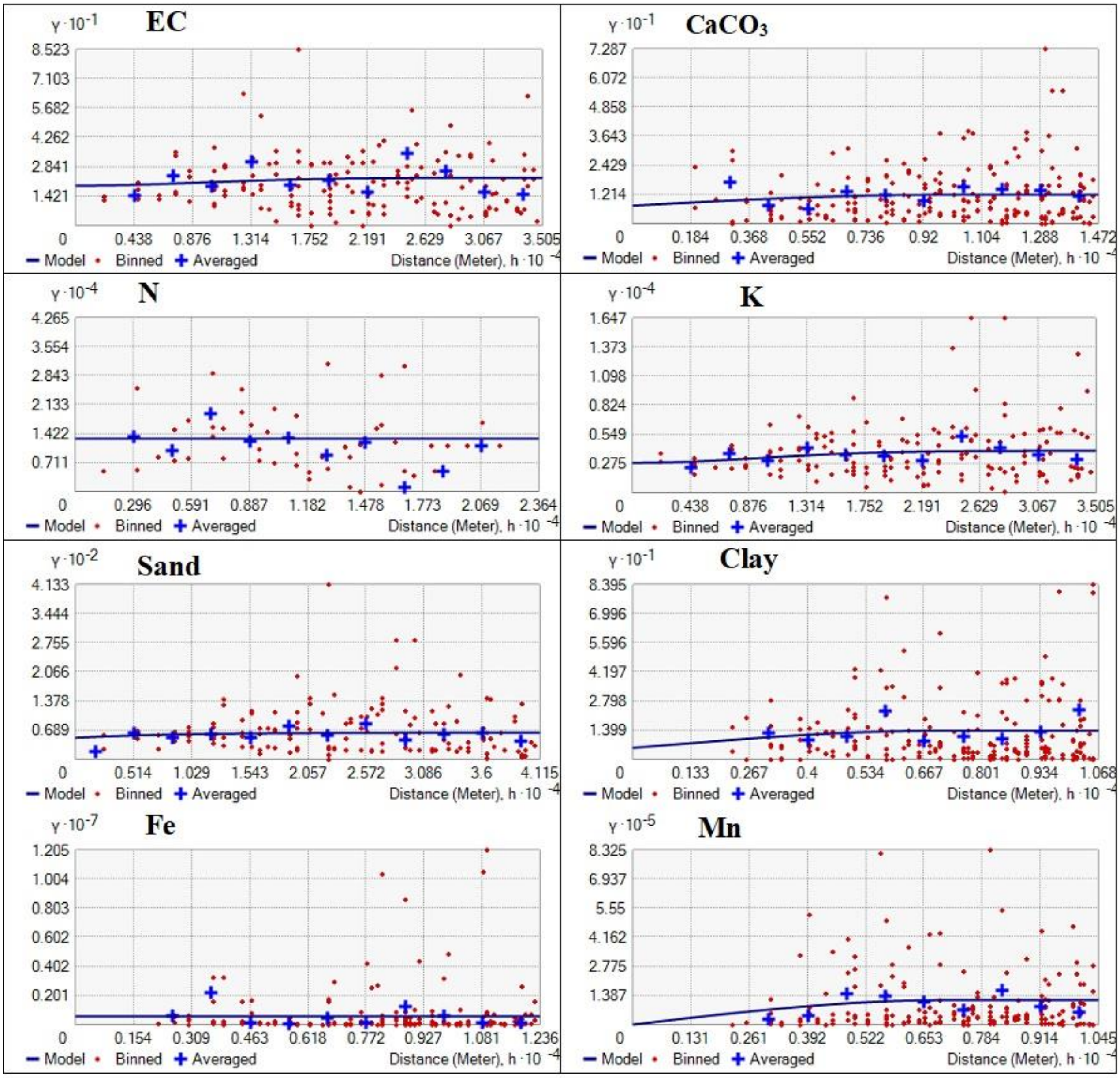


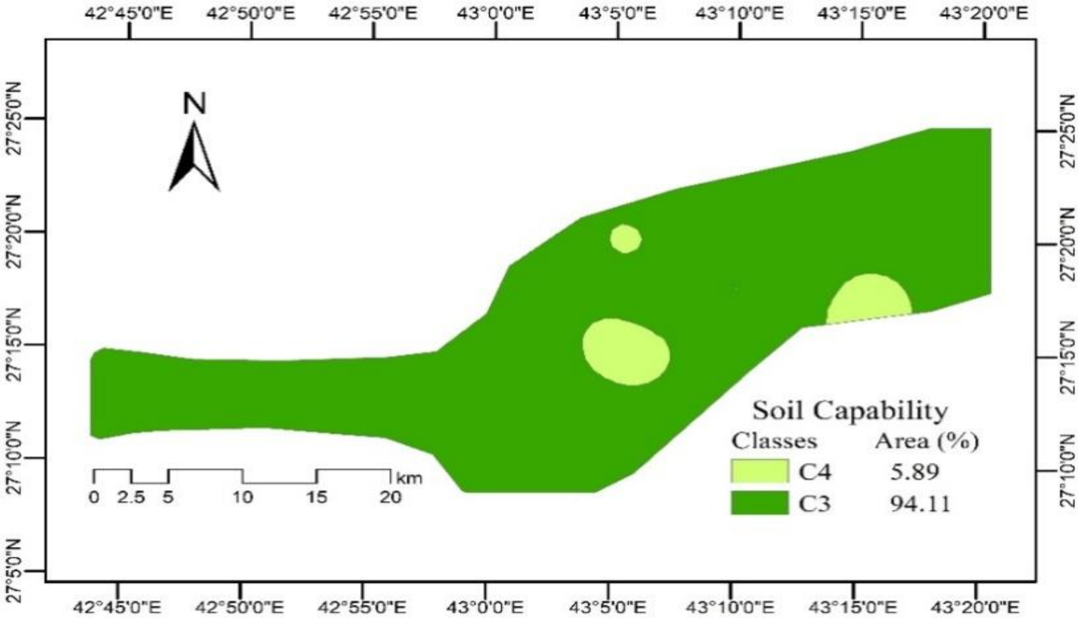
Fig.1. Semi-variograms of soil properties in the Hail area of Saudi Arabia

Land capability classes: The ALES-Arid model provides prediction for general land use capability for a broad series of possible uses. According to the model prediction, most of the study area (89.19%) was classified as C3 (t, AW, Ks, ECe), which indicated fair capability with soil texture, available water, saturated hydraulic conductivity and total salinity as limiting factors. While 10.81% of the area classified as C4 indicate poor capability with severe limits in C3, map (5) illustrates the distribution and percentage of each land capability class in the study area.

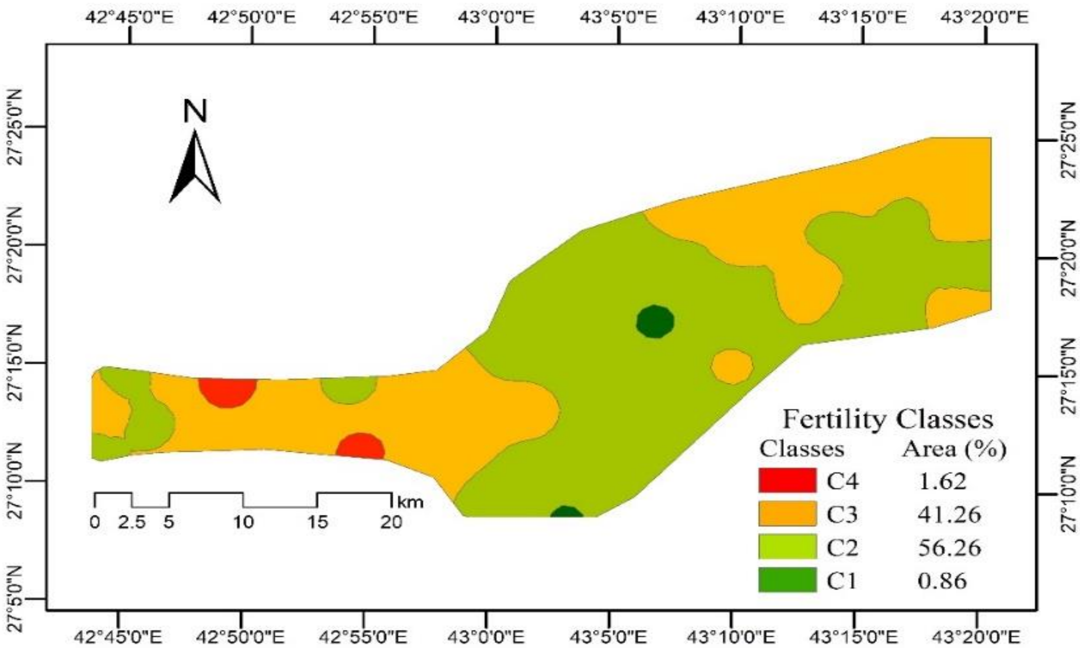
Land fertility class: The model also predicts the fertility class of the area under study as shown in Map (6). The model output showed that about 13.51% of the area with no fertility limits was classified as C1, whereas 37.84% of the area was classified as C2 (k) with potassium limits. Also, about 40.54% of the area was classified as C3 (p and k) while 8.11% was classified as C4 (p and k) with severe phosphorus and potassium limitations.

Water quality classes: Water classes were also predicted by the ALES-Arid model and presented in Map (7). Data illustrated that 53.07% of water resources were classified as highly suitable (C1), 27.42% of resources were classified as moderately suitable (C2), 18.57% classified as marginally suitable (C3) and

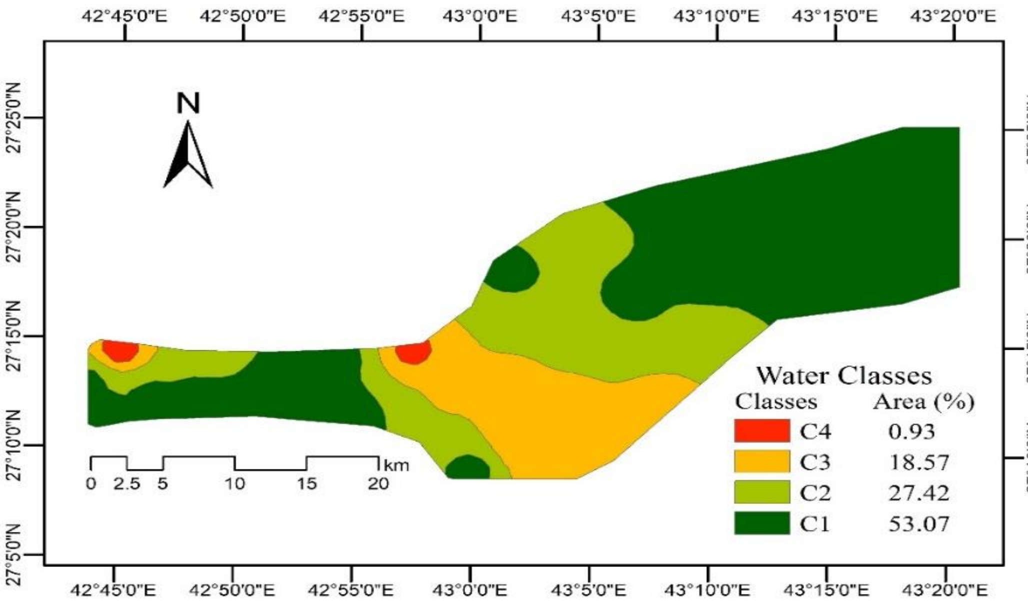
0.93% of resources classified as conditionally suitable (C4). The limiting factors for water suitability include sodium and chloride concentrations in water resources. In the area under investigation, no unsuitable water resources were noticed.



Map 5. Soil capability classes of the area under investigation



Map 6. Soil fertility classes of the area under investigation

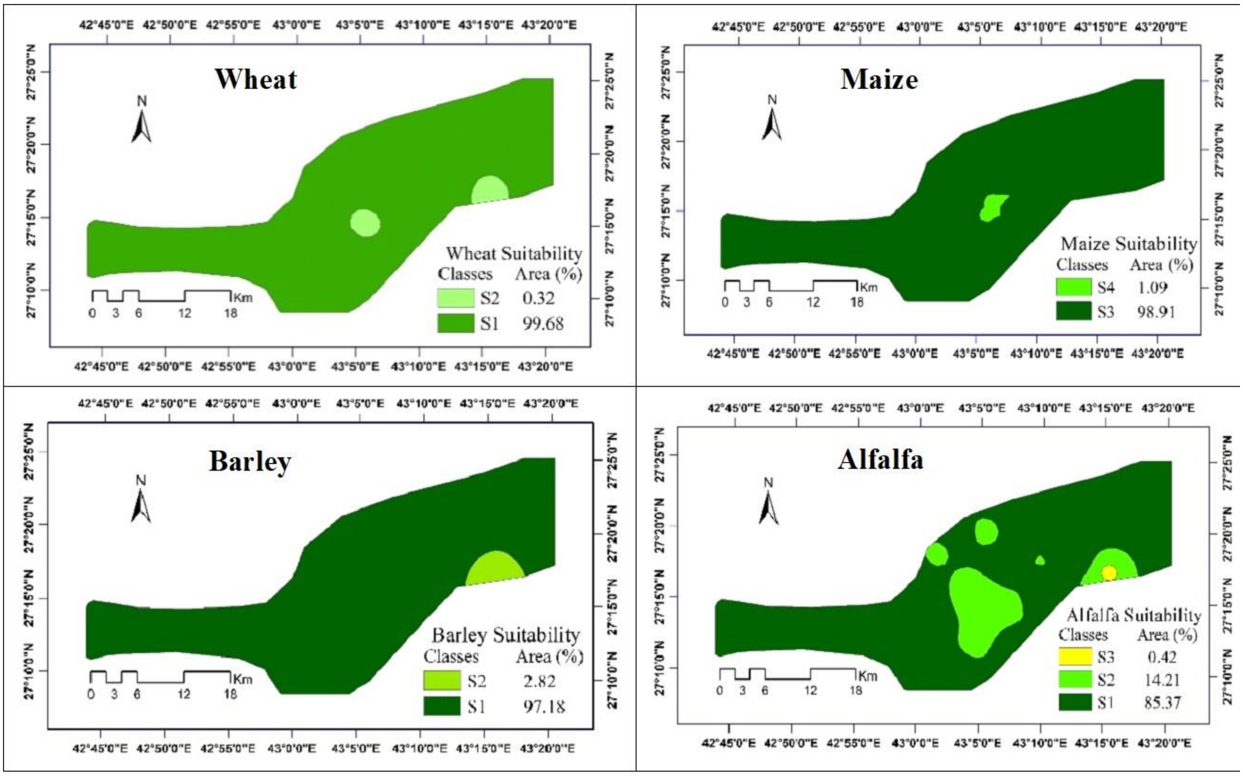


Map 7. Water classes of the area under investigation

Land suitability classes for specific uses: The ALES-Arid Model was used to predict soil suitability for wheat, maize, barley and alfalfa. Table (6) and Map (8) present a summary of agricultural soil suitability classes and percentages for the selected crops. Suitability classes for selected crops indicate that most of the area classified as S1 for wheat covers about 99.68% of the total area followed by S2 which covers 0.32%. For maize, most of the area classified as S3 covers 98.91% of the area and S4 covers 1.09% of the total area under investigation. Most of the area classified as S1 for barley covers 97.18% of the total area and 2.82% of the area classified as S2 with salinity limits. Also, the alfalfa suitability classified as S1 covers 85.37% of the total area whereas 14.21% of the area was classified as S2 and 0.42% was classified as S3 with salinity limitations. According to water availability in the area and from the obtained data, the growers were advised to cultivate barley or wheat in winter and maize in summer instead of alfalfa, in order to reduce the irrigation water consumed. Also, this was because the expected productivity of either wheat or barley was high. The results stated above could be useful for the management of agricultural activity in the south of the Hail area. Neswati et al. (2016) performed land suitability for sugarcane using a parametric approach with Storie's index equation, followed by correlation analysis. They found that a high correlation coefficient exists between land suitability index and sugarcane productivity. This also indicates that land suitability index can be used to estimate the potential crop yield in relatively dry climate regions. With precise soil fertility management, the potentials of these soils can be increased to moderately suitable (S2) for maize, if the recommended fertilization is applied and organic manure is used to improve soil physical and chemical constraints as well as remove soil salinity. A similar result was reported by (Selassie et al., 2014; Harms et al., 2015; Jimoh et al., 2016; Tamfuh et al., 2018).

Table 6. Soil suitability class and percentage for each crop in the study area

Crops	Suitability Class	Area (ha)	Area, %
Wheat	Highly suitable (S1)	75132.9	99.68
	Moderately suitable (S2)	2425.5	0.32
Maize	Marginally suitable (S3)	76710.3	98.91
	Currently not suitable (S4)	848.2	1.09
Barley	Highly suitable (S1)	75371.97	97.18
	Moderately suitable (S2)	2186.46	2.82
Alfalfa	Highly suitable (S1)	66210.01	85.37
	Moderately suitable (S2)	11023.75	14.21
	Marginally suitable (S3)	324.67	0.42



Map 8. Soil suitability classes of wheat, maize, barley and alfalfa

CONCLUSION

The results revealed that the study area is suitable for the selected crops (wheat, barley, maize and alfalfa) with the texture, high salinity and low fertility limitations, which could be eliminated by optimum agricultural management practices. Geostatistical analysis (Kriging) determines the most appropriate distance between sampling locations and reducing the number of samples needed for mapping, and consequently decreased the time, efforts, and costs required to carry out the soil survey. The topographical attributes (DEM, slope and aspect) were very important, and should be taken into consideration when designing irrigation and drainage networks for the area under investigation. The obtained results provide possible alternatives for decision-makers to determine the best uses while preserving environmental resources from damage.

ACKNOWLEDGMENT

The authors wish to acknowledge the financial support provided by the Chair of Sustainable Development in Agricultural Communities in the University of Hail.

REFERENCES

Abdel Kawy, O. 2004. Integrating GIS, remote sensing and modeling for agricultural land suitability evaluation at east Wadi el-Natrun, Egypt, M. SC. Thesis, Faculty of Agriculture, University of Alexandria. Egypt.

Abdel Rahman, M.A., A. Natarajan and R. Hegde. 2016. Assessment of land suitability and capability by integrating remote sensing and GIS for agriculture in Chamarajanagar district, Karnataka, India. The Egyptian J. of Remote Sensing Space Sci. 19:125-141.

Aggag, A. and H. Yehia. 2006. GIS mapping of land suitability and soil quality for some soils of El-Sharkeya Governorate, Egypt. J. Agric.Env. Sci. 5:40-64.

Alharbi, A. 2020. Quality Assessment of Groundwater for Agriculture in the Hail Region, Saudi Arabia. Alex. Sci. Exch. J. 41 (3): 361-369.

Alharbi, A., E. Abd-Elmoniem and K. A.Asiry. 2017. Correlation of Soil Salinity with the Physico-chemical Properties of Agricultural Soils from the Hail Region of Saudi Arabia. ciencia-e-tecnica. 2:2-24.

Barakat, A., W. Ennaji, A. El Jazouli, R. Amediaz and F. Touhami. 2017. Multivariate analysis and GIS-based soil suitability diagnosis for sustainable intensive agriculture in Beni-Moussa irrigated subperimeter (Tadla plain, Morocco). Modeling Earth Systems. 3(1):1-8.

Bastida, F., A. Zsolnay, T. Hernández and C. García. 2008. Past, present and future of soil quality indices: a biological perspective. Geoderma. 147:159-171.

Bizuwerk, A., D. Peden, G. Taddese and Y. Getahun. 2005. GIS Application for analysis of Land Suitability and Determination of Grazing Pressure in Upland of the Awash River Basin, Ethiopia. International Livestock Research Institute , Addis Ababa, Ethiopia.

Blake, G.R. and K.H. Hartge. 1986. Bulk Density, in: A. Klute (Ed.), methods of soil analysis, part 1-physical mineralogical methods, Soil Sci. Society of America, American Society of Agronomy, Madison, WI. pp. 363-375.

Bodaghabadi, M.B., J. Martínez-Casasnovas, P. Khakili, M. Masihabadi and A. Gandomkar. 2015. Assessment of the FAO traditional land evaluation methods, a case study: Iranian land classification method. Soil Use Management. 3:384-396.

Boroushaki, S. and J. Malczewski. 2008. Implementing an extension of the analytical hierarchy process using ordered weighted averaging operators with fuzzy quantifiers in ArcGIS. Computers Geosciences. 34:399-410.

Bremer, E. and K. Ellert. 2004. Soil quality indicators: a review with implications for agricultural ecosystems in Alberta AESA.

Burgess, T.M. and R. Webster. 1980. Optimal interpolation and isarithmic mapping of soil properties. J. of soil sci. 31:315-331.

Cassel, D. and D. Nielsen. 1986. Field capacity and available water capacity, Methods of Soil Analysis: Part 1—Physical Mineralogical Methods, Soil Sci. Society of America, American Society of Agronomy, Madison, WI. pp. 901-926.

Chen, J. 2014. GIS-based multi-criteria analysis for land use suitability assessment in City of Regina. Environmental Systems Research. 1:1-10.

El Baroudy, A.A. 2016. Mapping and evaluating land suitability using a GIS-based model. CATENA 140:96-104. DOI: https://doi.org/10.1016/j.catena.2015.12.010.

Ennaji, W., A. Barakat, M. El Baghdadi, H. Oumenskou, M. Aadraoui, L.A. Karroum and A. Hilali. 2018. GIS-based multi-criteria land suitability analysis for sustainable agriculture in the northeast area of Tadla plain (Morocco). J. of Earth System Sci. 127:79. DOI: 10.1007/s12040-018-0980-x.

ESRI. 2015. ArcGIS version 10.4.1.

FAO. 1985. Guidelines: Land evaluation for irrigated agriculture, FAO Soils Bulletin No.55. pp. 212.

Filep, T., D. Zacháry and K. Balog. 2016. Assessment of soil quality of arable soils in Hungary using DRIFT spectroscopy and chemometrics. Vibrational Spectroscopy. 84:16-23.

Gee, G.W. and J.W. Bauder. 1986. Particle-size analysis, in: A. Klute (Ed.), methods of soil analysis, part 1-physical mineralogical methods, Soil Sci. Society of America, American Society of Agronomy, Madison, WI. 383-399.

Girmay, G., W. Sebnie and Y. Reda. 2018. Land capability classification and suitability assessment for selected crops in Gateno watershed, Ethiopia. Cogent Food & Agriculture. DOI: 10.1080/23311932.2018.1532863.

Halder, J.C. 2013. Land suitability assessment for crop cultivation by using remote sensing and GIS. J. of geography and Geology 5:65.

Harms, B., D. Brough, S. Philip, R. Bartley, D. Clifford, M. Thomas, R. Willis and L. Gregory. 2015. Digital soil assessment for regional agricultural land evaluation. Global Food Security 5:25-36. DOI: https://doi.org/10.1016/j.gfs. 04.001.

He, Y., Y. Yao, Y. Chen and L. Ongaro. 2011. Regional land suitability assessment for tree crops using Remote Sensing and GIS, Computer Distributed Control and Intelligent Environmental Monitoring (CDCIEM) International Conference on, IEEE. 354-363.

Isaaks, E.H. and R.M. Srivastava. 1989. An introduction to applied geostatistics, Oxford university press. New York.

Jimoh, A.I., Y.O. Yusuf and S.L. Yau. 2016. Soil suitability evaluation for rain-fed maize production at Gabari District Zaria Kaduna State, Nigeria. Ethiopian J. of Environmental Studies and Management 9:137-147. DOI: http://dx.doi.org/10.4314/ejesm.v9i2.2.

Kazemi, H., S. Sadeghi and H. Akinci. 2016. Developing a land evaluation model for faba bean cultivation using geographic information system and multi-criteria analysis (A case study: Gonbad-Kavous region, Iran). Ecological Indicators 63:37-47. DOI: https://doi.org/10.1016/j.ecolind.2015.11.021.

Khiddir, S.M., B. Tagliafierro, G. Viccione, O. Ginsburg, R. Badwe, P. Boyle, G. Derricks, A. Dare, T. Evans and A.J.S. Eniu. 1986. A statistical approach in the use of parametric systems applied to the FAO framework for land evaluation. 100:250.

Klute, A. and C. Dirksen. 1986. Hydraulic conductivity and diffusivity: Laboratory methods, Methods of soil analysis: part 1-physical mineralogical methods, Soil Sci. Society of America, American Society of Agronomy, Madison, WI. 687-734.

Loeppert, R. and D. Suarez. 1996. Carbonate and gypsum, in: D. S. (ed.) (Ed.), Methods of soil analysis. Part 3. Chemical methods, SSSA Book Ser. 5. SSSA,Madison, WI, USA. 437–474.

Malczewski, J. 2006. GIS-based multicriteria decision analysis: a survey of the literature. International j. of geographical information sci. 20:703-726.

Neswati, R., C. Lopulisa, M. Nathan and A. Ramlan. 2016. Land Suitability Index for Estimating Sugar Cane Productivity in the Humid Tropics of South Sulawesi Indonesia. J. Trop. Soils. 21:115-122.

Page, A., R. Miller and D. Keeney. 1982. Methods of soil analysis. Part 2. Chemical and microbiological properties. Agronomy, No. 9, Soil Sci. Society of America, Soil Sci. Society of America, American Society of Agronomy, Madison, WI, USA.

Pan ,G. and J. Pan. 2011. Research in crop land suitability analysis based on GIS, International Conference on Computer and Computing Technologies in Agriculture, Springer. 314-325.

Romano, G., P. Dal Sasso, G. Trisorio Liuzzi and F. Gentile. 2015. Multi-criteria decision analysis for land suitability mapping in a rural area of Southern Italy. Land Use Policy 48:131-143. DOI: https://doi.org/10.1016/j.landusepol. 05.013.

Rossiter, D.G. 1996. A theoretical framework for land evaluation. Geoderma. 72:165-190.

Safari, Y., I. Esfandiarpour-Boroujeni, A. Kamali, M.H. Salehi and M. Bagheri-Bodaghabadi. 2013. Qualitative Land Suitability Evaluation for Main Irrigated Crops in the Shahrekord Plain, Iran: A Geostatistical Approach Compared with Conventional Method. Pedosphere. 23:767-778. DOI: https://doi.org/10.1016/S1002-0160(13) 60068-5.

Selassie, Y.G., G. Ayalew, E. Elias and M. Getahun. 2014. Soil Characterization and Land Suitability Evaluation to Cereal Crops in Yigossa Watershed, Northwestern Ethiopia. J. of Agricultural Sci. 6 (5):199-206.

Storie, R. 1964. Soil and land classification for irrigation development. Trans. 8th Int. Cong. Soil Sci. 5:873-881.

Sys, C. 1975. Guidelines for the interpretation of land properties for some general land utilization types [Europe]. Soils Bulletin. 29.

Sys, C., E. Van Ranst and J. DEBAVEYE. 1991. Land Evaluation. Part I: principles in land evaluation and crop production calculations. , Agricultural Publications nr. 7. GADC, Brussels, Belgium.

Sys, C., E. Van Ranst, J. DEBAVEYE and F. BEERNAERT. 1993. Land Evaluation. Part III: crop requirements. Agricultural Publications n° 7. GADC, Brussels, Belgium. 191.

Tamfuh, P.A., E. Temgoua, P. Wotchoko, A. Boukong and D. Bitom. 2018. Soil Properties and Land Capability Evaluation in a Mountainous Ecosystem of North-West Cameroon. J. of Geoscience and Environment Protection. 6:15-33.

Warrick, A.W., D.E. Myers and D.R. Nielsen. 1986. Geostatistical methods applied to soil science, Methods of Soil Analysis: Part 1—Physical Mineralogical Methods, Madison, WI. 53-82.

Webster, R. 1977. Quantitative and numerical methods in soil classification and survey. Quantitative Numerical Methods in Soil Classification Survey, Clarendon press, Oxford.

الملخص العربي

تقييم الأراضي للمحاصيل البديلة للبرسيم الحجازى باستخدام نظم المعلومات الجغرافية في جنوب حائل، المملكة العربية السعودية

عبد العزيز بانى الحربى و أحمد محمد عجاج

تقييم ملاءمة التربة للزراعة المكثفة المستدامة أمر مهم لاختيار إتاحية الأراضي للإنتاج الزراعي بأقل التكاليف الاقتصادية والبيئية. أجريت هذه الدراسة لتقييم صلاحية التربة الزراعية في جنوب محافظة حائل، المملكة العربية السعودية لاقتراح محاصيل بديلة باستخدام نموذج نظام تقييم الأراضي الزراعية للمناطق الجافة ونظام المعلومات الجغرافية. تغطي منطقة الدراسة حوالي ٧٧٥٥٨ هكتار، وتم تجميع عدد ١١١ عينة من التربة بالإضافة الى ٣٧ عينة مياه ابار من منطقة الدراسة لتقدير خصائصها الفيزيائية والكيميائية والخصوبة. استُخدمت مؤشرات منظمة الأغذية والزراعة لتقييم مدى ملاءمة الأراضي للمحاصيل المختارة، واستُخدمت نظم المعلومات الجغرافية لتحليل التربة ووضع خرائط لمنطقة الدراسة. كانت الأهداف البحثية الرئيسية هي تحديد خصائص التربة والموارد المائية في منطقة الدراسة، من أجل الحصول على أفضل المحاصيل البديلة للبرسيم الحجازى باستخدام تقييم الأراضي لأغراض مختلفة (القدرة والملاءمة). أشارت النتائج إلى أن تربة المنطقة تتميز بقوام لومى رملي، وانخفاض الخصوبة، وانخفاض الكربونات الكلية، ومعظم تربة المنطقة معتدلة إلى مرتفعة في الاملاح. ذات قدرة إنتاجية تتراوح بين C3 و C4 والتي تغطي حوالي ٨٩.١٩٪ و ١٠.٨١٪ من المساحة الإجمالية، على التوالي. وتقع الفئات الأكثر خصوبة في C2 و C3 التي تغطي ٣٧.٨٤ و ٤٠.٥٤٪ من المنطقة مع ضعف محتواها من الفوسفور والبوتاسيوم. وتبين نتائج ملاءمة الأرض أن ٩٩.٦٨ و ٩٧.١٨ و ٨٥.٣٧ في المائة من المساحة مصنفة على أنها S1 (مرتفعة الإتاحية) للقمح والشعير والبرسيم على التوالي؛ في حين أن ٩٨.٩١٪ من المنطقة تصنف على أنها S3 (متاحة على الحد) للذرة. من البيانات التي تم الحصول عليها، ينصح المزارعون بزراعة الشعير أو القمح في الشتاء والذرة في الصيف بدلاً من البرسيم الحجازى، من أجل توفير مياه الري. بالإضافة إلى أن الإنتاجية المتوقعة من القمح أو الشعير مرتفعة. من المهم أن يحدد صانعو القرار أفضل طريقة لاستخدام الأراضي في الأغراض الزراعية، لأنها بمثابة قرار ودعم للتخطيط.