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Development of an environmental decision support system for predicting the natural distribution of Festuca ovina in land restoration efforts

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Abstract

Anthropogenic activities, species invasions, and ecological factors are rapidly altering rangeland ecosystems, challenging the sustainability of plant species habitats. To address this, reliable prediction models are needed to forecast and map species distribution under varying ecological conditions. This study compares three machine learning methods—Multilayer Perceptron (MLP), Radial Basis Function (RBF), and Support Vector Machine (SVM)—in predicting the distribution of Festuca ovina in Eshkevarat Protected Area eastern Guilan province in Iran. This 30,347-ha mountainous protected area is located in the hills of the Alborz Mountains, ranging from 200 to 3600 m in elevation. We analyzed F. ovina distribution in 305 randomly selected plant sample plots, recording 10 ecological variables in each plot. Three machine learning models were developed to predict the likelihood of F. ovina distribution. Results showed that the RBF model had more misclassifications (11 samples) compared to MLP and SVM models (10 samples), suggesting that MLP and SVM were more accurate for distribution modeling. Additionally, MLP demonstrated a higher R2 value (0.87) compared to SVM (0.85), indicating that MLP was the most precise model for predicting F. ovina distribution. Thus, we developed the F. ovina Distribution Model (FODM) using the MLP model. Sensitivity analyses revealed that soil texture, soil depth, electrical conductivity (EC), pH, and vegetation density significantly influenced F. ovina distribution, with sensitivity coefficients of 0.48, 0.47, 0.45, 0.41, and 0.41, respectively. Based on the finalized FODM, we designed an Environmental Decision Support System (EDSS) tool to assist rangeland managers in mapping F. ovina distribution. The practical application of the EDSS tool demonstrated its effectiveness in using the FODM for decision-making and land management. This tool is a valuable resource for rangeland managers, enabling them to make informed decisions regarding F. ovina restoration and effectively utilize the predictive capabilities of the FODM in real-world applications.

Introduction

Festuca ovina is a perennial, cool-season plant that holds both agricultural and ecological significance. This valuable rangeland species is currently being threatened in Iran's rangelands due to livestock and human activities. Known for its palatability and high nutritional value for livestock, F. ovina also plays a crucial role in soil conservation and fertility through nitrogen fixation (Acharya et al., 2006). Besides its nutritional benefits for wildlife and soil protection, F. ovina is ecologically important due to its excellent drought tolerance, robust bunch-type root systems, and adaptability to various soil types, making it ideal for reclamation projects in areas with 30 to 61 cm of annual precipitation. This stress-tolerant grass thrives in a wide range of soils, including poor soils, and provides effective ground cover in areas with limited precipitation. As we explore the impact of ecological variables on the distribution of F. ovina to model its distribution across the study area, Hulvey et al. (2017) suggested that plant distribution modeling can help identify restoration islands that can eventually be expanded to the entire area. In some state of art studies, MLP models were designed for planning environmental enhancement based on natural condition (Aboufazeli et al., 2021, 2022; Jahani et al., 2023). The main objectives of this study are: (1) to model the distribution of F. ovina in a protected rangeland, (2) to compare various machine learning techniques to identify the most accurate model, (3) to prioritize model inputs (plant and ecological variables) through sensitivity analysis, and (4) to design an environmental decision support tool for the distribution of F. ovina.

Methods

To model the impact of ecological variables on the distribution of Festuca ovina, we utilized machine learning techniques including MLP, RBF, and SVM, prioritizing the ecological factors that influence its distribution. Building on previous research regarding the environmental requirements of F. ovina, the majority of the plot data collection was guided by this prior work. We then determined the quantitative impact of each variable on F. ovina distribution. A graphical user interface was subsequently developed as a decision support system for mapping F. ovina habitats under the ecological conditions of degraded rangelands.

To model and predict F. ovina distribution under varying ecological conditions, a grid network was established to randomize sampling across the entire habitat. The grid dimensions were 1000 × 1000 m within the boundaries of the Eshkevarat Protected Area. During the summer of 2021, F. ovina distribution was recorded within 2 × 2 m sample plots at 305 sampling points. Based on available resources, maps, and the region's ecological conditions, including landform, soil, and vegetation, 10 ecological characteristics were recorded at each sample plot. These included landform variables such as elevation, land slope, and geographic aspect; soil variables like soil depth, soil electrical conductivity (EC), soil pH, and soil texture class; and vegetation variables including vegetation density, vegetation type, and land use. The variables of soil depth, soil EC, and soil pH were recorded as continuous data without classifying their variability.

Annual temperature (ºC) and annual precipitation (mm) also affect species distribution; however, these variables were highly correlated with elevation. Due to the insufficient number of climate stations in the region, they were not included as input variables in the model. The selected variables were then used to build a model to predict F. ovina distribution across the study area.

Results

Based on the accuracy analysis of the three models, the most effective model for predicting Festuca ovina distribution (FODM) was developed using the MLP approach. Although MLP and SVM exhibited similar accuracy rates (0.967), the MLP model demonstrated a higher R^2 (0.87) and a lower MSE (0.02), indicating that it provides a more precise classification of F. ovina distribution (Table 1).

Figure 1 illustrates the results of the sensitivity analysis, which quantifies the impact of FODM input variables on the model's output. The FODM output classifies F. ovina distribution into two categories: 0 and 1. According to the average sensitivity coefficients, soil texture (0.48), soil depth (0.47), electrical conductivity (EC) (0.45), pH (0.41), and vegetation density class (0.41) are identified as the most significant factors influencing F. ovina distribution (Figure 1).

Table 1. Results of parameter tuning in MLP structure

Structure	10-21-2			
Training function	Scaled Conjugate Gradient			
Activation function	logistic sigmoid -Linear			
Training	**R^2**	0.99	**Precision**	1
	MSE	0.001	**Accuracy**	1
	RMSE	0.03	**FAR**	0
	MAE	0.01	**POD**	1
			Bias	1
Validation	**R^2**	0.76	**Precision**	0.93
	MSE	0.04	**Accuracy**	0.93
	RMSE	0.2	**FAR**	0.07
	MAE	0.06	**POD**	0.98
			Bias	0.96
Test	**R^2**	0.63	**Precision**	0.94
	MSE	0.08	**Accuracy**	0.9
	RMSE	0.28	**FAR**	0.06
	MAE	0.09	**POD**	0.89
			Bias	0.95
All	**R^2**	0.87	**Precision**	0.98
	MSE	0.02	**Accuracy**	0.97
	RMSE	0.14	**FAR**	0.02
	MAE	0.03	**POD**	0.98
			Bias	1

Discussion [Conclusions/Implications]
In this study, we identified the most accurate distribution model for Festuca ovina by analyzing various ecological factors and employing machine learning techniques. An Environmental Decision Support System (EDSS) application was developed to classify degraded lands for F. ovina distribution and to assist in making informed decisions on restoration plans. Ecological evaluation and plant restoration planning often depend heavily on spatial data, making it crucial to link a Decision Support System (DSS) with a Geographic Information System (GIS) containing the necessary thematic layers. This integration of GIS and DSS has become a common approach for addressing decision-making challenges in plant restoration planning and land allocation. Based on the findings of this study and the developed EDSS for F. ovina

distribution modeling, we successfully addressed the primary concern of decision-makers in identifying optimal land areas for vegetation restoration through F. ovina planting.

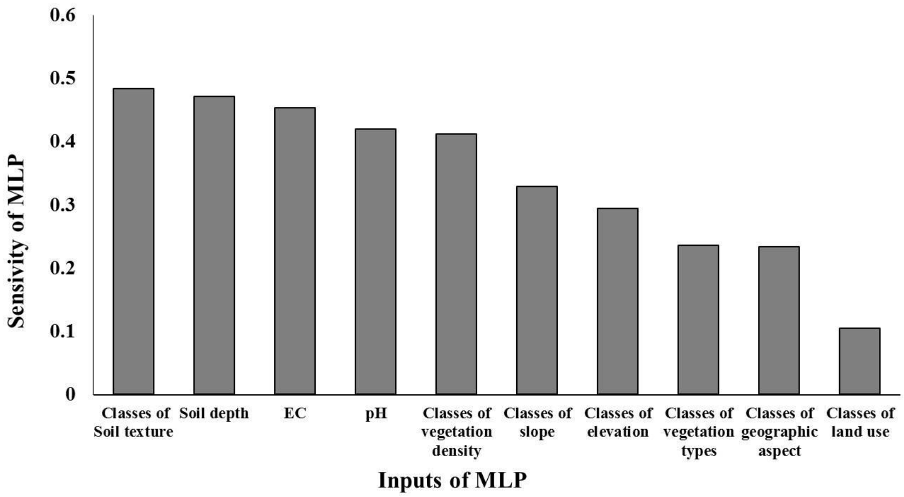

Figure 1. The impact value (0 to 1) of input variables on the FODM outputs in sensitivity analysis of model

One advantage of this research is our use of machine learning models to understand the distribution of F. ovina, whereas previous studies (Hulvey et al., 2017) assessed plant distribution in dryland ecosystems solely by overlaying ecological maps. Initially, we applied three modeling techniques—MLP, RBF, and SVM—to model the distribution of F. ovina in the Eshkevarat protected area, where ecological factors alone influence plant distribution. The results showed that, according to the RBF confusion matrix, there were more misclassifications in the data (11 samples) compared to MLP and SVM (10 samples), making MLP and SVM more accurate in classifying F. ovina distribution. In terms of species distribution prediction models, artificial neural networks (ANN) generally have higher prediction accuracy compared to other methods like regression (Piri Sahragard et al., 2015). While the differences between the studied machine learning models were minimal, these models, particularly MLP, provided satisfactory results in F. ovina distribution classification, making them highly applicable for studying plant communities and rangeland habitats. Overall, it is important to note that machine learning methods offer a more robust approach than spatial statistical methods due to their ability to analyze complex nonlinear relationships between input and output variables.

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