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Soil texture classes mapping as a way in soil sustainable management

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ABSTRACT

The spatial distribution map of soil classes is highly useful in planning sustainable agriculture. One of the most important soil characteristics is soil texture, and providing a map of it can help identify lands suitable for various agricultural products. For growers, the soil texture class map is more important than the map of the percentage of soil texture particles. The aim of this study was to compare the efficiency of two models—Decision Tree (DT) and Artificial Neural Network (ANN)—in forecasting soil texture class in the Bardeh region of Chaharmahal and Bakhtiari province, Iran. In this study, 96 soil profiles were excavated, described, and sampled from surface horizons across an area of 6,875 hectares, with the locations recorded using GPS. The percentages of clay, sand, and silt were measured, and the soil texture classes were determined. Results showed that the RMSE, Kappa Index, R square, and overall accuracy for estimating soil texture class based on test data were 0.6, 0.09, 0.24, and 0.59 for the Neural Network model, and 0.76, 0.75, 0.6, and 0.41 for the Decision Tree model, respectively. According to the results, the Decision Tree model was the better predictor for providing soil texture class maps. The results suggest that digital mapping of soil texture class could be an effective method for soil resource assessment.

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Introduction

Food security is a key principle in agricultural policies (Skaf et al., 2019). One of the goals of Iran's five-year development plans is to increase agricultural production and ensure healthy food. All policies and decisions regarding various issues such as soil and water management, mechanization, research, and education are designed to boost agricultural production (Mohammadi Torkashvand and Sobhe Zahedi, 2015). Various factors influence the production process, with climatic conditions and population growth being particularly important in Iran (Committee on Global Change Research, National Research Council, 1999). Population growth has significantly increased land exploitation, leading to the degradation of vegetation, pastures, forests, water resources, and soils due to the unsustainable exploitation of resources for short-term benefits. Monitoring the Earth's surface is essential for global change research (Committee on Global Change Research, National Research Council, 1999; Jung et al., 2006; Lambin et al., 2001). Like many developing countries, Iran faces unsustainable and uneconomic land uses, making it urgent to adopt scientifically sustainable land use practices. Land use planning involves agricultural development with a focus on accurately recognizing soil and water resources, assessing current land use, identifying priorities, and allocating land for sustainable use (Mohammadi Torkashvand and Sobhe Zahedi, 2015).

Sustainable agriculture plays a vital role in protecting agricultural ecosystems (Skaf et al., 2019). Soil resource management should ensure the preservation of their potential for future production (Tashakori et al., 2020). In sustainable agricultural management, soil science and pedometry (the preparation of soil maps and related information) are fundamental studies. Soil science, or the inventory of soil resources, includes soil mapping, describing soils in mapping units, and predicting the behavior of different soil types for various uses and management practices. Users of these studies include agricultural producers, farm managers, consultants, bankers, investors, agricultural extension agents, credit agencies, tax planners, researchers in agricultural and natural sciences, soil and rangeland conservation specialists, road engineers, health organizations, state department divisions, and other land resource users (Jamshidi, 2006).

Natural resource mapping is crucial for studying changes in natural resources and planning for their future use, which is a key goal in sustainable development (Mohammadi Torkashvand and Sobhe Zahedi, 2015). In sustainable development, five factors are important: resources, environment, population, economy, and society (Alavi Panah, 2004). One of the objectives of Iran's five-year development plans is to increase agricultural production. All policies and decisions related to issues such as soil and water management, mechanization, research, and education are aimed at boosting agricultural output (Mohammadi Torkashvand and Sobhe Zahedi, 2015). One of the most valuable maps for planning sustainable agriculture is the soil types map, along with soil characteristics maps (Forghani et al., 2020).

Field studies for identifying soil are the primary methods for obtaining soil characteristics, such as soil texture. These point data are then interpolated to produce soil maps. Various interpolation methods, including spline and inverse distance weighted (IDW), are used for this purpose. For instance, Anderson (2002) evaluated spatial interpolation methods for air temperature in Phoenix, and Musashi (2018) compared the IDW and natural neighbor interpolation methods for air temperature data in the Malang region.

Mondal et al. (2017) predicted soil carbon using remote sensing data. Xu et al. (2018) estimated soil total nitrogen in smallholder farm settings by employing remote sensing spectral indices and regression-kriging. Kumar et al. (2018) studied the geospatial mapping of soil organic carbon using regression-kriging and remote sensing. Regarding the co-kriging method, Wang et al. (2013) created a predictive map of soil total nitrogen on a regional scale. Sun et al. (2014) produced a map of soil particle size using compositional kriging, cokriging, and additive log-ratio cokriging. A limitation of these interpolation methods is the continuity of spatial distribution and the changes in the interpolated characteristics. It is evident that these methods require a large amount of data to generate high-resolution soil maps (Gee & Bauder, 1986). To improve interpolation accuracy, various kriging methods have been modified (McBratney et al., 2003). However, these methods still require some real data from the region. To address this issue, auxiliary data or a combination of other methods with kriging is often used. Despite these improvements, the accuracy of the maps remains dependent on the density and distribution of the original point data (Thattai & Islam, 2000; McBratney et al., 2000).

Although the accuracy of soil maps can be enhanced by increasing the number of sampling points, it is important to note that field studies for identifying soil are costly and time-consuming (Pahlavan-Rad & Akbarimoghaddam, 2018). Due to the high spatial variability of soil, many sampling points are needed to produce highly accurate soil maps (Poggio & Gimona, 2017). Therefore, developing more efficient methods for producing high-accuracy soil texture maps is both logical and cost-effective. A study compared support vector machines, ANN, and classification trees for identifying soil texture classes in southwestern China (Wei Wu et al., 2018). Additionally, statistical methods have been used at different scales to produce soil moisture maps (Fernández-Gálvez et al., 2005). In recent years, data mining techniques such as ANN and DT have become increasingly popular in digital soil mapping. The DT classification method and regression were first developed by Breiman et al. (1984). Minasny & McBratney (2007) studied spatial prediction and digital mapping of soil classes. Zhao et al. (2009) used an ANN model to produce a soil texture map. Kheir et al. (2010) employed the DT model for zoning the zinc content distribution using auxiliary terrain parameter data in Lebanon. Khanbabakhani et al. (2018) utilized a neural network model to predict soil texture in the Gaveshan region of Kurdistan Province, Iran. The aim of the present study was to predict soil texture using the DT and ANN models.

Methodology

Study Area

The study area is part of Bardeh village, located between 50°25′42″ and 50°35′42″ east longitude and 32°31′22″ and 32°38′47″ north latitude (Fig. 1), approximately 45 km northeast of Shahrekord in Chaharmahal and Bakhtiari province, Iran. The area covers 6,875 hectares. In this region, Mesozoic and Tertiary sediments are arranged in an isoclinal manner. The soil moisture and temperature regimes are Xeric and Mesic, respectively, with an average annual rainfall of 54.1 mm and an average annual temperature of 9.7°C.

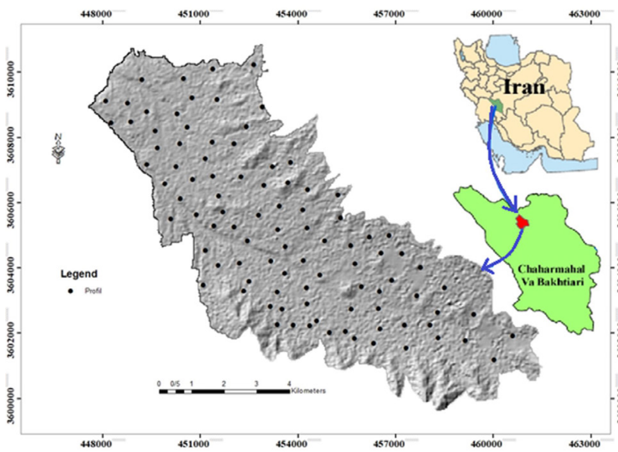

Figure 1. Location of the Study Area

Field operations and laboratory analysis

Based on the variations in geomorphic units, 96 profiles were excavated, and the necessary information, including the location of each profile on the land feature, the type of geomorphic unit, and the type of material, was recorded. Samples were then taken from the horizons of each profile. After drying and passing the soil samples through a 2 mm sieve, the soil texture of the surface horizons was measured using the hydrometric method (Gee & Bauder, 1986).

Preparing data for modelling

For soil texture class zoning, each soil particle type (clay, sand, and silt) was considered as a dependent variable. The soil texture classes were modelled by combining the obtained maps for clay, sand, and silt with their spatial variations. Additionally, all information, including auxiliary layers, was provided in Raster format with a 30-meter cell size. This data served as the dependent variables in the Scorpion model. All soil and environmental variable data were then converted to a final .txt format and prepared for the modelling process in the relevant software.

Soil modelling

Decision Tree (DT) is a non-parametric algorithm that can predict quantitative or classified variables based on a set of quantitative and qualitative predictor variables (Barthold et al., 2013; Pahlavan Rad et al., 2014). This method uses a series of logical conditions (if-then statements) in a tree-like structure to classify or quantitatively predict a variable (Moonjun et al., 2010). Creating a DT involves two main steps: the first step is tree creation and growth, which includes grafting and splitting. The second step is stopping and pruning, which aims to minimize forecast error (Lieb et al., 2012). In the present study, SAS software, JMP Version 13.1 (WWW.SAS.COM), was used to construct the DT for predicting relative soil particles (clay, sand, and silt) and texture class.

Artificial Neural Network (ANN): A multi-layer perceptron algorithm with 9 hidden layers was used, featuring a sigmoid activation function in the hidden layers and a linear activation function in the output layer. The number of neurons in the algorithm was determined through trial and error. In this study, JMP software (SAS Institute) version 13.1 was used to construct the ANN and predict soil relative particles (clay, sand, and silt) and texture class. The digital maps of sand, silt, clay, and texture classes, prepared using ANN and DT techniques, were combined with pixel precision. The combined data for each pixel were then compared with the soil texture triangle to determine the soil texture class for each pixel. To evaluate the accuracy of both DT and ANN models, the samples were randomly divided into two groups: training (80% of the data) and testing (20% of the data).

Evaluation of models

R Square and Root Mean Squared Error (RMSE) were used to evaluate the performance of different models in estimating the dependent variables (clay, sand, and silt).

$$\text{RMSC}=[\tfrac{1}{n}\textstyle\sum_{i=1}^{n}(Pi-Oi)^2]^{1/2}$$
$$R^2=\textstyle\sum_{i=1}^{n}(Pi-\bar{O})^2/\sum_{i=1}^{n}(Oi-\bar{O})^2$$

Where, Oi: observed value, Pi: predicted value, n: number of observation, $\bar{O}$: average observation values (Shekofteh et al., 2018). Overall Accuracy and Kappa coefficients were also used to compare the methods.

$$\text{Overall Accuracy} = \frac{tt+ff}{tt+ft+tf+ff}$$

The overall accuracy describes the relationship between all data used and the classified data (ff, tt). The kappa index calculates the ratio of the presence or absence of a class that is correctly predicted by the model. Therefore, the Kappa index is always slightly less than the purity of the map.

$$\text{Kappa index} = \frac{\textit{Observed accuracy}-\textit{Change agreement}}{1-\textit{Chance agreement}}$$

The range of changes in the Kappa is between zero and one. Kappa index above 0.8, 0.4-0.8, and less than 0.4 represent a strong, moderate, and weak agreement, respectively (Taghizadeh-Mehrjardi, et al., 2015; Abbaszadeh Afshar, et al., 2017).

Results and Discussion

The investigation of soil profiles revealed that the differentiation and separation of soils were influenced by soil depth, texture, organic matter, drainage, gravel content, and accumulated lime in the surface and soil profile. These factors indicate that the soils can be classified into a single category: Inceptisols.

Statistical indices

The summary of soil texture components

(Clay, Silt, and Sand) is shown in Table 1. The skewness and kurtosis for Clay are normal. The skewness of Silt is normal, but its kurtosis is abnormal. Both skewness and kurtosis for Sand are normal. The soil texture classes observed in the study area range from average (Silty Loam, Loam) to heavy (Sandy Clay Loam, Silty Clay Loam, Clay Loam) and very heavy (Silty Clay, Clay).

Table 1
Statistical Indicators for Sand, Clay and Silt Propertie.

Properties (%)	Number	Mean	Variance	SD	Median	Min	Max	Range	Skewness	Kurtosis
Sand	96	20.9	51.0	7.14	18.6	13.6	53.8	40.2	2.1	5.6
Silt	96	44.1	22.5	4.75	44.1	22.8	60.4	37.6	-0.9	4.0
Clay	96	34.8	23.4	4.84	35.6	20.0	44.0	24.0	-0.7	0.7

SD: standard deviation

Spatial modelling

Network topology is crucial in designing an Artificial Neural Network (ANN) as it affects both the learning speed and accuracy of the final classification. The number of hidden layers and neurons are key components of the perceptron network. In this model, the input layer consists of 57 inputs, and the output layer contains one neuron. The network was designed with 9 hidden layers, and the number of neurons in these layers, as well as the number of epochs, were optimized through trial and error. The best combination was determined using RMSE and the coefficient of determination.

For the ANN, the RMSE values for the Clay, Sand, Silt components, and texture class were 2.71, 4.33, 2.68, and 0.6, respectively (Table 2). When tested on the 20% of data reserved for testing, the RMSE values for Clay, Sand, Silt, and texture class were 3.67, 4.01, 5.32, and 0.59, respectively. The coefficient of determination (R Square) for these components were 0.41, 0.62, 0.25, and 0.09, respectively. The overall accuracy and kappa coefficient for the neural network texture class were 58.3 and 0.24 percent, respectively. In the Decision Tree (DT) method, logical conditions are used in a tree structure to predict soil particles. During the training phase, the RMSE for Clay, Sand, Silt, and texture classes were 3.85, 5.42, 3.59, and 0.45, respectively, with R Square values of 0.38, 0.44, 0.46, and 0.81, respectively. On testing the DT model on 20% of the data, the RMSE for Clay, Sand, Silt, and texture class were 2.97, 3.02, 2.02, and 0.41, respectively, with R Square values of 0.52, 0.75, 0.61, and 0.75, respectively. The DT model demonstrated a good ability to simulate Clay, Sand, Silt, and soil texture classes. The R Square values ranged from 0.52 to 0.75, which are considered acceptable compared to similar studies (Ryan et al., 2000; Florinsky et al., 2002; Malone et al., 2009). R Square values above 0.70 are less common, while those below 0.50 are more common (Malone et al., 2009). Previous research has confirmed the effectiveness of DTs in digital soil mapping (Taghizadeh-Mehrjardi et al., 2013; Moran & Bui, 2002; Minasny & McBratney, 2007; Mendonça-Santos et al., 2006; Henderson et al., 2005; Bui & Moran, 2001; Bui et al., 1999). Overall, the DT model showed better performance in predicting clay, sand, silt, and texture class compared to the ANN (Tables 2-3). Similar findings were reported by Luoto & Hjort (2005), who noted higher efficiency of DT compared to ANN. Kheir et al. (2010) also found that DT better classified regions with high organic matter. However, Moonjun et al. (2010) observed no significant difference between ANN and DT for soil unit prediction.

Table 2
Results of the Comparison of Different Models for Predicting Clay, Sand, and Silt Content Based on Training and Test Data..

Type of data	Model	R Square			RMSE		
		Silt	Sand	Clay	Silt	Sand	Clay

Training	ANN	0.61	0.64	0.68	2.68	4.33	2.71
	DT	0.47	0.47	0.38	3.59	5.42	3.85
Test	ANN	0.25	0.63	0.41	0.32	4.01	3.67
	DT	0.47	0.47	0.39	2.02	3.02	2.97

Table 2

Results of the Comparison of Different Models for Predicting Clay, Sand, and Silt Content Based on Training and Test Data..

Type of data	Model	RMSE	R square	Overall accuracy	Kappa
Training	ANN	0.6	0.41	0.41	0.24
	DT	0.45	0.81	0.76	0.6
Test	ANN	0.59	0.09	0.6	0.24
	DT	0.41	0.75	0.76	0.6

The soil texture maps

Figures 2-3 display different classes of soil texture. The figures indicate that clay content is predominant in landforms with a very heavy silty clay soil texture class. Low-level landforms, which are located at the bottom of the region, primarily feature transitional materials and smaller texture classes. These areas are influenced by upstream landforms due to weathering and erosion processes, leading to an increase in clay content. Consequently, the soil texture in these areas ranges from silty clay loam to clay loam. Ungaro et al. (2008) studied arsenic contamination in the Brenta area of Northern Italy using a soil map at a scale of 1:150,000. Their findings showed that low-lying plain landforms had soils with finer textures compared to other areas, highlighting a strong relationship between soil type and landform features.

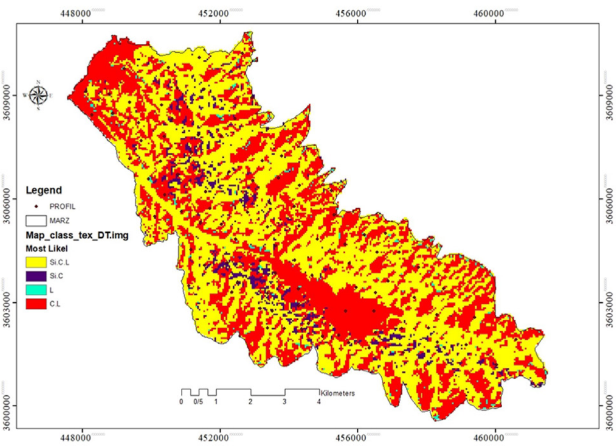

Figure 2. Digital Form of Texture Classes Using DT

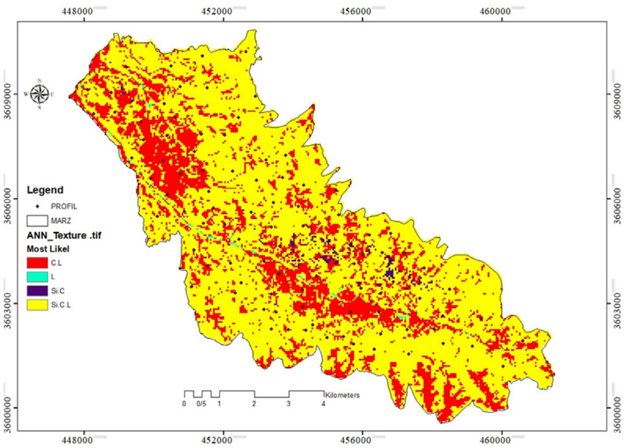

Figure 3. Digital Form of Texture Classes Using ANN

Conclusion

Preparing a map of stable soil characteristics, including soil texture, can reduce laboratory costs for soil analysis. It can also benefit farmers and beneficiaries by providing valuable information on a regional scale, particularly for managers involved in irrigation and drainage management, as well as agricultural mechanization. The study evaluated the capabilities of both ANN and DT models in predicting soil texture. The findings indicated that DEM derivatives were relatively more significant for both models, highlighting the importance of topography as a key factor in soil formation and the spatial distribution of soil texture.

The comparison results indicated that the DT (Decision Tree) model outperformed the ANN (Artificial Neural Network) model in predicting soil texture classes and the proportion of fine soil particles. Both models achieved higher accuracy in classifying clay loam and silty clay loam textures compared to loam and silty clay textures. This disparity could be attributed to the limited number of samples available for certain soil texture classes. However, it is crucial to acknowledge that the accuracy of the models can also be influenced by the strong correlation between soil data and environmental parameters. Multicomponent analysis outperforms single-component soil prediction. A dataset consisting of local agricultural soil measurements yields more accurate predictions of soil properties compared to a dataset encompassing diverse geographic locations. By conducting repeated measurements and averaging similar soil samples, the accuracy of describing soil properties can be enhanced. The findings presented support the hypothesis that machine learning significantly boosts the precision of soil property prediction by incorporating specialized input data.

The comparison of ANN and DT for predicting soil texture demonstrated that the DT model has higher efficiency in predicting clay, sand, silt particles, and texture classes. Therefore, the DT model is recommended for zoning these soil components. The results indicate that pedometric techniques, particularly DT, can significantly enhance the soil mapping process by handling a wide range of natural complexities, improving traditional methods, increasing the speed and efficiency of data transfer, and making the results applicable across various scientific fields.

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Conflict of interests' statement

This article has no financial conflict of interest.

Data availability statement

All data is available in the manuscript.

Author's contribution

All authors have accepted responsibility for the entire of this manuscript and consented to its submission to the journal, reviewed all the results and approved the final version of the manuscript. Kamran Eftekhari and Mehrdad Esfandiari designed the experiment and Mohammad Ali Sabaghi carried them up. Ali Mohammadi Torkashvand provided necessary tools and performed the simulation. Kamran Eftekhari prepared the manuscript with contribution from all co-authors.

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