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Original article (Orijinal araştırma)

Comparative assessment of AHP and FRM approaches for susceptibility mapping of pine processionary moth[1]

Çam kese böceğinin duyarlılık haritalamasında AHP ve FRM yaklaşımlarının karşılaştırmalı değerlendirmesi

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Abstract

This study aims to develop susceptibility maps for the Pine Processionary Moth (PPM) via multi-criteria decision-making methodologies. This study utilized data on forest stands affected by PPM damage within the Nurdağı Forest Planning Unit in Gaziantep province from 2018 to 2024. Parameters including stand structure, crown closure, development stage, elevation, slope, aspect, annual mean temperature, solar radiation, and annual mean precipitation parameters were used to create the PPM susceptibility maps according to the Analytical Hierarchy Process (AHP) and the Frequency Ratio Method (FRM). Their precision was evaluated by Relative Operating Characteristic (ROC) analysis. The AHP model indicates that 73% of the forest stands with PPM damage fall into the high and extreme susceptibility groups, whereas the FRM model shows that 68% of such forest stands are similarly categorized. The AUC values for the FRM and AHP models were determined to be 0.830 and 0.835, respectively. The results reveal that the PPM susceptibility maps generated using the AHP and FRM models are reliable.

Keywords: Annual mean precipitation, Geographic Information Systems, ROC, *Thaumetopoea wilkinsoni*

Öz

Bu çalışmada, çok kriterli karar verme metodolojileri kullanılarak Çam Kese Böceği (ÇKB) için duyarlılık haritalarının geliştirilmesi amaçlanmıştır. Çalışmada, Gaziantep ili Nurdağı Orman İşletme Şefliğinde 2018-2024 yıllarındaki ÇKB zararı olan meşcere verileri kullanılmıştır. Meşcere yapısı, kapalılık, gelişim çağı, yükselti, eğim, bakı, yıllık ortalama sıcaklık, güneş radyasyonu ve yıllık ortalama yağış parametreleri ÇKB duyarlılık haritalarının oluşturulmasında kullanılmıştır. ÇKB duyarlılık haritaları Analitik Hiyerarşi Süreci (AHP) ve Frekans Oranı Yöntemi (FRM) kullanılarak geliştirilmiş ve doğrulukları Göreceli İşletme Karakteristiği (ROC) analizi ile değerlendirilmiştir. AHP modeli, ÇKB zararı olan ormanlık alanların %73'ünün yüksek ve aşırı duyarlılık gruplarına girdiğini gösterirken, FRM modeli bu ormanlık alanların %68'inin benzer şekilde kategorize edildiğini göstermektedir. FRM ve AHP modelleri için AUC değerleri sırasıyla 0,830 ve 0,835 olarak belirlenmiştir. Sonuçlar, AHP ve FRM modelleri kullanılarak oluşturulan ÇKB duyarlılık haritalarının güvenilir sonuçlar verdiğini göstermiştir.

Anahtar sözcükler: Yıllık ortalama yağış, Coğrafi Bilgi Sistemi, ROC, *Thaumetopoea wilkinsoni*

[1] The current study was carried out based on an MSc thesis authored by first author and supervised by second author, affiliated with the Institute of Natural and Applied Science at Kastamonu University, Türkiye

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Introduction

Forests are renewable natural resources that are vital for meeting the growing demand for wood raw materials, contributing to climate change mitigation, and conserving biodiversity (Ollikainen, 2014; Griscom et al., 2017). Forests are significantly affected by many abiotic and biotic factors (Campoa et al., 2021), and coniferous forests are especially vulnerable to these factors (Seidl et al., 2017). Natural factors such as storms, fires, drought, diseases, and insect outbreaks change the structure of forests, negatively affecting the sustainability and functioning of the forest ecosystem (Seidl et al., 2017) and disrupting the flow of goods and services (Jactel et al., 2021).

The negative impact of insect pests, which are biotic factors, is higher than abiotic factors (Kautz et al., 2017). Among these, insect pests have a particularly significant impact on forest structure. In healthy forests, insects and diseases are an essential part of the forest ecosystem (Dajoz, 1998), while intense insect outbreaks negatively affect the growth and survival of trees (van Lierop et al., 2015). Outbreaks of these pests negatively affect ecosystem services, forest economy, biodiversity, and sustainable ecosystem management (Seidl et al., 2017). It is also possible that forests will face more frequent and severe insect outbreaks in the coming decades due to global climate change (Logan et al., 2003).

Foliage-damaging insects damage trees by eating needles or leaves and eliminating photosynthetic tissue (Senf et al., 2017). Among these pests, one of the most destructive species in forests is the Pine Processionary Moth (PPM) [*Thaumetopoea pityocampa* (Denis & Schiffermüller) 1776 & *Thaumetopoea wilkinsoni* Tams, 1925 (Lepidoptera: Thaumetopoeidae)] (Kerdelhué et al., 2009). It is one of the most important pests of pine forests (İpekdal et al., 2015) in Mediterranean countries, especially in coastal areas (Bonamonte et al., 2013). Pine and cedar tree species are the main hosts of PPM (FAO, 2009). *Pinus nigra* J.F.Arnold, *Pinus brutia* Ten., *Pinus sylvestris* Gouan and *Pinus halepensis* Mill. (Pinales: Pinaceae) are the tree species it damages in Türkiye (Can & Özçankaya, 2003; Onaran & Katı, 2010).

Since PPM causes damage to needles, it can cause serious economic losses (Kanat et al., 2005). Numerous studies on this subject reveal that PPM causes significant reductions in diameter and volume increments in trees (Kanat & Sivrikaya, 2005; Durkaya et al., 2009; Erkan, 2011). It is also alarming that outbreaks of pests are increasing in the Mediterranean region due to global warming and the expansion of forest areas (Azcárate et al., 2003).

The dispersal abilities of species, interactions between habitat selection, or individuals influence the spatial distribution of populations. Spatial analyses facilitate the understanding of the ecological processes in which an organism is found. Spatial and temporal analysis are important for finding out about the severity and spread of insect infestations and how outbreaks happen. This helps people take the right measures and find areas that are more likely to get infected (Aukema et al., 2006; Özcan et al., 2022). Determining the spatial distribution of insect damage, determining the factors affecting the spatial distribution, and understanding outbreaks, as well as tree mortality, will contribute to the sustainability of the forest ecosystem. Information technologies that enable the collection, storage, analysis, and presentation of spatial information on insect damage (Campbell & Shin, 2011) are effectively used in susceptibility analysis of insect outbreaks, assessments of stand, topography, and climate characteristics, and determination of outbreak susceptibility (Vasquez et al., 2020; Özcan et al., 2022).

In recent years, interest in new models and tools to support decision-making processes and planning in forestry has increased significantly. This increased interest encourages the use of new methods/models and technologies developed to solve complex forestry problems more effectively (Vacik & Lexer, 2014). These developments allow for more accurate, flexible, and optimized forestry decision-making processes. Geographic Information System (GIS)-based Multi-Criteria Decision Analysis (MCDA) is used as an effective tool in complex decision-making processes by integrating multiple variables with spatial and temporal data (Greene et al., 2011; Atanasova-Pacemska et al., 2014). GIS-based MCDA is a process that combines spatial data with the decision maker's preferences to produce results (Drobne & Lisec, 2009). Forestry widely employs various decision-making techniques. The Analytic Hierarchy Process (AHP), Logistic Regression (LR), and statistically based quantitative Frequency Ratio Methods (FRM) have been effectively used, especially in fire, landslide susceptibility, insect susceptibility maps, and forest road studies (Hong et al., 2017; Naghibi et al., 2020; Sivrikaya & Küçük, 2022). However, no studies are using AHP and FRM to estimate PPM susceptibility in Calabrian pine forests in Türkiye, and limited studies involving decision-making techniques to predict insect damage in the world (Özcan et al., 2022; Sivrikaya et al., 2022; Tahri et al., 2022).

It is crucial to identify potential threats in forest ecosystems early on and identify relevant strategies to deal with them (Kunegel-Lion & Lewis, 2020). An important step for sustainable forest management for ecosystem managers is to find out what causes the PPM to spread and which areas are most likely to get it using GIS-based MCDA and FRM (Kärvemo et al., 2014). In this context, determining the parameters affecting insect damage and creating susceptibility maps will help reduce the impact of potential infestations (Kunegel-Lion & Lewis, 2020). For planners, identifying areas that may be prone to insect infestations is a critical step to ensure the sustainability of forests. This process makes sure that possible risks are correctly identified and managed, which lets effective plans for protecting forest ecosystems be created (Kärvemo et al., 2014; Alkan Akıncı et al., 2022; Fetting et al., 2022).

The initial and important stage in pest management is the creation of susceptibility maps. The aim of this study is to identify the parameters influencing PPM damage through various parameters and thereafter create susceptibility maps utilizing two different models based on these parameters.

Materials and Methods

Study area

The study area was determined as the Nurdağı Forest Planning Unit (FPU) of Gaziantep Forest Enterprise (FE) under the Kahramanmaraş Regional Directorate of Forestry (RDF), located at the intersection of the Mediterranean and Southeastern Anatolia regions. Nurdağı FPU is located in Gaziantep province, neighboring Osmaniye and Kahramanmaraş provinces. Geographically, it is located at 37°02'00''-37°00'00'' North latitude and 36°39'00''-37°01'30'' East longitude (Figure 1).

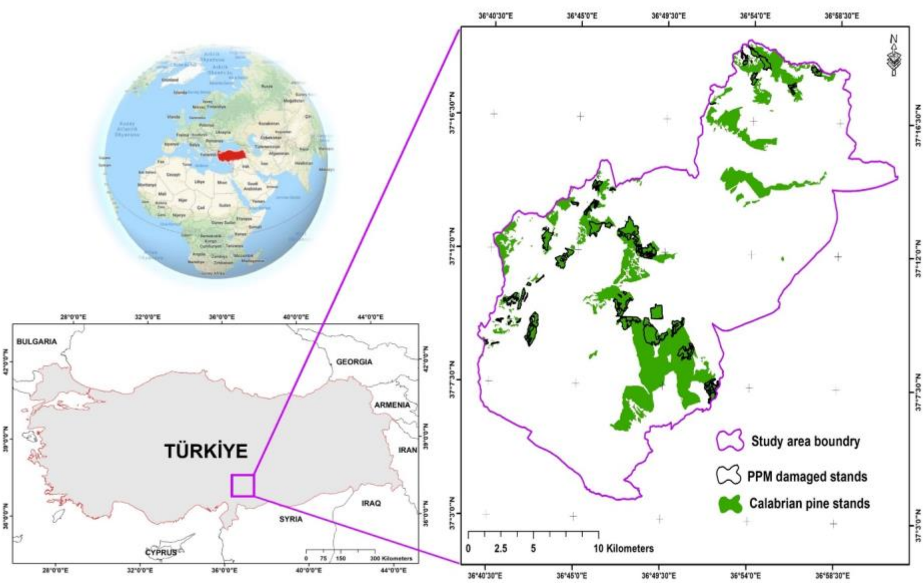

Figure 1. Study area.

The study area covers a total area of 43576.2 hectares, of which 6735.1 hectares are productive forest and 2341.2 hectares are degraded forest. The elevation of Nurdağı FPU from the sea varies between the lowest 475 m and the highest 1643 m, and the average elevation is 713 m. The average slope of the study area is 7.7%, the lowest slope is 0%, and the highest slope is 45.7% (FMP, 2022).

The study area has a Mediterranean climate and is characterized by coniferous and scrub vegetation. The main tree species commonly found in this region are *P. brutia*, *P. pinea, P. nigra, Cedrus libani* A.Rich. (Pinales: Pinaceae), and *Juniperus* spp. L. (Pinales: Cupressaceae). The study area is located in the Csa (warm summer Mediterranean) climate zone in the Köppen climate classification system. This climate type is characterized by mild winters and hot and dry summers (Beck et al., 2018).

Database development

In the last 10 years, the forests of Nurdağı FPU have suffered a significant amount of PPM damage. In this context, Kahramanmaraş RDF, Gaziantep FE, and Nurdağı FPU have filled out "Forest Pest Control Project" forms regarding the damage of PPM. We identified the stands with PPM damage using the Forest Pest Control Project forms and field studies. We digitally obtained the forest cover type map of the study area from Kahramanmaraş RDF using the ArcGIS software. We looked at 9 parameters in this study to see how vulnerable the PPM was. These parameters were stand structure, crown closure, development stage, elevation, slope, aspect, solar radiation, annual mean temperature, and annual mean precipitation (Avcı, 2000; Blas, 2000; İpekdal, 2005; Régolini et al., 2014; Ziouche et al., 2017; Bulut, 2024). Stand structure, crown closure, and development stage were obtained from the digital forest cover type map. Slope, aspect, elevation, and solar radiation data were derived from a digital elevation model with a resolution of 25 meters downloaded from the USGS website (https://earthexplorer.usgs.gov/). Annual mean temperature and annual mean precipitation data were obtained from digital raster data with a resolution of approximately 750 meters obtained from WorldClim (https://www.worldclim.org/) (Table 1). These 750-meter resolution data were converted to 25-meter resolution using the resampling method with nearest neighbor in the ArcGIS environment. The method applied in the production of the PPM susceptibility maps is given in Figure 2.

Table 1. Description of the data utilized in the research

Data description	Source	Data type	Resolution (m)
Forest cover type map	Kahramanmaraş RDF	Vector	
Digital elevation model	USGS	Raster	25
Annual mean temperature	WorldClim	Raster	750
Annual mean precipitation	WorldClim	Raster	750

Parameter selection

Recognizing potential dangers to the forest ecosystem is crucial for formulating solutions and developing strategies (Kunegel-Lion & Lewis, 2020). Finding out how insect damage is spread, what factors affect this, and how outbreaks and tree deaths happen will help the managing sustainability of the forest ecosystem. Studies on the parameters affecting the susceptibility of the PPM are limited. Recent studies have focused on the vulnerability of trees and forests to PPM attacks, but there is still no conclusive evidence (Jactel et al., 2014). Some studies have shown that the PPM prefers to lay its eggs in the southern aspect (south and west) of trees (İpekdal, 2005; Régolini et al., 2014). Parlak et al. (2019) emphasized that PPM prefers sunny aspects. Ziouche et al. (2017) reported in their study that the attack of *P. halepensis* trees was not affected by region or elevation, with nests typically located in the east and south directions, and that the polyphenol content of the attacked individuals in healthy trees was high. Temperature is considered to be the most important factor in the spread of the PPM. Warm and dry seasons favorably affect the spread of the insect (Blas, 2000). Although there is no significant difference in the insect's preference for stand location (Keten et al., 2010), it prefers the edges of the stand more (Çanakçıoğlu &

Mol, 1998). In general, PPM can cause more damage in pine forests with abundant open areas (Azcárate et al., 2023). In this study, stand structure, crown closure, development stage, elevation, slope, aspect, solar radiation, annual mean precipitation, and annual mean temperature parameters were used to determine the spatial distribution and susceptibility of the PPM.

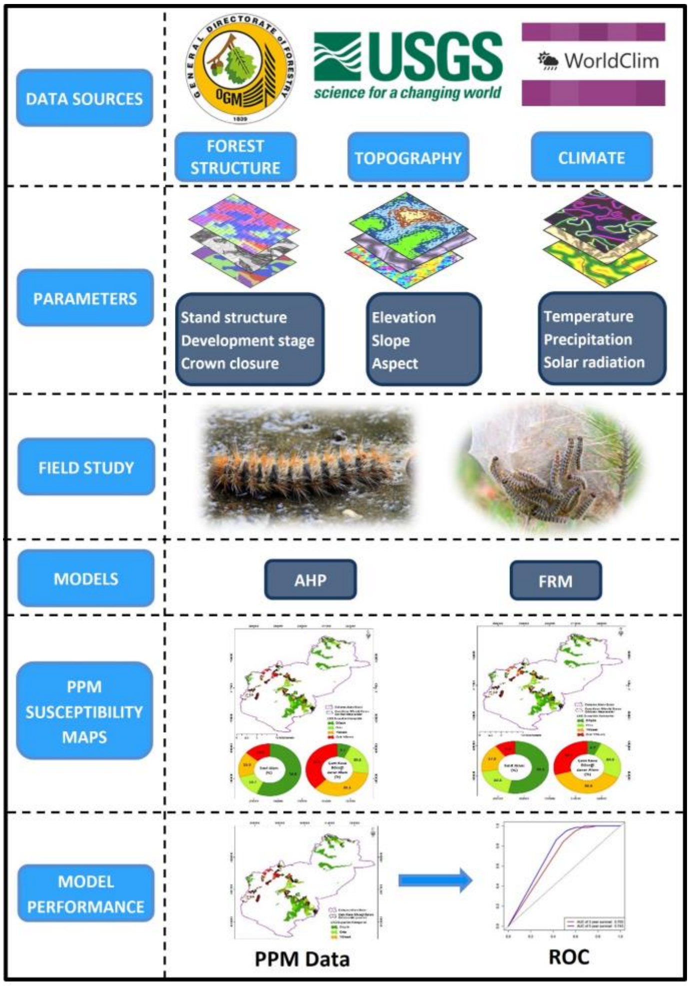

Figure 2. The conceptual framework of the PPM susceptibility map.

Analytic hierarchy process (AHP)

The AHP developed by Saaty (1980) is a widely used method in multi-criteria decision-making (MCDM) processes. This method has a flexible and powerful structure for solving complex decision-making problems (Kumar & Garg, 2017). AHP assesses the optimal solution among various options (Saaty, 1980). AHP, also known as alternative method analysis, is based on a hierarchical structure that shows the relationships between possible alternatives and objectives. One of the most important advantages of AHP is that intangible factors such as subjective preferences, experiences, and intuitions can be handled logically and structurally (Kara, 2023). AHP is used in many fields, such as insect susceptibility, fire risk, and landslide risk mapping (Pourghasemi et al., 2013; Bentekhici et al., 2020; Sari, 2021; Aksoy, 2023; Ürker & Günlü, 2024).

AHP uses mathematical calculations to derive priority weights for criteria and alternatives once the pairwise comparisons are complete. The steps in the process are to normalize the pairwise comparison matrix, find the principal eigenvector, and use the Consistency Ratio (CR) to make sure the evaluation is accurate. This method takes pairwise decisions and turns them into a prioritized list of criteria and options. This ensures that decisions are based on consistent and logical evaluations. We accept the decision matrix as passing the consistency evaluation when the CR value is less than 0.1. If the CR is higher than 0.10, the matrix fails the consistency test. This means that pairwise comparisons need to be re-evaluated and changed (Chen et al., 2010; Saaty, 1980). We calculated the index and CR using the following formulas Eqs. (1 &2).

$$CR = CI / RI \quad \text{Eq. (1)}$$

$$CI = \lambda_{max} – n / n -1 \quad \text{Eq. (2)}$$

In the formula, CI (consistency index) refers to the comparability level, λmax is the largest eigenvalue, n is the number of criteria compared in the matrix, and RI is the random index based on the number of criteria compared (Eq. 2). This research employed the conventional RI values established by Saaty (1980). These values were predetermined according to the number of criteria compared and used for a consistency check.

Frequency ratio method (FRM)

The FRM, which plays an active role in the creation of fire, landslide, and insect susceptibility maps, stands out as an understandable and easy-to-use probability model. This model is based on the concept of frequency ratio, which represents the ratio of the probability of an event occurring to the probability of it not occurring (Erener et al., 2010; Kara, 2023). Each factor affecting insect susceptibility was categorized, and the frequency ratio value was calculated for each category using GIS functions. *FR* is the frequency ratio (Eq. 3). The ratios of the number of pixels with insect damage (M_i) to the total number of stands with insect damage (M) and the ratio of the number of pixels of each parameter (N_i) to the total number of pixels (N) were used to figure this out.

$$FR = (M_i/M) / (N_i/N) \quad \text{Eq. (3)}$$

Relative frequency (RF) was computed by dividing the FR of the variable class by the total frequency ratio of the variable. The RF value was utilized to compute the prediction ratio (PR). The RF was calculated the for each class. The Prediction Rate (PR) for each parameter was calculated using the training dataset to consider the interactions among the independent variables (Eq. 4).

$$PR = (RF_{max} – RF_{min}) / (RF_{max} – RF_{min})_{min} \quad \text{Eq. (4)}$$

Frequency ratio values are an important measure to determine the level of insect susceptibility. Values above 1 indicate a high level of insect susceptibility, while values less than 1 indicate a low level of insect susceptibility. Using available insect damage data and the relationships of relevant parameters, we constructed a contingency table based on this methodology.

The PPM susceptibility index (PPMSI) was determined by summing the products of each factor's PR and each class's RF, as seen below (Eq. 5).

$$PPMSI = \sum (PR \times RF) \quad \text{Eq. (5)}$$

PPM susceptibility maps

The PPM susceptibility map was created with the help of PPMSI. PPMSI expresses the susceptibility of PPM, and the higher the value of PPM, the higher the sensitivity, and the lower the value of PPM, the lower the sensitivity. The weights of each parameter were determined according to AHP and FRM methods, and the weights determined for each parameter were transferred to the database in the ArcGIS environment. The layers of all parameters were overlaid, and the PPMSI value was calculated by summing the weights of all parameters (Eq. 6).

$$PPMSI_i = PPMSI_1 + PPMSI_2 + \ldots\ldots + PPMSI_n \quad \text{Eq. (6)}$$

Based on the Jenks natural breaks classification method in ArcGIS 10.8 software, PPMSI was categorized into four classes: low, medium, high, and extreme. We created PPM susceptibility maps using two different methods (AHP and FRM).

Accuracy assessment of PPM susceptibility maps

One of the main steps of this study is to test the accuracy of the Relative Operating Characteristic (ROC) susceptibility maps. ROC, which is frequently used to evaluate the validity of the developed models, is widely used in forest fires, landslides, and insect susceptibility mapping studies (Pradhan et al., 2009; Pourghasemi et al., 2016; Gheshlaghi et al., 2020; Sevinc et al., 2020; Özcan et al., 2022; Sivrikaya et al., 2022; Kara, 2023). This method is crucial for verifying the reliability of the obtained results and assessing the model's performance.

ROC curve is a graph. The X-axis shows the number of false positives, and the Y-axis shows the number of true positives (Kumar & Indrayan, 2011). Area Under the Curve (AUC) scores are a widely used metric to measure the accuracy of the model (Nandi & Shakoor, 2010). This score is a measure of the model's performance. The highest AUC score indicates the best performance of the model, and an AUC score approaching 1 indicates that the model provides an excellent prediction (Yeşilnacar, 2005). Generally, we classify AUC scores as follows: 0.9-1.0: Excellent, 0.8-0.9: Very Good, 0.7-0.8: Good, 0.6-0.7: Fair, and 0.5-0.6: Poor. The literature frequently uses this classification as a common standard for assessing the predictive ability of the model (Pourghasemi et al., 2012; Özcan et al., 2022).

Results and Discussion

Parameters influencing PPM damage

Analysis of PPM damage in relation to stand structure revealed that 75.9% (913.6 ha) of the damage occurred in pure stands, while 24.1% (289.7 ha) occurred in mixed stands. The result indicates that PPM favors pure stands over mixed stands. 73.2% (881.0 hectares) of PPM damage occurred in full coverage stands (Table 2). The PPM damage rates for development stages of the young, middle-aged, mature, and over-mature are 74.8% (900.3 ha), 19.6% (236.2 ha), 1.9% (22.3 ha), and 3.7% (44.5 ha), respectively. These findings indicate that PPM damage usually occurs in young stands. Despite the claim of no significant difference in the evaluation of insect choice for stand position (Keten et al., 2010), it exhibits a greater preference for stand edges (Çanakçıoğlu & Mol, 1998). Generally, they may cause greater harm in forests with open spaces (Azcárate et al., 2023). Buxton (1983) stated that young trees exhibit greater susceptibility to PPM. However, Regolini et al. (2014) documented higher infestation rates in mature trees.

The PPM damage in relation to topographic variables revealed that 79% of the damage occurred at elevations below 650 m. In other words, PPM damage was more prevalent in low-altitude regions. The slope results indicated that roughly 83% of the damage occurred in areas with a slope exceeding 10%, and the extent of the damaged area increased with the rise in slope. PPM damage was shown to be greater in sunny aspects compared to shady aspects. Ziouche et al. (2017) concluded that location and altitude did not influence the infestation of PPM on *P. halepensis* trees, that nests were predominantly oriented towards the east and south, and that the polyphenol content in the afflicted individuals of healthy trees was increased. Temperature is regarded as the most significant component in the dissemination of PPM. High temperatures and arid conditions facilitate the increase of the insect (Blas, 2000). Research indicates that PPM exhibits a preference for oviposition on the southern sides of trees (namely south and west directions) and that a substantial correlation exists between the stand edge and the insect's spread (Avcı, 2000; İpekdal, 2005; Régolini et al., 2014). Parlak et al. (2019) highlighted that PPM favors sunny aspects and stand edges.

Table 2. Spatial distribution of parameters based on forest stand and PPM damaged stand

Parameters	Class	Forest stand		PPM damaged stand area	
		ha	%	ha	%
Stand structure	Pure	5648.6	85.9	913.6	75.9
	Mixed	924.6	14.1	289.7	24.1
Crown closure	Low coverage (10-40)	4336.4	66.0	291.1	24.2
	Medium coverage (40-70)	87.4	1.3	31.2	2.6
	Full coverage (>70)	2149.4	32.7	881.0	73.2
Development stage	Young	5979.6	91.0	900.3	74.8
	Middle-aged	511.7	7.8	236.2	19.6
	Mature	23.8	0.3	22.3	1.9
	Over-mature	58.1	0.9	44.5	3.7
Elevation (m)	<550	1664.2	25.3	324.2	26.9
	550-650	3031.1	46.1	627.7	52.2
	>650	1877.9	28.6	251.4	20.9
Slope (%)	<10	1364.1	20.7	208.3	17.3
	10-20	2253.9	34.3	461.9	38.4
	>20	2955.2	45.0	533.1	44.3
Aspect	Sunny	3087.9	47.0	721.1	59.9
	Shady	3485.3	53.0	482.2	40.1
Annual mean temperature (°C)	<16	1810.6	27.5	279.4	23.2
	16-17	1823.4	27.8	390.4	32.5
	>17	2939.2	44.7	533.5	44.3
Solar radiation (WH/m^2)	<1150000	370.8	5.6	52.8	4.4
	1150000-1250000	640.4	9.8	139.7	11.6
	1250000-1350000	1913.5	29.1	402.9	33.5
	>1350000	3648.5	55.5	607.9	50.5
Annual mean precipitation (mm)	<58	4304.1	65.5	541.1	45.0
	58-60	1858.4	28.3	425.1	35.3
	>60	410.7	6.2	237.1	19.7

When assessing PPM damage in relation to climatic conditions, a linear correlation was established between temperature and PPM damage, indicating that harm increased with higher temperatures. Climatic factors, particularly elevated temperatures, are crucial for larval growth, with the optimal temperature range being 20-25°C (Bonamonte et al., 2013). PPM is mostly affected by weather conditions. Mild winters (Battisti et al., 2005; Barbaro et al., 2013) and hot summers (Battisti et al., 2006) make it easier for the PPM population to grow. PPM damage increases linearly with sun radiation. An inverse correlation exists between the amount of rainfall and the PPM damage, with observations indicating that damage diminishes as rainfall increases.

PPM susceptibility map using AHP

Determining the coefficients of the parameters influencing PPM damage is essential for the development of PPM susceptibility maps, and the AHP approach is employed for this purpose. The AHP pairwise comparison matrix is utilized to ascertain the coefficients of the parameters. This matrix facilitates the generation of susceptibility maps with improved accuracy and reliability by establishing the priority among the parameters. The CR for the parameters of crown closure, stand structure, development stage, elevation, slope, aspect, annual mean temperature, solar radiation, and annual mean precipitation was computed (Table 3). The CR value of the parameters was calculated to be 0.036, which is less than 0.1. The results indicated that all pairwise comparison matrices were consistent. The main factor influencing PPM susceptibility was identified as annual mean precipitation, assigned a weight of 22%. The subsequent stages included the development stage at 20%, crown closure at 18%, and stand structure at 12%. The least significant indicator for PPM susceptibility was identified as annual mean radiation, accounting for 3%. The PPM susceptibility map produced by AHP method is shown in Figure 3.

Table 3. Weight and consistency ratios of all criteria

Parameters	Weights	CR
Stand structure	0.1228	
Crown closure	0.1831	
Development stage	0.1974	
Elevation	0.0670	
Slope	0.0312	0.036
Aspect	0.0997	
Annual mean temperature	0.0465	
Solar radiation	0.0310	
Annual mean precipitation	0.2214	

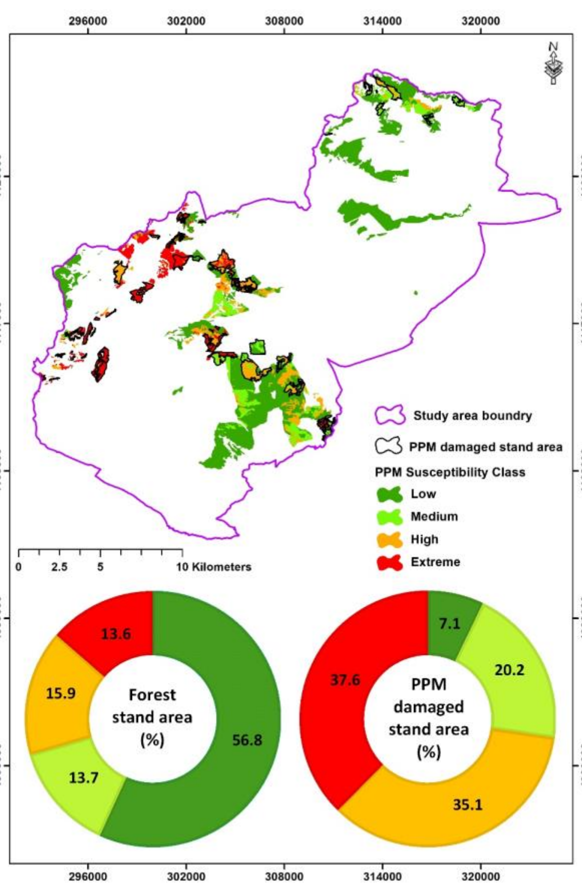

Figure 3. PPM susceptibility map prepared by AHP method.

The PPM susceptibility map, developed using the AHP approach, displays areas categorized by susceptibility and the forest stand area affected by PPM damage in Table 4. The PPM susceptibility map shows that 56.8% (3735.7 ha) of the area is in the low group, 13.7% (900.4 ha) is in the medium group, 15.9% (1042.4 ha) is in the high group, and 13.6% (894.7 ha) is in the extreme group. Upon examination of the stands with PPM damage, 7.1% (85.8 ha) fall into the low category, 20.2% (243.4 ha) in the medium, 35.1% (421.9 ha) in the high, and 37.6% (452.2 ha) in the extreme group. The research area is 30% more likely to be affected by PPM than the extreme and high categories, but 73% of the stands that have PPM damage are in these categories. According to the results, the PPM susceptibility map made with the AHP method is accurate and can be used in PPM management.

Table 4. Forest stand and PPM damaged stand area according to PPM sensitivity categories based on AHP

PPM susceptibility category	Forest stand		PPM damaged stand	
	ha	%	ha	%
Low	3735.7	56.8	85.8	7.1
Medium	900.4	13.7	243.4	20.2
High	1042.4	15.9	421.9	35.1
Extreme	894.7	13.6	452.2	37.6
Total	6573.2	100.0	1203.3	100.0

PPM susceptibility map using FRM

The frequency ratio method (FRM) was used to find the spatial relationships between the factors that affect the PPM susceptibility. The coefficient values (PR) for each parameter are presented in Table 5. The PR values indicate that annual mean precipitation (4.992), crown closure (4.233), development stage (3.499), and stand structure (3.287) are identified as significantly influential parameters for PPM susceptibility. The parameter of least significance for PPM susceptibility was identified as slope (1.000). Azcárate et al. (2023) demonstrated in their research that the primary factors influencing PPM damage were tree species, stand density, elevation, slope, and aspect. The PPM susceptibility map produced by FRM method is shown in Figure 4.

The PPM susceptibility map, developed from the FRM, illustrates the regions categorized by sensitivity and the stand area affected by PPM damage, as presented in Table 6. The PPM susceptibility map indicates that 53.3% (3504.3 ha) of the region falls under the low group, 19.1% (1253.3 ha) within the medium category, 17.8% (1168.4 ha) within the high category, and 9.8% (647.2 ha) within the extreme category. Upon examination of the stands exhibiting PPM damage, 6.7% (80.9 ha) fall under the low class, 24.9% (300.1 ha) within the medium class, 38.6% (464.9 ha) within the high class, and 29.7% (357.4 ha) within the extreme class. While roughly 28% of the research area falls into the high and extreme categories of PPM sensitivity, 68% of the stands exhibiting PPM damage are classified in these categories. The results obtained validate the precision of the PPM susceptibility map developed in accordance with FRM and its potential use in PPM management initiatives. Annual mean precipitation is the most important parameter in both methods. The average annual precipitation was determined to be the primary variable influencing the PPM's vulnerability based on both the AHP and FRM models. The primary reason is that average annual precipitation strongly influences both the insect's life cycle and the physiological condition of host trees, particularly pine species.

Table 5. Coefficient values of frequency parameters for the PPM susceptibility map

Parameters	Class	Forest stand area		PPM damaged stand area		FR	RF	PR
		ha	%	ha	%			
Stand structure	Pure	5648.6	85.9	913.6	75.9	0.884	0.340	3.287
	Mixed	924.6	14.1	289.7	24.1	1.712	0.660	
Crown closure	Low coverage	4336.4	66.0	291.1	24.2	0.367	0.080	4.233
	Medium coverage	87.4	1.3	31.2	2.6	1.950	0.428	
	Full coverage	2149.4	32.7	881	73.2	2.239	0.491	
Development stage	Young	5979.6	91.0	900.3	74.8	0.822	0.065	3.499
	Middle-aged	511.7	7.8	236.2	19.6	2.522	0.199	
	Mature	23.8	0.4	22.3	1.9	5.118	0.405	
	Over-mature	58.1	0.9	44.5	3.7	4.184	0.331	
Elevation (m)	<550	1664.2	25.3	324.2	26.9	1.064	0.364	1.408
	550-650	3031.1	46.1	627.7	52.2	1.131	0.387	
	>650	1877.9	28.6	251.4	20.9	0.731	0.250	
Slope (%)	<10	1364.1	20.8	208.3	17.3	0.834	0.284	1.000
	10-20	2253.9	34.3	461.9	38.4	1.119	0.381	
	>20	2955.2	45.0	533.1	44.3	0.985	0.335	
Aspect	Sunny	3087.9	47.0	721.1	59.9	1.276	0.628	2.636
	Shady	3485.3	53.0	482.2	40.1	0.756	0.372	
Annual mean temperature	<16	1810.6	27.5	279.4	23.2	0.843	0.281	1.120
	16-17	1823.4	27.7	390.4	32.4	1.170	0.389	
	>17	2939.2	44.7	533.5	44.3	0.992	0.330	
Solar radiation	<1150000	370.8	5.6	52.8	4.4	0.778	0.193	1.058
	1150000-1250000	640.4	9.7	139.7	11.6	1.192	0.296	
	1250000-1350000	1913.5	29.1	402.9	33.5	1.150	0.285	
	>1350000	3648.5	55.5	607.9	50.5	0.910	0.226	
Annual mean precipitation	<58	4304.1	65.5	541.1	45.0	0.687	0.135	4.992
	58-60	1858.4	28.3	425.1	35.3	1.250	0.245	
	>60	410.7	6.2	237.1	19.7	3.154	0.620	

Table 6. Forest stand and PPM damaged stand area according to PPM sensitivity categories based on FRM

PPM susceptibility category	Forest stand		PPM damaged stand	
	ha	%	ha	%
Low	3504.3	53.3	80.9	6.7
Medium	1253.3	19.1	300.1	24.9
High	1168.4	17.8	464.9	38.6
Extreme	647.2	9.8	357.4	29.7
Total	6573.2	100.0	1203.3	100.0

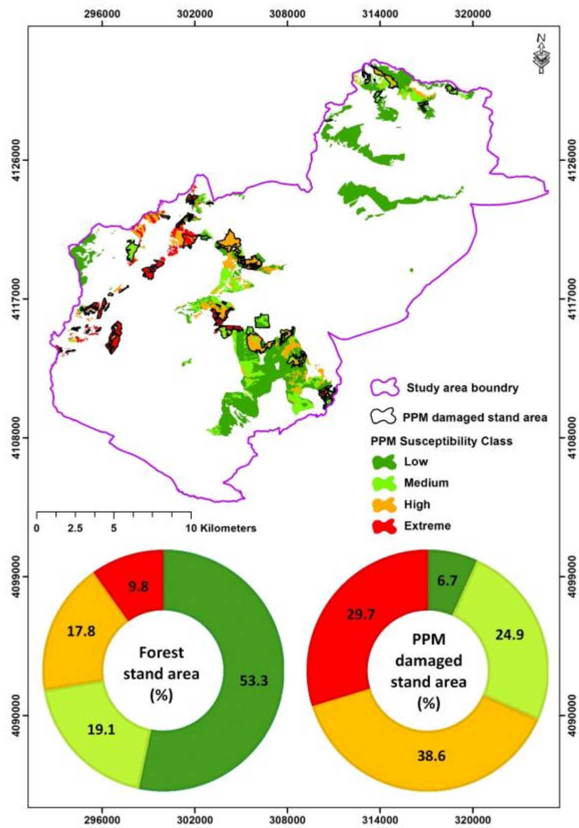

Figure 4. PPM susceptibility map prepared by FRM method.

Accuracy of PPM susceptibility maps

Verifying the precision of the produced models is a critical phase of model analysis. The ROC curve approach demonstrated the precision of the PPM susceptibility maps created using AHP and FRM. The AUC values for the constructed AHP and FRM models were established at 0.835 and 0.830, respectively (Figure 5). The FRM and AHP models were shown to be highly effective in assessing PPM sensitivity (AUC=0.8-0.9, indicating very strong performance). While both models effectively assessed PPM sensitivity, the AHP model demonstrated superior success compared to the FRM model.

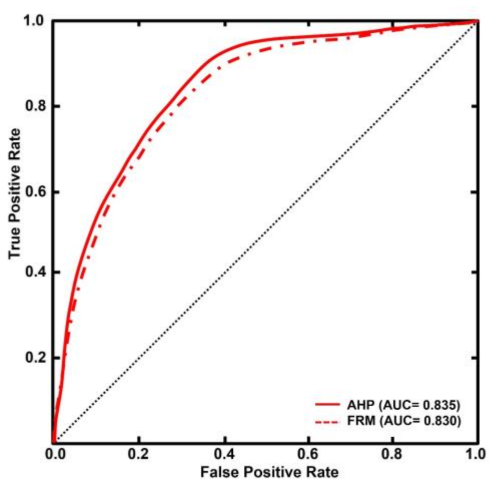

Figure 5. ROC curves of PPM susceptibility maps based on AHP and FRM models.

Conclusion

The assessment of insect infestation severity and distribution, along with the parameters influencing damage and creation of susceptibility maps, is crucial for sustainable forest management. To our knowledge, this is one of the first studies to use AHP and FR models along with GIS to figure out how vulnerable *T. wilkinsoni* is. This study assessed the regional distributions of characteristics influencing the damage caused by *T. wilkinsoni* and developed a PPM susceptibility map utilizing AHP and FRM models based on nine distinct parameters. The characteristics incorporated in the models included stand structure, crown closure, development stage, elevation, slope, aspect, annual mean temperature, solar radiation, and annual mean precipitation. Both AHP and FRM identified the annual mean precipitation as the key parameter. ROC demonstrated the reliability of the PPM susceptibility maps generated using AHP and FRM. The ROC analysis results classified both the AHP and FRM models as having very good accuracy. Furthermore, we concluded that the AHP model outperforms the FRM model.

The PPM susceptibility maps generated using two different modeling methodologies demonstrate notable accuracy and precision, underscoring the importance of this study in finding suitable stands for PPM sensitivity in advance and enacting requisite measures. This study has demonstrated that multi-criteria decision-making methodologies are a suitable and effective tool for the creation of PPM susceptibility maps. The advancement of information technologies and modeling approaches (machine learning, artificial intelligent, etc.) necessitates that such investigations be performed on a broader scale and employing diverse modeling techniques. Strategies should be created to disseminate the models that produce the most favorable outcomes all over the country, based on the modeling the results achieved. Such investigations will enhance the health of the forest ecosystem and promote a more resilient ecological framework.

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