Determination of Natural and Anthropogenic Caused Forest Fire Susceptibilities Threatening the Pine Honey Production and Marchalina Hellenica Population

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Research Article

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Abstract

Every year, an average of 250 forest fires occur in Turkey and 10,000 hectares of forest area are destroyed by natural and human-caused forest fires. Moreover, 90% of the world's pine honey production is produced in red pine (*Pinus brutia*) forests infested with *Marchalina Hellenica*. However, the limited production sites for pine honey are destroyed by forest fires and most of the sites overlap with the regions where susceptibility to forest fires is highest. In particular, in 2021 and 2022, pine honey production in Muğla province decreased by half due to the large forest fires.

In this study, susceptibility to forest fires caused by lightning, cigarette butts, stubble burning and power lines was modeled separately for all pine honey production sites via MaxEnt. Each risk map overlapped with the *Marchalina Hellenica* distribution map to determine which fire causes put each region at risk. When the results were examined, 1357.6 km^2 (56.6%) of the 2396 km^2 pine honey production site was found to be at risk from lightning-caused forest fires. For human-caused forest fires, 184.7 km^2 (7.7%) were at risk from power lines and 136 km^2 (5.7%) from stubble fires. 116.8 km^2 of pine honey production areas are threatened by forest fires caused by cigarette butts, which is the least threatening cause in the study area. The findings obtained in this study provide important information on the measures that can be taken against forest fires and on the planning of early intervention procedures to protect pine honey production areas.

1. Introduction

Forests are the most important indicator of biodiversity and habitat richness in a region, which is closely related to species distribution and conservation of ecosystems (Demeke and Afework 2014; Suryabhagavan et al. 2016). One of the most important examples of this issue in Turkey is the pine honey produced by *Marchalina Hellenica* in red pine (*Pinus brutia*) forests. Pine honey can only be produced by honeybees that collect honeydew from *M. Hellenica* in the *Pinus brutia* forests in Turkey and Greece that are infested with *M. Hellenica*. The produced pine represents 40% of the annual honey production in Turkey and 65% in Greece, and all of the world's pine honey production comes from these countries. (Santas 1983; Thrasyvoulou and Manikis 1996; Sunay et al. 2003; Sunay and Boyacioglu 2008, Bouga et al. 2011) where 90% of the world's pine honey production occurs only in Turkey (Miguel et al. 2014). The *M. Hellenica.*is the most prevalent on *P.brutia* in the Mediterranean coasts of Turkey (Selmi 1983; Yesil et al. 2005; Akkuzu et al. 2006) and has been included in the European and Mediterranean Plant Protection alert list (Bouga et al. 2011).

In Turkey, there is only one project entitled "Project for the Sustainability of Pine Honey Production in the Red Pine Forests of the Muğla Region and the Solution of the Problems Occurred" (URL 1), which aims to determine the existence of *M. Hellenica* and the current locations of pine honey production through field studies. According to the project, the *P. brutia* forests infested by *M. Hellenica* are mainly located in the center of Muğla with 28.4%, in Milas with 19.4%, in Marmaris with 16.8% and Köyceğiz district with 12.5%. In this project, the *P. brutia* forests infested by *M. Hellenica* were defined and the results of the project showed that the pine honey production areas are gradually decreasing due to forest fires. With regard to the sustainable production of pine honey, the idea was developed to ensure the continuity of production by introducing *M. Hellenica* into new areas where pine honey has not been produced before.

However, the possibility of forest fires must be known both in current and potential pine honey production sites to specify effective planning procedures and to ensure the sustainability of pine honey production. Since both *P. brutia* and *M. Hellenica* must be present together to produce pine honey, it cannot be produced if either species is damaged or destroyed. Although the population of *M. Hellenica* is declining for many reasons, the greatest threat to *P. brutia* is forest fires. Muğla Province has a high forest fire potential in Turkey and more than 500 hectares of forest, including *P. brutia* forests, are completely destroyed by forest fires every year (URL 2). Very large areas of forest were damaged in the major forest fires occurred in 2021 and 2022 in Muğla province. Along with the burned *P. brutia* trees, numerous *M. Hellenica* populations were also destroyed, causing significant damage to pine honey production. For this reason, honey production in Muğla, which produced an average of 15,000 tons of honey until 2019, has decreased to 6,104 tons in 2020 and 3,820 tons in 2021, according to Turkish honey production statistics (URL 3). Considering that pine honey accounts for the largest share of honey production in Muğla Province, the damage caused by forest fires becomes even more evident. Also, considering that the optimal age of *P. brutia* for pine honey production ranges from 40 to 120 years (URL 2), it becomes even clearer that the restoration of pine honey production sites in damaged areas takes many years. Therefore the limited pine honey production sites should be evaluated in terms of forest fire risk to ensure the sustainability of production to protect *M.Hellenica* population and *P. brutia* existence.

According to the forest fire records of the General Directorate of Forestry of the Republic of Turkey, a total of 4647 fires occurred in the study area between 2013 and 2021 where most of them occurred in Muğla province. The causes of forest fires are divided into two groups: natural and human-caused, and it can be seen that forest fires are mostly caused by natural causes such as lightning. While forest fires caused by lightning cannot be predicted, human-caused forest fires such as thrown cigarette butts, electrical arcing on power lines, campfires and stubble burning can be predicted. In order to avoid the negative and irreversible effects of forest fires as much as possible and to know the value of risk, the need to determine the spatial relationships of fires has emerged (Tian et al. 2013) and this importance has become crucial in the last decade (Miller and Ager 2013).

It should be noted that there is no study in the literature that examines the spatial relationship between the distribution of *M. Hellenica*, pine honey production sites and forest fires. However, there are many methods to reliably and accurately estimate the probability of forest fire occurrence, such as multi-criteria decision analysis (MCDA) (Iwan et al. 2004; Vadrevu et al. 2010; Suryabhagavan et al. 2016; You et al. 2017; Sakellariou et al. 2019; Sarı 2021), geographic information systems (GIS) (Jaiswal et al. 2002; Setiawan et al. 2004; Chuvieco et al. 2010; Sowmya and Somashekar 2010; Adab et al. 2013; Hernandez et al. 2006; Puri et al. 2011; Ajin et al. 2016; Pourghasemi 2016), machine learning-based algorithms such as MaxEnt (Renard et al. 2012; Bar-Massada et al. 2012, 2013; De Angelis et al. 2015; Vacchiano et al. 2018; Bekar et al. 2020; Banerjee 2021; Tariq et al. 2022) and logistic regression (Chang et al. 2013; Guo et al. 2016a; Guo et al. 2016b; Jafari et al. 2016; Wang et al. 2018; Ashok et al. 2020; Milanović et al. 2021). Although methods such as GIS and MCDA do not consider existing forest fire points, machine learning-based analyzes provide more accurate probability distribution by considering the relationships between current forest fire points and criteria. It is very important to consider points where forest fires have already occurred, especially in cause-based forest fire probability studies, to reveal the spatial relationship between criteria and forest fire points. Therefore, the MaxEnt method was preferred in this study because it determines the potential for forest fire occurrence by examining the interaction of forest fire locations with the criteria and provides an effective and detailed analysis by calculating the important values of each variable that most affect forest fire occurrence.

When examining forest fire risk studies conducted using the MaxEnt method in the literature, it is seen that some of the studies examine both human and natural causes of forest fire together (Hu and Zhou 2014; Vacchiano et al. 2018; Dijkstra et al. 2022; Sarı 2022), while some studies focus only on human-caused (Wang et al. 2010; Guo et al. 2016a; 2016b; Martín et al. 2019) or natural-caused forest fires (Liu et al. 2016; Müller et al. 2018; Abdollahi et al. 2019; Heidari et al. 2021). Because each forest fire is caused by different factors, combining all causes into a single risk study leads to a superficial result in terms of the risk value of the region. However, the risk maps generated based on the causes show that each region studied is at risk to different degrees for different reasons. It is very important to know which regions are more threatened by the cause of forest fires, especially for fire prevention and precautionary measures. When studying the pine honey production sites, the fact that it covers a large area and has different characteristics means that each pine honey production area may be at risk for different reasons. For example, pine honey production areas in urban centers and near dense tourist areas are more at risk from human-caused forest fires, while pine honey production areas in high-elevation areas where there is no human activity are at risk from forest fires caused by lightning. Since the aim of the study is to identify the predominant causes of forest fires in each pine honey production site and to determine appropriate prevention and preparedness measures, each cause was studied individually.

In this study, the susceptibilities to forest fires caused by lightning, cigarette butts, power lines and stubble burning, which are the most common causes in the study area, were determined and evaluated separately based on a total of 25 criteria using the MaxEnt method. Rather than conducting holistic forest fire risk research that examines all causes together, the objective of this study is to identify region-specific susceptibilities by creating separate risk maps based on forest fire causes. The generated forest fire susceptibility maps were overlapped with pine honey production sites and the most vulnerable production sites for each cause were identified to guide fire prevention and early intervention studies that can be used by relevant institutions and organizations. In addition, pine honey production sites were prioritized to determine which areas need to be protected first to ensure sustainability of production.

2. Material Method

2.1. Study Area

The study area comprises Muğla, Aydin and Antalya provinces and is located between 26° 10' 30.1"and 30° 44' 3.05" W longitude and 36° 3' 7.24" and 39° 3' 49.63" N latitude. The study area is located at the intersection of the Mediterranean and Aegean Seas and is of great importance for the production of pine honey (90% of the world production) (Miguel et al. 2014), the forest industry and tourism. *M. Hellenica* is located in red pine (*Pinus brutia*) forests and 75–80% of the population of *M. Hellenica* is located in Muğla province. The production of pine honey depends on the existence of *P. brutia* and *M. Hellenica* and about 15,000 beekeepers locate to the study area every year from all over Turkey for pine honey production. However, red pine forests are threatened by forest fires, of which about 22% of forest fires in Turkey (10.55% in Muğla, 9.50% in Antalya and 2% in Aydın) occur in the study area (URL 2), destroying thousands of hectares of valuable *P. brutia* forests every year. The provinces of Muğla and Antalya are the most important tourism centers in Turkey and because of this importance, the population of these provinces increases greatly during the summer months. Both the vulnerability to forest fires and the tourism activities put a great strain on the production of pine honey by decreasing the production sites. The boundaries of the study area (Antalya, Aydın and Muğla provinces) were given in Fig. 1.

2.2. Forest Fire Data and their Spatial Distribution

This study used data from a total of 4647 forest fires that occurred in Aydın, Muğla and Antalya provinces between 2013 and 2021 (Fig. 2). The locations of the forest fires, the extinguishing times, the causes, the duration of the fires, the area of damage and other information were obtained from the database of the General Directorate of Forestry of the Ministry of Forest Fires of Turkey. The main causes of forest fires are stubble burning, lightning, power lines, cigarette butts and unknown causes that threaten pine honey production sites.

When evaluating the distribution of forest fires, it was found that pine honey production sites were most often threatened by forest fires started by lightning. This is disadvantageous in that lightning is a natural phenomenon that is very difficult to prevent and predict. Muğla province has the highest rate of pine honey production and forest fires occurrence in the study area and 68% of the forest fires caused by lightning occurred in Muğla because it is intensively forested and located at higher elevations. The distribution of forest fires by years and causes were given in Fig. 3.

2.3. *Marchalina Hellenica* Distribution and Pine Honey Production Sites

The pine honey production sites were retrieved from the project of "Project for the Sustainability of Pine Honey Production in the Red Pine Forests of the Muğla Region and the Solution of the Problems Occurred" (URL 1) by combining pine honey production sites and *P. brutia* forest boundaries. In total, 2396 km^2 production sites were specified and mapped in Muğla, Aydın and Antalya provinces and the boundaries were given in Fig. 4.

The project results showed that the sites for pine honey production decreased dramatically due to the forest fires and new production locations must be established by moving *M. Hellenica* to other *P. brutia* forests. In 2021, the production volume in Adana increased by 1.4% compared to the previous year, while it decreased by 33.9% in Ordu and 37.4% in Muğla. This situation led to a decrease in the production of pine honey and yield losses in the regions concerned. This situation has caused Muğla, which leads Turkey with a 10.9% share of the number of hives, to fall to fourth place in honey production. The decline in the population of *M. Hellenica* was due to both climatic adversities and forest fires on the Mediterranean and Aegean coasts in 2021. Considering that 40–120 years old *P. brutia* trees are required for the production of pine honey, the restoration of damaged forest cover for the production of pine honey takes at least 40 years and this period is quite long. Moreover, damaged forest covers and reduced locations for pine honey production have very negative consequences both for economic income and for social relations of beekeepers who have to settle in close distances to each other. The damaged and decreased forest areas were shown in Fig. 5 for the years 2020, 2021 and 2022, and about 1734 ha of forest area along with valuable pine honey production sites were destroyed by forest fires in the last three years. Considering all these important and negative aspects, it is very important to identify the areas where pine honey can be potentially produced in the region and to know the risk of forest fires in the current production sites.

2.4. Maximum Entropy Method

The MaxEnt method is a prediction algorithm used to detect the spatial distribution of a given sample locations by considering the locations of occurrence and dependent variables that are critical to spatial distribution. The MaxEnt method uses the locations of presence (training data) or occurrence to predict the possible distribution of the desired variables outside the locations of presence using maximum entropy theory. MaxEnt uses a series of iterative comparisons of given variables for the study area to determine the probability of occurrence based on presence locations (Elith et al. 2011). Therefore, presence locations are used as training data and should be as many as possible to show the spatial relationships between presence locations and variables for accurate and reliable results.

The overlapping values of presence sites with each variable determine the highly related values in each variable, and the probability for the most uniform or scattered values is adjusted according to the variables (Phillips et al. 2006). Therefore, assessing the probability of forest fire occurrence using the MaxEnt method requires presence data (historical forest fire locations) and independent variables (specified 25 criteria). One of the most important issues in studies assessing forest fire risk using the MaxEnt method is the number of variables involved in susceptibility. Since forest fires depend on several variables in the field of meteorological, climatic, topographical and environmental criteria, all variables should be considered as much as possible to establish a reliable susceptibility distribution. Therefore, the MaxEnt method requires the use of sufficient and detailed presence locations and variables to simulate susceptibility by evaluating a large number of spatial relationships between variables and presence locations.

2.5. Variable Selection

There are several spatial variables in the literature that have been used to generate maps of forest fire susceptibilities. Considering the criteria used in the studies of forest fire risk and *M. Hellenica* distribution, it was found that both subjects are very similar, as they are directly related to the forest. This situation shows that both subjects have a very close spatial relationship and share common decisive variables. Therefore, the determination of forest fire susceptibility will make it possible to directly identify the most threatened distribution areas of M. Hellenica and the production areas of pine honey.

In examining the studies in the literature, it was found that the most commonly used criteria for forest fire susceptibility are elevation and slope (Jaiswal et al. 2002; Iwan et al. 2004; Hernandez et al. 2006; Syphard et al. 2008; Archibald 2009; Parisien and Moritz 2009; Vadrevu et al. 2010; Henrique et al. 2011; Oliveira et al. 2012; Kwak et al. 2012; Bar Massada et al. 2013; Ajin et al. 2016; Pourghasemi 2016; Rahmati et al. 2016; Suryabhagavan et al. 2016; Costafreda-Aumedes et al. 2017; Güngöroğlu 2017; You et al. 2017; Vacchiano et al. 2018; Banerjee 2021; Sarı 2021). Since the criterion of elevation affects both the distribution of forest species and the occurrence of natural events such as lightning, it was used as a criterion in almost all studies. Since the *M. Hellenica* population mostly located at an altitude of 100–1000 meters, it can be assumed that the susceptible zones in this altitudinal strip directly threaten pine honey production.

In forest fire assessment studies, vegetation type (Jaiswal et al. 2002; Syphard et al. 2008; Parisien and Moritz 2009; Puri et al. 2011; Kwak et al. 2012; Oliveira et al. 2012; Suryabhagavan et al. 2016; Costafreda-Aumedes et al. 2017; Güngöroğlu 2017) and tree cover criteria (Aldersley 2011; Banerjee 2021; Sarı 2021) were included to involve the different vulnerability rates of species to ignition. It is important to use this criterion because coniferous forests are generally more susceptible to fire and *P. brutia* forests are found in this forest type class. Since both forest fires and *M. Hellenica* distribution occur exclusively in forests, forest boundaries are generally used as a class within the land use criterion (Iwan et al. 2004; Hernandez et al. 2006; Henrique et al. 2011; Puri et al. 2011; Aldersley 2011; Bar Massada et al. 2013; Ajin et al. 2016; Eugenio et al. 2016; Pourghasemi 2016; Vilar et al. 2016; Güngöroğlu 2017; Martin et al. 2019; Sarı 2021). In this study, the criteria of leaf type, forest type and tree cover density were used to distinguish between coniferous forests, which include *P. brutia* and their density, because dense forests are more susceptible to ignition.

Meteorological conditions are among the criteria that affect both the occurrence of forest fires and the rate of their spread after forest fires occur. Generally, the average temperature (Syphard et al. 2008; Parisien and Moritz 2009; Vadrevu et al. 2010; Aldersley 2011; Oliveira et al. 2012; Eugenio et al. 2016; Pourghasemi 2016; Costafreda-Aumedes et al. 2017; Güngöroğlu 2017; Banerjee 2021; Sarı 2021), precipitation (Archibald 2009; Aldersley 2011; Eugenio et al. 2016; Pourghasemi 2016; Costafreda-Aumedes et al. 2017; Güngöroğlu 2017; Banerjee 2021; Sarı 2021) and wind (Pourghasemi 2016; Costafreda-Aumedes et al. 2017; Banerjee 2021; Sarı 2021) variables have been used in forest fire research studies. In this study, for detailed analysis, the bioclimatic variables (BIO2,3,4,5,6,7 and 15), precipitation, temperature and wind speed criteria were included in the meteorological criteria category.

Although environmental criteria refer to human-caused forest fires and fire spread, most studies have considered environmental criteria such as distance from roads, settlements, water resources and power lines (Jaiswal et al. 2002; Iwan et al. 2004; Hernandez et al. 2006; Syphard et al. 2008; Archibald 2009; Lein and Stump 2009; Aldersley 2011; Puri et al. 2011; Kwak et al. 2012; Oliveira et al. 2012; Ajin et al. 2016; Eugenio et al. 2016; Pourghasemi 2016; Suryabhagavan et al. 2016; Vilar et al. 2016; Costafreda-Aumedes et al. 2017; Güngöroğlu 2017; You et al. 2017; Martin et al. 2019; Banerjee 2021; Sarı 2021). Thus, susceptibility to forest fires, which are caused by cigarette butts, burning stubble and power lines, can be determined obviously. Moreover, the criterion of distance from water sources completely determines the risk of ignition of objects in the forest. Therefore, in addition to this criterion, criteria such as riparian zones, wetness, wetness probability and imperviousness, which determine the wetness and moisture of the forest floor, were included in the analyzes in this study.

A total of 25 criteria were specified and downloaded from the global and local data sources listed in Table 1. All variables were mapped in WGS84 projection in ArcGIS 10.5 software and converted to ASCII file format for use in the MaxEnt analysis. Each variable map consists of 15183 columns and 10049 rows (total 152,573,967 pixels with a size of 0.0031 pixels in WGS84 projection).

Table 1
Specified variables and data sources

Variables	Units	Data Source	Resolution
BIO2 (Mean Annual Temperature)	*C^o*	WorldClim (Fick and Hijmans 2017)	1 x 1 kilometer
BIO3 (Isothermality)	*%*	"	"
BIO4 (Temperature Seasonality)	*C^o*	"	"
BIO5 (Max Temperature of Warmest Month)	*C^o*	"	"
BIO6 (Min Temperature of Coldest Month)	*C^o*	"	"
BIO7 (Temperature Annual Range)	*C^o*	"	"
BIO15 (Precipitation Seasonality)	*mm/m^2*	"	"
Precipitation	*mm/m^2*	"	"
Temperature	*C^o*	"	"
Wind Speed	*m/s*	"	"
Elevation	*Meter*	ASTER GDEM	30 x 30 meter
Slope	*%*	Derived from ASTER GDEM	"
Land-Use	*Class*	CORINE Project	100 x 100 meter
Settlements	*Meter*	Derived from CORINE	"
Water Resources	*Meter*	"	"
Power Lines	*Meter*	OSM Database	20 x 20 meter
Roads	*Meter*	OSM Database	"
Rivers	*Meter*	OSM Database	"
Riparian Zones	*Meter*	Copernicus Web Site	20 x 20 meter
Imperviousness	*%*	"	"
Forest Type	*Class*	"	"
Forest Density	*%*	"	"
Leaf Type	*Class*	"	"
Wetness	*Class*	"	"

Variables	Units	Data Source	Resolution
Wetness Probability	%	"	"

3. Generation Of Forest Fire Risk Maps Via Maxent Method

3.1. Lightning Susceptibility

Lightning-induced forest fires are the most common wildfires in the study area and causing more damage to forest cover than other causes. Since lightning occurs suddenly and is a natural event, it is difficult to predict and prevent forest fires compared to human-related causes (Liu et al. 2016; Müller et al. 2018). From 2013 to 2021, a total of 805 forest fires occurred in the study area and most of them occurred (72.3%) in Muğla Province. For lightning-induced forest fire susceptibility mapping, 490 of occurrence data were used as training data and 315 as test data. Considering the spatial distribution of lightning-induced forest fires, it can be seen that they usually occur and cluster at higher elevations and in dense forest covers. The highest contribution rates to lightning-induced forest fires was determined for BIO7 (22.3%), land use (16.7%), BIO3 (15.3%) and leaf type (13.8%). In other words, 68.1% of the probability of occurrence of a forest fire triggered by lightning is determined by these variables. Since the BIO7 variable is an annual temperature range, it can be seen that the occurrence of lightning is highly related to the lowest temperature differences between maximum and minimum values (21.5–34.5 C^{O}).

Evaluating the relationship between the variables and forest fires, it can be seen that the location of forest fires is very closely related to values below 31 C^{O} for BIO7 and above this value the probability of occurrence is minimal. Forest fire risk is highest at a value of 38% for the variable BIO3 and lowest at a value of 41%. The land use variable is very closely related to mixed forest classes, which primarily include *P. brutia* forests. Since both coniferous and mixed forests have a high proportion of *M. Hellenica*, forest fires caused by lightning are a major threat to the existence of *M. Hellenica*. Elevation and temperature have a linear intersection and higher elevations are more susceptible to lightning-caused forest fires. However, since forest fire areas are generally located between 800 and 2030 meters, the elevation variable has less influence since most of the population of *M. Hellenica* is located below 1000 meters.

The AUC results showed that the specification of the training and test data was performed accurately with 0.836 for the training data and 0.783 for the test data. The AUC value of the training data is the lowest value compared to other forest fire causes because lightning is a natural cause and does not occur systematically. Therefore, the occurrence of wildfires caused by lightning is more random compared to other causes. The contribution rates, variable graphs, ROC curve, and AUC values were given in Fig. 6.

The generated map of forest fire susceptibility triggered by lightning was shown in Fig. 7 along with the locations of the training and test data. A total of 2296.48 km^2 of the study area was classified as extremely susceptible to lightning-induced forest fire and 3239.91 km^2 was classified as highly susceptible. The results indicate that the study area has the potential for excessive occurrence of lightning-induced forest fires compared to other causes. *M. Hellenica* population and pine honey production sites are at high risk from lightning-induced forest fires because the distribution of *M. Hellenica* and lightning-induced forest fires share similar characteristics. This result represents the most important finding of the study, since the prevention of lightning-induced fires is much more difficult than the causes of human-induced forest fires.

Figure 7 shows the forest fire susceptibility values caused by lightning in the *M. Hellenica* population and the pine honey production sites. The susceptibility map shows that 1357.6 km^2 of the total 2396 km^2 pine honey production area is extremely susceptible to lightning-induced forest fires, and the pine honey production areas in Yatağan, Marmaris, Ula, Merkez and Köyceğiz districts are highly susceptible to forest fires. The classification of risk values showed that all regions in Yatağan district (more than 80% of the total pine honey production sites) are totally susceptible to forest fires. Therefore, lightning is the only reason that threatens *M. Hellenica* population and pine honey production in Yatağan district. Bodrum, Fethiye and Datça are the districts with the lowest susceptibility to lightning-induced forest fires in the study area.

3.1.1. Cigarette Butt Susceptibility

Discarded cigarette butts are one of the most common causes of forest fires and are less related to environmental variables because cigarettes can be thrown from anywhere, including cars, roads, campgrounds and residential areas (Sari 2022). For this reason, it is more difficult to identify areas that are susceptible to cigarette butt-induced forest fires than other causes. However, discarded cigarette butts can often be related with the land use variable. The spatial distribution of the cigarette butt-induced forest fire susceptibility map was generated using 110 forest fire locations, of which 74 assigned as training data and 46 assigned as test data. AUC values were calculated as 0.868 for sample data and 0.806 for test data. Since the AUC results for the training and test data are very close, it can be assumed that they were selected as homogeneous.

Contribution rates showed that the variables BIO15 (23.1%), land use (9.7%) and wind (8.5%) play a crucial role in cigarette butt-caused forest fires. BIO15 (seasonal precipitation) is the largest contributor to forest moisture, and the higher BIO15 is, the less likely cigarette butts will ignite dry material on the forest floor. The land use variable is also a major contributor as people frequently throw cigarette butts on roads, campsites and settlements. Wind can accelerate the ignition of cigarette butts and increase the ignition rate. The average wind speed was determined to be 2.5 km/h, which is higher than the wind speed determined for other causes of forest fires. When evaluating land use variable, 30.7% of forest fires overlapped with coniferous forests and 19.3% with agricultural lands. The road variable contributes to 6.0% and roads adjacent to the forest represent high-risk areas susceptible to fire. BIO15, imperviousness, roads and riparian zones showed a linear relationship with forest fire and the highest correlation was determined for roads within 10 meters. Imperviousness and riparian zones show the same graph and the susceptibility value tends to increase where these variables have minimum values. For the land use variable, most of the forest fire locations intersected with urban areas (1) and mixed forests (27). The contribution rates, variable graphs, ROC curves and AUC values were given in Fig. 8.

In the map of forest fire susceptibility caused by cigarette butts, an area of 1426 km^2 was classified as extremely susceptible and an area of 2420.9 km^2 was classified as highly susceptible to forest fires. The results showed that the study area was less susceptible to forest fires caused by cigarette butts than other causes and was located outside of the pine honey production sites. Since cigarette butts are usually discarded from roads and settlements, the risk areas did not overlap with dense forest cover and pine honey production sites. As can be seen in Fig. 9, risk areas were clustered in coastal and camping areas where tourism activities are intense in the inner regions of Aydın and Muğla provinces.

When the areas where pine honey is produced were examined, only an area of 116.8 km^2 was found to be extremely sensitive to forest fires caused by cigarette butts. The distribution of susceptibility values determined for districts showed that Marmaris, Datça and Fethiye districts have extremely susceptible areas, while other districts are not susceptible to forest fires caused by cigarette butts. These districts are the main centers of tourism in this region and cigarette butts have caused forest fires only in these districts due to the high population density in summer. For this reason, pine honey production sites near hotels and settlements are much more sensitive than other areas. Susceptibility map and graphs were given in Fig. 9.

3.1.2. Power lines Susceptibility

Contact of trees with high-voltage power lines can cause arcing (Mitchell 2013) and wind can move branches toward the power lines. The arc can fall to the ground and ignite trees directly. There are several ways that forest fires can be caused, including falling power lines, contact with vegetation and conductor slap. In this case, trees near power lines are more at risk than others. Although 80 forest fires were occurred between 2013 and 2021, power lines pose a significant risk because they overlap with dense forests and pine honey production sites. Therefore, this cause of forest fire should be considered a threat to pine honey production in the study area. The spatial distribution of the power line-based forest fire susceptibility map was generated using 80 wildfire locations, 49 of which were assigned as training data and 31 as test data. AUC values were calculated as 0.904 for sample points and 0.765 for test points. In this study, the highest gain was obtained with a value of 0.904 for power lines. On the other hand, due to the limited sample size, the largest difference between test and training AUC values was calculated for power lines.

In the evaluation of contribution rates, the variable roads has the highest contribution rate (33.8%) because power lines are usually installed along the road due to the topography of the region. After that, power lines (12.3%), precipitation (8.5%) and land use (7.8%) were determined as the most important variables. The power line variable has the highest gain below 50 meters from the power lines, while above 2000 meters the gain is minimal. The power line variable achieves the highest gain at distances between 10 and 30 meters from roads, since most power lines are installed at these distances. The precipitation and BIO15 variables formed graphs where 85 mm/m^2 of precipitation and 36% BIO15 values showed the highest gain. These upper values refer to wet and windy objects that can easily make a bow, since precipitation in the study area is generated by wind and contact with power lines often occurs in windy weather conditions. The elevation variable is directly related to the locations of power lines, which are very difficult to install at higher elevations. The contribution rates, variable graphs, ROC curves and AUC values were given in Fig. 10.

The generated susceptibility map showed that the areas of highest susceptibility were clustered in the coastal areas of the study area and an area of 943.9 km^2 was classified as extremely susceptible to forest fire. It was found that 184.7 km^2 of the identified risk areas overlapped with areas where pine honey is produced, as most power lines intersect with dense forests. The highest susceptibility values were determined in Ortaca, Marmaris, Ula, Datça, Dalaman and Fethiye districts. Since the locations of power lines are known and the risk value can be estimated by evaluating the areas under the power lines in terms of their contact with vegetation and combustible objects, it is possible to prevent power lines causing forest fires and to take precautions compared to other reasons. Power lines should be designed with sufficient distance from trees to avoid contact. The susceptibility map and graphics were given in Fig. 11.

3.1.3. Stubble Burning Susceptibility

Stubble burning remains the most common method of grain residue destruction and is prohibited by local authorities because of fire damage to the soil and the risk of forest fires. Fires on agricultural land can spread very quickly because the materials are very small and dry. For this reason, stubble fires often spread quickly and it is not possible to prevent them from spreading to undesirable places such as forests. Since stubble fires occur only on agricultural land, the highest gain should be calculated for the land use variable. To generate a map of forest fire susceptibility caused by stubble fires, a total of 58 forest fire locations were used, 32 of which assigned as training data and 26 as test data. AUC values were calculated as 0.870 for the training data and 0.690 for the test data. The AUC values showed that the specification of the training and test data was performed homogeneously. However, similar to the evaluation of power lines-induced forest fire assessment, the training and test data resulted in a higher difference in AUC values due to the limited data on forest fires.

When examining the contribution rates of the variables, the highest rate was found for the land use variable with a value of 55.7%. Considering the results of forest fire locations overlapping with land use classes, 38.3% overlapped with agricultural land and 13.8% overlapped with transitional forests, which are the boundary between agricultural land and forests. The road variable is also a major contributor, as stubble burning originates from the side of the agricultural lands facing the road, so fire spread can be easily controlled. Irrigated and non-irrigated agricultural land use classes and distances less than 30 meters from roads have the highest gains for the land use and road variables. Broad-leaved forest types provide the highest gain because agricultural lands are located in or near such forests. The elevation variable has a decreasing gain graph when agricultural lands are located at higher elevations due to meteorological conditions and at lower elevations on slopes. Contribution rates, variable graphs, ROC curves and AUC values were given in Fig. 12.

The stubble burning susceptibility map shows that forest areas near agricultural land are extremely susceptible to forest fires. An area of 1432.3 km^2 was determined to be extremely susceptible to stubble fires and an area of 136 km^2 overlapped with areas where pine honey is produced. Most of the susceptible areas are located in Aydın, where pine honey is not produced. Due to the fact that agricultural activities are more intensive than in other districts, Bodrum and Ortaca districts are the districts with the highest sensitivity value. Yatağan, Datça, Köyceğiz and Ula districts have the lowest sensitivity values and the pine honey production areas in these regions are not susceptible to forest fires. The Susceptibility maps and graphics were given in Fig. 13.

Discussion

The most striking result of this study is that more than half of the pine honey production areas are threatened by lightning-induced forest fires. It appears that lightning-induced forest fires, which are the most difficult to prevent and control, will continue to be a threat to pine honey production in the region. Lightning and extreme heat are considered to be the main causes of forest fires caused by natural causes and lightning has been studied separately in many studies (Liu et al. 2016; Müller et al. 2018; Abdollahi et al.2019; Heidari et al. 2021). Although other causes of forest fires pose a threat to the region, forest fires started by lightning are a much greater threat because they are very difficult to prevent and predict. The fact that each cause of forest fire threatens the region's pine honey production sites to varying degrees, emphasizing the importance of cause-related forest fire researches. Given the frequency of occurrence and frequency of fires, it is necessary to consider the causes separately (Oliveira et al. 2017). Although there are studies that evaluate all the causes together, it will be more effective to study the causes individually, since the priority is to establish precautionary and protective mechanisms for pine honey production areas (Bar Massada et al. 2012; Hu and Zhouu 2014; Suresh et al. 2016; Vacchiano et al. 2018; Kim et al. 2019; Vilar et al. 2019 Banerjee 2021, Sarı 2021,2022; Dijkstra et al. 2022). Thus, the measures that can be taken for each pine honey production site are determined taking into account the structure, topography and environmental conditions of the region. Human-caused forest fires have been the subject of much research (Wang et al. 2010; Guo et al. 2016b; Martín et al. 2019) and offered more spatial and applicable solutions in terms of preparedness and prevention measures, as they are easier to prevent than natural causes.

Conclusion

When the fire susceptibility obtained as a result of the study is examined, it is seen that most of the pine honey production areas are threatened by lightning-induced forest fires. Lightning, which is one of the causes of natural fires, creates a much more difficult process to predict and prevent than human-made forest fires. Therefore, since pine honey production areas are less threatened by human-induced forest fires, ensuring sustainable pine honey production largely depends on the prevention of lightning-induced forest fires. Although there is no study that produces definitive results in terms of preventing lightning-induced forest fires, it is seen that there are some studies in China on the elimination of lightning by lightning rods. However, this issue is still in the idea stage and its applicability and reliability have not been proven yet. At this point, the only remaining solution is to determine the early intervention procedures for lightning-induced forest fires. As a result of this study, according to the risk map produced, the deployment of early intervention vehicles to the points where pine honey production is concentrated, during the periods when fires are experienced very frequently, appears as the most applicable solution proposal.

Although pine honey production sites are much less threatened by human-induced forest fires, the probability of human-induced forest fires should also be evaluated in order to minimize the risk. Considering that many pine honey production areas are adjacent to regions where tourism activities are intense, additional measures should be taken in the dates and locations where tourism activities are very intense. At this point, people were prohibited from entering the forests during the summer months in 2022, and criminal sanctions were imposed on those who violated this rule. In particular, warning signs have been hung at the forest entrances where pine honey is produced, and it is aimed to minimize human activity in the forests. Similarly, although stubble burning is completely prohibited, unfortunately, farmers still use this way to prepare their fields for the new season. At this point, it is foreseen that the increase of penal sanctions and the intensification of controls during the stubble burning season will greatly reduce the possibility of forest fires caused by stubble burning.

Since pine honey production sites and forest fires have so many common points, this process is a problem that will be encountered as a threat in the future, as it was in the past. Although it is not possible to completely reduce the risk to zero, at least it is possible to reduce or control the causes that may cause the fire. Apart from the measures that can be taken at this point, it is anticipated that focusing on the earliest intervention options when a fire occurs will be a very beneficial approach in terms of sustainable pine honey production. Especially, districts of Milas, Marmaris, Ula, Köyceğiz and Datça should be declared as priority protected areas and these areas should be prioritized for fire prevention works. Although it is on the agenda to create new production areas by moving *M. Hellenica* to other regions to ensure the continuity of pine honey production in our country, it is necessary to take fire prevention measures to achieve real sustainability. For these measures, not only the responsible institutions, but also the local population and the pine honey producers should be trained and sensitized to fire prevention and early intervention.

Declarations

The authors have no relevant financial or non-financial interests to disclose.

The authors have no competing interests to declare that are relevant to the content of this article.

All authors certify that they have no affiliations with or involvement in any organization or entity with any financial interest or non-financial interest in the subject matter or materials discussed in this manuscript.

The authors have no financial or proprietary interests in any material discussed in this article.

Data Availability Statement

The datasets generated during and/or analysed during the current study are available from the corresponding author on reasonable request.

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Figures

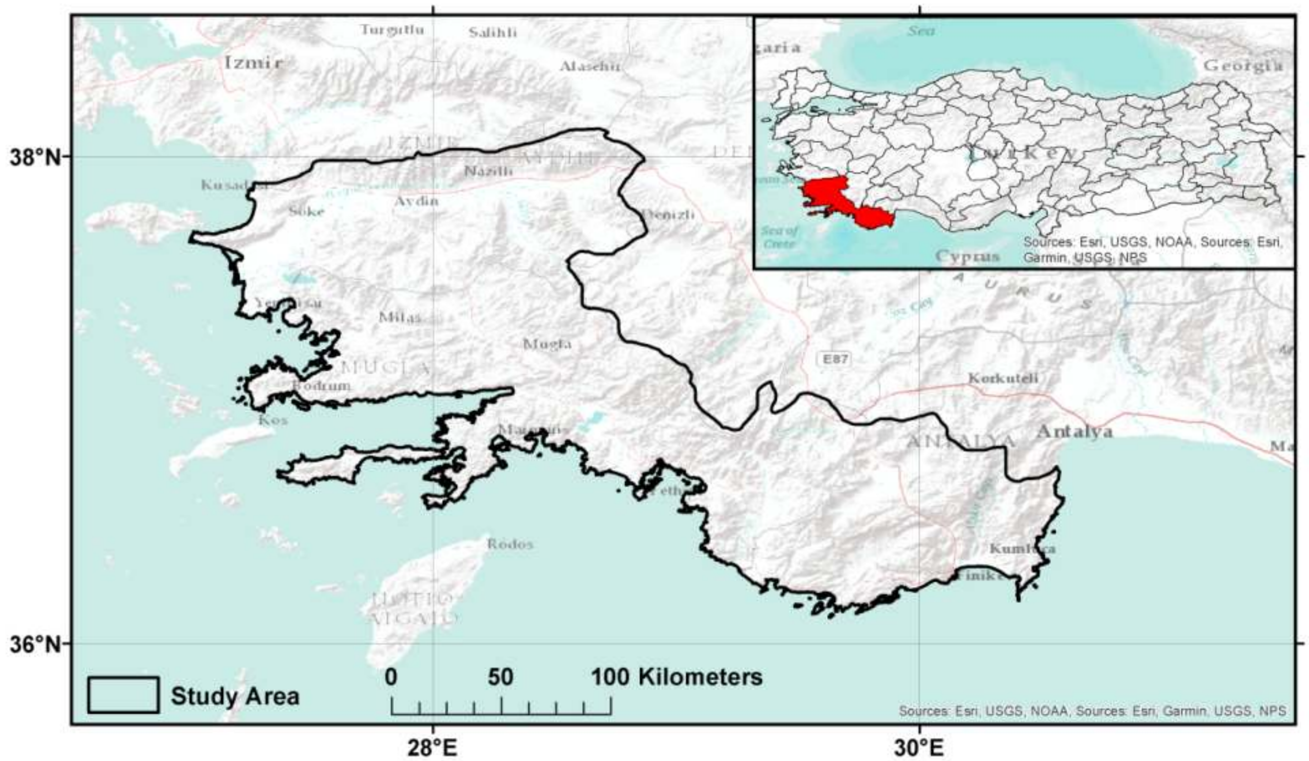

Figure 1

Study Area Boundaries

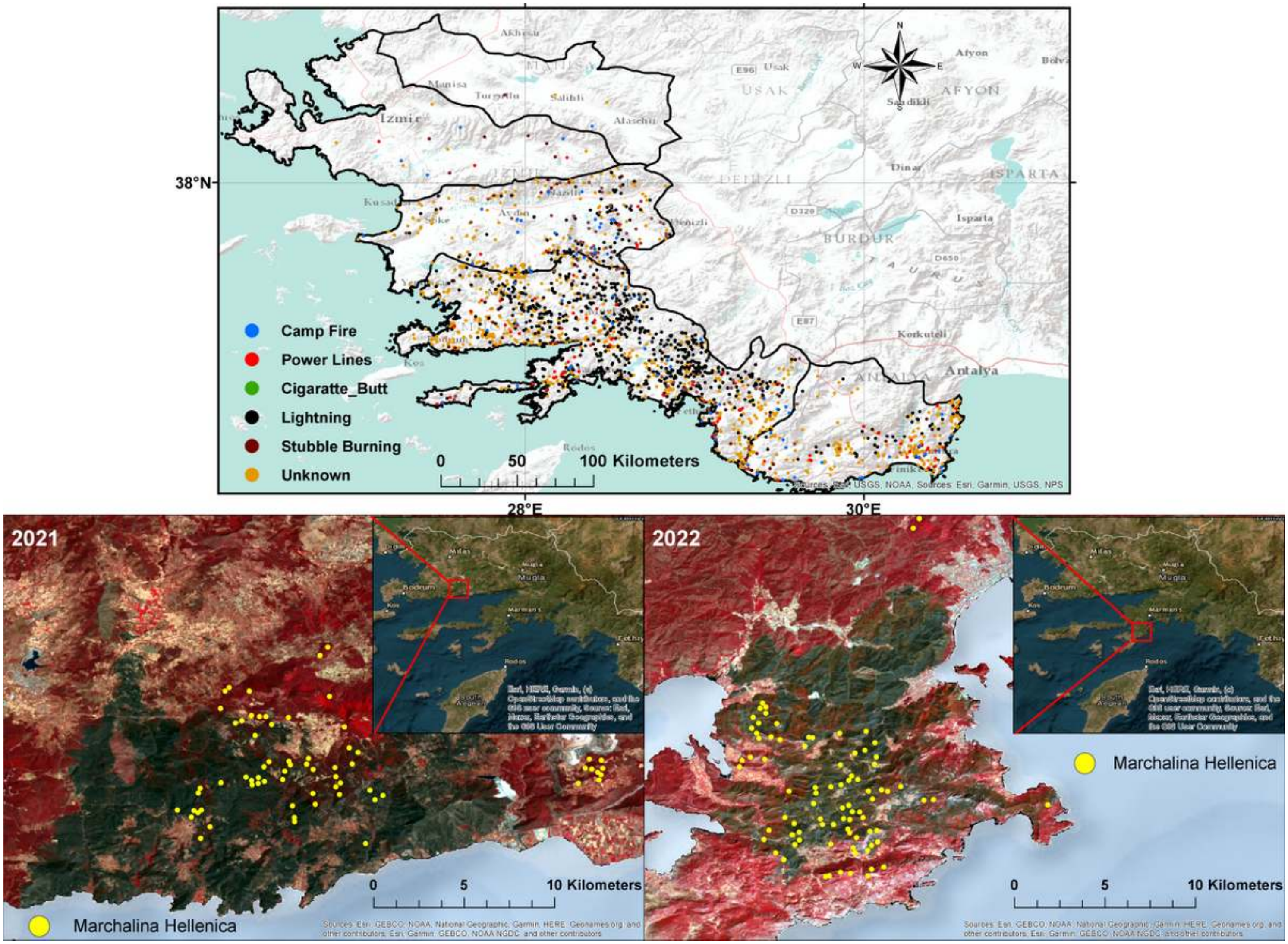

Figure 2

Forest fire causes and their distributions

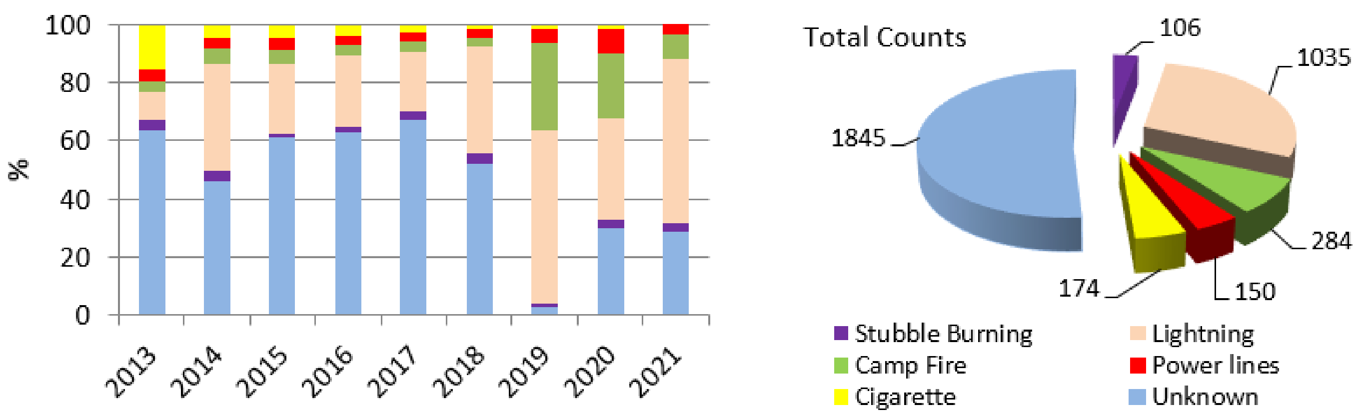

Figure 3

Forest Fire Occurrence Statistic from 2013 to 2021

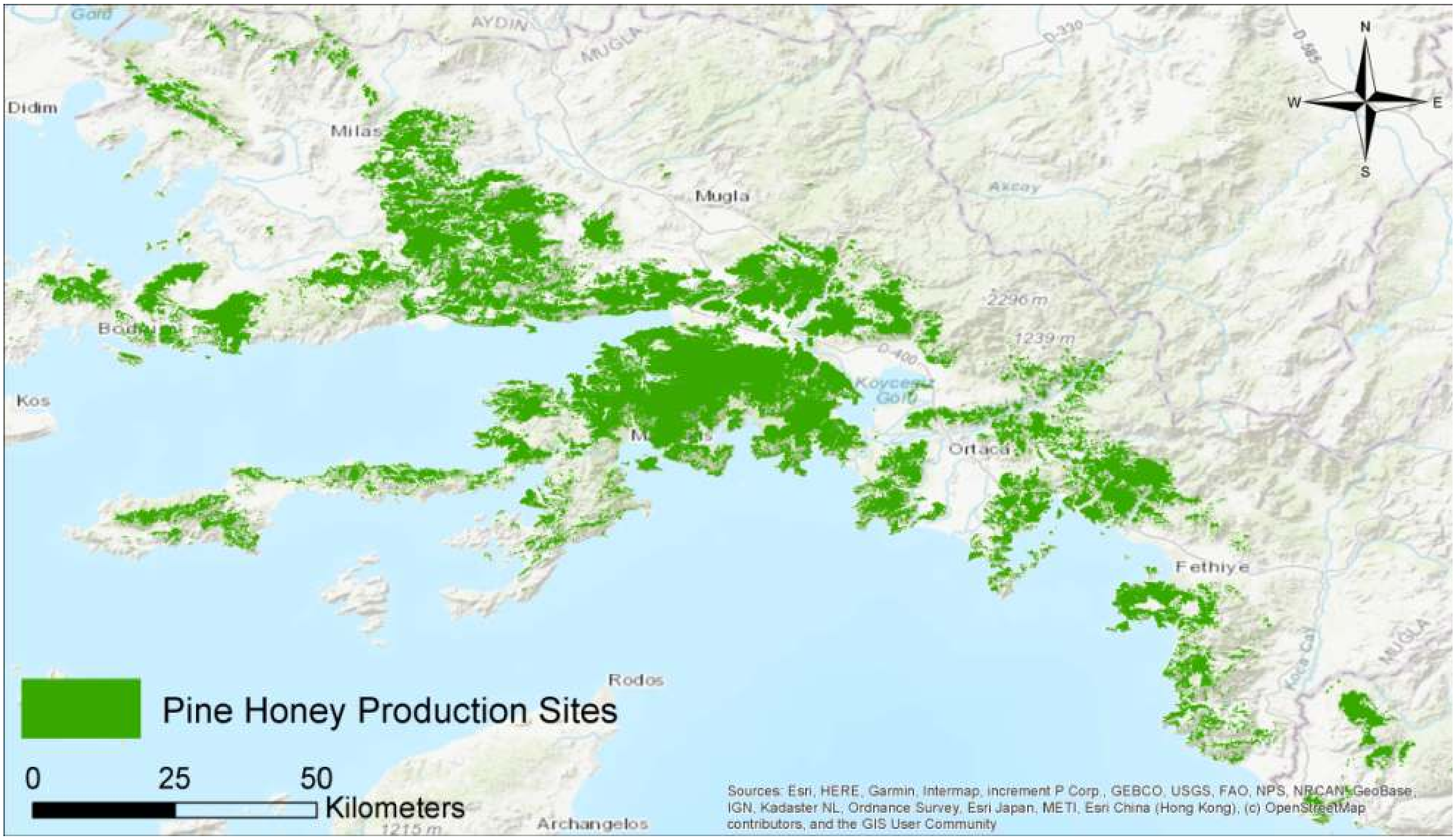

Figure 4

Pine honey production sites and Red Pine forests

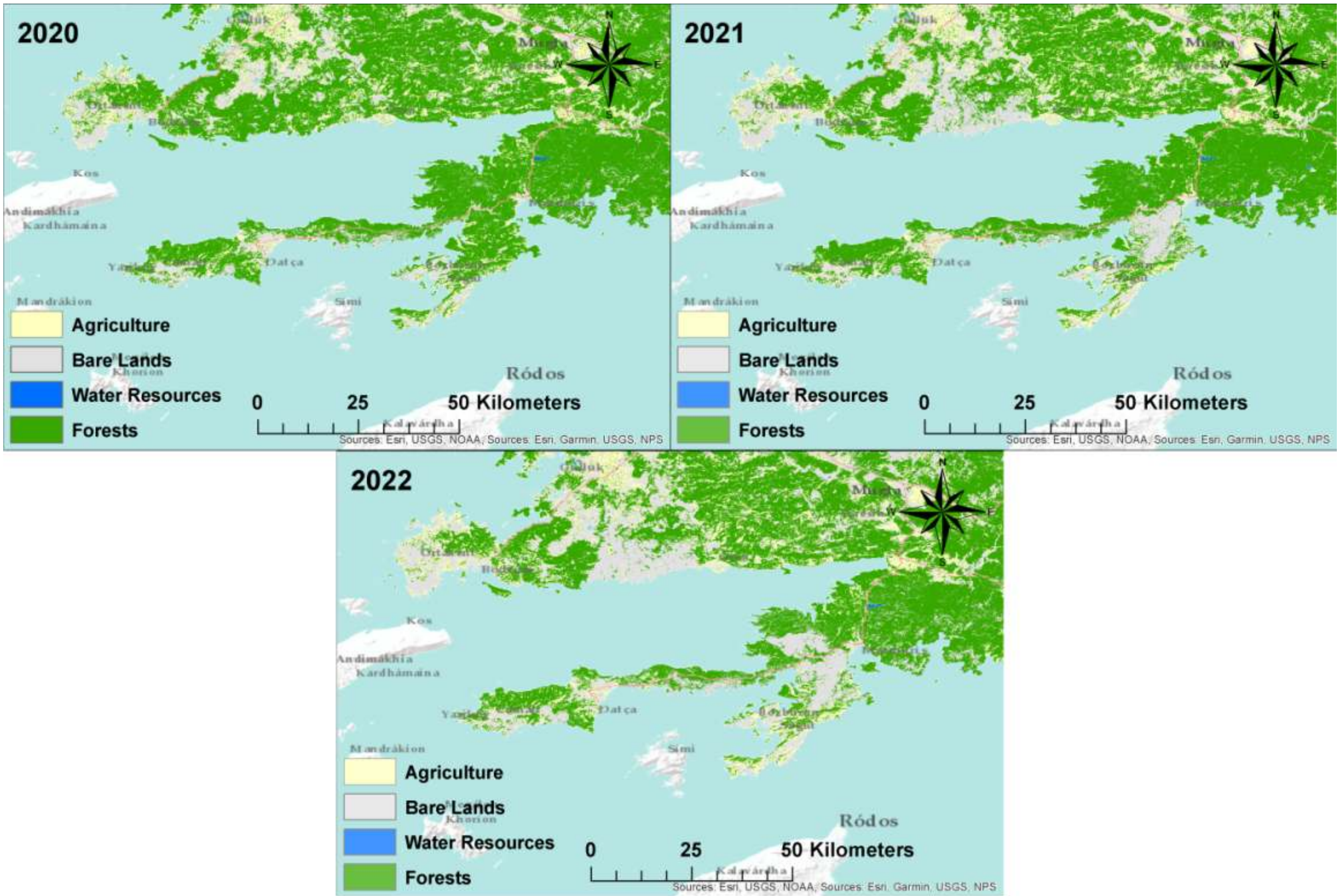

Figure 5

Forest cover change in 2020, 2021 and 2022 years

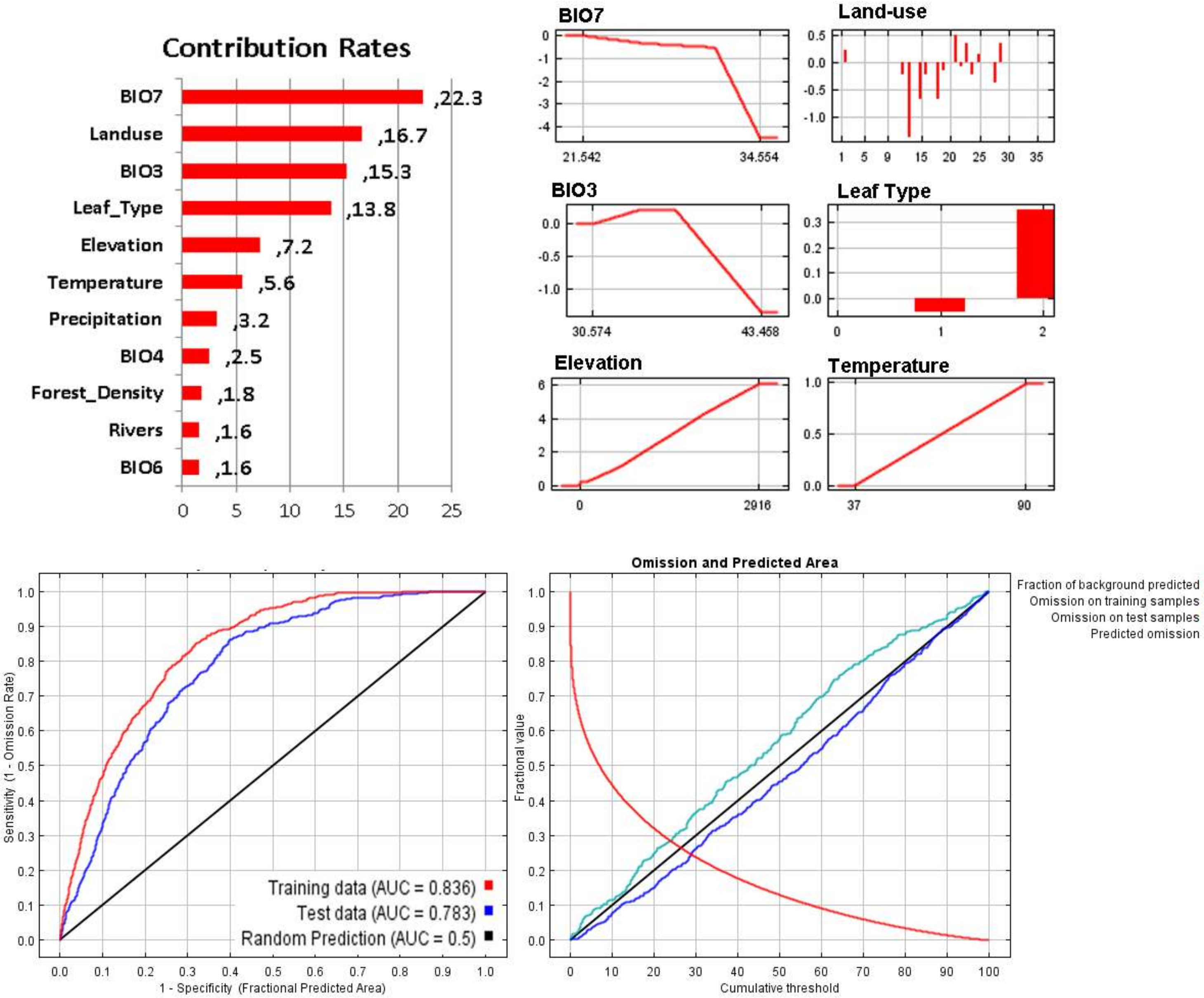

Figure 6

Contribution rates, variable graphics and ROC curves for lightning-induced forest fire susceptibility

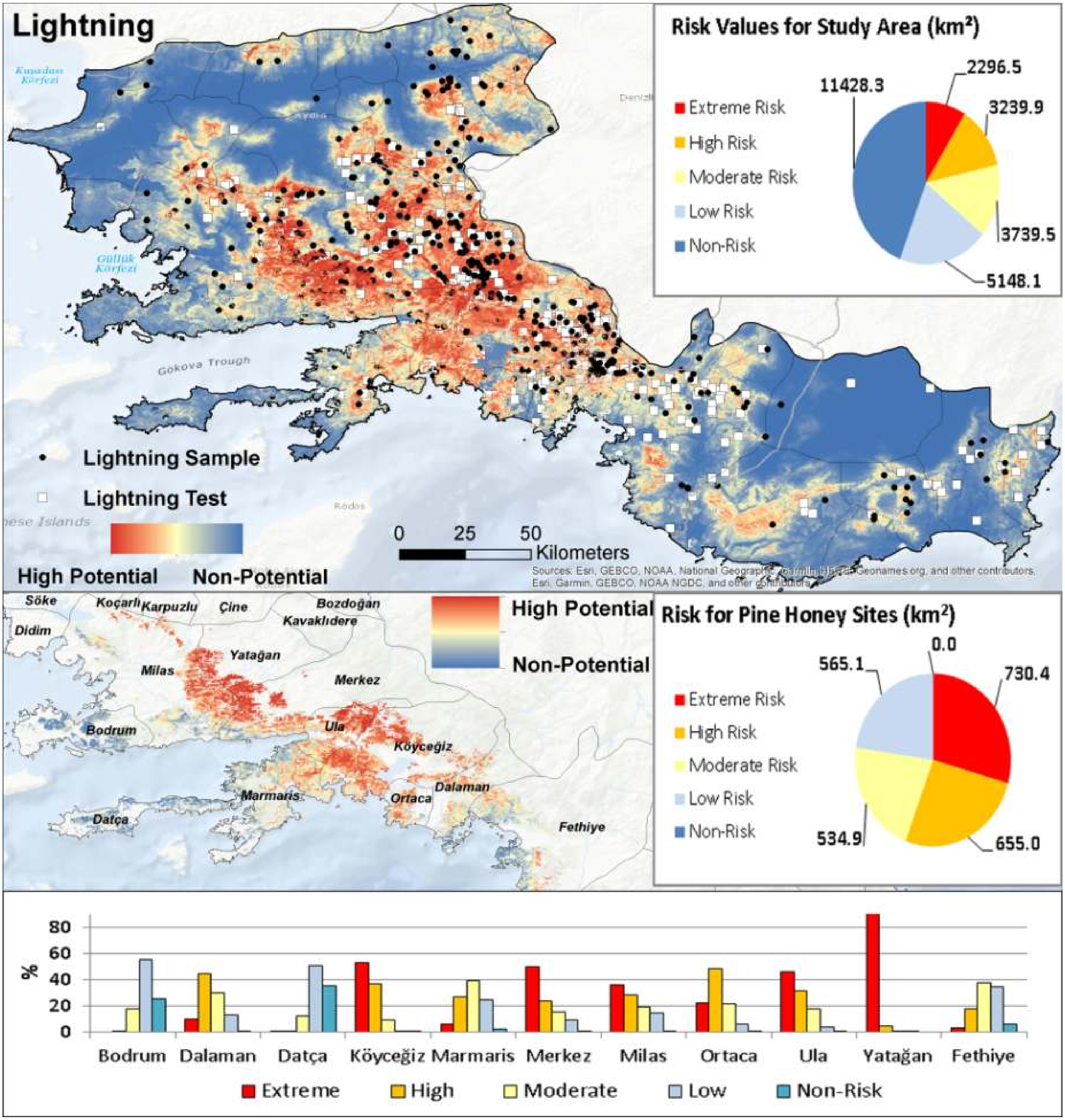

Figure 7

Lightning-induced forest fire susceptibility and risk distributions to pine honey production sites

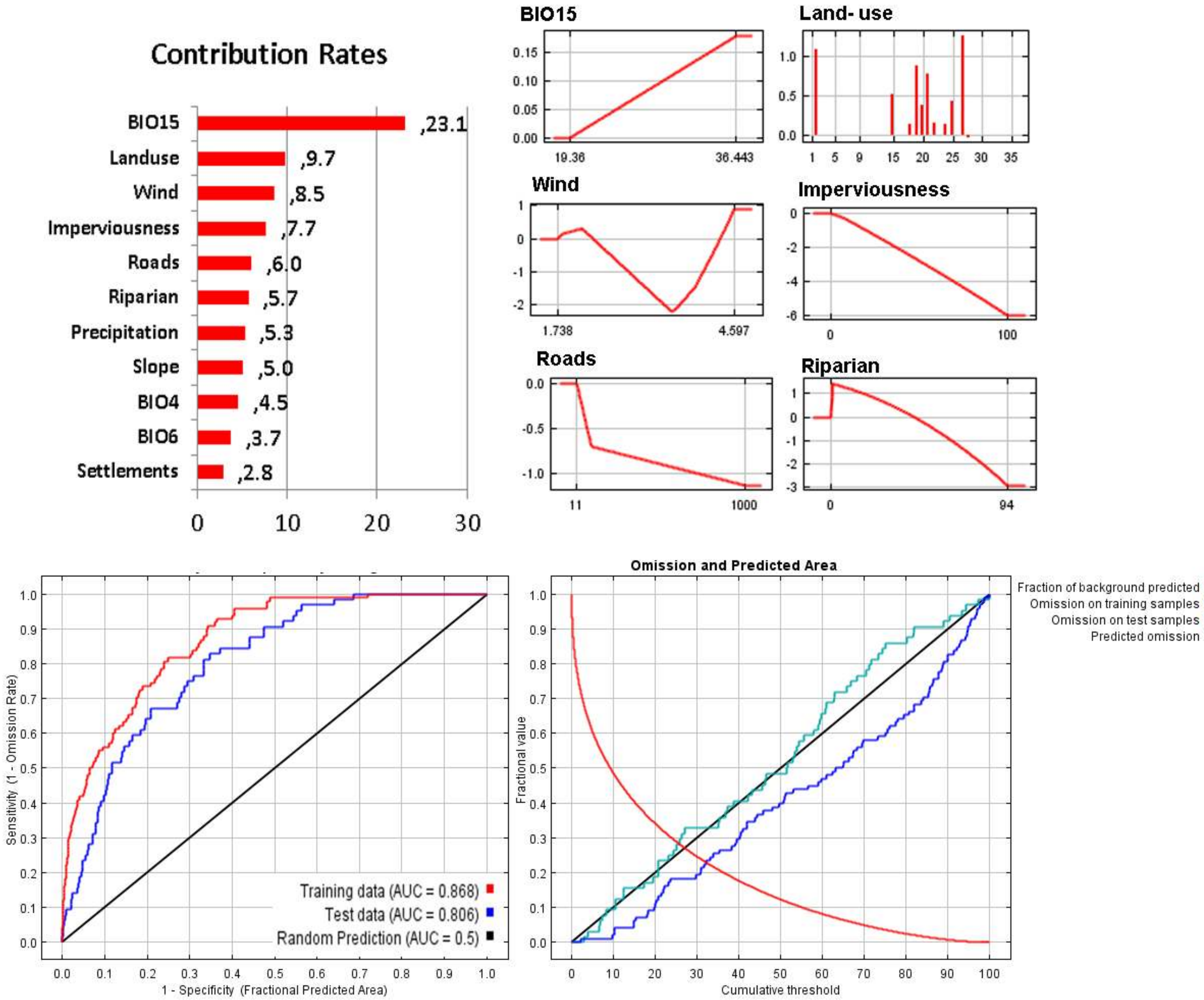

Figure 8

Contribution rates, variable graphics and ROC curves for cigarette butt forest fire susceptibility

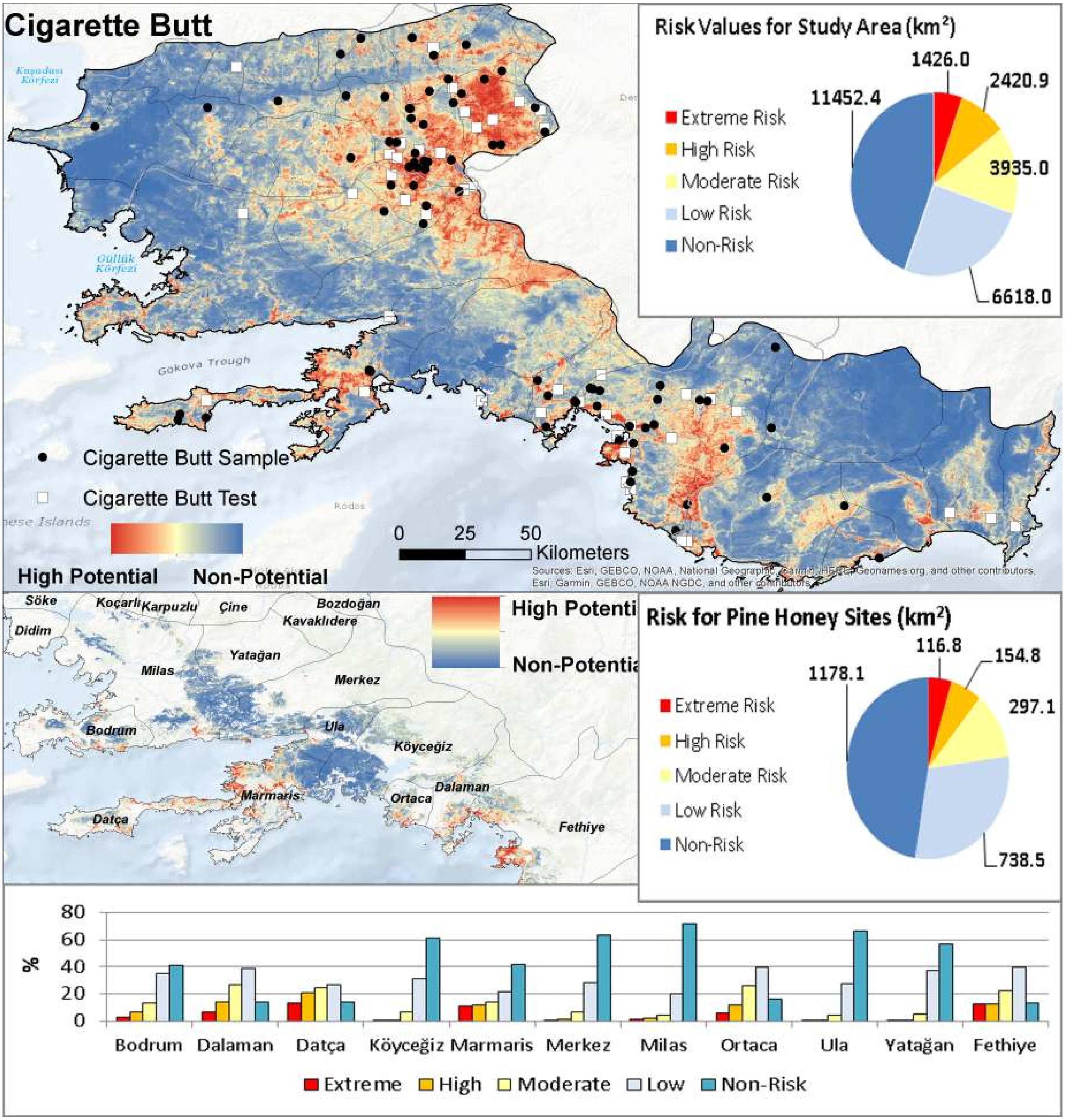

Figure 9

Cigarette butt caused forest fire susceptibility and risk distributions to pine honey production sites

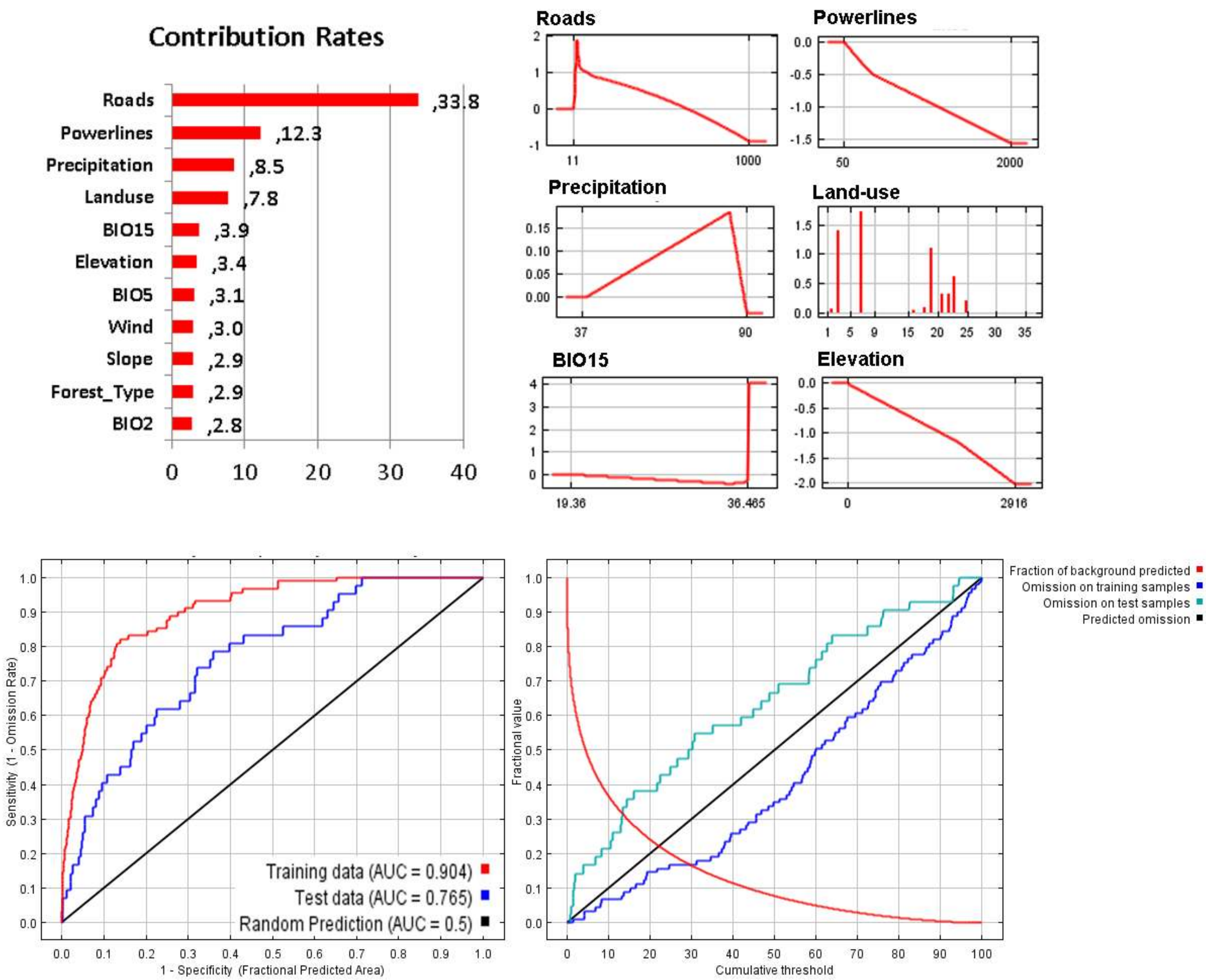

Figure 10

Contribution rates, variable graphics and ROC curves for power lines caused forest fire susceptibility

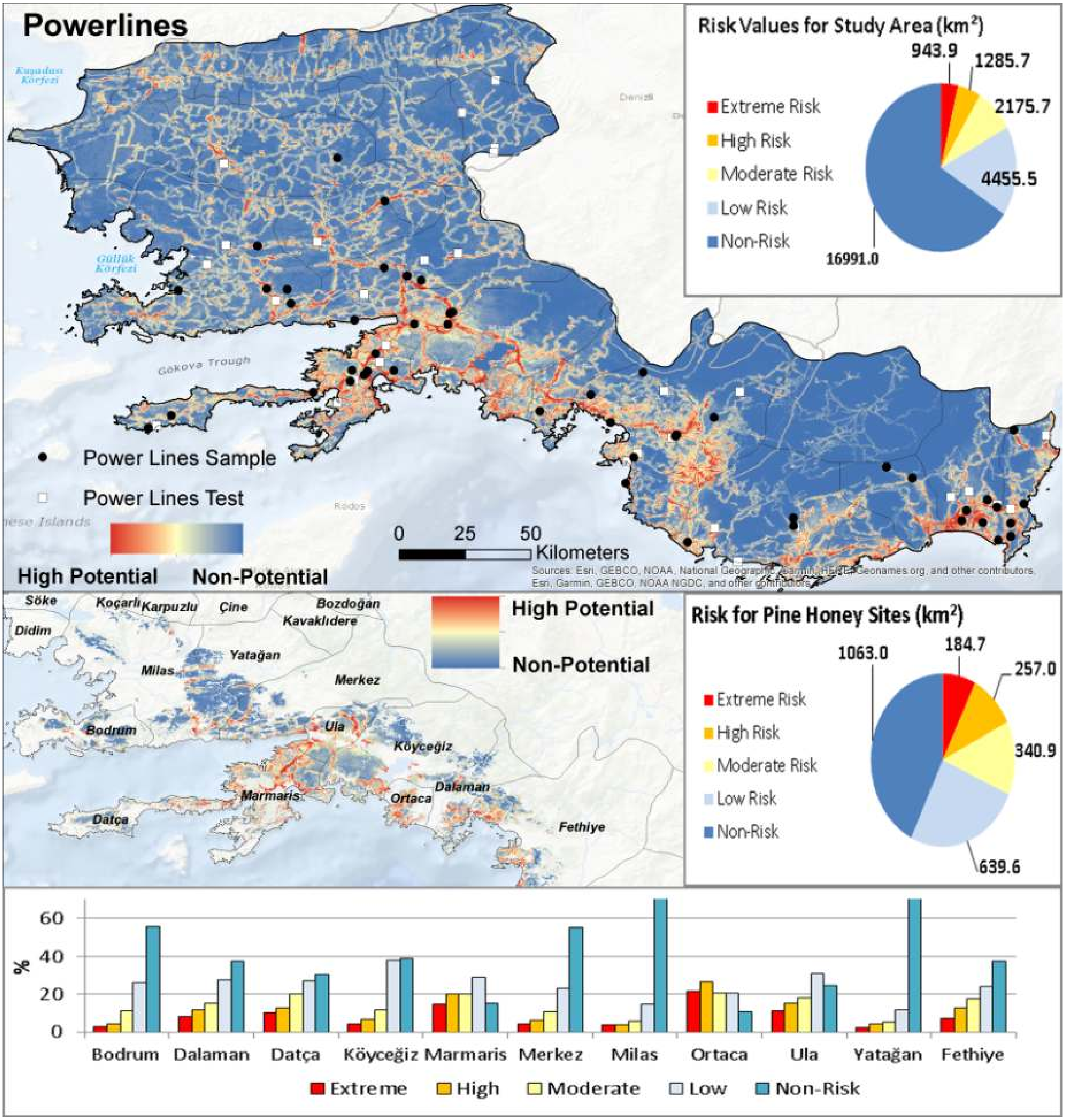

Figure 11

Power lines caused forest fire susceptibility and risk distributions to pine honey production sites

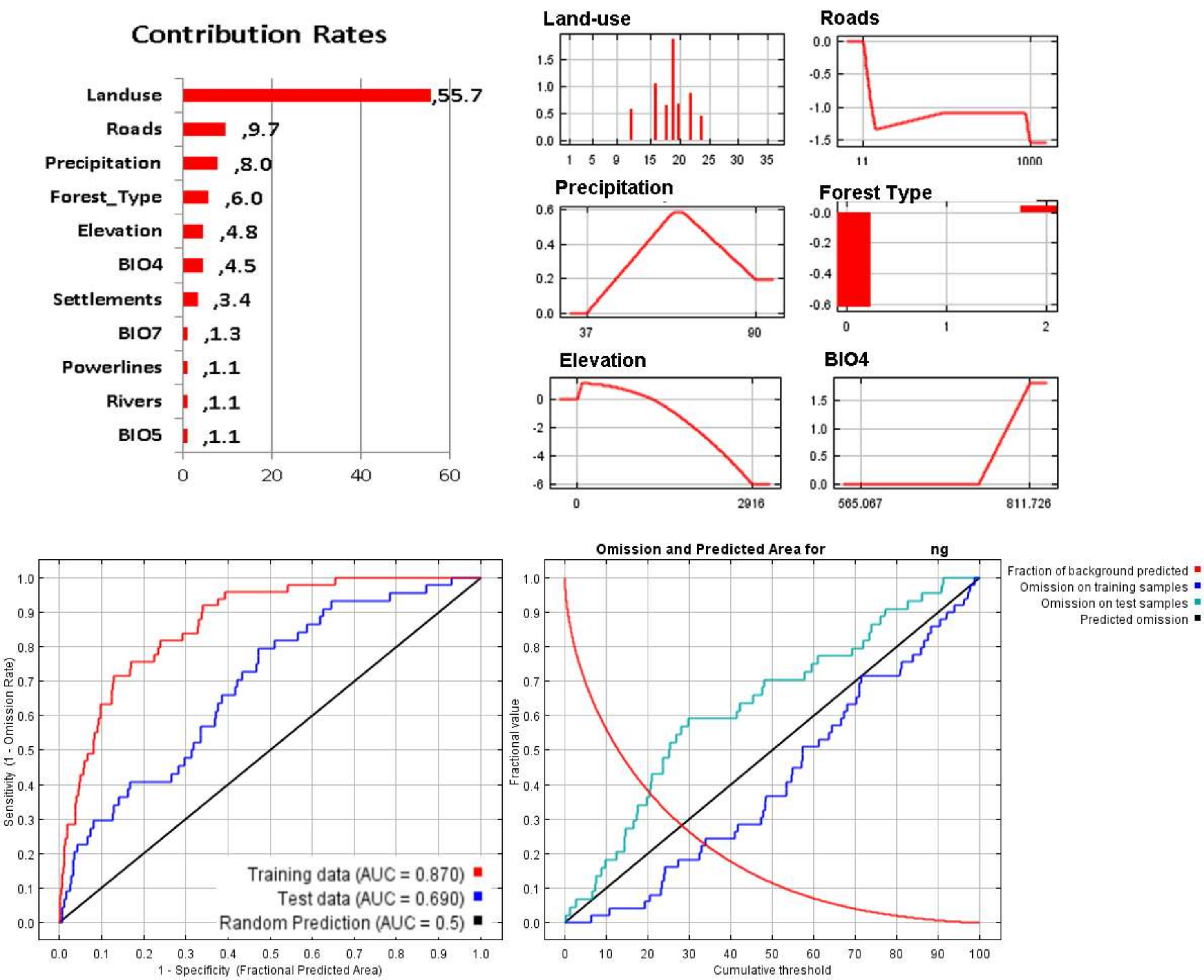

Figure 12

Contribution rates, variable graphics and ROC curves for stubble burning caused forest fire susceptibility

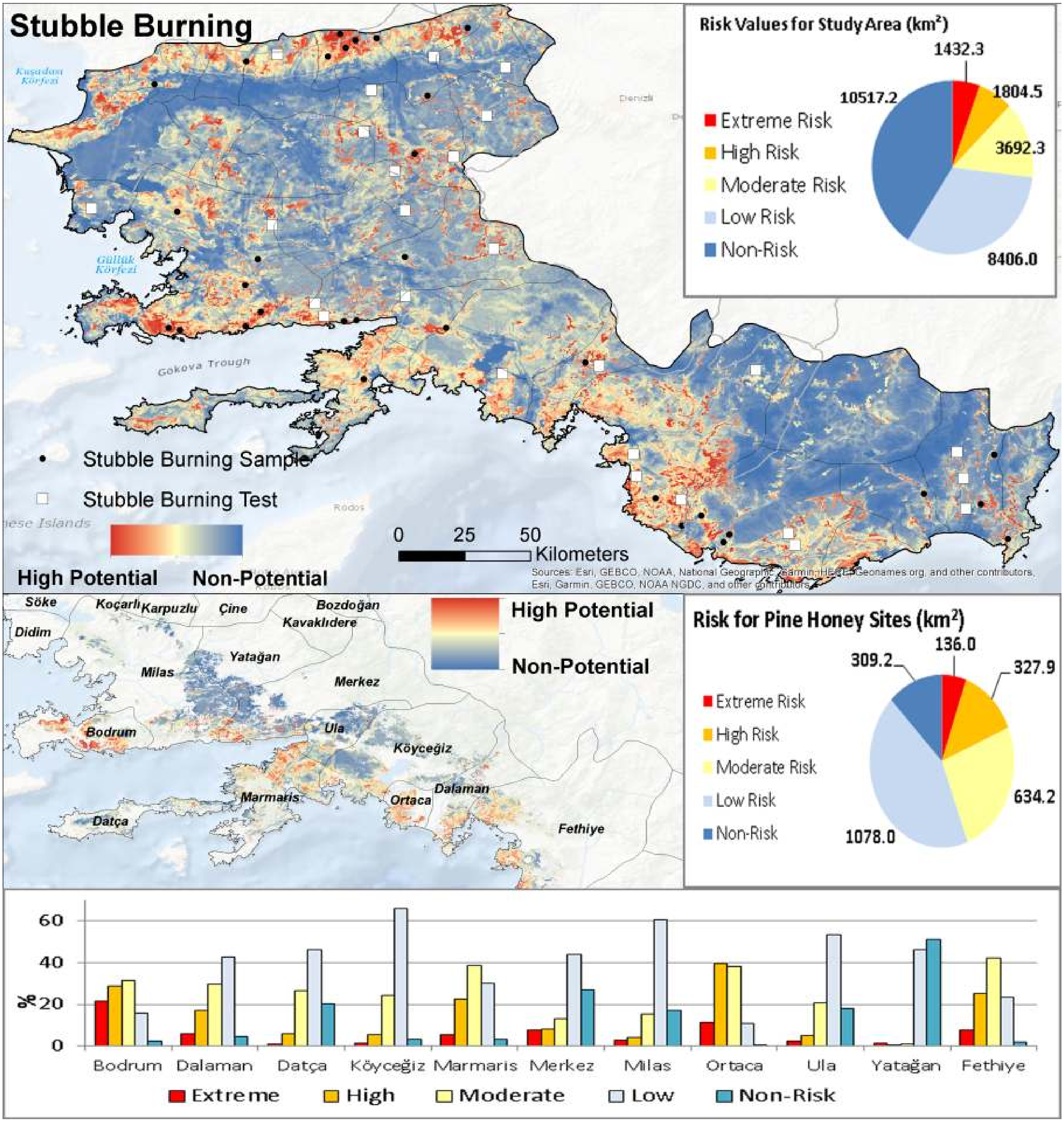

Figure 13

Stubble Burning caused forest fire susceptibility and risk distributions to pie honey production sites