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Geospatial and common methods for the assessment of land suitability for wheat production in Iran

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Abstract. Wheat is considered the most important crop in Iran; however, not all of the land in Iran is equally suitable for growing wheat. This study aimed to apply a spatial model for land suitability assessment integrated with geographic information system (GIS) techniques for the wheat crop. Climate and Soil parameters were recognized as factors affecting land suitability for wheat crop in the study area. Three indices were used in assessing land suitability, soil fertility, chemical and physical quality indices. The results of the proposed model (LSI) were compared with the square root and Storie methods. The results showed that most of the units fall within the Moderate suitable class (S2) and the Marginally suitable class (S3) which together represent 88.66% of the total area. About 7.08% of the study area was High suitable and About 2.37% of the study area was unsuitable for wheat crops and those areas correspond to the adverse physical and chemical properties of the soil. The comparison of the results of the three approaches used showed that the present model has a Moderate level of agreement with the square root method (0.516) and showed that the present model has a low level of agreement with the Storie method (0.243). Comparing the results showed that the story model has a high agreement with the square root method (0.884). In the current model, the use of different indicators allows for obtaining results that seem to be more consistent with the current conditions of the region.

Keywords: Cropland suitability, geospatial index, Inceptisols, Mollisols, Entisols.

1. Introduction

The land is one of the most important natural resources, and maintaining its health is essential for meeting an ever-increasing demand for food, fiber, fodder, and fuel (Khan & Khan, 2014). It is a significant resource mainly for countries where their economy is based on rural activities, such as agriculture (AGRA, 2013). The concept of ‘land’ should not be confused with ‘soil’ because soil represents only one aspect of the land, alongside vegetation, physiography, hydrology, climate, infrastructure, etc. (Kishore, 2016).

Agriculture is important as a source of food and income, but How, Where, and When to cultivate are the main issues that farmers and land managers have to face day to day. Land evaluation is carried out to estimate the suitability of land for a specific use such as arable farming or irrigated agriculture. Land evaluation results from a complex interaction of physical, chemical, and bioclimatic processes, and evaluation models are reliable enough to predict accurately the behavior of land (Ball & De la Rosa, 2006; Shahbazi et al., 2009). Crop suitability indices are novel management tools for identifying the optimum agricultural production areas at the farm, Tribal, or regional levels, and are an important step for sustainable intensification. However, little work has been done to develop crop suitability indices via high-resolution digital soil mapping approaches, particularly for Tribal nations. Such landscape-specific crop suitability indexing would facilitate sustainable land use (FAO, 2017) aid in matching crops with soils (Karthikeyan et al., 2019), and identify areas in landscapes in need of soil conservation (Vázquez-Quintero et al., 2020). To manage land resources properly, a land suitability assessment is often conducted to determine which type of land use is most appropriate for a particular location (Bodaghabadi et al., 2015). Land suitability assessment can be either qualitative or quantitative. The qualitative approach is used to assess land potential on a broad scale and the results are given in qualitative terms. The quantitative approach involves more detailed land attributes by using parametric techniques which allow various statistical analyses to be performed. The land suitability assessment procedure in the quantitative approaches involves many simulation modeling systems (Van de Graaff, 1988; Shields et al., 1996) to quantify the potential of land for specific uses. FAO guidelines on land assessment systems (FAO, 1976, 1985) and physical land assessment methods (Sys et al., 1991) were widely used for land suitability assessment. In the parametric method, a quantitative classification is allocated to each characteristic of the land. If a characteristic of land for a specific product was completely desired and provided optimum conditions for that, a maximum degree of 100 would belong to that character and if it has a limitation, the lower degree will be given to it. Later, allocated ranks will be used in the calculation of the land index. In the parametric method, different classes of land suitability are defined as completely separate and discrete groups and are separated from each other by distinguished and consistent range. Thus, land units that have moderate suitability can only choose one of the characteristics of predefined classes of land suitability (Mohammadrezaei et al., 2014).

Fuzzy sets theory for the first time defined by Zadeh (1965) to quantitative defining and determining of some classes that are expressed vaguely such as "very important" and so on. Wheat, due to its important role in the political and economic arena of different countries, is regarded as a strategic crop all over the world; particularly in developing countries. The economic importance of wheat, in terms of production and nutrition, is higher than the other agricultural products in the world. Wheat is the most important agricultural product of Iran in terms of production and area under cultivation, and the Increasing wheat production is receiving more attention these days and is of great importance from the economic point of view and the supply of the main food (Shahriar & Ghashghaei, 2018). Cereals, including wheat, can meet humans' daily needs, including carbohydrates, proteins, fats, minerals, and some vitamins; provided that bran is not completely absorbed. As economic and agricultural experts have acknowledged, wheat production in Iran does not have a favorable increasing trend because of the natural geographical problems and lack of financial and installation resources in the field of irrigation and drainage networks. On the other hand, traditional and rainfed cultivation is prevalent. Also, there is a lack of mechanized operations, a lack of quality seeds and suitable chemical fertilizers, soil and water problems, and lack of access to technology and modern science, poor marketing, etc. (Shewry & Hey, 2015). The wheat production time series trend plot from 1961-1962 to 2018-2019 is shown in Figure 1. According to the Food and Agriculture Organization of the United Nations (FAO, 2020), between 1961-1962 and 2018-2019, wheat production had an increasing trend in the world and more than tripled.

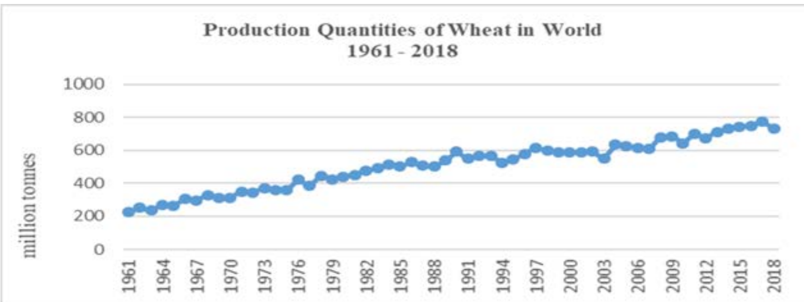


Figure 1. Wheat production time series trend plot (FAO, 2020)

Soil fertility indicates the soil's capability to provide optimum conditions for plant growth. Assessing soil fertility is an essential need to identify environmental-friendly strategies leading to more sustainability in agricultural systems. Soil fertility, directly and indirectly, affects yield and crop quality. For food security and increased food production to be achieved, the development of a useful method for assessing soil fertility and productivity is fundamental.

Various modeling techniques have been proposed as useful tools to determine soil fertility. An assessment of the soil fertility status by using a soil index could provide key information to improve strategies and effective techniques for the future to achieve sustainable agriculture. Remote sensing and Geographic Information Systems (GIS) hold great promises for improving the convenience and accuracy of spatial data, more productive analysis, and improved data access. These technologies have been used to assess the criteria required to define the suitability of land (Booty et al., 2001; De la Rosa & Van Diepen, 2002; Darwish et al., 2006; Mokarram et al., 2010; El Baroudy, 2011; Hamzeh et al., 2014) and were also adopted for the present study. The present study was conducted: (1) to determine land suitability indices (CL, PQI, FQI, CQI). (2) Identifying the main soil limiting factors for wheat production and (3) comparing the assessment method used with the story and second root methods (Fayyaz et al., 2021). The Storie index was developed for rating soils based on the characteristics that govern the productive capacity, and was originally developed for California soils, but has been widely replicated in many parts of the world for soil suitability assessments (El Baroudy, 2011; Vasu et al., 2018).

2. Material and methods

2.1. Study area

The study area is located in the southwestern region of Iran, part of Valiasr town in the west of Badra city, in the southeast of Ilam province (Fig.2), The geographical location is in UTM zone 38 (33° 14′ 33″–33° 22′ 15″ N; 46° 52′ 24″–47° 12′ 25″E). The average height of the studied lands from the open sea level is between 700 and 1100 meters and the gross land area is 1500 lands. Based on the calculations of the new Newhall software (Waltman, 2012) and referring to the map of Iran's humidity and temperature regimes (Banaei, 1998), the mentioned area has a Xeric humidity regime. The characteristic surface horizons are ochric and mollic, and the characteristic subsurface horizons are Cambic, calcic, and gypsic. Based on the American soil classification system, the soils were classified into Inceptisols, Mollisols and Entisols. the thermal regime is thermic, which is confirmed by the morphological condition of soils and observations and field studies. The studied area has a Mediterranean climate with cold and wet winters and dry summers. The amount of annual rainfall is 554.5 mm and it rains mostly in winter. According to the geological maps, the studied area is located in the mountainous region of Zagros in terms of geological divisions, and it is a part of the geological zone of Zagros with an approximate west-east extension. The fourth, third, and second eras have been identified in the Arena watershed. The morphology of the area is in the form of rolling hills and high terraces with complex side slopes and valley-like grooves covered with vegetable soil that is prone to the growth of all kinds of pasture plants and forest and fruit trees. The formations of the study area include the Holocene and Pleistocene periods, and the high mountain ranges of the province, including Kabirkoh, and the north of the region is along the main Zagros. The habitats and agricultural areas are mainly built in the fourth period. The study area, based on the standard of the Research Institute. Soil and Water (Mansoori, 1992) is located on a set of physiographic units (Land Types) of plateaus and upper terraces and hills, known as Plateaux and Piedmont Alluvial Plains and gravelly slopes. The main products below Cultivation in the region are wheat, barley, chickpeas, lentils (in dry form), and other aquatic crops such as beans, alfalfa, summer crops, and some fruitful trees.

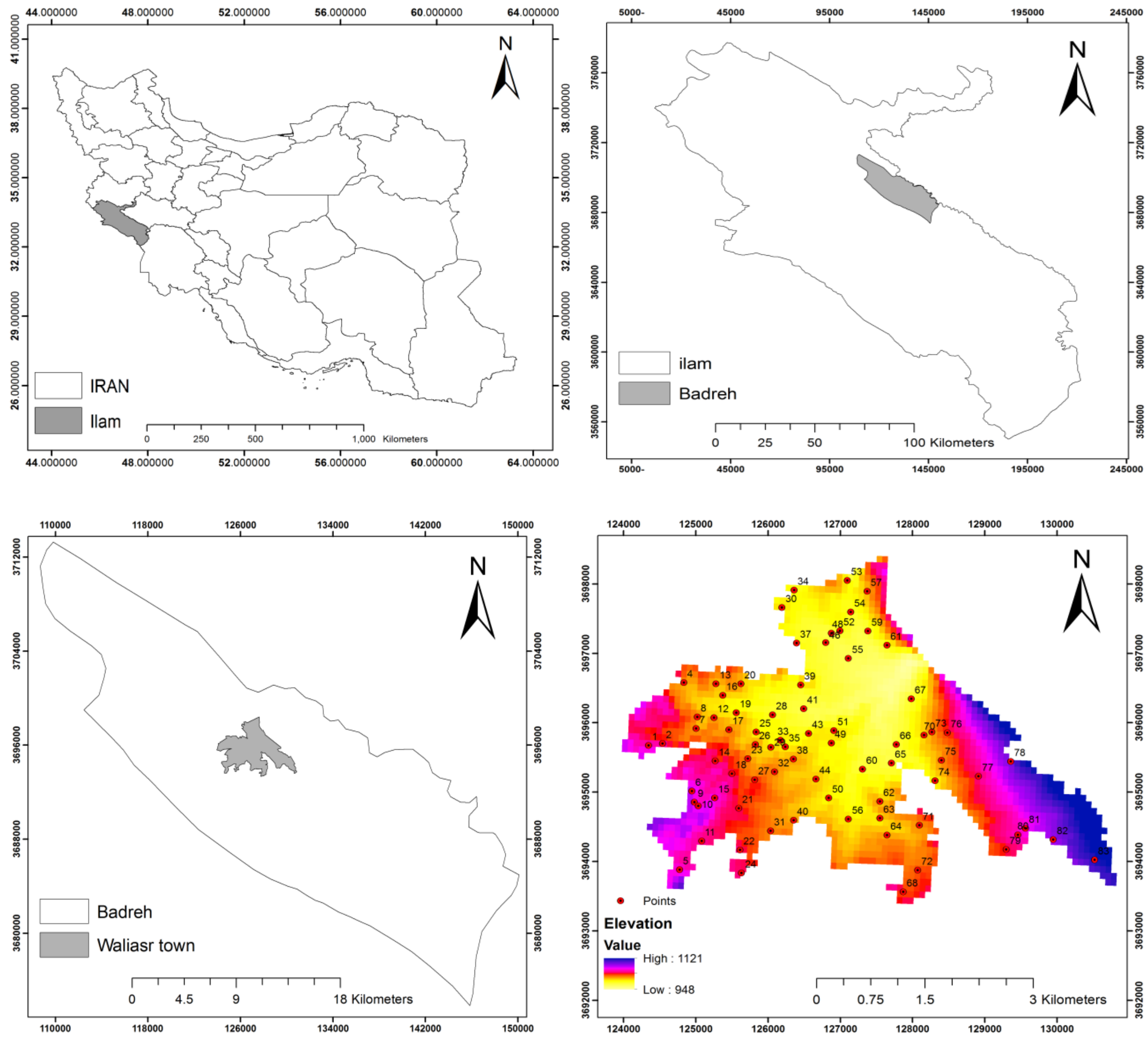


Figure 2. Location of the study area and soil profiles

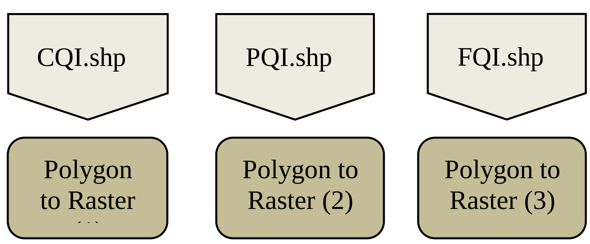
2.2. Digital image processing and physiographic map

Due to the multi-spectral data of the Landsat-8 satellite, it is possible to study different sources in different wavelengths from visible to infrared. Another feature of these data is their diversity. The data of this satellite includes 11 bands that are imaged every 16 days by the OLI-TIRS sensor. In this research, the sensor image belonging to the Landsat Eight satellite and dated August 18, 2018, was used. Geometrical and atmospheric corrections were made to the images. The image used is related to WRS-Path 167 and WRS-Row 37. The available maps of the studied area were scanned and georeferenced and used as a base map (Jackson, 1967; Zahirnia & Matinfar, 2016).

2.3. Methods

Crop suitability mapping has also been used to optimize regional resource use, such as irrigation. For example, in northwest China, researchers found that crop water consumption could be optimized through crop suitability tools and found overall 31–33% efficiency gains through optimization (He et al., 2018). Overall, crop suitability mapping can be a useful tool for sustainable resource management and planning, enhanced socioeconomic outcomes, and for closing yield gaps at the local, regional, and national levels (Van Wart et al., 2013; Akpoti et al., 2019; Vázquez-Quintero et al., 2020). Similar to these results, previous studies found that producers were not necessarily cultivating crops based on the prime suitability of biophysical conditions but rather based on the suitability of socioeconomic parameters (He et al., 2018; Jain et al., 2020).

In the proposed model (Fig. 3), three indicators of fertility quality, chemical quality, and physical quality of the soil were used to check the land suitability of the study area. The values of each index are calculated and then, using interpolation and reclassification methods, a zoning map related to each index is prepared, and finally, using the method of weighting and matching the produced layers with each other, the maps prepared from the three indices were merged and the final suitability index (LSI) map of the studied area was prepared .



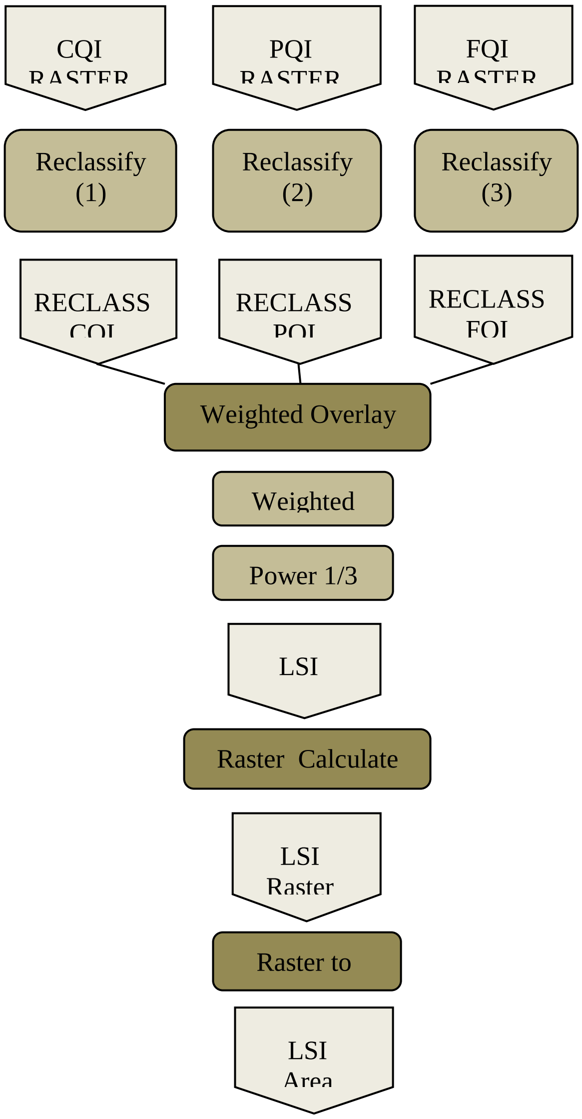


Figure 3. Flowchart of the designed land suitability modeling

2.3.1. Fieldwork and laboratory analysis

Field and laboratory studies were carried out to increase the accuracy of the detected in satellite images and better and more complete separation of the soil samples on the ground surface. An integral clause in the digital mapping process is the sampling method, which provides a work plan to collect representative samples covering the investigated area and creates a reliable input for building a predictive model with environmental variables (Kidd et al., 2015). The sampling method is a very important process since it affects the results of subsequent experiments and data analysis (De Zorzi et al., 2008). According to the identification of 83 soil profiles in an area of about 1400 hectares of the lands of Valiasr Badreh and based on the formula (Hengl et al., 2003) from the ALOS PALSAR satellite digital altitude model with a spatial resolution of 12.5 meters and its primary and secondary derivatives for modeling Sampling points were used based on the conditional Latin cube method (cLHS). The conditional Latin cube sampling method is an modern sampling method which is a stratified or stratified method (Minasny & McBratney, 2006). In this method, auxiliary variables are divided into uniform categories. In the cLHS method, the user decides to use a specific number of samples, this technique divides the data of environmental variables into the same number of desired samples as clusters and selects a random sample of the input data of environmental variables of each cluster in such a way that the Latin square condition is met. and this condition is that there is only one sample in each dimension b and a. The number of 11 geomorphometric, hydrological, and climatic features including topographic location index, convergence index, Saga wetness index, direct radiation, maximum height, landform components, The smoothness index of the valleys with high resolution, the relative position of the slope, the gradient of the slope and the steep elevations and the landform were extracted in the environment of SAGA GIS software version 7/3. In the current sampling methods for soil mapping, the selection of the sampling location is up to the personal decisions of the surveyors. Minasny and McBratney (2007) compared the cLHS method with simple random sampling, stratified random sampling, and spatial Latin hypercube sampling and observed that the cLHS method more accurately shows the true distribution of environmental variables.83 profiles were dug in the studied lands and 325 soil samples were collected from the horizons of the profiles and transferred to the soil science laboratory.

2.3.2. Geo spatial parameter selection

From the digital elevation model with a spatial resolution of 12.5 meters of the ALOS PALSAR satellite, there are 11 geomorphometric, hydrological, and climatic features, topographic position index, convergence index, Saga wetness index, direct radiation, maximum height, landform components, smoothness index of valleys with high resolution, the relative position of the slope, the gradient of the slope and the elevations of the slope and the landform was extracted in SAGA GIS software version 7/3. According to the digging of 83 soil profiles in an area of about 1400 hectares from the lands of Waliasr Badreh were sampled at a resolution of 25 meters and used to prepare the final digital map of soil classes. Finally, based on the sensitivity analysis using the variable importance approach in the "VariableImportant" sub-program in the RStudio environment based on the "MeanDecreaseAccuracy" index of five geomorphometric variables including "Convergence index", "Maximum Height", "Land form", "Slope Height" and "SAGA Wetness". They were identified as the most effective environmental layers in the formation of soils in the studied area. Spatial modeling with the relationship of spatial data of soil classes and five selected geomorphometric variables using the random forest model with 800 trees with a general accuracy of 65 and a Kappa index of 54% Digital map of 11 phases of the soil family in a raster format with a spatial resolution of 25 meters in RStudio modeling software and ArcGIS software version 10.5 into polygonal units based on the detailed and semi-detailed study level (Table 1), taking into account the minimum separable area of 0.4 cm^2, units with an area of more than 1 hectare on a scale of 1:25000. The final map was applied (Fig. 4).

Table 1. geographical location and classification of soils based on the key to Soil Survey Staff (2014).

Profile number	Soil unit	Longitude (meter)	Latitude (meter)	Soil family
1	8.3	682853	3690120	Fine-silty, carbonatic,thermic Typic Halploxerepts
2	4	683044	3690160	Fine-silty, carbonatic,thermic Typic Calcixerepts
4	2	683287	3691050	Fine, gypsic,thermic Typic Calcixerepts
5	MIS*	683383	3688360	Fragmental,calcareous,shallow, thermic Typic Xerorthents
6	4	683488	3689500	Fine-silty, carbonatic,thermic Typic Calcixerepts
7	6	683495	3690400	Fine-silty, carbonatic,thermic Typic Calcixerepts
8	6	683501	3690570	Fine-silty, carbonatic,thermic Typic Calcixerepts
9	1	683532	3689340	Fine-silty, carbonatic,thermic Typic Calcixerepts
10	1	683589	3689290	Fine-silty, carbonatic,thermic Typic Calcixerepts
11	5.6	683666	3688790	Fine-silty, carbonatic,thermic Typic Calcixerepts
12	5.5	683731	3690570	Fine-silty, carbonatic,thermic Typic Calcixerepts
13	5.15	683732	3691060	Fine-silty, carbonatic,thermic Typic Calcixerepts
14	6	683784	3689950	Fine-silty, carbonatic,thermic Typic Calcixerepts
15	MIS	683807	3689420	Fragmental,calcareous,shallow, thermic Typic Xerorthents
16	5.15	683835	3690900	Fine-silty, carbonatic, thermic Typic Calcixerepts
17	5.10	683949	3690410	Fine-silty, carbonatic,thermic Typic Calcixerepts
18	1	684026	3689780	Fine-silty, carbonatic,thermic Typic Calcixerepts
19	5.5	684036	3690660	Fine-silty, carbonatic,thermic Typic Calcixerepts
20	5.14	684076	3691080	Fine-silty, carbonatic,thermic Typic Calcixerepts
21	6	684147	3689290	Fine-silty, carbonatic,thermic Typic Calcixerepts
22	7	684200	3688690	Fine-silty, carbonatic,thermic Typic Calcixerolls
23	11	684232	3690010	Loamy-skeletal,carbonatic,thermic Typic Calcixerepts
24	5.6	684241	3688360	Fine-silty, carbonatic,thermic Typic Calcixerepts
25	5.10	684324	3690400	Fine-silty, carbonatic,thermic Typic Calcixerepts
26	5.10	684327	3690220	Fine-silty, carbonatic,thermic Typic Calcixerepts
27	5.9	684346	3689710	Fine-silty, carbonatic,thermic Typic Calcixerepts
28	5.5	684538	3690660	Fine-silty, carbonatic,thermic Typic Calcixerepts
29	1	684541	3690190	Fine, carbonatic,thermic Typic Calcixerepts
30	5.3	684579	3692210	Fine-silty, carbonatic,thermic Typic Calcixerepts
31	5.6	684606	3688990	Fine-silty, carbonatic,thermic Typic Calcixerepts
32	5.9	684611	3689840	Fine-silty, carbonatic,thermic Typic Calcixerepts
33	5.10	684666	3690300	Fine-silty, carbonatic,thermic Typic Calcixerepts
34	5.3	684733	3692470	Fine-silty, carbonatic,thermic Typic Calcixerepts
35	6	684740	3690210	Fine-silty, carbonatic,thermic Typic Calcixerepts
37	6	684810	3691710	Fine-silty, carbonatic,thermic Typic Halploxerepts
38	6	684861	3690040	Fine-silty, carbonatic,thermic Typic Calcixerepts

39	5.14	684903	3691110	Fine-silty, carbonatic,thermic Typic Calcixerepts
40	5.6	684916	3689160	Fine-silty, carbonatic,thermic Typic Calcixerepts
41	9	684961	3690770	Fine-silty, mixed,shallow, thermic Typic Calcixerepts
43	5.10	685051	3690420	Fine-silty, carbonatic,thermic Typic Calcixerepts
44	9	685191	3689770	Fine-silty, mixed,shallow, thermic Typic Calcixerepts
46	5.13	685212	3691740	Fine-silty, carbonatic,thermic Typic Calcixerepts
48	5.13	685282	3691880	Fine-silty, carbonatic,thermic Typic Calcixerepts
49	8.2	685374	3690300	Fine-silty, carbonatic,thermic Typic Halploxerepts
50	5.6	685381	3689510	Fine-silty, carbonatic,thermic Typic Calcixerepts
51	5.9	685398	3690480	Fine-silty, carbonatic,thermic Typic Calcixerepts
52	3	685399	3691920	Fine, gypsic,thermic Typic Haploxerepts
53	5.12	685460	3692650	Fine-silty, carbonatic,thermic Typic Calcixerepts
54	5.12	685531	3692200	Fine-silty, carbonatic,thermic Typic Calcixerepts
55	5.13	685538	3691530	Fine-silty, carbonatic,thermic Typic Calcixerepts
56	5.2	685671	3689220	Fine-silty, carbonatic,thermic Typic Calcixerepts
57	5.4	685741	3692510	Fine-silty, carbonatic,thermic Typic Calcixerepts
58	5.4	685781	3692180	Fine-silty, carbonatic,thermic Typic Calcixerepts
59	5.4	685783	3691940	Fine-silty, carbonatic,thermic Typic Calcixerepts
60	5.6	685826	3689950	Fine-silty, carbonatic,thermic Typic Calcixerepts
61	5.4	686061	3691750	Fine-silty, carbonatic,thermic Typic Calcixerepts
62	4	686090	3689500	Fine-silty, carbonatic,thermic Typic Calcixerepts
63	5.2	686106	3689260	Fine-silty, carbonatic,thermic Typic Calcixerepts
64	5.2	686217	3689020	Fine-silty, carbonatic,thermic Typic Calcixerepts
65	5.6	686218	3690060	Fine-silty, carbonatic,thermic Typic Calcixerepts
66	8.1	686270	3690330	Fine-silty, carbonatic,thermic Typic Halploxerepts
67	11	686440	3691000	Loamy-skeletal,carbonatic,thermic Typic Calcixerepts
68	5.1	686486	3688220	Fine-silty, carbonatic,thermic Typic Calcixerepts
69	8.1	686624	3690160	Fine-silty, carbonatic,thermic Typic Halploxerepts
70	8.1	686646	3690490	Fine-silty, carbonatic,thermic Typic Halploxerepts
71	1	686655	3689190	Fine, carbonatic,thermic Typic Calcixerepts
72	5.1	686671	3688540	Fine-silty, carbonatic,thermic Typic Calcixerepts
73	5.7	686751	3690540	Fine-silty, carbonatic,thermic Typic Halploxerepts
74	8.1	686836	3689840	Fine-silty, carbonatic,thermic Typic Halploxerepts
75	8.1	686906	3690140	Fine-silty, carbonatic,thermic Typic Halploxerepts
76	5.7	686965	3690540	Fine-silty, carbonatic,thermic Typic Calcixerepts
77	5.8	687432	3689940	Fine-silty, carbonatic,thermic Typic Calcixerepts
78	7	687865	3690180	Fine-silty, carbonatic,thermic Typic Calcixerolls
79	1	687873	3688910	Fine, carbonatic,thermic Typic Calcixerepts
80	5.11	688025	3689130	Fine-silty, carbonatic,thermic Typic Calcixerepts
81	5.11	688122	3689230	Fine-silty, carbonatic,thermic Typic Calcixerepts
82	5.11	688516	3689090	Fine-silty, carbonatic,thermic Typic Calcixerepts
83	5.11	689103	3688830	Fine-silty, carbonatic,thermic Typic Calcixerepts

* Miscellaneous lands

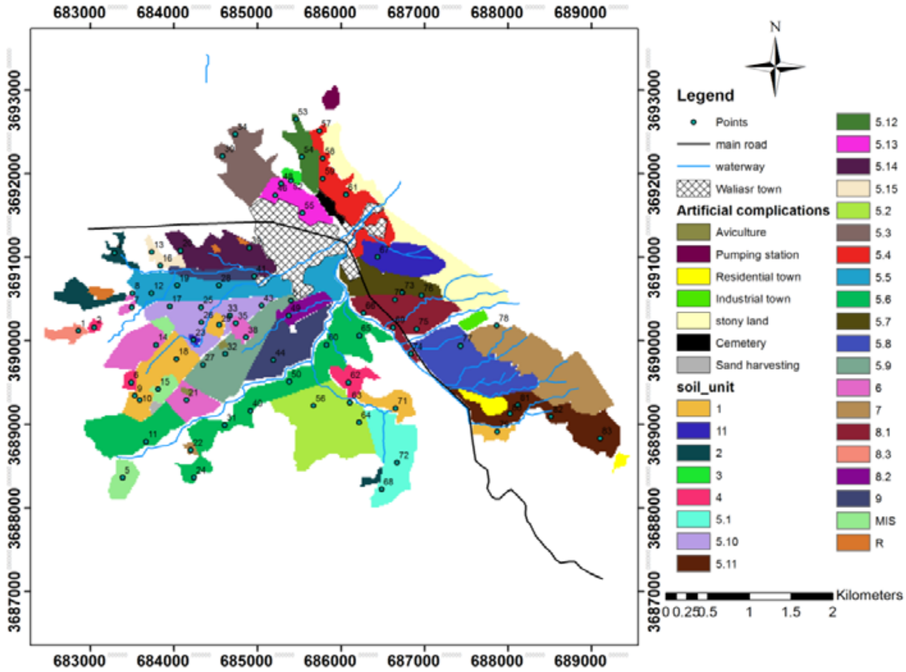


Figure 4. major soil groups of the study area (Soil Survey Staff , 2014)

2.3.3. Analysis of physical properties

Soil color was measured according to Munsell color chart in dry and wet conditions. The true specific gravity was determined using a pycnometer, as well as the apparent specific gravity of each horizon using standard cylinders with a certain volume (Jackson, 1973). Soil hydraulic conductivity was determined using the method of applying constant height of soil saturated water (Lindsay & Norvell, 1978), and soil texture was measured by the hydrometric method (Gee & Bauder, 1986). Drainage conditions and flood restrictions, surface gravel (the number of stones with a diameter of more than 25 cm based on the distance between the stones in meters and the number of coarse particles between 2 cm and 25 cm in volume), soil depth in cm. were measured. Soil hydraulic conductivity was determined at saturation under a constant head (Klute & Dirksen, 1986).

2.3.4. Analysis of chemical properties

chemical analyses were performed on the samples collected in the soil science laboratory of Ilam University. The samples collected in the laboratory were air-dried, crushed, and passed through a 2 mm sieve. Then the following analyzes were performed on them based on standard methods: Electrical conductivity (EC) parameters: using a conductivity meter in saturated soil extract (Rhodes, 1982), soil acidity (pH): glass electrode method in saturated extract Soil, organic carbon (OC), Available nitrogen in the soil was extracted in the 2.0 M KCl and determined by micro-Kjeldahl apparatus. by wet burning method with potassium dichromate in the vicinity of concentrated sulfuric acid (Nelson & Summers, 1982), Total calcium carbonate by back titration method using one normal hydrochloric acid and half normal soda (Nelson, 1982), cation exchange capacity of soil by sodium acetate method, soluble calcium and magnesium cations by titration with EDTA, soluble sodium and potassium cations by film photometry method, gypsum by acetone method, Exchangeable sodium percentage (ESP) was determined by Ammonium acetate (NH_4OAC) according to the method developed by Lavkulich (1981).

3. Land suitability assessment

The characteristics affecting soil quality indicators are defined as processes and characteristics of soil that are sensitive to changes in soil use (Aparicio & Costa, 2007; Doran & Jones, 1996), these characteristics are important for performing a simple and practical assessment of soil quality (Dumanski & Pieri, 2000). The characteristics affecting soil quality can be a set of physical, chemical, biological, or a combination of them (Herrick et al., 2002; Aparicio & Costa, 2007). Many researchers have determined various sets of characteristics affecting soil quality to determine the proposed soil quality index (Karlen et al., 1998), and the soil quality index has been determined based on the set of all characteristics affecting soil quality (TDS)[1]. Also, Researchers have proposed a limited number of soil properties that are a better representative of soil quality, as a set of minimum properties affecting soil quality (MDS)[2]. The selection of these properties is based on the highest correlation with the total soil quality (total index) and the ease of their measurement, which has been done (Andrews et al., 2002; Govaerts et al., 2006). This issue reduces the number of desired characteristics and makes it easier and lowers the cost of determining the soil quality index.

The selection of effective factors in the assessment was done based on the growth requirements of the wheat plant and by the method of (Sys et al, 1993). In this research, 14 factors were investigated to study soil quality index for wheat. Eighteen parameters have been used in this work to study land suitability for. These parameters are organic matter, N, P, K, drainage, texture, depth, topography, surface stoniness, water holding capacity, salinity, ESP, $CaCO_3$, and pH.

[1].Total Data Set
[2].Minimum Data Set

Rating is an assessment, usually expressed in numerical terms, of how suitable a site is supporting a specific land use and there is no uniform standard for rating factors. The parameters or factors were rated based on experts' suggestions and a review of the literature (FAO, 1976, 1985; Sys et al., 1991, 1993; Rezaei et al., 2006; Ashraf et al., 2010; Maleki et al., 2010; Mustafa et al., 2011; Halder, 2013; Chen, 2014). In this study, rates were assigned to the elements of a particular parameter with valid scores ranging from 0, the worst conditions, to 100, the best conditions (Table 2). Each class was given a weighted index according to the importance of its role in land suitability for crop production. A value of 0 was assigned to unclassified areas. The suitability ratings were then divided into four classes (S1: highly suitable, S2: moderately suitable, S3: marginally suitable, and N: unsuitable). The results of the proposed model were then compared with two classical parametric methods; the Square root and Storie methods.

Table 2. Factor score of land quality parameters for wheat crop in the study area. Source: FAO 1976 and Sys et al. 1993.

Proportion Class		S1		S2	S3	N	N2	
level of restriction			**1**	**2**	**3**	**4**		
Grading	**unit**	**100**	**95**	**85**	**60**	**40**	**25**	**0**
N	mg/kg	>80	80-60	60-40	40-20	<20		
P	mg/kg	>15	15-12.5	12.5-10	10-7.5	7.5-5	<5	
K	mg/kg	>400	400-300	300-200	200-150	150-100	<100	
Organic matter	g/100 g	>0.8	0.8-0.4	<0.4				
Physical properties								
Drainage		Well	Moderate	Poor	Very poor			
Slope		0-2	2-5	5-8	8-16	16-25	>25	
Depth	cm	>90	90-60	60-30	30-0			
Texture	g/100 g	L,SCL ,SL,LS , CL	SC, SiL, SiCL	Si,C, SiC	G, S			
Surface stoniness	g/100 g	0-3	3-15	15-35	35-55			
Water holding capacity(WHC)	g/100 g	>50	50-40	40-30	30-20	20-15	<15	
Chemical properties								
Salinity hazard (EC)	dS m	0-4	4-8	8-12	12-16	>16		
ESP	g/100 g	0-4	4-8	8-16	16-24	>24		
CaCO3 content	g/100 g	0-3 3-15	15-30	30-40	40-50	50-60	>60	
Soil reaction (pH)	7-6.5 7-7.5	6.5-6 7.5-8.2	6-5.6 8.2-8.3	5.6-5.2 8.3-8.5	<5.2 >8.5			

To evaluate land suitability, three indicators were used, which are:(Fertility Quality Index), (Soil Chemical Quality Index) and (Physical Quality Index).The following equation was used to calculate land suitability using GIS spatial model: Eq. 1.

$$\mathrm{Ls} = (\mathrm{FQI} \times \mathrm{CQI}_{\times}\mathrm{PQI})^{\frac{1}{3}} \qquad (1)$$

where LS is the land suitability factor, FQI is a fertility quality index, CQI is a soil chemical quality index and PQI is a soil physical quality index.

The fertility quality index was calculated using the Eq. 2.

$$\mathrm{FQI} = (S_{X1} \times S_{X2\times}S_{X3\times\ldots\ldots\times}S_{Xn)}^{\frac{1}{N}} \qquad (2)$$

where the SN, SP, SK, and SOM are parameters that express factors for, respectively the available nitrogen, the available phosphorous, available potassium, and organic matter content. The chemical quality index was calculated using the Eq. 3.

(3)

$$\mathrm{CQI} = (S_{X1} \times S_{X2\times}S_{X3\times\ldots\ldots\times}S_{Xn})^{\frac{1}{N}}$$

where the SS, SE, SC, and SH are parameters that express factors for, respectively the soil salinity, the exchangeable sodium percent, the CaCO3 content and the soil pH.
The physical quality index was calculated using the Eq. 4.

(4)

$$\mathrm{PQI} = (S_{X1} \times S_{X2\times}S_{X3\times\ldots\ldots\times}S_{Xn})^{\frac{1}{N}}$$

where the SR, ST, SD, SF, SY, SP, SG, and SW are parameters that express factors for, respectively the drainage, the texture, the soil depth, the topology, the surface stoniness, the hard pan depth, the hydraulic conductivity and the water holding capacity.
Storie method is used for calculating the land index (I) Eq. 5.

(5)

$$\mathrm{I} = \mathrm{A} \times \mathrm{B}/100 \times \mathrm{C}/100 \times \mathrm{D}/100 \times \ldots$$

where, I is the suitability index, A is the rating of surface texture parameter and B, C, D are the rating values for other parameters. A score rangingfrom0 to 100% is determined for each factor, and the scores are then multiplied together to generate an index rating (Storie, 1978).
The Square root method uses Eq. 6 to calculate soil suitability:

(6)

$$I = Rmin\sqrt{\frac{A}{100} \times \frac{B}{100} \times \frac{C}{100} \times \ldots}$$

where I is the square root index, Rmin is the minimum rating, and A, B, C,… are the remaining rating values (Khiddir, 1986). To compare the used method with the story and square root method, Cohen's kappa coefficient (Cohen, 1960) was used.
The Kappa coefficient was calculated using the Eq. 7.

(7)

$$K = \frac{P(A) + P(E)}{1 - P(E)}$$

where K is the Kappa coefficient, P(A) is the proportion of times that the coders agree and P(E) is the proportion of times that we would expect them to agree by chance. A Kappa value of 0 indicates that there is a poor agreement between the methods and a value of 1 indicates an almost perfect agreement.

Determining land suitability classes

To determine land suitability classes, the following steps were performed:

1. Converting the physical, chemical, and soil fertility indicators to the raster layer
2. Classification of raster layers based on the information in tables (2, 3, and 4) (triple soil quality indices)
3. Weighting and matching the created layers to each other
4. Reclassification of all pixels in the raster layer (to determine land suitability classes based on the table)
5. Preparation of a land suitability map of the studied area.

4. Results

Based on the Landsat Eight satellite image on August 18, 2018, and field survey and sampling, the physiography of the study area was determined. The study area, based on the standard of the Soil and Water Research Institute (Mansoori, 1992)

on a set of physiographic units (Land Types), plateaus and upper terraces and hills, known as Plateaux and alluvial plains with sloping slopes under the title: Piedmont Alluvial Plains and deposits Gravelly is located in a domain with the following characteristics.

A: The physiographic unit of the upper plateaus and terraces (Plateaux): this type of land has a lot of elevation and main and secondary slopes between 2-5% in different directions and the presence of stones and gravel on the ground surface and profile layers, parts of This area has a natural cover mainly of the semi-dense forest of oak and other perennial shrubs and annual pasture plants, the soils of this type are deep to semi-deep soils which are observed in some parts of the soil unit in the layers of the soil profile, lime in the form of powder and scattered spots. But the other parts of the units of this land type have thick vegetation with low and medium heights and slopes of 8-5% with a little erosion, and their soil is deep to very deep with heavy texture. Rainfed grain cultivation is common in this type of land.

B: Piedmont Alluvial Plains physiographic unit: This unit includes relatively smoother plains, which are mainly located in the middle of the studied area. The slope of this land type is 0-2% with a little low and high erosion. The soils of this land unit are mostly very deep to semi-deep with more profile development and heavy to very heavy texture and in some units there are stones and pebbles on the surface and depth of the soil.

C: Physiographic unit of gravelly colluvial fane deposits: the soils of this type are deep to relatively deep soils that were formed on parent materials accumulated from the heights and gravelly slopes, and in some parts have main and side slopes of 5-8 The percentage is in different directions, along with a little elevation and erosion.

4.1. Soil fertility quality index

The information related to this index is given in (Table 3) and (Fig. 5). The results show that 7.08% of the lands are in the high-quality class (S1), 84.77% of the lands are in the medium-quality class (S2), 5.76% of the lands are in the low-quality class (S3), and 2.37% of the lands are in the unsuitable class (N) in terms of fertility.

Table 3. Soil fertility index in the study area.

Soil fertility index	Class	Score	area (hectares)	Percentage
High Quality	S1	> 90	84.18761504	7.0870525996
medium quality	S2	70-90	945.1031771	84.77151127
low quality	S3	50-70	68.53944844	5.769764068
Unsuitable	N	<50	28.17326517	2.371672034

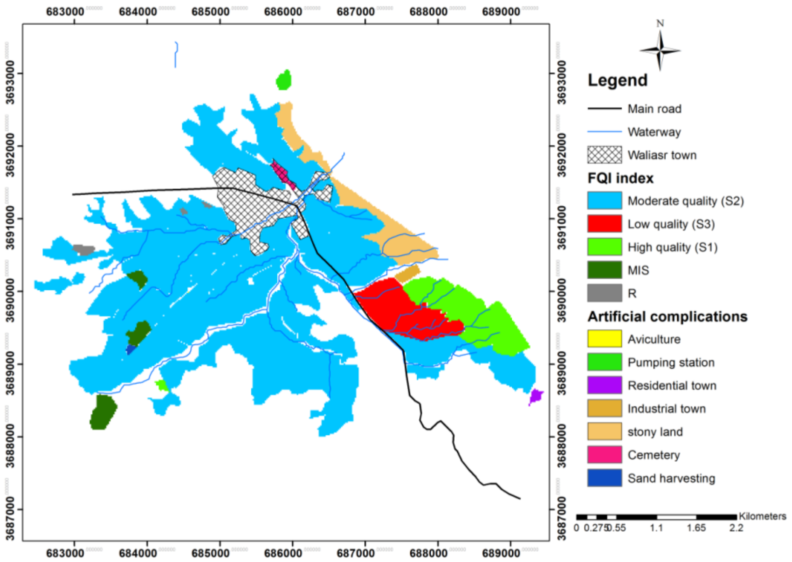


Figure 5. Fertility quality classes of the study area

4.2. Soil chemical quality index

The chemical properties of soils largely depend on the soil collides. It is, therefore, important to know about the soil colloids and their nature to have an insight into their influence on various chemical properties of soils. Soil colloids refer to the most reactive part of the soil solids. Soil colloids can roughly be grouped into two phases namely the organic and inorganic phases. The organic phase consists of either fresh or decomposed residues of plant, animal, and microbial residues which may remain associated with the inorganic phase or may be present in free form. The inorganic phase of soil colloids is dominated by the clay which governs almost all the soil properties. The soil supplies all the essential minerals elements required by the plants. Depending on their requirements by plants these elements are grouped into two types viz. (Macroelements & Microelements) The availability of plant elements depends on the type of soil. The total amount of elements contained in the soil depends on the nature of the parent material. The chemical composition of different horizons of soil also shows a good deal of variation. Usually, some of the elements that are commonly leached out are the ones that are also required by plants (Mandal, 2016).

The information related to the chemical quality index of the studied area is presented in Table 4 and Figure 6. The results of the table show that 0% of lands in the high-quality class (S1), 29.03% of lands in medium quality class (S2), 68.59% of lands in the low-quality class (S3), and 2.37% of lands in unsuitable class (N) of in terms of soil chemical quality.

Table 4. Chemical quality index in the study area.

Soil chemical index	Class	Score	area (hectares)	Percentage
High Quality	S1	> 90	0	0
medium quality	S2	70-90	344.9395196	29.03757896
low quality	S3	50-70	784.9802979	68.59074898
Unsuitable	N	<50	28.17326517	2.371672034

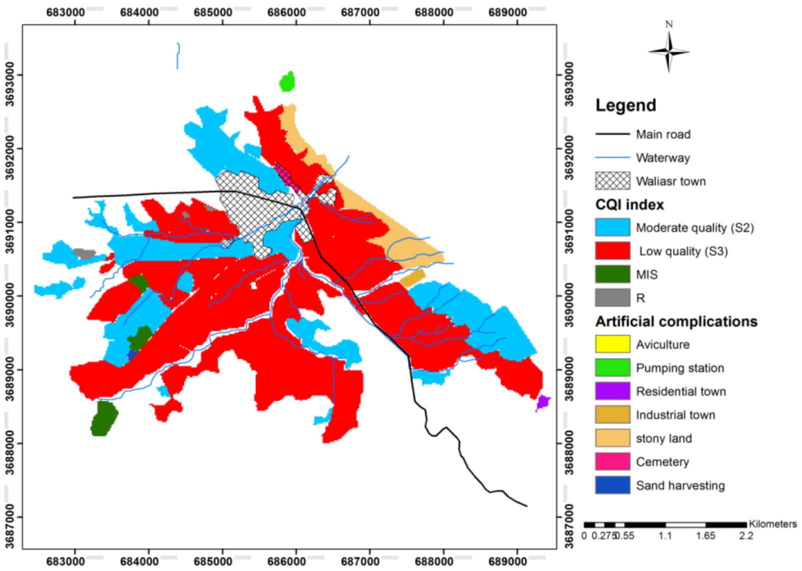


Figure 6. Soil chemical quality (CQI) classes of the study area

4.3. Soil physical quality index

The physical properties of soil are important since they determine the manner in which it can be used either for agricultural or non-agricultural purposes. Properties viz. infiltration rate, water-holding capacity, permeability, aeration, plasticity, and nutrient-supplying ability, are influenced by the size, proportion, arrangement, and mineral composition of the soil particles (Mandal, 2016). The analysis of the results obtained from the soil physical quality index (Table 5 and Fig. 7) shows that 7.08% of the lands are in the high-quality class (S1), 90.54% of the lands in the medium-quality class (S2), 0% of the lands in the low-quality class (S3) and 2.37% of The lands are in the unsuitable class (N) of in terms of physical quality.

Table 5. Physical quality index in the study area.

Soil physical index	Class	Score	area (hectares)	Percentage
High Quality	S1	>75	84.18761504	7.0870526
medium quality	S2	50-75	1010.734556	90.54127534
low quality	S3	25-50	0	0
Unsuitable	N	<25	28.17326517	2.371672034

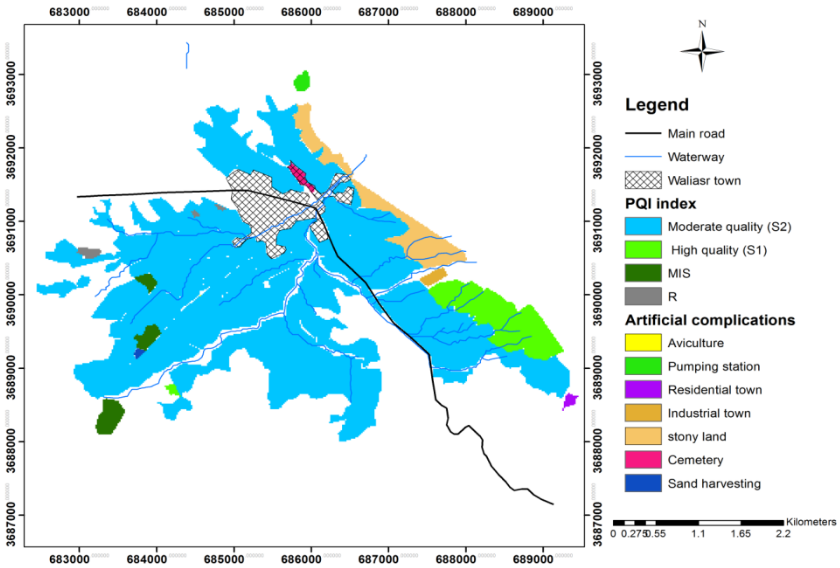


Figure 7. Soil physical quality (PQI) classes of the study area

4.4. Assessment of land suitability

The results of the proposed model are given in (Fig. 8) and (Table 6). These results show that most of the lands are in the class with Moderate suitability (S2), (55.56 percent of the total area) and lands with High suitability (S1), (7.08 percent of the total area). 33.07% of the study lands were found to be Marginally Suitable (S3) and 2.37% unsuitable lands (N) for wheat plants.

Table 6. Suitability of lands in the study area (LS).

Suitability of lands	Class	Score	area (hectares)	Percentage
High Suitable	S1	80-100	84.18761504	7.0870526
Moderate Suitable	S2	60-80	682.6989718	55.5627348

Marginally Suitable	S3	40-60	392.8474456	33.07054737
Unsuitable	N	<40	28.17326517	2.371672034

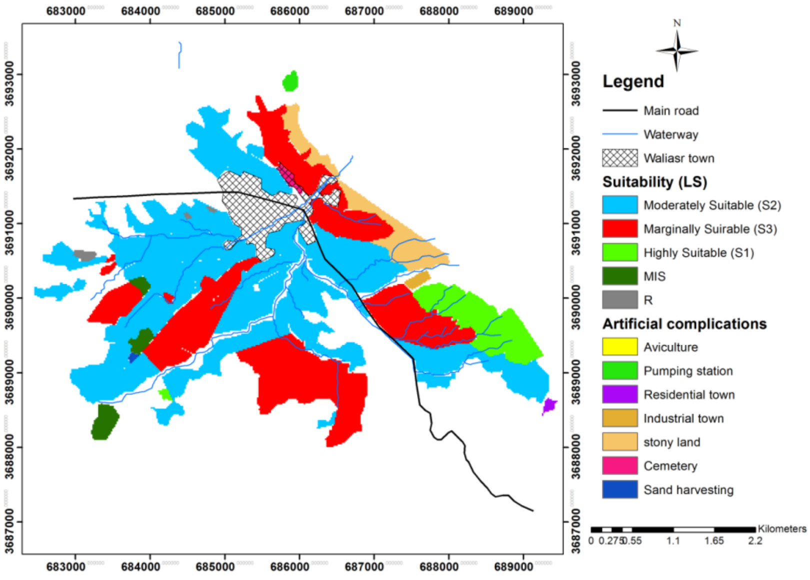


Figure 8. Suitability map of the study area

The climate index is one of the factors needed to evaluate land suitability using the square root method, which includes several effective factors. To calculate the climate index, first, the climatic parameters are calculated using the square root formula, and the obtained number, along with other land suitability factors, is again put into the square root formula to calculate the final degree of land suitability. (Table 7) is related to the climatic parameters used in this research.

Table 7. assessment of climate index for wheat planting using square root method in the study area.

Climatic feature investigated	**Average temperature**	**The degree of each climatic parameter**	**The final degree of climate**	**Final climate fitness class**
The average temperature of the growth period (C)	13.85	91.16		
Average vegetable temperature (C)	8.18	99.55		
Average flowering temperature (C)	18.6	99.25		
Average ripening temperature (C)	23.49	95.63	96.41	S1
Average daily minimum temperature of the coldest month (C)	-0.7	100		
Average daily maximum temperature of the coldest month (C)	11.9	100		

The results of the square root assessment method showed that 7.08% of lands with high suitability (S1), 59.63% of lands with Moderate suitability (S2), 30.90% of lands with

Marginally suitability (S3), and 2.37% of unsuitable lands (N) were diagnosed were given (Table 8 and Fig. 9).

Table 8. Suitability of lands by square root method in the study area.

Suitability of lands by square root method	Class	Score	area (hectares)	Percentage
High Suitable	S1	75-100	84.18761504	7.0870526
Moderate Suitable	S2	50-75	708.3907791	59.63350678
Marginally Suitable	S3	25-50	367.1556383	30.90776855
Unsuitable	N	<25	28.17326517	2.371672034

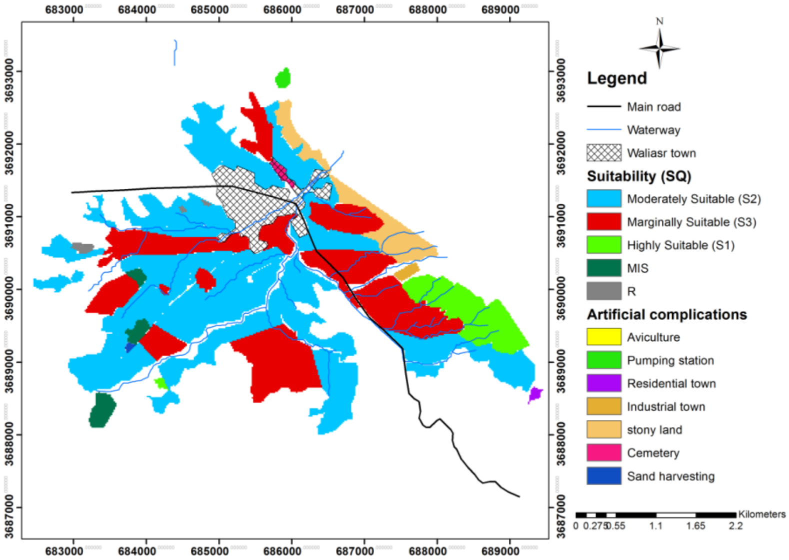


Figure 9. Suitability map of the studied area with the square root method

The climate index is one of the factors needed to evaluate land suitability using the story method, which includes several effective factors. To calculate the climate index, first, the climatic parameters are calculated using the story formula, and the obtained number, along with other land suitability factors, is again put into the story formula to calculate the final degree of land suitability. (Table 9) is related to the climatic parameters used in this research.

Table 9. assessment of climate index for wheat planting using story method in the study area.

Climatic feature investigated	Average temperature	The degree of each climatic parameter	The final degree of climate	Final climate fitness class
The average temperature of the growth period (C)	13.85	91.16		
Average vegetable temperature (C)	8.18	99.55		
Average flowering temperature (C)	18.6	99.25		
Average ripening temperature (C)	23.49	95.63	94.18	S1
Average daily minimum temperature of the coldest month (C)	-0.7	100		
Average daily maximum temperature of the coldest month (C)	11.9	100		

The results of the story method showed that 7.08% of lands with high suitability (S1), 62.78% of lands with Moderate suitability (S2), 27.75% of lands with Marginally suitability (S3), and 2.37% of unsuitable lands (N) were diagnosed were given (Table 10 and Fig. 10).

Table 10. Suitability of lands by story method in the study area.

Suitability of lands by story method	Class	Score	area (hectares)	Percentage
High Suitable	S1	75-100	84.18761504	7.0870526
Moderate Suitable	S2	50-75	745.8176158	62.78415976
Marginally Suitable	S3	25-50	329.7288017	27.75711558
Unsuitable	N	<25	28.17326517	2.371672034

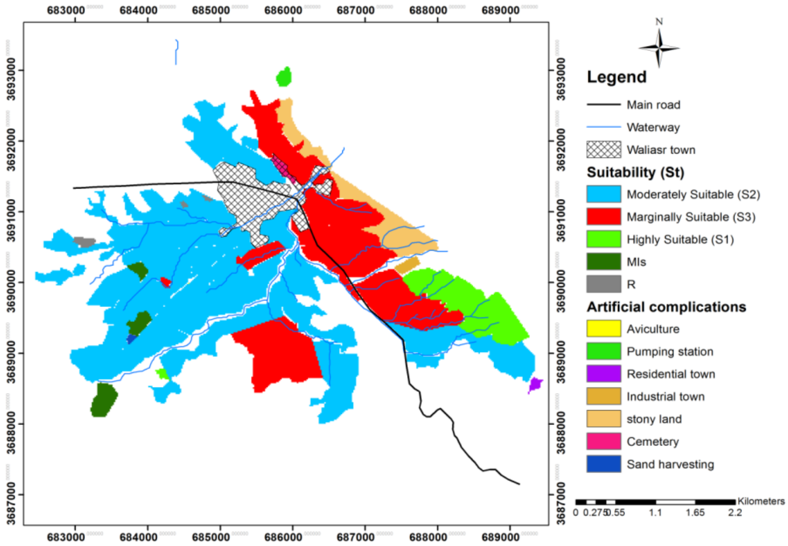


Figure10. Suitability map of the studied area with Story method

5. Discussion and Conclusions

Several methods that have been coined “traditional” but are still widely used and include Boolean logic (Hoseini & Kamrani, 2018), weighted linear combination (WLC) (Silva-Gallegos et al., 2017), weighted overlay (WO) (Hassan et al., 2020), storie and square root (Ghanbarie et al., 2016), multiple linear regression models (Leroux et al., 2019) and multivariate statistics (Akpoti et al., 2019). Among the traditional methods, categorical data is limited except for the WLC and qualitative approach (Munene et al., 2017). According to the literature, the Food and Agriculture Organisation approach has been used as a major LSA framework for assessing crop suitability(Kurukulasuriya & Mendelsohn, 2008) (IIASA, FAO, 2012). (Manna et al., 2009) concluded that changing land use and management practices must be based on land assessment results on suitability and vulnerability, thus transcending the reductionistic approaches of qualitative and quantitative methods. Parametric methods are derived from the numerical inferred effects of various land characteristics on a land use system

(Malczewski, 2006). These methods allocate a numerical value to the most significant land characteristics. They account for interactions between factors expressed through a simple multiplication or addition of single-factor indices (Liebig, 1857). The main weakness of parametric methods is that the scores can be either very small or very large, which affects the overall suitability (El Baroudy, 2016). Another bottleneck of the parametric method is the absence of any uncertainty or vagueness associated with factors determining land use suitability for crops (Danvi et al., 2016).

According to (Manna et al., 2016) and (Akpoti et al., 2019), qualitative approaches assess land potential in terms of the degree of suitability, such as highly, moderately, or not suitable (Bodaghabadi, et al., 2015). On the other hand, quantitative assessment methods give numeric indicators and use mathematical models to describe the physical conditions of geo-biophysical scenarios (Nordgren, 2016). Qualitative approaches evaluate land on a broader scale depending mostly on land uses while the quantitative approach comprises more detailed technical procedures (Akpoti et al., 2019; Mendoza & Martins, 2006). Within these procedures, arithmetical or parametric methods consisting of statistical analysis are applied (Kaim et al., 2018). The difference between the two approaches lies in the technical procedures adopted for land assessment (Mendoza & Martins, 2006; Ghansah et al., 2018). Using GIS tools, the information is combined to form a single index of assessment (Esmail & Geneletti, 2018). Geographic information system tools are best suited for handling a wide range of criteria data with different spatial and temporal scales from different sources for a time-efficient and cost-effective analysis (Greene et al., 2011). The coefficient of Kappa was used for comparing the results of the proposed model and both Square root and Storie methods to assess the level of agreement between the proposed model and parametric methods. The Kappa coefficient is 0.516 between the proposed model and the Square root methods. This value indicates a moderate agreement between the two methods, while the Kappa coefficient is calculated to be 0.243 between the proposed model and the Storie method which shows low agreement between the two methods for land suitability in the study area. Comparing the results showed that the story model has a high agreement with the square root method (about 0.884).

The results showed that most of the units fall within the Moderate suitable class(S2) for wheat crop production. GIS is a valuable tool to store, retrieve and manipulate the huge amount of data needed to compute and map different quality indices for land suitability (El Baroudy, 2016). The Soil maps for agricultural suitability designed in this research could be helpful in management decisions. Future studies should focus on using new predictive tools in forecasting. It is observed that the majority of the studies in resource allocation utilized primitive GIS techniques. In resource allocation, GIS is a powerful tool for spatial analysis. As land resources are being depleted drastically, effective land use planning needs to be done to identify new crop production areas. However, the studies by Rey et al. (2016), and Singh and Rathore (2017) have used advanced geomatic tools to improve resource allocation. Models for simulating crop production and distribution are gaining attention from the research community (Phillips et al., 2009). The use of advanced simulation software helps to remove the redundancy of the other processes and increase accuracy. Hence, researchers should focus on carrying out studies involving new and upgraded GIS software. Aerial vehicles (UAVs) may increase outreach to enhance resource allocation effectiveness (Yu et al., 2014). Modeling techniques can be used for practical impact assessment of resources. This is evidenced by the study carried out by Estes et al (2013). Future studies can focus on the use of mathematical tools for enhanced output.

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