

Assessment of forest fire vulnerability in Chir pine forest of Pallandri, Azad Jammu and Kashmir (AJK) Pakistan



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Abstract

This study assesses the vulnerability of Chir Pine (*Pinus roxburghii*) forests to wildfires in Pallandri, Azad Jammu and Kashmir (AJK), Pakistan, using spatial modeling and bioclimatic data. The MaxEnt (Maximum Entropy) model was employed to predict fire-prone zones by analyzing environmental variables and field-based presence data. A total of 63 sampling plots were established to collect data on tree height, diameter, stocking density, and spatial coordinates, alongside 19 bioclimatic variables. Key factors influencing fire vulnerability included forest density, fuel load from dry pine needles, and topographical aspects, particularly in north- and east-facing slopes. The model exhibited high accuracy, validated by area under the curve (AUC) metrics and jackknife tests, highlighting NDVI and land cover type (GLC2000) as major contributors. Results indicated that high-density stands with reduced tree spacing and smaller diameters were more prone to fire, especially during the peak fire season from May to July. The results highlight the critical importance of implementing effective forest management strategies, enhancing fire prevention efforts, and promoting community education initiatives to reduce the risk of wildfires in the area. This study provides critical insights for conservation planning, habitat suitability mapping, and resource allocation in the face of escalating climate-induced wildfire threats.

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1. Introduction

Forests are among the most vital ecosystems on Earth, providing a diverse range of ecological, economic, and cultural benefits. According to the Food and Agriculture Organization and cited by (Allison *et al.*, 2023), a forest is defined as a land area covering more than 0.5 hectares, with trees taller than 5 meters and a canopy cover exceeding 10%. Chir Pine (*Pinus roxburghii*), a prominent coniferous species in South Asia, can reach 30–50 meters and diameters exceeding 2 meters (Binjola, 2023). Forests support biodiversity, mitigate climate change through carbon sequestration, regulate water cycles, prevent soil erosion, and offer valuable resources such as timber, medicinal plants, and fuelwood (Krishnaswamy *et al.*, 2013).

Despite these benefits, forests face increasing threats from wildfires. Wildfires are among the most destructive natural disturbances, especially in forest ecosystems. They are typically unplanned fires that ignite and spread rapidly, causing significant damage to vegetation, wildlife, property, and human health (Cao *et al.*, 2017; Jaiswal *et al.*, 2002). Forest fires not only alter the composition and structure of forests but also contribute to deforestation and climate change. In Pakistan, where forest cover constitutes only 5.2% of the total land area (Aslam *et al.*, 2021), even small-scale fires pose a serious ecological and economic threat. Wildfires carriage a significant threat to biodiversity and territories, leading to environmental transformation, variations in land use, deforestation, and climate change (Bernier, 2009). Fire season severity and duration are expected to rise worldwide, particularly in northern high latitudes (Flannigan *et al.*, 2013). The spread of fire in forests and the Wildland-Urban Interface (WUI) involves a combination of two primary tactics: the direct advancement from surrounding vegetation and the ignition of spot fires through the infiltration of embers (Storey *et al.*, 2021). The incidence of fires is most prevalent and perilous during drought periods, as they facilitate frequent fire ignition and rapid fire spread.

Land managers often use intentional forest ignition to encourage the growth of new grass shoots, clear vegetation for improved visibility of prey, or expand agricultural lands. Wildfire ignition and spread are subject to a complex interplay of environmental and human dynamics. Key natural contributors include topography, vegetation characteristics, and climatic variables such as temperature, humidity, and wind speed. Human-induced causes such as discarded cigarette butts, campfires, agricultural burning, and negligence are often the primary ignition sources (Tamang, 2015). Fires are particularly frequent during periods of drought, where dry conditions promote rapid ignition and spread. Forest fires can be viewed as a mixed blessing. Low-intensity fires play a beneficial role by clearing the canopy cover and removing dead wood, creating space for new plant growth. Moreover, the dry pine needles shed by *Pinus roxburghii* during summer months, particularly between May and July, create a continuous layer of highly flammable material on the forest floor, increasing the likelihood of ground and surface fires. The wildland-urban interface (WUI) is another critical zone where fire risks are elevated. Fires in these areas are often sparked by the encroachment of human settlements into forest regions, resulting in spot fires from ember intrusion or direct flame spread (Manzello, 2020). In many rural areas, intentional burning is still practiced to promote pasture regeneration or clear agricultural land, further exacerbating fire hazards.

Moreover, forest fires can release nutrients stored in vegetation, which can enhance soil fertility and stimulate forest regeneration. These fires may also lead to the formation of new ecological habitats that benefit various wildlife species. Nonetheless, intense fires can be highly destructive, causing the death of soil organisms, depletion of essential soil nutrients, heavy soil erosion, and significant reductions in biodiversity and forest biomass. These impacts can have long-lasting negative consequences for the ecosystem. Overall, while low-intensity fires can have some positive ecological effects, high-intensity fires pose significant risks and challenges for forest ecosystems and their sustainability. It is important to manage and mitigate fire events effectively to minimize the negative impacts and promote the health and resilience of forests (Chandra and Bhardwaj, 2015). The wildfires can lead to a temporary increase in soil carbon stocks. Wildfires can have complex effects on soil carbon stocks and soil fertility. Although wildfires do eliminate surface vegetation and built-up dry material, they also emit greenhouse gases, particulate pollutants, and trace chemicals, while affecting local microclimates, soil composition, and nutrient levels (Tzaros, 2021).

Once-green and moist vegetation transforms into highly flammable fuel due to prolonged dry weather. Additionally, the occurrence of high winds facilitates the rapid spread of fire across land, while warm temperatures promote combustion. In such conditions, a single spark, be it from lightning, a burning campfire, or any other ignition source, can be sufficient to initiate a wildfire. These wildfires have the potential to devastate tens of thousands of acres and continue burning for weeks. The spread of fire is primarily influenced by the elements of the fire triangle: heat, oxygen, and fuel type (Pandey, 2025). This conclusion stems from recent reports by climatologists concerning the advancement of global climate change that are already being experienced at the local level. Based on these projections, it is anticipated that our region will witness a greater frequency and larger scale of fires. This trend is primarily attributed to the ongoing rise in average annual air temperatures, which will result in prolonged periods of drought. These drought periods are particularly hazardous due to the frequent ignition and rapid spread of fires (Piao *et al.*, 2022).

Wildfires are driven by a range of environmental elements such as landscape features, types of vegetation, available fuel sources, weather patterns, human interventions, and ignition triggers. These factors collectively contribute to the likelihood of a wildfire being ignited (Jun-bing *et al.*, 2022). The impacts of wildfires are not confined to ecosystems; they extend to human health and livelihoods. Fires contribute to respiratory problems, displace communities, and cause significant economic losses. The increasing frequency and severity of wildfires have been linked to global climate change, which intensifies drought periods and elevates fire-prone conditions (Ruffault *et al.*, 2018). To formulate actual strategies for fire prevention and suppression, it is vital to generate regional-scale maps that assess the vulnerability of an area to fires (Argañaraz *et al.*, 2015).

While vegetation characteristics associated with fire risk are commonly studied, the specific dataset of vegetation parameters can vary across different research studies. These parameters may include variables such as tree height, canopy

cover, and vegetation type. The choice of these parameters may differ depending on the focus and objectives of each study (Heinrich, 2022). Accurate determination of these positions is a fundamental aspect of land surveying, and GPS has emerged as a valuable instrument due to its superior precision across extensive areas compared to traditional surveying methods (Gili *et al.*, 2000). The GIS-based maps play a dual role by facilitating the proper allocation of resources needed for fire prevention and suppression, as well as providing significant assistance in land use planning endeavors. (Esposito *et al.*, 2019). Worldwide, numerous wildfires occur each year, resulting in the combustion of over a million hectares of forests. This extensive devastation significantly disrupts the ecological equilibrium and poses substantial risks to socioeconomic progress and human well-being (Bryan *et al.*, 2018). To effectively manage and mitigate fire risks, there is a growing need for spatial modeling tools that can predict fire-prone zones and assess landscape vulnerability. Geographic Information Systems (GIS) and remote sensing have become essential technologies in evaluating forest fires, allowing the incorporation of climate, terrain, and vegetation-related factors into analysis. Among the various modeling techniques, MaxEnt (Maximum Entropy) has gained popularity due to its robustness, minimal data requirements, and effectiveness in predicting species and phenomenon distributions based on environmental variables (Peavey, 2010).

MaxEnt's performance has been validated in numerous fire risk studies, including those in the Himalayan and Mediterranean regions. While wildfires are a natural occurrence, fires of high intensity can result in significant ecological and socioeconomic consequences. These impacts encompass various aspects, including human casualties and injuries, as well as respiratory problems. (Kim and Kwon, 2023), researched to analyze and model the severity and risk zones of forest fires in the Cross-Niger transition forest. To accomplish this, remotely sensed data from sources like Landsat-8 OLI (acquired in 2020), Land cover maps and topographic parameters such as aspect, elevation, and slope were derived using ASTER DEM. Furthermore, information on human settlements and road networks was obtained through the interpretation of topographic maps and Google Earth imagery.

While there have been numerous studies examining the correlation between wildfires and environmental conditions, accurately modeling the probability of wildfire occurrence in specific areas remains an ongoing area of research. The task of predicting the likelihood of an area to burn is continuously evolving and improving (Parisien *et al.*, 2019). Given these considerations, this study focuses on the Chir Pine forests of Pallandri, Azad Jammu and Kashmir (AJK), which are increasingly vulnerable to fire due to climate change, dense forest structure, and human activity. The objectives of this research are: (1) to predict the occurrence of high-severity fires based on vegetation structure (e.g., stocking rate and fuel ladders), and (2) to identify high-risk fire zones using topographic and climatic variables through the application of MaxEnt and GIS tools. The outcomes aim to support local conservation planning, fire management strategies, and community-based awareness initiatives.

2. Materials and Methods

2.1 Study area

Pallandri is a tehsil that serves as the administrative center of the Sudhanoti District in Azad Kashmir. Located at coordinates 33°42'54"N and 73°41'9"E, it spans an area of about 569 square kilometers and lies roughly 90 kilometers (56 miles) from Islamabad. Pallandri is situated at an elevation of 1,372 m. In summer temperature reaches approximately 20 - 35 °C, and in winter -4 – 20 °C. The area of Pallandri is dominated by Chir Pine. The *Pinus Roxburghii* needles start falling in May and continue till July. The needles on the ground act as a fuel and support the forest fire.

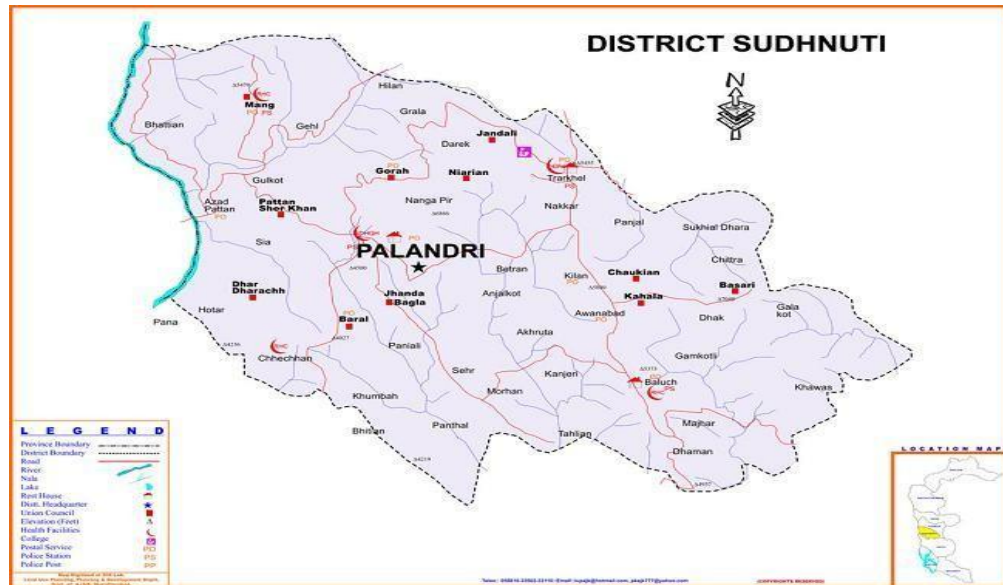


Figure. 1: Map of the study area.

The material used in this study is a Global Positioning System (Garmin GPS device), measuring tape, clinometer, Maxent, ArcGIS and Google map.

2.2 Tree height (cm)

Tree height was recorded in all plots the height of trees was recorded by the clinometer.

2.3 Tree diameter (mm)

Diameters were measured with a measuring tape in each plot at the DBH.

2.4 Distance between trees

The distance between trees was measured with a measuring tape.

2.5 Number of trees

The number of trees was calculated in each plot.

2.6 Presence points

Coordinates of the previously burned area were collected from GPS.

2.7 Climatic data

Climatic data of the study area (Palandri) were collected from an online website (Power Data Access Viewer).

For the data collection, 63 plots of 100 X 100 meter plots were selected the tree height, diameter and distance between trees were observed, as all these parameters are responsible for fire spread in an area. For the Maxent app, the coordinates of the hotspots in the area were collected with the help of GPS. To run MAXENT, we needed three folders: one for environmental layers, one for presence data, and one for the output. It's crucial to ensure that all the cropped environmental layers are of the same size and pixel format. We saved these layers in a folder named "Environmental Variables." To prepare for the analysis, we gathered the necessary environmental layers and placed them in the designated folder. Additionally, we collected presence data from field surveys. We include an adequate number of randomly selected background points in each run. To estimate the overall historic fire events, we performed 100 replicate runs of MAXENT using the presence data and environmental layers. This generated the predicted distributions for each run. After running MAXENT, we analyzed the output using ArcGIS version 10 software. This allowed us to examine and interpret the results effectively.

2.8 Statistical analysis

The final Forest Fire Risk Zone (FFRZ) map was developed by integrating multiple factors land cover, elevation, slope, aspect, and distances from roads and settlements, using the ArcGIS platform. By incorporating these factors, the FFRZ map provides an assessment of the areas susceptible to forest fires. This comprehensive

analysis allows for a better understanding of the potential severity and risk of forest fires in the study area. The forest fire risk zones (FFRZ) in the study were classified into three categories: low, moderate, and high-risk zones based on their susceptibility to fire.

3. Results

3.1 Vegetation cover

The forest fire analysis by Vegetation cover was observed in the field during May 2023. The area of Pallandri is dominated by Chir Pine (*Pinus Roxburghii*) species.

The species observed there during the survey are listed as follows

Table 1. Species found in the study area.

Common name	Scientific name
Chir Pine	<i>Pinus roxburghii</i>
Tun	<i>cedrela toona roxburghii</i>
Shisham	<i>Dalbergia sissoo</i>
Kikar	<i>Acacia nilotica</i>
Walnut, Akhrot	<i>Juglans regia</i>
Anar	<i>Punica granatum</i>
Poplar, Sufaida	<i>Populus Salicaceae</i>
Dates	<i>Phoenix dactylifera</i>
Paper mulberry	<i>Broussonetia papyrifera</i>
Plum	<i>Prunus domestica</i>
Himalayan pear	<i>Pyrus pashia</i>

3.2 Density

The dense forest observes more forest fires in the area as the dense forest sheds more needles, which promote forest fires. The dense forest usually has a fuel ladder, which helps fire to reach the crown of the tree and cause severe crown fire. Mostly, the North and East aspects have dense forest in the area.

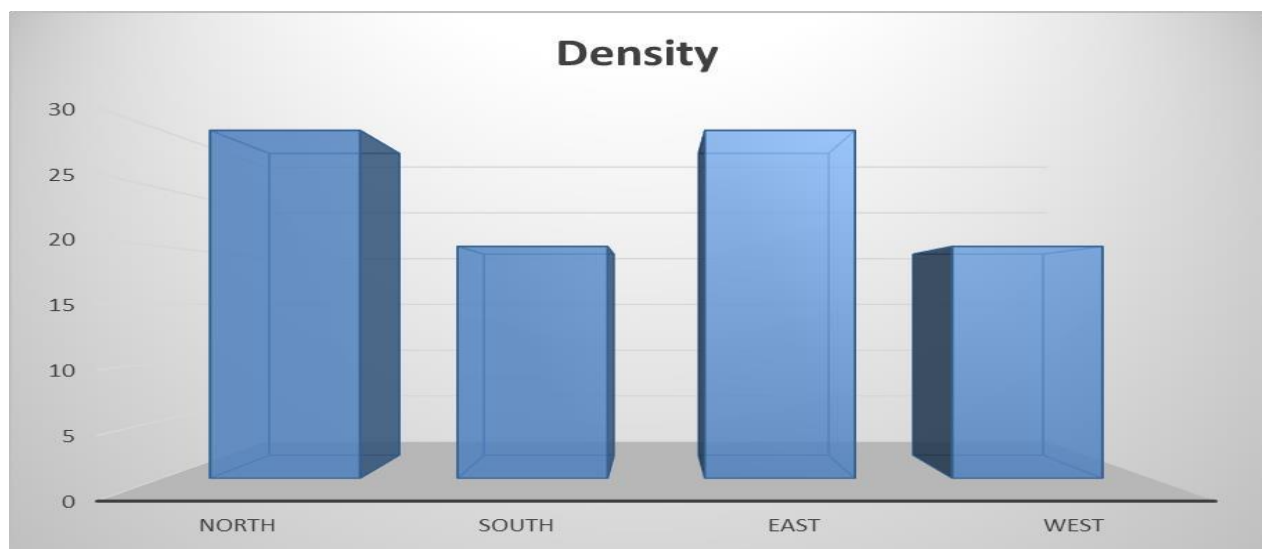


Figure 2. Density of forest vegetation on different aspects

3.3 Tree Height

The tree height also has an impact on the forest fire; taller trees are less affected by the fire and newly planted trees of height 10 feet (3 meters) were highly affected in the area. The area of Pallandri has not observed any crown fire till now, the fire burned only up to 6 to 7 feet of trees because of its tall height, the fire cannot spread up, mostly the area was covered by trees having a height of 150-200 feet.

3.4 Distance between trees

The distance between trees was observed and the distance varied among the trees; some trees were in the distance of 7 feet and some were in the distance of 13 feet. The average distance between trees was 10 feet; each plot had around 400 to 500.

3.5 Tree Diameters

The trees with a small diameter are more susceptible to forest fire. Larger diameter trees have thicker bark and provide better insulation against forest fire.

3.6 Climate

The temperature during the winter season is $-4^{\circ}\text{C} - 20^{\circ}\text{C}$ and in summer the temperature ranges from $20^{\circ}\text{C} - 35^{\circ}\text{C}$. The fire season starts in May when the temperature rises, and continues to July.

3.7 Omission and predicted area for forest fire

The following figure shows the omission rate and predicted area as a function of the cumulative threshold. The omission rate is calculated both on the training presence records and on the test records. The omission rate should be close to the predicted omission, because of the definition of the cumulative threshold. The spatial distribution for each category was as follows: the low-risk FFRZ spanned 2,731.7 km², making up 12.5% of the total area; the moderate-risk FFRZ extended over 17,997.69 km², constituting 82.59%; while the high-risk FFRZ occupied 1,061.63 km², or 4.87% of the entire area. These categorizations demonstrate the varying levels of fire susceptibility within the study area.

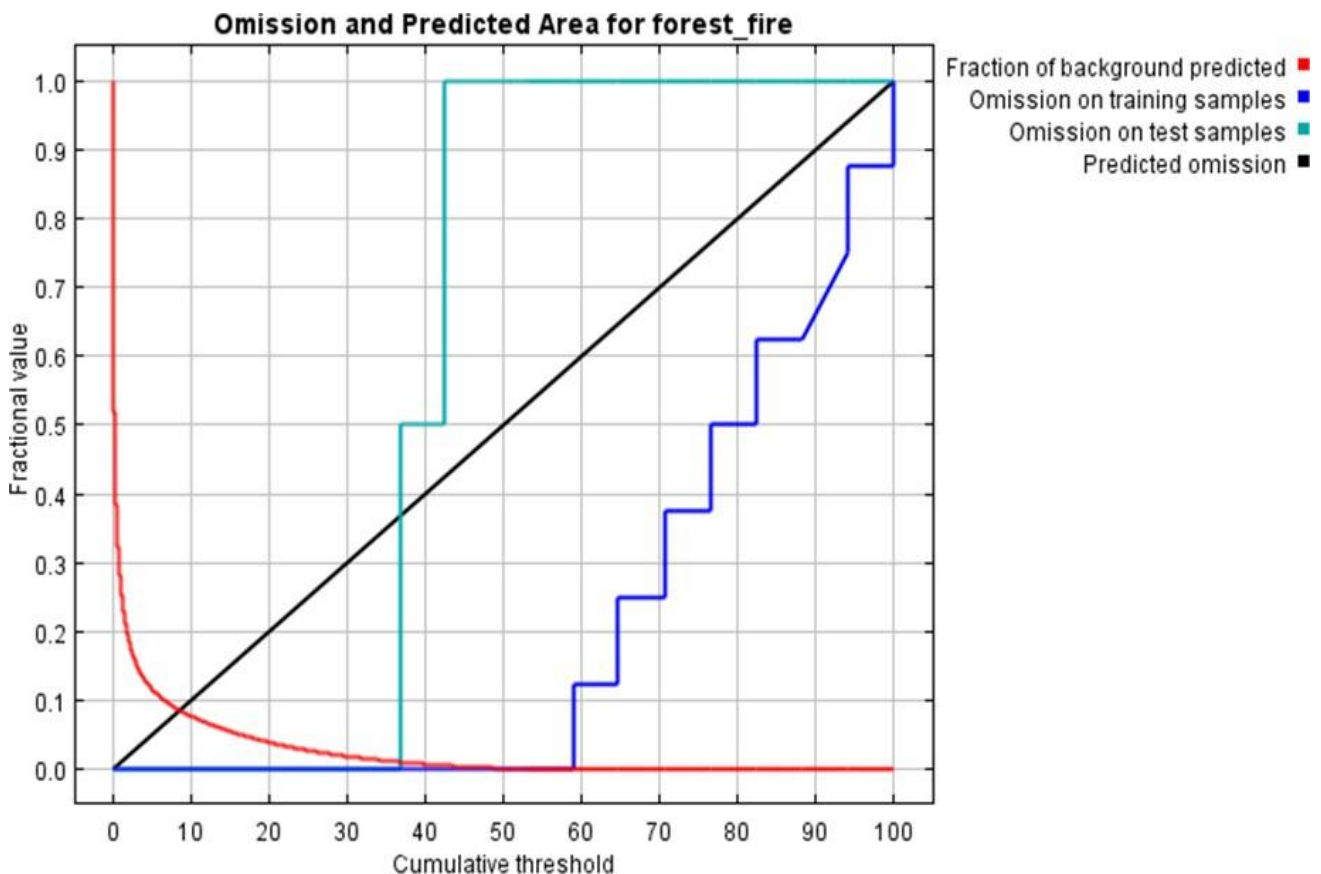


Figure 3. Omission and Predicted Area for Forest Fire.

3.8 Sensitivity vs specificity for forest fire

The figure below presents the Receiver Operating Characteristic (ROC) curve based on the same dataset. It's important to highlight that specificity here is calculated using the predicted area instead of true commission. As a result of this approach, the highest attainable Area under the Curve (AUC) is less than 1. When test data originates directly from the Maxent

distribution, the theoretical maximum AUC would be 0.967 rather than a perfect 1. However, in real-world scenarios, the observed test AUC may occasionally surpass this theoretical limit.

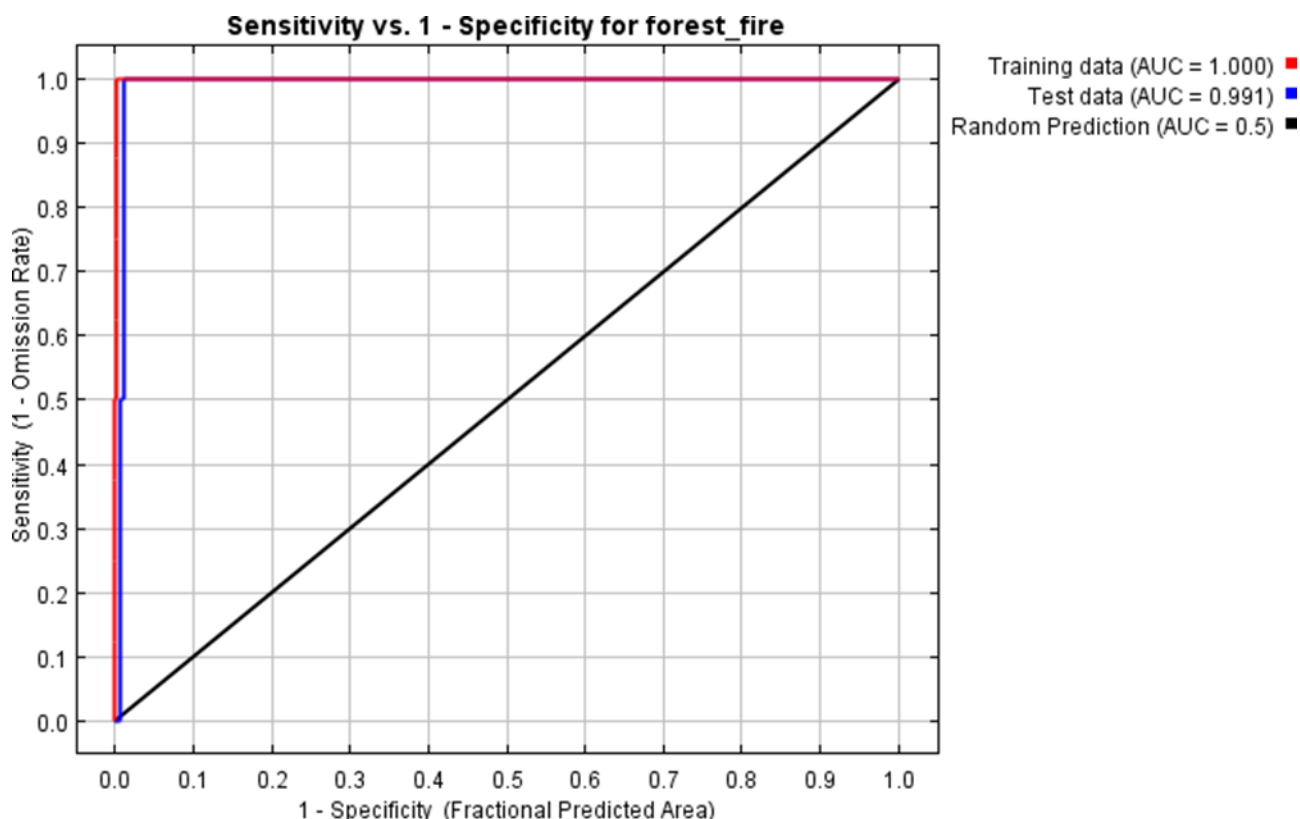


Figure 4. Sensitivity vs specificity for forest fire

3.9 Response curves

The following graphs illustrate the influence of individual environmental variables on the Maxent model's predictions. They depict how the logistic output shifts when one environmental factor is adjusted, while all others remain fixed at their average sampled values. However, interpreting these graphs can be challenging when variables are highly correlated, as the model may leverage these correlations in complex ways not directly visible in the plots. Essentially, the graphs reflect the isolated impact of altering a single variable, even though the model might utilize combined changes in multiple variables, as demonstrated in the figures below.

3.10 Analysis of variable contributions

The table below outlines the estimated relative influence of environmental variables in the Maxent model. For the first estimate, during each iteration of the training process, the change in regularized gain, whether increased or decreased, depending on the lambda value, is attributed to the corresponding variable. The second estimate involves randomly permuting the values of each environmental variable across both presence and background training data. The model is then re-run using this altered data, and the resulting decrease in training AUC is recorded and expressed as a percentage. Similar to the variable jackknife method, these contributions should be interpreted carefully, particularly when predictor variables are correlated. The table includes the percentage contribution and permutation importance of each environmental factor in the Maxent-based fire probability model. Variables like NDVI, BIO_6 (minimum temperature of the coldest month), and distance to settlements emerged as the most influential in shaping the model's outcomes.

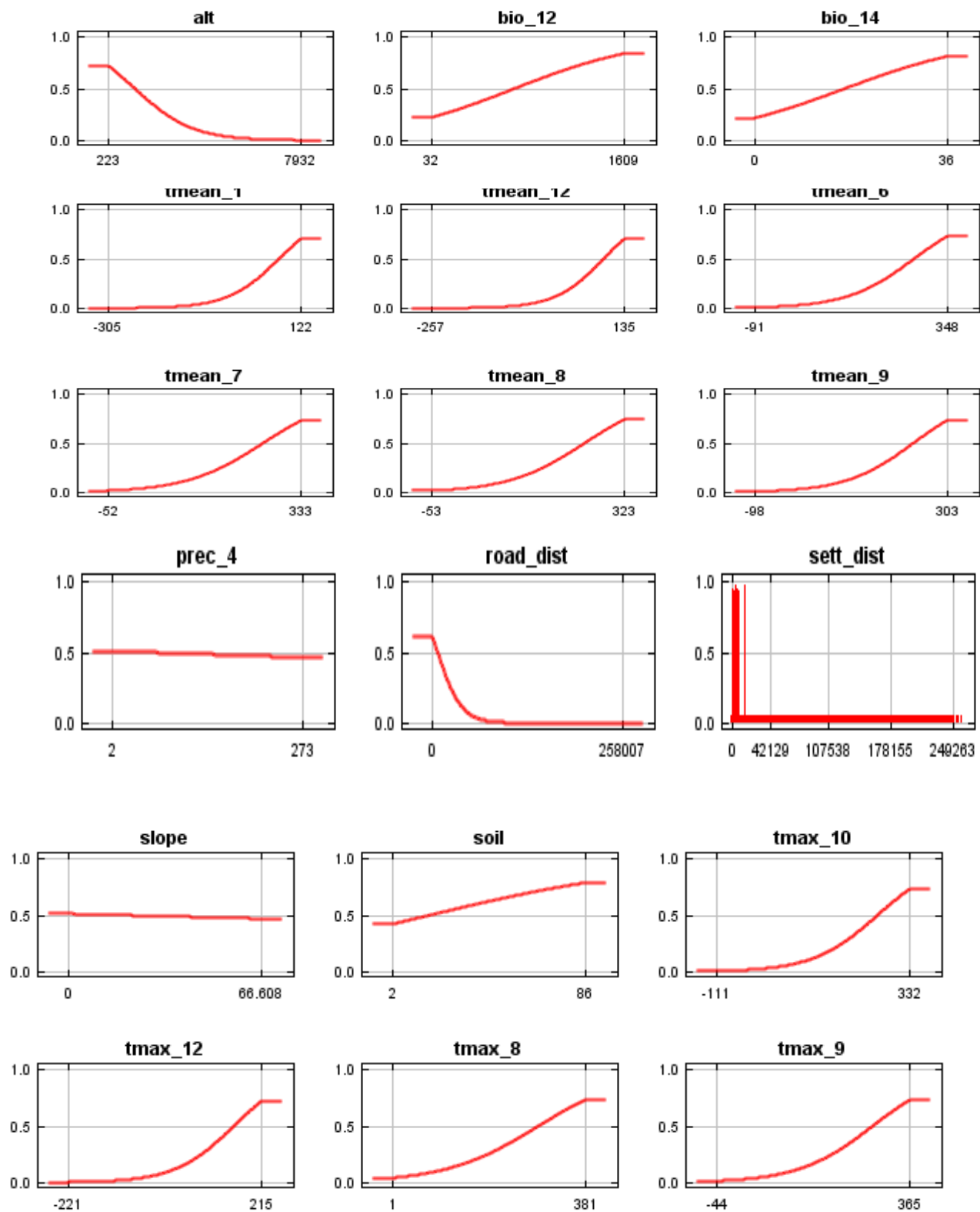


Figure 5. Influence of individual environmental variables on fire occurrence prediction

Table 2. Relative Contribution and Permutation Importance of Environmental Variables in the Fire Predictability Model

Variable	Percent contribution	Permutation importance
ndvi	34.7	0.3
bio_6	29.5	94
sett_dist	18.7	0.5
tmean_1	6.5	0
glc2000	4.3	0
road_dist	3.5	0.1
tmax_8	1.5	5
bio_14	0.7	0
prec_4	0.5	0
slope	0.1	0
bio_16	0	0
soil	0	0
tmin_12	0	0
tmean_9	0	0
tmean_8	0	0
tmean_7	0	0
tmean_6	0	0
tmean_12	0	0
tmax_9	0	0
tmax_12	0	0
tmax_10	0	0
prec_12	0	0
bio_2	0	0
bio_12	0	0
alt	0	0

3.11 Jackknife test of forest fire

The graph below presents the outcomes of the jackknife test for assessing variable importance. Among the environmental variables, NDVI yields the highest gain when used alone, indicating it provides the most valuable independent information. In contrast, omitting GLC2000 results in the greatest decrease in gain, suggesting it contains unique information not captured by the other variables

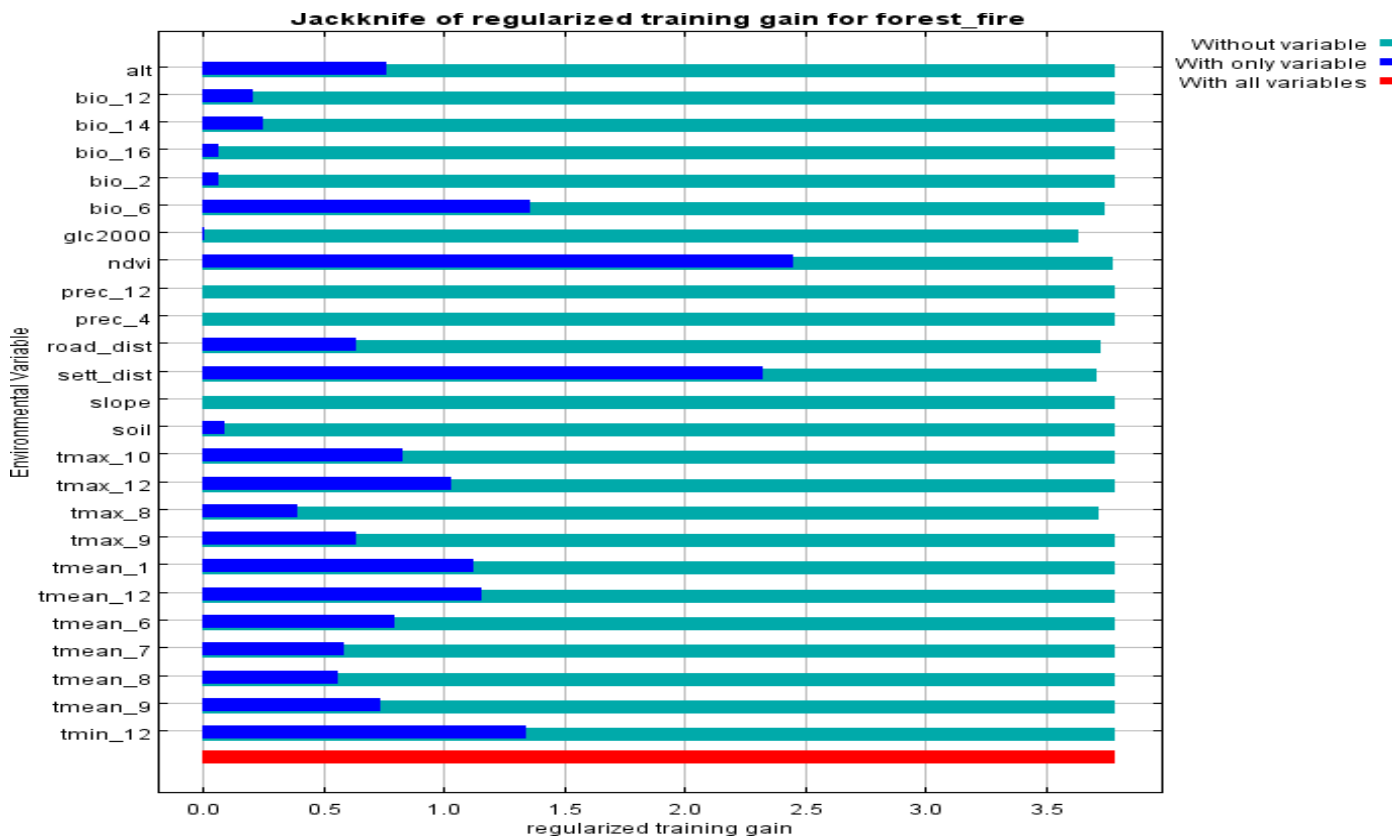


Figure 6. Jackknife of regularized training gain on forest fire.

The graph below presents the jackknife test again, but this time using test gain instead of training gain. Keep in mind that the conclusions regarding the most important variables may differ since we are now analyzing test data.

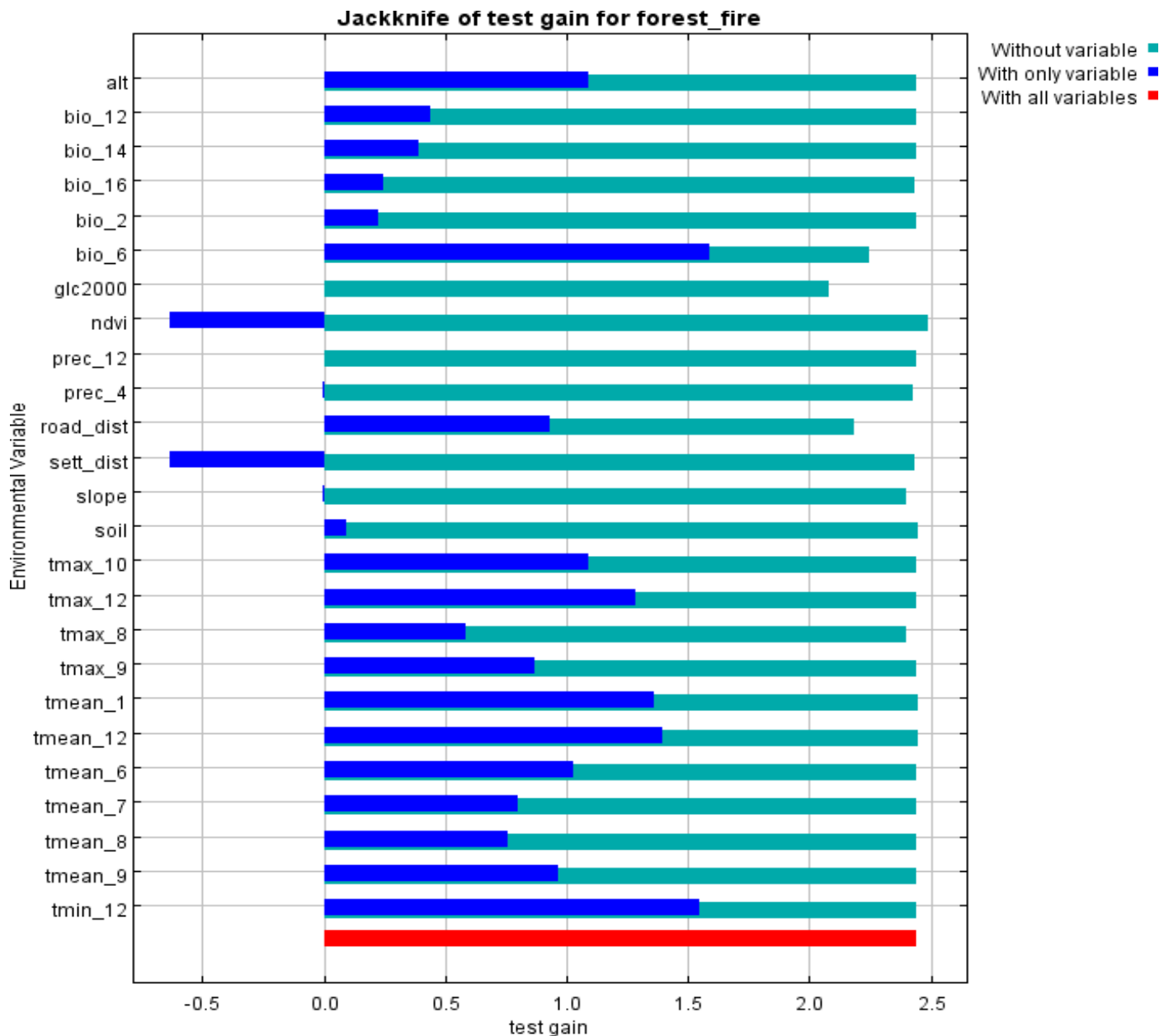


Figure 7. Jackknife of test gain for the forest fire

4. Discussion

This study presents a comprehensive assessment of forest fire vulnerability in the Chir Pine (*Pinus roxburghii*) forests of Pallandri, Azad Jammu and Kashmir, using ecological field data and the MaxEnt modeling approach. The findings reveal that the region is highly susceptible to wildfires, particularly during the dry summer months, with significant influence from forest structure, topographic orientation, and human activity. These results align with existing literature, which highlights the compounding impact of climate, vegetation characteristics, and anthropogenic pressures on forest fire occurrence (Sun *et al.*, 2025).

The dominance of Chir Pine in the study area, combined with its seasonal needle fall, creates a highly flammable forest floor. The study confirmed that these needles, particularly when accumulated in dense forest stands, act as surface fuel that facilitates the ignition and rapid spread of fires. This finding is consistent with prior research indicating that forests with high fuel loads and closed canopies are more likely to experience severe fires (Chandra and Bhardwaj, 2015). Topographic factors also played a critical role in fire distribution. The north- and east-facing slopes were identified as more vulnerable to fire events due to their prolonged exposure to direct sunlight and

relatively higher forest density. These areas tend to dry out faster during the pre-monsoon months, increasing the likelihood of ignition. This observation is supported by similar studies conducted in the Himalayan region, which found that aspect and elevation significantly influence fire frequency and severity (Tariq *et al.*, 2022).

Vegetation structure further impacts fire susceptibility. Areas with smaller tree diameters and shorter distances between trees were more prone to crown fire potential, attributed to the formation of “fuel ladders” that allow surface fires to climb into the canopy. The importance of vertical and horizontal fuel continuity has been emphasized in wildfire behavior models globally, including in California and the Mediterranean basin (Thomason, 2015). The MaxEnt model applied in this study showed strong predictive performance, as evidenced by the area under the curve (AUC) values and the analysis of variable contributions. Out of the 19 bioclimatic and environmental variables considered, NDVI (Normalized Difference Vegetation Index) and land cover (GLC2000) were the most influential in enhancing the model's predictive accuracy. These variables are known indicators of vegetation health and biomass distribution, both of which are critical to understanding fire behavior (Phillips *et al.*, 2006; Adab *et al.*, 2018). The reliability of MaxEnt for predicting forest fire zones has also been corroborated by recent studies in China and India (Banerjee, 2021). In addition to biophysical factors, human activity was identified as a major driver of forest fire incidents. Local practices such as burning dry grass and needles for pasture regeneration, careless disposal of cigarettes, and campfire remnants were frequently cited as causes of fire outbreaks. These findings highlight the critical role of community awareness and behavioral change in forest fire prevention, a concern echoed across wildfire-prone regions worldwide (Jaiswal, 2002; Sewak *et al.*, 2021).

Although the study provides valuable insights, certain limitations should be acknowledged. The data were collected from a single season, and long-term temporal trends were not analyzed. Furthermore, while MaxEnt offers robust predictions with presence-only data, it does not account for fire suppression efforts or future land-use changes that might influence fire risk. Incorporating remote sensing time-series data and climate projections in future studies could enhance model robustness and allow dynamic fire risk assessments. Overall, the results highlight the critical importance of proactive forest management, focused fire prevention measures, and community-driven engagement initiatives. Addressing forest fire risks in Pallandri will not only help preserve biodiversity and forest resources but also protect local livelihoods and reduce greenhouse gas emissions associated with biomass burning.

Conclusion

This study assessed the vulnerability of Chir Pine (*Pinus roxburghii*) forests in Pallandri, Azad Jammu and Kashmir, to forest fires using the MaxEnt model and field-based ecological and bioclimatic data. The results indicate that the region is highly susceptible to wildfire outbreaks during the dry summer months of May through July, primarily due to the accumulation of dry pine needles, high forest density, and anthropogenic activities. North and east-facing slopes were found to be particularly at risk due to higher solar exposure and greater forest cover. Key contributing factors to fire vulnerability included small tree diameters, closely spaced trees (which promote fuel ladders), and community practices such as open burning of grass and needles for livestock forage. MaxEnt modeling, validated through AUC and jackknife tests, identified NDVI and land cover type as the most influential variables in predicting fire-prone zones. These findings emphasize the critical need for integrated fire management strategies and community engagement to prevent ecological degradation and economic loss in the region.

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References

- Allison, H., & Amelia Holcomb, V. K. (2023). A discussion paper on the definition of forest degradation prepared for FAO.
- Argañaraz, J. P., Pizarro, G. G., Zak, M., Landi, M. A., & Bellis, L. M. (2015). Human and biophysical drivers of fires in Semiarid Chaco Mountains of Central Argentina. *Science of the Total Environment*, 520, 1-12.
- Aslam, A., Rana, I. A., & Bhatti, S. S. (2021). The spatiotemporal dynamics of urbanisation and local climate: A case study of Islamabad, Pakistan. *Environmental Impact Assessment Review*, 91, 106666.
- Banerjee, P. (2021). Maximum entropy-based forest fire likelihood mapping: analysing the trends, distribution, and drivers of forest fires in Sikkim Himalaya. *Scandinavian Journal of Forest Research*, 36(4), 275-288.
- Bernier, P., & Schoene, D. (2009). Adapting forests and their management to climate change: an overview.
- Binjola, R. (2023). Master of Science Forestry (silviculture).
- Bryan, B. A., Gao, L., Ye, Y., Sun, X., Connor, J. D., Crossman, N. D., ... & Hou, X. (2018). China's response to a national land-system sustainability emergency. *Nature*, 559(7713), 193-204.
- Cao, Y., Wang, M., & Liu, K. (2017). Wildfire susceptibility assessment in Southern China: A comparison of multiple methods. *International Journal of Disaster Risk Science*, 8, 164-181.
- 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. *International Journal of Agriculture and Forestry*, 5(2), 69-78.
- 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. *International Journal of Agriculture and Forestry*, 5(2), 69-78.
- Esposito, S., Toni, G., Tascini, G., Santi, E., Berio, M. G., & Principi, N. (2019). Environmental factors associated with type 1 diabetes. *Frontiers in endocrinology*, 10, 592.
- Flannigan, M., Cantin, A. S., De Groot, W. J., Wotton, M., Newbery, A., & Gowman, L. M. (2013). Global wildland fire season severity in the 21st century. *Forest Ecology and Management*, 294, 54-61.

- Gili, J. A., Corominas, J., & Rius, J. (2000). Using Global Positioning System techniques in landslide monitoring. *Engineering geology*, 55(3), 167-192.
- Heinrich, M., Jalil, B., Abdel-Tawab, M., Echeverria, J., Kulić, Ž., McGaw, L. J., ... & Wang, J. B. (2022). Best practice in the chemical characterisation of extracts used in pharmacological and toxicological research—the ConPhyMP—guidelines. *Frontiers in Pharmacology*, 13, 953205.
- Jaiswal, R. K., Mukherjee, S., Raju, K. D., & Saxena, R. (2002). Forest fire risk zone mapping from satellite imagery and GIS. *International journal of applied earth observation and geoinformation*, 4(1), 1-10.
- Jun-bing, B. A. I., Xu-hong, C. H. A. N. G., De-mei, W. A. N. G., Yu-shuang, Y. A. N. G., & Yu-jiao, W. A. N. G. (2022). Effects of meteorological factors on grain characteristics in different wheat varieties in the southern of Huang-Huai planting. *Chinese Journal of Agrometeorology*, 43(06), 474.
- Kim, E., & Kwon, Y. J. (2023). Analyzing indirect economic impacts of wildfire damages on regional economies. *Risk Analysis*, 43(12), 2631-2643.
- Krishnaswamy, J., Bonell, M., Venkatesh, B., Purandara, B. K., Rakesh, K. N., Lele, S., ... & Badiger, S. (2013). The groundwater recharge response and hydrologic services of tropical humid forest ecosystems to use and reforestation: Support for the “infiltration-evapotranspiration trade-off hypothesis”. *Journal of Hydrology*, 498, 191-209.
- Manzello, S. L. (Ed.). (2020). *Encyclopedia of wildfires and wildland-urban interface (WUI) fires*. Cham: Springer International Publishing.
- Pandey, P., & Gupta, A. P. (2025). A Review on Current Modelling Techniques for Predicting Forest Fires. *Remote Sensing and GIS Application in Forest Conservation Planning*, 269-304.
- Parisien, M. A., Dawe, D. A., Miller, C., Stockdale, C. A., & Armitage, O. B. (2019). Applications of simulation-based burn probability modelling: a review. *International journal of wildland fire*, 28(12), 913-926.
- Peavey, L. (2010). Predicting pelagic habitat with presence-only data using maximum entropy for olive ridley sea turtles in the Eastern Tropical Pacific.
- Piao, Y., Lee, D., Park, S., Kim, H. G., & Jin, Y. (2022). Forest fire susceptibility assessment using google earth engine in Gangwon-do, Republic of Korea. *Geomatics, Natural Hazards and Risk*, 13(1), 432-450.
- Ruffault, J., Curt, T., Martin-StPaul, N. K., Moron, V., & Trigo, R. M. (2018). Extreme wildfire events are linked to global-change-type droughts in the northern Mediterranean. *Natural Hazards and Earth System Sciences*, 18(3), 847-856.
- Sewak, R., Vashisth, M., & Gupta, L. (2021). Forest fires in India: A review. *Journal of University of Shanghai for Science and Technology*, 23(07), 247-259.
- Storey, M. A., Bedward, M., Price, O. F., Bradstock, R. A., & Sharples, J. J. (2021). Derivation of a Bayesian fire spread model using large-scale wildfire observations. *Environmental Modelling & Software*, 144, 105127.
- Sun, M., Zhang, X., & Jin, R. (2025). Visualization of Post-Fire Remote Sensing Using CiteSpace: A Bibliometric Analysis. *Forests*, 16(4), 592.
- Tamang, D. (2015). *Forest fire hazard modeling a case study of Dumkibas village development committee of Nawalparasi district in Nepal* (doctoral dissertation, Tribhuvan University).
- Tariq, A., Shu, H., Siddiqui, S., Munir, I., Sharifi, A., Li, Q., & Lu, L. (2022). Spatio-temporal analysis of forest fire events in the Margalla Hills, Islamabad, Pakistan using socio-economic and environmental variable data with machine learning methods. *Journal of Forestry Research*, 33(1), 183-194.
- Thomason, A. C. (2015). *Modeling Burn Probability: A Maxent Approach to Estimating California's Wildfire Potential* (Master's thesis, University of Southern California).
- Tzaros, C. (2021). *Wildlife of the box-ironbark country*. CSIRO publishing.