Spatial assessment of forest fire susceptibility in the Kodaikanal hill range using GIS-based fuzzy AHP

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Abstract

Forest fires pose a significant threat to ecosystems, biodiversity and human livelihoods, particularly in ecologically sensitive regions like the Kodaikanal Hill range in Tamil Nadu, India. This study integrates Geographic Information System (GIS)-based Fuzzy Analytical Hierarchy Process (Fuzzy-AHP) to assess forest fire susceptibility through a comprehensive spatial analysis. Key physiographic and climatic factors including elevation, slope, aspect, temperature, precipitation and vegetation, were prioritized using expert judgment and fuzzy logic. These factors were spatially analyzed to produce a detailed forest fire susceptibility map for the region. Model validation using historical fire data demonstrated high accuracy, classifying 31% of the area as highly susceptible, 30% as moderately susceptible and 39% as less susceptible. Proximity analysis further identified vulnerable infrastructure revealing that 28.68% of road networks and 30% of settlement areas fall within high-risk zones.

The findings underscore the necessity for targeted mitigation strategies and highlight the importance of incorporating spatial tools into forest management and disaster preparedness. This study provides critical insights for policymakers, forest managers and disaster management authorities, enabling informed decision-making to reduce the adverse impacts of forest fires.

Keywords: Forest Fire Susceptibility, GIS-Based Fuzzy AHP, Spatial Risk Assessment, Anthropogenic Factors.

Introduction

Forest fires pose a significant environmental threat impacting ecosystems, economies and societies on a global scale. Their increasing frequency and intensity are largely driven by climate change, shifting land-use patterns and human activities[3]. In ecologically sensitive regions like the Kodaikanal Hill range in Tamil Nadu, India, forest fires pose a significant threat to biodiversity, ecosystem services and human livelihoods. The Kodaikanal Hill range, part of the Western Ghats biodiversity hotspot, is characterized by its rich flora and fauna, steep terrain and diverse climatic conditions, making it particularly vulnerable to fire outbreaks[19]. Understanding and mitigating the risks associated with forest fires is therefore essential for preserving this ecologically significant region. The current state of research highlights the importance of integrating advanced geospatial tools and multi-criteria decision-making frameworks to assess and predict forest fire susceptibility. Geographic Information Systems (GIS) and remote sensing technologies have emerged as indispensable tools for mapping and monitoring fire-prone areas[17]. Fuzzy-AHP is widely recognized for its capability to address uncertainties in multi-criteria decision-making, particularly in fire risk assessment. Studies by Nuthammachot and Stratoulias[24] highlight the effectiveness of integrating GIS with Fuzzy-AHP for fire susceptibility mapping, reinforcing the importance of region-specific models that consider localized topographical and climatic variables.

Despite these advancements, challenges remain in accurately predicting fire-prone areas implementing targeted mitigation strategies. For instance, while some studies prioritize physiographic factors like slope and elevation[2], others emphasize the role of climatic variables such as temperature and humidity[36]. This divergence in focus underscores the complexity of forest fire dynamics and the need for comprehensive assessments that integrate both natural and anthropogenic factors. Furthermore, the influence of human activities including road networks and settlements, on fire ignition and spread remains a topic of ongoing debate[33].

This study aims to address these gaps by developing a comprehensive Forest Fire Susceptibility (FFS) map for the Kodaikanal Hill range using a GIS-based Fuzzy-AHP approach. The primary objectives include analyzing key physiographic and climatic factors, integrating these variables into a spatial model and validating the results using historical fire data. By identifying high-risk zones and assessing the vulnerability of anthropogenic infrastructure, this research seeks to provide actionable insights for policymakers, forest managers and disaster management authorities. The findings underscore the importance of adopting integrated spatial tools for effective forest fire management and highlight the potential of the Fuzzy-AHP methodology as a robust framework for risk assessment.

Material and Methods

Study area: The Kodaikanal Hill range, located in Tamil Nadu's Dindigul district, spans 1820 km² and is positioned between 77°14'26"–77°45'28" E longitude and 10°6'25"–10°26'54" N latitude. Known as the "Princess of Hill Stations," this ecologically significant region is celebrated for its rich biodiversity, pristine landscapes and vital ecosystem services. The area's varying elevation fosters distinct vegetation zones, including tropical moist deciduous forests at lower elevations, subtropical forests at mid-elevations (1000–2000 m) and Shola forests and grasslands at higher elevations (>2000 m), making it a global

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biodiversity hotspot. Due to its diverse flora, steep terrain and varied climate, the region is particularly vulnerable to forest fires, requiring thorough fire susceptibility evaluations[8,13].

The physiography of the region includes undulating terrain, steep slopes, ridges and narrow valleys, with significant features like Bajada, Barren Slopes and Escarpments. Human settlements are primarily located in isolated pockets with agriculture as the main livelihood. The Kodaikanal Hill Range's fire season typically runs from February to June, peaking in May, with historical data highlighting the severe ecological threat posed by wildfires that have caused extensive forest cover loss, underscoring the need for effective fire management strategies[10].

Methodology: This study aimed to assess and map forest fire susceptibility (FFS) in the Kodaikanal Hill range, Tamil Nadu, India, using a structured three-phase methodology. The first phase involved selecting and categorizing factors influencing fire susceptibility which included physiographic, climatic and anthropogenic parameters such as elevation, slope, terrain ruggedness, land cover, rainfall, land surface temperature and wind speed. Data for these parameters were sourced from reputable datasets like Landsat 9 OLI/TIRS, ASTER GDEM, Copernicus C3S, Wind Atlas and IMD[6,11,15,30,34]. In the second phase, a GIS-based fuzzy analytical hierarchy process (Fuzzy-AHP) was employed to integrate these factors, applying fuzzy logic to account for uncertainties in expert judgments. Pairwise comparison matrices were created to assign weights to each factor and GIS-based overlay analysis was used to generate a composite FFS map, classifying the study area into five susceptibility zones based on quantile methods[29,35].

The third phase focused on validating the FFS map using historical fire data from the Visible Infrared Imaging Radiometer Suite (VIIRS) for 2023 and 2024, with model accuracy assessed using the receiver operating characteristic–area under curve (ROC-AUC) method[21]. All datasets were standardized to a 30-meter spatial resolution for compatibility in GIS analysis. The methodology, utilizing ArcGIS Pro for data processing, enabled the creation of a clear FFS map that aids in identifying high-risk fire zones, supporting better forest management and disaster preparedness. This approach provided a reliable and comprehensive assessment of forest fire susceptibility, integrating diverse data sources and advanced spatial analysis techniques to address fire risks in the region.

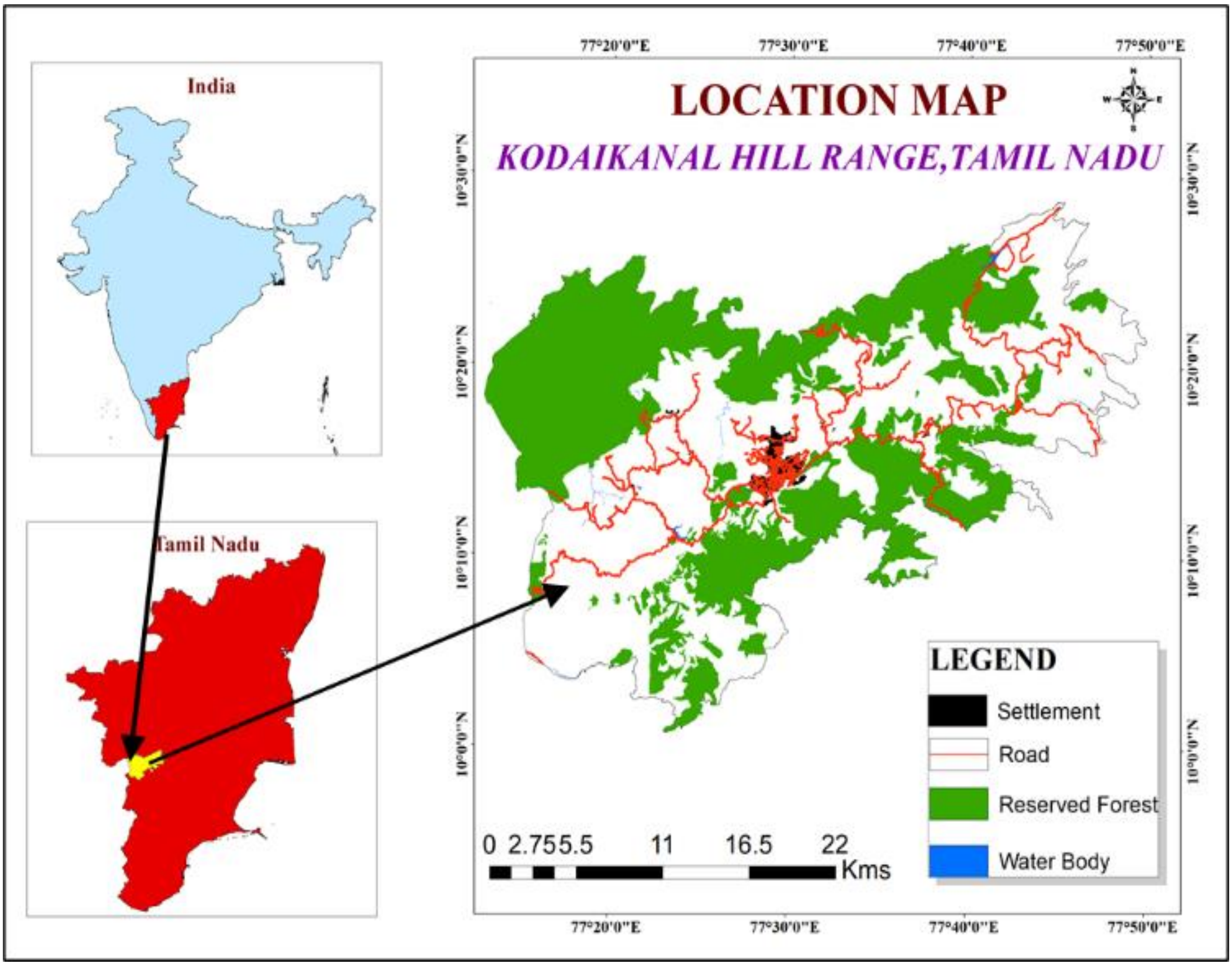

Figure 1: Location Map of Kodaikanal Hill Range

Results

Rainfall: Rainfall is a critical climatic parameter influencing forest fire susceptibility. In the Kodaikanal region, annual rainfall was classified into five categories: very low (594–758 mm), low (759–850 mm), moderate (851–950 mm), high (951–1050 mm) and very high (1060–1350 mm). Areas with very low rainfall experience limited moisture availability, increasing fire risk, while regions with very high rainfall are less prone to fires due to lush vegetation and damp conditions[15].

Relative Humidity: Relative humidity affects the dryness of vegetative fuels. Low humidity levels temporarily increase fire risk by drying out potential fuel. In the Kodaikanal region, relative humidity was classified into five categories: very low (53.71–55.5%), low (55.5–57%), moderate (57–58.5%), high (58.5–60.5%) and very high (60.5–62.84%). Higher humidity levels reduce fire susceptibility by limiting fuel dryness[25].

Wind Speed: Wind speed significantly influences fire behavior by accelerating fire spread and intensity. In the study area, wind speed was categorized into five classes: very low (0.76–2.5 m/s), low (2.5–4 m/s), moderate (4–5.5 m/s), high (5.5–7 m/s) and very high (7–11 m/s). Very high wind speeds can cause extreme fire behavior and rapid spread over large areas[11].

Soil Moisture: Soil moisture is critical in determining forest fire susceptibility, as it directly influences vegetation flammability and overall fire risk. In this study, the soil moisture index (SMI) was derived from Landsat 9 satellite imagery using a formula based on land surface temperature (LST) extremes.

$$SMI = \frac{(LST_{Max} - LST_{Min})}{(LST_{Max} - LST)}$$

where LST max and LST min represent the maximum and minimum land surface temperatures within a given area respectively and LST is the pixel-specific land surface temperature. The SMI values were classified into five categories: very low (1.88–2.17), low (2.18–2.28), moderate (2.29–2.37), high (2.38–2.49) and very high (2.50–2.88). Areas with low SMI values are more susceptible to fires due to dry soil, while high SMI values indicate moist conditions that help to reduce fire risk. This classification provides insights for identifying high-risk zones and implementing fire management strategies in ecologically sensitive regions like the Kodaikanal Hill Range[24].

Land Surface Temperature (LST): Landsat 9 thermal bands provide crucial insights into Land Surface Temperature (LST), a key determinant of forest fire risk. Variations in LST impact vegetation moisture levels, influencing fuel dryness and ignition potential. Elevated LST readings correspond to intensified surface heating, leading to faster vegetation desiccation and an increased likelihood of fire outbreaks. In the Kodaikanal Hill range, LST was calculated using a systematic methodology that involved several steps:

I. Conversion of Top of Atmospheric (TOA) Spectral Radiance to Brightness Temperature: The raw digital numbers (DN) from the thermal bands were converted into TOA spectral radiance using the formula:

$$TOA(L) = ML \times Qcal + AL$$

where ML is the multiplicative rescaling factor, Qcal is the quantized calibrated pixel value and AL is the additive rescaling factor.

II. Brightness Temperature Calculation: The TOA spectral radiance was then converted into brightness temperature (BT) using Planck's equation:

$$BT = \ln(L\, K1 + 1)\, K2 - 273.15$$

Here, K1 and K2 are calibration constants specific to the thermal bands and L represents the TOA spectral radiance.

III. Estimation of Emissivity (ε): Emissivity was estimated using the proportion of vegetation (Pv), which was calculated based on NDVI values:

$$\varepsilon = 0.004 \times Pv + 0.986$$

IV. Final LST Computation: The final LST was derived using the formula:

$$LST = 1 + W \times BT \times \ln(\varepsilon)\, BT$$

where W is the wavelength of emitted radiance (11.5 μm).

The derived LST values were classified into five categories: very low (<20°C), low (20–25°C), moderate (25–30°C), high (30–35°C) and very high (>35°C). Areas with very high LST (>35°C) were identified as critical hotspots for forest fire susceptibility due to their association with sparse vegetation and prolonged dry conditions. These classified LST layers were integrated with other climatic variables such as rainfall, relative humidity and wind speed, to assess their combined impact on fire risk[26]. This approach provided a comprehensive understanding of how temperature dynamics contribute to fire susceptibility across the study area.

Land use/land cover (LULC): Land use/land cover (LULC) plays a vital role in assessing forest fire susceptibility by influencing the availability of fuel and the spread of fires. In the Kodaikanal Hill range, LULC was categorized into forests, plantations, croplands, barren lands and water bodies, with forests and scrublands considered high-risk areas due to abundant dry vegetation. Water bodies and agricultural lands act as natural firebreaks, reducing fire risks. To map LULC, supervised classification using satellite imagery and ground-truth data was employed, with algorithms like Maximum Likelihood Classification (MLC) or Support Vector Machines (SVM) used for accurate classification[17,25]. The resulting map, combined with other factors such as vegetation moisture and historical fire data, supports the identification of high-risk areas and effective fire management strategies[19].

Normalized Difference Vegetation Index (NDVI): The Normalized Difference Vegetation Index (NDVI) is a widely used remote sensing index that measures vegetation health and density based on the reflectance of near-infrared (NIR) and red light. It is calculated using the following formula:

$$NDVI = \frac{(NIR+Red)}{(NIR-Red)}$$

In this study, NDVI values derived from Landsat 9 OLI/TIRS imagery were classified into five categories to assess forest fire susceptibility: very low (-0.23 to 0.17), low (0.18 to 0.25), moderate (0.26 to 0.32), high (0.33 to 0.38) and very high (0.39 to 0.6). Lower NDVI values indicate sparse or stressed vegetation, which is more susceptible to fires due to reduced moisture and fuel load, while higher NDVI values represent denser vegetation, which is less prone to ignition but may intensify fires under dry conditions. NDVI also aids in post-fire recovery assessments, identifying areas of significant vegetation loss which is crucial for restoration efforts[14,25]. By integrating NDVI with elevation and other physiographic data, this analysis provides insights for targeted fire management and mitigation strategies in ecologically sensitive regions like the Kodaikanal Hill range.

Differenced Normalized Burn Ratio (dNBR): The Differenced Normalized Burn Ratio (dNBR) is a critical index used to assess the severity of wildfires and monitor post-fire recovery in ecosystems. It quantifies changes in vegetation and surface conditions by comparing pre- and post-fire Normalized Burn Ratio (NBR) values which are derived from satellite imagery using the formula:

$$NBR = \frac{(\mathrm{NIR+SWIR})}{(\mathrm{NIR-SWIR})}$$

where NIR is the near-infrared band and SWIR is the shortwave infrared band. The dNBR is derived by subtracting post-fire NBR from pre-fire NBR, helping to quantify fire intensity and impact. In this study, Landsat 9 imagery was used to calculate dNBR values for the Kodaikanal Hill range, which were classified into three categories: low (-0.81 to -0.28), moderate (-0.27 to -0.062) and high (-0.061 to 0.62). Higher dNBR values indicate severe disturbances and areas more prone to future fires, while lower values suggest minimal vegetation change and reduced fire risk. This classification assists in forest management by highlighting high-risk areas for restoration and prevention efforts[9,33]. Integrating dNBR with other environmental factors provides critical insights for wildfire mitigation in ecologically sensitive regions like the Kodaikanal Hill range.

Elevation: Elevation indirectly influences forest fire susceptibility by affecting temperature, precipitation and vegetation types. In the Kodaikanal Hill range. Elevation was classified into five categories: 344–750 meters, 750–1100 meters, 1100–1500 meters, 1500–2000 meters and 2000–2542 meters. Lower elevations, characterized by higher temperatures and sparse vegetation, are more susceptible to fires. In contrast, higher elevations with cooler temperatures and increased moisture exhibit reduced fire risk but remain vulnerable during prolonged dry spells[31].

Aspect: Aspect refers to the orientation of slopes and plays a crucial role in determining solar exposure, moisture retention and wind patterns. South-southeast-facing slopes in the Kodaikanal region are particularly susceptible to fires due to higher solar radiation and reduced moisture levels. Aspect was classified into eight directional categories including North, South, East, West, Northeast, Northwest, Southeast and Southwest, to capture its influence on fire dynamics[16].

Curvature: Curvature measures the shape of the terrain and is categorized into convex, planar and concave zones. Convex slopes, often exposed to higher wind speeds and faster drying of vegetation, are more prone to fires. Concave areas such as valleys, retain moisture for longer periods, reducing fire susceptibility. The distribution of curvature types significantly influences fire ignition and spread patterns[28].

Terrain Ruggedness Index (TRI): The Terrain Ruggedness Index (TRI) quantifies the complexity of the terrain by measuring elevation changes within a specific neighborhood. TRI values in the study area ranged from smooth (0–0.286) to highly rough (0.656–1). Areas with higher TRI values represent rugged terrains that can act as natural barriers to fire spread. However, these areas also hinder firefighting efforts due to their inaccessibility. Conversely, smoother terrains with lower TRI values are more prone to rapid fire propagation due to uniform topography[28].

GIS-based fuzzy analytical hierarchy process (FUZZY-AHP): The Analytical Hierarchy Process (AHP), developed by Saaty[29], is a widely-used multi-criteria decision-making tool that structures complex problems into hierarchical levels. It synthesizes expert opinions and is applied in both academic and industrial settings to tackle decision-making challenges. Despite its broad use, AHP faces limitations such as reduced effectiveness when the number of criteria and alternatives increase. Difficulty in handling the ambiguity is inherent in expert judgments. These limitations can impact the method's performance, especially in real-world applications[18,28]. To address these shortcomings, the integration of fuzzy logic (FL) into AHP, known as Fuzzy-

AHP, has gained traction. Fuzzy logic, proposed by Zadeh[35], deals with uncertainty by using membership values between 0 and 1 which represent the degree of an element's association within a set. Fuzzy-AHP helps to overcome the ambiguity in expert judgment and is particularly effective in situations where precise data is unavailable. The combination of qualitative and quantitative methods makes Fuzzy-AHP ideal for applications like forest fire susceptibility mapping where linguistic terms are assigned numerical values and fuzzy numbers represent the relative importance of factors[5,35,37].

Geometric mean fuzzy-AHP method: In this study, Buckley's[4] Fuzzy-AHP method was employed to analyze forest fire risk factors and delineate susceptibility zones. The process followed several key steps:

The primary objective was established and a hierarchical structure was constructed to identify risk factors and their corresponding sub-factors. A pairwise comparison matrix was created where each element $[\tilde{a}_{ij}]_k$ represents the preference of the k^{th} expert for risk factor i over risk factor j. The reciprocal relationship is given by $(\tilde{a}_{ij})\cdot(\tilde{a}_{ji})=1$ (Saaty)[29].

The average pairwise comparison matrix [a] was computed by averaging the preferences of all experts using equation (1):

$$A_{ij} = \frac{\sum_{k=1}^{n} (aij1+aij2+\cdots+aijk)}{n} \tag{1}$$

where n denotes the number of experts involved.

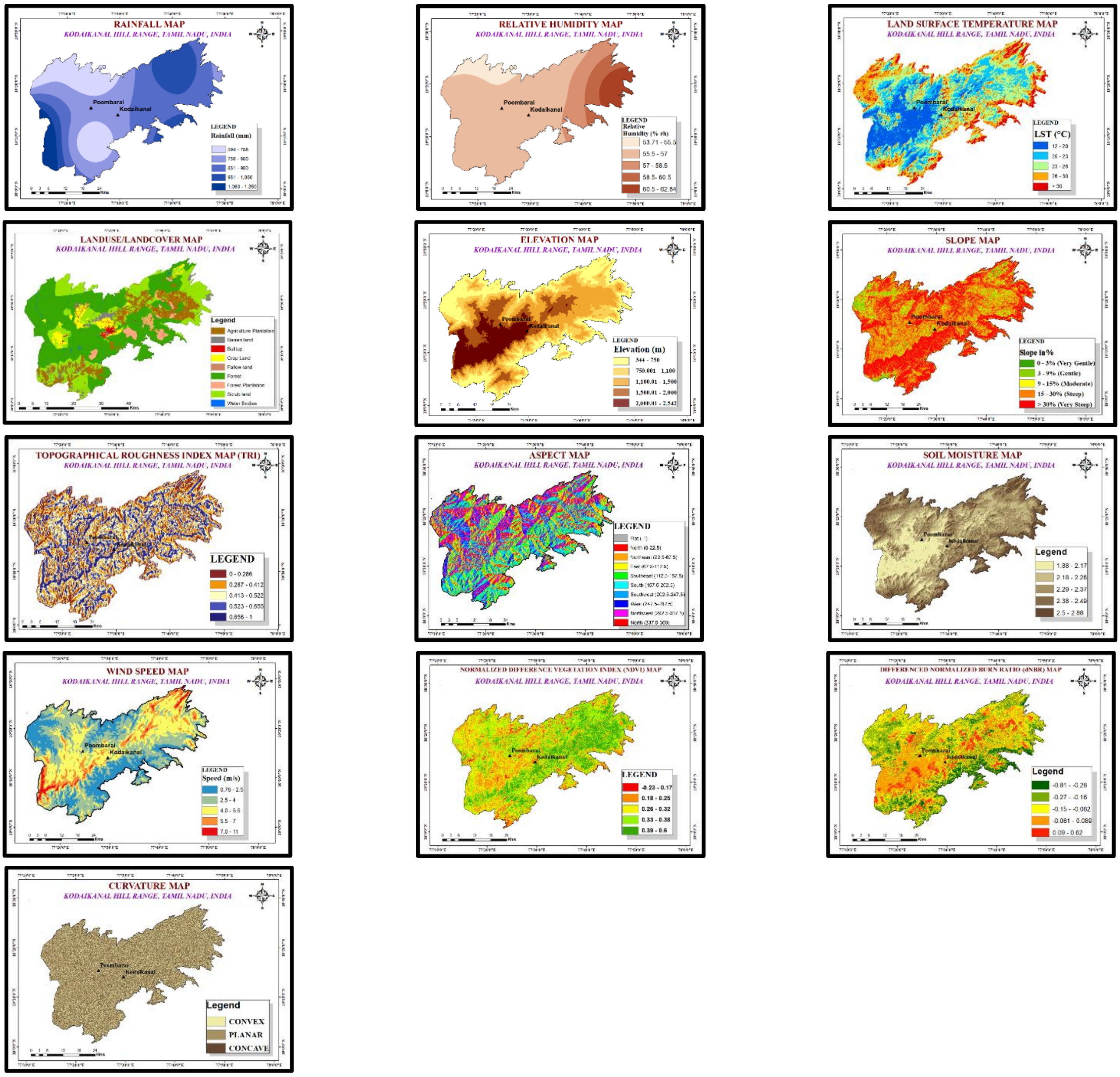

Figure 3: Forest Fire Inducing Parameters
(a) Rainfall; (b) Relative Humidity; (c) Soil Moisture; (d) Wind Speed; (e) LST; (f) LULC; (g) NDVI; (h) dNBR; (i) elevation; (j) Slope; (k) Aspect; (l) Curvature; (m)TRI

The AHP weights were calculated and validated based on the consistency ratio (CR). If CR≥0.10, the matrix was revised to ensure reliability[29]. A fuzzy pairwise comparison matrix $\tilde{a}$ was constructed, with elements represented as fuzzy values derived from the linguistic scale and triangular fuzzy number (TFN) conversion methods[4].

The fuzzy geometric mean for each risk factor R_i was estimated using equation (2):

$$R_{ij} = \{\prod_{j=1}^{n} \bar{A}_{ij}\}^{1/n} = (\tilde{A}_{i1} * \tilde{A}_{i2} * \tilde{A}_{i3} * \ldots \tilde{A}_{in})^{1/n} \quad (2)$$

The vector of fuzzy geometric risk factors was then formulated as:

$$R_i = [R_1, R_2, R_3, \ldots, R_n]^T$$

The fuzzy relative weights W_i, were determined using equation (3):

$$W_i = \tilde{R}_i * \left[\sum_{j=1}^{n} R_j\right]^{-1} \quad (3)$$

The fuzzy weights were converted into crisp values using the CoA method, as shown in equation (4):

$$W_i = \frac{L.W_i + M.W_i + U.W_i}{3} \quad (4)$$

The de-fuzzified weights were standardized using equation (5):

$$W_{Ni} = W_i / (\sum_{i=1}^{n} w_i \quad (5)$$

Finally, all thematic layers were combined to generate the FFS map using equation (6):

$$FFS = \sum_{i=1}^{n} x_i . W_{Ni} \quad (6)$$

where W_{Ni} represents the normalized fuzzy weight for factor X_i.

Forest fire susceptibility mapping: The Forest fire susceptibility (FFS) mapping in the Kodaikanal Hill Range was conducted using a GIS-based Fuzzy Analytical Hierarchy Process (Fuzzy-AHP), which integrated thirteen key factors influencing forest fire occurrence. These factors, categorized into physiographic and climatic elements, were ranked in terms of influence through pairwise comparison matrices based on expert judgment and fuzzy logic. The climatic factors ranked highest in influence, followed by physiographic ones, with rainfall, relative humidity and windspeed being the top contributors. Fuzzy weights for each factor were calculated and validated with a consistency ratio (CR) of 0.091, below the acceptable threshold of 0.1, confirming the robustness of the methodology[25].

The final FFS map was generated by integrating normalized weights into thematic layers using ArcGIS, classifying the study area into five susceptibility zones. Approximately 31% of the Kodaikanal Hill Range was found to have high or very high fire susceptibility, primarily in lower elevations with dense vegetation, steep slopes and proximity to human settlements. Higher elevations, with cooler climates and sparse vegetation, exhibited lower fire risk. These results align with findings from similar ecologically sensitive regions, providing valuable insights for fire management and mitigation strategies[2].

MAP validation using ROC-AUC: To ensure model reliability, the Forest Fire Susceptibility (FFS) map underwent validation using VIIRS-derived historical fire data (375m resolution) from 2023 and 2024. Performance assessment through Receiver Operating Characteristic–Area Under Curve (ROC-AUC) analysis yielded a high accuracy score of 0.824, confirming the robustness of the model's predictive capabilities. This outcome underscores the effectiveness of the GIS-based Fuzzy-AHP methodology in capturing the complexities of forest fire risk assessment and highlights its potential as a reliable tool for spatial risk mapping[17].

Table 1
Pairwise Comparison Matrix

PARAMETER	RAINFALL	HUMIDITY	WIND SPEED	MOISTURE	LST	LULC	NDVI	NBR	SLOPE	ELEVATION	ASPECT	CURVATURE	TRI
RAINFALL	1	2	2	1/2	1/3	1/2	4	5	1	1	1/2	1	1
HUMIDITY	1/2	1	1/3	1/3	1	3	2	5	1	1	3	1/5	1
WIND SPEED	1/2	3	1	1/2	1	3	2	3	1	1	2	1/4	1
MOISTURE	2	3	2	1	1	2	2	3	2	1/2	1	1/3	4
LST	3	1	1	1	1	2	3	4	1	1/2	1	1/3	3
LULC	2	1/3	1/3	1/2	1/2	1	1/2	1	1	1	1	1/2	2
NDVI	1/4	1/2	1/2	1/2	1/3	2	1	2	1	1	2	1/2	3
NBR	1/5	1/5	1/3	1/3	1/4	1	1/2	1	1/2	1/3	1/2	1/4	1/4
SLOPE	1	1/2	1	1/2	1	1	1	2	1	1	2	1/2	3
ELEVATION	1	1	1	2	2	1	1	3	1	1	1	1	2
ASPECT	2	1/3	1/2	1	1	1	1/2	2	1/2	1	1	1/3	1
CURVATURE	1	3	4	3	3	2	2	4	2	1	3	1	2
TRI	1	1	1	1/4	1/3	1/2	1/3	4	1/3	1/2	1	1/2	1
	15.45	16.86	14.99	11.41	12.74	20.00	19.83	39.00	13.33	10.83	19.00	6.69	24.25

Table 2
Fuzzy Pairwise Comparison Matrix

PARAMETER	RAINFALL	HUMIDITY	WIND SPEED	MOISTURE	LST	LULC	NDVI	NBR	SLOPE	ELEVATION	ASPECT	CURVATURE	TRI
RAINFALL	(1,1,1)	(1,2,3)	(1,2,3)	(1/3,1/2,1/1)	(2,3,4)	(1/3,1/2,1/1)	(3,4,5)	(4,5,6)	(1,1,1)	(1,1,1)	(1/3,1/2,1/1)	(1,1,1)	(1,1,1)
HUMIDITY	(1/3,1/2,1/1)	(1,1,1)	(1/4,1/3,1/2)	(1/4,1/3,1/2)	(1,1,1)	(2,3,4)	(1,2,3)	(4,5,6)	(1,1,1)	(1,1,1)	(2,3,4)	(1/6,1/5,1/4)	(1,1,1)
WIND SPEED	(1/3,1/2,1/1)	(2,3,4)	(1,1,1)	(1/3,1/2,1/1)	(1,1,1)	(2,3,4)	(1,2,3)	(2,3,4)	(1,1,1)	(1,1,1)	(1,2,3)	(1/5,1/4,1/3)	(1,1,1)
MOISTURE	(1,2,3)	(2,3,4)	(1,2,3)	(1,1,1)	(1,1,1)	(1,2,3)	(1,2,3)	(2,3,4)	(1,2,3)	(1/3,1/2,1/1)	(1,1,1)	(1/4,1/3,1/2)	(3,4,5)
LST	(2,3,4)	(1,1,1)	(1,1,1)	(1,1,1)	(1,1,1)	(1,2,3)	(2,3,4)	(3,4,5)	(1,1,1)	(1/3,1/2,1/1)	(1,1,1)	(1/4,1/3,1/2)	(2,3,4)
LULC	(1,2,3)	(1/4,1/3,1/2)	(1/4,1/3,1/2)	(1/3,1/2,1/1)	(1/3,1/2,1/1)	(1,1,1)	(1/3,1/2,1/1)	(1,1,1)	(1,1,1)	(1,1,1)	(1,1,1)	(1/3,1/2,1/1)	(1,2,3)
NDVI	(1/5,1/4,1/3)	(1/3,1/2,1/1)	(1/3,1/2,1/1)	(1/3,1/2,1/1)	(1/4,1/3,1/2)	(1,2,3)	(1,1,1)	(1,2,3)	(1,1,1)	(1,1,1)	(1,2,3)	(1/3,1/2,1/1)	(2,3,4)
NBR	(1/6,1/5,1/4)	(1/6,1/5,1/4)	(1/4,1/3,1/2)	(1/4,1/3,1/2)	(1/5,1/4,1/3)	(1,1,1)	(1/3,1/2,1/1)	(1,1,1)	(1/3,1/2,1/1)	(1/4,1/3,1/2)	(1/3,1/2,1/1)	(1/5,1/4,1/3)	(1/5,1/4,1/3)
SLOPE	(1,1,1)	(1/4,1/3,1/2)	(1,1,1)	(1/3,1/2,1/1)	(1,1,1)	(1,1,1)	(1,1,1)	(1,2,3)	(1,1,1)	(1,1,1)	(1,2,3)	(1/4,1/3,1/2)	(2,3,4)
ELEVATION	(1,1,1)	(1,1,1)	(1,1,1)	(1,2,3)	(1,2,3)	(1,1,1)	(1,1,1)	(2,3,4)	(1,1,1)	(1,1,1)	(1,1,1)	(1,1,1)	(1,2,3)
ASPECT	(1,2,3)	(1/4,1/3,1/2)	(1/3,1/2,1/1)	(1,1,1)	(1,1,1)	(1,1,1)	(1/3,1/2,1/1)	(1,2,3)	(1/3,1/2,1/1)	(1,1,1)	(1,1,1)	(1/4,1/3,1/2)	(1,1,1)
CURVATURE	(1,1,1)	(2,3,4)	(3,4,5)	(2,3,4)	(2,3,4)	(1,2,3)	(1,2,3)	(3,4,5)	(1,2,3)	(1,1,1)	(2,3,4)	(1,1,1)	(1,2,3)
TRI	(1,1,1)	(1,1,1)	(1,1,1)	(1/5,1/4,1/3)	(1/4,1/3,1/2)	(1/3,1/2,1/1)	(1/4,1/3,1/2)	(3,4,5)	(1/4,1/3,1/2)	(1/3,1/2,1/1)	(1,1,1)	(1/3,1/2,1/1)	(1,1,1)

Table 3
Defuzzification of Weight (Fuzzy AHP)

FUZZY GEOMETRIC MEAN (GM) =MULTIPLE OF ((*l1,m1,u1*) * (*l2,m2*,u2)….)^1/13	FUZZY WEIGHT(Wi)= R̃i *(R̃1, R̃2, R̃3)^-1	FUZZY WEIGHT(Wi)	DE-FUZZIFICATION TO WEIGHT =(li+mi,ui)/3	NORMALISED WEIGHT = (Wi/W)
(0.990, 1.299, 1.711)	(0.990, 1.299, 1.711)*(1/18.36, 1/13.99, 1/11.44)	(0.053, 0.092, 0.149)	0.098	0.0936
(0.791, 0.999, 1.248)	(0.791, 0.999, 1.248)*(1/18.36, 1/13.99, 1/11.44)	(0.043, 0.071, 0.109)	0.074	0.07068
(0.874, 1.063, 1.498)	(0.874, 1.063, 1.498)*(1/18.36, 1/13.99, 1/11.44)	(0.047, 0.075, 0.130)	0.084	0.08023
(0.999, 1.497, 2.026)	(0.999, 1.497, 2.026)*(1/18.36, 1/13.99, 1/11.44)	(0.054, 0.107, 0.177)	0.092	0.08787
(1.054, 1.316, 1.607)	(1.054, 1.316, 1.607)*(1/18.36, 1/13.99, 1/11.44)	(0.057, 0.094, 0.140)	0.097	0.09265
(0.571, 0.750, 1.064)	(0.571, 0.750, 1.064)*(1/18.36, 1/13.99, 1/11.44)	(0.031, 0.053, 0.093)	0.059	0.05635
(0.596, 0.852, 1.359)	(0.596, 0.852, 1.359)*(1/18.36, 1/13.99, 1/11.44)	(0.032, 0.060, 0.118)	0.07	0.06686
(1.109, 0.373,0.532)	(1.109, 0.373, 0.532)*(1/18.36, 1/13.99, 1/11.44)	(0.060, 0.026, 0.046)	0.044	0.04202
(0.783, 0.968, 1.184)	(0.783, 0.968, 1.184)*(1/18.36, 1/13.99, 1/11.44)	(0.042, 0.069, 0.103)	0.071	0.06781
(1.054, 1.276, 1.433)	(1.054, 1.276, 1.433)*(1/18.36, 1/13.99, 1/11.44)	(0.057, 0.091, 0.125)	0.091	0.08691
(0.619, 0.796, 1.064)	(0.619, 0.796, 1.064)*(1/18.36, 1/13.99, 1/11.44)	(0.033, 0.056, 0.093)	0.06	0.05731
(1.465, 2.148, 2.751)	(1.465, 2.148, 2.751)*(1/18.36, 1/13.99, 1/11.44)	(0.079, 0.153, 0.240)	0.157	0.14995
(0.535, 0.653, 0.885)	(0.535, 0.653, 0.885)*(1/18.36, 1/13.99, 1/11.44)	(0.029, 0.046, 0.077)	0.05	0.04776
		(11.44, 13.99, 18.36)	1.047	1

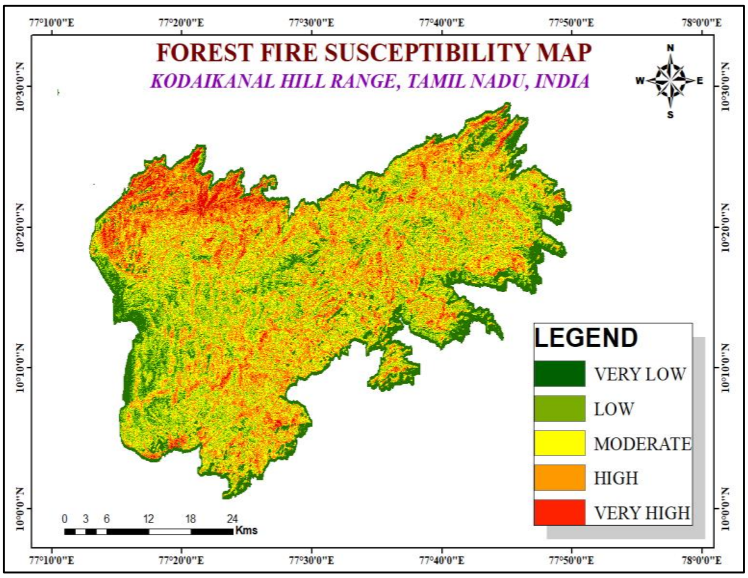

Figure 4: Forest Fire Susceptibility Map

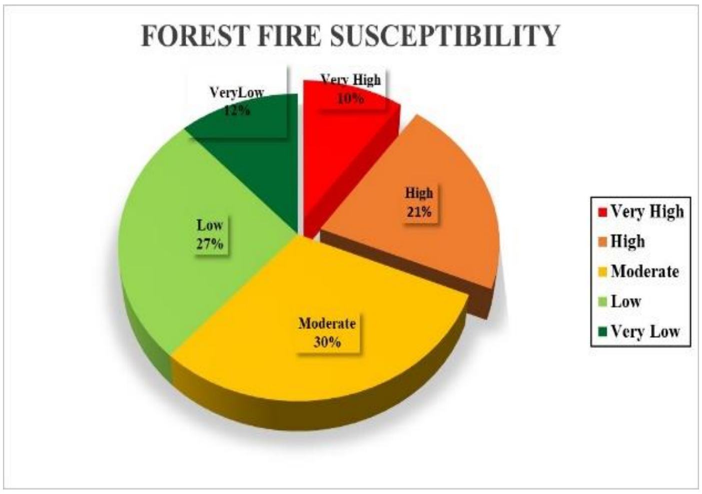

Figure 5: Pie Chart of Susceptibility Area coverage

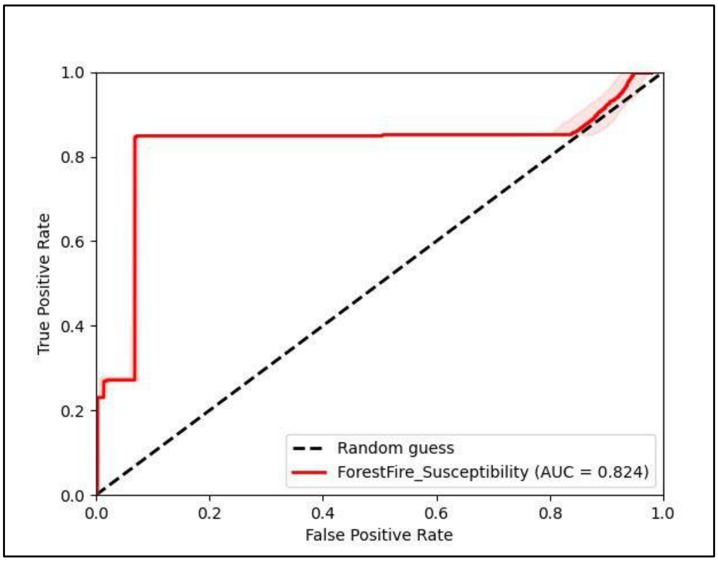

Figure 6: ROC-AUC Curve

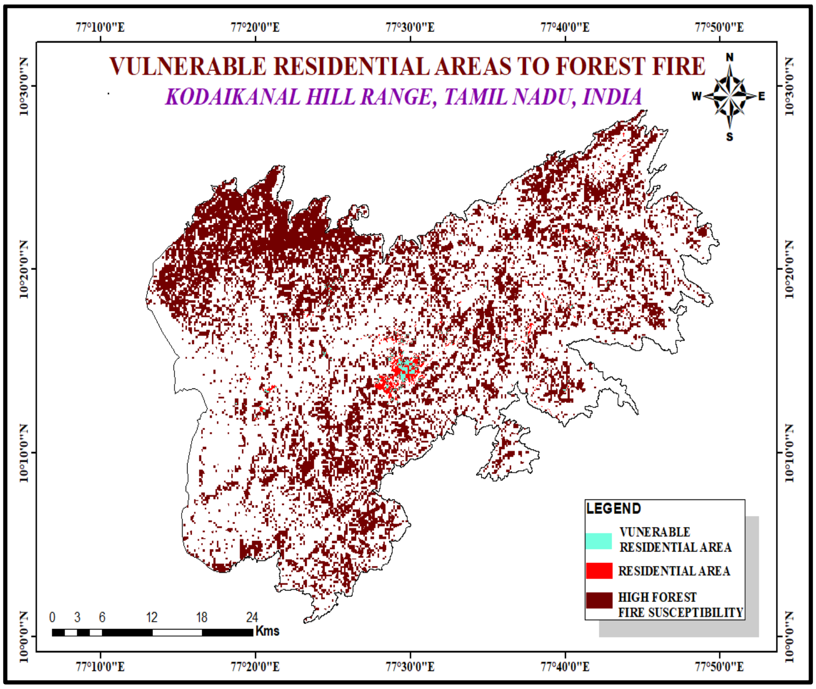

Figure 7: Residential Area Vulnerability Map

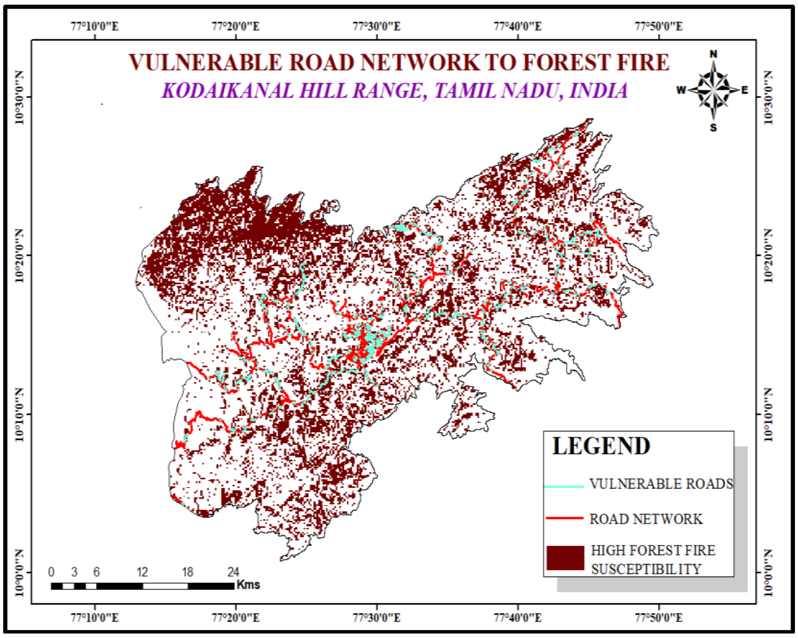

Figure 8: Road Networks Vulnerability Map

Analysis of vulnerability to forest fires by anthropogenic factors: The vulnerability of anthropogenic infrastructure to forest fires was further analyzed by overlaying the FFS map with road networks and settlement areas. The results indicated that approximately 28.68% of the total road length (155.48 km out of 542 km) and 30% of settlement areas (10.32 sq. km out of 24.6 sq. km) fall within high or very high susceptibility zones. Roads and settlements in these areas act as both ignition points and conduits for fire spread, particularly in regions with dry vegetation and steep slopes. These findings emphasize the critical role of anthropogenic factors in exacerbating forest fire risks and underscore the need for targeted mitigation strategies such as creating firebreaks, regulating human activities near forest edges and enhancing firefighting resources in vulnerable zones[33].

Discussion

The spatial analysis of fire susceptibility demonstrated considerable variability across the Kodaikanal Hill Range. Areas at lower elevations, especially those covered by tropical moist deciduous forests, exhibited heightened vulnerability due to conducive climatic factors and intensified human presence. In contrast, higher elevations, characterized by Shola forests and grasslands, exhibited lower susceptibility attributed to cooler temperatures, higher moisture levels and reduced human interference. Elevation emerged as a key indirect factor influencing fire vulnerability by regulating parameters such as temperature, rainfall and vegetation type[27].

The integration of physiographic and climatic factors through the Fuzzy-AHP approach provided a comprehensive understanding of forest fire dynamics in the region. The model's ability to accurately classify high-risk zones was validated using historical fire data, demonstrating its utility for informed decision-making in forest fire management. These findings offer critical insights for policymakers, forest managers and disaster management authorities, enabling the formulation of region-specific strategies to mitigate the adverse impacts of forest fires while promoting ecological conservation[14].

Future Perspectives

- Establish firebreaks near roads and settlements using fire-resistant, climate-adapted plants to prevent fire spread during extreme weather conditions.
- Focus on planting fire-resistant species that can withstand changing climate patterns, reducing fuel loads and enhancing ecosystem resilience.
- Enforce stricter controls on open burning and agricultural fires, particularly during dry seasons, to minimize human-induced fire risks.
- Use real-time climate and weather data to improve fire predictions and enhance early warning systems, focusing on temperature and rainfall patterns.
- Educate local populations on fire prevention, using both local knowledge and climate data to adapt to shifting fire risks.

Conclusion

The Kodaikanal Hill range, known for its rich biodiversity and ecological importance, faces significant forest fire risks due to a combination of physiographic, climatic and human-related factors. This study employed a GIS-based Fuzzy Analytical Hierarchy Process (Fuzzy-AHP) to develop a comprehensive Forest Fire Susceptibility (FFS) map, integrating critical factors such as slope, vegetation density, elevation, climatic variables and proximity to human settlements. The analysis revealed that approximately 31.26% of the region was classified as highly or very highly susceptible to forest fires, with physiographic factors like slope, vegetation density (NDVI) and curvature being primary contributors. Climatic factors, such as temperature and wind speed, further intensified the fire risk. Model validation with historical fire data resulted in a strong Area under Curve (AUC) score of 0.824, confirming the accuracy and reliability of the methodology. Human factors, including road networks and settlement proximity, also exacerbated fire risks, with 28.68% of road length and 30% of settlements found in high-risk zones. Lower elevations, characterized by higher temperatures and dense vegetation, emerged as the most fire-prone, while higher elevations exhibited reduced susceptibility.

The study underscores the urgency of implementing strategic fire mitigation measures including the establishment of firebreaks near critical infrastructures, restricting human interventions in high-risk zones and fostering afforestation with fire-resistant plant species. Despite some limitations, including expert-driven fuzzy weight assignments and dataset constraints, this study provides valuable insights for forest managers and policymakers in the Kodaikanal Hill range, offering a robust framework for forest fire management. Future studies could expand the GIS-Fuzzy AHP approach to other ecologically sensitive regions and incorporate real-time fire data to enhance early warning systems and resource allocation[8].

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