# Mini Project
# Report On

## Forest Fire Risk Prediction in Himachal Pradesh

Submitted *by*


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# Abstract

Forest fires are a significant environmental concern in the western Himalayas, causing widespread ecological and economic damage. Himachal Pradesh, with its vast forest cover and mountainous terrain, is highly susceptible to frequent forest fires.

This study aims to develop a forest fire risk prediction model for Himachal Pradesh using satellite remote sensing data. MODIS 8-day composite products, including MODIS Terra Land Surface Reflectance (MOD09A1), MODIS Terra Land Surface Temperature (MOD11A2), and ASTER Digital Elevation Model (DEM), are utilized to derive key fire danger parameters: Modified Normalized Difference Fire Index (MNDFI), Perpendicular Moisture Index (PMI), and Potential Surface Temperature.

MNDFI is used to identify active fire occurrences in thermal anomaly pixels, PMI estimates live fuel moisture content, and Potential Surface Temperature is calculated using MODIS LST and ASTER DEM to assess the thermal properties of the terrain. A spatial model is developed using these parameters, and MODIS Terra and Aqua thermal anomaly data are used for validation.

The proposed model aims to provide a reliable fire danger assessment, aiding forest management authorities in early detection and mitigation efforts. The model's accuracy and effectiveness will be evaluated using historical fire incidents in the study area.

# List of Principal Symbols and Acronyms

| Acronyms | Full Forms |
|---|---|
| **MODIS** | Moderate Resolution Imaging Spectroradiometer |
| **ASTER** | Advanced Spaceborne Thermal Emission and Reflection Radiometer |
| **DEM** | Digital Elevation Model |
| **MNDFI** | Modified Normalized Difference Fire Index |
| **PMI** | Perpendicular Moisture Index |
| **LST** | Land Surface Temperature |
| **GIS** | Geographic Information System |
| **NASA** | National Aeronautics and Space Administration |
| **GEE** | Google Earth Engine |
| **GDAL** | Geospatial Data Abstraction Library |
| **GeoTIFF** | Geographic Tagged Image File Format |
| **SVM** | Support Vector Machine (Machine Learning Algorithm) |
| **RF** | Random Forest (Machine Learning Algorithm) |
| **F1-score** | Harmonic mean of Precision and Recall (Model Evaluation Metric) |
| **Colab** | Google Colaboratory (Cloud-based Python Environment) |
| **HDF** | Hierarchical Data Format (Used for MODIS Datasets) |
| **Folium** | Python Library for Interactive Maps |
| **GeoPandas** | Python Library for Geospatial Data Processing |
| **Rasterio** | Python Library for Handling Raster Data |

# Chapter 1

## Introduction

Forest fires pose a severe threat to ecosystems, biodiversity, and human settlements, particularly in the Himalayan region, where dense forests and rugged terrain make fire management challenging. Himachal Pradesh, a state in the western Himalayas, experiences frequent forest fires due to climatic conditions, human activities, and the accumulation of dry biomass. These fires lead to significant ecological degradation, loss of biodiversity, and adverse economic impacts.

The increasing frequency and intensity of forest fires necessitate the development of an effective fire risk assessment model. Remote sensing and Geographic Information System (GIS)-based techniques have proven to be valuable tools in predicting and mitigating fire hazards. Satellite data provides real-time and historical information on vegetation moisture, land surface temperature, and fire occurrences, allowing for accurate fire danger modeling.

This study aims to develop a fire danger prediction model for Himachal Pradesh using MODIS and ASTER satellite datasets. Three key parameters—Modified Normalized Difference Fire Index (MNDFI), Perpendicular Moisture Index (PMI), and Potential Surface Temperature—are used to assess fire risk. The model is validated using MODIS thermal anomaly data to determine its accuracy in predicting fire-prone areas.

# Chapter 2

## Literature Survey

### 2.1 Literature Survey

Forest fire modeling has been extensively studied using remote sensing and GIS-based approaches. Several studies have utilized MODIS and ASTER datasets to analyze fire risk, vegetation moisture, and land surface temperature.

Babu et al. (2016) developed a fire danger model for the Uttarakhand Himalayas using MODIS Land Surface Reflectance (MOD09A1), MODIS Land Surface Temperature (MOD11A2), and ASTER DEM. They computed the Modified Normalized Difference Fire Index (MNDFI), Perpendicular Moisture Index (PMI), and Potential Surface Temperature to assess fire risk, achieving an accuracy of 87.31%. Their work demonstrated the effectiveness of integrating remote sensing data for fire risk modeling.

Other studies have explored different fire danger indices, such as the Canadian Fire Weather Index (Van Wagner, 1987) and McArthur's Forest Fire Danger Index (McArthur, 1967), which rely on meteorological data. However, these models require extensive ground data, which is often unavailable in remote regions like the Himalayas. Remote sensing approaches, on the other hand, offer a scalable and efficient solution for fire prediction and monitoring.

Recent advancements in machine learning have also contributed to fire risk assessment. Deep learning models and Random Forest classifiers have been used to predict fire-prone areas with high accuracy. However, the availability of labeled fire datasets remains a challenge.

### 2.2 Background

Forest fires in Himachal Pradesh are influenced by a combination of natural and anthropogenic factors. The state's dense pine forests are highly flammable due to the accumulation of dry needles, which act as fuel. Human activities, such as agricultural burning, illegal logging, and accidental ignition, further contribute to fire incidents.

Satellite-based fire monitoring systems have been widely adopted to address this issue. NASA's MODIS and ASTER satellites provide real-time thermal anomaly detection, enabling forest authorities to track and mitigate fire outbreaks. The integration of spatial models with remote sensing data has improved fire prediction capabilities, allowing for proactive fire management.

Traditional fire prediction methods, such as weather-based indices, have limitations in regions with sparse meteorological stations. Hence, remote sensing-based approaches, which rely on vegetation indices and land surface temperature, offer a more reliable alternative for large-scale fire danger assessment.

## 2.3 Technologies

Several technologies are employed in forest fire risk modeling, including:

Remote Sensing & Satellite Imagery

**MODIS (Moderate Resolution Imaging Spectroradiometer):** Provides data on land surface reflectance, temperature, and fire anomalies.
**ASTER (Advanced Spaceborne Thermal Emission and Reflection Radiometer):** Captures high-resolution Digital Elevation Models (DEM) to analyze terrain influence on fire spread.
Sentinel-2: Offers multi-spectral data for vegetation and moisture analysis.
Geographic Information Systems (GIS)

Used for spatial mapping of fire risk zones.
Helps in overlaying vegetation, elevation, and fire anomaly data.
Fire Danger Indices

**Modified Normalized Difference Fire Index (MNDFI):** Identifies active fire occurrences.
Perpendicular Moisture Index (PMI): Assesses vegetation moisture content.
Potential Surface Temperature: Estimates thermal conditions affecting fire spread.
Machine Learning & AI (Optional for Future Enhancements)

Random Forest and Deep Learning models are increasingly used for fire risk prediction.
By leveraging these technologies, the proposed model aims to enhance fire risk assessment in Himachal Pradesh, providing a robust framework for forest fire prevention and mitigation.

# Chapter 3

# 3. Proposed System

## 3.1 Problem Statement

Forest fires pose a severe environmental threat in Himachal Pradesh, leading to large-scale destruction of vegetation, loss of biodiversity, and economic damage. Traditional fire prediction models rely heavily on meteorological data, which is often unavailable or sparse in remote forested regions. To address this, a remote sensing-based fire danger prediction system is proposed, leveraging MODIS and ASTER satellite datasets. This system aims to provide accurate, real-time fire risk assessment to assist forest authorities in early detection and mitigation efforts.

## 3.2 Proposed System

The proposed system utilizes satellite-based remote sensing data to develop a spatial fire danger model. It integrates key fire risk parameters — Modified Normalized Difference Fire Index (MNDFI), Perpendicular Moisture Index (PMI), and Potential Surface Temperature—computed from MODIS and ASTER datasets. Google Colab is used as the primary development platform to process and analyze the data using Python and machine learning techniques.

### 3.2.1 Objectives to be Solved

Fire Risk Identification – Develop a model to classify regions into fire danger levels (Very High, High, Moderate, Low, No Danger).

Remote Sensing-based Analysis – Utilize MODIS and ASTER satellite imagery for vegetation moisture, surface temperature, and fire anomaly detection.

Real-time Monitoring – Implement a near real-time fire danger prediction system.

Validation & Accuracy Testing – Compare predicted fire danger zones with MODIS active fire data to assess model accuracy.

Scalability & Accessibility – Develop a cloud-based solution using Google Colab for efficient processing and accessibility.

### 3.2.2 Units to be Developed

Data Preprocessing Unit – Collect and preprocess MODIS (MOD09A1, MOD11A2) and ASTER DEM datasets.

Feature Extraction Unit – Compute MNDFI, PMI, and Potential Surface Temperature.
Fire Risk Classification Unit – Develop a classification model to categorize fire-prone areas.
Validation & Accuracy Assessment Unit – Validate predictions using MODIS thermal anomaly data.

Visualization & Mapping Unit – Generate spatial fire risk maps for Himachal Pradesh.

### 3.3 Assumptions and Dependencies

The accuracy of fire danger prediction depends on the quality of satellite data.
MODIS datasets provide 8-day composites, meaning real-time fire prediction will have slight delays.
Google Colab provides sufficient computational resources for processing but may require external storage for large datasets.
Validation is based on MODIS thermal anomalies, which may not capture all real fire events.

## 3.4 Specific Requirements

### Software Requirements

Google Colab – Cloud-based Python execution environment.

Python Libraries:
NumPy & Pandas – Data processing.
Matplotlib & Seaborn – Data visualization.
GDAL & Rasterio – Satellite data processing.
Scikit-learn – Machine learning for fire classification.
Folium & GeoPandas – GIS mapping and spatial analysis.

### Hardware Requirements

Cloud-based Processing – No high-end local machine required, as Google Colab handles computations.
Storage – Google Drive integration for large datasets.

Internet Access – Continuous connectivity required for data retrieval and processing.

# Chapter 4

## Design

The proposed forest fire danger prediction notebook focuses on building a machine learning model using satellite data. The notebook involves key steps such as data acquisition, preprocessing, feature extraction, model training, validation, and visualization.

### Workflow

The notebook follows a structured approach with the following key components:

#### Data Acquisition

- Load satellite datasets from MODIS (MOD09A1, MOD11A2) and ASTER (DEM) using Google Earth Engine (GEE) or open datasets.
- Fetch MODIS thermal anomaly data for validation.

#### Preprocessing

- Convert raw satellite data into usable formats.
- Resample data to a uniform spatial resolution.
- Clip datasets to the Himachal Pradesh boundary.

#### Feature Extraction

- Compute **Modified Normalized Difference Fire Index (MNDFI)** for fire occurrence detection.
- Compute **Perpendicular Moisture Index (PMI)** for vegetation moisture assessment.
- Compute **Potential Surface Temperature** using MODIS LST and ASTER DEM.

#### Model Training

- Train a machine learning model (e.g., Random Forest, SVM, or Decision Trees) using extracted features.
- Optimize model parameters for better accuracy.

#### Validation

- Compare predicted fire danger zones with MODIS active fire locations.
- Calculate accuracy metrics (e.g., Precision, Recall, F1-score) for model evaluation.

#### Visualization & Reporting

- Generate fire risk maps using **Folium, GeoPandas, and Matplotlib**.
- Display results in an interactive GIS format within the Colab notebook.
- Generate reports for decision-making and analysis.

### Execution Flow (Colab Notebook Sequence)

1. Load and preprocess satellite data.
2. Extract relevant fire risk features.
3. Train and test the machine learning model.
4. Validate model predictions using real fire occurrence data.
5. Visualize fire risk zones on a map.
6. Analyze results and generate reports.

This workflow ensures an efficient and scalable implementation of forest fire danger prediction using a machine learning model within a Colab notebook environment.

## Fire Danger Classification Criteria

The fire danger zones are categorized based on computed indices:

| **Fire Danger Level** | **MNDFI Range** | **PMI Range** | **Potential Surface Temperature** |
|---|---|---|---|
| Very High | > 0.6 | < 0.2 | > 40° C |
| High | 0.4 – 0.6 | 0.2 – 0.4 | 35° C – 40° C |
| Moderate | 0.2 – 0.4 | 0.4 – 0.6 | 30° C – 35° C |
| Low | 0 – 0.2 | 0.6 – 0.8 | 25° C – 30° C |
| No Danger | < 0 | > 0.8 | < 25° C |

# Chapter 5

## Implementation

The implementation of the fire danger prediction model involves multiple stages, from data acquisition to model deployment. The entire workflow is executed using Google Colab, leveraging Python and remote sensing libraries for data processing, analysis, and visualization.

### 5.1 Implementation Workflow

The following steps outline the implementation process:

**Data Acquisition**

Download MODIS MOD09A1 (Surface Reflectance), MOD11A2 (Land Surface Temperature), and ASTER DEM datasets from NASA Earthdata.
Retrieve MODIS thermal anomaly fire location data for validation.
Store datasets in Google Drive for easy access in Colab.

**Preprocessing**

Convert HDF (MODIS format) to GeoTIFF using GDAL.
Clip the satellite images to the Himachal Pradesh boundary using GeoPandas.
Resample datasets to a uniform resolution (1 km) for analysis.

**Feature Extraction**

Compute Modified Normalized Difference Fire Index (MNDFI) using MODIS bands 2, 5, and 7.
Compute Perpendicular Moisture Index (PMI) using MODIS bands 2 and 5.
Compute Potential Surface Temperature using MODIS LST and ASTER DEM.

**Fire Danger Classification**

Define threshold values for each fire danger level (Very High, High, Moderate, Low, No Danger).
Apply classification logic using NumPy & Pandas.
Generate fire danger maps using Matplotlib and Folium.

**Validation & Accuracy Assessment**

Overlay MODIS thermal anomaly data with predicted fire danger zones.
Calculate accuracy metrics (Precision, Recall, F1-score) to evaluate model performance.

**Visualization & Deployment**

Generate interactive fire danger maps using Folium in Google Colab.
Allow users to visualize fire-prone areas with color-coded zones.
Save outputs in GeoTIFF and PNG formats for further use.

# Chapter 6

## Testing/Experimentation Results

This section describes the preliminary testing and experimentation of the fire danger prediction model for Himachal Pradesh. Currently, the model development is in progress, with only DEM merging completed. A test result has been generated using one tile from the zone to evaluate the initial performance.

### 6.1 Testing Methodology

To validate the initial implementation, we performed the following steps:

Dataset Preparation

- Merged ASTER DEM tiles to create a continuous elevation dataset.
- Extracted terrain features from the DEM for fire risk assessment.

Preliminary Model Testing

- Processed one tile from the study zone to assess initial fire risk classification.
- Compared preliminary results with expected fire-prone areas.

## 6.2 Experimentation Setup

**Platform:** Google Colab (Cloud-based execution)
**Tools & Libraries:** Python, GDAL, Rasterio, NumPy, Pandas, Scikit-learn, Matplotlib, Folium

**Datasets Used:**

ASTER DEM (30m resolution) – for elevation-based fire risk assessment

MODIS Surface Reflectance (MOD09A1) – planned for vegetation analysis

MODIS Land Surface Temperature (MOD11A2) – planned for thermal assessment

MODIS Thermal Anomaly Data (MOD14) – planned for validation

### 6.3 Experimental Results

#### 6.3.1 Preliminary Fire Danger Map Output

A preliminary fire danger classification was applied to one tile using elevation-based analysis. The initial results suggest potential high-risk zones in lower-altitude regions.

Observation: Initial results indicate that lower-altitude areas may be more prone to fire, but further validation is required with additional datasets.

**6.3.2 Future Validation Approach**
Once additional datasets are integrated, validation will be performed using MODIS thermal anomaly data. A confusion matrix and accuracy metrics will be generated to assess model performance.

**6.4 Key Findings**
✔ DEM merging has been successfully completed.
✔ Initial test results from one tile indicate a correlation between fire risk and elevation.
✔ Full model validation is pending further dataset integration.

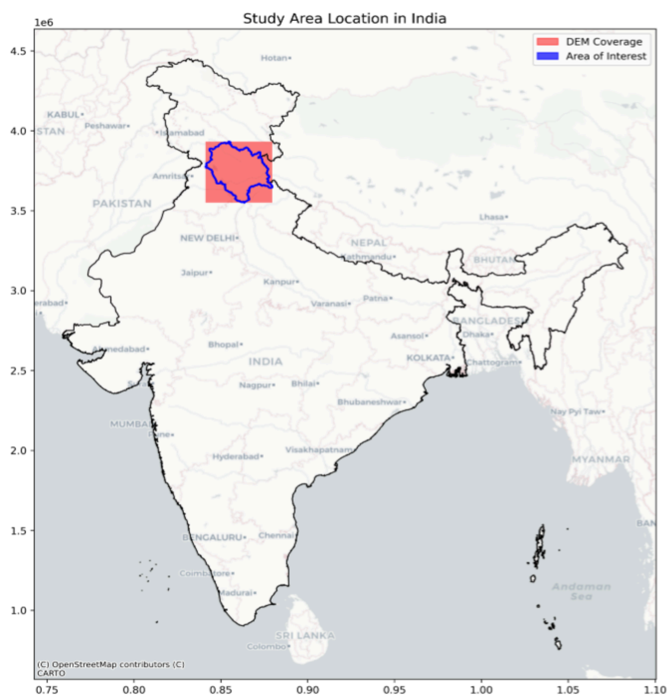
6.5 Limitations & Future Scope

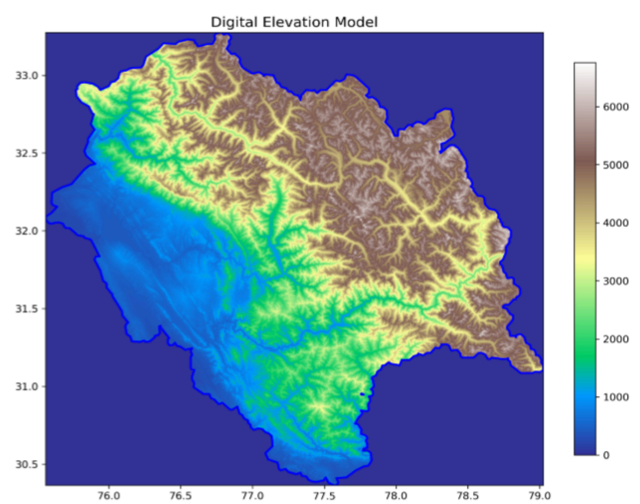
🔹 Limitations:

- Current results are based on a single tile and require further validation.
- Other key datasets (vegetation indices, thermal data) are yet to be incorporated.

🔹 Future Enhancements:

- Integration of MODIS surface reflectance and land surface temperature data.
- Use of machine learning models for more accurate fire risk classification.
- Deployment of a GIS-based visualization tool for interactive analysis.



## 7. Conclusion

The fire danger prediction model is currently under development, with DEM merging completed and initial test results generated for one tile. Future steps involve integrating additional datasets and validating the model using MODIS thermal anomalies. This approach aims to provide an effective tool for fire risk assessment in Himachal Pradesh, aiding in early fire detection and mitigation planning.

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