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Land Suitability Prediction Modelling for Agricultural Crops Using Machine Learning Approach: A Case Study of Khuzestan Province, Iran

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Abstract**—**The sharp increase in population growth leads to more pressure on agricultural areas to satisfy the food supply. This necessitates increased resource consumption and underscores the importance of addressing sustainable agriculture development along with other environmental considerations. Land-use management is a crucial factor in obtaining optimum productivity. Machine learning is a widely used technique in the agricultural sector, from yield prediction to customer behavior. This method focuses on learning and provides patterns and correlations from our data set. In this study, nine physical control factors, namely, soil classification, electrical conductivity, normalized difference water index (NDWI), groundwater level, elevation, annual precipitation, pH of water, annual mean temperature, and slope in the alluvial plain in Khuzestan (an agricultural hotspot in Iran) are used to decide the best agricultural land use for both rainfed and irrigated agriculture for 10 different crops. For this purpose, each variable was imported into Arc GIS, and a raster layer was obtained. In the next level, by using training samples, all layers were imported into the python environment. A random forest model was applied, and the weight of each variable was specified. In the final step, results were visualized using a digital elevation model, and the importance of all factors for each one of the crops was obtained. Our results show that despite 62% of the study area being allocated to agricultural purposes, only 42.9% of these areas can be defined as a suitable class for cultivation purposes.

Keywords**—**Land suitability, machine learning, random forest, sustainable agriculture.

I. Introduction

SHARP population growth and economic development lead to a considerable increase in the global need for the crop production sector [1]. To achieve more crop production, more resources, more fertilizers, and fossil fuels are consumed and putting pressure on natural resources, and the agricultural sector [2]. Besides global food security, climate change and other environmental concerns highlight sustainable agricultural development which is a multi-dimensional issue that covers economic, social, and environmental aspects [3]. Sustainable farming aims to optimize the use of soil and advanced technologies by considering environmental, social, and economic limits [4]. To achieve the optimum productivity of lands, it is necessary to have appropriate land use management based on proper information [5]. Considering local conditions and characteristics is a key factor in making an appropriate decision on sustainable crop production [1]. A combination of geographical information systems and decision support systems is widely used, and this combination can provide powerful spatial referencing [6]. To achieve optimum productivity, and sustainability and minimize the environmental impacts for the future, appropriate use of land is crucial and for this purpose, effective land use management based on comprehensive information is necessary [7]. Accurate land use management ensures environmental sustainability for future generations and evaluation of land suitability is an effective tool for this purpose [5]. Land suitability assessment is the first step in agricultural land use planning and a method of land evaluation that determines the most suitable type of land use for each point [8]. This assessment shows how well the qualities of the land unit match the requirements of a particular form of land use [10], [9]. Land suitability assessment specifies appropriate soil property for each class of land use and also characterizes its limitation [8]. Qualitative information about climate, hydrology, topography, soil properties, and vegetation cover are used in this process [8]. This assessment includes the grouping of specific areas for defined uses [11]. Different categories are shown in Table I.

TABLE I
LAND SUITABILITY CLASSIFICATION [11]

Suitability classes	Code	Description
Highly suitable	S1	Lands with no significant or only minor limitations
Moderately suitable	S2	Lands with limitations that in aggregate are moderately severe for sustainable agriculture
Marginally suitable	S3	Lands with limitations which in the aggregate are severe for sustainable agriculture
Currently not suitable	NS	Lands with limitations which cannot be corrected for sustainable agriculture with existing knowledge

Advances in technology such as big data, artificial intelligence (AI), and remote sensing improved the efficiency of agricultural activities significantly [12]. Decision support systems (DSS) help to transfer available data into practical knowledge appropriately which helps stockholders to overcome difficulties in the decision-making procedure.

Reference [13] located the optimum land suitable for agriculture both rainfed and irrigated of Ma'an Governorate, Jorden, and applied five weighted physical control factors including temperature, slope percentage, rainfall, type and distribution of groundwater well, and soil type through multi-criteria evaluation to generate a land suitability map.

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Reference [14] used fuzzy logic in the GIS environment to evaluate land suitability to extend agriculture in arid regions of east Iran considering the combination of physical, ecological, and climatic factors and multi-criteria decision-making method to prioritize the significance and effect of each factor. Agricultural land suitability analysis can be done through two different traditional and modern systems. An increase in available data leads to improved prediction of changes and better identification opportunities [15]. Location intelligence technologies are widely used with a combination of AI technologies like machine learning and deep learning algorithms to identify patterns in data sets which are largely generated as a result of digitalization [15].

Machine learning (ML) is defined as the scientific study of computational models and algorithms which use experiences for accurate forecast and can be classified into three main classes: (1) supervised learning, (2) unsupervised learning, and (3) reinforcement learning [15]. Advance development in computational technologies especially in geographical information systems and AI improved understanding of many environmental problems and managing them [16]. ML approaches in comparison to traditional methods are more capable to model high-dimensional and non-linear datasets [16].

The traditional agricultural land suitability analysis (ALSA) methods are qualitative, quantitative, and parametric and based on biophysical factors. Modern ALSA combines GIS, computer, and ML algorithms [17]. GIS-based analysis generally can be classified into three main categories: (i) computer-assisted overlay mapping, (ii) multi-criteria evaluation (MCE), and (iii) AI or soft computing [17]. The ML algorithm can be helpful in order to improve crop selection and estimation of crop yield [18]. Random Forest (RF) with good performance for field mapping application which is chosen as a feature extraction method, K-nearest neighbor, and artificial neural network is among the most used learning algorithms [18]. This algorithm is based on generating a large number of decision trees and then the combination of them to provide a final classification [19]. Reference [18] used GIS and remote sensing datasets to classify suitable lands in drought-prone areas in Java for maize production based on defined potential criteria. In a RF classifier as supervised learning, a predictive model is developed by using the labeled data with prior knowledge of inputs and the final goal is mapping desired output variable [15]. To have a more accurate agro-environment assessment and space information about crop production and farmland, characterization and mapping of crops should be done. Reference [20] applied two vegetation indexes, NDVI and DVI, from the MODIS sensor to identify the seasonal agricultural pattern in the central zone of Myanmar, and three ML algorithms: support vector machine (SVM), RF, and the C5.0 are used to improve the accuracy of their pattern classification. Since the expansion of arable lands in Iran is geographically limited, there is a deep concern for agriculture management in these areas [21]. In this paper, we tried to distinguish the crop production patterns based on our defined criteria and define the correlation between them.

II. Materials and Methods

A. Study Area

Khuzestan province is in the southwest of Iran between 47° 32′ and 50° 39′ of eastern longitude and 29° 57′ and 33° 00′ of northern latitude and is one of the main agricultural hotspots in Iran, including lands under fallow, rainfed and irrigated cultivation, and gardens. Khuzestan province covers 64055 km^2 with an elevation range from 0 m in the southern part to 3000 m in the western mountainous region. The maximum temperature is 50 °C and the annual rainfall is 150 mm. In this study, land suitability prediction modeling for 10 main crops, barley, date, rice, forage alfalfa, grain maize, grape, potato, soybean, sugar beet, and wheat, in the alluvial plain of Khuzestan province has been conducted. Fig. 1 is representing the study area. The main agricultural class includes areas under rainfed cultivation, irrigated agriculture, gardens, and fallow lands.

Fig. 2 is showing a brief description of the main steps of this work.

The overall procedure of the present study is as follows:

(1) Preparation of input variables for modeling in GIS environment,
(2) Creating train and test data,
(3) Coding in the python environment,
(4) Model assessment,
(5) Visualization of results to obtain a land suitability map for agricultural products.

In this paper, we tried to use different databases to predict the land suitability of crops in the alluvial plain of Khuzestan province.

Maximum production capacity considering existing and applied technology, determines the land production potential and was obtained in a comprehensive procedure of various input data (including soil classification based on FAO procedure, topography (elevation, slope, etc.), climate data (temperature, precipitation and etc.) [6]. Approximately three quarters of Iran are in arid and semi-arid areas experiencing climate change [22]. In Iran, water shortage is combined with dryness, rapid socio-economic development, and growing water demand for agriculture [23]. More than 70% of rainfall occurs in 25% of the country, especially during winter, and it means agriculture in Iran mostly depends on irrigation [22] and it is around 90% of Iran's water withdrawal [23]. For this reason, the most critical and influential variable for agriculture in arid areas is groundwater level (data obtained from the ministry of energy and provide the name and geographical position of springs and wells), which is influenced by both anthropogenic and natural droughts [23]. Water level affects soil moisture and provides flows to water bodies [24]. Other applied variables are annual precipitation and annual mean temperature as two important climate factors [25]. NDWI[1] is a measure of water molecules in vegetation canopies and

[1] Normalized difference water index.

estimation of soil moisture [26] to detect surface water changes and soil water content [27]. Electrical conductivity (data from the ministry of energy) as a proxy for groundwater salinity assessment to evaluate water quality [23]. Other parameters are pH (water), soil classes based on the FAO classification system [28], elevation, and slope. In the first step, all variables were converted to the raster format, imported to the Arc GIS environment, and standardized cell size and the number of columns and rows. Fig. 3 represents the water level sampling points from piezometric wells in the study area and data for electrical conductivity and pH from wells and springs, both data obtained from the Ministry of Energy.

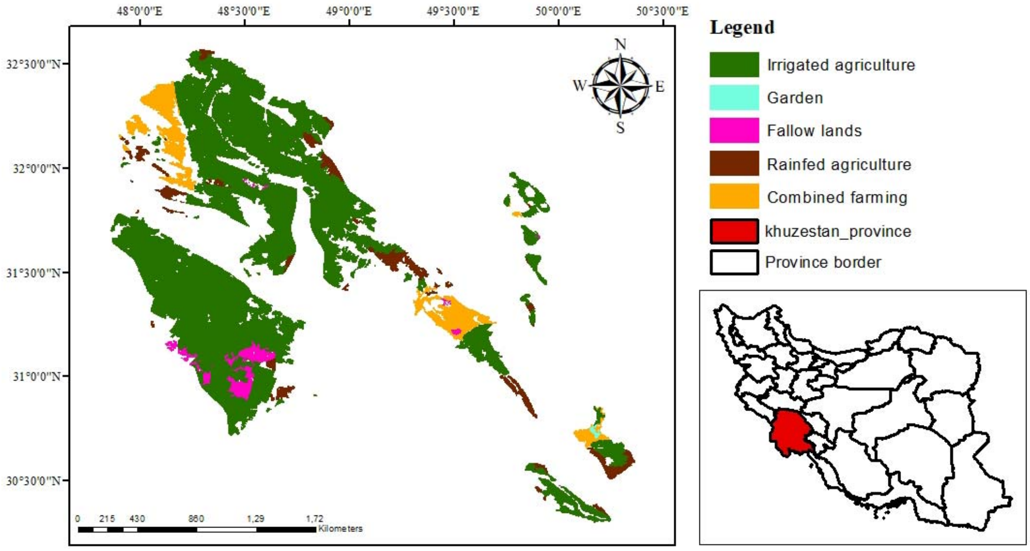


Fig. 1 Study area

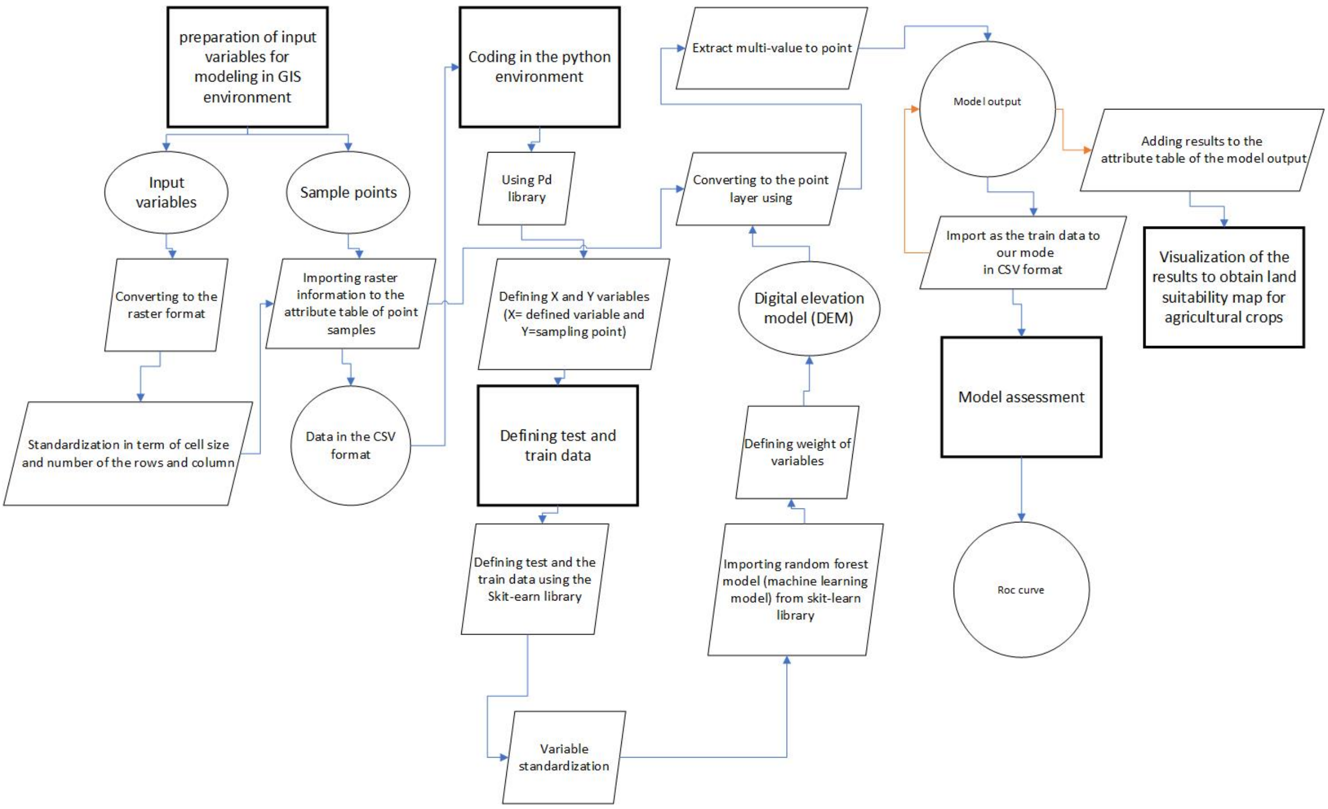
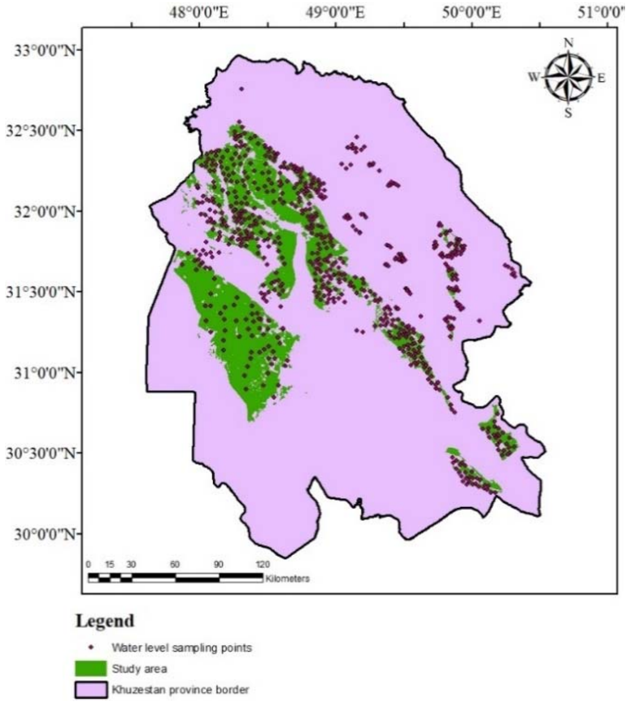
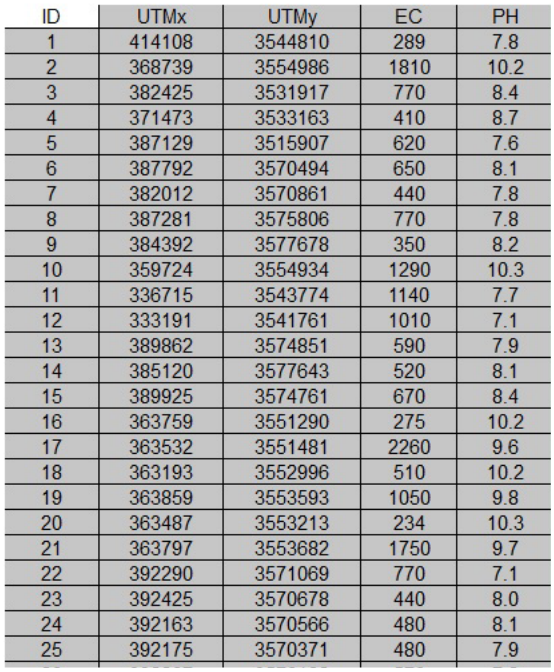


Fig. 2 Flowchart





ID	UTMx	UTMy	EC	PH
1	414108	3544810	289	7.8
2	368739	3554986	1810	10.2
3	382425	3531917	770	8.4
4	371473	3533163	410	8.7
5	387129	3515907	620	7.6
6	387792	3570494	650	8.1
7	382012	3570861	440	7.8
8	387281	3575806	770	7.8
9	384392	3577678	350	8.2
10	359724	3554934	1290	10.3
11	336715	3543774	1140	7.7
12	333191	3541761	1010	7.1
13	389862	3574851	590	7.9
14	385120	3577643	520	8.1
15	389925	3574761	670	8.4
16	363759	3551290	275	10.2
17	363532	3551481	2260	9.6
18	363193	3552996	510	10.2
19	363859	3553593	1050	9.8
20	363487	3553213	234	10.3
21	363797	3553682	1750	9.7
22	392290	3571069	770	7.1
23	392425	3570678	440	8.0
24	392163	3570566	480	8.1
25	392175	3570371	480	7.9

Fig. 3 pH and electrical conductivity data from wells and springs and groundwater level data from piezometric wells, obtained from the Ministry of Energy

TABLE II
THE CORRELATION MATRIX OF VARIABLES

Layer	Soil classification	Groundwater level	Annual mean temperature	Annual precipitation	Elevation	Electrical conductivity	NDWI	pH (water)	Slope
Soil classification	1	0.1254	0.1421	0.1558	0.6571	0.46259	0.57237	0.2365	0.6948
Groundwater level	0.1254	1	-0.52997	0.5548	0.57237	-0.48615	-0.26239	-0.0482	0.56259
Annual mean temperature	0.1421	-0.52997	1	-0.40503	-0.9408	0.51673	0.21683	-0.12779	-0.58046
Annual precipitation	0.1558	0.5548	-0.40503	1	0.51587	-0.49159	-0.41858	-0.21097	0.47736
Elevation	0.6571	0.57237	-0.9408	0.51587	1	-0.47622	-0.41359	-0.02073	0.6348
Electrical conductivity	0.46259	-0.48615	0.51673	-0.49159	-0.47622	1	0.00597	-0.4054	-0.28066
NDWI	0.57237	-0.26239	0.21683	-0.41858	-0.41359	0.00597	1	0.17112	-0.43332
pH (water)	0.2365	-0.0482	-0.12779	-0.21097	-0.02073	-0.4054	0.17112	1	-0.03635
Slope	0.6948	0.56259	-0.58046	0.47736	0.6348	-0.28066	-0.43332	-0.03635	1

OBJE	Shape *	LAT	LONG	LAT2	LONG2	LSC_S	slope	soil	toxicity	bio1	bio12	dem	erosion	workability	hydro_soil	ndvi	ndwi
613	Point	32.08529	48.2586	32° 5' 7.057" N	48° 15' 30.944"	N2	36000	1	1	246	296	60	8	1	13	1620	0.01601
287	Point	31.59066	48.12039	31° 35' 26.372"	48° 7' 13.398" E	N2	21183	3	1	246	220	12	8	1	13	2178	0.04409
225	Point	31.26186	49.6352	31° 15' 42.703"	49° 38' 6.728" E	S3	18356	1	1	252	342	188	8	1	3	2272	0.05013
271	Point	31.5702	48.14999	31° 34' 12.713"	48° 8' 59.948" E	S3	28460	3	1	246	220	15	8	1	3	2108	0.11822
575	Point	31.5506	49.8705	31° 33' 2.154" N	49° 52' 13.785"	S1	14843	1	1	223	381	710	8	2	3	2923	-0.0293
90	Point	31.16226	48.63645	31° 9' 44.137" N	48° 38' 11.212"	S2	28460	3	1	249	210	14	8	1	3	1439	0.05891
687	Point	32.29598	48.39989	32° 17' 45.531"	48° 23' 59.602"	N2	40749	1	2	246	343	94	8	1	13	4602	0.11036
404	Point	31.62082	48.92393	31° 37' 14.936"	48° 55' 26.145"	N2	20875	1	2	256	303	31	8	1	3	2134	0.04095
130	Point	31.38553	48.78838	31° 23' 7.912" N	48° 47' 18.163"	S2	50911	3	1	252	243	19	8	1	3	1927	0.01517
308	Point	31.63733	48.05337	31° 38' 14.375"	48° 3' 12.130" E	N2	18089	3	1	246	222	11	8	1	3	2402	-0.0140
72	Point	31.30668	48.40512	31° 18' 24.037"	48° 24' 18.446"	S1	64899	3	1	247	206	15	8	1	3	2230	0.14291
107	Point	31.22776	48.64606	31° 13' 39.953"	48° 38' 45.807"	S3	54000	3	1	249	212	15	8	1	3	2341	0.06853
263	Point	31.53454	48.03133	31° 32' 4.349" N	48° 1' 52.801" E	S2	96932	3	1	245	208	9	8	1	3	2521	0.09001
710	Point	32.34402	48.36423	32° 20' 38.483"	48° 21' 51.230"	N2	27534	1	2	245	346	109	8	1	13	3616	0.14383
49	Point	31.02082	48.39129	31° 1' 14.957" N	48° 23' 28.627"	S2	63639	3	2	247	192	11	8	1	3	3422	0.04962
92	Point	31.17107	48.6273	31° 10' 15.855"	48° 37' 38.295"	S2	40249	3	1	249	208	13	8	1	3	1369	0.06772
784	Point	32.30008	48.5132	32° 18' 0.296" N	48° 30' 47.534"	N2	11384	1	2	247	354	101	8	1	3	3336	0.09663
822	Point	30.36958	50.14434	30° 22' 10.486"	50° 8' 39.641" E	S2	29604	13	1	248	293	131	8	1	13	1807	0.24994
832	Point	30.56994	50.29991	30° 34' 11.789"	50° 17' 59.677"	S3	10495	1	2	240	321	340	8	1	3	1622	0.09522
51	Point	31.02875	48.41031	31° 1' 43.503" N	48° 24' 37.099"	S2	12727	3	2	247	196	15	8	1	3	3583	0.08352
53	Point	31.03444	48.41025	31° 2' 3.994" N	48° 24' 36.916"	S2	13104	3	2	247	196	6	8	1	3	2912	0.05543
585	Point	31.68093	49.88841	31° 40' 51.363"	49° 53' 18.275"	N2	12791	2	1	197	371	905	7	3	3	1606	-0.0376
524	Point	31.93827	48.85905	31° 56' 17.777"	48° 51' 32.585"	S2	15326	1	2	256	342	38	8	1	3	1703	0.06903
530	Point	31.94979	48.8715	31° 56' 59.261"	48° 52' 17.398"	S2	64899	1	2	257	346	32	8	1	13	2187	0.09341
864	Point	30.73772	50.19338	30° 44' 15.786"	50° 11' 36.183"	S2	13288	1	1	240	328	332	8	1	3	3749	0.22752
328	Point	31.68954	47.96096	31° 41' 22.361"	47° 57' 39.448"	S2	25455	3	1	245	220	9	8	1	3	2806	0.00319
262	Point	31.5396	48.14811	31° 32' 22.566"	48° 8' 53.190" E	N2	38183	3	1	246	217	13	8	1	3	1745	0.01979
91	Point	31.17259	48.69667	31° 10' 21.309"	48° 41' 47.995"	S3	40249	3	2	250	214	14	8	1	3	1697	0.00508
252	Point	31.48892	48.06799	31° 29' 20.117"	48° 4' 4.764" E	S2	23675	3	1	245	206	11	8	1	3	1886	0.06811

Fig. 4 Attribute table

The correlation matrix between defined variables is represented in Table II.

In the second step, the land suitability data for each of the 10 crops were obtained from the Khuzestan province ministry of agriculture. For each of the ten crops (900 samples for each), an Excel file includes the geographical location (name and geographical position of the villages where the specific crop is cultivated), and the degree of suitability has been derived. In the following, all these points were imported into the software. To add the data from the raster layer to the point layer, *extract multi-value to point* function has been used. As a result, for each of the 10 crops, besides the previous columns for the geographical position and degree of suitability, other columns which were indicated the value of our variables were added and exported as a CSV file (Fig. 4).

In the next phase, by using the *pd* function in the *Pandas* library of Python, the CSV file from the previous step was imported and two new variables, *x*, and *y* were defined. *X* is our variable and *Y* was referred to our sampled points. In the following, by using the *Scikit-learn* library, our data were classified into two groups: the test data group and the train data group. 30% of our data were used for test and model assessment. *Standardscaler* also was applied for standardization. In the next step, the ML model in the scikit-learn library in Python was imported, and the RF model was applied. 70% of data were used to train ML algorithms (RF) and 30% to compile to predict how well the model is trained. The model was run, and each variable's weight and importance by using *Matplotlib* was obtained. The DEM layer using the *raster to point* function was converted into the point layer to visualize and generalize results into the whole study area. To have properties of other variables, *extract multi-value to point* function were used. As a result, a point layer with properties of all variables in the study area was obtained and converted to a CSV file. These train points were imported to the model, and obtained data were fitted as a table for them. The model classified other variables based on the test result and, considering the test model's cell value, specified the value for the train data. In the final step, by using the metric function in scikit-learn, roc curves for each crop were obtained.

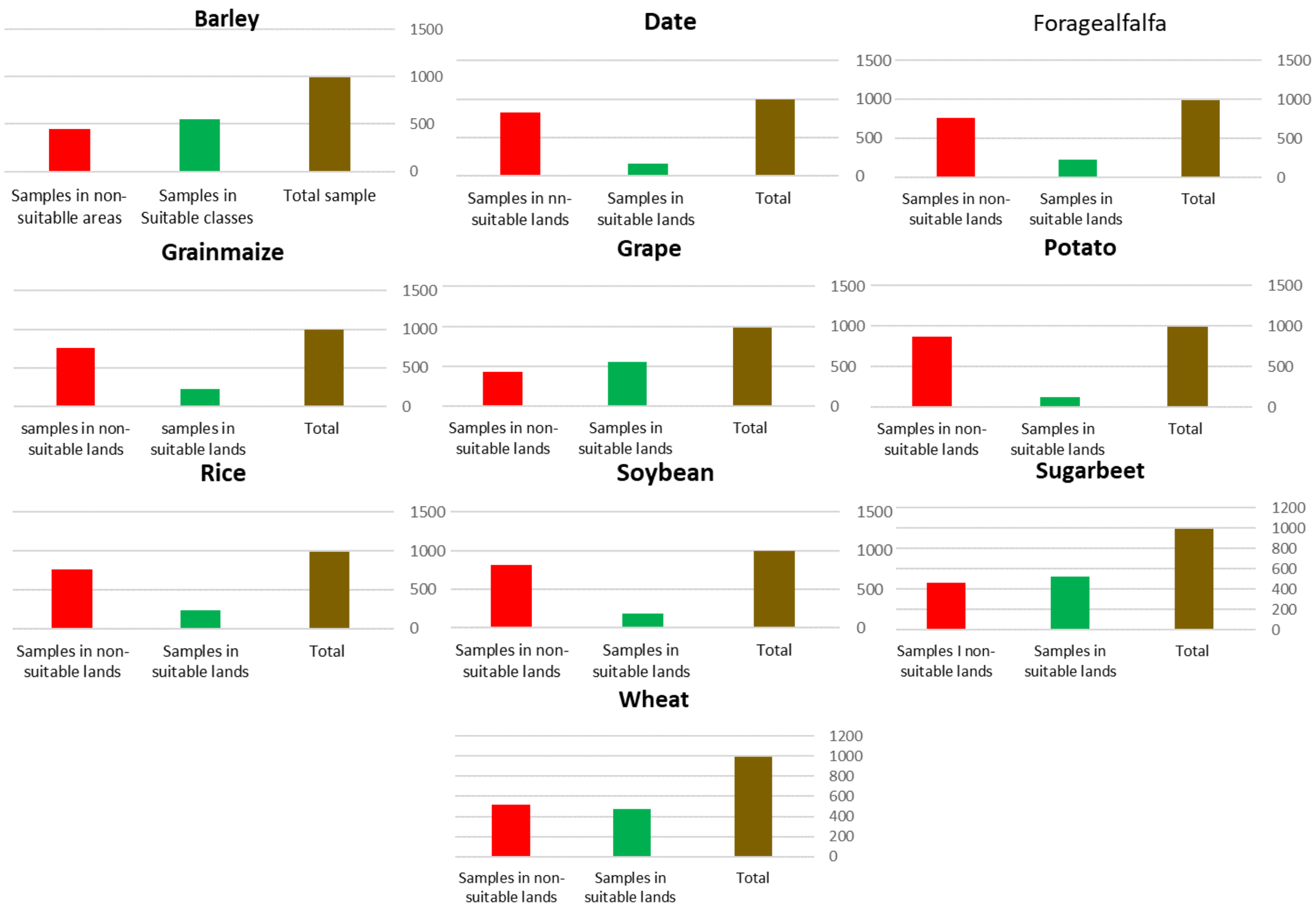


Fig. 5 Number of samples of crops in two classes

III. Results

Land suitability map for each agricultural crop based on forest model and considering environmental variable are represented in Fig. 6.

In the following, the final suitability map was obtained by overlaying all suitability maps of each crop. The maximum overlap indicates the areas that have the most suitability to cultivate a variety of agricultural products, and the lowest overlap indicates the lowest suitability (Fig. 7).

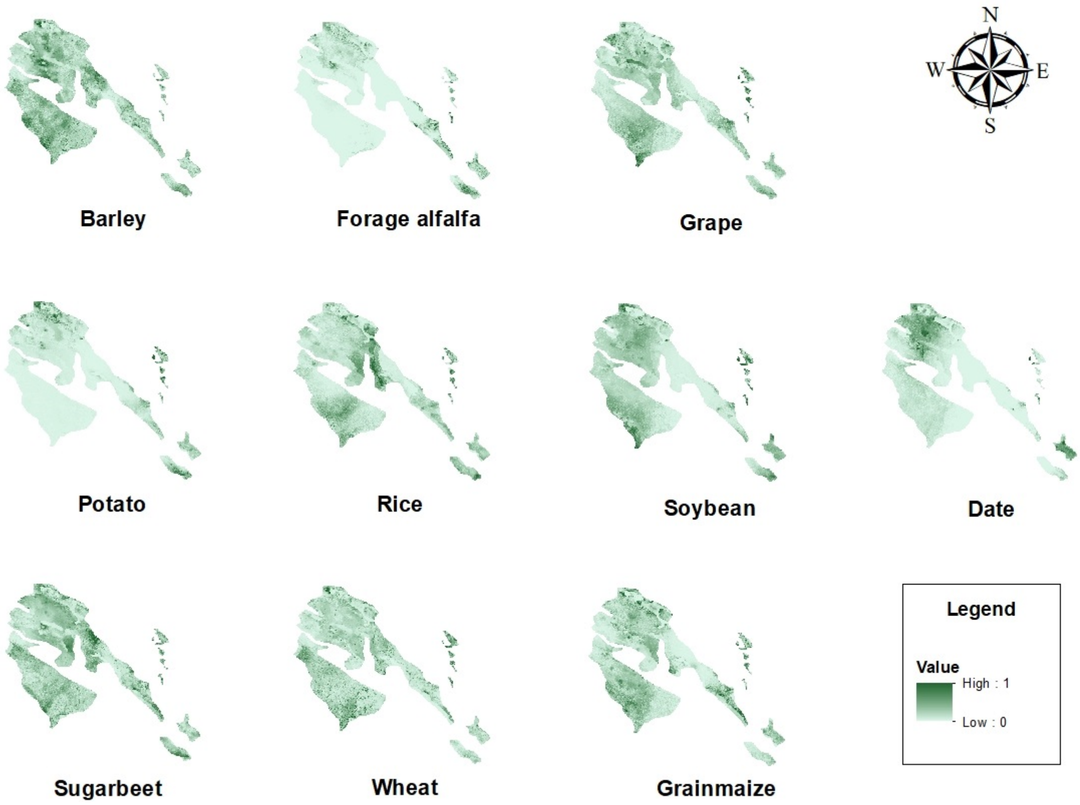


Fig. 6 Land suitability map for each agricultural crop

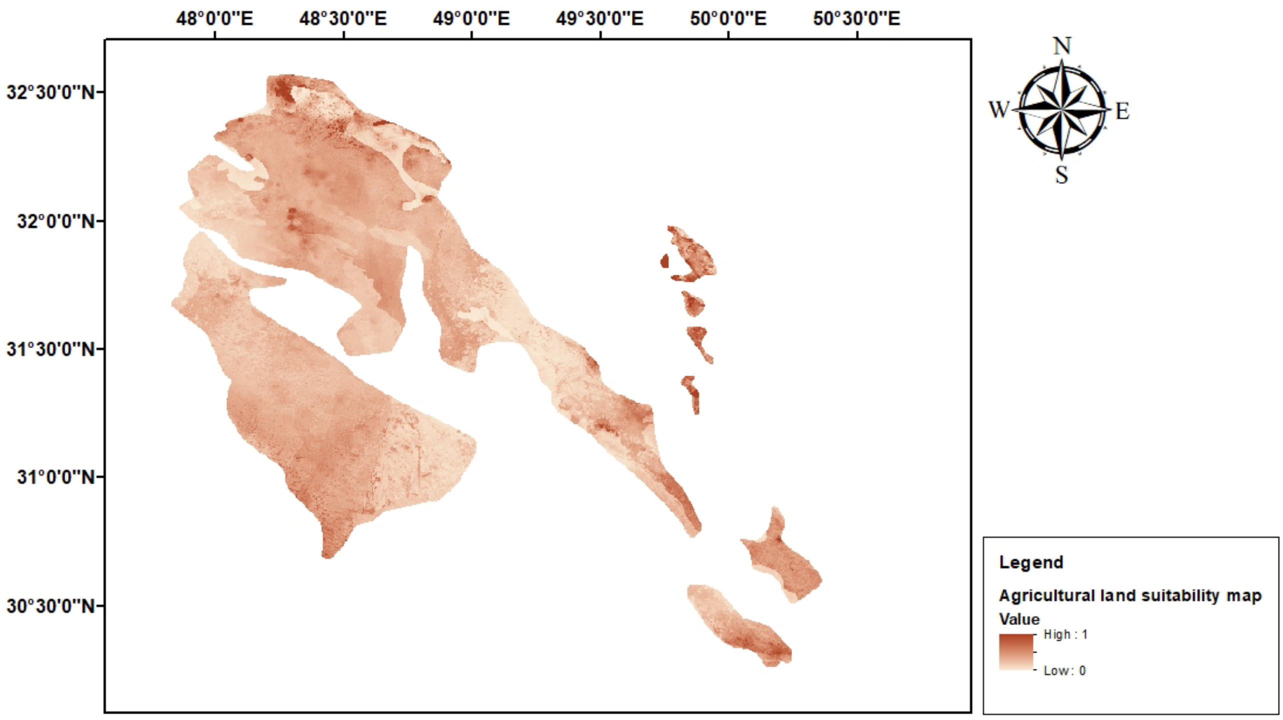
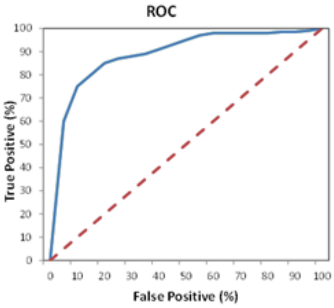
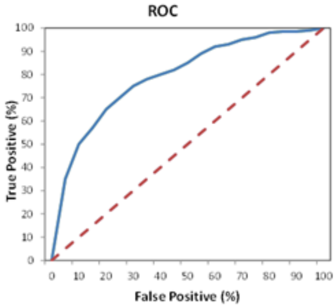


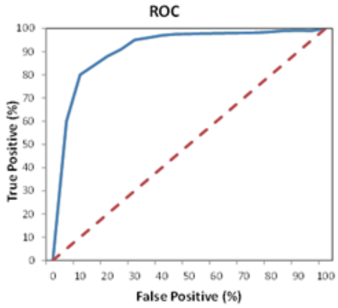
Fig. 7 Total land suitability map



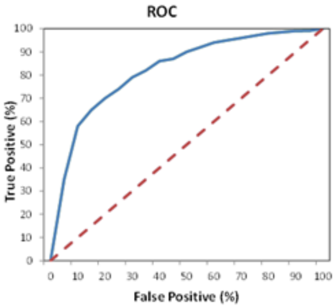
Date



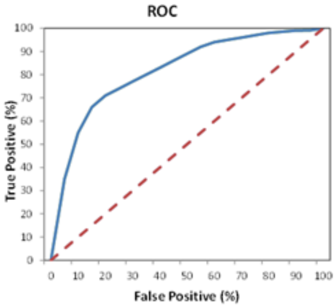
Barely



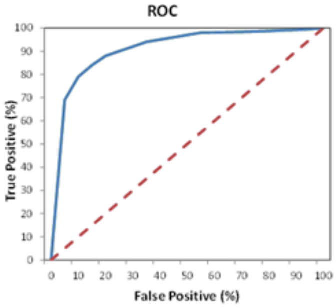
Forage alfalfa



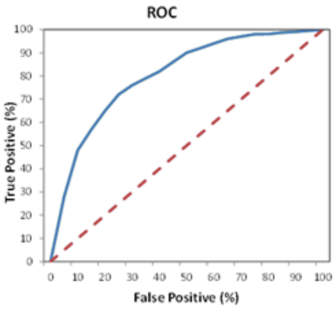
Grain maize



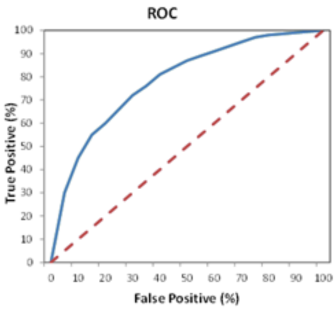
Grape



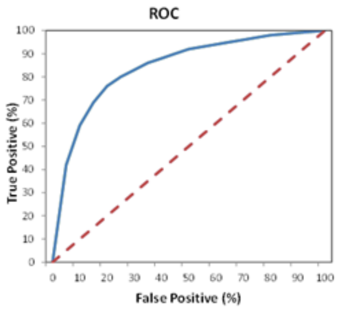
Potato



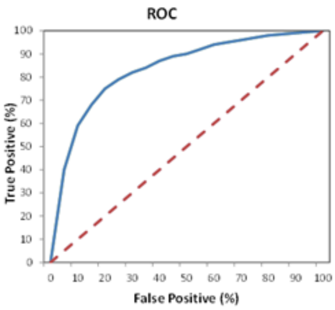
Wheat



Sugar beat



Soybean



Rice

Fig. 8 ROC curves for each crop

TABLE III
APPLIED LIMITING FACTORS AND THEIR WEIGHT

Variables	Crop: Barely	Date	Rice	Forage alfalfa	Grain maize	Grape	Potato	Soybean	Sugar beat	Wheat
The importance of variables for each crop (Percentage)										
Soil classification	36	21.4	17.3	28.3	15.4	23.8	17.5	15.6	31.4	31.6
Electrical conductivity (EC)	15.4	34.1	2.3	1.8	15.3	46	2.6	19.2	14.3	12.4
NDWI	13	2.3	9	3.1	5.7	3.6	2.5	3.2	16.9	18.8
Groundwater level	12.8	13	40.1	5.7	21.4	5.5	54.9	31.2	15.9	13
Elevation	12.2	5.4	2.5	40.7	2.3	1.8	17.2	2.5	13.1	10.4
Annual Precipitation	7.3	0.7	20.3	2.5	11.7	5.3	1.1	10	5.4	5.3
pH (water)	1.8	4.1	3.3	3.7	3.4	0.9	0.1	0.4	1.6	3.4
Annual Mean Temperature	1.2	18.7	4.2	13.5	23.4	12.6	3.7	17.2	0.9	4.4
slope	0.3	0.3	1	0.7	1.4	0.5	0.4	0.7	0.5	0.7

TABLE IV
ROC RESULTS FOR EACH CROP

Product	Date	Barley	Forage alfalfa	Grain maize	Grape	Potato	Rice	Soybean	Sugarbeet	Wheat
ROC	90	80.2	92	84.1	84.7	92.5	84.5	84.9	79.7	81.2

Based on our results, 42.9% of total area under cultivation in the study area (1058128 ha) can be classified as suitable area for all crops.

Generally, the process of ALSA is based on FAO guidance, and land suitability order is divided into suitable (S) and not suitable (NS) [29]. The study used four FAO land suitability classes, as shown in Table II.

Receiving operating characteristic curve (ROC) is one of the appropriate methods to assess a classifier's results and its capability to identify the intended class. The greater the deviation from the baseline for a particular class in the ROC curve, the greater the efficiency of that classifier in identifying that class. In addition to examining the trend of the desired floor diagram, the area below that diagram is also calculated. This area indicates the probability that a randomly selected cell is correctly classified and the higher it is, the more reliable the method is. Table IV represents the results of the ROC curve for crops. Based on results, the model with 92.5% accuracy has the highest precision for potato, and the lowest precision of the model is for sugar beet with 79.9%.

IV. DISCUSSION

Land allocation is one of the most critical concepts in land use management and sustainable development and refers to matching a homogenous area to a specific usage. Based on climate change effects, especially on agricultural and food supply sector and water crisis problems in Iran, using spatial factors and ML techniques to obtain appropriate cropping patterns of farming can be a suitable method for sustainable agriculture. Defining an appropriate cropping pattern based on carrying capacity is necessary to minimize water consumption and soil erosion. Lack of enough attention to carrying capacity is one of the main weaknesses of agricultural planning in Iran, which leads to the highest rate of soil erosion. Considering spatial parameters and spatial analysis, land allocation for crop production can lower these problems to achieve sustainable development and prevent social, economic, and environmental issues. Although 62% of our study area is agricultural lands and gardens, overlying our outputs showed that only 42.5% of these areas could be considered as suitable lands for all crops. Roughly 20% of the study area is under cultivation despite inadequate agricultural potential. From 10582128 hectares of agricultural land we have considered, 52.65% are compatible with our modeling results, and 47.35% of them are in areas classified as the unappropriated class for agriculture.

Results showed that agricultural lands had been cultivated without considering carrying capacity, leading to high environmental loads, land degradation, and social and economic crises. It is necessary to revise agricultural land use planning using DSS and spatial modeling to provide scientific information, assist decision-makers, and specify suitable lands for cultivation.

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