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Evaluation of Machine Learning Performance in Wildfire Susceptibility Mapping Under Limited Training Data Condition

Sınırlı Eğitim Verileri Durumunda Orman Yangını Duyarlılık Haritalamasında Makine Öğrenimi Performansının Değerlendirilmesi

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ABSTRACT

Wildfire susceptibility mapping can be affected by several factors. One of the most influential factors is inventory data, its extent, format, and reliability. This study aims to evaluate if the Support Vector Machine (SVM) has the capability to identify wildfire susceptible regions under limited training data conditions. To test this hypothesis wildfires in Mugla province in the Eastern Mediterranean Region of Turkey have been selected as a pilot study area. The wildfire started in Mugla, on 29 July 2021, that considerably affected the residential areas, animals, and vast areas of forests. Fourteen wildfire influential variables have been used in the analysis as independent variables. Accuracy assessment has been implemented using the Area Under the Curve (AUC) technique. Success rate and prediction rates were (91.42%) and (87.69%) respectively. According to the prediction rate, SVM successfully recognized other burnt areas as the most susceptible regions.

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Anahtar Kelimeler:

Orman Yangını, Envanter, Türkiye, Duyarlılık, Jeo-uzamsal

ÖZET

Orman yangını duyarlılık haritalaması çeşitli faktörlerden etkilenebilir. En etkili faktörlerden biri envanter verileri, kapsamı, biçimi ve güvenilirliğidir. Bu çalışma, Support Vector Machine'in (SVM) sınırlı eğitim verisi koşulları altında orman yangınına duyarlı alanları tespit etme ve haritalama kabiliyetine sahip olup olmadığını değerlendirmeyi amaçlamaktadır. Bu hipotezi test etmek için Türkiye'nin Doğu Akdeniz Bölgesi'nde yer alan Muğla ilindeki orman yangınları pilot çalışma alanı olarak seçilmiştir. Bahsedilen orman yangını Muğla'da 29 Temmuz 2021'de başlamış ve yerleşim alanlarını, hayvanları ve geniş ormanlık alanları önemli ölçüde etkilemiştir. Bağımsız değişkenler olarak on dört orman yangını etkili değişken analizinde kullanılmıştır. Doğruluk değerlendirmesi için Area Under thr Curve (AUC) tekniği kullanılarak uygulama yapılmıştır. Başarı oranı ve tahmin oranları sırasıyla (%91.42) ve (%87.69)'dir. Tahmin oranına göre, SVM diğer yanık alanları en hassas bölgeler olarak başarıyla tanımladı.

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1. INTRODUCTION

Wildfire is among the most harmful natural disasters affecting both lives and properties around the world [1]. Global temperature rise, reduction in precipitation, and human activities led to an increase in wildfire occurrences [2; 3]. Natural hazards usually occur under specific conditions and in partially predicted areas [4]. Therefore, they can be studied and prevented up to some levels [5]. Remote Sensing (RS) technology and Geographical Information Systems (GIS) are wonderful systems to monitor and analyze wildfires over large areas in a timely and cost-effective manner [6]. Studying the wildfire can be done from different aspects. Some of the most popular studies are related to wildfire susceptibility [7], hazard [8], vulnerability [9], risk [10] and etc. Wildfire susceptibility considers a basis for other evaluations. In the natural hazard scope, a susceptibility map recognizes regions that are more or less disposed to a potential wildfire occurrence using low to high possibility values/classes [11]. In order to perform wildfire susceptibility, two main datasets of previous wildfire extent (dependent variable) and a set of conditioning factors (independent variables) are essential [12]. Inventory data, conditioning factors, and the used method, each play an important role in the precision and reliability of the results. Therefore, they have to be selected carefully. This research focuses on the role of wildfire inventory. In some cases, an inventory extent might be limited due to non-accessibility to all affected areas. Therefore, the hypothesis is that performing a robust method along with an adequate conditioning factors dataset could compensate for the limitation of wildfire inventory data.

In summer 2021, due to the severe heatwave and dry weather, Turkey faced its worst wildfires in years [13]. During that summer around 130 wildfires have been detected in 30 provinces [14]. Wildfires mostly occurred along the Mediterranean and the Aegean Sea coasts. According to the European Forest Fire Information Service, about 136,000 hectares have burned which was about three times the average for an entire year [13]. Fortunately, a complete set of inventories is available for this region. Therefore, a small portion of this dataset was used for training and performing the wildfire susceptibility modeling. The rest of the inventory has been kept and used for accuracy assessment. The aim was to examine whether SVM can predict other susceptible areas or not. There are a large number of methods available in order to perform wildfire susceptibility mapping. They can be grouped into qualitative and quantitative methods [15]. Qualitative methods like Analytical Hierarchy Process (AHP) [9] and fuzzy logic have been utilized by several researchers to assign weight to wildfire conditioning factors according to their significance in wildfire occurrence. Such techniques are mostly based on experts' knowledge that in some cases might contain errors.

Quantitative techniques predict wildfire susceptibility regions using mathematical assessment of the data [16]. In addition, the subjectivity of qualitative approaches is not included in quantitative techniques. Logistic Regression (LR) [17], Frequency Ratio (FR) [18], Evidential Belief Function (EBF) [19], the Weight of Evidence (WOE) [18], Artificial Neural Network (ANN) [20], etc. are a few examples of quantitative methods. Among the broad range of quantitative methods, Machine Learning (ML) techniques are widely used in natural hazard studies [12; 21]. They recognize and model non-linear correlations among wildfire and their relevant conditioning factors. Wildfire inventory is an essential factor in ML analysis. Compared to qualitative techniques like AHP, the proficiency of ML methods is that they perform more reliable and faster outcomes [22]. The undeniable efficiency of ML in natural hazard solutions motivated us to test the hypothesis of this study using this technique. Among all ML methods, Support Vector Machine (SVM) [23] has been selected to find the association between wildfire conditioning factors and inventory data.

2. STUDY AREA

Mugla province has been chosen as the study area. It is between 27◦13′30″ and 29◦41′00″W longitude and 36◦18′22″ and 37◦35′10″N latitude. Mugla is situated at the intersection between the Aegean and the Mediterranean Sea. Pine honey production makes the forests of this region so valuable. According to Forest General Directorate (https://www.ogm.gov.tr/tr), 9% of Turkey's wildfires have occurred in Mugla province [24]. Every year around 500 ha of its forests has been destroyed. Mugla has a warm temperature and rain falls mostly in the winter. The study area's location along with a few wildfire figures that occurred in 2021 are represented in Figure 1.

Figure 1. Mugla province and wildfire inventory.

3. METHODOLOGY

3.1. Data Used

As has been mentioned in the introduction section, wildfire inventory and conditioning factors are two essential elements in wildfire susceptibility mapping. Both dataset details and their sources have been listed in Table I. The wildfire inventory map (summer 2021 wildfires) in Mugla has been received from Fire Information for Resource Management System Website (FIRMS). Selected areas in Figure 2 represents the portion of the inventory map which was utilized for training purpose, and the rest of the inventory points were used in order to test the outcomes.

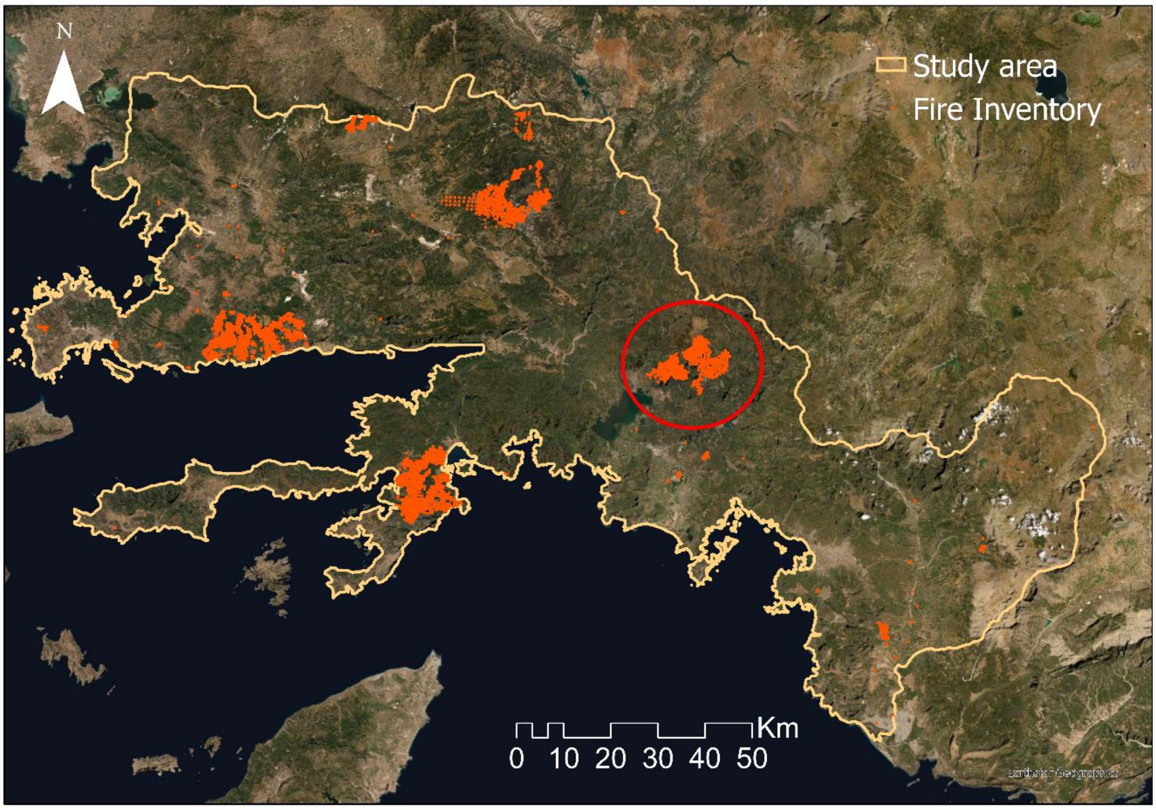


Figure 2. Training and testing points.

Wildfire conditioning factors have been chosen according to the literature. Altitude, slope, aspect, curvature, TWI, TRI, TPI, precipitation, NDVI, wind, distance to rivers, distance to reads, temperature, and LULC have been used as the wildfire's most influential factors in the analysis (Figure 3). Altitude has an influence on the wind behavior and climatic conditions such as precipitation and temperature [25]. Altitude data was received with a 30 m resolution. Subsequently, other wildfire conditioning factors were resampled to the same spatial resolution. The direction of fire spread and fire rate is controlled by the slope factor [26]. In addition, the slope has a significant role in wind speed. Higher slopes cause faster wildfire spread. Aspect which shows the slope faces directions affects the amount of sunlight received [27]. Knowing the slope aspect, the temperature and humidity of the region can be predicted. For instance, the southern faces received more sunlight compared to the northern faces. Therefore, they are more prone to wildfires as they have the longest exposure time to sunlight. Meaning that fuels on the southern faces dry faster compared to other aspects of the region. The morphology of topography is represented by curvature [28]. Positive and negative curvatures show that the surface is convex and concave at that cell respectively. Also, a value of zero shows that the surface is flat at that cell. In wildfire studies the wetness of the ground is important, therefore, TWI has been measured as well, which is calculated based on (1) [29]:

$$TWI = \ln \frac{\alpha}{\tan \beta} \tag{1}$$

where α is the cumulative up slope area and tan β is the slope angle at the point. TRI is another wildfire influential factor. TRI is the ratio of the variable surface area to the planimetric surface area that is given as (2):

$$TRI = \frac{(Area_V - Area_I)}{(Area_P - Area_I)} \tag{2}$$

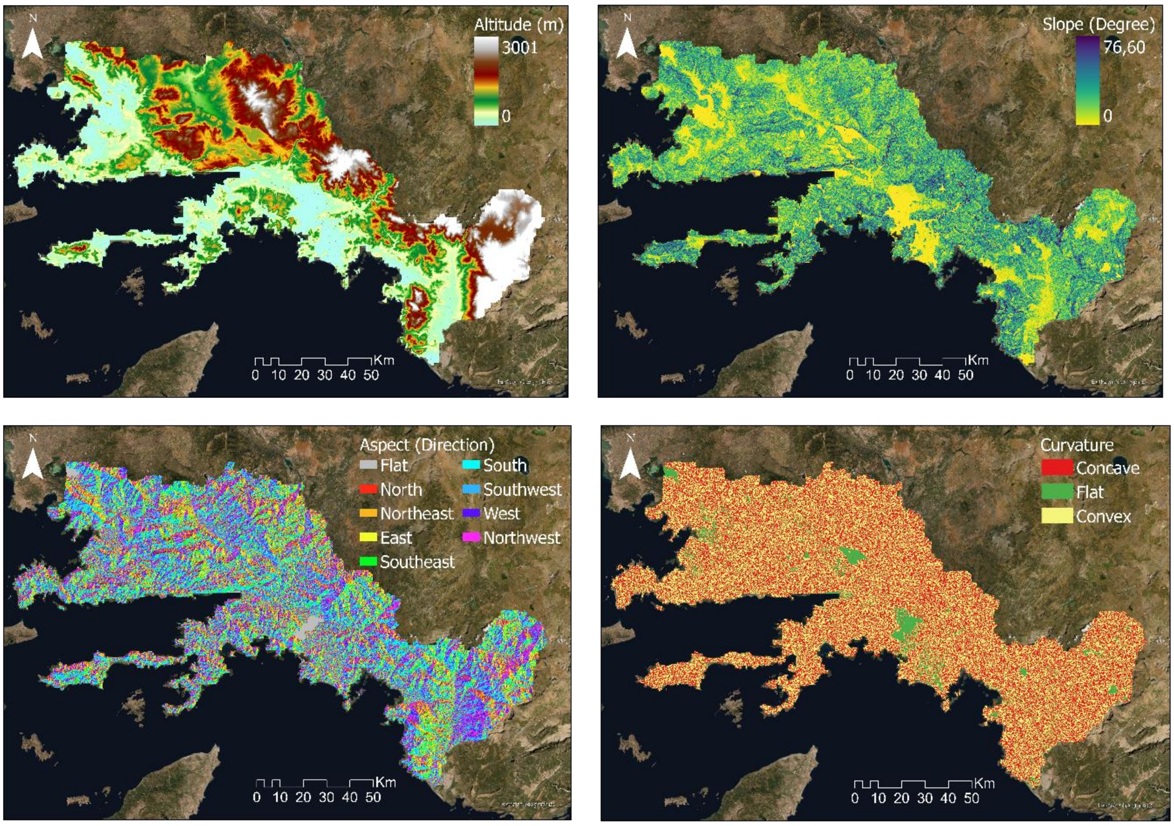
The higher the TRI values the greater the topographic roughness. This factor can range from 1 to 800. Value 1 represents the completely flat area [30]. Precipitation is another wildfire influential factor that has a great impact on fuel moisture and soil moisture. NDVI factor has been used in order to measure the vegetation cover. It was prepared using Landsat-8 images according to (3):

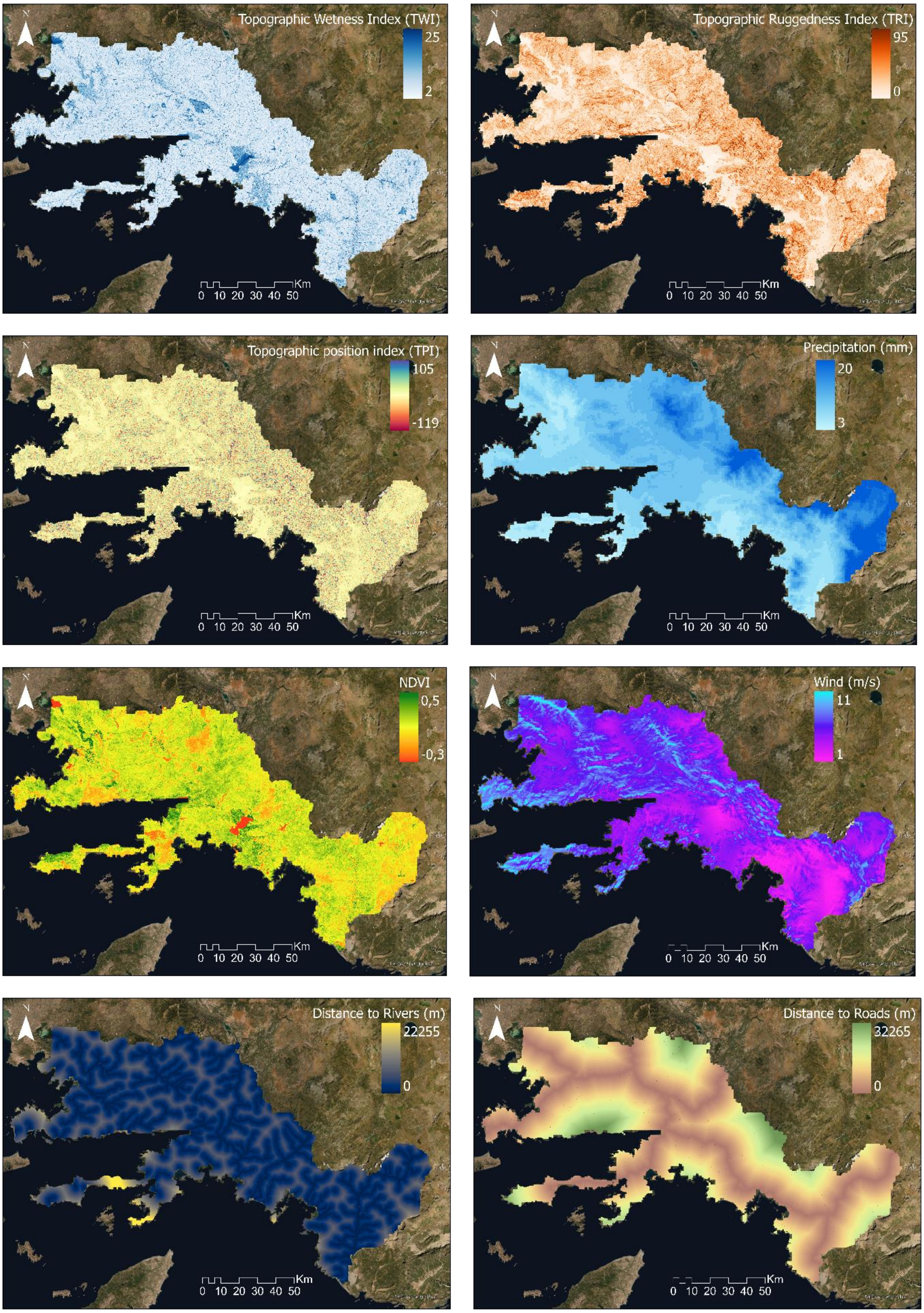
$$NDVI = \frac{NIR - R}{NIR + R} \tag{3}$$

where NIR and R values are the infrared and red bands, respectively. Another critical conditioning factor is wind. It has a great effect on the spread and direction of the wildfire [32]. Therefore, it is necessary to consider it as one of the conditioning factors as well. Rivers and roads are liner features that act as a barrier to wildfire spread. Therefore, the distance to these factors has been measured and used in the analysis. Another factor that has an impact on fuel availability and condition is the temperature [23]. Therefore, this factor also has been included in the wildfire susceptibility assessment. Wildfires act differently in different types of forests [33]. For instance, shrub species and flammable forest vegetation types increase the ignition risk [34]. Dense and dry forests are more susceptible to wildfire occurrences compared to moist vegetated areas [35].

Table 1. The sources of data used.

Data	Sources
Forest fire inventories	Fire Information for Resource Management System Website https://firms.modaps.eosdis.nasa.gov/
Altitude	Digital Elevation Model (DEM) from Earthdata Website https://www.earthdata.nasa.gov/
Slope, Aspect, Curvature, TWI, TRI, TPI,	Derived from Digital Elevation Model (DEM)
Precipitation	WorldClim Website https://www.worldclim.org/
NDVI	Landsat 8
Wind	https://globalwindatlas.info/area/Australia
Distance to rivers	https://land.copernicus.eu/imagery-in-situ
Distance to roads	OpenStreetMap https://www.openstreetmap.org/
Temperature	WorldClim Website https://www.worldclim.org/
LULC	CORINE https://land.copernicus.eu/pan-european/corine-land-cover




Topographic Wetness Index (TWI)
25
2
Topographic Ruggedness Index (TRI)
95
0
Topographic position index (TPI)
105
-119
Precipitation (mm)
20
3
NDVI
0,5
-0,3
Wind (m/s)
11
1
Distance to Rivers (m)
22255
0
Distance to Roads (m)
32265
0
Km
0 10 20 30 40 50

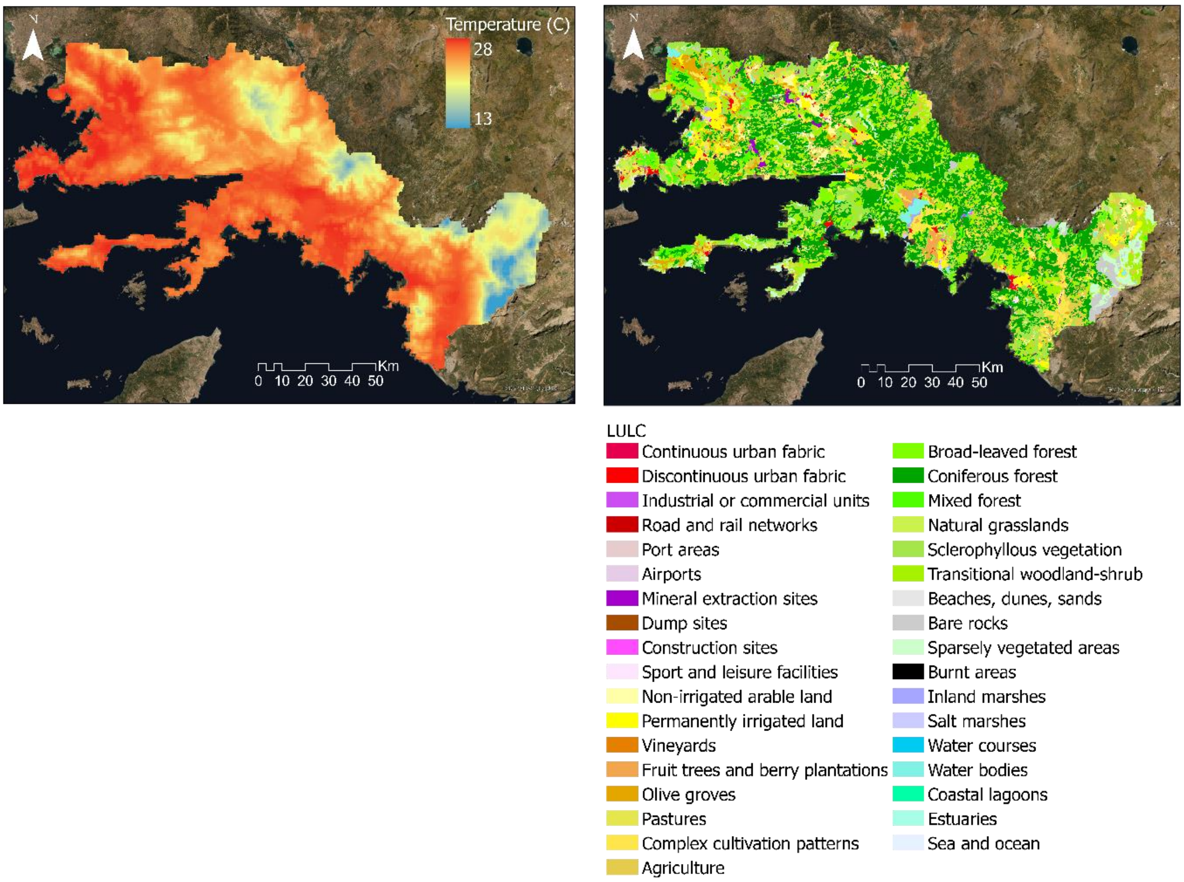


Figure 3. Wildfire conditioning factors.

3.2. Support Vector Machine (SVM)

In the literature, the SVM method has been used to solve complex classification and regression problems in flood [36], landslide [37], wildfire [38], earthquake [39], etc. domains. It is a supervised ML method that performs based on statistical learning theory [40]. SVM reforms the nonlinear world into the linear using hyper-plane which makes it simple and processable [41]. The aforementioned data transformation will be done using a mathematical function called kernel function [42]. SVM is able to transform the original input into a high-dimensional feature space. A separating hyper-plane is generated in the original space of n coordinates (xi parameters in vector x) between the points of two distinct classes. SVM finds a maximum margin of separation between the classes and builds a classification hyper-plane in the center of the maximum margin [43]. The point will be classified as +1, in the case that it is overhead the hyper-plane and if not, it will be classified as -1. Subsequently, new data will be grouped according to its characteristics. The closest training points to the hyperplane are called support vectors.

For instance, consider a training dataset of instance-label pairs (x_i, y_i) with $x_i \in R^n$, $y_i \in \{-1, 1\}$, and $i = 1, \dots, m$. In the present circumstance of wildfire susceptibility, x is a vector of input space that contains altitude, slope, aspect, curvature, TWI, TRI, TPI, precipitation, NDVI, wind, distance to rivers, distance to reads, temperature, and LULC. The two classes $\{-1, 1\}$ specify wildfire pixels and non-wildfire pixels. Recognizing the optimal separating hyper-plane is the goal of SVM, which can separate the two classes into wildfire and non-wildfire $\{-1, 1\}$ from the training dataset. For the case of linearly separable data, a separating hyper-plane can be defined as (4):

$$y_i\,(w.x_i + b) \geq 1 - \xi_{i,} \quad (4)$$

where w is a coefficient vector that defines the orientation of the hyper-plane in the feature space, b is the offset of the hyper-plane from the origin, and ξ_i is the positive slack variables. A comprehensive description of SVM and its internal calculations are presented in Noble [44], Suthaharan [45], Meyer *et al.* [46], etc.

3.3. Area Under the Curve (AUC)

Among a variety of accuracy assessment techniques, AUC is the most popular technique in natural hazard studies which provides the prediction and success rates [18; 47; 48]. The proficiency of AUC in evaluating the susceptibility mapping outcomes has been assessed in the literature. AUC evaluates the existence of the known natural hazard inventory data in the derived susceptibility map. Firstly, the wildfire susceptibility map was divided into equal intervals and hierarchically ranked from minimum to maximum. The calculated values of all cells were sorted into descending order, and cell values were split into 100 classes with 1% accumulation intervals. The "tabulate area" tool in ArcGIS was utilized to examine the existence of wildfire in each class. Finally, the success curve and prediction curve indicated the percentage of wildfires in each interval.

4. RESULTS AND DISCUSSION

SVM has been applied and a wildfire susceptibility map has been generated. The correlation between wildfire inventory and conditioning factors was evaluated using SVM. The wildfire inventory map (summer 2021 wildfires) in Mugla has been received from FIRMS. A small portion of inventory data (30%) was used to train SVM and 70% was utilized for accuracy assessment. The reason is to test if SVM was able to perform accurately in case of limited training data. Regarding the conditioning factors, altitude, slope, aspect, curvature, TWI, TRI, TPI, precipitation, NDVI, wind, distance to rivers, distance to reads, temperature, and LULC have been used. Altitude was derived from DEM downloaded from "Earthdata Website" which ranged from 0 to 3001 meters.

Other topographical factors of slope (0-76.60°), aspect (nine slope directions), curvature (concave, flat, and convex), TWI (2-25), TRI (0-95) and TPI (-119-105) were derived from DEM. WorldClim Website was used to extract the annual precipitation (3-20) in the study area. NDVI factor (-0.3-0.5) was calculated from Landsat imagery. Wind factor (1-11 m/s) was downloaded from the global wind atlas website. Distance to rivers (0-22255m) and roads (0-32265) were calculated using the Euclidean distance tool in ArcGIS. The temperature (13-28C) factor was received from WorldClim Website and detailed LULC with 35 categories was received from CORINE Website.

Figure 4 shows the wildfire susceptibility map for Mugla province. It illustrates the susceptibility of wildfire incidents according to the related wildfire conditioning variables. The quantile classification technique has been used to group the wildfire susceptibility maps into classes of "very high", "high", "moderate", "low", and "very low". Figure also represents the inventory point around the region. Interestingly, inventory points are mostly placed in "high" and "very high". In order to prove the success of the SVM in detecting susceptible areas, AUC has been applied. Success rate and prediction rates were (91.42%) and (87.69%) respectively. Hence, visually and mathematically it has been proven that SVM can undertake wildfire susceptibility mapping under limited training data conditions with high accuracy. As can be seen in figure, the most susceptible areas are the regions with high slope degrees, high temperature, less precipitation, and higher wind speed. These areas need to be carefully monitored and managed for future planning and disaster management.

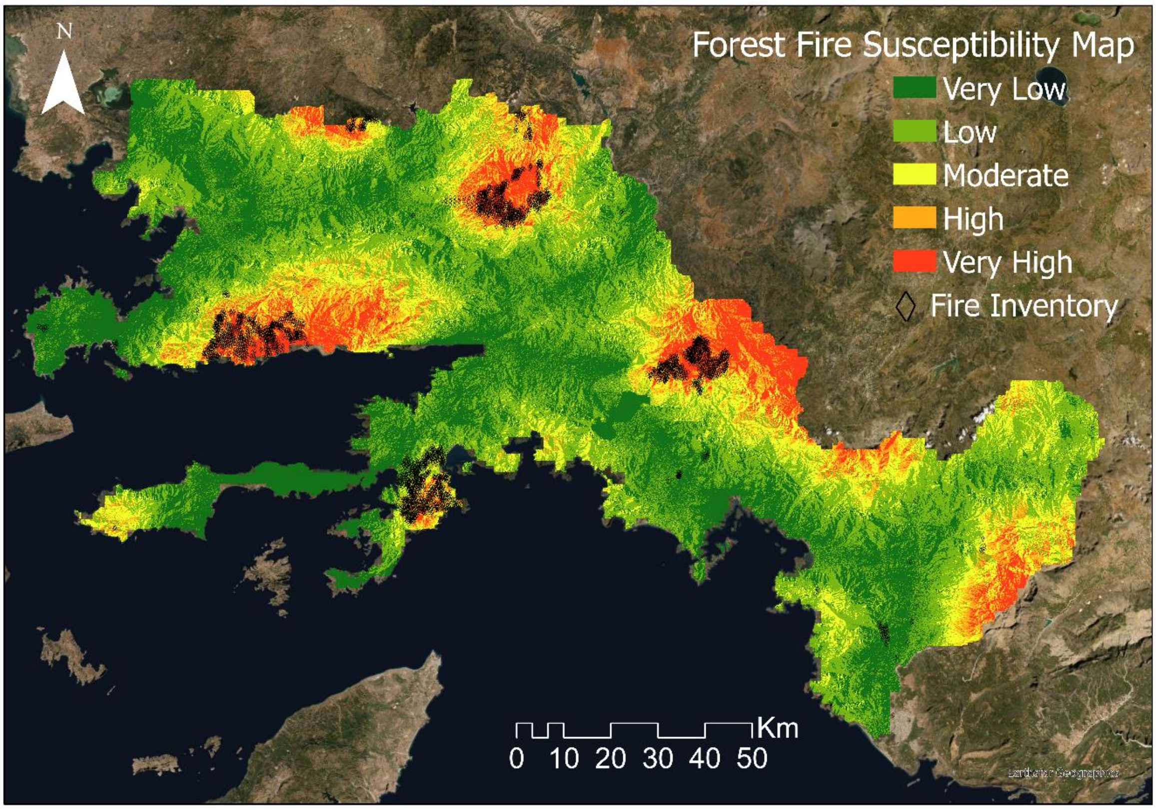


Figure 4. Wildfire susceptibility map.

5. CONCLUSION

The wildfire susceptibility map helps several sectors in order to study, plan, manage and mitigate this disaster. It can considerably contribute to detecting the susceptible zones and subsequently prevent possible damage in the future. RS and GIS technologies proved to be promising tools in the natural hazard studies domain. This study performed wildfire susceptibility mapping using small inventory data and tested the reliability of the outcomes using the actual inventory which has not been used in training the method. The aim was to examine if SVM is capable to provide accurate susceptibility analysis in the case of lack of training. In some regions, there is limited access to the affected areas, therefore, the inventory dataset will not be as accurate as possible. The susceptibility mapping has been performed and the study area has been classified into different susceptible regions. Subsequently, the AUC method has been applied and the prediction rate of 87.69% has been achieved. It has been concluded that a combination of relevant and accurate conditioning factors datasets with the ML method can compensate for the limited inventory dataset in similar cases.

Statement of Conflict of Interest:

Author has declared no conflict of interest.

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