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Communication

Determining relationships between soil properties and plant distribution in a protected area in central Iran

Mohammad Homayoun[1], Ahmad Jalalian[1], Ali A. Besalatpour [2,] *, Ali Basirat [3] and Inge Aalders [4]

[1] Department of Soil Science, College of Agriculture, Islamic Azad University, Khorasgan (Isfahan) Branch, Isfahan, Iran
[2] Department of Soil Science, College of Agriculture, Vali-e-Asr University of Rafsanjan, Rafsanjan 7718897111, Iran
[3] Natural Language and Text Processing Laboratory, School of Electrical and Computer Engineering, College of Engineering, University of Tehran, Tehran, Iran
[4] The James Hutton Institute, Craigiebuckler, Aberdeen AB15 8QH, United Kingdom
* Corresponding author, email: a_besalatpour@yahoo.com; a.besalatpour@vru.ac.ir

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Abstract: A hybrid algorithm specifically designed to work with optimised support vector machine with genetic algorithm (GA-SVM) was developed for determining the relationships between soil properties and plant distribution and vegetation cover densities in a protected area (Ghomeshlu, central Iran). The bulk density, porosity, silt, total nitrogen and chloride contents are the main essential factors (with a screen accuracy of 100%) for the establishment and growth of Scariola. For Astragalus, surface fragment content has the greatest influence, while available phosphorus was screened by the GA-SVM analysis as the factor with a closer relationship with Anabasis growth in the study sites. Particle density, aggregate stability, available magnesium and pH are the more important combination of soil properties affecting the coverage density of Stipa. Soil organic matter content, available phosphorus, total nitrogen, electrical conductivity, porosity and particle density have a closer relationship with the coverage density of Noaea. This study provides a strong basis for identifying habitat characteristics of vulnerable and/or endangered species in Iran.

Keywords: soil-plant relationships, endangered plant species, Iran, support vector machines

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INTRODUCTION

Plants differ in their requirements and tolerance to site conditions created by soil and landscape characteristics [1]. Variations in soil resource levels and landscape features influence patterns in biodiversity and natural processes including soil-nutrient-water interactions [2]. In fact, soil characteristics (such as nutrients, salinity and moisture conditions) determine the resources available to plants. Therefore, the change in soil type and their spatial variation may affect the distribution of plant species [3]. In addition, plant community and soil conditions are influenced by landscape features including topography, landscape position, slope gradient and elevation [4]. Thus, it is important to understand the ecological relationship between soil variables and plant species in order to plan and execute a successful forest and rangeland restoration programme.

In several studies, traditional regression models, principal component analysis (PCA), cluster analysis and geostatistic analysis approaches have been employed to recognise the relationships between landscape feature, soil factors and vegetation distribution [1, 3, 5, 6]. Nevertheless, many of the methods have focused on controls over spatial variability in local scales (less than 2 km) and have not been recommended for large areas as various soils and environmental factors are involved and a large amount of samples are required to characterise the above-mentioned relationships [5].

In this study the potential use of optimised support vector machine (SVM) models with genetic algorithm (GA) for determining the relationships between soil properties and plant distribution and vegetation cover density in a protected area (Ghomeshlu, central Iran) is evaluated. SVMs are a promising machine learning method originally developed for a pattern recognition problem based on structural risk minimisation. SVMs are closely related to artificial neural networks (ANNs) and they can be divided into two categories: support vector classification (SVC) machines and support vector regression (SVR) machines [7-11]. Recently they have attracted greater interest in agricultural and biological engineering [7].

Conservation, sustainable management and possible restoration of endangered or vulnerable plantations in natural forests and rangelands require knowledge of the relationship between the distribution and regeneration of native species and the pattern of soil properties [1]. A major goal of this study is to understand the relationship between natural vegetation and soil as an environmental variable in the rangelands of the Ghomeshlu exclusion area, central Iran. The information obtained could increase the effectiveness of current restoration programmes, which aim to replace exotics with native species in this protected area. The native species restoration is thought to be more effective if plant species requirements are matched with soil and site characteristics in the area. Therefore, the specific objectives of our study are: (i) to investigate the relationship between the distribution of native plant species in these natural rangelands and soil characteristics and (ii) to evaluate the potential use of the hybrid support vector machine with genetic algorithm (GA-SVM) for this investigation. The hypothesis of the study is that the distribution of native species within the natural rangelands depends on the physical and chemical properties of the soil.

METHODS

Study Area

The study area is part of the Ghomeshlu exclusion area (32° 43′ to 33° 2′ N and 50° 59′ to 51° 28′ E) in Isfahan province, central Iran (Figure 1). The elevation ranges from 1687 m at the western part of the study area to 2767 m on the southern part. The long-term average rainfall and temperature in the region are 165 mm and 11.5°C respectively. The zonal vegetation cover of the study region is mostly herbaceous vegetation which includes Scariola (*Scariola viminea*), Anabasis (*Anabasis aphylla*), Stipa (*Stipa barbata*), Astragalus (*Astragalus gummifer*) and Noaea (*Noaea*

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mucronata). These plant species are the dominant vegetation covering around 98% of the study area.

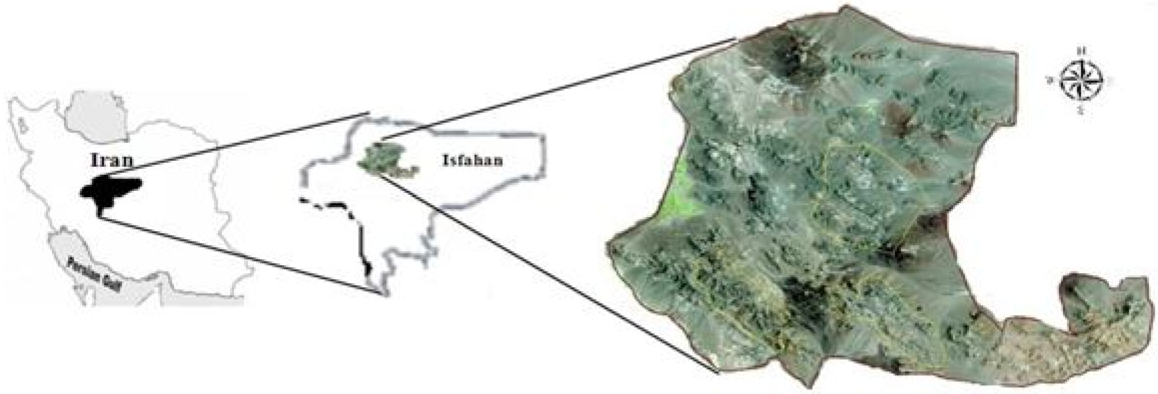

Figure 1. Location of the Ghomeshlu protected area in central Iran (32° 43′ - 33° 2′ N and 50° 59′ - 51° 28′ E)

Vegetation Investigation, Soil Sampling and Analysis

A stratified random sampling was designed using digital topography, soil, and land cover maps in the environment of ILWIS 3.4 software (ITC, University of Twente, Netherlands) to determine the investigation sites in the study area. A total of 59 sites were selected. At each of these sites, one homogeneous plot of 400 m^2 (20 m × 20 m) was chosen randomly for a detailed vegetation inventory. Within each plot, three quadrates (1 m × 1 m) on the diagonal line were randomly chosen for detailed inventory of herbaceous vegetation. In each plot all the individual herbs were identified and their layer coverage and height measured. Environmental variables such as altitude and landscape position and aspect were recorded for each plot.

Soil samples were obtained from three points in each quadrate at a depth of 0-30 cm. The three replicate samples were homogenised by hand. Large plant material (roots and shoots) and pebbles in each sample were separated and discarded. The soil samples were air-dried and sieved for the determination of soil properties. For aggregate stability assessment, separate soil samples were taken such that minimum structural deformation and/or destruction happened to the soil aggregates.

The soil samples were air-dried and ground to pass a 2-mm sieve. Soil organic matter (SOM) content was determined by the Walkley-Black method [12]. Soil pH and electrical conductivity (EC) were measured in saturated paste with a conductivity meter. Calcium carbonate equivalent (CCE) content was determined by the back-titration method [13]. Available phosphorus content (P_{ava}) was determined by a colorimetric method [14]. Total nitrogen was measured by the micro-Kjeldahl method [15]. Concentrations of available calcium (Ca_{ava}) and magnesium (Mg_{ava}) were determined by the methods described by Black [14]. Available potassium (K_{ava}) was measured using 1N ammonium acetate as the extractant [16], and cation exchangeable capacity (CEC) was determined using 1N sodium acetate [17].

Soil bulk density was measured by the core method [18] and soil particle density was predicted by the method described by Saxton et al. [19]. Percentages of clay, silt and sand particles were measured using the procedure described by Gee and Bauder [20]. The method of Kemper and

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Rosenau [21] was used to determine the mean weight diameter (MWD) of aggregates. The MWD (mm) of water-stable aggregates was calculated using the following equation:

$$MWD=\sum_{i=1}^{n} w_i \overline{X}_i \tag{1}$$

where $\overline{X}_i$ is the arithmetic mean diameter of each size fraction (mm) and w_i is the proportion of the total weight of water-stable aggregates in the corresponding size fraction after deducting the weight of sand/gravel particles (upon dispersion and passing through the same sieve).

After measuring the soil parameters, descriptive statistics of the experimental data, i.e. mean, minimum, maximum, standard deviation (SD) and skewness, were determined using the SPSS statistical software (IBM, USA). The data set were then divided into two subsets of training and testing. The training subset was randomly chosen from 80% of the total set of the data and the remaining samples were used as the testing set.

Brief Description of SVM Technique

SVM is a type of learning machine which was first proposed by Vapnik [9]. It is based on the structure risk minimisation principle that seeks to minimise an upper bound of the generalisation error. A detailed description of SVM model can be found in the literature [7, 8, 9, 11]. Very briefly, suppose there is a training dataset (D) [9, 22]:

$$D=\{(x_i,y_i)|i=1,2,...,l\}, x_i \in R^n, y_i \in R \tag{2}$$

where x_i is the input value, y_i is the target value and i is the number of sample data. Let $f(x)$ define the estimated regression function:

$$f(x)=(w,x)+b \tag{3}$$

and let ξ_i^* define the slack variable:

$$\xi_i^* = \begin{cases} 0 & |f(x)-y_i| < \varepsilon \\ |f(x)-y_i|-\varepsilon & |f(x)-y_i| > \varepsilon \end{cases} \tag{4}$$

The dimension of w is the dimension of the feature space. With the slack variables (ξ_i and ξ_i^*), punishment coefficient (C) and insensitive loss (ε) based on the SVM theory, the original SVM optimum model in the feature space (ϕ) can be described as:

$$\min_{w,b,\xi_i,\xi_i^*} \phi = \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{l}(\xi_i + \xi_i^*) \tag{5}$$

subject to: $y_i - (w.x_i + b) \le \varepsilon + \xi_i$,

$(w.x_i + b) - y_i \le \varepsilon + \xi_i^*$,

$\xi_i \ge 0, \xi_i^* \ge 0, i = 1,2,\ldots,l$

The dual optimisation model of the original SVM model can be obtained as follows:

$$\max_{a,a^*} w = -\frac{1}{2}\sum_{i=1}^{l}\sum_{j=1}^{l}(a_i - a_i^*)(a_j - a_j^*)\langle x_i, x_j\rangle + \sum[a_i(y_i-\varepsilon) - a_i^*(y_i+\varepsilon)] \tag{6}$$

subject to: $\sum_{i=1}^{l}(a_i - a_i^*) = 0$

$0 \le a_i, a_i^* \le C \qquad i = 1,2,\ldots,l$

Based on this, w can be expressed as:

$$w=\sum_{i=1}^{l}(a_i - a_i^*)x_i \tag{7}$$

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Thus, the regression estimation function can be expressed as:

$$f(x) = \sum_{i=1}^{l} (a_i - a_i^*) K(x_i, x) + b \tag{8}$$

where $K(x_i, x)$ is named the kernel function. A common example of kernel functions is the radial basis function [7, 8, 10, 22]:

$$K(x_i, x) = exp\left(-\frac{\|x_i - x\|^2}{2\sigma^2} \right) \tag{9}$$

where σ is the kernel parameter.

Optimisation of SVM Parameters Using GA

The identification of optimal values for the SVM parameters (i.e. punishment coefficient (C) and insensitive parameter (ε)) is important for a good forecast and estimation performance [22]. The procedure of parameter optimisation we used for the SVM models can be described as follows:
Step 1: Initialising the parameters of SVM such as punishment coefficient C and insensitive parameter ε.
Step 2: Initialising the parameters of genetic algorithm including the parent population, maximum number of iteration and genetic operators (crossover and mutation values).
Step 3: Defining the fitness function.
Step 4: Calculating the fitness. If this value is acceptable according to the fitness, the population is the optimal solution. Otherwise, generate new population.
Step 5: Judge the condition for stop; if the new population meets the stopping criterion, then stop the iteration and this will be the optimal solution which represents the best parameters for SVM. Otherwise, generate new population and repeat from step 2.
Step 6: According to the optimised parameter of C and ε, the SVM model is established and is ready for the prediction. The schema of the hybrid GA-SVM model is presented in Figure 2.

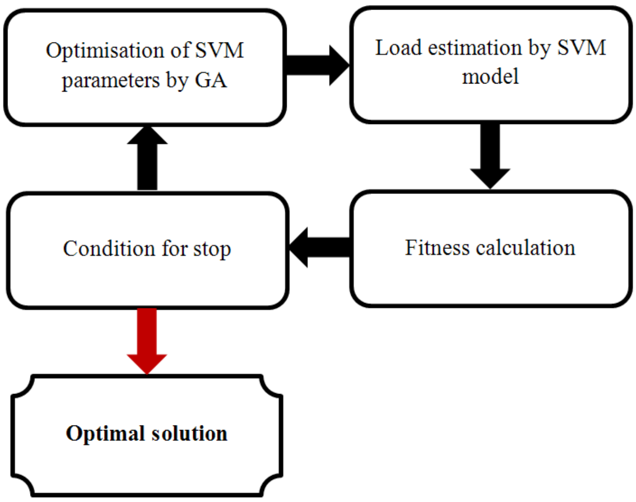

Figure 2. Diagram of GA-SVM model

RESULTS

Descriptive statistics of the measured soil properties including mean, minimum, maximum, standard deviation (SD) and skewness are presented in Table 1.

Table 1. Summary of statistics of measured soil properties

Soil property	Mean	Minimum	Maximum	SD	Skewness
Clay (%)	18.47	6.66	31.67	6.29	0.37
Silt (%)	30.93	7.5	52.5	10.04	-0.14
Sand (%)	50.59	20.83	77.50	13.74	0.14
pH	8.01	7.70	8.53	0.16	1.05
EC (dS m^{-1})	0.27	0.17	0.56	0.07	1.09
SOM (%)	0.25	0.0	0.67	0.15	0.77
CCE (%)	49.84	4.0	88.0	25.50	-0.08
TN (%)	0.08	0.01	0.15	0.03	-0.08
CEC (cmol kg^{-1} soil)	11.74	4.80	24.60	5.53	0.76
K_{ava} (mg kg^{-1})	356.94	151.01	626.10	128.42	0.35
Ca_{ava} (meq l^{-1})	1.84	0.80	2.80	0.64	-0.21
Mg_{ava} (meq l^{-1})	0.71	0.20	1.80	0.38	0.68
Na_{ava} (meq l^{-1})	0.21	0.05	1.11	0.25	0.28
P_{ava} (mg kg^{-1})	41.51	0.17	93.89	21.39	0.61
Cl^- (meq l^{-1})	0.66	0.25	1.50	0.29	0.81
MWD (mm)	0.22	0.17	0.28	0.03	0.55
SF (%)	37.18	10.0	83.0	15.09	0.39
Por	0.42	0.36	0.49	0.03	-0.08
Inf (cm h^{-1})	1.19	0.34	4.24	0.82	1.39
PD (g cm^{-3})	2.53	2.43	2.67	0.06	0.63
BD (g cm^{-3})	1.45	1.32	1.62	0.08	0.21

Note: EC = electrical conductivity, SOM = soil organic matter content, CCE = calcium carbonate equivalent content, TN = total nitrogen, CEC = cation exchangeable capacity, K_{ava} = available potassium content, Ca_{ava} = available calcium content, Mg_{ava} = available magnesium content, Na_{ava} = available sodium content, P_{ava} = available phosphorus content, Cl^- = chloride content, MWD = mean weight diameter, SF = surface fragment content, Por = porosity, Inf = infiltration rate, PD = particle density, BD = bulk density, SD = standard deviation

The GA analysis has generated optimal values for the SVM parameters, i.e. punishment coefficient (C) and insensitive parameter (ε) (Table 2). Parameter C determines the trade-off between the model's complexity and the degree to which deviations larger than ε are tolerated. In the case that C is too large, the rate of accuracy of the estimation is high in the training phase, but may be low in the testing phase. If C is too small, the accuracy of the estimation is unsatisfactory, and the model is useless. The value of ε illustrates the anticipated value for sample data error. Large ε will reduce the reliability of results [22]. The SVM parameter results for both the constructed SVM model types (i.e. SVR and SVC models) seem to be satisfactory in terms of C and ε parameter values. The elegance of using the kernel function lies in the fact that one can deal with feature spaces of arbitrary dimensionality without having to calculate the feature condition. Any function that satisfies the conditions can be used as the kernel function. In this study the radial basis function (Eq. 9) and the Gaussian kernel (i.e. $K(x,y)=exp(-(x-y)^2=\sigma^2)$) show satisfactory results.

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Table 2. Optimal values of SVM parameters resulting from GA analysis

SVM model type	Plant studied	SVM parameter		
		Kernel type	**Insensitive parameter (ε)**	**Punishment coefficient (C)**
SVC	Scariola	RBF	0.24	46.47
	Stipa	RBF	0.33	70.29
	Astragalus	RBF	0.84	80.32
	Anabasis	RBF	0.80	112.45
	Noaea	RBF	0.45	76.59
SVR	Scariola	Gaussian	0.005	4.50
	Stipa	Gaussian	0.0	7.0
	Astragalus	Gaussian	0.005	15.50
	Anabasis	Gaussian	0.0	6.0
	Noaea	Gaussian	0.0	15.50

Note : SVC = support vector machines for classification, SVR = support vector machines for regression, RBF = radial basis function

The results of SVM classifications of soil variables that influence the establishment and growth of plant species in the study sites are depicted in Table 3. According to the SVC results, bulk density, porosity, silt, total nitrogen and chloride content are the main factors (with a screen accuracy of 100%) that account for the occurrence of Scariola in the study area. The CCE is the determinant parameter that affects the establishment and development of Stipa in the study sites. For Astragalus, surface fragment content has the greatest influence, while available phosphorus content is screened by the SVC analysis as the factor with the closest relationship with the occurrence and distribution of Anabasis. Soil bulk density is identified as the essential factor (with a screen accuracy of 80%) influencing Noaea occurrence.

Table 3. Soil variables influencing occurrence of investigated plant species according to SVC analysis

Plant	**Characteristic**	**Accuracy (%)**
Scariola	Silt, BD, Por, Cl^-, TN	100
Stipa	CCE	80
Astragalus	SF	85
Anabasis	P_{ava}	80
Noaea	BD	80

Note: BD = bulk density, Por = porosity, Cl^- = chloride content, TN = total nitrogen, CCE = calcium carbonate equivalent content, SF = surface fragment content, P_{ava} = available phosphorus content

The application of SVR approach, which discerns and determines the main factors affecting the vegetation cover density and height, results in different findings (Table 4). The CEC, SOM, Na_{ava}, Mg_{ava}, pH, EC, infiltration rate and porosity are components influencing Scariola density while particle density, aggregate stability, Mg_{ava} and pH are, according to the SVR model, the more

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important combination of soil properties affecting Stipa occurrence. The combination of total nitrogen, Na_{ava} and surface fragment content has a close relationship with Astragalus vegetation cover density and height while the vegetation cover percentage and height of Anabasis are more related to the combination of CEC, Na_{ava}, CCE, Cl^-, infiltration rate, clay content and bulk density. SOM, P_{ava}, total nitrogen, EC, porosity and particle density are the most important factors affecting Noaea presence.

Table 4. Soil variables influencing coverage density and height of investigated plant species according to SVR analysis

Plant	Characteristic	MSE
Scariola	CEC, SOM, Na_{ava}, Mg_{ava}, pH , EC, Inf, Por	0.076
Stipa	PD, MWD, pH, Mg_{ava}	0.008
Astragalus	TN, Na_{ava}, SF	0.133
Anabasis	CEC, CCE, Na_{ava}, Cl^-, Inf, BD, Clay	0.032
Noaea	SOM, TN, P_{ava}, EC, Por, BD	0.047

Note: MSE = mean estimation error, CEC = cation exchangeable capacity, SOM = soil organic matter content, Na_{ava} = available sodium content, Mg_{ava} = available magnesium, EC = electrical conductivity, Inf = infiltration rate, Por = porosity, PD = particle density, MWD = mean weight diameter, TN = total nitrogen, SF = surface fragment content, CCE = calcium carbonate equivalent content, Cl^- = chloride content, BD = bulk density, P_{ava} = available phosphorus content

DISCUSSION

Soil characteristic spatial variations influence plant diversity and community features by affecting the movement and persistence of organisms, as well as the redistribution of organic matter and nutrients [23]. Especially in semi-arid terrestrial ecosystems, patchiness may play a critical role in maintaining ecosystem productivity by concentrating limited resources [24]. On the other hand, variations in plant type and landscape condition can affect soil characteristics and water interactions [2].

A strong relationship between soil available nitrogen, phosphorus and magnesium contents and the occurrence and distribution of plant species in the study site was observed, which is expected since they are generally considered essential plant nutrients. The SVC results suggest that bulk density, porosity and silt are the main factors accounting for the occurrence of Scariola. These are the main soil physical properties which affect the establishment and growth of plants by improving the structure and fertility of soil. The Stipa occurrence is most responsive to calcium carbonate content. Calcium carbonate in soil plays a considerable role in the creation of good structure. Together with soil pH, they are two important factors which determine plant-type distribution [25, 26]. According to the SVC analysis results, surface fragment content is the key factor for the occurrence, growth and development of Astragalus in the study area. It is well known that this species prefers mountainous and slightly eroded soil with surface fragment [27]. Its relatively deep and straight root system is well adapted to this condition. This species is a good competitor species because it can absorb essential nutrients from the soil better than species with more shallow root systems [27]. The bulk density influences soil formation and aeration and thus may affect the Noaea occurrence in the study area. Noaea is a strong plant species which can handle challenging conditions of high bulk density and adverse aeration conditions [28].

Available phosphorus content is most important for the occurrence of Anabasis, which is a perennial plant that can grow in nutrition-poor soils, although phosphorus has an essential role in its growth and metabolism. Its root system is strong and penetrates down into the ground for several meters, thus enabling the plant to absorb phosphorus from both deep and shallow soils. The relationship between the abundance of Anabasis and clay content is due to the impact of clay particles on the soil moisture/aeration conditions and to the positive effect of clay on exchangeable nutrient contents. Higher amounts of clay generally indicate an improved soil nutrient status [1].

A positive correlation between pH and densities of Scariola and Stipa species indicates that in this study area pH levels affect the availability of essential plant nutrients and the spatial distribution of these species. A strong relationship between soil extractable sodium contents and Scariola, Astragalus and Anabasis species composition is unexpected since sodium is not generally considered as an essential plant nutrient. There is some evidence, however, that for potassium-deficient soils in particular, sodium may substitute for potassium [24]. This would indicate that the effect of potassium was being masked by sodium. The possible substitution of potassium by sodium requires further investigation [1].

Soil fertility and nutrient availability are closely connected to SOM content and its mineralisation. The extent of carbon mineralisation determines the release of soil nutrients and hence nutrient availability [3]. The actual soil water content, total water capacity, bulk density and porosity are also the main physical characteristics of soil that affect plant growth. These characteristics improve the soil structure and fertility, and consequently they affect growth, regeneration and establishment of plants. Therefore, the results of our work confirm that the investigated plant species have very different demands from their environment, which are important to consider when planning a restoration process in areas with very high spatial variability in soils.

CONCLUSIONS

The results in this study support the hypothesis that plans for the restoration of native plant communities can benefit from establishing the levels of soil variables. The SVC and SVR results indicated that, although some of the native species were not related specifically to any of the soil variables, other species responded to a varying set of variables. Therefore, soil properties should be considered when explaining and managing the variability in plant distribution and coverage density. The study also shows that there is a possibility of using GA-SVM approach in determining the relationships between soil properties and plant occurrence. However, further research in this area should be conducted and needs to be validated, especially for soils in different management systems.

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