AN ARTIFICIAL INTELLIGENCE-BASED SOLUTION FOR THE CLASSIFICATION OF OAK DECLINE POTENTIAL

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ABSTRACT:

Oak decline is a complex phenomenon. The classification of oak decline potential could be a valuable tool for forest management. This paper identified seven factors that influence oak decline: height, slope, aspect, temperature, perception, soil type, and aerosol. Then, factor analysis is used to determine factors that should be included in oak decline potential classification and reduce data complexity.
As a result, five components explaining 92.49% of total variance are selected. The first component explains 40.34% of the variance, and three factors, including perception with positive and temperature and aerosol with negative load, have contributed to its construction. The second component is composed of a positive load of aspect, and soil type explains 14.89% of the variance. By explaining 14.10% of the variance, the third component consists of soil type and aspect with positive and negative loads, respectively. Slop and height have a positive load in constructing the fourth and fifth components.
Five extracted components are used as input sets of PNN, MLC and SVM methods. 80% of samples are used for training methods, and 20% are used for testing purposes. Results are compared based on the overall accuracy of the methods.
These components are used as an input set of three classification methods, including Probabilistic Neural Network (PNN), Maximum Likelihood Classification (MLC) and a Support Vector Machine (SVM). Based on the results, the SVM, with an overall accuracy of 0.87%, has proved its capability in oak decline potential classification.

1. INTRODUCTION

Oak plays a vital role in ecosystem services, such as soil and water conservation, groundwater recharge and quality protection, and biodiversity conservation. Also, its acorns are essential nourishment for many wild and domestic animals (Attarod et al., 2016; Caliskan, 2014).

Oak "dieback" or "decline" is used to describe poor health in oak trees (Denman et al., 2010). This is a complex phenomenon where the number of damaging agents and factors interact to severely deteriorate the oaks' condition (Gibbs, 1999). Oak decline or oak mortality has raised concerns in the forestry sector over the past decade (Sanders et al., 2014).

Oak decline was assumed to be caused by a complex interaction of factors which can be living ("biotic"), e.g., pest and fungal attack, or nonliving ("abiotic") factors, e.g., drought (Denman et al., 2010).

Oak decline is a widespread phenomenon in oak forests all around the world, like in Europe (Costa et al., 2010; Denman et al., 2010; Ferreira et al., 2000; Oleksyn and Przybyl, 1987; Siwkcki and Ufnalski, 1998) and North America (Costa et al., 2010; Kabrick et al., 2008) and Iran's Forests (Ahmadi et al., 2016; Azizi et al., 2015; Karami et al., 2015; Mahdavi et al., 2015; mir abolfathi, 2013; Taghimollaei, 2017; Talebi et al., 2006; Alesheikh and Mehri, 2019)

The occurrence of oak decline was assumed to be caused by a complex interaction of different factors (Costa et al., 2010;

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Franklin et al., 1987; Wargo et al., 1983), which can be living (‘biotic’), e.g. pest and fungal attack or nonliving (‘abiotic’) factors, e.g. drought (Denman et al., 2010). According to scientific findings, weak trees are more likely to decline (Shifley et al., 2006).

Tree weakening is caused by environmental stresses such as drought (Lee et al., 2014). In stressed trees, chemicals changes happen in the roots, allowing the fungus to infect and kill them (Wargo et al., 1983). Tree mortality owes a great complexity and importance to forest ecosystem dynamics (Adame et al., 2010).

Iran is categorized under a Low Forest Cover Countries (LFCC) (Vahedi, 2017), Meaning that forests cover less than 10% of the total area. According to official documentation, only 8% (approximately 13.4 million hectares) of Iran’s territory is covered by forest.

Iran’s forests are divided into three ecological zones; the northern zone, the southern and the Irano-Turanian zone, divided into the Zagros and the central plateau zone (Sagheb-Talebi et al., 2014).

Among Iran’s forests, the Zagros zone has 6 million hectares and almost half of Iran’s forests (Talebi et al., 2006). Oak is a common species in Iran and the most important and dominant one in Zagros forests (Mirabolfathi, 2013).

The earliest reports of abnormal oak mortality in Iran were from Zagros forests in 2013, with many trees succumbing (Mirabolfathi, 2013). In 2015 considerable dieback within Zagros forests was reported (Azizi et al., 2015).

Classifying oak forests’ decline potential could be indispensable for forest management. Therefore, this paper evaluates different classification methods.

2. METHODOLOGY

The Flowchart of the applied experimental work in this research is shown in figure 1.

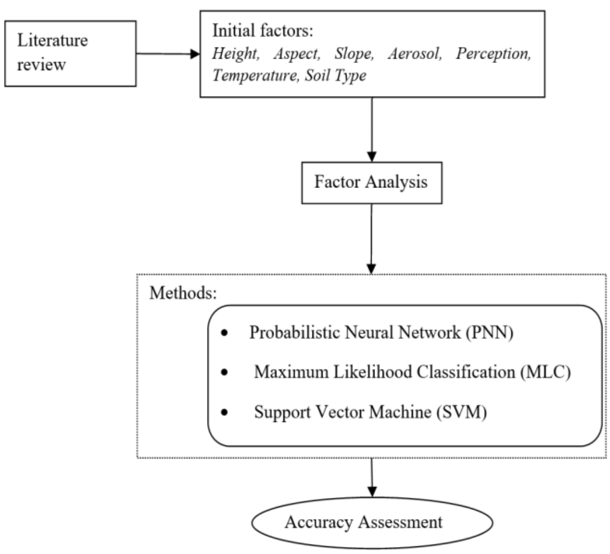

Figure 1. Flowchart of applied methodology

This paper divided oak decline potential classification into three main stages (see Figure 2). At first, the literature review identifies all factors that might contribute to the oak decline.

In the second stage, factor analysis is applied for data dimension reduction and to create a good combination of factors called the input set.

Finally, different models with created input sets are evaluated in the third stage to identify the best classification method.

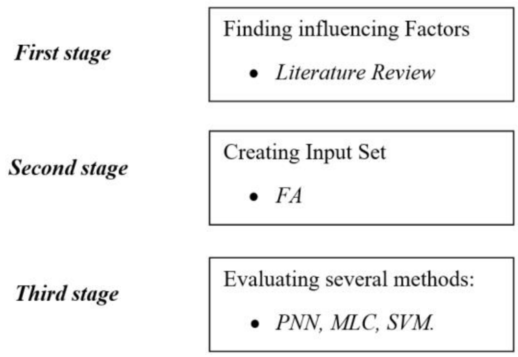

Figure 2. Main stages of oak decline potential modeling.

A literature review was conducted in the first phase to identify the most robust variables affecting tree health and vigor. As a result, seven factors, including height, aspect, slope, aerosol, perception, temperature, and soil type, were identified (Table 1).

Factors	Reference
Aspect	(Ahmadi et al., 2014) (Costa et al., 2010) (Hosseini et al., 2014)
Aerosol	(Ahmadi et al., 2014)
Height	(Ahmadi et al., 2014) (Karami et al., 2015)
Perception	(Ahmadi et al., 2014) (Azizi et al., 2015) (Hosseini et al., 2014) (Wargo et al., 1983) (Attarod et al., 2016) (Kabrick et al., 2008) (Jönsson, 2004) (Siwkcki and Ufnalski, 1998) (Corcobado et al., 2014)
Slope	(Costa et al., 2010) (Karami et al., 2015)
Soil type	(Ahmadi et al., 2014) (Jönsson, 2004) (Costa et al., 2010) (Jönsson, 2004) (Martín-García et al., 2015) (Kabrick et al., 2008)
Temperature	(Attarod et al., 2016)

Factors	Reference
	(Siwkcki and Ufnalski, 1998)

Table 1. Factors influencing oak decline (Alesheikh and Mehri, 2019)

Also, the exact contribution of different variables and their interaction in the creation and propagation of the oak decline potential is unknown. As a result, there is a high degree of ambiguity and uncertainty.

Determining which factor should be included in oak decline potential classification is becoming one of the most critical questions as several factors affect oak decline.

As data become increasingly high-dimensional, determining which predictors should be included in a model becomes one of the most critical questions (Kuhn and Johnson, 2013). From a practical point of view, a model with fewer inputs seems to be more interpretable (Kuhn and Johnson, 2013).

In analysis, which is bounded by several related factors, to gain a better understanding of the inter-correlations among variables and to select prepared variables, Factor Analysis (FA) is needed. Therefore, this paper uses a factor analysis for dimension reduction.

Having different measurement units, normalization is required, which allows for comparing variables expressed in different measurement units (Nardo et al., 2005).

The Z-score statistical method was used for normalization and converting IFs to a common scale with a mean of zero and standard deviation of one by the following equation (1):

$$Z_{ij} = \frac{x\text{-}\mu_j}{\sigma_j} \tag{1}$$

where μ_j = mean of the x

σ_j = the standard deviation of the x

Prior to the extraction of factors, several tests are needed to ensure the suitability of data for factor analysis (Williams et al., 2014); Therefore, the Kaiser-Meyer-Olkin (KMO) was done to ensure sampling adequacy. The KMO index ranges from 0 to 1, with 0.50 considered suitable for factor analysis (Yong and Pearce, 2013).

Also, Bartlett's Test of Sphericity was done to ensure factor analysis will yield distinct and reliable factors (Field, 2013). Bartlett's Test of Sphericity should be significant ($p<.05$) for factor analysis to be suitable.

Components with eigenvalues greater than 0.7 were extracted (Jolliffe 1972). Extracted components are used as input for different classification models, including PNN, MLC, and SVM.

3. DATA SOURCES

The study area is located in Iran and encompasses the entire Lorestan province, which has 1.2 million hectares of forests (figure 3).

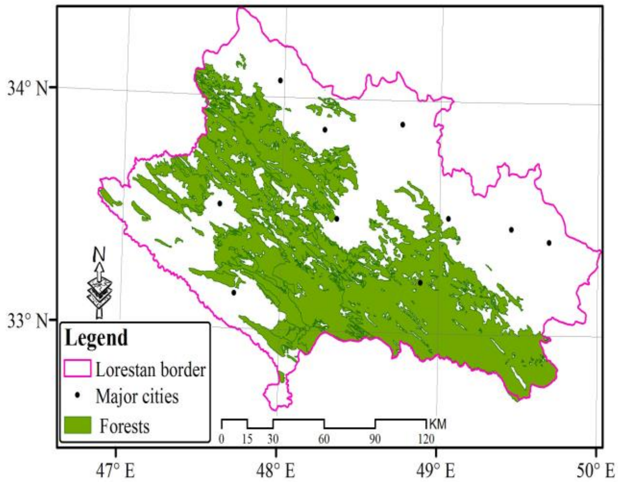

Figure 3. Flowchart of applied experimental work.

Based on the data created by Iran's Forests, Range and Watershed Management Organization, the forests of the study area are divided into five decline classes (Table 2. Then a grid with a cell size of 30 meters is used for sampling, and 2000 randomly distributed samples are collected for each decline class. Characteristics of samples are summarized in Table 3

Class No.	% of declined trees	% of Total Area
1	< 1	53.84
2	1 – 25	26
3	25.1 – 50	16.07
4	50.1 – 75	2.28
5	75.1 – 100	1.81

Table 2. Oak decline classes in the study area

	Min	Max	Mean	St.d
Height (meter)	343	3413	1653.74	450.40
Aspect (degree)	0	359	169.14	103.51
Slope (degree)	0	78	18.17	10.26
Perception (mm)	33	55	40.20	5.07
Temperature (°C)	11.78	16.68	14.28	1.17
Aerosol[1]	40	62	52.45	4.70

Table 3. Characteristics of sampling sites

Also, a soil map of the study area was used (figure 4). According to the soil taxonomy system (Service. 1988) study area contains three soil orders, including Inceptisols, Entisols, Vertisols and their combination (table 4). Also, some parts of the study area have rock outcrops that lie outside the range of specific subgroups (Service. 1988).

Order	Area (km^2)	% of the total area
Inceptisols/Vertisols	575	4.7
Inceptisols	1855	15.1
Rock Outcrops/Inceptisols	7192	58.6

[1] Number of days in which aerosol density is higher than permissible amount

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Order	Area (km^2)	% of the total area
Rock Outcrops/Entisols	2611	21.3
Bad Lands	31	0.3

Table 4. Soil order details in the study area

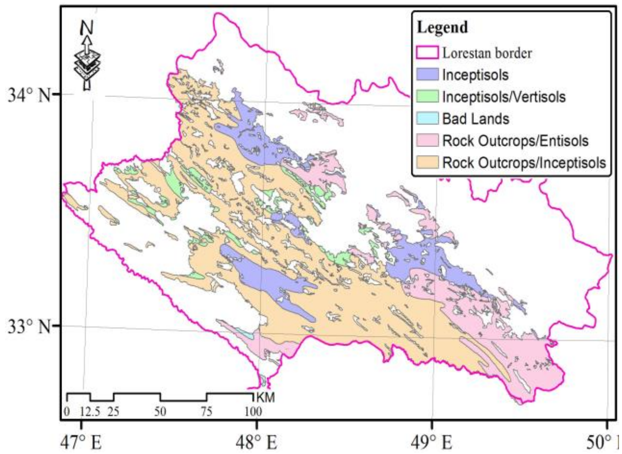

Figure 4. Soil order in oak forests of the study area

Climate data collected in ground-based climate stations, including the amount of perception, mean temperature and the number of days in which aerosol density is higher than the acceptable amount, were used.

The aspect and slope maps of the study area were constructed with a 30-m spatial resolution based on the digital terrain model (DTM), which is derived from a 1: 25000 topographic map from Iran's National Cartographic Centre.

4. RESULTS AND DISCUSSIONS

As the KMO index is 0.705, and Bartlett's test of sphericity is highly significant ($p < .001$), factor analysis is conducted. Five components with an eigenvalue greater than 0.7 are selected for further analysis. These components explain 92.49% of the total variance (Table 5).

Component	1	2	3	4	5
% of variance	**40.34**	**14.89**	**14.10**	**12.24**	**10.93**
Height	0.568	0.003	0.209	0.176	0.770
Aspect	0.014	0.736	-0.60	0.309	0.056
Slope	0.442	-0.296	0.099	0.795	-0.273
Aerosol	-0.863	0.002	0.086	0.132	0.070
Perception	0.825	0.039	-0.091	-0.224	-0.236
Temperature	-0.937	-0.055	0.051	0.171	0.056
Soil type	0.057	0.639	0.745	0.039	-0.176

Table 5. Component matrix

Perception with positive and temperature and aerosol with negative load have contributed to the first extracted component, which explains 40.34% of the total variance. The second component explains 14.89% of the total variance. Aspect and soil type have a positive load on this component.

The third component is made of soil type with a positive load and aspect with a negative load and explains 14.10% of the total variance. Slop and height have a positive load in constructing the fourth and fifth components.

Five extracted components are used as input sets of PNN, MLC and SVM methods. 80% of samples are used for training methods, and 20% are used for testing purposes. Results are compared based on the overall accuracy of the methods (Table 6).

No	Method	Overall accuracy
1	SVM	0.87
2	MLC	0.79
3	PNN	0.82

Table 6. Component matrix

Among three classification methods, SVM has proved its capability to classify oak decline potential with an overall accuracy of 0.87% and performed better than other methods.

Although results of neural networks with probabilistic topology showed that the performance of PNN has little difference from SVM, implementation of SVM is more straightforward. Therefore, factor analysis and SVM could be used for oak decline potential classification.

5. CONCLUSION

This research focuses on the classification of oak decline potential, which could be a valuable tool for oak forest management and macro-level planning. Oak mortality is a complex and irregular phenomenon, and its occurrence is assumed to be caused by an interaction of several complex factors.

This paper identified seven factors: height, slope, aspect, temperature, perception, soil type, and aerosol influencing oak decline, creating a high-dimensional dataset. Therefore, determining which factor should be included used is one of the most critical steps in oak decline potential classification.

To reduce data complexity, this paper uses a factor analysis. Based on the factor analysis results, five components are extracted, used in three classification methods.

Evaluating SVM, PNN and MLC indicated that SVM has better accuracy than others and can be used for oak decline potential classification.

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