International Journal of Multidisciplinary Research and Growth Evaluation.

# A Geospatial Risk Map of Forest Fires: A Case Study in Nowshera Forest Division, District Rajouri, Jammu and Kashmir, India

**Dr. Rakesh Verma**
Range Forest Officer, J&K Forest Department, Jammu and Kashmir, India

* Corresponding Author: **Dr. Rakesh Verma**

## Article Info

**ISSN (online):** 2582-7138
**Volume:** 05
**Issue:** 06
**November-December** 2024
**Received:** 02-10-2024
**Accepted:** 05-11-2024
**Page No:** 565-582

**Abstract**
This study examines forest fire occurrences, distribution, and risk mapping in Nowshera Forest Division, District Rajouri, Jammu and Kashmir a northern state of India, using advanced geospatial techniques validated through methods like Multi-Criteria Decision Making (MCDM), Space-Time Cube Analysis (STC), and Emerging Hot Spot (EHS) Analysis. It utilizes archive data from the Moderate Resolution Imaging Spectroradiometer (MODIS) Near Real-Time (NRT) fire data, sourced from NASA's Fire Information for Resource Management System (FIRMS). A NetCDF file, capable of storing four-dimensional data, was developed using two decades of data to analyze forest fire trends and project future scenarios. The study establishes relationships between fire incidents and triggering factors such as human settlements, roads, climate, elevation, slope, aspect, forest type, canopy density, soil moisture, wind speed, and forest health. A forest fire risk map with four risk classes—extreme, severe, moderate, and mild—has been generated. These findings are invaluable for managers, planners, and stakeholders involved in disaster management, providing a robust methodology for forest fire preparedness.

**Keywords:** Forest Fire, Geospatial, MCDM, EHS, STC, FIRMS, NASA, NetCDF, Nowshera Forest Division, Rajouri, Hot spot analysis, space time cube analysis, MODIS, NRT, Disaster Management, Biodiversity, Fire Risk Mapping

## 1. Introduction

Forests are a critical global resource, providing essential services such as clean air, firewood for fuel, recreation, and habitats for countless flora and fauna species. However, forest fires are the leading cause of deforestation globally. Research indicates that climate change exacerbates extreme heat and dryness, triggering wildfires across various regions of the Earth (Yue et al., 2013) [70]. According to a recent study by the Forest Survey of India, approximately 36% of India's forest canopy is vulnerable to fires, with over 10% facing high-risk levels (Ghosh et al., 2019) [28]. Forest degradation due to fires compromises ecosystem services and goods, further highlighting the importance of consistent protection, monitoring, and mapping in fire-prone areas (Chand et al., 2006) [15].

The impact of forest fires extends beyond ecology to economic and socio-cultural dimensions on local, regional, and global scales. Fires release aerosols into the atmosphere, significantly affecting cloud formation, rainfall patterns, and atmospheric circulation (Ramanathan et al., 2001; Andreae et al., 2004) [53, 5]. Experts predict that climate change will lead to more challenging fire weather conditions, prolonged fire seasons, and an increase in the frequency and intensity of large-scale wildfires (IUFRO, 2018; Sankey, 2018; Jolly et al., 2015) [33, 56, 36]. Factors such as steep slopes, high summer temperatures, strong winds, and abundant combustible materials further amplify the damage caused by forest fires (Roy, 2003) [55].

Modern forest fire protection and management strategies emphasize using advanced technologies, including satellite remote sensing, GIS, and geospatial analytics, to map, monitor, and mitigate fire risks (Jain et al., 1996; Potić et al., 2018; Ahmad et al., 2018) [36, 51, 4]. India, with 22% of its geographical area under forest cover (FSI, 2021), faces significant challenges due to a lack of comprehensive data on burned areas, ecological and economic losses, and regeneration statuses (Bahuguna & Singh, 2002) [6].

Since the Indian Forest Act of 1927 declared forest fires a penal offense, efforts to prevent and manage fires have gained prominence, reinforced by the National Forest Policy of 1988 (Gupta et al., 2018) [31]. However, forest depletion caused by natural events like fires and human activities such as clear-cutting and land conversion remains a significant concern for forest management (Bhatta, 2008) [8].

This study advances earlier research by analyzing spatiotemporal dynamics and correlating fire-influencing factors using two decades of data. It evaluates fire-prone regions, temporal windows, and the interplay of vegetation, landscape, climate, hydrology, and human activity with MODIS, SNPP fire points. Satellite imagery from Sentinel-2 MSI and MODIS C6.1, processed through Google Earth Engine and ArcGIS 10.7.1 software, and thermal anomaly data from NASA's FIRMS, were utilized to conduct this research.

Focused on Nowshera Forest Division, a biodiversity hotspot, this study aims to:

1. Identify temporal patterns of forest fires.
2. Map their spatial distribution.
3. Analyze correlations between fire-influencing factors and fire incidents.

The region's vulnerability, necessitates a robust understanding of fire dynamics. This research provides valuable insights for fire managers, enabling effective monitoring, prediction, and decision-making to mitigate the risks and impacts of forest fires.

## 2. Study area

The present study was conducted in Nowshera Forest Division of Rajouri District of Jammu and Kashmir Union Territory during September 2021 to January 2023. The study area lies between 33.366784 and 32.936094 to 73.998561and 74.676321. The territorial jurisdiction of Nowshera Forest Division is managed by three Territorial Ranges viz: Nowshera Forest Range, Lamberi Forest Range and Sunderbani Forest Range. Nowshera is a mountainous region comprising of Lower or Shivalik Chir Pine Forest, Northern Dry mix deciduous forest, Himalayan Sub tropical Scrub, Dry Deciduous Scrub, Upper or Himalayan Chir Pine Forest and Khair Sissu Forest. Chir Pine, Sissoo, and Banj Oak are the characteristic vegetation of the study area. The mean sea level elevation of the study area ranges from 291 to 2120mtr. The study area encompasses mountains, pasture lands, rivers, springs and number of bowlies. The mean annual temperature of the study area ranges between 15 degrees Celsius to 44 degrees Celsius with mean annual rainfall of 951 mm. Pool frost is one of the characteristic features of Sunderbani Forest during the winter months, where valley areas of Nowshera, Lamberi, Seot receives frost from mid-December to mid-January.

## 3. Methodology

To identify fire-prone regions within the Nowshera Forest Division, Jammu and Kashmir (J&K), the factors contributing to forest fires were systematically identified and categorized. These factors were broadly classified into Vegetation, Landscape, Climate, and Human Interference. Each category was further subdivided as follows:

- **Vegetation:** Classified into Forest Health, Forest Type, and Forest Canopy Cover.
- **Landscape:** Segregated into Elevation, Slope, and Aspect.
- **Climate and Hydrology:** Divided into Temperature, Precipitation, Wind Speed, and Soil Moisture.
- **Human Interference:** Comprised Distance from Habitation Patches and Distance from Road Networks.

### Data Collection and Processing

- **Forest Health:** Extracted using Sentinel-2 MSI data.
- **Landscape Information:** Derived from Shuttle Radar Topographic Mission (SRTM) void-filled data at 1 arc-second resolution for elevation, slope, and aspect.
- **Climate and Hydrology Data:** Obtained from WorldClim 2.1, providing temperature and precipitation data at 30 arc-second resolution, and soil moisture data from the Copernicus Climate Change Service (C3S), 2018.
- **Human Interference Data:** Habitation patches were sourced from the Socioeconomic Data and Applications Center (SEDAC), and road network information was collected from OpenStreetMap.

**Table 1:** Sources and Details of Experimental Data

| Data | Sources | Spatial Resolution | Temporal Resolution | Satellite sensor |
|---|---|---|---|---|
| Fire | Fire Map-NASA | About 0.375 mtrx0.375 mtr and 1 km x1 km | Mid-latitudes will experience 3-4 looks a day | VIIRS SNPP,VIIRS NOAA-20,MODIS/Aqua, MODIS/Terra |
| Meteorological | ERA5-Land hourly data from 2004 to present | $0.1^0$x$0.1^0$ ; Native resolution is 9 km | Update hourly | None |
| Landcover | Esri_2024_Landcover_V2 ImageServer | 10m x10m | Release in 2024 | Sentinel-2L2A/B |
| Terrian | Shuttle Radar Topography Mission DEM | 30m x30m | Acquired 11-22 February 2024 | STS Endeavour OV-105 |
| Vegetation | "One Map" of Forest Inspection and Forest Resource Management in 2024 | 2km x2km | Released in 2024 | None |
| Normalized Vegetation Index (NDVI) | Landsat 8 Image of USGS | 30m x30m ; 15m x15m | 16 days | Operational Land Imager (OLI) and the Thermal Infrared Sensor (TIRS). |
| Climate and Hydrology | WorldClim 2.1 | 1km x1km | Aggregated data from 1970-2000 | WorldClim 2.1 utilizes satellite data to generate its climate grids, there isn't a single designated "satellite sensor" specifically mentioned in the WorldClim documentation; instead, it |

| | | | | |
|---|---|---|---|---|
| | | | | aggregates data from various sources including satellite observations, weather station data, and terrain information to create its climate layers, with the primary source for elevation data being the SRTM (Shuttle Radar Topography Mission) |

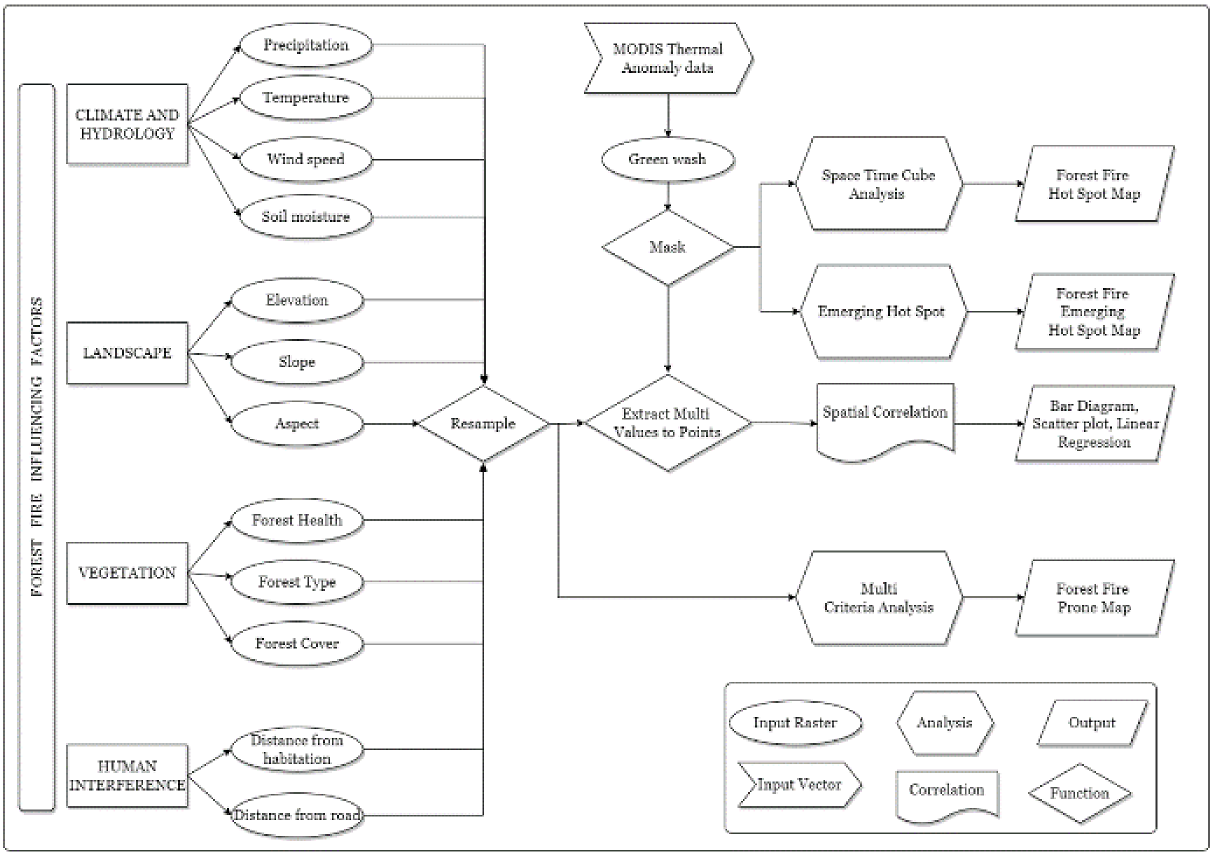



**Fig 1:** All forest fire-triggering factors

All forest fire-triggering factors were gathered from various portals, pre-processed, and masked to align with the boundaries of the Nowshera Forest Division. The processed layers were stored in a geodatabase for subsequent weighted overlay analysis. Multiple Criteria Decision-Making (MCDM) techniques were employed, assigning weights to individual factors to produce a fire-prone map. This resultant map was classified into five fire intensity classes: extreme, severe, moderate, mild, and non-forest.

**Fire Data Analysis**

MODIS thermal anomaly data were downloaded from the Fire Information for Resource Management System (FIRMS), a NASA web service. The data, representing thermal anomalies with a spatial resolution of 1 km², were masked to fit the study area polygon. The spatial resolution of the fire detection pixel for the Visible Infrared Imaging Radiometer Suite (VIIRS) on the Suomi National Polar-orbiting Partnership (SNPP) is 375 meters, due to which it can detect small forest fire incidences. In the present study both data sets were used to study the thermal anomaly data of Nowshera Forest Division. 2308 points of MODIS and 4464 points of SNPP were used to study the thermal anomaly. A total of 6771 MODIS and SNPP fire points from 2004 to 2024 were initially considered. After masking against the green cover layer of the Nowshera Forest Division, 6771 fire points remained for analysis (Table 1).

**Table 2:** Showing year wise/ month wise distribution of fire incidences from 2004 to 2024

| Month/Year | January | February | March | April | May | June | July | August | September | October | November | December | Total |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 2004 | 2 | 2 | 2 | 48 | 26 | 43 | | | | | 9 | 3 | 135 |
| 2005 | 3 | | 3 | | 2 | 44 | | | | | 1 | 3 | 56 |
| 2006 | | | 2 | 9 | 44 | 13 | | | | | | | 68 |
| 2007 | | | | | 14 | 51 | | | | | | | 65 |
| 2008 | | 3 | 14 | | 21 | 26 | | | | | | | 64 |
| 2009 | | 3 | 6 | 19 | 112 | 1 | | | | | | | 141 |
| 2010 | 2 | | | 4 | 25 | 14 | | | | | | | 45 |
| 2011 | | | 1 | | 11 | 44 | | | | | 1 | 2 | 59 |
| 2012 | 1 | | 6 | | 58 | 1 | | | | | | | 66 |

| | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 2013 | | | | | 14 | 99 | | | | | | | 113 |
| 2014 | 5 | | | | 6 | 4 | | | | | | 4 | 19 |
| 2015 | 4 | | | | 3 | 62 | | | | 2 | | 2 | 73 |
| 2016 | 2 | 3 | 2 | 6 | 47 | 16 | | | | 3 | 7 | 5 | 91 |
| 2017 | 1 | 4 | | 1 | 3 | 3 | | | | 2 | | | 14 |
| 2018 | 6 | 6 | 6 | 2 | 103 | 350 | | | | | | | 473 |
| 2019 | | | | 2 | 218 | 206 | 156 | | | | 2 | | 584 |
| 2020 | 4 | 12 | | | 840 | | | | | | | | 856 |
| 2021 | | | | | | 780 | | | | | 30 | 32 | 842 |
| 2022 | | 2 | 15 | 724 | 1890 | 16 | | | | | 2 | | 2649 |
| 2023 | | 4 | 32 | | 42 | | | | | | | 12 | 90 |
| 2024 | 104 | 82 | 50 | | 32 | | | | | | | | 268 |
| **Total** | **134** | **121** | **139** | **815** | **3511** | **1773** | **156** | **0** | **0** | **7** | **52** | **63** | **6771** |

**Temporal and Spatial Analysis**

Analysis revealed that the fire season spans from April to June annually, accounting for over 80% of forest fire incidents. May emerged as the most vulnerable month, with 51.85% (3511) of fire incidents, followed by June 26.18% (1773) and April 12.03% (815) (Figure 3). The highest number of fire alerts was recorded in 2022(2649 incidents), while the lowest was in 2017 (14 incidents).

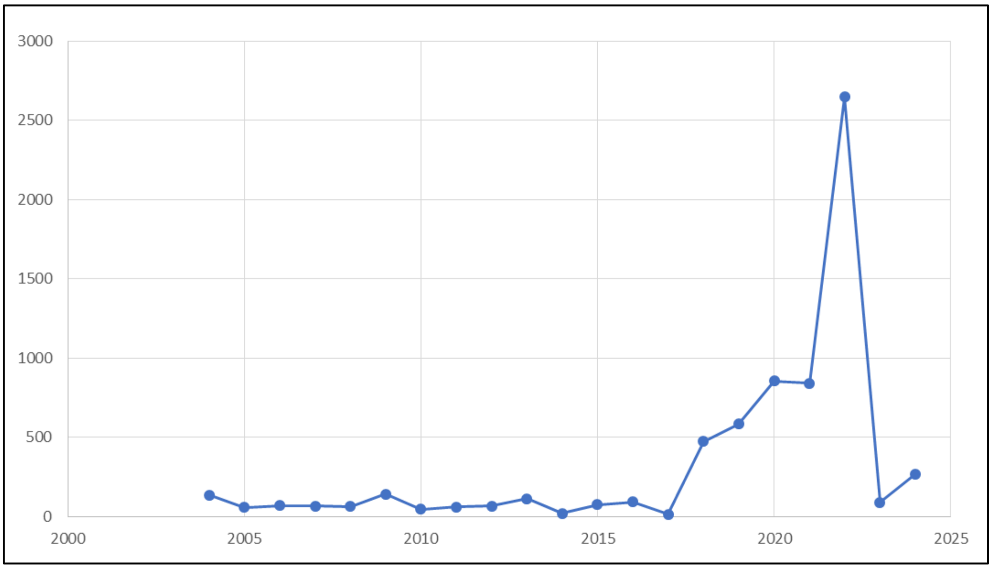



**Fig 2:** Yearly distribution of fire points

The yearly trend of forest fires indicates a fluctuating pattern, with the number of incidents increasing over time. In 2005, there were 56 whereas the lowest points were recorded in the year 2017 with 14 fire incidents. While studying the distribution of fire incidences in forest block, it has been observed that Jhangar Forest block has highest number of fire incidences 2439 followed by Kangri Forest block 1435 incidences. Lowest number was recorded in Devak Forest Block 51 incidences followed by Treru Forest Block having 52 incidences. In the similar way Nowshera Forest Range experiences 47 % of fire incidences followed by Sunderbani Forest Range 30% and Lamberi Forest Range 23% fire incidences w.e.f. 2004 to 2024.

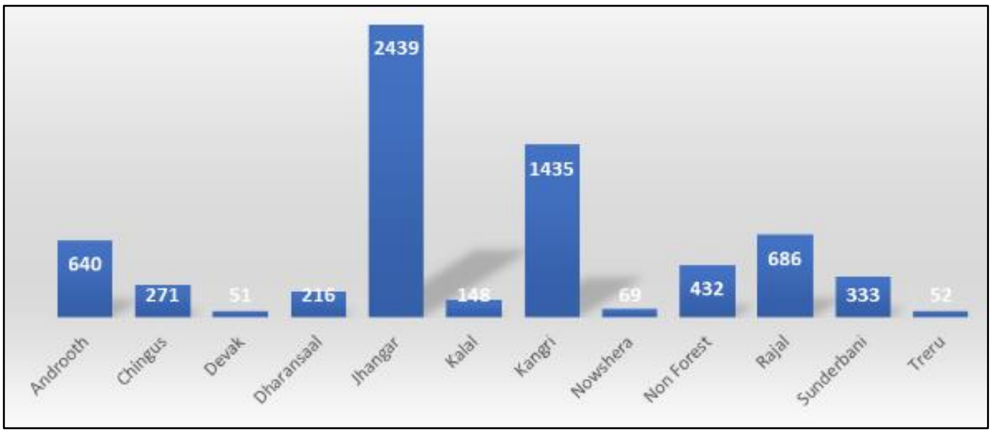



**Fig 3:** Blockwise distribution of fire points

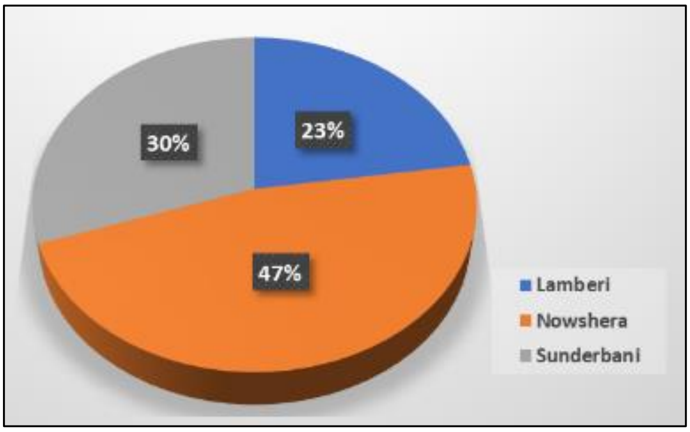



**Fig 4:** Rangewise distribution of fire points

**Detailed Temporal Analysis**

Focusing on May, the peak month for fire incidents, analysis of two decades of MODIS and SNPP data revealed that fire incidents were lower during the first and last ten days of the month. However, from the 10th to the 20th day of May, fire incidents exceeded the two-decade average

## 4. Exploratory Analysis

### 4.1. Vegetation

#### 4.1.1. Forest Health and Forest Fire

To assess vegetation health during the fire-prone month of May, the entire Nowshera Forest Division was studied using Google Earth Engine (GEE) (Georelick et al., 2017). A composite of Sentinel-2 images was created, encompassing seven Sentinel-2 scenes with less than 15% cloud cover for three time periods:

- **T1:** 1st May to 15th May 2022
- **T2:** 15th May to 30th March 2022
- **T3:** 1st June to 15th June 2022

Normalized Difference Vegetation Index (NDVI) was calculated for these composites and classified into four density classes: Very Low, Low, Moderate, and High, based on NDVI values (< -0.5, -0.5 to 0, 0 to <0.5, and ≥0.5 respectively).

The reclassified NDVI files were integrated with an area column. Tabular summaries for each Forest Block revealed that Forest Block like Sunderbani, Dharamsaal, Kalal and Androoth exhibited high vegetation health (NDVI > 0.5) during T1, which declined below 1,000 sq. km in T3. A decreasing trend in NDVI was particularly noted in regions such as Kangri, Jhanger and Rajal, correlating with higher fire incidents.

#### 4.1.2. Forest Type and Forest Fire

Forest type is a critical factor influencing fire ignition, spread, and dispersal (Prasad et al., 2008) [52]. The forests in the Nowshera Forest Division are categorized into 09 major types based on the Champion and Seth classification (1968). Approximately 80% of the forested area consists of Upper or Himalayan Chir Pine Forest, with Himalayan subtropical Scrub and Lower or Shivalik Chir Pine Forest being most susceptible to fires, covering 64% of the total forest area (FSI, Forest Types of India, 2020).

Nine specific forest types within the division were analyzed:

1. 9/DS1 Himalayan subtropical scrub
2. 9C1b Upper or Himalayan chir pine forest
3. 9C1a Lower or Shivalik Chir Pine Forest
4. 5B/C2 Northern dry mixed deciduous forest
5. 5/DS1 Dry deciduous forest
6. 12/C1f Low level blue pine forest (*Pinus wallichiana*)
7. 12C1b Western mixed coniferous forest
8. 12/C1a Ban Oak scrub
9. 12/C1/DS1 oak Scrub

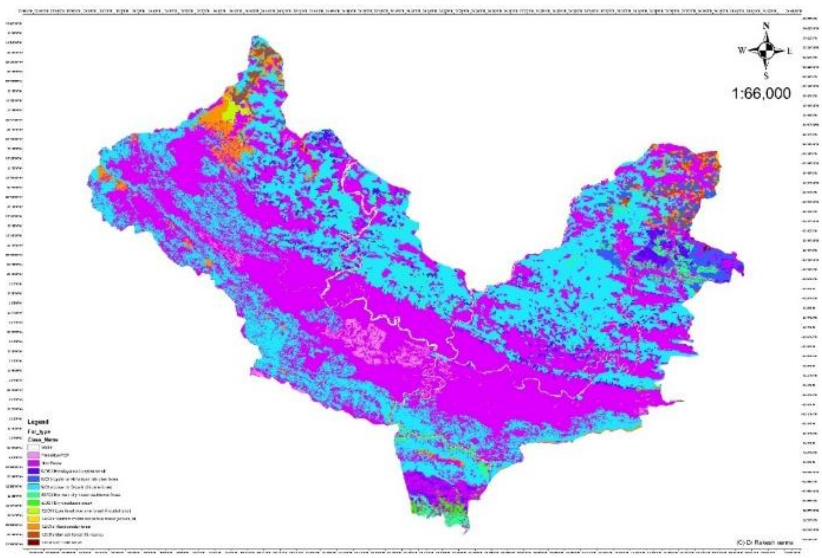



**Fig 5:** Forest type of India map of nowshera forest division

In 2022, the highest number of fire points (2649) occurred in the Sub tropical Chir Forest, particularly in areas such as Jhanger and Kangri. Analysis of two decades of MODIS and SNPP data corroborated these findings, showing Sub tropical Chir forests , with dominant species including *Pinus roxburghii*, *Mallotus phillipinensis*, and *Linea coromendilica*. A total of 5284 fire alerts were recorded in this forest type from 2004 onward.

### 4.1.3. Forest Canopy Cover

The Forest Cover Map (FCM) for 2019 in the Nowshera Forest Division was analyzed alongside fire points. Forest canopy was classified into four categories based on crown density:

- **Very Dense Forest (VDF):** >15%
- **Moderately Dense Forest (MDF):** 30%
- **Open Forest (OF):** 35% to 45 %
- **Scrub:** <10%

Fire incidents were predominantly observed in the Open Forest category, which is prevalent along forest peripheries near cattle grazing areas, settlements, and roads (Figure 15). Specifically, over 1890 fire points were recorded in Open Forests, followed by more than 1620 incidents in Moderately Dense Forests, and fewer in Scrub areas.

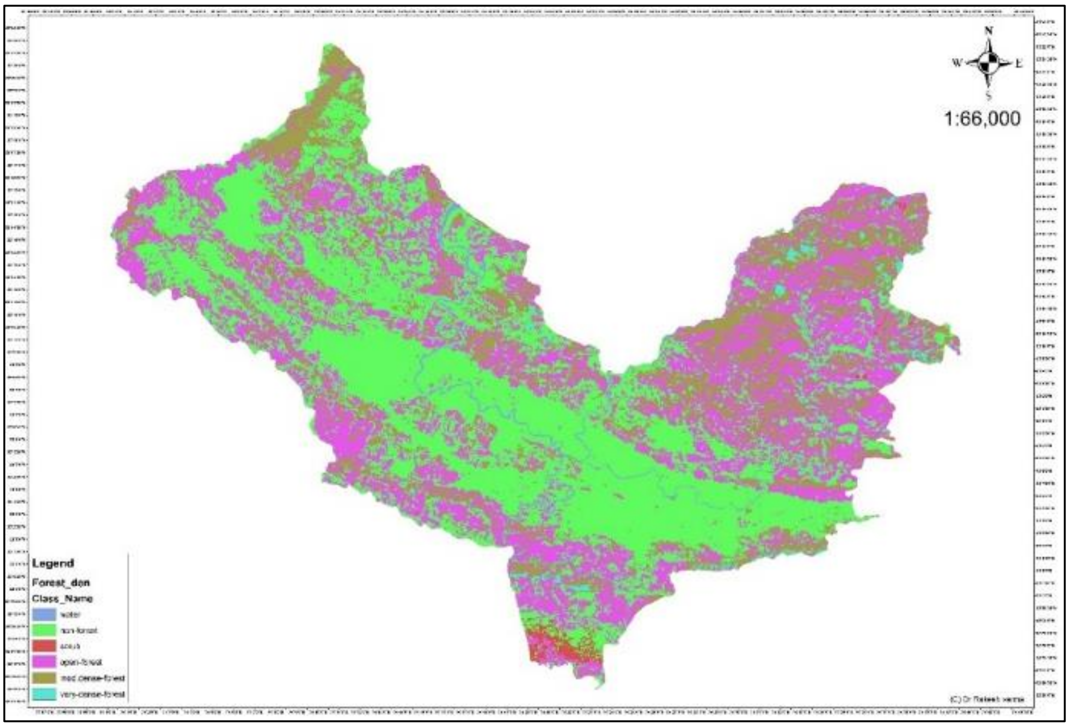



**Fig 6:** Forest Density map of nowshera forest division

## 4.2. Landscape

### 4.2.1. Elevation and Forest Fire

Terrain significantly affects forest resilience to wildfires (Prasad et al., 2008; Kushla & Ripple, 1997) [52, 39]. The Digital Elevation Model (DEM) for the study area was obtained from Earth Explorer, using SRTM void-filled data at 1 arc-second resolution (~30 meters). Elevation was classified into three broad categories:

1. Below 500 meters
2. 500-1500 meters
3. 1500 meters – 2000 meters
4. Above 2000 meters

Analysis revealed that lower elevation areas (<500 meters) are more prone to forest fires, likely due to slash-and-burn agricultural practices prevalent among the 86.15% tribal population (Census of India, 2011). In contrast, higher elevation zones (>1500 meters) experienced significantly fewer fire incidents.

### 4.2.2. Slope and Forest Fire

Slope angle influences fire intensity and spread, as steeper slopes facilitate faster fire movement upslope (McCullum et al., 2022; Weise & Biging, 1996) [44, 69]. In the Nowshera Forest Division, 70% of the area has slopes below 30 degrees, yet these regions account for over 95% of fire incidents (Figure 13). Fires predominantly occur on gentle slopes where traditional forest dwelling communities are residing in the periphery of forest, allowing easier agricultural access (Ramkrishnan, 1993; Tomich & Lewis, 2002; Joseph et al., 2009; Stolle et al., 2003) [54, 67, 37, 65].

### 4.2.3. Aspect and Forest Fire

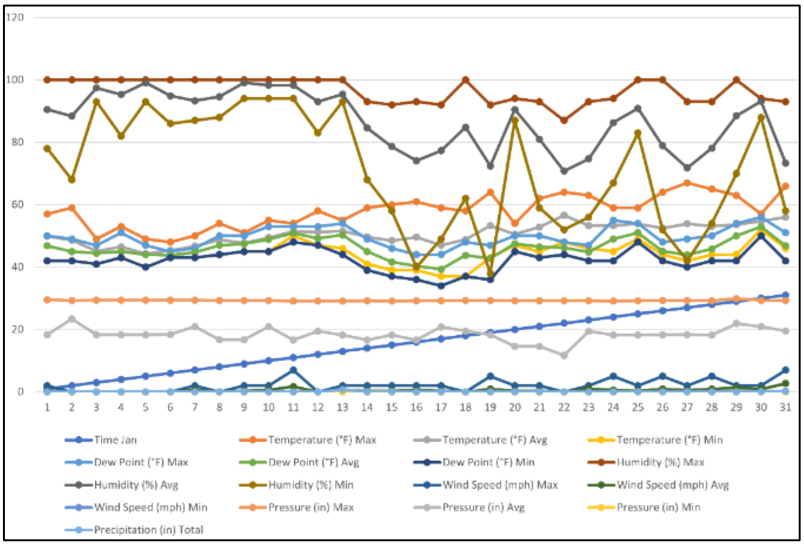
Slope aspect affects solar radiation exposure, moisture retention, and fire behavior (Ebel, 2012; Estes et al., 2017; McCullum et al., 2022) [19, 20, 44]. In the northern hemisphere, south-facing slopes receive more sunlight, resulting in drier conditions conducive to fires (Thornbury, 1954) [66]. Overlaying fire points on aspect data showed higher fire incidences on east and northwest-facing slopes compared to others, with the least fires on northeast-facing slopes.

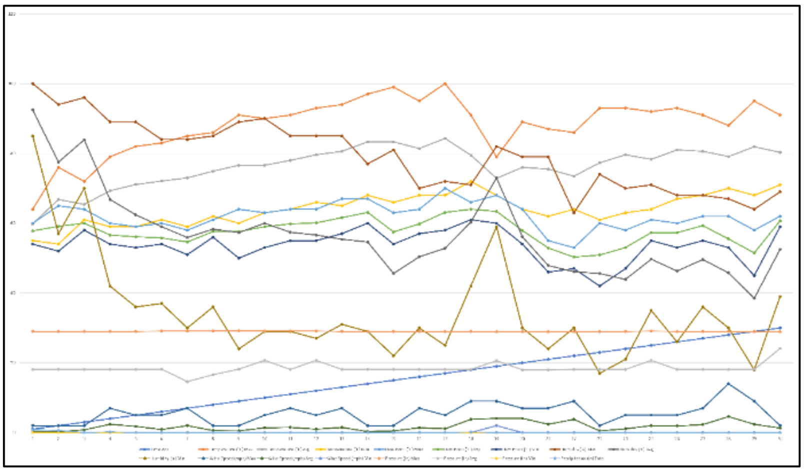
## 4.3. Climate and Hydrology

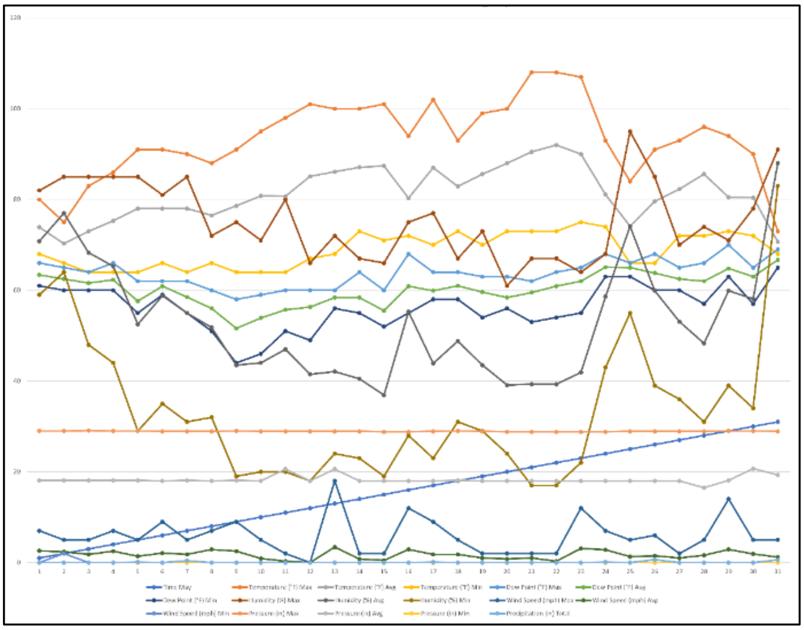
Climate factors, particularly temperature and precipitation, significantly influence forest fire dynamics (Parry et al., 2007) [50]. WorldClim 2.1 provided average monthly climate data at ~1 km resolution (Fick & Hijmans, 2017) [21]. This study extracted monthly total precipitation and average temperature to analyze their relationship with forest fire incidents.

#### 4.3.1. Temperature and Forest Fire

Land Surface Temperature (LST) data from MODIS Terra satellite represents the temperature of the earth's surface, crucial for estimating sensible heat fluxes between forests and the atmosphere (NASA, 2018). Annual average temperature data from WorldClim 2.1, derived from MODIS LST averages and top-of-atmosphere solar radiation (Fick & Hijmans, 2017) [21], was classified into three temperature classes . A positive correlation was established between higher annual average temperatures and increased forest fire incidents (Sayad et al., 2019) [60].





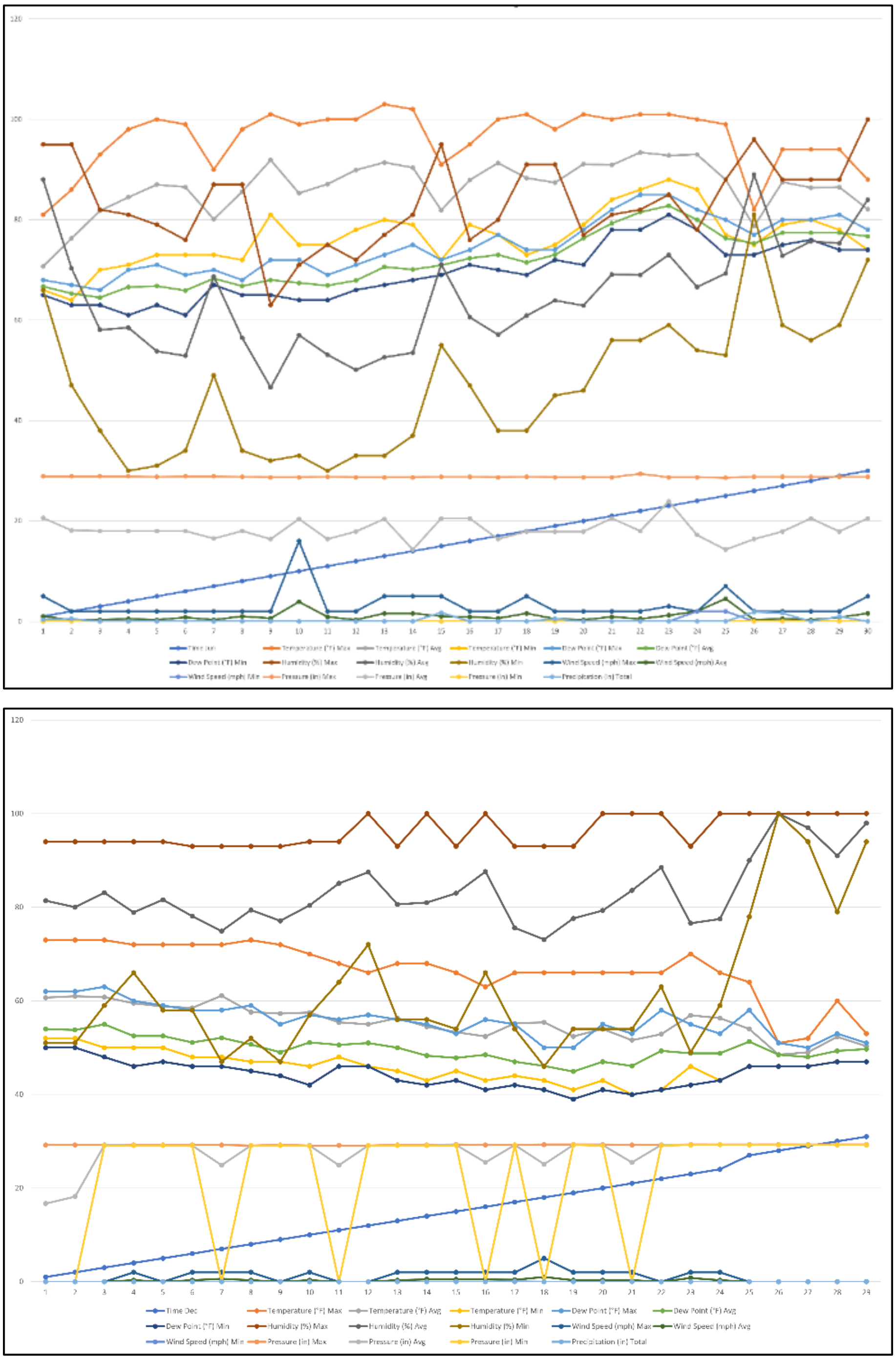



**Fig 7:** Land Surface Temperature (LST)

#### 4.3.2. Precipitation and Forest Fire

Nowshera Forest Division receives substantial rainfall, particularly in regions like Channi Prat, Lamberi and Androoth area of the division. Adequate rainfall promotes vegetation growth, which serves as fuel during dry seasons (McCullum et al., 2022) [44]. The study found that increased precipitation correlates with higher fire incidents during the fire season, as lush vegetation dries out.

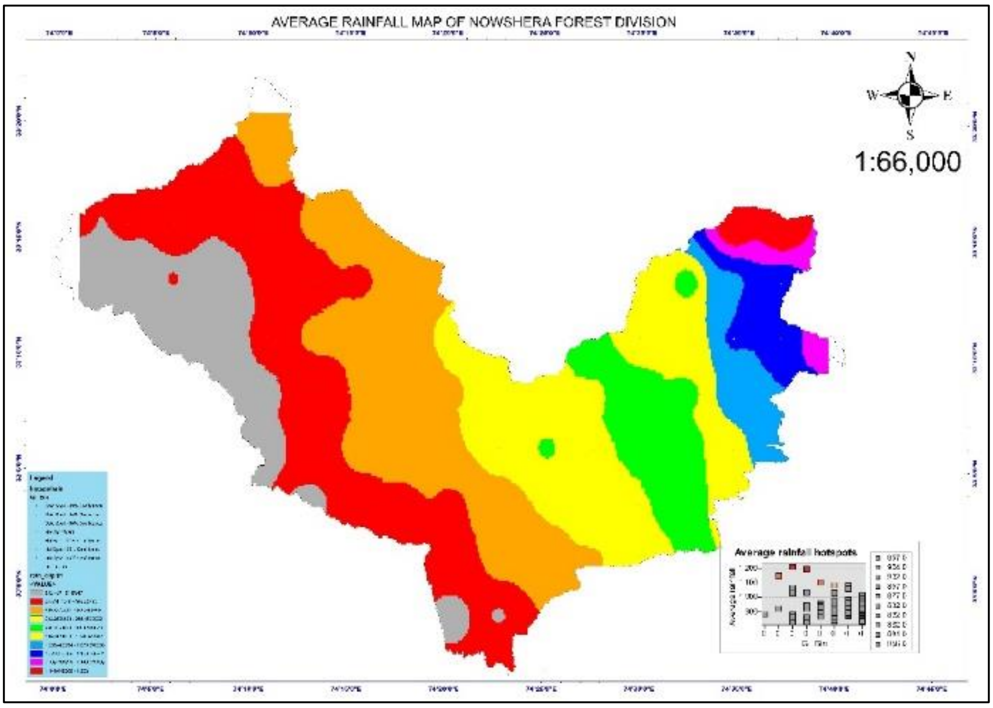



**Fig 8:** Average Rainfall map of nowshera forest division

### 4.3.3. Wind Speed and Forest Fire

Wind speed data from WorldClim 2.1 were supplemented with higher-resolution data from the Global Wind Atlas 3.0 (2019), providing wind speeds in meters per second at 250-meter spatial resolution. Wind speed is a critical factor in fire spread intensity (Adab et al., 2013; Schoennagel et al., 2004; Keeley, 2004) [2, 62, 38]. In the study area, wind speeds ranged from 1 to 6 m/s, with over 85% of the region experiencing winds below 4 m/s. A positive relationship between wind velocity and forest fire incidents was observed (Figure 20i). The wind speed distribution map is presented in.

(Byram, 1954) identified specific wind profiles associated with blow-up forest fires, while Schaefer (1957) [61] linked jet streams to wildfire behavior.

### 4.3.4. Soil Moisture and Forest Fire

Soil moisture data were obtained from the Copernicus Climate Change Service (C3S), 2018, with a spatial resolution of 0.25°x0.25° and varying temporal resolutions (daily, 10-day, monthly) in NetCDF format. Soil moisture was measured using scatterometer and radiometer data, representing volumetric soil moisture ($m^3/m^3$) in the top 2-5 cm of soil.

In the Nowshera Forest Division, volumetric soil moisture above 0.04 $m^3/m^3$ was prevalent in over 80% of the area. Fire points showed a higher incidence in zones with elevated soil moisture compared to drier areas.

### 4.4. Human Interference

The rural population of Nowshera Forest Division heavily relies on forest and forest resources. The region is rich palatable grasses, mushrooms, NTFPs like Dioscoria Spp., Guchii, Anardhana, which are usually covered by surface vegetation, are vulnerable to disturbances from resource exploitation. Additionally, traditional clearing of cultivated land before the onset of monsoon practices near forest fringes and road networks contribute to higher fire incidences.

### 4.4.1. Distance from Habitation Patches

Habitation data were sourced from the Socioeconomic Data and Applications Center (SEDAC), NASA, utilizing gridded population estimates based on the 2011 Census of India and the Global Human Settlement Layer (Balk et al., 2019) [7]. Analysis indicated that forest fires are more frequent closer to habitation areas (Figure 20k), consistent with findings by Sowmya & Somashekar (2010) [64] in their study of Bhadra Wildlife Sanctuary. Distance from habitation was categorized into five groups:

1. Below 2 km
2. 2-5 km
3. 5-10 km
4. 10-15 km
5. Above 15 km

The highest number of fire incidents occurred in forests within 10 km of habitation.

### 4.4.2. Distance from Road Networks

Human-induced fires are closely linked to accessibility via roads (Bhusal & Mandal, 2020; Veena et al., 2017; Jacob et al., 2014) [9, 68, 49]. Forest areas near roads are more susceptible to fire incidents. Distance from roads was classified into five categories:

1. Below 2 km
2. 2-5 km
3. 5-10 km
4. 10-20 km
5. Above 20 km

In the Nowshera Forest Division, fire activities were predominantly high in forests located within 10 km of road networks.

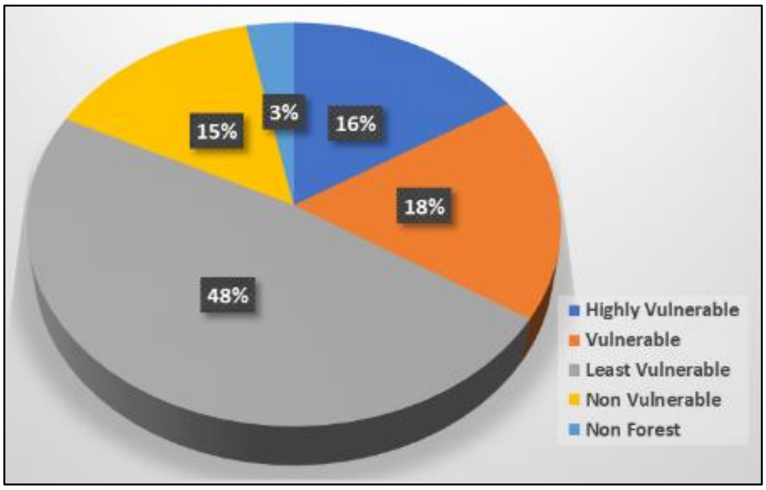
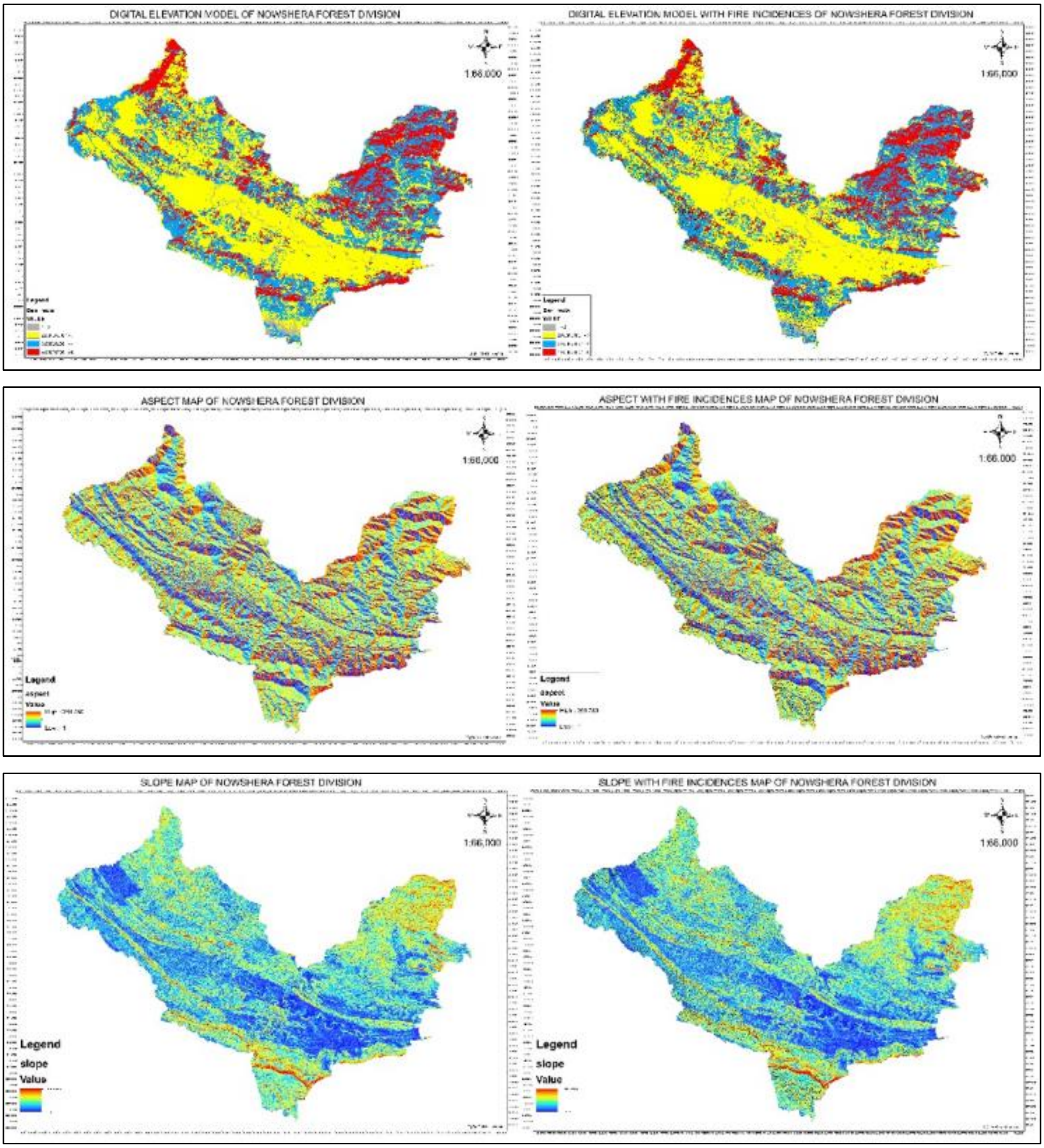
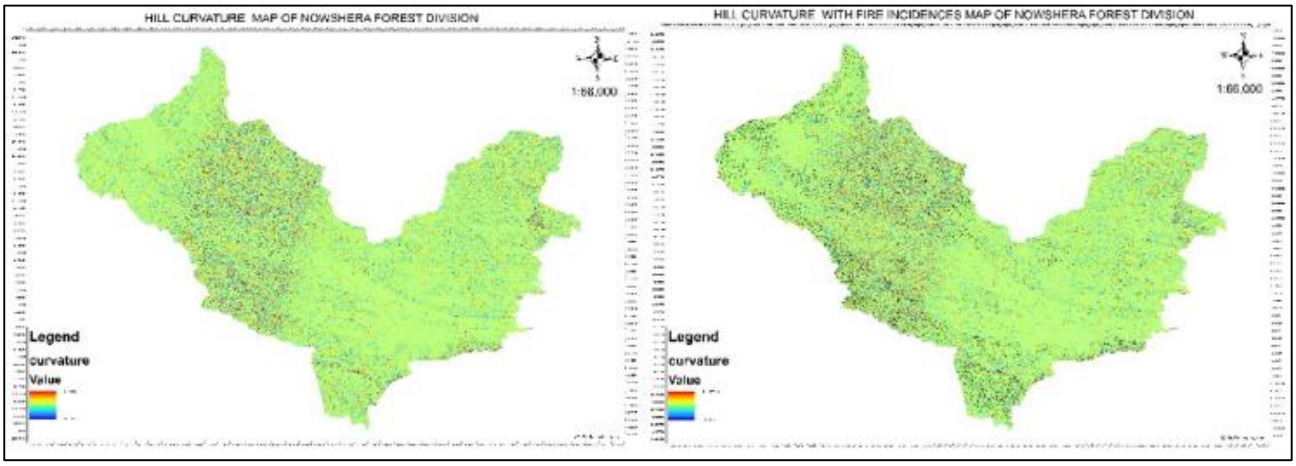
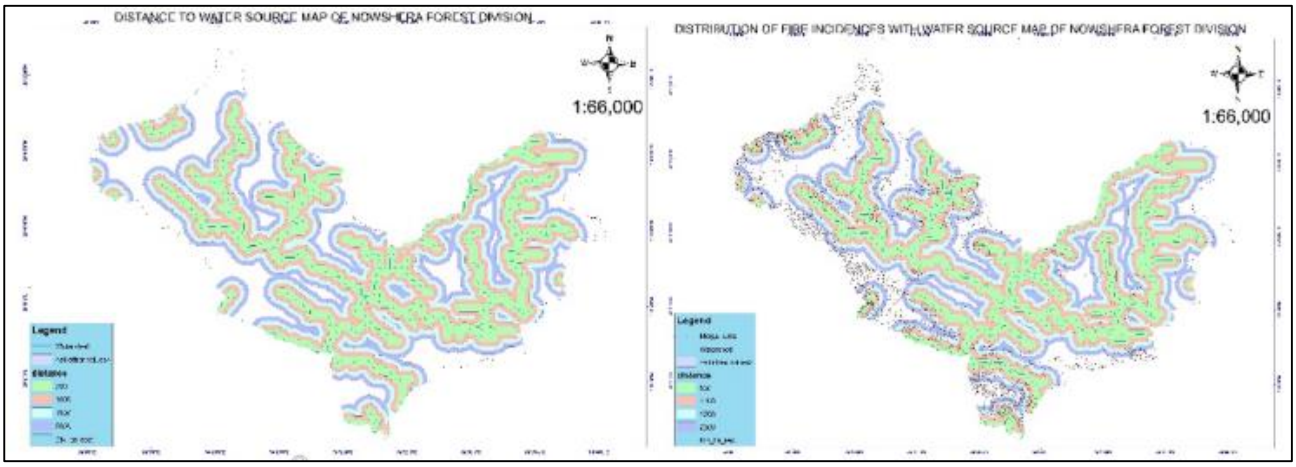
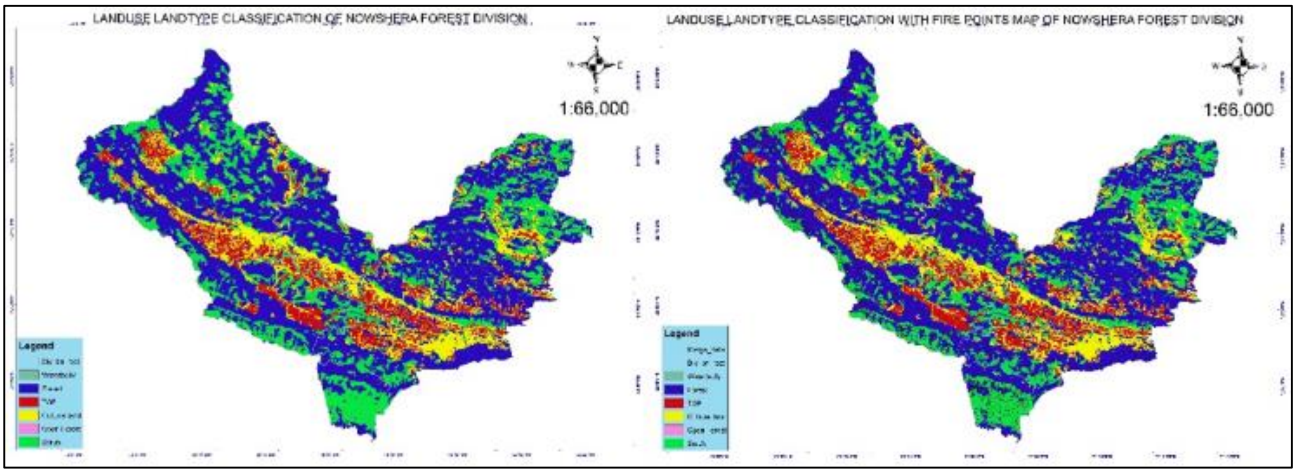


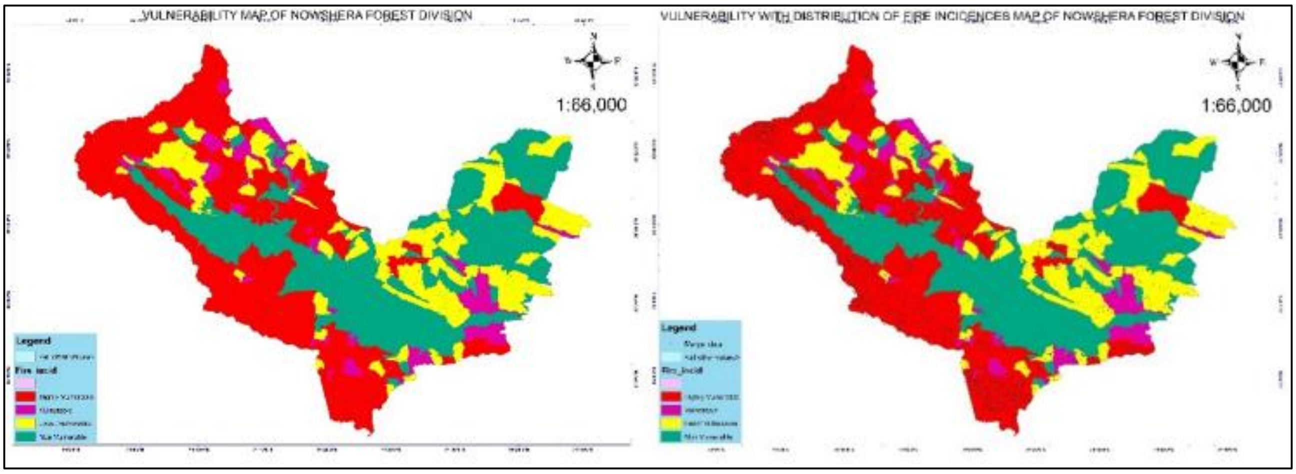

**Fig 9:** Fire vulnerability diagram




HILL CURVATURE MAP OF NOWSHERA FOREST DIVISION
Legend
curvature
Value
HILL CURVATURE WITH FIRE INCIDENCES MAP OF NOWSHERA FOREST DIVISION
1:66,000
Legend
curvature
Value


DISTANCE TO WATER SOURCE MAP OF NOWSHERA FOREST DIVISION
1:66,000
Legend
DISTRIBUTION OF FIRE INCIDENCES WITH WATER SOURCE MAP OF NOWSHERA FOREST DIVISION
1:66,000
Legend


LANDUSE LANDTYPE CLASSIFICATION OF NOWSHERA FOREST DIVISION
1:66,000
Legend
LANDUSE LANDTYPE CLASSIFICATION WITH FIRE POINTS MAP OF NOWSHERA FOREST DIVISION
1:66,000
Legend


VULNERABILITY MAP OF NOWSHERA FOREST DIVISION
1:66,000
Legend
VULNERABILITY WITH DISTRIBUTION OF FIRE INCIDENCES MAP OF NOWSHERA FOREST DIVISION
1:66,000
Legend

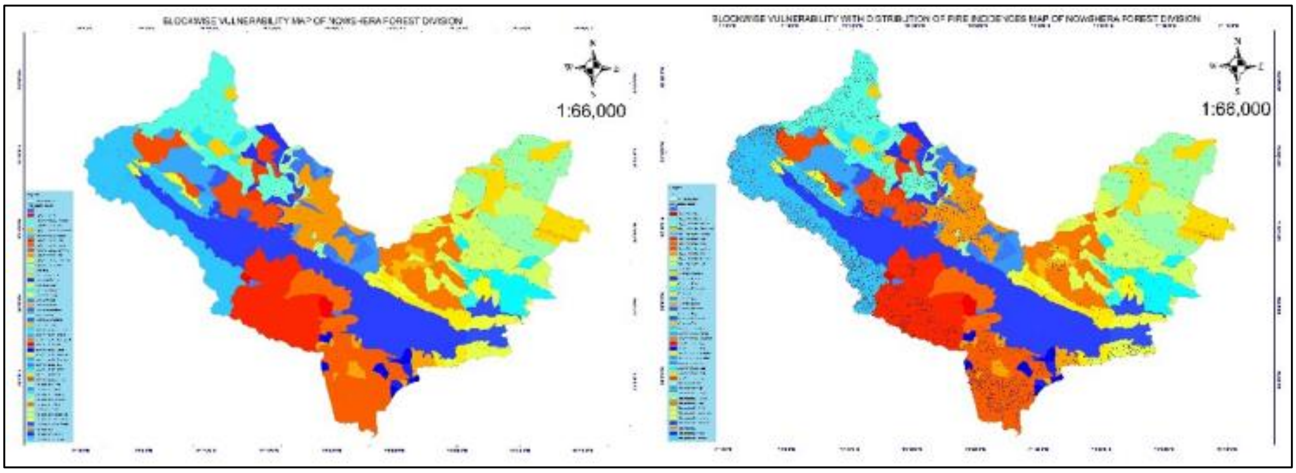



**Fig 10:** Volumetric soil moisture is defined

**Note:** Volumetric soil moisture is defined as the content of liquid water in a surface soil layer of 2 to 5 cm depth, expressed as cubic meters of water per cubic meter of soil.

This methodology provides a comprehensive framework for analyzing and mapping forest fire risks in the Nowshera Forest Division, J&K. By integrating various geospatial datasets and employing advanced analytical techniques, the study aims to deliver actionable insights for effective forest fire management and mitigation strategies.

### 5. Emerging Hot Spot Analysis

The analysis utilized a NetCDF (Network Common Data Form) file as input, as this file format can store multidimensional data, including location (x, y), count (z), and time (t). The Hot Spot Analysis involved calculating the Getis-Ord Gi* statistic (commonly pronounced as "G-i-star") as introduced by Ord and Getis (1995) [48] for each fire point in the MODIS fire dataset. This method considers each feature in relation to its proximity to other features.

The analysis employed the NetCDF file to create a multidimensional data cube , storing all relevant information. Based on this information, the data was classified into various categories. While high feature values might seem notable, they do not necessarily indicate statistically significant hot spots. For a feature to qualify as a significant hot spot, it must not only exhibit a high value but also be surrounded by other features with similarly high values.

The total of all features is analyzed in proportion to the local sum of a specific feature and its neighboring features. The positive and negative Gi* statistics correspond to clusters of fire points with high and low fire event densities, respectively (Manepalli et al., 2011) [42].

### Analysis of Gi* Statistics for Forest Fire Points in the Nowshera Forest Division

The results of the Gi* statistics for forest fire points in the Nowshera Forest Division are self-explanatory. Using two decades of MODIS fire data with a four-month time lapse, the findings were categorized into nine distinct classes:

1. **Oscillating Hot Spot**: Represents areas that are currently fire-prone but have a history of being cold spots.
2. **No Pattern Detected**: Zones primarily consisting of built-up areas and non-forest regions, showing no discernible pattern.
3. **Sporadic Cold Spot**: Refers to regions that have never been hot spots and were classified as cold spots in less than 90% of the time steps.
4. **Oscillating Cold Spot**: Areas currently identified as cold spots but with a history of being hot spots, occurring as cold spots in less than 90% of the time steps.
5. **Persistent Cold Spot**: Regions where at least 90% of the time steps are cold, showing no upward or downward trend over time.
6. **Diminishing Cold Spot**: Areas where at least 90% of the time steps are cold, but the cold trend weakens over time.
7. **New Hot Spot**: Recently identified locations experiencing forest fires.
8. **Historical Cold Spot**: Areas that are no longer cold in the most recent time period but were statistically significant cold spots in at least 90% of the time steps.
9. **Sporadic Hot Spot**: Locations with an intermittent pattern of forest fires, where less than 90% of the time steps are statistically significant hot spots, and none were statistically significant cold spots.

These classifications, provide valuable insights into the temporal and spatial dynamics of forest fires within the Nowshera Forest Division.

$$G_i^* = \frac{\sum_{j=1}^{n} w_{i,j} x_j - \bar{X} \sum_{j=1}^{n} w_{i,j}}{S \sqrt{\frac{\left[ n \sum_{j=1}^{n} w_{i,j}^2 - \left( \sum_{j=1}^{n} w_{i,j} \right)^2 \right]}{n-1}}}$$

Where,

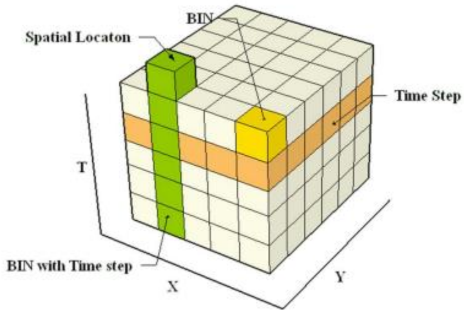
$x_j$ is attribute value for feature $j$

$w_{i,j}$ is the spatial weight between feature $i$ and $j$

$n$ is the Total number of features.

$$\bar{X} = \frac{\sum_{j=1}^{n} x_j}{n}$$

$$S = \sqrt{\frac{\sum_{j=1}^{n} x_j^2}{n} - (\bar{X})^2}$$



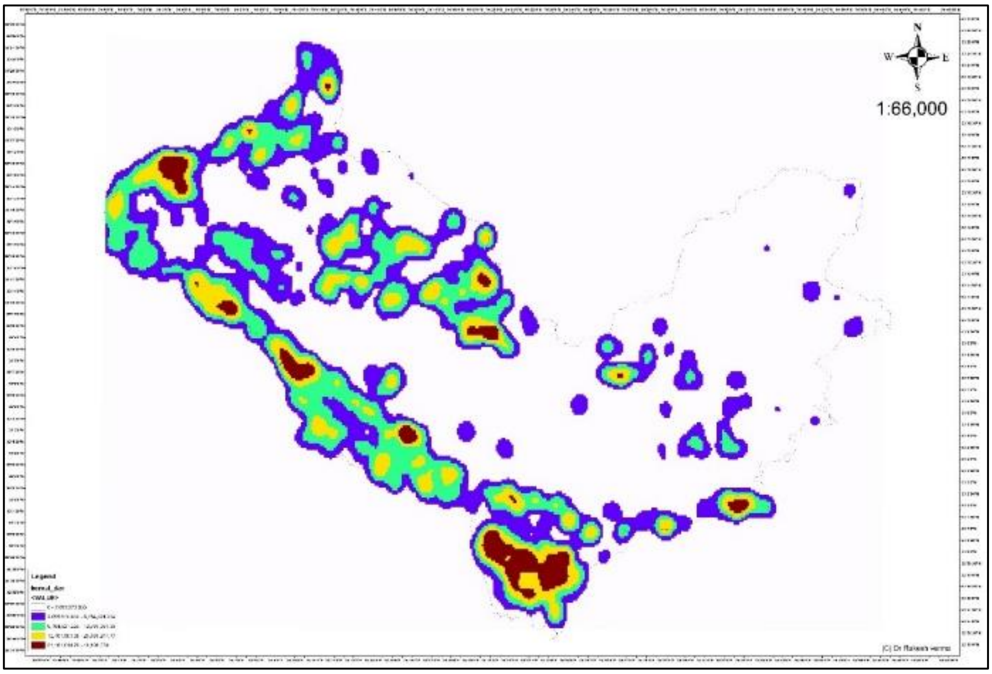




**Fig 11:** Hotspot analysis of nowshera forest division

### 5.1. Space-Time Cube Analysis

A Space-Time Cube Analysis was conducted to better understand the trends of forest fires in the Nowshera Forest Division. This analysis utilized a NetCDF file containing spatial and temporal data (x, y, z, and t), which represent location, count of fire points, and time. The analysis organizes the data into a three-dimensional cube.

Each bin within the cube corresponds to a specific location, a four-month time step, and a count value. The count value indicates the number of fire points recorded at a given location during the associated time step.

The findings for the Nowshera Forest Division are visualized in the map . The analysis reveals that certain regions within the division are particularly prone to forest fires. Notably, a significant portion of the forest cover is identified as fire-prone. Furthermore, a discernible pattern in fire activity was observed, influenced by human intervention. Local practices, such as periodic burning by nearby communities, contribute to this pattern, with forest fires often occurring every alternate year due to traditional land-use practices.

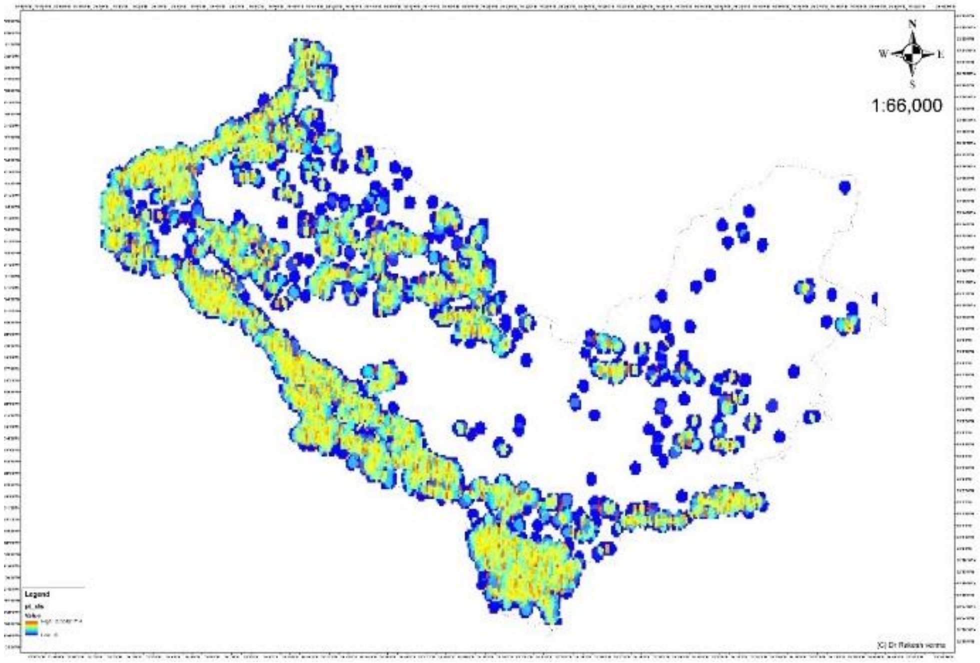



**Fig 12:** Space cube analysis of nowshera forest division

### 5.2. Multiple Criteria Decision Making

A Multiple Criteria Decision-Making (MCDM) analysis was carried out to assess forest fire risk in the Nowshera Forest Division. This analysis incorporated twelve factors influencing forest fire susceptibility. All input raster files were standardized by converting them into discrete integer raster layers with consistent pixel spacing.

MCDM is a powerful tool for identifying suitable sites based on specified parameters. Users define the weightage for each layer influencing forest fire risk. Using the Weighted Overlay technique, all input raster layers were reclassified onto a common scale ranging from 1 to 9, where 1 represents the lowest suitability and 9 the highest. Each pixel value was then multiplied by the assigned weight of importance.

For forest fire risk mapping in the Nowshera Forest Division, higher weightage was allocated to critical factors such as Distance from Roads, Distance from Habitation, Forest Type, Annual Average Temperature, and Annual Average Precipitation. These factors, along with their assigned weights, are detailed in Table 2 , with the total weightage summing to 100 percent.

Finally, the weighted values from all layers were combined to generate the Fire Risk Prone Map for the division , highlighting regions most susceptible to forest fires.

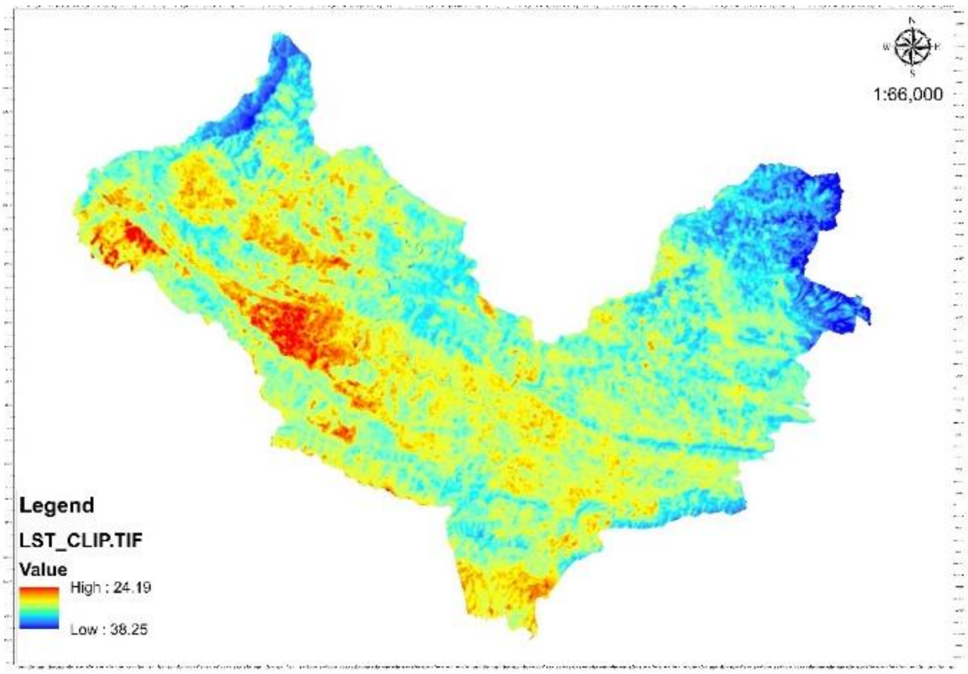



**Fig 13:** LST map of nowshera forest division

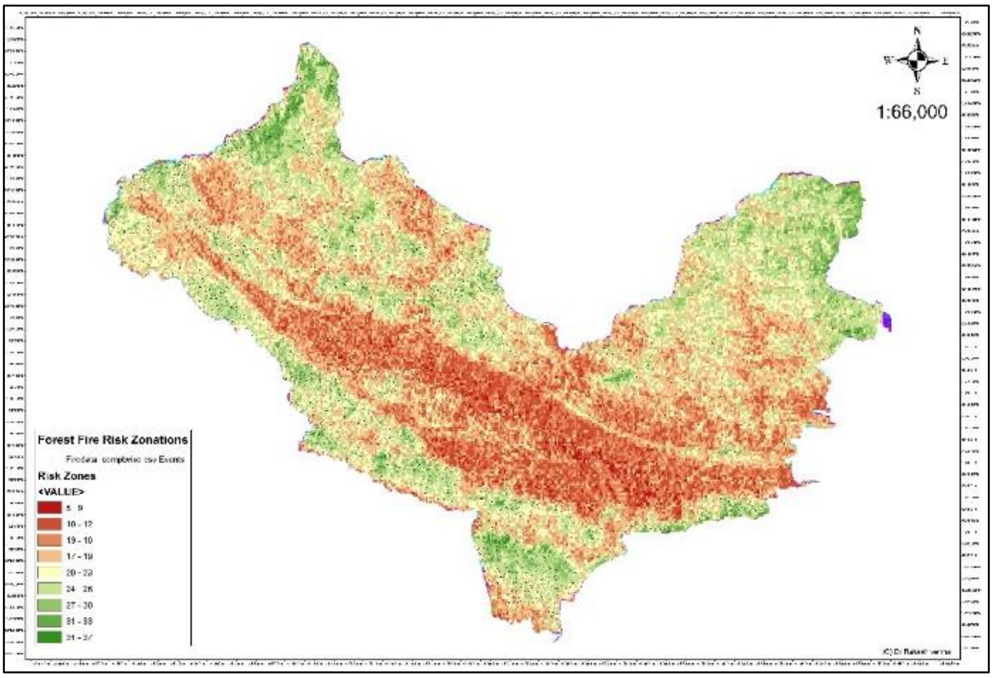



**Fig 14:** Forest fire risk zonation map of nowshera forest division

**Table 3:** Fire Influencing Variables with Weightage Value

| Sl. No. | File | Influence | Field | Weightage Value (1-9) | Sl. No. | File | Influence | Field | Weightage Value (1-9) |
|---|---|---|---|---|---|---|---|---|---|
| **1** | Wind Speed | 5 | Below 1 | 3 | **8** | Distance from Habitation | 12 | Below 2 kms | 5 |
| | | | 1 to 2 | 9 | | | | 2 To 5 kms | 9 |
| | | | 2 to 4 | 7 | | | | 5 To 10 kms | 7 |
| | | | 4 to 6 | 1 | | | | 10 To 15 kms | 3 |
| | | | Above 6 | 1 | | | | Above 15 | 1 |
| | | | | | | | | kms | |
| **2** | Soil Moisture | 8 | Below 0.02 | 3 | **9** | Aspect | 5 | N | 5 |
| | | | 0.02 to 0.03 | 5 | | | | NE | 1 |
| | | | 0.03 to 0.04 | 7 | | | | E | 9 |
| | | | Above 0.04 | 9 | | | | SE | 5 |
| **3** | Slope | 5 | 0 to 5 | 5 | | | | S | 7 |
| | | | 5 To 15 | 9 | | | | SW | 3 |
| | | | 15 To 30 | 7 | | | | W | 5 |
| | | | 30 To 45 | 3 | | | | NW | 7 |
| | | | 45 To 60 | 1 | **10** | Annual Avg. Temp | 10 | Below 15 °c | 5 |
| | | | 60 To 90 | 1 | | | | 15 To 30°c | 7 |
| **4** | NDVI 1 to 15 march | 5 | Below -0.5 | 1 | | | | Above 30°c | 9 |
| | | | -0.5 To 0 | 3 | **11** | Annual Avg. Precipitation | 10 | Below 40 mm | 3 |
| | | | 0 To 0.5 | 7 | | | | 40 To 50 mm | 5 |
| | | | Above 0.5 | 9 | | | | 50 To 100 mm | 9 |
| **5** | Tree Cover- 2024 | 8 | VD | 3 | | | | Above 100 mm | 7 |
| | | | MD | 5 | **12** | Forest Type | 12 | 1/2S1 | 1 |
| | | | Open | 9 | | | | 9/DS1 | 1 |
| | | | Scrub | 7 | | | | 9C1b | 3 |
| | | | Water | Restricted | | | | 9C1a | 9 |
| | | | NF | Restricted | | | | 5B/C2 | 5 |
| **6** | Elevation | 8 | Below 500 | 9 | | | | 5/DS1 | 1 |
| | | | 500 To 1500 | 7 | | | | 12/C1f | 7 |
| | | | 1500 To<br>3000 | 3<br>7 | | | | 12C1b | 1<br>1 |
| **7** | Distance from road | 12 | Below 2 kms<br>2 To 5 kms | 9 | | | | 12/C1a | 1 |
| | | | 5 To 10 kms | 5 | | | | 12/C1/DS1 | 1 |
| | | | 10 To 20<br>kms Above 20 | 3<br>1 | | | | TOF | 1 |

## 6. Conclusions

This research addresses a critical issue that threatens ecosystems and human livelihoods alike: forest fires. Globally, thousands of hectares of forest are destroyed annually by fires, as noted by the Food and Agriculture Organization (2020). These fires not only alter forest structure and composition but also degrade biodiversity, expose forests to invasive species, disrupt water cycles, deplete soil fertility, and impact the lives of forest-dependent communities.

In this study, geospatial technology was applied to the Nowshera Forest Division to better understand and manage this hazard. The analysis identified fire-prone hotspots and examined MODIS thermal anomaly data to determine fire-prone months and dates. The results provide critical insights for forest managers, planners, and policymakers, enabling them to enforce strict rules and develop preventive measures based on the spatiotemporal distribution of forest fires.

Twelve variables influencing forest fire risks were analyzed and assigned weightages using Multiple Criteria Analysis (MCA). Raster files were classified on a scale of 1 to 9, with 9 representing the highest fire risk. These outputs were validated with ground-verified data and compared to MODIS-derived fire hotspot maps, yielding consistent and reliable results. The month of May was identified as the most fire-prone period, particularly between the 10th and 20th days of the month, aligning with findings from other studies (Matin et al., 2017; Prasad et al., 2008; Ahmad et al., 2018) [4, 52].

In the Nowshera Forest Division, forest fires are predominantly human-induced, often linked to traditional practices like collection of grasses for livelihood. This study highlights the need for awareness campaigns during critical fire-prone periods. By collaborating with forest-dependent communities, local administrations, and governing bodies, joint forest management strategies can be implemented to reduce dependence on forest resources and mitigate fire risks. Future work aims to develop a comprehensive forest fire alert system for the Nowshera Forest Division, incorporating the analyzed influencing factors and archived MODIS and SNPP NRT data to forecast fire risks more effectively.

## 7. Acknowledgments

The author expresses heartfelt gratitude to NASA, USGS, the European Union/ESA/Copernicus, WorldClim, World Wind Atlas, Google Earth Engine (GEE), and the Forest Survey of India for providing the essential data that made this study possible. Special thanks are extended to The Worthy Principal Chief Conservator of Forests Dr Mohiet Gera, IFS, colleagues from the Nowshera Forest Division, Forest Survey of India, Dehradoon, for their unwavering support and assistance. My sincere thanks are extended to my mentors Sh.K.Ramesh Kumar, IFS, Dr K. Anand, IFS and Dr V.S. Senthil Kumar IFS, who were instrumental behind my research temperament. My sincere thanks are due to Dr. C. M. Seth, IFS(Retd), Additional Pr. Chief Conservator of Forests who guided me during whole of my research work since 1999 till date as a mentor. The author also acknowledges the useful insights of Sh. B.M. Sharma, IFS Chief Conservator of Forests, Jammu, Sh. Vivek Verma, IFS Conservator of Forests West circle, Rajouri and Mrs Neelima Shah, IFS Divisional Forest Officer Nowshera. A deep sense of appreciation is conveyed to Sh. Sandeep Kumar, IFS Conservator of Forests West circle Rajouri, and Mrs. Shweta Deonia SFS, DFO Nowshera Forest Division for their scientific guidance. Last but not the least, the author expresses gratitude to Sh. Anil Bhagat Range Officer Nowshera and Sh. Sudesh Kumar Range Officer Lamberi for their help and support. Finally, the author sincerely thanks the anonymous reviewers for their invaluable comments and suggestions, which greatly enhanced the quality of this article.

## 8. References


1. Achu A, JT, Aju C, Gopinath G, Kumar S, Reghunath R. Machine-learning modelling of fire susceptibility in a forest-agriculture mosaic landscape of southern India. Ecological Informatics. 2021;64:101348. doi:10.1016/j.ecoinf.2021.101348.
2. Adab H, Kanniah KD, Salaimani K. Modeling forest fire risk in the northeast of Iran using remote sensing and GIS techniques. Natural Hazards. 2013;65:45-58. doi:10.1007/s11069-012-0450-8.
3. Ahmad F, Goparaju L. Forest fire trend and influence of climate variability in India: A geospatial analysis at national and local scale. Ekológia (Bratislava). 2019;38:49-68. doi:10.2478/eko-2019-0005.
4. Ahmad F, Goparaju L, Quayum A. Himalayan forest fire characterization in relation to topography, socio-economy and meteorology parameters in Arunachal Pradesh, India. Spatial Information Research. 2018;26:305-315. doi:10.1007/s41324-018-0175-1.
5. Andreae M, Rosenfeld D, Artaxo P, Costa A, Frank G, Longo K, Silva-Dias M. Smoking rain clouds over the Amazon. Science. 2004;303:1337-1342.
6. Bahuguna V, Singh S. Fire situation in India. International Forest Fire News. 2002;26:23-27. Available from: https://gfmc.online/iffn/country/in/in_5.html.
7. Balk D, Montgomery MR, Hancher E, Jones B. SEDAC. 2019. doi:10.7927/gya1-wp91.
8. Bhatta B. Remote Sensing and GIS. New Delhi: Oxford University Press; 2008.
9. Bhusal S, Mandal R. Forest fire occurrence, distribution and future risks in Arghakhanchi district, Nepal. Journal of Geography. 2020;2:10-20.
10. Bobsien A, Hoffmann E. Plantations and forest fires in Indonesia. Presented at: Indonesian Development Conference on Democratization in the Era of Globalization; 1998.
11. Buchhorn M, Smets B, Bertels L, Roo BD, Lesiv M, Tsendbazar NE, et al. Copernicus Global Land Service: Land Cover 100m: Collection 3: epoch 2019 Globe (Version V3.0.1). 2018. doi:10.5281/zenodo.3518038.
12. Byram GM. Atmospheric conditions related to blowup fires. Southeastern Forest Experiment Station. 1954;(35). Available from: https://www.fs.usda.gov/treesearch/pubs/45778.
13. Census of India. Census of India. Office of the Registrar General & Census Commissioner, India. 2011. Available from: https://sedac.ciesin.columbia.edu/data/set/india-spatial-india-census-2011/data-download.
14. Champion HG, Seth SK. A Revised Survey of the Forest Types of India. Delhi: Government of India Press; 1968.
15. Chand TK, Venkataraman B, Sudhakar V, Manohar SR, Elvidge CD, Tuttle BT. Monitoring forest fires over the Indian region using Defense Meteorological Satellite Program-Operational Linescan System nighttime

satellite data. Remote Sensing of Environment. 2006;103(2):165-178.
16. Copernicus Climate Change Service. Copernicus Climate Change Service (C3S). 2018. Available from: https://cds.climate.copernicus.eu/cdsapp#!/dataset/satellite-soil-moisture?tab=overview.
17. David MB, Grant J, Rebecca K, Ross A, Rodney J. The severity and extent of the Australia 2019–20 Eucalyptus forest fires are not the legacy of forest management. Nature Ecology & Evolution. 2021;5(7):1003-1010. doi:10.1038/s41559-021-01464-6.
18. Earth Explorer. USGS. 2022. doi:10.5066/F7F76B1X.
19. Ebel B. Impacts of wildfire and slope aspect on soil temperature in a mountainous environment. Vadose Zone Journal. 2012;11(3):vzj2012.0017. doi:10.2136/vzj2012.0017.
20. Estes B, Knapp E, Skinner C, Miller J, Preisler H. Factors influencing fire severity under moderate burning conditions in the Klamath Mountains, northern California, USA. Ecosphere. 2017;8(5):e01794. doi:10.1002/ecs2.1794.
21. Fick SE, Hijmans RJ. WorldClim 2: new 1-km spatial resolution climate surfaces for global land areas. International Journal of Climatology. 2017;37(12):4302-4315. doi:10.1002/joc.5086.
22. Food and Agriculture Organization. Global Forest Resources Assessment. Rome; 2020. doi:10.4060/ca8753en.
23. Forest Survey of India (FSI). Indian State of Forest Report. Dehradun: Forest Survey of India; 2003. Available from: https://fsi.nic.in/documents/sfr_2003_hindi.pdf.
24. Forest Survey of India (FSI). Indian State of Forest Report. Geomatics Division. Dehradun: Forest Survey of India; 2019. Available from: https://fsi.nic.in/forest-report-2019.
25. Forest Survey of India (FSI). Forest Types of India. Forest Survey of India, Geomatics Division. Dehradun: Forest Survey of India; 2020. Available from: http://webline.co.in/fsi-result/atlas-forest.pdf.
26. Forest Survey of India (FSI). Indian State of Forest Report. Dehradun: Forest Survey of India; 2021. Available from: https://fsi.nic.in/forest-report-2021.
27. Gorelick N, Hancher M, Dixon M, Ilyushchenko S, Thau D, Moore R. Google Earth Engine: Planetary-scale geospatial analysis for everyone. Remote Sensing of Environment. 2017;202:18-27. doi:10.1016/j.rse.2017.06.031.
28. Ghosh S, Biswas T, Chaudhary A, Kumar S. Identification of fire-prone forest areas based on GIS analysis of archived forest fire points detected in the last thirteen years. Technical Information Series. 2019;1:1-2.
29. Global Land Cover Facility. Global Land Cover Facility. 2022. Available from: http://glcf.umiacs.umd.edu/.
30. Global Wind Atlas 3.0. Global Wind Atlas 3.0. Technical University of Denmark (DTU); 2019. Available from: https://globalwindatlas.info.
31. Gupta S, Roy A, Bhavsar D, Kala R, Singh S, Kumar A. Forest fire burnt area assessment in the biodiversity-rich regions using geospatial technology: Uttarakhand forest fire event 2016. Journal of the Indian Society of Remote Sensing. 2018;46:945-955. doi:10.1007/s12524-018-0757-3.
32. Gupta S, Roy A, Bhavsar D, Kala R, Singh S, Kumar A. Forest fire burnt area assessment in the biodiversity-rich regions using geospatial technology: Uttarakhand forest fire event 2016. Journal of the Indian Society of Remote Sensing. 2018;46:945-955. doi:10.1007/s12524-018-0757-3.
33. International Union of Forest Research Organizations (IUFRO). IUFRO Annual Report. Vienna: IUFRO Publications; 2018.
34. Jain A, Roy P, Ravan S, Singh R, Das K. Fire risk modelling using remote sensing and geographic information system. Current Science. 1996;70(10):928-933.
35. Janzen D. Tropical dry forests: the most endangered major tropical ecosystem. In: Wilson EO, Peter FM, editors. Biodiversity. Washington (DC): National Academies Press; 1988. Available from: https://www.ncbi.nlm.nih.gov/books/NBK219281/.
36. Jolly W, Cochrane M, Freeborn P, Holden Z, Brown TJ, Williamson G, Bowman DM. Climate-induced variations in global wildfire danger from 1979 to 2013. Nature Communications. 2015;6:7537. doi:10.1038/ncomms8537.
37. Joseph S, Anitha K, Murthy MSR. Forest fire in India: a review of the knowledge base. Journal of Forest Research. 2009;14(3):127-134. doi:10.1007/s10310-009-0116-x.
38. Keeley JE. Impact of antecedent climate on fire regimes in coastal California. International Journal of Wildland Fire. 2004;13(2):173-182. doi:10.1071/WF03037.
39. Kushla JD, Ripple WJ. The role of terrain in a fire mosaic of a temperate coniferous forest. Forest Ecology and Management. 1997;95(2):97-107. doi:10.1016/S0378-1127(97)82929-5.
40. Lamat R, Kumar M, Kundu A, Lal D. Forest fire risk mapping using analytical hierarchy process (AHP) and earth observation datasets: a case study in the mountainous terrain of Northeast India. SN Applied Sciences. 2021;3:Article 43. doi:10.1007/s42452-021-04391-0.
41. Landmann G, Held A, Schuck A, Van Brusselen J. A scoping study in support of the development of a European Forest Risk Facility. European Forest Institute. 2015. doi:10.13140/RG.2.1.1927.2169.
42. Manepalli UR, Bham GH, Kandada S. Evaluation of hot-spots identification using kernel density estimation and Getis-Ord on I-630. In: International Conference on Road Safety and Simulation; 2011. Rolla, MO, USA. Available from: https://onlinepubs.trb.org/onlinepubs/conferences/2011/RSS/2/Manepalli,UR.pdf.
43. Matin M, Chitale V, Murthy MSR, Uddin K, Bajracharya B, Pradhan S. Understanding forest fire patterns and risk in Nepal using remote sensing, geographic information system, and historical fire data. International Journal of Wildland Fire. 2017;26(4):276-286. doi:10.1071/WF16056.
44. McCullum A, Torres-Perez J, Beaudry B, Pippin H. Using Earth observations for pre- and post-fire monitoring. NASA Applied Remote Sensing Training Program (ARSET); 2022. Available from: https://appliedsciences.nasa.gov/join-mission/training/english/arset-using-earth-observations-pre-and-post-fire-monitoring.
45. Murphy PG, Lugo AE. Ecology of tropical dry forest.

Annual Review of Ecology and Systematics. 1986;17:67-88. doi:10.1146/annurev.es.17.110186.000435.
46. Myers N. Biodiversity hotspots revisited. BioScience. 2003;53(10):916-917. doi:10.1641/0006-3568(2003)053[0916:BHR]2.0.CO;2.
47. NASA. NEO. NASA Earth Observation; 2018. Available from: https://neo.gsfc.nasa.gov/view.php?datasetId=MOD_LSTAD_M&date=2018-12-27.
48. Ord JK, Getis A. Local spatial autocorrelation statistics: distributional issues and an application. Geographical Analysis. 1995;27:286-306. doi:10.1111/j.1538-4632.1995.tb00912.x.
49. V PG, R S A, Jacob MK, Menon A. Forest fire risk analysis using geoinformation technology: a study of Peppara Wildlife Sanctuary, Thiruvananthapuram, Kerala, India. In: Proceedings of DRVC2014; 2014; Thiruvananthapuram. Available from: https://www.academia.edu/9684109.
50. Parry ML, Canziani OF, Palutikof JP, van der Linden PJ, Hanson CE, editors. Impacts, adaptation, and vulnerability: contribution of Working Group II to the Fourth Assessment. IPCC. Cambridge: Cambridge University Press; 2007. Available from: https://www.ipcc.ch/site/assets/uploads/2018/03/ar4_wg2_full_report.pdf.
51. Potić I, Ćurčić N, Potić M, Stanojević G, Milinčić M. Forest fires analysis using remote sensing techniques: a case study in East Serbia. Journal of the Geographical Institute "Jovan Cvijić" SASA. 2018;67(3):249-264. doi:10.2298/IJGI1703249P.
52. Prasad VK, Badarinath KVS, Eaturu A. Biophysical and anthropogenic controls of forest fires in the Deccan Plateau, India. Journal of Environmental Management. 2008;86(1):1-13. doi:10.1016/j.jenvman.2006.11.017.
53. Ramanathan V, Crutzen PJ, Kiehl JT, Rosenfeld D. Aerosols, climate, and the hydrological cycle. Science. 2001;294(5549):2119-2124. doi:10.1126/science.1064034.
54. Ramkrishnan PS. Shifting agriculture and sustainable development. Man and the Biosphere Series. UNESCO; 1993;10. Available from: http://14.139.206.50:8080/jspui/bitstream/1/4250/1/Shifting%20agriculture%20and%20sustainable%20development.pd.
55. Roy P. Forest fire and degradation assessment using satellite remote sensing and geographic information system. In: Satellite Remote Sensing and GIS Applications in Agricultural Meteorology; 2003. p. 361-380.
56. Sankey S. Blueprint for Wildland Fire Science in Canada (2019–2029). Edmonton: Natural Resources Canada; 2018. doi:10.1139/39429.
57. Sannigrahi S, Pilla F, Basu B, Basu AS, Sarkar K, Chakraborti S, et al. Examining the effects of forest fire on terrestrial carbon emission and ecosystem production in India using remote sensing approaches. Science of The Total Environment. 2020;725:138331. doi:10.1016/j.scitotenv.2020.138331.
58. Sarma G. Effect of fire on soil microorganisms in a Meghalaya pine forest. Folia Microbiologica. 1981;26(4):321-327. doi:10.1007/BF02927260.
59. Satendra, Kaushik AD. Forest fire disaster management. New Delhi: National Institute of Disaster Management; 2014. Available from: https://nidm.gov.in/pdf/pubs/forest%20fire.pdf.
60. Sayad YO, Mousannif H, Moatassime HA. Predictive modeling of wildfires: A new dataset and machine learning approach. Fire Safety Journal. 2019;104:130-146. doi:10.1016/j.firesaf.2019.01.006.
61. Schaefer V. The relationship of jet streams to forest wildfires. Journal of Forestry. 1957;55(6):419-425. Available from: https://www.nrfirescience.org/resource/11470.
62. Schoennagel T, Veblen TT, Romme WH. The interaction of fire, fuels, and climate across Rocky Mountain forests. BioScience. 2004;54(7):661-676. doi:10.1641/0006-3568(2004)054[0661:TIOFFA]2.0.CO;2.
63. Singh K, Neethu K, Madhurekaa K, Harita A, Mohan P. Parallel SVM model for forest fire prediction. Soft Computing Letters. 2021;3:100014. doi:10.1016/j.socl.2021.100014.
64. Sowmya S, Somashekar RK. Application of remote sensing and geographical information system in mapping forest fire risk zone at Bhadra Wildlife Sanctuary, India. Journal of Environmental Biology. 2010;31(6):969-974. Available from: https://pubmed.ncbi.nlm.nih.gov/21506484/.
65. Stolle F, Chomitz K, Lambin E, Tomich T. Land use and vegetation fires in Jambi Province, Sumatra, Indonesia. Forest Ecology and Management. 2003;179(1-3):277-292. doi:10.1016/S0378-1127(02)00547-9.
66. Thornbury W. Principles of Geomorphology. Soil Science. 1954;78(2):157. doi:10.1097/00010694-195408000-00023.
67. Tomich T, Lewis J. Reducing smoke pollution from tropical forests. ASB Policy Brief. 2002;4. Available from: http://asb.cgiar.org/download_count?id=2632&link=http://www.asb.cgiar.org/PDFwebdocs/ASBPolicyBriefs4.pdf.
68. Veena H, RS A, Loghin AM, Sipai R, Adarsh P, Viswam A, et al. Wildfire risk zonation in a tropical forest division in Kerala, India: A study using geospatial techniques. International Journal of Conservation Science. 2017;8(3):475-484.
69. Weise DR, Biging GS. Effects of wind velocity and slope on flame properties. Canadian Journal of Forest Research. 1996;26(10):1849-1858. doi:10.1139/x26-210.
70. Yue X, Mickley LJ, Logan JA, Kaplan J. Ensemble projections of wildfire activity and carbonaceous aerosol concentrations over the western United States in the mid-21st century. Atmospheric Environment. 2013;77:767-780. doi:10.1016/j.atmosenv.2013.06.003.