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Support Vector Machines Based-Modeling of Land Suitability Analysis for Rainfed Agriculture

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Abstract Soil evaluation plays important role in the sustainable agriculture development. Based on the value of several soil and environment indicators, the agricultural land evaluation methodology is applied to land mapping units in order to compute the suitability index. This index characterizes these land-mapping units. However, there are different methodologies which have been reviewed for land capability and suitability evaluation. In the present study, the potential use of support vector machines (SVMs) algorithm was evaluated for land suitability analysis for rainfed wheat based on FAO land evaluation frameworks (FAO, 1976, 1983, 1985) and the proposed method by Sys et al. (1991). The study area was divided into thirteen land units (with thirty two representative soil profiles) and ten land characteristics including climatic (precipitation, temperature), topographic (relief and slope) and soil-related (texture, $CaCO_3$, OC, coarse fragment, pH, gypsum) parameters were considered to be relevant to rainfed wheat. In this study economic factors have been excluded and moderate management has been assumed. The data points were divided by randomization technique and 80% data was selected to train the model and the remaining 20% was used to test the model. The Root Mean Square Error (RMSE) and coefficient of determination (R^2) were used as evaluation criteria. The results showed that the corresponding values for RMSE and R^2 between the measured and predicted land suitability indices using the SVMs model were 3.72 and 0.84 respectively. Moreover, the most important limiting factors for rainfed wheat cultivation are climatic and topographic conditions, and 84.38% of total lands are classified as S_2 class (moderately suitable) while the remaining 15.62% are classified as S_3 class (marginally suitable). It appears that SVMs approach could be a suitable alternative to performance of land suitability scenarios.

Keywords: *SVM, land characteristics, land suitability analysis, rainfed wheat*

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1. Introduction

Due to constant decrease in farmlands, it is important to identify the best lands for sustainable agriculture (productive and profitable agriculture that protects the environment and that is socially equitable). This requirement has resulted in the development of land suitability scenarios for agriculture (Mendas and Delali, 2012). Land evaluation procedures focus increasingly on the use of quantitative procedures to enhance the qualitative interpretation of land resource surveys. Crucial to the estimation of land suitability is the matching of land characteristics with the requirements of envisaged land utilization types. Land evaluation results from a complex interaction of physical, chemical, and bioclimatic processes and evaluation models are reliable enough to predict accurately the behaviour of land (Held et al., 2003; Ball and De la Rosa, 2006).

The FAO (1976) first developed a common framework for land evaluation that was based on biophysical factors and the socioeconomic characteristics of an area. However, this approach was difficult to apply over large areas before the development of geographical information systems (GIS), which permitted the use of computerized techniques for assessing and mapping land suitability. These techniques have become increasingly important as integral components of urban planning (Marull et al., 2007), agricultural utilization (Olivas et al., 2007), habitat selection (Manton et al., 2005), and environmental planning (Oleszczuk, 2007). Many studies have assessed the potential suitability of land and guide the selection of areas that are suitable for a particular use. There are two general kinds of land suitability evaluation approaches: qualitative and quantitative. A qualitative approach is used to assess land potential at a broad scale, or employed as a preliminary to more detailed investigations (Baja et al., 2002). The results of classification are generally given in qualitative terms only, such as highly suitable, moderately suitable, and not suitable. The second approach is that using parametric techniques involving more detailed land attributes which allow various statistical analyses to be performed.

In recent years, soft computing techniques have been successfully developed for soil and land evaluation. Support vector machines (SVMs) algorithm is one of new mathematic tools which is used as a universal constructive learning procedure based on the statistical learning theory developed by Vapnik (Vapnik, 1995) and have attracted greater interest recently in geosciences and agricultural engineering. It provides non-linear solutions to regression and classification problems by transforming the input variables in a large-dimension space, whose inner product is given by positive definite kernel functions. SVMs are trained using dual optimisation techniques with constraints. Recently several research groups about engineering have shown excellent performance of SVMs on different problems of regression and classification. SVMs are a promising machine learning method originally developed for pattern recognition problem based on structural risk minimization (Li et al., 2009). Basically, SVMs are closely related to artificial neural networks (ANNs). In fact, SVMs model using sigmoid kernel function is equivalent to a two-layer perceptron neural network. Using a kernel function, SVMs are alternative training methods for polynomial, radial basis function, and multilayer perceptron classifiers in which the weights of the network are found by solving a quadratic programming problem with linear constraints, rather than by solving a non-convex, unconstrained minimization problem as in standard ANN training (Huang et al., 2010).

To our knowledge, the land suitability assessment using SVMs algorithm has not previously been used for the modelling of cultivated wheat. The main objective of this study was to investigate the potential use of the SVMs algorithm for land suitability analysis for rainfed wheat in a hilly plateau region of Iran.

2. Materials and Methods

2.1. Study Area

A hilly area in the northwestern province of Qazvin (Kouhin region), Iran was selected for this study (Figure 1). Height amplitude varies from 1300 m to 1600 m above sea level with 1 to 6 percent slope. This belt covers about 1000 hectares, situated between latitudes 36° 20' and 36° 23' North and longitudes 49° 34' and 49° 38' East. The climate is semi-arid in nature. Soil temperature and moisture regimes are mesic and xeric, respectively (Newhall and Berdanier 1996). The soils have been developed on alluvial deposits of marl and brown to grey limestone parent materials and are plateau from east to west direction. According to US Soil Taxonomy system, the soils have been classified as Entisols and Inceptisols (Soil Survey Staff, 2006) and are used for rainfed farming. During 1993-2006, the average annual rainfall and average annual temperature were recorded to be 327 mm and 11.2°C, respectively (Iran Meteorological Organization).

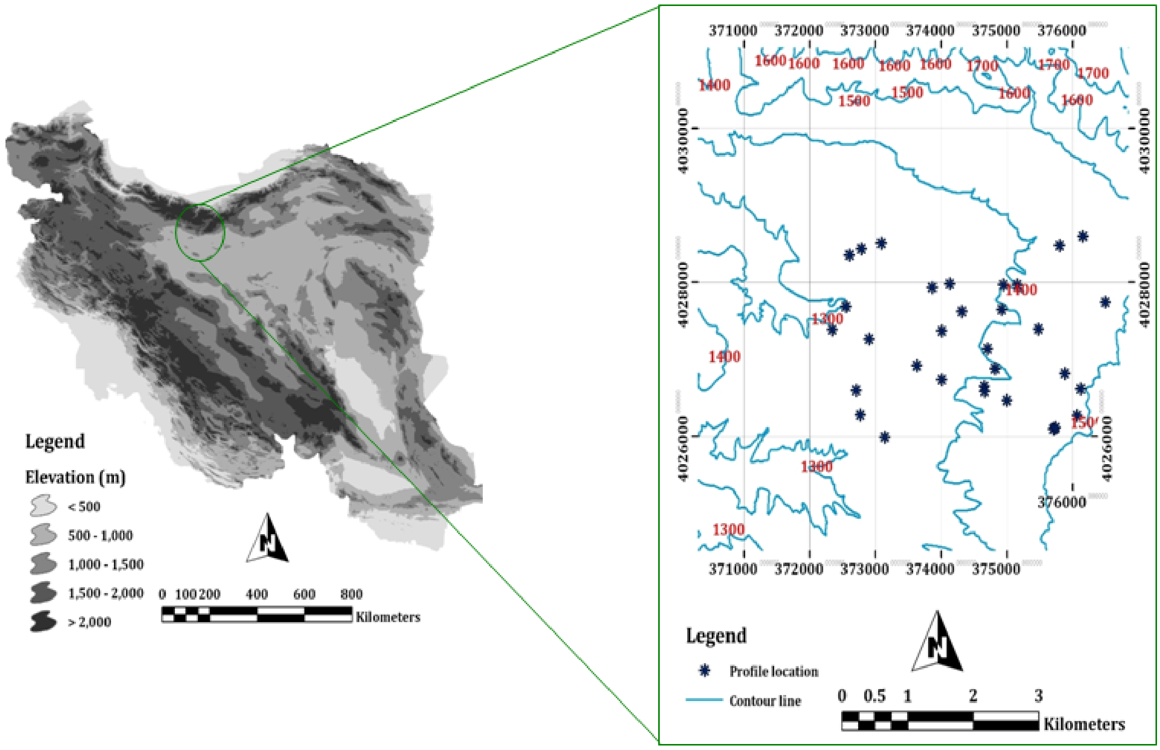

Figure 1. Location of study area and representative soil profiles

2.2. Data Collection and Soil Sample Analysis

As sampling is constrained by financial resources, efficient sampling strategies are desirable. In this paper, Soil-Land Inference Model (SoLIM) with respect to environmental covariates (soil and terrain attributes) was used for sampling design optimization (Yang et al., 2012). A Digital Elevation Model (DEM) with grid size of 10×10m was extracted from a paper-based topographic map using GIS platform with scale of 1:25000 and contour lines interval of 10 meter (National Cartographic Center, 2010). The terrain attributes such as slope value, aspect, elevation and plan curvature were extracted from a digital elevation model (DEM) with a resolution of 10 meter (Wilson and Gallant, 2000). A total of 120 soil samples were collected from different horizons of thirty two representative soil profiles located in Kouhin region in Qazvin Province, Iran. Geographical location of sampling points was recorded by Global Positioning System (GPS). The soil samples were air dried, crushed and sieved using 2 mm sieve size and subjected to laboratory analysis using standard methods (Sparks et al., 1996).

2.3. Physical Land Suitability Procedure

The basis of the present methodology lies in the traditional qualitative land evaluation, and land qualities/characteristics are matched with each specific crop requirements in order to find the suitability class of land for the same crop (FAO, 1976). The methodology comprises two key steps: Step 1 is to identify land units with a similar topography and soil conditions, Step 2 is to match the properties of the land units with crop requirements including the traditional matching process, as described in the FAO qualitative land evaluation system (FAO, 1976, 1983, 1985) used to compare land qualities/ characteristics of topography, erosion hazard, wetness, soil physical properties, soil fertility and chemical properties, soil salinity and alkalinity with each specific crop requirements developed by Sys et al. (1991). The physical land suitability evaluation consists of a model that assigns a score to every land quality and characteristic. Land quality is a complex attribute of land, which in a distinct manner influences its suitability for a specific kind of use, while land characteristics are any measurable features of land that can be used to characterize a land unit. In this study, the land indices were calculated based on parametric method according to the square root equation (Samir, 1986; Bagherzadeh and Mansouri Daneshvar). In parametric method, a quantitative classification is allocated to each characteristic of land. If a characteristic of land for a specific product was completely desired and provided optimum conditions for that, maximum degree 100 would belong to that characteristic and if it has limitation, the lower degree will be given to it. Later, allocated ranks will be used in calculation of the land index.

2.4. Crop Requirements

A requirement table for rainfed wheat is established using the structure of the FAO framework for land evaluation. Both previously established requirement tables (Sys and Debaveye, 1991) and conditions proper to Kouhin area were considered.

2.5. Support Vector Machines (SVMs) Methodology

Among many machine-learning methods, SVMs, originally developed by Vapnik (1995), are considered to be a new generation of learning algorithms. SVMs have several appealing characteristics for modellers, including: they are statistically based models rather than loose analogies with natural learning systems, and they theoretically guarantee performance (Cristianini and Scholkopf, 2002). SVM have been applied successfully to text categorization, handwriting recognition, gene-function prediction, remote sensing classification and ecology (Guo et al., 2005) demonstrating the utility of the method across disciplines, and proving that SVM produce very competitive results with the best available classification methods, and require just a minimum amount of model tuning (Huang et al., 2010). Typically, SVMs are designed for two-class problems where both positive and negative objects exist. For these classification problems, two-class SVM seek to find a hyper plane in the feature space that maximally separates the two target classes. The basic idea of SVMs is to use a linear model to implement non-linear class boundaries through nonlinear mapping of the input vector into a high-dimensional feature space. The linear model constructed in the new space can represent a non-linear decision boundary in the original space. In this study, MATLAB 8.2 (The MathWorks, Inc.) software was used for the design and testing of SVMs model. Data points were randomized by Excel software and 80% of data was applied as training data, while remaining 20% set as a test data. For more details about SVMs algorithm, one can refer to Xu et al. (2012).

2.6. Performance Criteria

The model performance was evaluated using test data points that were not used in the training stage. The parameters used for the evaluation of model were root mean square error (RMSE) and coefficient of determination (R^2), which were calculated using equations 1 and 2 (Wosten et al., 2001):

$$RMSE = \sqrt{\sum_{i=1}^{N}\left(y_o - y_p\right)/N} \tag{1}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{N}(y_o - y_p)^2}{\sum_{i=1}^{N}(y_o - \bar{y}_i)^2} \tag{2}$$

where y_o is the measured value, y_p is the predicted value, $\bar{y}_i$ is the mean value, and N is the total number of data points. RMSE was used to measure accuracy and validity of the training and test data sets.

3. Results and Discussion

The crop requirements in terms of soil and land characteristics are presented in Table 1. The study area was divided into thirteen land units (with thirty two representative soil profiles) and ten land characteristics including climatic (precipitation, temperature), topographic (relief and slope) and soil-related (texture, $CaCO_3$, OC, coarse fragment, pH, gypsum) parameters were considered to be relevant to rainfed wheat. In similar study, Kamkar et al. (2014) studied a GIS-based plan to assess the possibility and performance of a canola-soybean rotation in Golestan province, one of the most important agricultural production regions of Iran. They used precipitation, temperature, aspect, slope, texture, pH and EC layers in GIS platform. According to their results, 11.82% of total lands are very suitable to rotate soybean after canola while most agricultural lands in the study area fell into the moderate and low suitability classes.

Table 1. Soil and land characteristics for rainfed wheat in Kouhin region

Profile No.	Soil and land characteristics									
	Texture (class)*	$CaCO_3$ (%)	OC (%)	Slope (%)	pH	Gypsum (%)	Coarse fragment (%)	Relief (code)	Precip (mm)	Temp. (°C)
1	C.L	12.43	0.87	11.18	7.85	0.00	0.00	3	256.30	10.18
2	C	19.00	0.90	3.95	7.98	1.58	0.00	3	256.30	10.18
3	C	12.79	0.85	5.00	7.95	0.00	0.00	0 to 1	256.30	10.18
4	C	17.77	0.78	5.30	7.68	0.00	0.42	0 to 1	256.30	10.18
5	S.C.L	22.82	0.83	10.00	8.04	0.00	14.50	0 to 1	256.30	10.18
6	S.C.L	16.13	0.74	15.20	8.03	0.00	16.32	0 to 1	256.30	10.18
7	C	12.86	0.82	9.01	7.95	0.00	7.00	0 to 1	256.30	10.18
8	S.C.L	12.67	0.59	23.25	7.87	0.00	33.00	2	256.30	10.18
9	C	14.17	0.78	5.00	7.86	0.00	0.00	0 to 1	256.30	10.18
10	C.L	10.70	0.85	1.77	7.99	0.00	0.00	0 to 1	256.30	10.18
11	C	13.84	0.66	5.30	7.74	0.00	0.00	1 to 2	256.30	10.18
12	C	15.82	0.65	14.25	8.00	0.00	0.00	2	256.30	10.18
13	C	14.20	1.03	5.00	7.70	0.00	1.63	1	256.30	10.18
14	C	13.22	0.89	11.18	7.81	0.00	6.60	0 to 1	256.30	10.18
15	S.C.L	11.26	0.75	14.25	8.00	0.00	15.00	1	256.30	10.18
16	C.L	13.34	0.75	24.04	7.90	0.00	3.00	2	256.30	10.18
17	C	7.14	0.98	1.77	8.06	0.00	4.00	0 to 1	256.30	10.18
18	C	14.23	1.02	5.30	8.16	0.00	0.00	0 to 1	256.30	10.18
19	C	14.80	0.85	3.95	7.97	0.00	3.30	0 to 1	256.30	10.18
20	C	15.38	0.93	5.59	7.97	0.00	0.00	0 to 1	256.30	10.18
21	C.L	16.88	0.70	11.18	7.84	0.00	0.00	2	256.30	10.18
22	C.L	14.88	0.80	13.81	7.95	0.00	3.75	1	256.30	10.18
23	C	8.77	1.04	23.25	7.92	0.00	15.00	2	256.30	10.18
24	C.L	15.97	1.12	3.95	7.85	0.00	6.50	2	256.30	10.18
25	C	15.35	0.74	11.18	7.85	0.00	10.00	0 to 1	256.30	10.18
26	S.C.L	14.40	0.94	8.84	8.09	0.00	27.00	0 to 1	256.30	10.18
27	S.C.L	14.24	0.87	9.52	7.81	0.00	8.50	3	256.30	10.18
28	C	15.97	0.63	22.36	8.08	0.00	2.00	2	256.30	10.18
29	S.C.L	19.90	0.81	10.00	7.89	0.00	16.38	2	256.30	10.18
30	S.C.L	19.71	0.93	5.00	8.07	0.00	5.63	1	256.30	10.18
31	C.L	16.48	0.49	25.00	7.65	0.00	9.96	1	256.30	10.18
32	C.L	17.30	0.68	7.07	7.80	0.00	4.36	0 to 1	256.30	10.18

*C = Clay, C.L = Clay Loam, S.C.L = Sandy Clay Loam.

Table 2. soils classification in the study area (Soil Survey Staff, 2006)

Land mapping unit	Soil classification
1	Fine – loamy, mixed, superactive, mesic Gypsic Haploxerepts
2	Fine, mixed, active, mesic Gypsic Calcixerepts
3	Fine, mixed, active, mesic Typic Calcixerepts
4	Fine – loamy, mixed, active, mesic Typic Calcixerepts
5	Fine – loamy over fragmental, mixed, active, mesic Typic Calcixerepts
6	Clayey over loamy-skeletal, mixed, active, mesic Typic Calcixerepts
7	Loamy-skeletal, mixed, superactive, mesic Typic Calcixerepts
8	Loamy-skeletal, mixed, active, calcareous, mesic Typic Xerorthents
9	Fine, mixed, active, mesic Vertic Calcixerepts
10	Fine, mixed, superactive, mesic Typic Haploxerepts
11	Fine – loamy, mixed, mesic Typic Calcixerepts
12	Fine – loamy over sandy-skeletal, mixed, superactive, mesic Typic Calcixerepts
13	Fine – loamy, mixed, superactive, mesic Typic Calcixerepts

In the present study, economic factors have been excluded and moderate management has been assumed. Soils classification in the study area is presented in Table 2. As it is highlighted in Table 2, 7.69% of soils are classified as Entisols order, whereas the remaining 92.31% are classified as Inceptisols order. Land suitability classes and land indices in Kouhin region are shown in Table 3. According to Tables 1 and 3, the most important limiting factors for rainfed wheat cultivation are climatic and topographic conditions, and 84.37% of total lands are classified as S_2 class (moderately suitable) while the remaining 15.62% are classified as S_3 class (marginally suitable). Emphasis should be placed on soil management techniques that conserve organic matter and enhance nutrient and water-holding capacity of the soil. In order to assess the SVMs algorithm performance, test data points were used to predict land suitability indices and the predicted values were plotted against measured values (Figure 2). The plot approximates a straight line, confirming normality of the data and angle close to 45 degrees (one to one line) also indicates a high accuracy of the SVMs algorithm for the estimation of land suitability indices. The RMSE and R^2 between the measured and predicted land suitability indices using the SVMs model were 3.72 and 0.84 respectively.

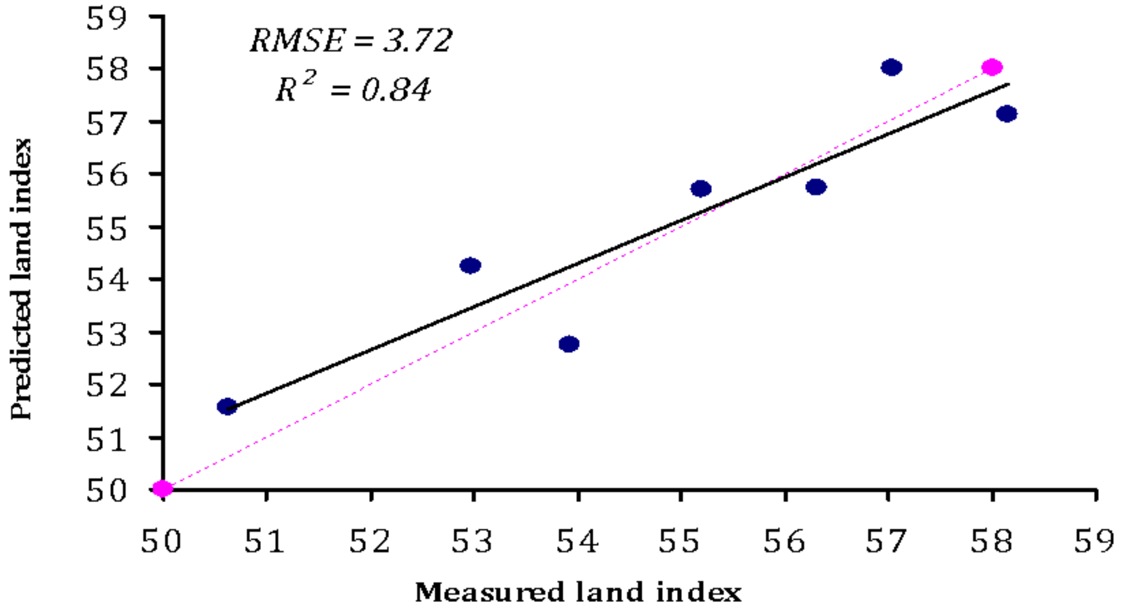

Figure 2. The scatter plot of the measured versus predicted values for land indices

Table 3. Land suitability classes and land indices in Kouhin region

Profile No.	Land index	Suitability class
1	32.70	S_3
2	33.63	S_3
3	57.36	S_2
4	57.42	S_2
5	51.87	S_2
6	51.23	S_2
7	51.23	S_2
8	31.07	S_3
9	58.96	S_2
10	58.90	S_2
11	57.76	S_2
12	52.88	S_2
13	56.84	S_2
14	55.86	S_2
15	52.42	S_2
16	32.31	S_3
17	58.73	S_2
18	58.53	S_2
19	57.19	S_2
20	58.13	S_2
21	54.76	S_2
22	53.70	S_2
23	50.02	S_2
24	52.66	S_2
25	57.03	S_2
26	52.88	S_2
27	30.88	S_3
28	50.25	S_2
29	50.85	S_2
30	54.11	S_2
31	50.63	S_2
32	58.28	S_2

There are limited published studies dealing with the use of SVMs in soil sciences especially in land evaluation. Lamorski et al. (2008), for instance, estimated soil hydraulic parameters from measured soil properties using SVMs. They reported that SVMs performed generally better than or/with the same accuracy as ANNs. Twarakavi et al. (2009) developed SVM models for estimating the hydraulic parameters describing the soil water retention and hydraulic conductivity. They stated that the SVM-based method predicted the hydraulic parameters better than the ANN-based method. Wang et al. (2009) compared different artificial intelligence methods for forecasting monthly discharge time series. They concluded that SVM model was able to obtain better forecasting accuracy in terms of the various evaluation measures during the both training and validation phases. Djurić et al. (2013) implemented SVM models in a typical supervised classification learning task. Two modelling schemes have been involved (since the main problem of the study was the unavailability of the land-use suitability in the testing area): Model1 has been built in the extents of the training area having only two land-use suitability classes at disposal (unsuitable and very unsuitable) and extrapolated to the testing area within which the same two classes were known (thus available for model performance evaluation), while Model2 has been trained on all four land-use suitability classes, and extrapolated to the testing area, with unknown land-use classes. The second model was then correlated with the first one in order to estimate its otherwise disputable performance. Results of Model1 were satisfactory, with high overall accuracy (85%). Model2 visually shows a good tendency, and since it has at least 85% accuracy for those coincident two classes (unsuitable and very unsuitable) with Model1, it is justified to assume that remaining two classes match similar accuracy rates.

In compare to this new method in land evaluation, the earlier fuzzy model has been used by many researchers in land suitability evaluation (Tang et al., 1991; Van Ranst et al., 1996; Keshavarzi and Sarmadian, 2009). Most of the researchers, have been compared the results of this evaluation with other conventional methods such as maximum limitation, parametric and multiple regression methods in order to predicting the yield of production. The weakest part of the fuzzy set methodology for land evaluation is the way in which membership functions, class centers, cross-over values and weight values are chosen (Keshavarzi and Sarmadian, 2009). The problem of how to define the parameters of the fuzzy membership functions is more complicated than the boolean equivalent because it requires not only specifications of what kind of membership function and class boundary values, but also the widths of the transition zones. Another critical issue is the choice of weights which clearly have a major impact on results. Some guidance can be obtained from the literature and expert experience on land properties relevant to particular crops, but ultimately subjective decisions have to be made.

4. Conclusions

In this study, SVMs —a novel machine learning algorithm— was evaluated for land suitability analysis for rainfed wheat using the Root Mean Square Error (RMSE) and coefficient of determination (R^2). The results showed that the most important limiting factors for rainfed wheat cultivation are climatic and topographic conditions. According to the advantages associated with the use of the SVM over this research, It appears that SVMs approach could be a suitable alternative to performance of land suitability scenarios and studies on this approach should continue in an effort to relate soil properties to the basic soil characteristics and its advantages should motivate soil scientists to work further on it in the future.

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