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# Assessing Fire Susceptibility of Threatened Plant Species in Temperate Forest Ecosystem of Azerbaijan Using MaxEnt Method

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#### Abstract

Natural and human-induced disturbances are major drivers of the decline and loss of vulnerable species worldwide. Among these, fires are particularly disruptive as they can devastate entire ecosystems. Assessing the likelihood and severity of such disturbances on plant communities is crucial for the management and conservation of biodiversity. This study aims to analyze fire susceptibility using the Maximum Entropy (MaxEnt) model to evaluate the potential impacts of fires on the biodiversity of a lowland forest in Azerbaijan. The research was conducted as part of the project on the evaluation of Red Book species in Azerbaijan based on IUCN categories and criteria. In this study, 21 rare plant species found in the Samur-Yalama National Park (SYNP) were assessed for fire susceptibility, as they have been significantly affected by fires in recent years. The fire susceptibility analysis included 12 driving factors, categorized into topographic, vegetation, and climatic factors, and identified 564 wildfire incidents. Model performance was evaluated using the AUC value, which was 0.855, indicating good model accuracy. Fire susceptibility was classified into three categories: low, moderate, and high. According to the results, 12,642 hectares (60.82%) of the SYNP area fall under low susceptibility, 5532 hectares (26.62%) under moderate susceptibility, and 2611 hectares (12.56%) under high susceptibility. Rare plant species in SYNP were evaluated based on their fire susceptibility. It was found that Alcea kusariensis (Iljin ex Grossh.) Iljin, Anacamptis morio subsp. picta (Loisel.) Jacquet & Scappat., Equisetum hyemale L., Orchis purpurea Huds., Pinus brutia var. eldarica (Medw.) Silba, Platanus orientalis L., Punica granatum L., and Quercus castaneifolia C.A.Mey are located in areas classified as having high susceptibility.

*Keywords: fire susceptibility, lowland forests, MaxEnt, vulnerable species, Samur-Yalama National Park* 

## 1. Introduction

Biodiversity conservation is essential for sustaining major economic activities and ensuring a sustainable way of life, as it plays a crucial role in ecosystem resilience and stability (UNDP 2014). The loss of biodiversity reduces the resilience of ecosystems, making them more vulnerable to shocks and disturbances and less capable of providing essential services to humans (Arrogante-Funes et al. 2022). Natural disasters, in particular, contribute significantly to the decline of endangered species across many regions of the world (Chandra and Bhardwaj 2015). These vulnerable species contribute to various ecological functions and the overall capacity of biological systems (Jain et al. 2014).

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The increasing risk of extinction faced by rare species and their functional importance underscores the need for further research into effective conservation strategies (Patykowski 2018).

Although one of the primary objectives of protected areas is to safeguard rare species, these plant populations remain vulnerable to anthropogenic fires and other threats. Fires, a critical environmental disturbance, can significantly alter ecosystem services and biodiversity in temperate forests (Secretariat of the Convention on Biological Diversity 2001, Babu et al. 2016). They can modify the structure of biodiversity (Thonicke et al. 2001), threaten species composition (Moretti et al. 2004), exacerbate land degradation and deforestation (Hernandez-Leal et al. 2006), reduce overall carbon storage, and increase air pollution (Healey et al. 2014, Jhariya and Raj 2014). Irregular or infrequent fires disrupt the ecological balance, affecting the soil, flora, fauna, and atmospheric conditions of fire-sensitive ecosystems (Hardesty et al. 2005).

Most plant communities in lowland temperate forests, which are sensitive to fire, exhibit high flammability. While some species, such as thick-barked pedunculate oak, can survive low-intensity fires, other fire-resistant communities may be destroyed (Secretariat of the Convention on Biological Diversity 2001). Therefore, understanding the potential impact of such disturbances on plant habitats is critical for the effective protection of biodiversity (Driscoll et al. 2010).

In fire management and biodiversity conservation, mapping fire susceptibility and risk is crucial for mitigating deforestation and desertification (Ghorbanzadeh et al. 2019b). Effective and sustainable firefighting resource planning requires addressing structural factors that influence fire ignition and propagation, such as topography, vegetation structure, human activities, and weather patterns (Chen and Jin 2022). The scientific literature suggests several methodologies for mapping fire susceptibility, including linear and logistic regression, artificial neural networks, support vector machines, random forests, fuzzy logic, deep learning, coevolutionary neural networks, multilayer perceptron, Analytic Hierarchy Process (AHP), Analytical Network Process (ANP), and maximum entropy (MaxEnt) models (Lozano et al. 2008, Chuvieco et al. 2010, Arpaci et al. 2014, Yakubu et al. 2015, Fonseca et al. 2016, Akay and Shahin 2019, Ghorbanzadeh et al. 2019a, Li et al. 2019, Zhang et al. 2019, Adaktylou et al. 2020, Gheshlaghi et al. 2020).

Among these, the MaxEnt algorithm is particularly effective in modeling the relationship between environmental variables and fire ignition probabilities (Elith et al. 2011, De Martino and De Martino 2018, Martín et al. 2018). When well-organized datasets – including natural, geological, woodland, and meteorological data – are integrated within a Geographic Information System (GIS), MaxEnt can provide a detailed understanding of changes in the spatial distribution of fire risk and the factors influencing these changes (Ebrahimi et al. 2018, Yang et al. 2021, Banerjee 2021).

As noted by Arrogante-Funes (2022), the Caucasian ecoregion is highly susceptible to fires and experiences prolonged delays in recovery following such events. Although fire is not a natural characteristic of Azerbaijan's forests, human activities have increasingly triggered fires, resulting in significant adverse impacts on biodiversity (UNECE/FAO 2000). In recent years, Azerbaijan has seen a continuous rise in fire incidents, particularly during the fire season, which spans the hot and dry period from June to September.

According to statistics, a total of 102,622 fire incidents, categorized as vegetation fires, were recorded over the past decade, burning a cumulative area of 262,696 hectares (ha) (Report of MES 2012-2022). Of these incidents, 261 occurred in forested areas, affecting 2924 ha, while 91,980 fires in shrublands burned 171,009 ha. Additionally, 554 fires in grain fields affected 4915 ha, and 9827 fires in harvested grain fields burned 83,848 ha (Report of MES 2012-2022). Despite occasional fires in gardens and haystacks, the majority of fire incidents have led to extensive damage in critical ecosystems, highlighting the need for effective fire management and prevention strategies.

The number of plant species listed in the Red Book of Azerbaijan has increased to 460 (RBA 2013, RBA 2023), indicating that current conservation measures may be insufficient. Many rare species, even those within protected areas, are not showing a positive trend in population recovery. This highlights the urgent need for establishing a scientific framework to evaluate these species and develop targeted conservation strategies.

The present study aims to analyze fire susceptibility using a machine learning technique, the Maximum Entropy (MaxEnt) model, to evaluate the vulnerability of threatened plant species in a lowland forest in Azerbaijan. The findings of this research could be crucial for understanding the impact of fire susceptibility on plant biodiversity, not only within the Caucasian ecoregion but also on a global scale. This study was conducted as part of a project focused on the evaluation of Red Book species in Azerbaijan according to IUCN categories and criteria. The primary goal is to analyze limiting factors affecting rare species and to assess their interactions with fire susceptibility through robust analytical methods rather than mere observation.

The results of this research are detailed for each species in the third edition of the Red Book, published in May 2023. While this study effectively evaluates the fire susceptibility of rare plant species, it is limited by not considering how individual species recover after a fire event. Furthermore, the study was conducted only in areas where these species are currently found. Future research, leveraging the MaxEnt model, should aim to compare the predicted distribution of these rare species across different risk zones. Although this article focuses exclusively on fire susceptibility, other risks have been documented based on field observations. Investigating these additional threats is challenging, but evaluating the potential impact of various risks, including fire, across both lowland and mountain ecosystems, will greatly enhance conservation management efforts.

# 2. Materials and Methods

### 2.1 Study Area

Approximately 15% of Azerbaijan's forests are located in the lowland plains, which are heavily affected by anthropogenic factors. A significant portion of these plain forests is situated in the Khachmaz district, a region highly susceptible to fire incidents due to its geographic and vegetative characteristics (Abbasov 2014). The Samur-Yalama National Park (SYNP), established to protect this unique forest ecosystem and its rich biodiversity, has been severely impacted by fires in recent years (Report of MES 2012–2022). SYNP is located in the Khachmaz district, with an approximate center at coordinates 41.750000° N, 48.650000° E, and an elevation ranging from 25 to 60 meters above sea level (a.s.l.). For comparison, the current level of the Caspian Sea is –27 meters a.s.l. (Report of MENR 2014). The park itself spans an area of 11,772 hectares, while the surrounding region covers a total of 20,785 hectares. It is bordered to the north by the Russian Federation, to the east by the Caspian Sea, to the west by the Baku-Moscow railway line, and to the south by the road from Khudat to the village of Istisu along the Caspian coast.

The forests in this area are named after the Samur River delta, where they are located. Approximately half of these forests lie within Russian territory. These forests, sharing the same ecosystem and facing similar ecological challenges, have been designated as protected areas in both countries (Report of MENR 2014, Ibilkasumov 2018, Abiyev et al. 2020a).

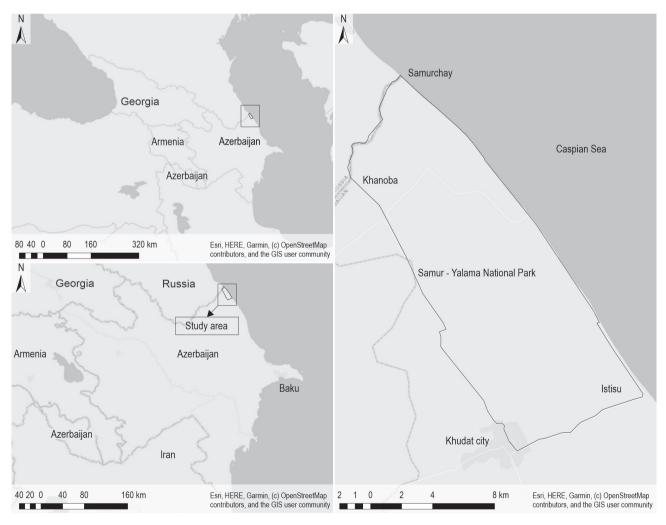


Fig. 1 Location of SYNP

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The climate of the Samur-Yalama National Park (SYNP) is characterized by dry, warm summers and mild winters. It falls under a temperate-warm climate type typical of semi-deserts and dry steppes, with minimal continental influence. The average annual temperature is around 13°C. During the fire season, which lasts from mid-May to the end of September, temperatures typically range between 22°C and 24°C. Annual precipitation in the SYNP is relatively low, between 300 and 400 mm, yet it is higher compared to the central parts of the country. However, as in all arid regions, evaporation rates are twice as high as precipitation levels. Wind speeds in the area range from 1 to 8 m/s throughout the year, with an average of 3 to 6 m/s, but can reach 10 to 20 m/s for approximately 20 days annually (Abiyev et al. 2020b).

The dominant tree species in the SYNP include *Quercus robur* subsp. *pedunculiflora* (K.Koch) Menitsky, *Carpinus betulus* L., *Populus alba* L., *Fraxinus excelsior* L., and *Alnus glutinosa* subsp. *barbata* (C.A.Mey.) Yalt. Under the forest canopy, various shrubs, small trees, and lianas are prevalent, such as *Cornus mas* L., *Crataegus pentagyna* Waldst. & Kit. ex Willd., *Prunus cerasifera* Ehrh., *Mespilus germanica* L., *Corylus avellana* L., and

*Hedera helix* L. (Abiyev et al. 2019). Due to environmental and anthropogenic factors, the forest density in the SYNP has decreased by approximately 12% over the last 30 years (Abiyev et al. 2020a).

#### 2.2 Endangered Plant Species

Twenty-one species listed in the 2023 edition of the Red Book are known to be distributed within this ecosystem. Considering the vegetation period, populations of rare species were surveyed in different routes without exception for twenty-four months (between 2020–2022) in high fire incidence areas and GPS coordinates were collected. Among these, *Quercus castaneifolia* C.A.Mey, *Parrotia persica* (DC.) C.A.Mey., *Pinus brutia* var. *eldarica* (Medw.) Silba, and *Platanus orientalis* L. have been planted from different ecosystems in 1970–1990 by the Forest Development Service for reforestation and landscape restoration purposes (Table 1).

The mentioned species belong to the group of rare species whose distribution overlaps with areas of high fire susceptibility. These species are particularly vulnerable during the growing season, as they are likely to be destroyed in the event of a fire (Fig. 2).

| Nº  | Name   | Category and Criteria* |
|-----|--|------------------------|
| 1.  | Alcea kusariensis (Iljin ex Grossh.) Iljin                             | Pink list              |
| 2.  | Anacamptis morio subsp. picta (Loisel.) Jacquet & Scappat.             | VU B1a+2b(ii,iii,v)    |
| 3.  | Crocus adamii J.Gay  | VU B1ab(i,iii)         |
| 4.  | Crocus speciosus M.Bieb.   | EN B1ab(i,ii,iii)      |
| 5.  | Diospyros lotus L.   | Pink list              |
| 6.  | Equisetum hyemale L.   | CR B1ab(ii)            |
| 7.  | Hedera pastuchovii Woronow   | Pink list              |
| 8.  | Iris reticulata M.Bieb.  | Pink list              |
| 9.  | Ophrys sphegodes subsp. taurica (Aggeenko) Soó ex Niketić & Djordjevic | EN B2ab(ii,iii)        |
| 10. | Orchis purpurea Huds.  | EN B2ab(iii,iv)        |
| 11. | Ornithogalum ponticum Zahar.   | Pink list              |
| 12. | Parrotia persica (DC.) C.A.Mey.  | NT                     |
| 13. | Pinus brutia var. eldarica (Medw.) Silba                               | NT                     |
| 14. | Platanthera chlorantha (Custer.) Reichenb.                             | EN 2b (iii)c(v)        |
| 15. | Platanus orientalis L.   | VU A2c+3c              |
| 16. | Punica granatum L.   | EN B2ab(ii,iii,iv,v)   |
| 17. | Pyracantha coccinea M.Roem.  | Pink list              |
| 18. | Quercus castaneifolia C.A.Mey  | EN B2ab(iii)           |
| 19. | Quercus pubescens Willd.   | NT                     |
| 20. | Tulipa sylvestris subsp. australis (Link) Pamp.                        | NT                     |
| 21. | Vitis vinifera L.  | LC                     |

\* IUCN Categories: EX – Extinct; EW – Extinct in the Wild; CR – Critically Endangered; EN – Endangered; VU – Vulnerable; NT – Near Threatened; LC – Least Concern; DD – Data Deficient; NE – Not Evaluated (IUCN 2024)

#### Table 1 Endangered plants common in SYNP

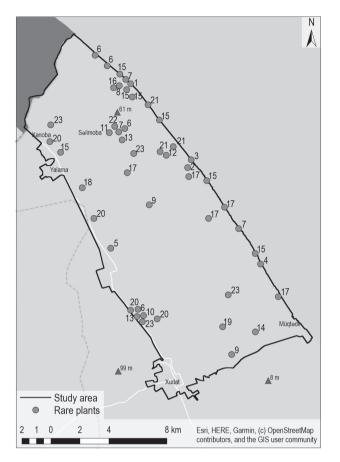


Fig. 2 Location of rare plants (Numbers are the same as in Tab. 1)

## 2.3 Fire Incidents and Driving Factors Data

According to statistics, Khachmaz is one of the most vulnerable districts to fire incidents due to its geographic and vegetative conditions, and fire incidents have been increasing over the last decade (Report of MES 2012–2022). In the present study, 564 vegetation fire ignition points recorded between 2012 and 2021 were obtained from the State Fire Protection Service of the Ministry of Emergency Situations of the Republic of Azerbaijan (Fig. 3).

Depending on the specific geographical area, specific parameters affecting fire-related processes are used in the methods employed for susceptibility assessments. Socio-economic, topographic, flammable, and climatic factors play a key role in early warning of fires or in evaluating their consequences. The most commonly applied parameters in general scientific literature was selected and used, taking into account their availability in Azerbaijan.

The study included environmental feature data at a 30-second resolution, such as rainfall patterns, average wind speed, and ambient air temperature during the arid period in Khachmaz, obtained from World-Clim2 (http://www.worldclim.com/version2). Annual Mean Temperature (BIO 1) was used as it is a significant parameter (Fig. 3). Topographic parameters were derived for analysis using a 12.5 m resolution Digital Elevation Model (DEM) from the ALOS PALSAR satellite (Fig. 3).

Forest types and density, as well as understory vegetation, were assessed using ESRI base maps, forest inventory maps, *NDVI*, *CIgreen*, and direct field research in the area. Multispectral images were obtained from the Landsat satellite of USGS and the SPOT satellite of Azercosmos in June 2022 (Abiyev et al. 2020a) (Fig. 3). *NDVI* and *CIgreen* were calculated using the formulas:

$$NDVI = \frac{(NIR - RED)}{(NIR + RED)}$$
(Abiyev et al. 2020a) (1)

$$CIgreen = \frac{NIR}{GREEN} - 1 \text{ (Abiyev et al. 2020b)} \quad (2)$$

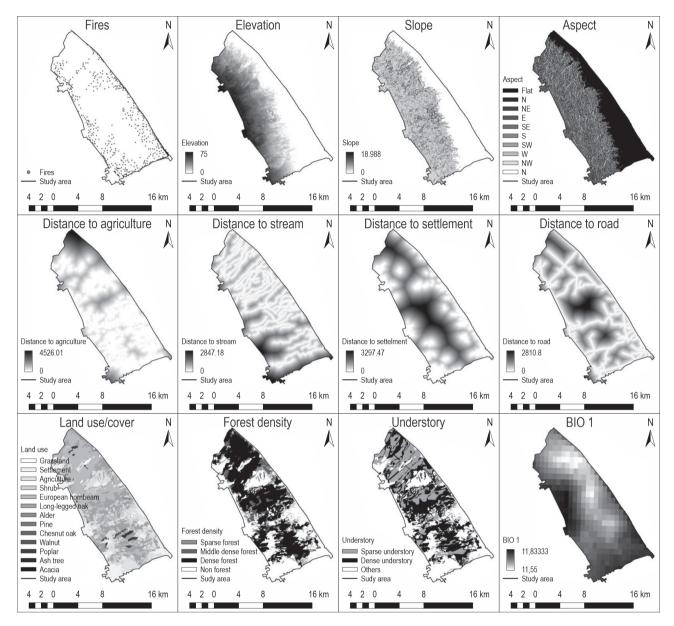
# 2.4 Fire Susceptibility Analysis with Maximum Entropy

The maximum entropy principle, derived from statistical mechanics and information theory, is used in ecological modeling to predict the most probable distribution of species given limited information (Phillips 2017). MaxEnt (Maximum Entropy Modeling) is a machine learning algorithm designed to estimate species distribution by analyzing presence-only data and identifying the environmental constraints that maximize entropy. This method is particularly advantageous when absence data is unavailable, making it ideal for ecological niche modeling and habitat suitability assessments (Elith et al. 2011, Sánchez et al. 2021).

MaxEnt produces a probability distribution over a set of environmental variables by selecting the distribution that is closest to uniform while adhering to the constraints imposed by the presence data. The algorithm iteratively adjusts the weights of these variables to maximize the likelihood of the observed presences, resulting in a final model that describes the potential distribution of the species across the study area. Key features of the MaxEnt algorithm include its ability to handle complex interactions between variables and its robustness to small sample sizes, which are common issues in ecological studies (Merow et al. 2013). For detailed information about MaxEnt please check Sánchez et al. (2021).

In this study, the MaxEnt model was used to assess fire susceptibility by integrating 564 vegetation fire ignition points recorded between 2012 and 2021 with





**Fig. 3** Parameters Used in the Study: 1 – fire ignition points, 2 – elevation, 3 – slope, 4 – aspect, 5 – distance to agricultural areas, 6 – distance to stream, 7 – distance to settlements, 8 – distance to road, 9 – vegetation cover, 10 – forest density, 11 – understory vegetation, and 12 – annual mean temperature (BIO 1)

various environmental and topographic factors. The AUC (Area Under the Curve) values and jackknife resampling method were used to validate model performance and assess the contribution of each variable to fire susceptibility. The jackknife test is particularly useful in this context as it evaluates the importance of each predictor by measuring the change in model performance when the predictor is excluded or used alone (Elith et al. 2011).

Default parameter settings were used during the MaxEnt model runtime, with a random selection of

training data. This includes setting the regularization parameter, which controls the complexity of the model to avoid overfitting, and selecting feature types such as linear, quadratic, and hinge, which define the shape of the response curves for each predictor variable. The resulting model outputs were then processed using ArcGIS Pro. Raster pixel scores ranged from 0 to 1, reflecting fire susceptibility, where higher values indicate more susceptibility to fire (Yang et al. 2021).

The spatial overlap between high fire susceptibility zones and rare plant localities was examined using the

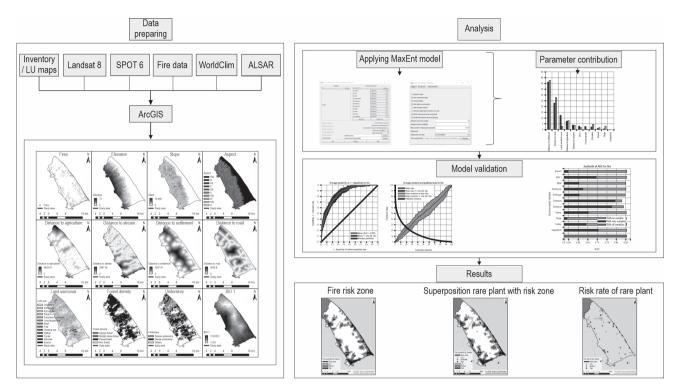


Fig. 4 Workflow of the study

»Extract Values to Points« tool (Spatial Analyst Tools/ Extraction) in ArcGIS Pro. This analysis is essential for understanding how fire susceptibility intersects with areas of conservation concern, thereby aiding in the prioritization of management efforts.

Fig. 4 outlines the methodological workflow of this study, including the following steps:

- ⇒ compiling the wildfire incident inventory and selecting independent variables
- ⇒ applying the MaxEnt model and evaluating parameter contributions
- ⇒ validating the model using AUC and jackknife tests
- $\Rightarrow$  interpreting the results for conservation planning.

# 3. Results and Discussion

The accuracy and performance of the MaxEnt model were evaluated using the Area Under the Curve (AUC) of the Receiver Operating Characteristic (ROC) analysis, a widely recognized metric for assessing model performance in binary classification problems. The AUC values obtained from both the training and test datasets were 0.855 (Fig. 5), which is significantly above the threshold of 0.8, indicating that the wildfire prediction model achieved a high level of predictive accuracy. This result demonstrates that the model is robust and reliable for delineating areas of specific vulnerability to wildfires, making it a valuable tool for fire susceptibility assessment and management in Samur-Yalama National Park (SYNP).

The robustness of the model was further validated using the jackknife test, which is effective in determining the significance and relative importance of each independent variable within the model (Sari 2023). The test results confirmed that the model's probability predictions for fire occurrence were stable and reliable. The analysis revealed that human activities were the predominant drivers of fire susceptibility, with anthropogenic factors such as settlement proximity, road networks, and land use/land cover (LU/LC) collectively accounting for 72.4% of the model's explanatory power. This finding is consistent with numerous studies that emphasize the critical role of human-induced factors in wildfire occurrences, particularly in areas with significant human influence (Martin et al. 2018, Devisscher et al. 2019).

In contrast, natural variables, including climatic conditions, vegetation, and topography, contributed relatively less to the overall model, with a combined impact of 22.5%. Notably, climatic conditions only accounted for 3.2%, which is relatively low compared to

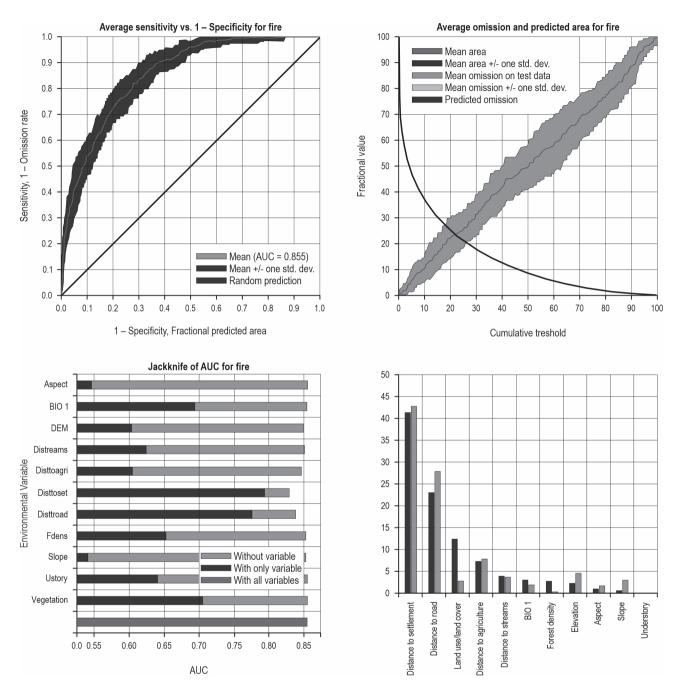


Fig. 5 ROC curve; Environmental variables. (Aspect, BIO 1, DEM, Distance to streams, Distance to agriculture, Distance to settlement, Distance to roads, Forest density, Slope, Understory, Vegetation); Percent contribution and permutation importance of variables

human-related factors. This suggests that although climatic variables such as temperature and precipitation can influence fire susceptibility and behavior, they may not be the primary drivers in this region. The relatively low contribution of natural variables could be attributed to the park specific environmental conditions, where human activities play a more dominant role in fire ignition and propagation. The model's findings also highlight the significant impact of vegetation (15.8%) on fire susceptibility. Vegetation type and density can influence fire spread, fuel consumption and intensity, as certain plant communities are more flammable or can sustain fires longer. This is particularly relevant in areas where vegetation and human activities intersect, increasing the likelihood of fire ignition. The relatively high

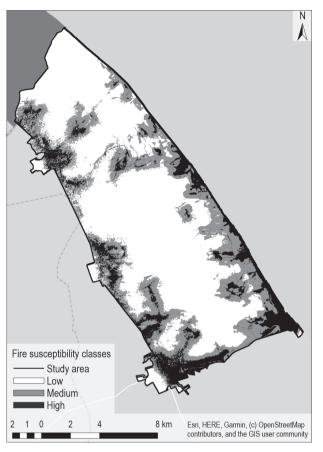


Fig. 6 Fire susceptibility map of Samur-Yalama National Park

contribution of vegetation in this study aligns with findings from other fire-prone regions, where vegetation management is considered a key component of fire susceptibility mitigation strategies (Yang et al. 2021).

A fire susceptibility map of Samur-Yalama National Park (SYNP) was developed using the MaxEnt modeling environment, classifying the park into three distinct levels of susceptibility: low, moderate, and high. These categories were derived using the maximum entropy method, which provides a probabilistic assessment of fire susceptibility based on environmental and anthropogenic variables. The results indicated that low-susceptibility areas, covering 12,642 hectares (60.82%), constituted the majority of the park. These zones are primarily dense forest regions with minimal human impact, where the probability of human-induced wildfires is relatively low. Factors such as forest density and understory vegetation in these areas likely contribute to reducing the potential for fire ignition and spread.

Moderate-susceptibility areas, accounting for 5532 hectares (26.62%), serve as buffer zones that include a mix of land-use types and settlements. These areas represent transitional zones between high and low

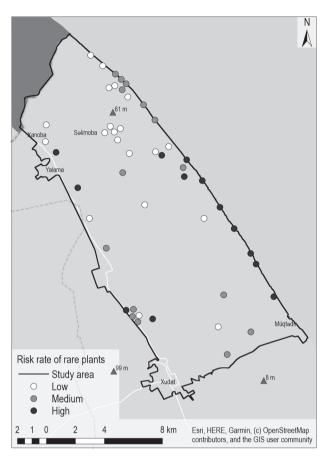


Fig. 7 Comparison of rare plant localities with risk areas

susceptibility regions and are characterized by a moderate level of human activity. The presence of settlements and fragmented landscapes may increase fire susceptibility due to higher accessibility and potential ignition sources.

High-susceptibility areas, covering 2611 hectares (12.56%), are primarily located in regions with high population density, developed transportation networks, significant economic activity, and a higher like-lihood of human-induced fires and forest disturbances. These findings indicate that human factors such as proximity to roads, settlements, and intensive land use play a crucial role in elevating fire susceptibility in these zones. Despite their relatively small proportion, these high-susceptibility areas are critical as they pose a greater threat to the park biodiversity and require targeted fire management strategies.

The fire susceptibility values in SYNP ranged from 0 to 0.97, reflecting a gradient of fire susceptibility across the park. High-susceptibility values are associated with areas that have greater human influence and more flammable vegetation types, making them more prone to fire incidents. This spatial distribution

highlights the need for focused management efforts in high-susceptibility zones to mitigate the impact of potential wildfires and protect vulnerable ecosystems.

Rare plant species in Samur-Yalama National Park are predominantly found in sparse forests, along roadsides, and in coastal open spaces, making them more vulnerable to anthropogenic influences. The locations of these rare plant species were compared with the fire susceptibility map and classified into high, medium, and low-susceptibility categories (Fig. 7). As shown in Table 2, species such as *Alcea kusariensis* (Iljin ex Grossh.) Iljin, *Anacamptis morio* subsp. picta (Loisel.) Jacquet & Scappat., *Equisetum hyemale* L., *Orchis purpurea* Huds., *Pinus brutia* var. *eldarica* (Medw.) Silba, *Platanus orientalis* L., *Punica granatum* L., and *Quercus castaneifolia* C.A. Mey are classified as being in the high susceptibility category.

Fires in SYNP predominantly recur in reed-dominated areas, which are characterized by high flammability. Fire can pose significant threats to rare plant species in temperate forests by causing habitat loss and altering ecosystems (Berlinck and Batista 2020). Intense or frequent fires can outpace the recovery of these plants, especially if they have limited seed banks or specific habitat requirements. Additionally, invasive species may thrive in post-fire conditions in firesensitive temperate forests like SYNP, further threatening the survival of native flora (Maringer et al. 2012). If fire regimes become altered due to human influence (McWethy et al. 2013), the delicate balance necessary for the survival of these rare plants may be disrupted, leading to further declines in their populations (Kitzberger et al. 2016).

The high-susceptibility zones include swamps dominated by Phragmites australis (Cav.) Steud., forests with dense understory such as those dominated by Quercus robur subsp. pedunculiflora (K.Koch) Menitsky, and shrub vegetation dominated by Rubus creticus Tourn. ex L.. These habitats, due to their structure and fuel load, are more prone to fires, and the impact on plant communities in these areas can be severe. For instance, in grasslands, an average of five plant species can be burned per square meter during a fire, while approximately ten species are affected per 100 square meters in forested areas. If a fire completely burns through one hectare of forest, it can result in the loss of approximately 350-400 cubic meters of timber. This not only affects the plant species but also disrupts the habitat for various fauna and the overall ecosystem services provided by these forests.

The study's use of the MaxEnt model for fire susceptibility mapping is consistent with methodologies

| Nº. | Name   | Fire Susceptibility Classes | Other risks             |
|-----|--|-----------------------------|-------------------------|
| 1.  | Alcea kusariensis (Iljin ex Grossh.) Iljin                             | 1, 2                        | Toursim                 |
| 2.  | Anacamptis morio subsp. picta (Loisel.) Jacquet & Scappat.             | 1                           | Toursim                 |
| 3.  | Crocus adamii J.Gay  | 2                           | Agriculture, trampling  |
| 4.  | Crocus speciosus M.Bieb.   | 2, 3                        | Toursim, wind           |
| 5.  | Diospyros lotus L.   | 2, 3                        | Antropogenic            |
| 6.  | Equisetum hyemale L.   | 1, 3                        | Toursim                 |
| 7.  | Hedera pastuchovii Woronow   | 2, 3                        | No risk                 |
| 8.  | Iris reticulata M.Bieb.  | 3                           | Trampling               |
| 9.  | Ophrys sphegodes subsp. taurica (Aggeenko) Soó ex Niketić & Djordjevic | 3                           | Toursim, mowing         |
| 10. | Orchis purpurea Huds.  | 1                           | Toursim, mowing         |
| 11. | Ornithogalum ponticum Zahar.   | 2, 3                        | Trampling, mowing       |
| 12. | Parrotia persica (DC.) C.A.Mey.  | 2                           | No riks                 |
| 13. | Pinus brutia var. eldarica (Medw.) Silba                               | 1, 2, 3                     | Mass drying, diseases   |
| 14. | Platanthera chlorantha (Custer.) Reichenb.                             | 3                           | Ecotoursim              |
| 15. | Platanus orientalis L.   | 1, 2, 3                     | No risk                 |
| 16. | Punica granatum L.   | 1                           | No risk                 |
| 17. | Pyracantha coccinea M.Roem.  | 3                           | No risk                 |
| 18. | Quercus castaneifolia C.A.Mey  | 1                           | No risk                 |
| 19. | Quercus pubescens Willd.   | 2, 3                        | Toursim                 |
| 20. | Tulipa sylvestris subsp. australis (Link) Pamp.                        | 3                           | Ecotoursim              |
| 21. | Vitis vinifera L.  | 2, 3                        | Rough picking of fruits |

**Table 2** Fire Susceptibility Classes and Associated Risks of Rare Plant Species

applied in similar research across different regions. Yang et al. (2021) reported an AUC value of 0.81, highlighting the effectiveness of climate and vegetation parameters in fire susceptibility assessment. Similarly, Banerjee (2021) found that climate factors and population density were significant drivers of fire susceptibility. Martin et al. (2018) identified roads and wildlandagricultural interfaces as critical factors, achieving an AUC of 0.86. Devisscher et al. (2019)) emphasized the importance of proximity to roads and recent deforestation as major contributors to fire susceptibility. These findings underscore the consistency in the identification of key drivers of fire susceptibility across various studies and geographic regions.

The current study's classification of fire susceptibility into three levels - low, moderate, and high - is suitable for SYNP due to its specific context. Although a five-class system, as suggested by Ferrarini (2012), is commonly used in larger and more diverse study areas, the relatively smaller scale of SYNP makes a threeclass system more effective and less ambiguous for practical applications. The three-class system allows a clearer identification of priority areas for fire management and conservation, making it easier to implement targeted interventions. This approach was chosen to balance the complexity of the data with the need for practical and actionable information for park management. By simplifying the model output into three clear categories, the study aimed to facilitate more effective susceptibility assessment and resource allocation for fire management. This method thus provides a robust and intuitive framework for identifying and prioritizing areas that require varying levels of intervention and conservation efforts within the park.

Overall, the study demonstrates that fire susceptibility, influenced predominantly by anthropogenic factors, poses a significant threat to the rare plant species in SYNP. To mitigate this susceptibility, it is essential to implement targeted fire management strategies, such as creating firebreaks, regulating human access to high-susceptibility areas, and enhancing fire monitoring and early warning systems. Future research should focus on integrating dynamic factors such as seasonal variations in vegetation and changing land use patterns to refine the model further and improve the accuracy of fire susceptibility assessments.

# 4. Conclusions

This study demonstrates the effective use of the MaxEnt model in assessing fire susceptibility for threatened plant species in the temperate forest ecosystem of Azerbaijan. The model's high predictive accuracy (AUC of 0.855) underscores its reliability in identifying areas of varying susceptibility levels. The findings reveal that a significant portion of Samur-Yalama National Park is categorized under low fire susceptibility, with smaller but crucial areas falling under moderate and high susceptibility. The high susceptibility zones, primarily influenced by anthropogenic factors such as proximity to settlements and intensive land use, pose a severe threat to the biodiversity of the park, particularly to rare and endangered plant species.

The spatial overlap between high fire susceptibility zones and the distribution of rare plant species underscores the urgent need for targeted conservation and fire management strategies. To mitigate these threats, targeted fire management strategies are imperative, including the creation of firebreaks, regulation of human activities in high susceptibility areas, and the enhancement of fire monitoring and early warning systems. Moreover, future research should explore the integration of dynamic factors, such as seasonal vegetation changes and evolving land use patterns, to refine the model further and improve its accuracy. Understanding the interplay between these factors will be essential for developing comprehensive conservation strategies and ensuring the long-term protection of vulnerable plant species in the region.

Despite the effectiveness of the MaxEnt model in predicting fire susceptibility, the study acknowledges certain limitations, including the lack of data on postfire recovery patterns of individual species and the focus on areas where these species are currently found. Future research should expand on this study by comparing the predicted distribution of rare species across different susceptibility zones and by evaluating other environmental risks that may threaten biodiversity in both lowland and mountainous regions. A more comprehensive understanding of the factors influencing fire susceptibility and their interactions with rare species will greatly enhance the development of effective conservation strategies, ensuring the long-term protection and resilience of vulnerable ecosystems in the Caucasus ecoregion.

# 5. References

Abbasov, R., 2014: TEEB scoping study for forestry sector of Azerbaijan. European Neighborhood And Partnership Instrument East Countries Forest Law Enforcement And Governance Ii Program, 25. https://www.enpi-fleg.org/docs/teeb-scopingstudy-for-forestry-sector-of-azerbaijan/ (Accessed on February 09, 2024)

#### Y. Abiyev et al. Assessing Fire Susceptibility of Threatened Plant Species in Temperate Forest Ecosystem ... (141–154)

Abiyev, Y., Agaguluev, I., Farzaliyev, V., 2019: Studying the current state of the Samur-Yalama National Park by the using of Geographic Information Systems. Proceedings of the Central Botanical Garden 12: 9–16.

Abiyev, Y., Karsli, F., Gumush, S., Seyfullayev, F., 2020a: Analysis of the forest covers dynamics in the Samur-Yalama National Park of Azerbaijan. Eur. J. For. Eng. 6(1): 23–30. https://doi.org/10.33904/ejfe.724022

Abiyev, Y., Farzaliyev, V., Seyfullayev, F., 2020b: Assessment of the forest productivity according to leaf chlorophyll content in the Samur-Yalama National Park of Azerbaijan. Plant & Fungal Research 3(2): 20–29. http://dx.doi.org/10.29228/plantfungalres.73

Adaktylou, N., Stratoulias, D., Landenberger, R., 2020: Wildfire Risk Assessment Based on Geospatial Open Data: Application on Chios, Greece. ISPRS Int. J. Geo-Inf. 9(9): 516. https://doi. org/10.3390/ijgi9090516

Akay, A.E., Shahin, H., 2019: Forest Fire Risk Mapping by using GIS Techniques and AHP Method: A Case Study in Bodrum (Turkey). Eur. J. For. Eng. 5(1): 25–35 . https://doi.org/10.33904/ejfe.579075

Arpaci, A., Malowerschnig, B., Sass, O., Vacik, H., 2014: Using multi variate data mining techniques for estimating fire susceptibility of Tyrolean forests. Appl. Geogr. 53: 258–270. https://doi.org/10.1016/j.apgeog.2014.05.015

Arrogante-Funes, F., Aguado, I., Chuvieco, E., 2022: Global assessment and mapping of ecological vulnerability to wildfires. Nat. Hazards Earth Syst. Sci. 22(9): 2981–3003. https://doi.org/10.5194/nhess-22-2981-2022

Azercosmos, 2022: Monitoring of Fires. Report 17, Baku, Azerbaijan

Babu, S., Roy, A., Prasad, P., 2016: Forest fire risk modeling in Uttarakhand Himalaya using TERRA satellite datasets. Eur. J. Remote Sens. 49(1): 381–395. https://doi.org/10.5721/Eu-JRS20164921

Banerjee, P., 2021: Maximum entropy-based forest fire likelihood mapping: analysing the trends, distribution, and drivers of forest fires in Sikkim Himalaya. Scand. J. Forest Res. 36(4): 275–288. https://doi.org/10.1080/02827581.2021.1918239

Berlinck, C.N., Batista, E.K.L., 2020: Good fire, bad fire: It depends on who burns. Flora 268: 151610. https://doi.org/https://doi.org/10.1016/j.flora.2020.151610

Chandra, K.K., Bhardwaj, A.K., 2015: Incidence of forest fire in India and its effect on terrestrial ecosystem dynamics, nutrient and microbial status of soil. Int. J. Agric. Forest. 5(2): 69–78. http://article.sapub.org/10.5923.j.ijaf.20150502.01.html

Chen, B., Jin, Y., 2022: Spatial patterns and drivers for wildfire ignitions in California. Environ. Res. Lett. 17(11): 055004. https://doi.org/10.1038/s41598-021-88131-9

Chuvieco, E., Aguado, I., Yebra, M., Nieto, H., Salas, J., Pilar Martin, M., Vilar, L., Martinez, J., Martin, S., Ibarra, P., de La Riva, J., Baeza, J., Rodriguez, F., Molina, J.R., Herrera, M.A., Zamora, R., 2010: Development of a framework for fire risk assessment using remote sensing and geographic information system technologies. Ecol. Model. 221(1): 46–58. https://doi. org/10.1016/j.ecolmodel.2008.11.017 De Martino, A., De Martino, D., 2018: An introduction to the maximum entropy approach and its application to inference problems in biology. Heliyon 4(4): e00596. https://doi. org/10.1016/j.heliyon.2018.e00596

Devisscher, T., Anderson, L.O., Aragão, L.E., Galván, L., Malhi, Y., 2016: Increased Wildfire Risk Driven by Climate and Development Interactions in the Bolivian Chiquitania, Southern Amazonia. PLoS One 11(9): e0161323. https://doi.org/10.1371/ journal.pone.0161323

Driscoll, D., Lindenmayer, D., Bennett, A., Bode, M., Bradstock, R., Cary, G., Clarke, M., Dexter, N., Fensham, R., Friend, G., Gill, M., James, S., Kay, G., Keith, D., Macgregor, C., Russell-Smith, J., Salt, D., Watson, J., Williams, R., York, A., 2010: Fire management for biodiversity conservation: Key research questions and our capacity to answer them. Biol. Conserv. 143(9): 1928–1939. https://doi.org/10.1016/j.biocon.2010.05.026

Ebrahimi, H., Rasuly, A., Mokhtari, D., 2018: Analyzing Fire Susceptibility and its Driving Factors Using Maximum Entropy Model (Case Study: Forest and Rangeland of East Azerbaijan). J. Geog. Environ. Hazards 7(1): 57–73. https://doi.org/10.22067/ geo.v7i1.59628

Elith, J., Phillips, S.J., Hastie, T.J., Dudík, M., Chee, Y.E., Yates, C.J., 2011: A statistical explanation of MaxEnt for ecologists. Divers. Distrib. 17(1): 43–57. https://doi.org/10.1111/j.1472-4642. 2010.00725.x

Ferrarini, A., 2012: Why not use niche modelling for computing risk of wildfires ignition and spreading? Environ. Skep. Crit. 1(4): 56–60.

First National Report to the Convention on Biological Diversity: Azerbaijan, 2004: Azerbaijan National Academy of Sciences, Part 1, 77 p.

Fonseca, M.G., Aragao, L.E.O., Lima, A., Shimabukuro, Y.E., Arai, E., Anderson, L.O., 2016: Modelling fire probability in the Brazilian Amazon using the maximum entropy method. Int. J. Wildland Fire 25(9): 955–969. https://doi.org/10.1071/WF15216

Gheshlaghi, H.A., Feizizadeh, B., Blaschke, T., Lakes, T., Tajbar, S., 2020: Forest fire susceptibility modeling using hybrid approaches. Trans. GIS 25(1): 311–333. https://doi.org/10.1111/tgis.12688

Ghorbanzadeh, O., Blaschke, T., Gholamnia, K., Aryal, J., 2019: Forest Fire Susceptibility and Risk Mapping Using Social/Infrastructural Vulnerability and Environmental Variables. Fire 2(3): 50. https://doi.org/10.3390/fire2030050

Ghorbanzadeh, O., Valizadeh, K.K., Blaschke, T., Aryal, J., Naboureh, A., Einali, J., Bian, J., 2019: Spatial prediction of wildfire susceptibility using field survey GPS data and machine learning approaches. Fire 2(3): 43. https://doi.org/10.3390/fire2030043

Hardesty, J.L., Myers, R., Fulks, W., 2005: Fire, ecosystems, and people: a preliminary assessment of fire as a global conservation issue. The George Wright Forum 22(4): 78–87.

Healey, S., Urbanski, S., Patterson, P., Garrard, C., 2014: A framework for simulating map error in ecosystem models. Remote Sensing of Environment 150: 207–217. https://doi.org/10.1016/j. rse.2014.04.028

#### Assessing Fire Susceptibility of Threatened Plant Species in Temperate Forest Ecosystem ... (141–154) Y. Abiyev et al.

Hernandez-Leal, P.A., Arbelo, M., Gonzalez-Calvo, A., 2006: Fire risk assessment using satellite data. Adv. Space Res. 37(4): 741–746. https://doi.org/10.1016/j.asr.2004.12.053

Ibilkasumov, A.R., 2018: Ecological problems of the Samur forest and ways to solve them. International J. Appl. Sci. Techn. »Integral« 3: 169–171.

IUCN, 2024: The IUCN Red List of Threatened Species. Version 2024-2. https://www.iucnredlist.org (Accessed on November 22, 2024)

Jain, M., Flynn, D.F.B., Prager, C.M., Hart, G.M., Devan, C.M., Ahrestani, F.S., Palmer, M.I., Bunker, D.E., Knops, J.M.H., Jouseau, C.F., Naeem, S., 2014: The importance of rare species: a trait-based assessment of rare species contributions to functional diversity and possible ecosystem function in tall-grass prairies. Ecol. Evol. 4(1): 104–112. https://doi.org/10.1002/ ece3.915

Jhariya, M., Raj, D., 2014: Effects of wildfires on flora, fauna and physico-chemical properties of soil-An overview. J. Appl. Nat. Sci. 6(2): 887–897. https://doi.org/10.31018/jans.v6i2.550

Kitzberger, T., Perry, G.L.W., Paritsis, J., Gowda, J.H., Tepley, A.J., Holz, A., Veblen, T.T., 2016: Fire–vegetation feedbacks and alternative states: common mechanisms of temperate forest vulnerability to fire in southern South America and New Zealand. New Zeal. J. Bot. 54(2): 247–272. https://doi.org/10.1080/002882 5X.2016.1151903

Li, J., Shan, Y., Yin, S., Wang, M., Sun, L., Wang, D., 2019: Nonparametric multivariate analysis of variance for affecting factors on the extent of forest fire damage in Jilin Province, China. J. For. Res. 30: 2185–2197. https://doi.org/10.1007/s11676-019-00958-1

Lozano, F.J., Suarez-Seoane, S., Kelly, M., Luis, E., 2008: A multi-scale approach for modeling fire occurrence probability using satellite data and classification trees: A case study in a mountainous Mediterranean region. Remote Sens. Environ. 112(3): 708– 719. https://doi.org/10.1016/j.rse.2007.06.006

Maringer, J., Wohlgemuth, T., Neff, C., Pezzatti, G.B., Conedera, M., 2012: Post-fire spread of alien plant species in a mixed broad-leaved forest of the Insubric region. Flora – Morphology, Distribution, Functional Ecology of Plants 207(1): 19–29. https://doi.org/10.1016/j.flora.2011.07.016

Martín, Y., Zúñiga-Antón, M., Mimbrero, M.R., 2018: Modelling temporal variation of fire-occurrence towards the dynamic prediction of human wildfire ignition danger in northeast Spain. Geomat. Nat. Hazards Risk 10(1): 385–411. https://doi.org/10.1 080/19475705.2018.1526219

McWethy, D.B., Higuera, P.E., Whitlock, C., Veblen, T.T., Bowman, D.M.J.S., Cary, G.J., Haberle, S.G., Keane, R.E., Maxwell, B.D., McGlone, M.S., Perry, G.L.W., Wilmshurst, J.M., Holz, A., Tepley, A.J., 2013: A conceptual framework for predicting temperate ecosystem sensitivity to human impacts on fire regimes. Glob. Ecol. Biogeogr. 22(8): 900–912. https://doi.org/https://doi. org/10.1111/geb.12038

Merow, C., Smith, M.J., Silander, Jr.J.A., 2013: A practical guide to MaxEnt for modeling species' distributions: what it does, and why inputs and settings matter. Ecography 36(10): 1058–1069. https://doi.org/10.1111/j.1600-0587.2013.07872.x

Moretti, M., Obrist, M.K., Duelli, P., 2004: Arthropod biodiversity after forest fires: winners and losers in the winter fire regime of the Southern Alps. Ecography 27(2): 173–186. https://doi. org/10.1111/j.0906-7590.2004.03660.x

Patykowski, J., Holland, G.J., Dell, M., Wevill, T., Callister, K., Bennett, A.F., Gibson, M., 2018: The effect of prescribed burning on plant rarity in a temperate forest. Ecol. Evol. 8(3): 1714–1725. https://doi.org/10.1002/ece3.3771

Phillips, S.J., 2017: A brief tutorial on MaxEnt. http://biodiversityinformatics.amnh.org/open\_source/maxent/ (Accessed on August 01, 2023)

Red Book of Azerbaijan Republic (RBA), 2013: Rare and endangered plant and mushroom species. II edition. Baku, East-West" Publishing House, Baku, 507 p.

Red Book of Azerbaijan Republic (RBA), 2023: Flora III edition. I, Baku, Koza Publishing, Baku, 512 p.

Report of Ministry of Ecology and Natural Resources, 2014: Samur-Yalama National Park Management Plan 2015–2019, 203 p.

Sari, F., 2023: Identifying anthropogenic and natural causes of wildfires by maximum entropy method-based ignition susceptibility distribution models. J. For. Res 34(2): 355–371. https://doi.org/10.1007/s11676-022-01502-4

Secretariat of the Convention on Biological Diversity, 2001: Impacts of human-caused fires on biodiversity and ecosystem functioning, and their causes in tropical, temperate and boreal forest biomes. Montreal, SCBD, 27. (CBD Technical Series Nº.5).

Sánchez, A.C., Bandopadhyay, S., Briceño, N.B.R., Banerjee, P., Guzmán, C.T., Oliva, M., 2021: Peruvian Amazon disappearing: Transformation of protected areas during the last two decades (2001–2019) and potential future deforestation modelling using cloud computing and MaxEnt approach. J. Nat. Conserv. 64: 126081. https://doi.org/10.1016/j.jnc.2021.126081

Thonicke, K., Venevsky, S., Sitch, S., Cramer, W., 2001: The role of fire disturbance for global vegetation dynamics: coupling fire into a dynamic global vegetation model. Glob. Ecol. Biogeogr. 10(6): 661–677. https://doi.org/10.1046/j.1466-822X.2001.00175.x

UNECE/FAO, 2000: Forest Resources of Europe, CIS, North America, Australia, Japan and New Zealand, Geneva Timber and Forest Study Papers № 17, Main report 445.

UNDP, 2014: Biodiversity for Sustainable Development: Delivering Results for Asia and the Pacific. Asia-Pacific Regional Centre, United Nations Development Programme, Thailand, 140.

Yakubu, I., Mireku-Gyimah, D., Duker, A., 2015: Review of methods for modelling forest fire risk and hazard. Afr. J. Environ. Sci. Technol. 9(3): 155–165. https://doi.org/10.5897/ AJEST2014.1820

Yang, X., Jin, X., Zhou, Y., 2021: Wildfire risk assessment and zoning by integrating Maxent and GIS in Hunan Province, China. Forests 12(10): 1299. https://doi.org/10.3390/f12101299

Zhang, G., Wang, M., Liu, K., 2019: Forest fire susceptibility modeling using a convolutional neural network for Yunnan Province of China. Int. J. Disaster Risk Sci. 10(3): 386–403. https://doi.org/10.1007/s13753-019-00233-1

Report of Ministry Emergency Situations, 2012–2022: Annual fire statistics. https://www.fhn.gov.az/index.php?eng/pages/150 (Accessed on 02.09.2024)

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