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Relationship between Physico-Chemical Soil Properties and Drying of Coniferous Trees in the South of Tehran and Alborz by Multiple Linear Regression Models

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Abstract

In recent years, as a result of environmental stress, a large number of pine trees in parks and forestry in Tehran and Alborz provinces have dried up, that has conditions provided for contamination by secondary pests such as pine bark beetles (*Orthotomicus erosus*). In one hundred pine growing locations, three trees were randomly selected in each location, and in these locations, the average percentage of trees canopy dryness (three trees), the percentage of soil area under the trees canopy and the number of irrigations during in growing season (spring and summer) were measured; and thus the soils were sampled from the root activity zone at two depths of 0-30 and 30-60 cm. The percentage of coarse particles (> 2 mm) was measured in the soil samples after being dried in the vicinity of air, pounded and passed through a 2 mm sieve. In each soil sample, soil texture (percentage of sand, silt and clay particles), soil pH, electrical conductivity (ECe), equivalent calcium carbonate (CCE), organic matter and available concentration of sodium, potassium and phosphorus elements were measured. At a depth of 30-60 cm (subsurface soil), a soil sample was taken with a cylinder in order to measure the bulk density and soil porosity. Regression analysis was carried out using three methods: Enter, stepwise by backward and forward with 15 series of variables as input variables to estimate or predict the percentage of pine drying (dryness of tree canopy). In total, the forward stepwise regression model, with R^2=0.757 and RMSE=15.02% error, is the most appropriate model for assessing the percentage of tree drying, with two variables, the percentage of subsurface sand of the soil (30-60 cm) and coarse material (> 2 mm) of soil surface depth (0-30 cm), a more suitable model was recognized.

Keywords: Drying, Dryness, Eldarica, MLR, Pine.

INTRODUCTION

A wide area of tree cover in Tehran is made up of conifers such as *Pinus eldarica, Cupressus arizonica* and *Thuja orientalis*. What causes concern is the increasing dryness of these trees (Javanmard *et al*., 2014). In recent years, as a result of environmental stress, a large number of pine trees in these parks have suffered from physiological weakness and the conditions for the proliferation and creation of contamination by secondary pests such as pine bark beetles (*Orthotomicus erosus*) have provided (Guarin and Taylor, 2005).

The drying and death of trees are multifactorial phenomena that have occurred in many forests of the world in the last century (Edburg *et al*., 2012). One of the long-term consequences of drought is increasing the sensitivity of plants to the damage of herbivorous insects. The current climate situation with mild winters and dry summers has led to an increase in the frequency and intensity of storm events, which has caused widespread infestations of bark beetles and tree mortality in North American and European forests in mountainous areas (Edburg *et al*., 2012; Seidl *et al*., 2017).

The growth of plant affected by soil charactersitics, plant nutrition and environment (Azizifar *et al*., 2022; Farahmandi *et al*., 2022; Jalali *et al*., 2022; Nouri *et al*., 2023; Talebi *et al*., 2022). The growth and development of plants is influenced by various factors, and soil is one of the important factors in this regard (Mohammadi Torkashvand *et al*., 2015 and 2016; Asadollahi *et al*., 2022). Baruch (2005) also stated soil fertility as one of the most important characteristics in differentiating vegetation and also evaluating the quality of soil under different types of vegetation. Jafari *et al*. (2004) reported the percentage of lime, potassium and soil texture as the most important factors affecting the distribution of plant and forest covers in Petkoh forests of Yazd province. Bakhshipour *et al*. (2012) by studying the characteristics of soil at a depth of 0-20 cm under teada pine and populus plantations showed that the teada of pine compared to spruce caused an increase in soil bulk density. The amount of organic carbon as well as microbial respiration in both types of cover had no significant difference. They reported that the trees were able to improve soil productivity to some extent.

Ahmadlou *et al*. (2008) investigated the growth status, biomass, survival and yield of coniferous seedlings of brusia pine (*Pinus brutia* Ten.) and Aleppo pine (*P. halepensis* Mill.) in different combinations of organic matter in Klode Amol nursery. The seeds were planted in a randomized complete block design with four replications in plastic pots and different soil treatments including: 1) Nursery soil (control); 2) Control soil + animal manure (1:5); 3) Control soil + leaf soil (1:5) and 4) Control soil + manure + leaf soil (1:1:5). After one year, it was found that in both species, seedlings grown in treatment 4 have the highest survival rate, stem length growth, stem dry weight, root dry weight, total dry weight and quality index. Also, there was a relatively strong positive correlation between most of the soil nutritional elements with survival traits, stem length, stem dry weight and root dry weight in both species. In most of the studied traits, Brusia pine showed a better response than Aleppo pine. The results of the research show that more soil organic matter combinations have increased the quantity and quality of seedlings due to the improvement of the physical and nutritional conditions of the planting bed.

Salehi *et al*. (2007) studied the effect of urban wastewater irrigation on the growth of 15-year-old Tehran pine trees (*Pinus eldarica* Medw.) in two treatments with urban wastewater and normal water located in the South of Tehran. The results revealed that the total height, crown length, average crown diameter, ground height and volume of Tehran pine trees were significantly ($P<0.01$) higher in the field irrigated with urban wastewater than in the field irrigated with normal water. The concentration of nitrogen, phosphorus, potassium, calcium and magnesium nutrients in the soil treated with urban sewage was significantly ($P<0.01$) higher than the soil treated with normal water.

Finding the relationship between the physical and chemical properties of the soil with the growth and development of pine can be useful in the planning and management of forestry and urban landscapes. Investigating the drying of pine trees as an important indicator in plant growth and its relationship with soil with the help of regression models is one of the goals of this research.

MATERIALS AND METHODS

Eldarica pine is a subspecies of Italian pine called Tehran pine, Iranian pine or Eldar pine (*Pinus eldarica*). This species is native to the Eldar Plain in Georgia and its entry into Iran is attributed to 800 years ago and also to the Safavid period, which was initially planted in the lands around Tehran and Qazvin. The most concentration of their planting in Tehran province is in forest parks such as Chitgar, Quchak and Sorkhehsar. Tehran pine is adaptable to temperature fluctuations and resistant to dehydration and grows well in deep clay soils. First, the vegetation status of Tehran province was assessed and the distribution of afforestation and the planting areas of Eldarica pine were determined and parts of the forests and urban parks of Tehran were selected. We define the parts where there are Eldarica pine trees and their relationship with the whole trees.

In one hundred pine growing locations, three trees were randomly selected in each location, and in these locations, the average percentage of drying trees, the percentage of soil area under the canopy and the number of irrigations during the growing season (spring and summer) were measured. Soil sampling was done from the root activity zone at two depths of 0-30 and 30-60 cm. After being transported to the laboratory and dried in the air, the soil samples were beaten with a plastic hammer and passed through a 2 mm sieve (Klute, 1986) and the percentage of coarse particles was measured. Each sample was collected in a separate plastic container. Soil texture was measured by hydrometer method and based on stocks law (Gee and Bauder, 1979). Soil pH was measured in saturated mud. To measure pH, an EYELA-2000 electric pH meter was used (Sparks *et al.,* 1996). The electrical conductivity in the saturated extract of the soil samples was measured using an electrical conductivity meter (Sparks *et al*., 1996). The amount of calcium carbonate equivalent to the samples was measured by the calcimetric method (or volumetric method) (Carter and Gregorich, 2008) and organic matter by the Walkey Black method (Sparks *et al*., 1996). The soil samples were extracted by Soltanpour and Schwab method (Soltanpour and Schwab, 1977). Soil was sampled with a cylinder at a depth of 30-60 cm (subsurface soil) in order to measure soil bulk density and soil porosity.

Multivariate linear regression is one of the statistical methods that tries to model the relationship between two or more independent variables and a dependent variable by fitting a linear equation to the observed data. In regression modeling, in addition to different linear models with different inputs (Table 1 shows different independent variables), two models were extracted from the backward and forward stepwise regression method which were evaluated along with the defined models.

Table 1. Independent variables as inputs of regression models and artificial neural network in relation with the variable of dryness percentage of tree (dependent variable).

Variable	Symbol	Variable	Symbol
Soil area under tree canopy	X_2	**Irrigation number**	X_1
Subsurface soil (depth 30-60 cm)		**Surface soil (depth 0-30 cm)**	
pH	X_{16}	pH	X_3
EC	X_{17}	EC	X_4
Organic matter	X_{18}	Soil porosity	X_5
particles > 2mm	X_{19}	Soil bulk density	X_6
Lime	X_{20}	Organic matter	X_7
Clay	X_{21}	particles > 2mm	X_8
Sand	X_{22}	Lime	X_9
Silt	X_{23}	Clay	X_{10}
Available phosphorus	X_{24}	Sand	X_{11}
Available potassium	X_{25}	Silt	X_{12}
Available sodium	X_{26}	Available phosphorus	X_{13}
		Available potassium	X_{14}
Age	X_{27}	Available sodium	X_{15}

The model for MLR is:

$$yi=b_0+b_1x_{i,1}+b_2x_{i,2}+\ldots+b_kx_{i,k}+e_i$$

Where y_i is the dependent variable, b_0 is a constant that called the intercept, $x_{i,k}$ = is a independent variables, b_k= is the vector of regression coefficients that called slope, and e_i represents random measured errors. In present study, the statistical software SPSS version 15 (Cary, NC., USA) was applied to calculate the MLR models.

By choosing different inputs, several models (15 series of variables, Table 2) were selected for modeling the pine drying percentage, and by dividing the collected data into two categories of training including 80% and testing including 20% of the data, modeling was done. After training the network with the data of the training and validation series, the accuracy and correctness of the created models were evaluated using the data of the test series.

Table 2. Definition of models and variables used in each model for dependent variable estimation.

Models	**Input variables**
Model-1	X1
Model-2	X1, X2
Model-3	X1, X2, X5 , X6
Model-4	X3, X4, X7, X8, X9, X10, X11, X12, X13, X14
Model-5	X1, X2, X5, X6, X8, X10, X11, X12
Model-6	X1, X27
Model-7	X1, X2, X5, X6, X27
Model-8	X1, X2, X5, X6, X8, X10, X11, X12, X27
Model-9	X16, X17, X18, X19, X20, X21, X22, X23, X24, X25, X26
Model-10	X3, X4, X7, X8, X9, X10, X11, X12, X13, X14, X16, X17, X18, X19, X20, X21, X22, X23, X24, X25, X26
Model-11	X1, X2, X27
Model-12	X1, X2, X5, X6, X8, X10, X11, X12
Model-13	X1, X2, X5, X6, X8, X10, X11, X12, X18, X21, X22, X23
Stepwise (Backward)	X4, X5, X8, X10, X11, X12, X17, X18, X19, X22, X24
Stepwise (Forward)	X8, X22

Data analysis

The effectiveness of different modeling methods is evaluated using three statistics: Root mean square error (RMSE), mean error (ME) and coefficient of explanation (R2):

$$R^2 = \frac{\left[\sum_{i=1}^{N}(y_i-\bar{y})(\hat{y}_i-\hat{\bar{y}})\right]^2}{\sum_{i=1}^{N}(y_i-\bar{y})^2 \sum_{i=1}^{N}(\hat{y}_i-\hat{\bar{y}})^2}$$

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{1}^{N}(y_i-\hat{y}_i)^2}{N}}$$

where: yi, $\bar{y}$ and $\hat{y}$ respectively the measurement dependent variable, its mean and the estimated dependent variable, and N is the number of observations.

Also, other criteria that are used to evaluate the models include; Geometric mean error ratio (GMER) and geometric standard deviation of error (GSDER) were:

$$\mathrm{GMER} = \exp\left(\frac{1}{N}\sum_{1}^{N}\ln\left(\frac{\hat{y}_i}{y_i}\right)\right)$$

$$\mathrm{GSDER} = \exp\left(\frac{1}{N-1}\sum_{i=1}^{N}\left[\ln\left(\frac{\hat{y}_i}{y_i}\right)-\ln(GMER)\right]^2\right)^{1/2}$$

The geometric mean error ratio (GMER) indicates the degree of agreement between the measured and estimated values. If the GMER is equal to one, it indicates perfect agreement between the measured and predicted values. A GMER greater than and less than one indicates that the predicted values are greater and less than the measured values, respectively. The geometric standard deviation of the error (GSDER) is a measure of the dispersion of the data, and closer to one indicates less dispersion.

Akaike's information criterion (Relation 6) is also one of the useful practical criteria in the field of checking the predictive power of the created transfer functions. The smaller this criterion states the more predictive power of model:

$$AIC = N\ln\left(\sum_{i=1}^{N}\frac{(y_i-\hat{y}_i)^2}{N}\right)+2n_p$$

Where in:

N: number of soil samples, yi: measured values of the output variable, $\hat{y}_i$: predicted values of the output variable and np: number of model parameters.

RESULTS AND DISCUSSION

According to the results of table 3, the percentage of tree drying had a significant correlation with the number of irrigations and the percentage of soil area under the canopy at the level of 1%. The percentage of tree drying had a significant correlation with salinity (EC) in both depths of 0-30 cm and sub-surface (30-60 cm). The percentage of tree drying was also correlated with surface sand and it was not correlated with other measured soil properties. There was the highest correlation (61%) between the percentage of tree drying and the soil area under the tree canopy, so that with the decrease of the soil area under the canopy, the percentage of tree drying increases. The more accessible soil area on the soil surface leads to more water distribution in the area of the tree roots and the gas exchange between the soil and the surrounding air increases. This can result in better plant growth and freshness.

Table 3. P-Value values for simple correlation values (r) between independent variables and the dependent variable (dryness percentage of tree).

r	P-Value		r	P-Value	
-0.22	0.12	X_{15}	-0.31^{**}	0.029	X_1
-0.04	0.78	X_{16}	-0.61^{**}	0.000	X_2
0.40^{**}	0.00	X_{17}	-0.15	0.30	X_3
-0.04	0.77	X_{18}	0.36^{**}	0.01	X_4
0.18	0.20	X_{19}	-0.03	0.81	X_5
0.19	0.18	X_{20}	0.17	0.23	X_6
0.14	0.35	X_{21}	0.11	0.45	X_7
-0.33^{**}	0.021	X_{22}	0.13	0.37	X_8
0.12	0.41	X_{23}	0.10	0.48	X_9
0.11	0.44	X_{24}	0.02	0.887	X_{10}
0.01	0.28	X_{25}	-0.06	0.70	X_{11}
-0.13	0.36	X_{26}	0.01	0.94	X_{12}
-0.08	0.57	X_{27}	0.00	0.99	X_{13}
			0.21	0.14	X_{14}

**: Significant at $P < 0.01$.

The results of the regression analysis related to the variable of tree drying percentage based on 15 models defined in table 4 can be seen. Table 5 also shows the statistical indices related to the fitted regression models with different input variables. According to the explanation coefficient (R2), the highest R2 with values of 0.852 and 0.808 corresponds to models 14 and 13, respectively. Model 14 is created based on step-by-step regression, therefore, with 11 input variables, and model 13 is fitted as enter with 12 input variables. Models 12 and 15 are ranked next with R2 of 0.790 and 0.757, respectively. The error value (RMSE) was the lowest in model 14 (backward stepwise regression). The same model (14) has the lowest AIC among the models. In terms of estimation accuracy, the lowest GMER with 1.001 corresponds to model 13, and this model also has the lowest GSDER.

Table 4. The results of regression analysis related to the percentage of tree drying based on 15 models.

Models	Model number	Sum of squares regress	df regress	Sum of squares residual	df residual	Mean squares regress	Mean squares residual	F	P-level
Enter	1	4438.96	1	41111.04	47	4438.96	874.70	5.07	0.029
	2	5874.21	2	17852.2	36	2937.10	495.89	7.08	0.000
	3	20014.94	4	25535.06	44	5003.74	580.34	8.62	0.000
	4	9963.42	10	35586.58	38	996.34	936.49	1.06	0.412
	5	22854.71	8	22695.29	40	2856.84	567.38	5.04	0.000
	6	5610.24	2	39939.76	46	2805.12	868.26	3.23	0.049
	7	20226.20	5	25323.8	43	4045.24	588.93	6.87	0.000
	8	22866.88	9	22683.12	39	2540.76	581.62	4.37	0.000
	9	14764.80	11	30785.2	37	1342.25	832.03	1.61	0.136
	10	23355.40	21	22194.6	27	1112.16	822.02	1.35	0.227
	11	33261.41	4	12288.59	44	8315.35	279.29	29.77	0.000
	12	35778.62	9	9771.38	39	3975.4	250.55	15.87	0.000
	13	36802.81	13	8747.19	35	2830.99	249.92	11.33	0.000
Stepwise (Backward)	14	38703.55	12	6846.45	36	3225.30	190.18	16.96	0.000
Stepwise (Forward)	15	34459.30	3	11090.70	45	11486.43	246.46	46.61	0.000

Table 5. The results of extracting the evaluation statistics of the regression models related to the variable of tree drying percentage based on the 15 models defined in table 2.

Model	Enter												Stepwise (Backward)		Stepwise (Forward)
Number	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**
R^2	0.097	0.614	0.458	0.219	0.528	0.123	0.466	0.529	0.324	0.517	0.732	0.790	0.808	0.852	0.757
RMSE	28.9	18.2	22.5	26.9	21.0	28.5	22.4	21.1	25.1	21.2	15.8	13.0	13.3	11.7	15.0
AIC	333.8	306.1	316.5	344.8	318.7	334.4	318.1	320.7	339.7	343.7	280.7	279.5	282.0	268.0	273.6
GMER	1.47	1.12	1.150	1.436	1.146	1.458	1.151	1.146	1.356	1.152	0.984	1.009	1.001	0.955	0.945
GSDER	2.71	2.02	2.534	2.586	2.358	2.638	2.517	2.359	2.545	2.657	2.001	2.030	1.887	1.995	2.240

Model 15 has a 9.5% difference in R^2 with model 14, the error difference is also 3.27%, and the difference in AIC, GMER and GSDER indices indicates the closeness of these two models in estimating the percentage of tree drying. Therefore, the important point in these two models is the difference in model inputs. While in the step-by-step regression model, the model is fitted with 11 variables including the soil characteristics in the soil surface subsurface depths, in the step-by-step regression model, it is fitted with only two variables including the percentage of particles larger than 2 and the percentage of sand in the subsurface layer of the soil. These two characteristics can be obtained by sieving the soil. According to the values of R^2, error (RMSE) and values of AIC, GMER and GSDER, in total, model 15, which is based on step-by-step regression, is the most appropriate model in estimating the percentage of tree drying. In fact, with two variables, the percentage of subsurface sand (30-60 cm) and the coarse material of the surface depth (0-30 cm), even the probability of planting these trees can be planned with 75.7% accuracy.

It should be noted that most of the studied pines are coniferous forests in the past decades and naturally the soil under the canopy has been affected by these trees over time. In addition to changing the cover, afforestation causes changes in the physicochemical characteristics and biochemical cycles of the soil (Jamshidnia *et al*., 2016). Vesterdal *et al*. (2013) considered the presence of broadleaf forests to be very effective on soil fertility. Studies have shown that the amount of nutrients in the soil, organic matter, changes in different forms of nitrogen are affected by forestry, which is due to the leaves of these trees in addition to the secretions of the roots (Gil-Sotres *et al*., 2005). Tree species even affect soil biochemical processes by affecting the population and microbial activity (Gillespie *et al.*, 2021). These studies and many others (Agusto *et al*., 2002; Balabane and Plante, 2004; Barua and Haque, 2013; Vesterdal *et al*., 2013; Fayissa *et al.*, 2015; Rasouli-Sadaghiani *et al*., 2018), show the effect of afforestation on the physicochemical properties of soils, so it is important to mention that in model 14, the model is fitted with two variables: Sand and the percentage of soil particles larger than two millimeters. These two variables cannot be influenced by trees in the short term (several decades of planting forests), because they are almost constant attributes of soils. Therefore, with these two almost constant and static characteristics, with the acceptance of error, it may be possible to say that different areas can be evaluated from the aspect of planting pines, or the drying of existing pines can be investigated.

CONCLUSION

The highest R^2 with values of 0.852 and 0.808 corresponds to models 14 and 13, respectively. Model 14 is created based on step-by-step regression, therefore, with 11 input variables, and model 13 is fitted as enter with 12 input variables. Regarding executive and economical aspects, the forward stepwise regression of model 15, with R^2=0.757 and RMSE=15.02% error, is the most appropriate model for assessing the percentage of tree drying, with two variables, the percentage of subsurface sand of the soil (30-60 cm) and coarse material (> 2 mm) of soil surface depth (0-30 cm).

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