A Hybrid GIS–Machine Learning Approach for Forest Fire Risk Zonation and Future Projections in Nainital, Uttarakhand: An Integrated AHP and XGBoost Framework

Presented by

Debisha Ghosh and Sampurna Saha

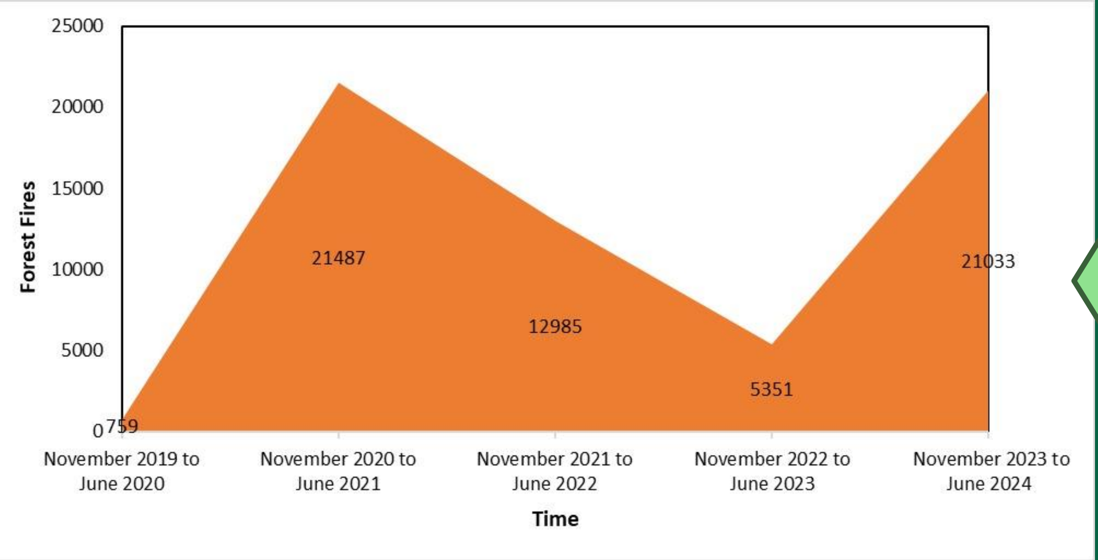
Table of Contents

Forest Fire in Nainital

Nainital, nestled in the Kumaon region of Uttarakhand, is highly prone to forest fires, especially during the dry summer. These fires are driven by factors like:

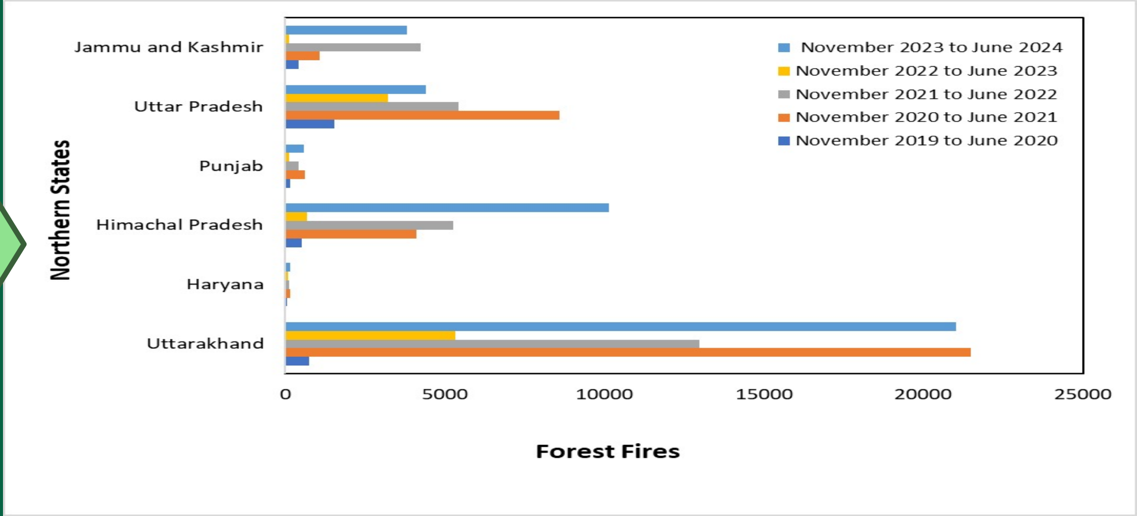
- **Rising Temperatures**
- **Prolonged Dry Spells**
- **Human Activities such as Tourism and Deforestation**

The region's dense pine forests, rich in resin, make it highly flammable, leading to rapid fire spread. Frequent wildfires threaten biodiversity, degrade air quality, and impact local livelihoods. With climate change intensifying fire risks, real-time monitoring, early warning systems, and community-based mitigation strategies are crucial for safeguarding Nainital's fragile ecosystem.



Forest Fire Incidents in Uttarakhand during Nov, 2019 to Jun, 2024

Comparison of Forest Fire Incidents among the Northern States of India



Data Source: Forest Survey of India (FSI)

Objectives

Forest Fire Determinants

Assessment of the determinant factors affecting forest fire occurrences based on existing studies and knowledge.

Geospatial Fire Risk Map

To develop a comprehensive forest fire risk map through the application of geospatial techniques and AHP.

Model Validation

To validate the forest fire risk zonation model using the XGBoost machine learning algorithm.

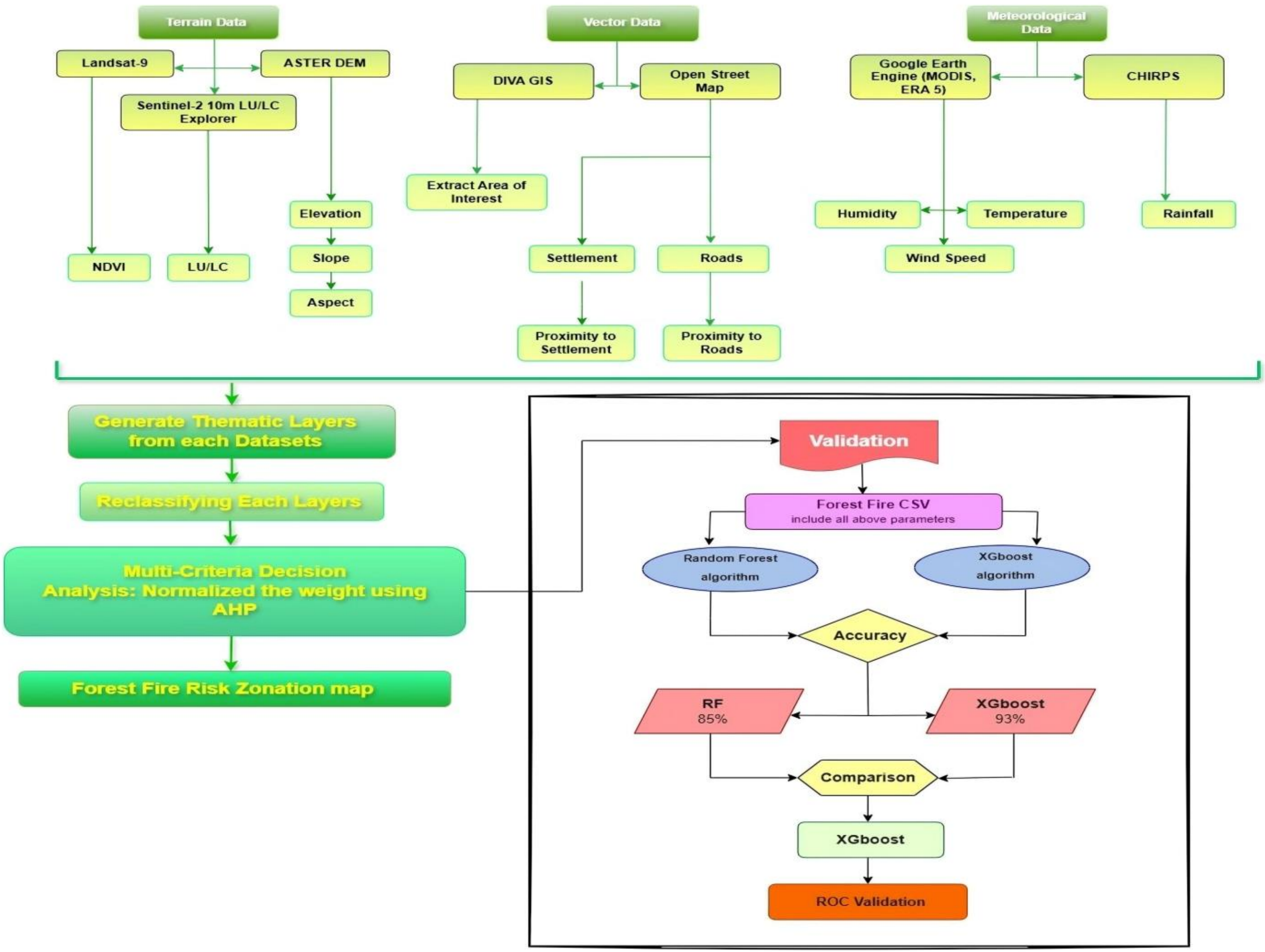
Future Wildfire Prediction

To predict future forest fire probabilities for the years 2025, 2030, and 2035 using the trained XGBoost model.

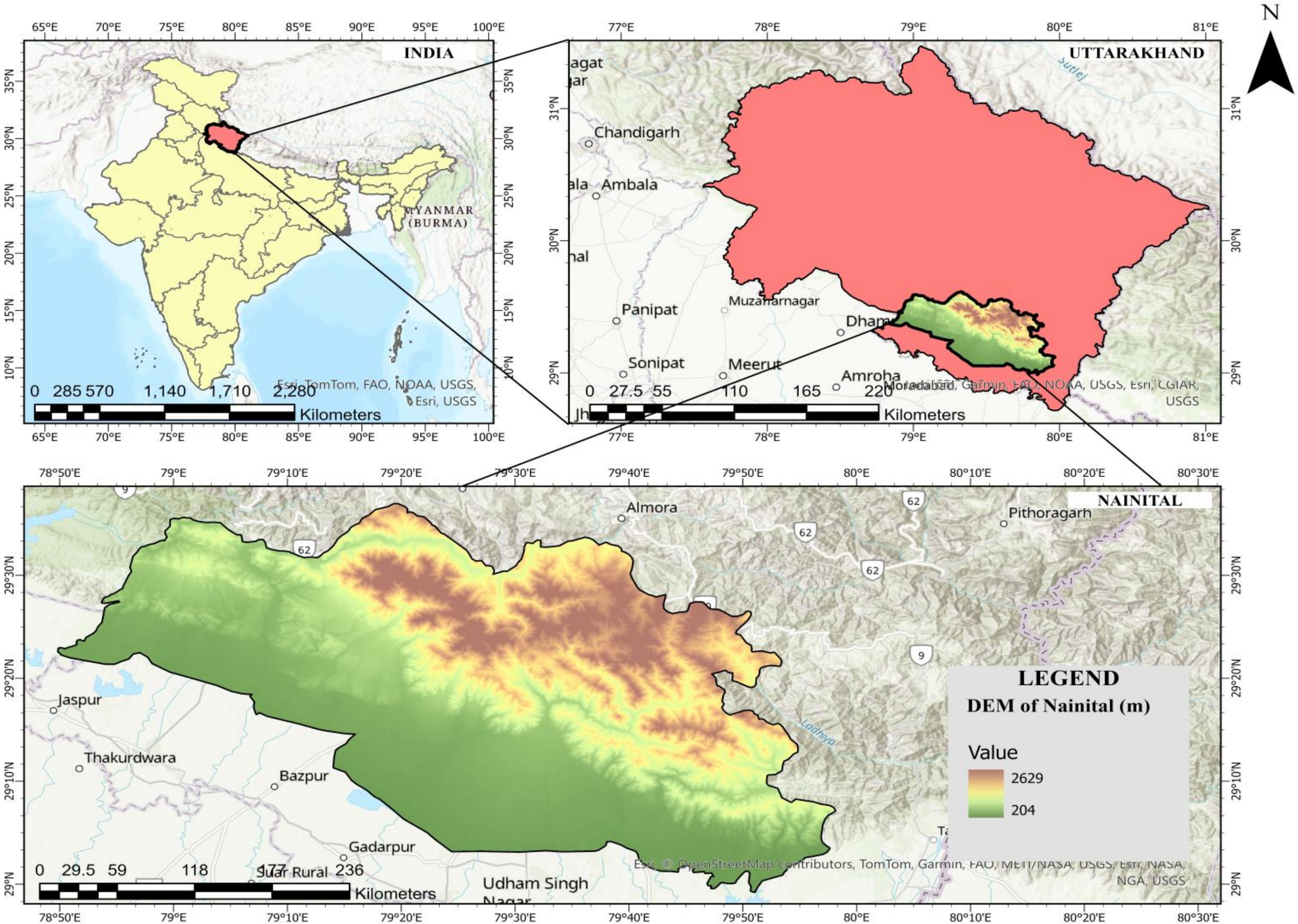
Datasets

Data Type		Data Source	Data Collected	Data Extracted
Raster Data	Terrain Data	USGS Earth Explorer	Landsat 9	https://earthexplorer.usgs.gov/
		Copernicus Data Source Ecosystem	Sentinel-2	https://dataspace.copernicus.eu/explore-data/data-collections/sentinel-data/sentinel-2
	Meteorological Data	Advanced Space Borne Thermal Emission and Reflection Radiometer	ASTER GDEM	https://gdemdl.aster.jspacesystems.or.jp/
		ArcGIS Living Atlas of the World	ESRI| Sentinel-2 Landcover Explorer	https://livingatlas.arcgis.com/landcoverexplorer/
		Google Earth Engine	MODIS	Google Earth Engine Script
			ERA5	Google Earth Engine Script
		Climate Hazard Centre-UC Santa Barbara	CHIRPS	https://data.chc.ucsb.edu/products/CHIRPS-2.0/global_annual/tifs/
Vector Data		DIVA-GIS	Shapefile	https://diva-gis.org/
		BBBike extracts OpenStreetMap	Shapefile	https://extract.bbbike.org/

Methodology

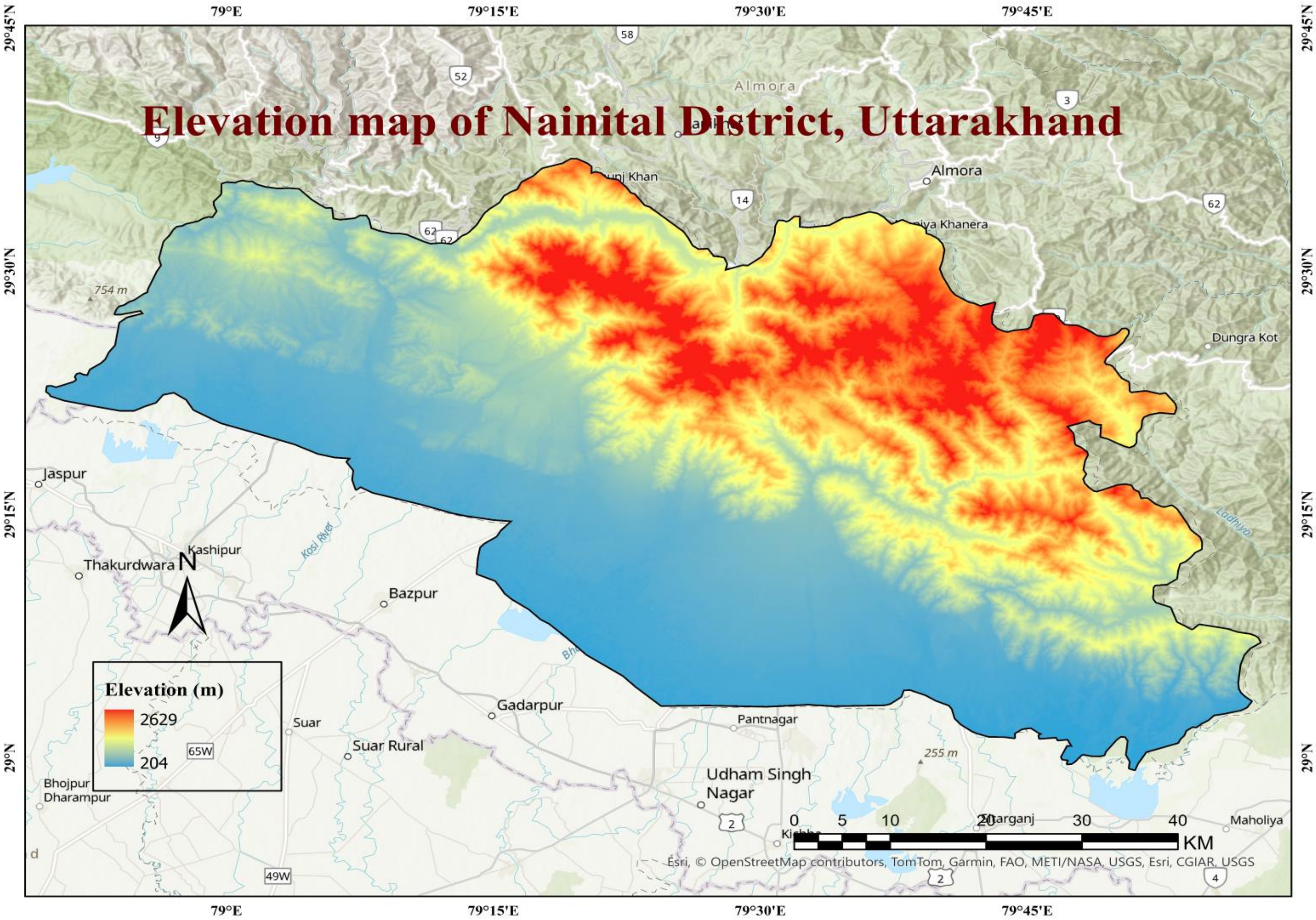


Study Area Map

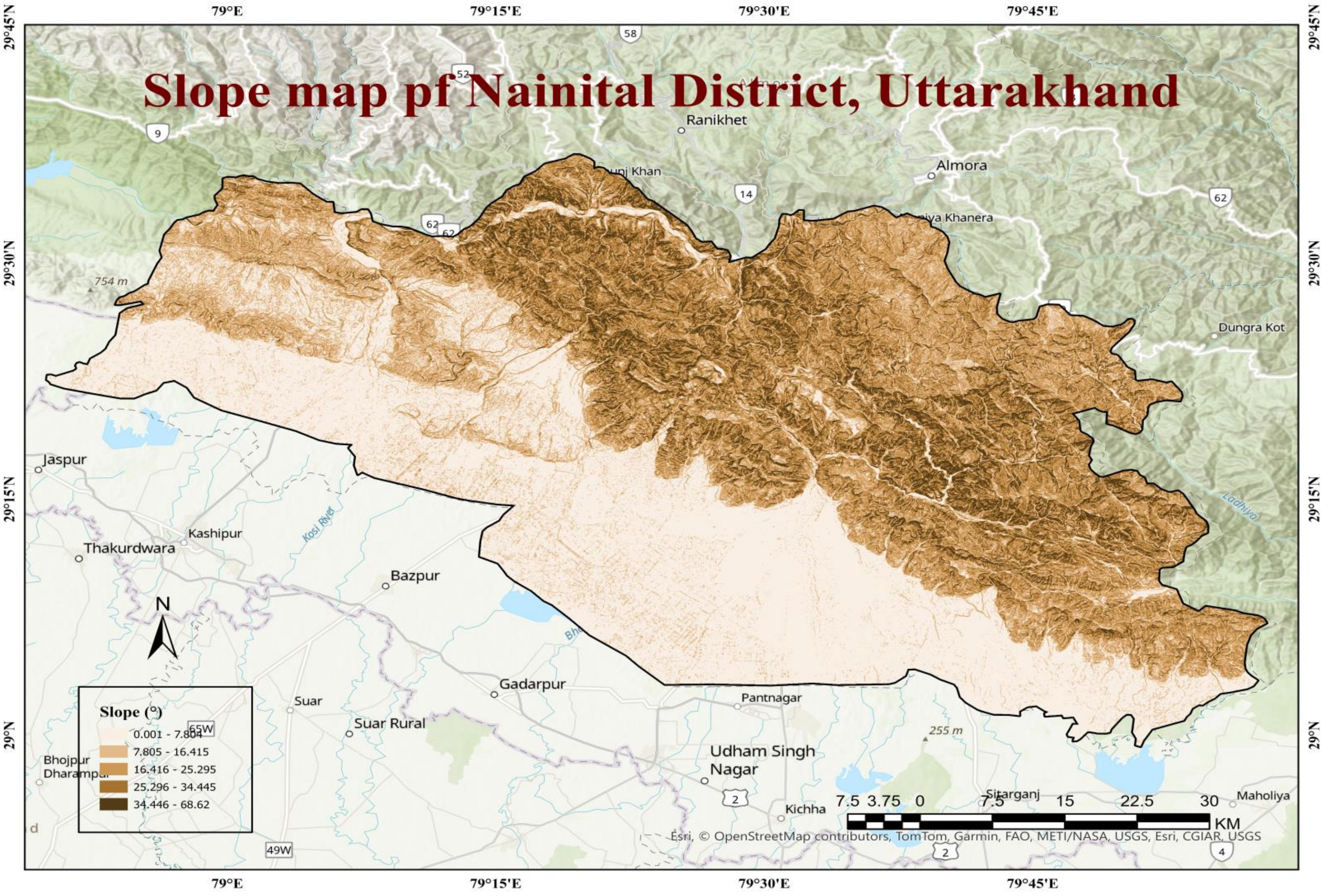



Determinant Factors for
Forest Fire Occurrences

Elevation Map

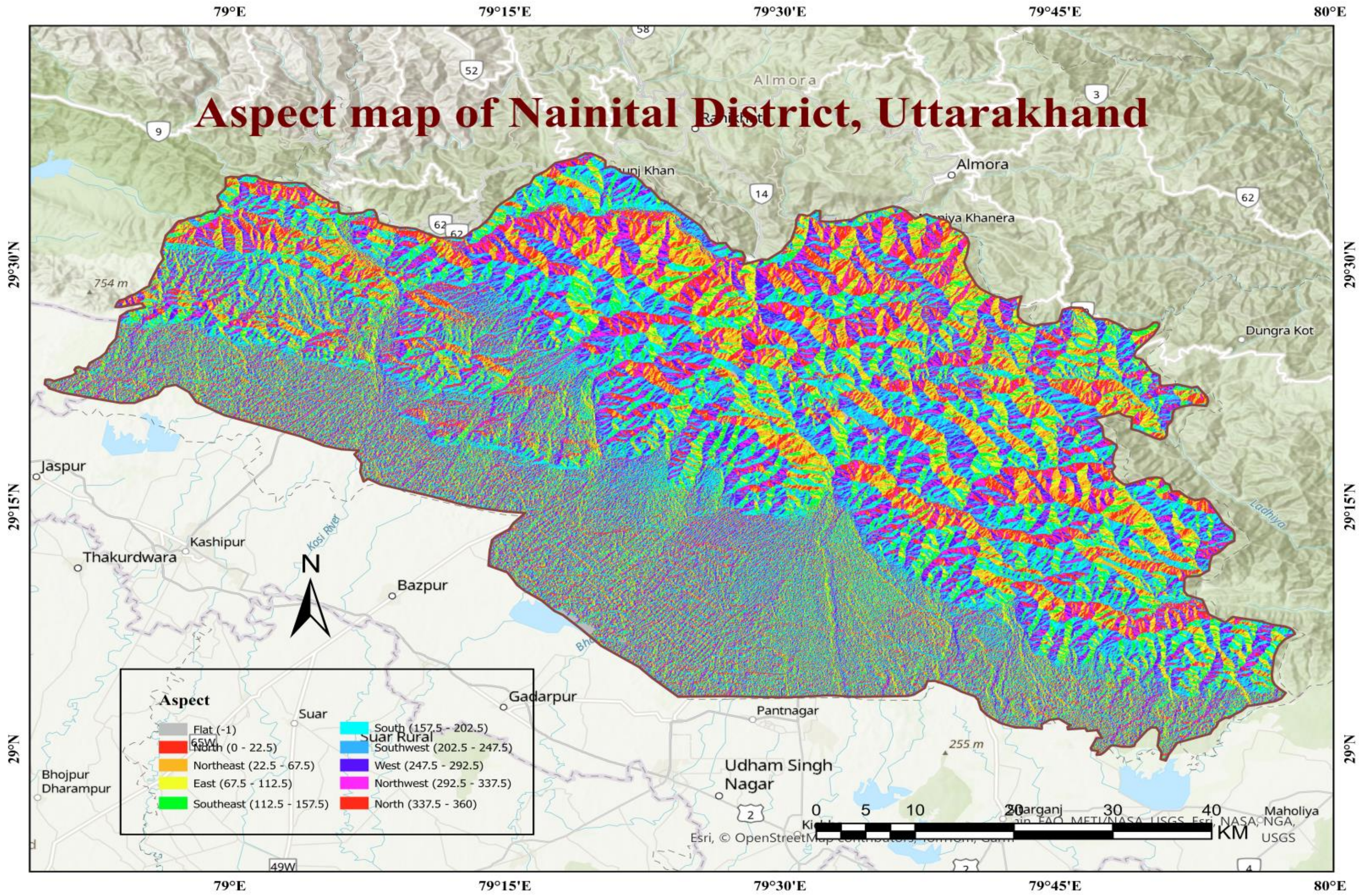


Slope Map



Slope map pf Nainital District, Uttarakhand
79°E
79°15'E
79°30'E
79°45'E
29°45'N
29°30'N
29°15'N
29°N
Ranikhet
Almora
Dungra Kot
Jaspur
Kashipur
Thakurdwara
Kosi River
Bazpur
Gadarpur
Pantnagar
Suar
Suar Rural
Udham Singh Nagar
Kichha
Sitarganj
Maholiya
Bhojpur Dharampur
Ladhiya
754 m
255 m
N
Slope (°)
0.001 - 7.804
7.805 - 16.415
16.416 - 25.295
25.296 - 34.445
34.446 - 68.62
7.5 3.75 0 7.5 15 22.5 30
KM
Esri, © OpenStreetMap contributors, TomTom, Garmin, FAO, METI/NASA, USGS, Esri, CGIAR, USGS

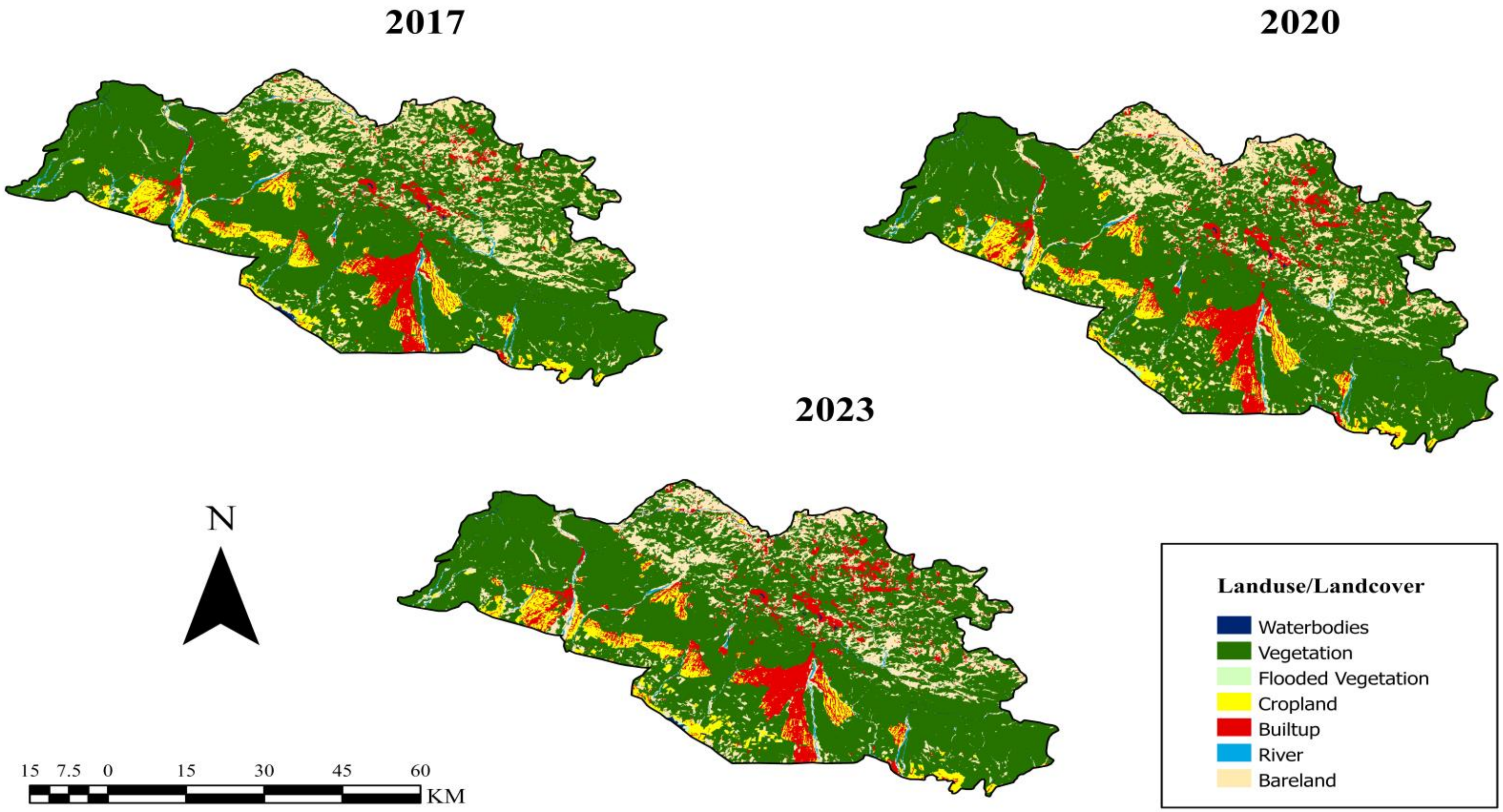
Aspect Map



Aspect map of Nainital District, Uttarakhand
79°E
79°15'E
79°30'E
79°45'E
80°E
29°30'N
29°15'N
29°N
Almora
Dungra Kot
Jaspur
Kashipur
Thakurdwara
Bazpur
Gadarpur
Pantnagar
Suar
Suar Rural
Udham Singh Nagar
Bhojpur Dharampur
Maholiya
Kosi River
Ladhiya
754 m
255 m
N
Aspect
Flat (-1)
North (0 - 22.5)
Northeast (22.5 - 67.5)
East (67.5 - 112.5)
Southeast (112.5 - 157.5)
South (157.5 - 202.5)
Southwest (202.5 - 247.5)
West (247.5 - 292.5)
Northwest (292.5 - 337.5)
North (337.5 - 360)
0 5 10 20 30 40 KM
Esri, © OpenStreetMap contributors

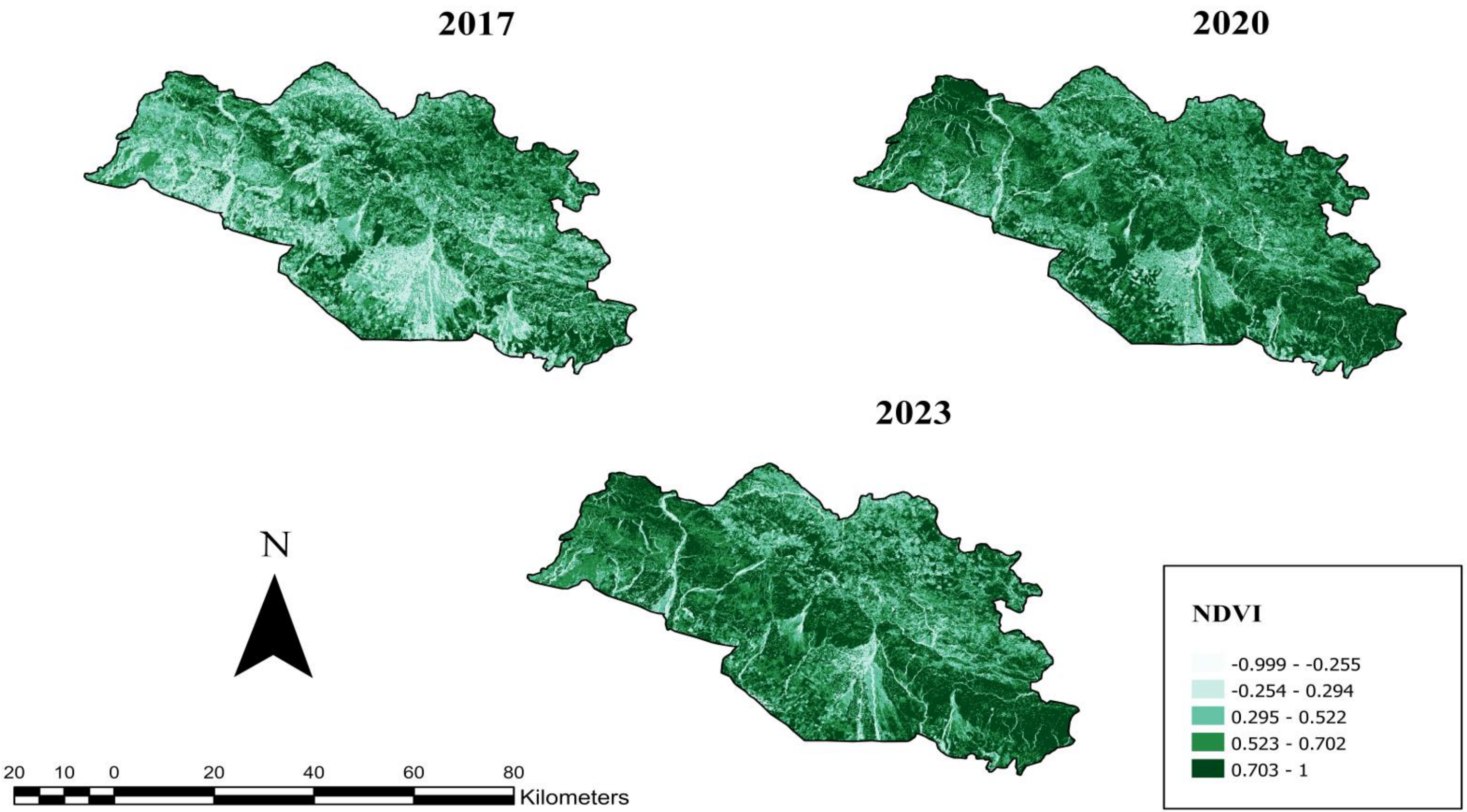
Land Use/Land Cover Map

LULC highlighting spatiotemporal variations between 2017 to 2023



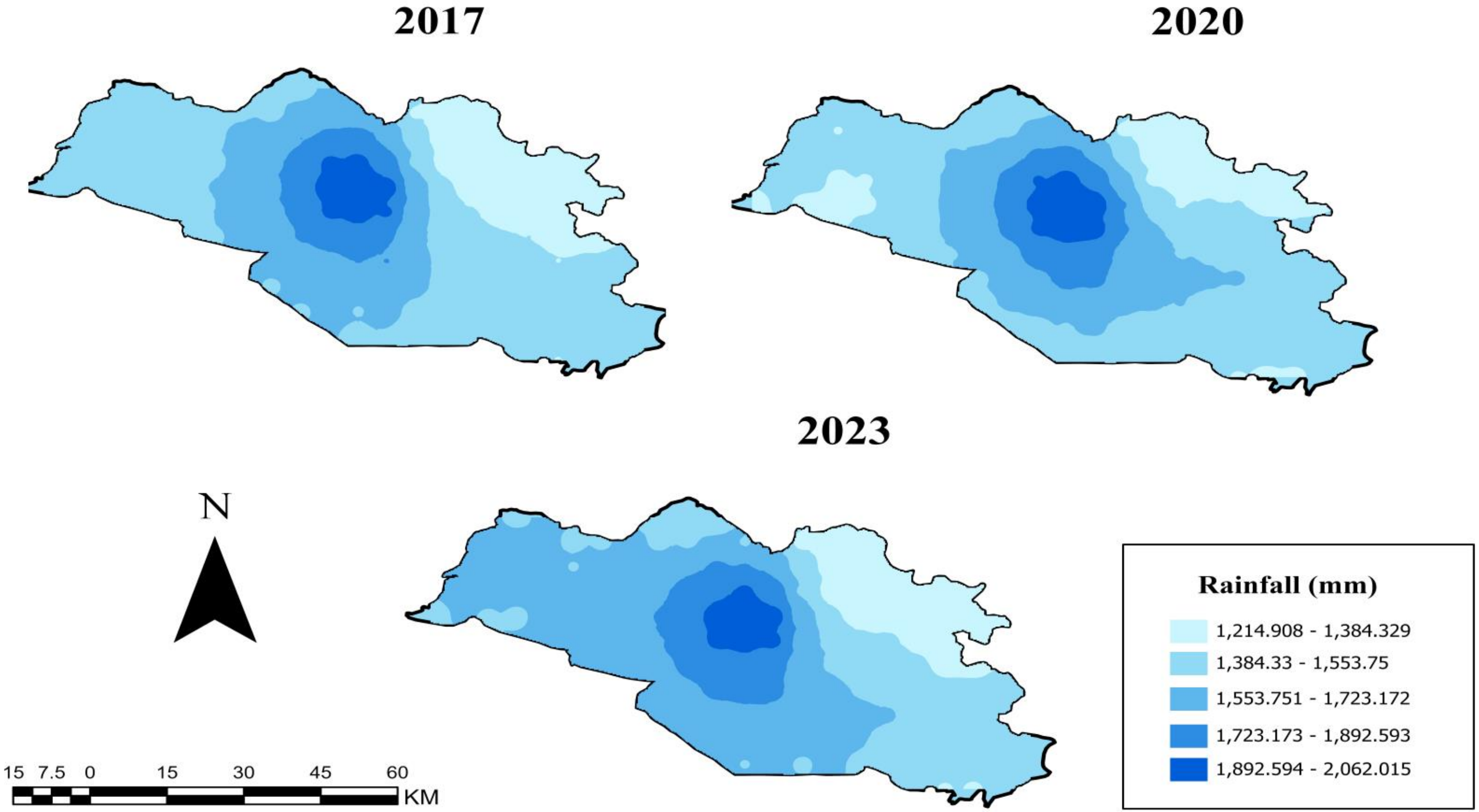
Normalized Difference Vegetation Index Map

NDVI highlighting spatiotemporal variations between 2017 to 2023



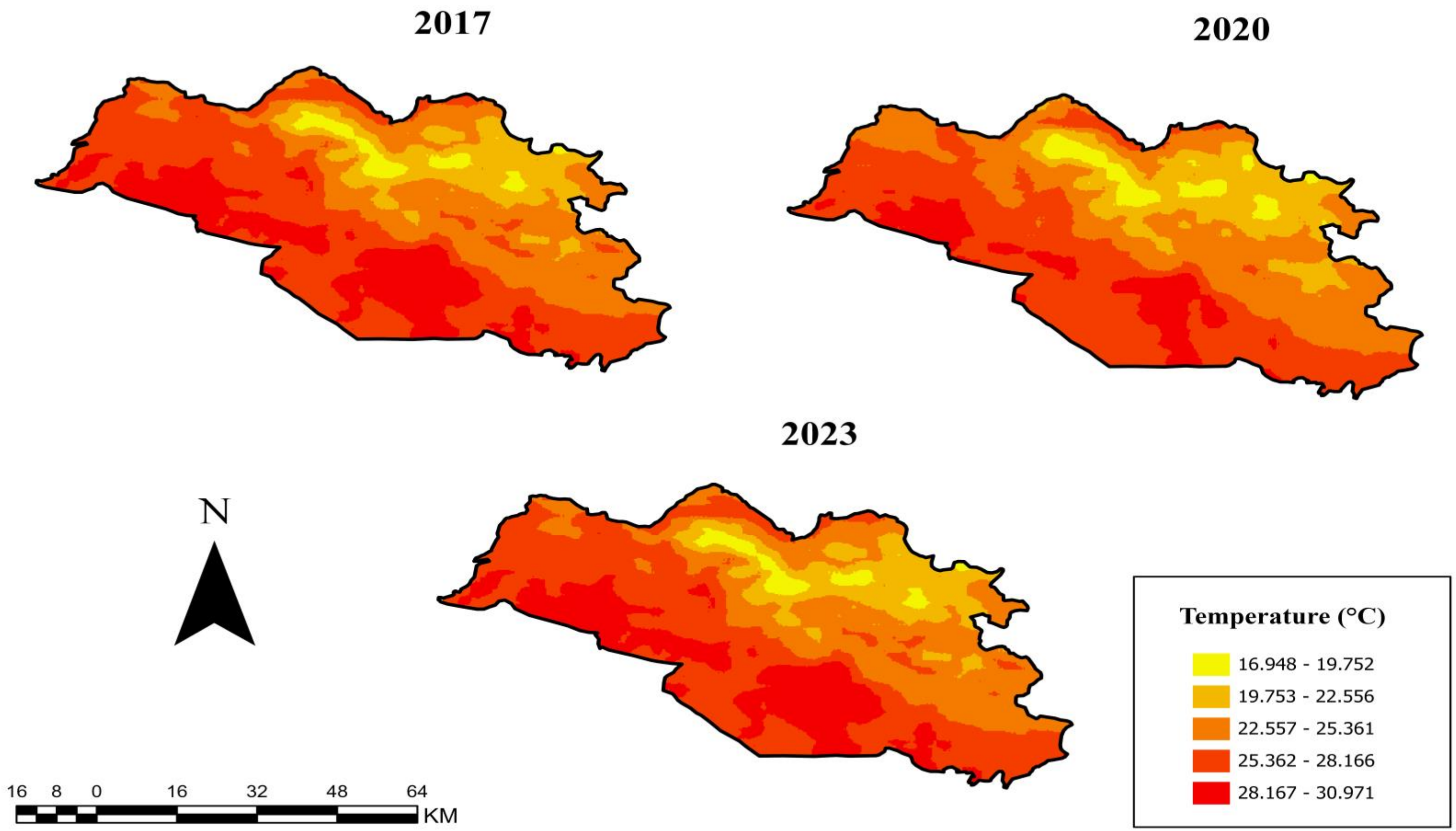
Rainfall Map

IDW showing Rainfall Variations between 2017 to 2023



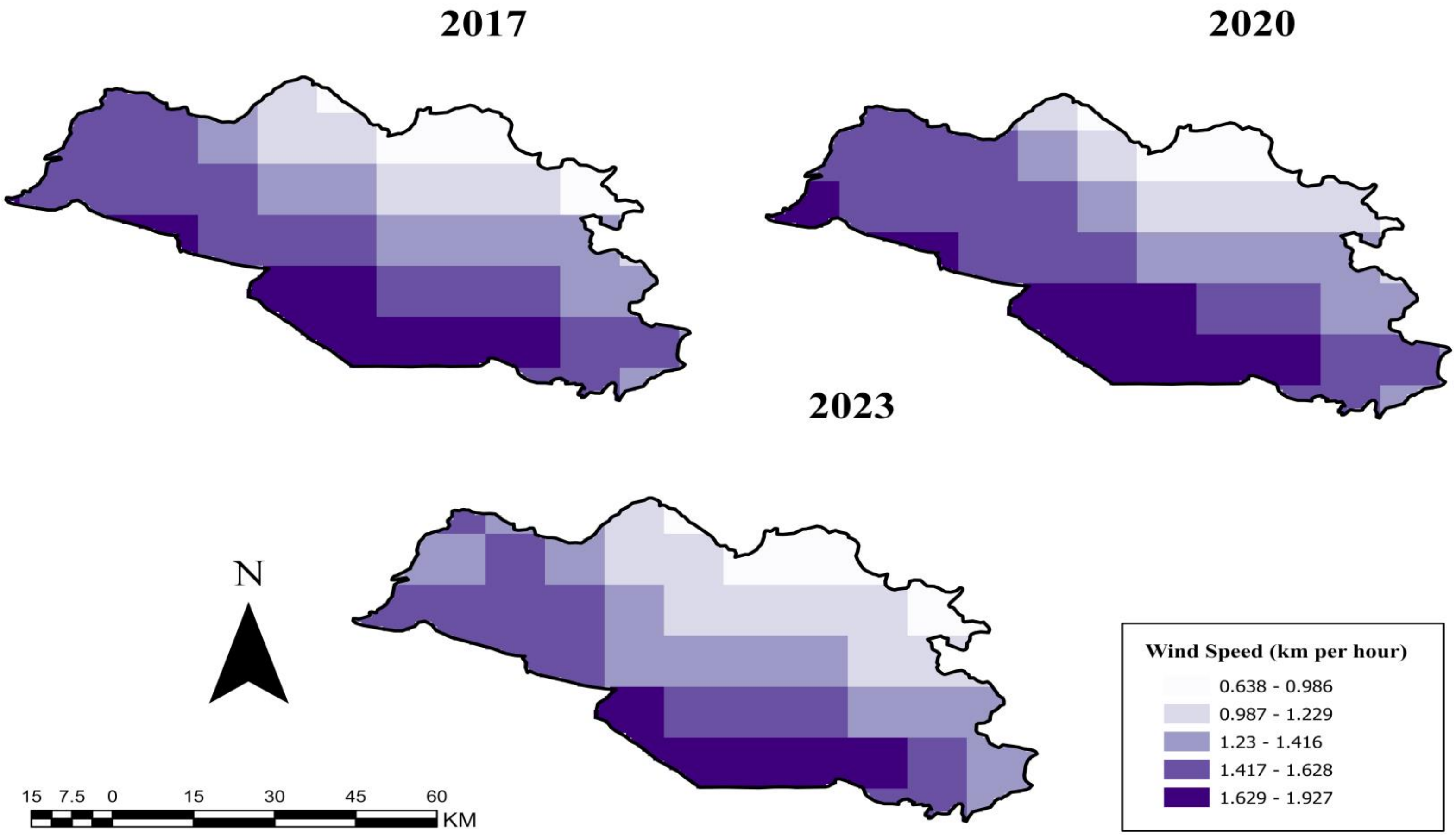
Temperature Map

IDW showing Temperature Variations between 2017 to 2023

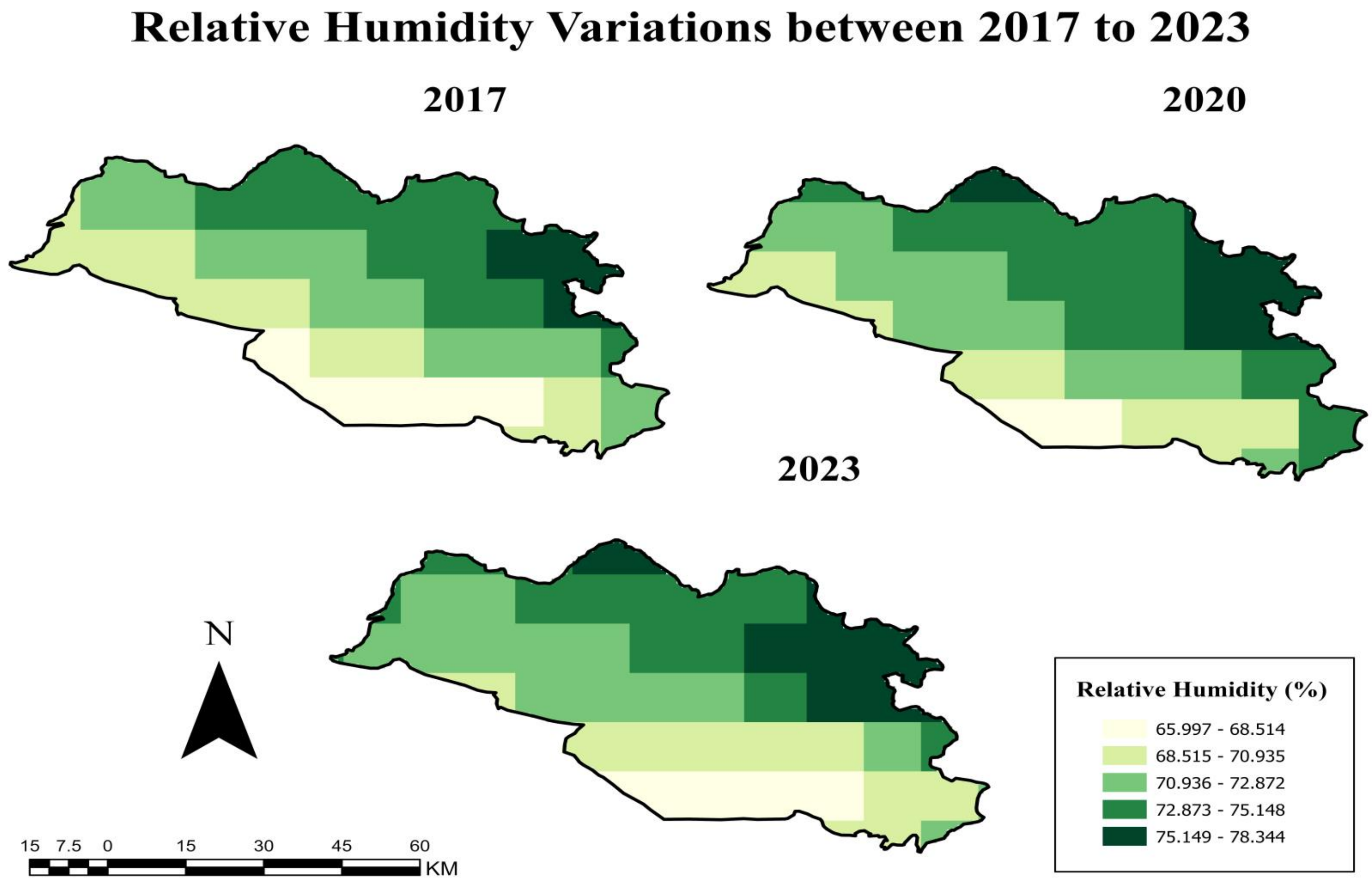


Wind Speed Map

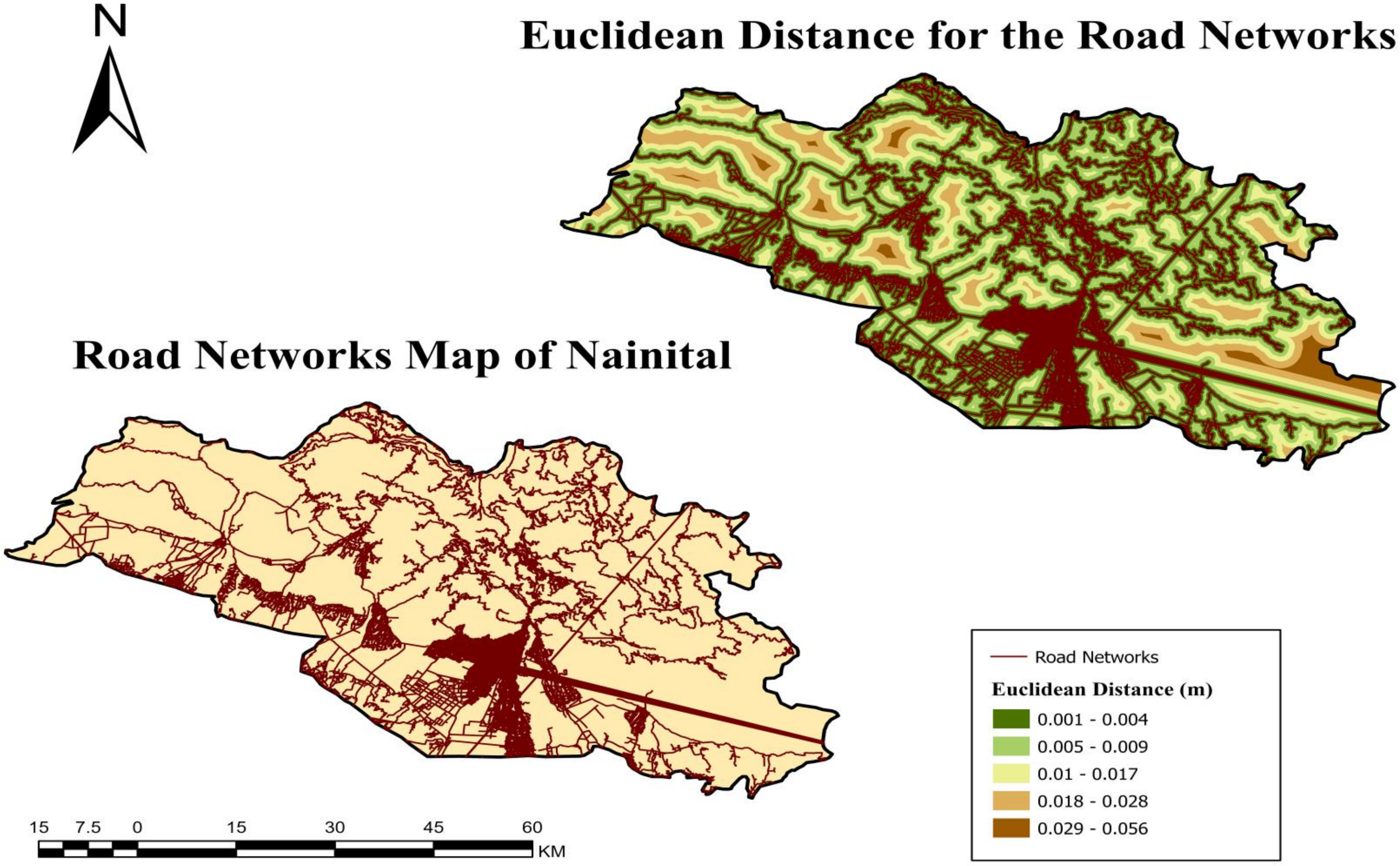
Wind Speed Variations between 2017 to 2023



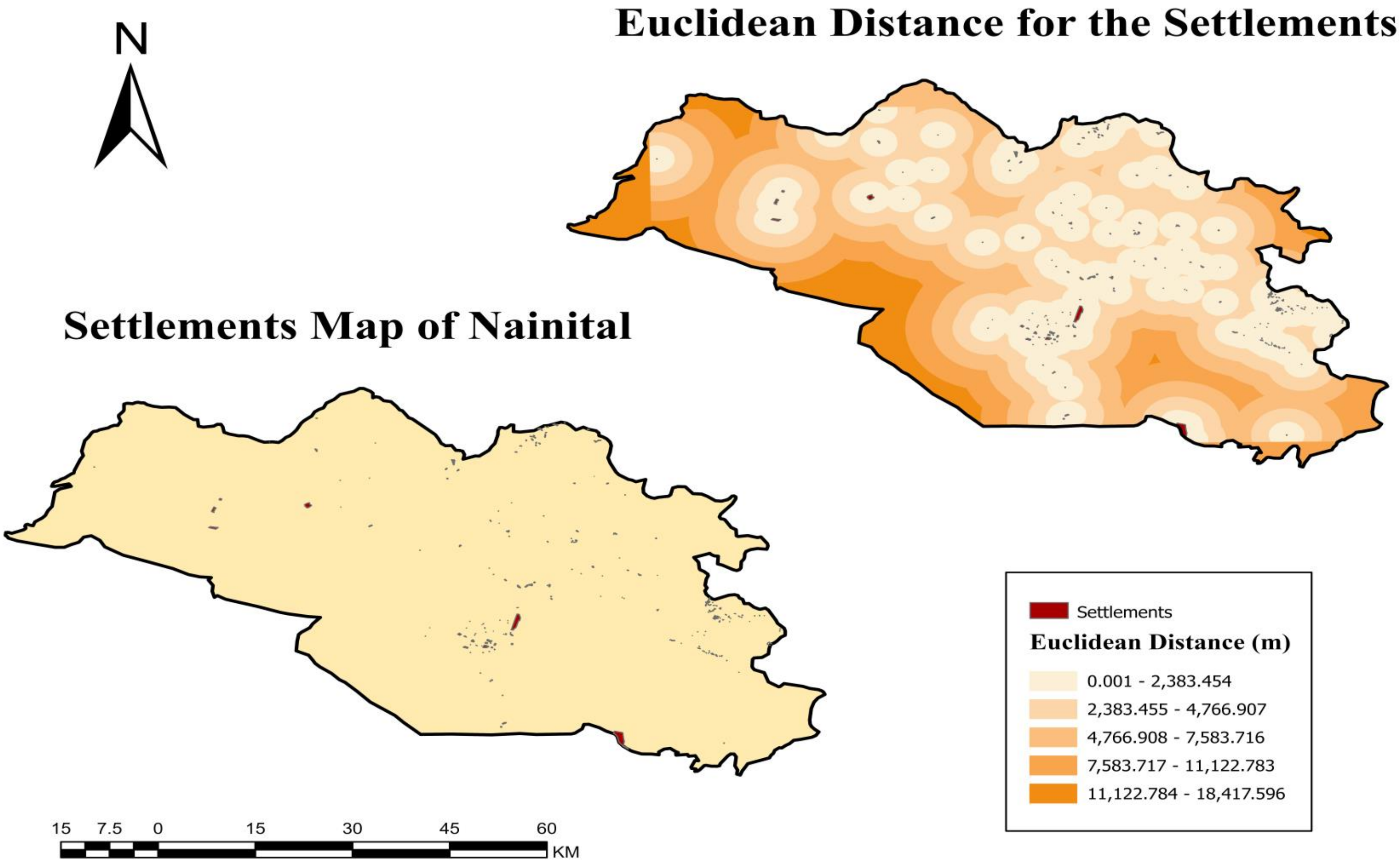
Relative Humidity Map



Proximity to Roads Map



Proximity to Settlements Map



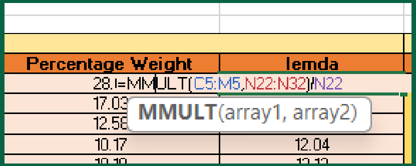

Weighted Overlay Analysis using Analytic Hierarchy Process (AHP)

Table 1

Pair-wise Comparison Matrix											
	NDVI	**LU/LC**	**Elevation**	**Slope**	**Aspect**	**Proximity to Settlement**	**Proximity to Roads**	**Humidity**	**Wind Speed**	**Temperature**	**Rainfall**
NDVI	1.00	4.00	3.00	3.00	3.00	6.00	8.00	4.00	9.00	9.00	9.00
LU/LC	0.25	1.00	3.00	2.00	2.00	4.00	4.00	5.00	6.00	8.00	5.00
Elevation	0.33	0.33	1.00	2.00	2.00	3.00	3.00	4.00	5.00	6.00	4.00
Slope	0.33	0.50	0.50	1.00	2.00	2.00	3.00	2.00	4.00	5.00	6.00
Aspect	0.33	0.50	0.50	0.50	1.00	3.00	2.00	4.00	4.00	4.00	9.00
Proximity to Settlement	0.17	0.25	0.33	0.50	0.33	1.00	3.00	2.00	2.00	3.00	4.00
Proximity to Roads	0.13	0.25	0.33	0.33	0.50	0.33	1.00	2.00	2.00	2.00	2.00
Humidity	0.25	0.20	0.25	0.50	0.25	0.50	0.50	1.00	4.00	4.00	5.00
Wind Speed	0.11	0.17	0.20	0.25	0.25	0.50	0.50	0.25	1.00	2.00	4.00
Temperature	0.11	0.13	0.17	0.20	0.25	0.33	0.50	0.25	0.50	1.00	3.00
Rainfall	0.11	0.20	0.25	0.17	0.11	0.25	0.50	0.20	0.25	0.33	1.00
Sum	3.13	7.53	9.53	10.45	11.69	20.92	26.00	24.70	37.75	44.33	52.00

Table 2

Normalised Pair-wise Comparison matrix													
	NDVI	**LU/LC**	**Elevation**	**Slope**	**Aspect**	**Proximity to Settlement**	**Proximity to Roads**	**Humidity**	**Wind Speed**	**Temperature**	**Rainfall**	**Criteria Weights**	**Percentage Weight**	**lemda**
NDVI	0.32	0.53	0.31	0.29	0.26	0.29	0.31	0.16	0.24	0.20	0.17	0.28	28.01	12.36
LU/LC	0.08	0.13	0.31	0.19	0.17	0.19	0.15	0.20	0.16	0.18	0.10	0.17	17.03	12.50
Elevation	0.11	0.04	0.10	0.19	0.17	0.14	0.12	0.16	0.13	0.14	0.08	0.13	12.58	12.27
Slope	0.11	0.07	0.05	0.10	0.17	0.10	0.12	0.08	0.11	0.11	0.12	0.10	10.17	12.04
Aspect	0.11	0.07	0.05	0.05	0.09	0.14	0.08	0.16	0.11	0.09	0.17	0.10	10.10	12.12
Proximity to Settlement	0.05	0.03	0.03	0.05	0.03	0.05	0.12	0.08	0.05	0.07	0.08	0.06	5.81	12.02
Proximity to Roads	0.04	0.03	0.03	0.03	0.04	0.02	0.04	0.08	0.05	0.05	0.04	0.04	4.13	12.31
Humidity	0.08	0.03	0.03	0.05	0.02	0.02	0.02	0.04	0.11	0.09	0.10	0.05	5.30	11.48
Wind Speed	0.04	0.02	0.02	0.02	0.02	0.02	0.02	0.01	0.03	0.05	0.08	0.03	2.96	11.51
Temperature	0.04	0.02	0.02	0.02	0.02	0.02	0.02	0.01	0.01	0.02	0.06	0.02	2.26	11.51
Rainfall	0.04	0.03	0.03	0.02	0.01	0.01	0.02	0.01	0.01	0.01	0.02	0.02	1.70	11.95
	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	100.0	12.50



To Calculate Lemda (λ), for NDVI,

ƒ **MMULT**(1st row of Pair-wise comparison Matrix, Criteria Weights column) / criteria weight of NDVI

CI	Random Index	CR
0.150430228	1.51	0.09962267

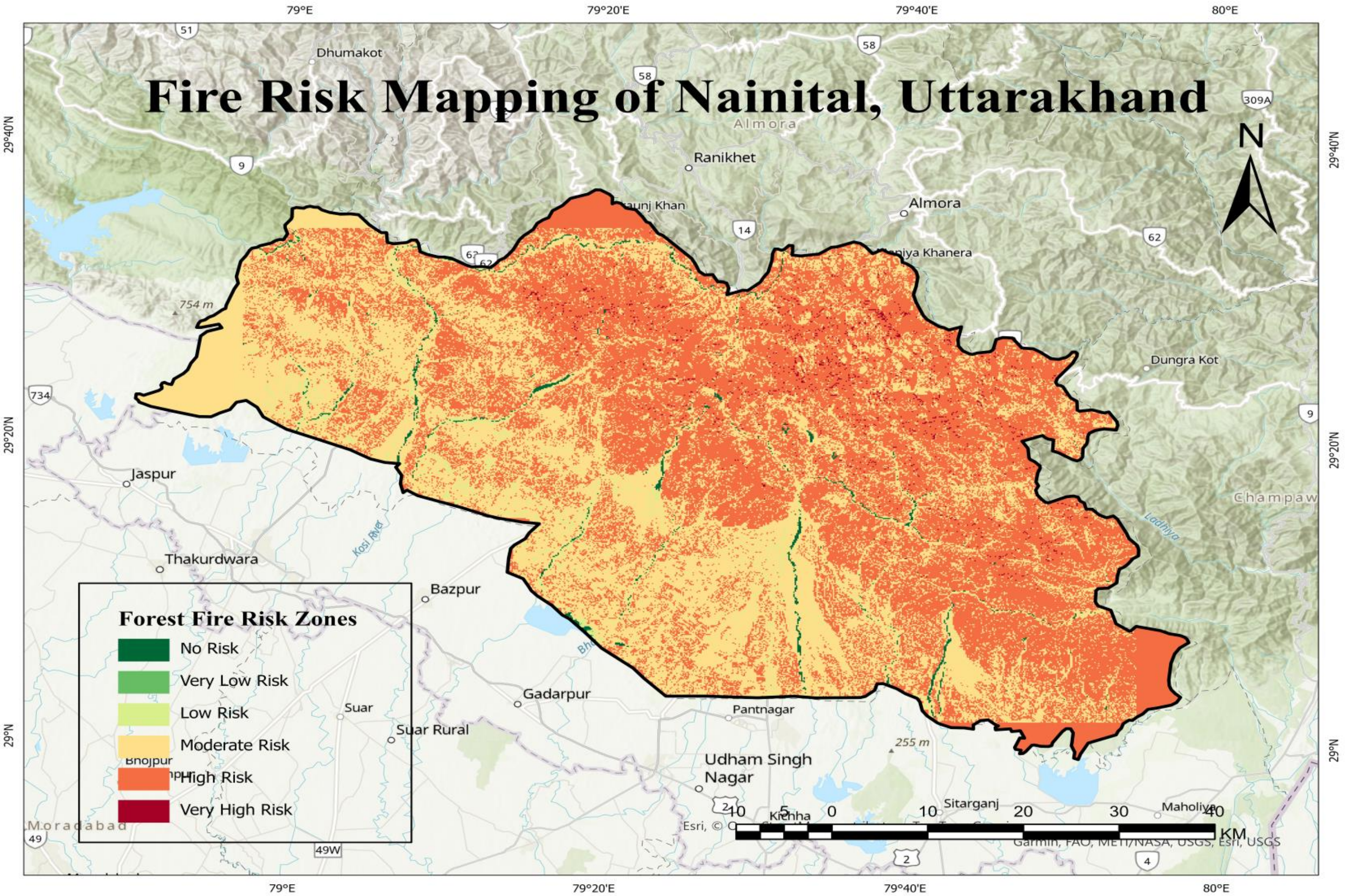
Consistency Index (CI) =
(λmax-n)/(n-1)

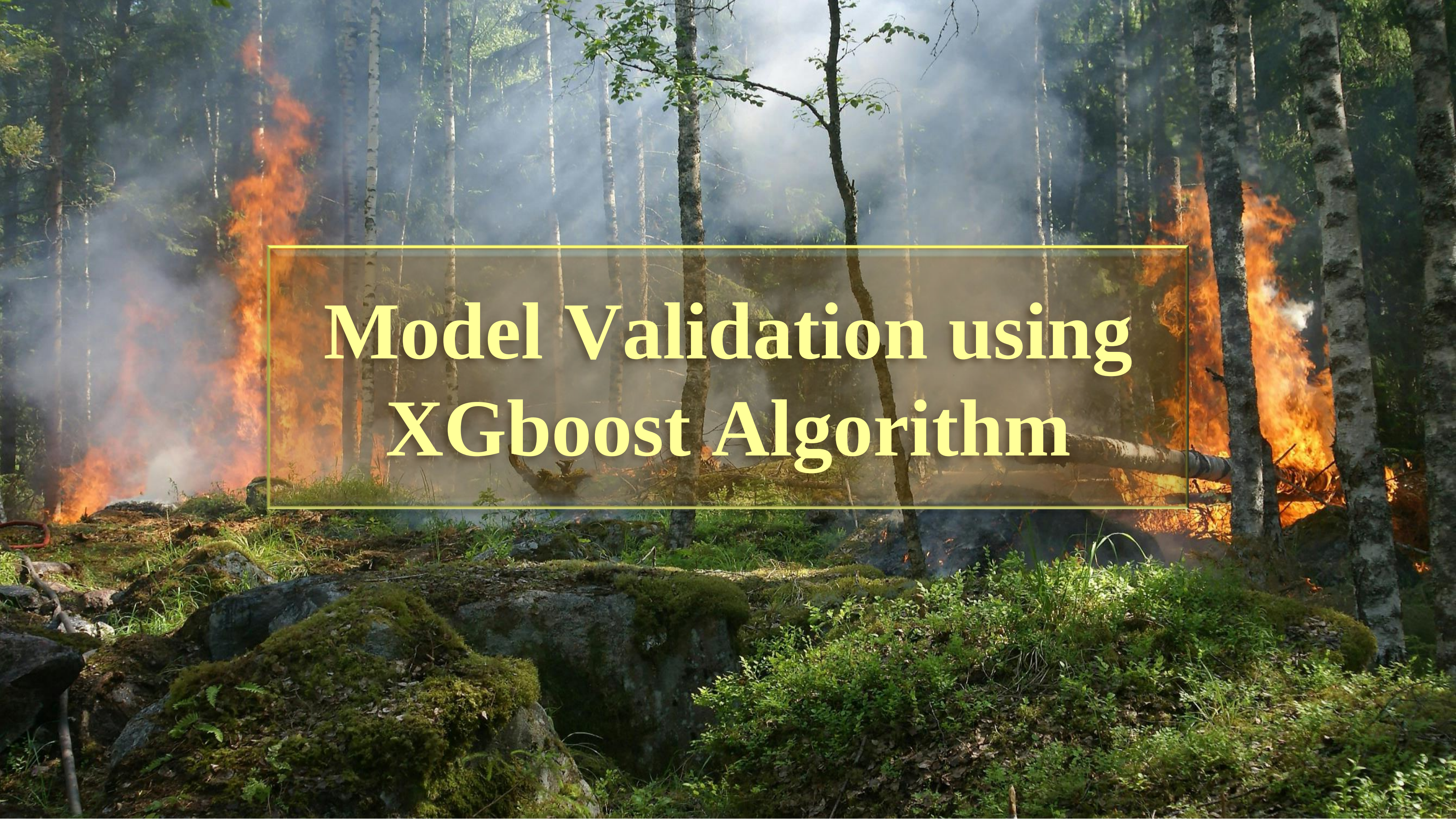
Consistency Ratio =
Consistency Index / Random Index

n	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
RI	0.00	0.00	0.52	0.89	1.11	1.25	1.35	1.40	1.45	1.49	1.51	1.54	1.56	1.57	1.58

Value of the random index R.I n = order of the matrix (Saaty, 2006)

Weighted Overlay Map




Model Validation using
XGboost Algorithm

Loading of the Dataset

```python
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler, LabelEncoder
from sklearn.metrics import (
    accuracy_score,
    roc_auc_score,
    roc_curve,
    confusion_matrix,
    ConfusionMatrixDisplay
)
from xgboost import XGBClassifier

# Load dataset
df = pd.read_csv(r"C:\Users\Debisha Ghosh\Downloads\nainital_forest_fire_CSV.csv")

# Label encode LULC
le = LabelEncoder()
df['LULC'] = le.fit_transform(df['LULC'])
```

Scaling the Dataset

```python
# Scale features
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)
```

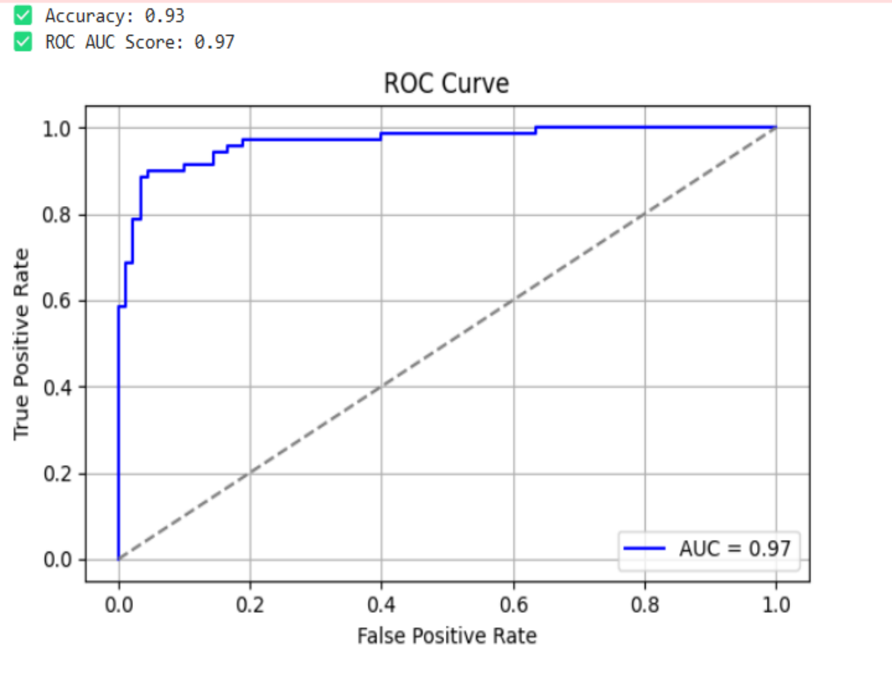
```python
# Train-test split
X_train, X_test, y_train, y_test = train_test_split(
    X_scaled, y, test_size=0.2, random_state=42
)

# Train XGBoost
model = XGBClassifier(
    n_estimators=50,
    max_depth=3,
    learning_rate=0.1,
    subsample=0.9,
    colsample_bytree=0.8,
    use_label_encoder=False,
    eval_metric='logloss',
    random_state=42
)
model.fit(X_train, y_train)
```

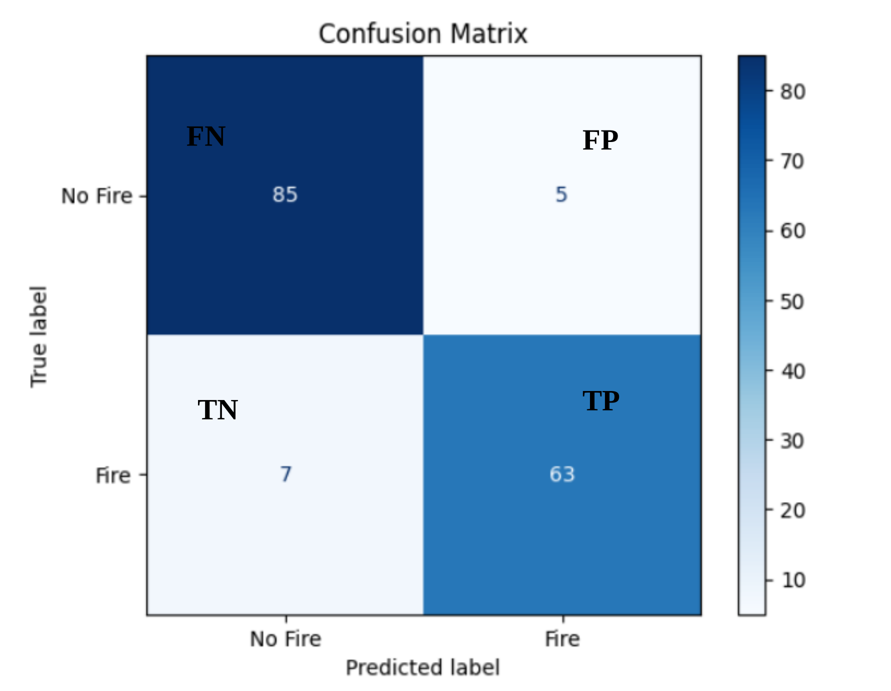
Training and Testing

```python
# Evaluate
y_pred = model.predict(X_test)
y_proba = model.predict_proba(X_test)[:, 1]

print(f"✅ Accuracy: {accuracy_score(y_test, y_pred):.2f}")
print(f"✅ ROC AUC Score: {roc_auc_score(y_test, y_proba):.2f}")

# ROC Curve
fpr, tpr, _ = roc_curve(y_test, y_proba)
plt.figure(figsize=(6, 4))
plt.plot(fpr, tpr, label=f"AUC = {roc_auc_score(y_test, y_proba):.2f}", color='blue')
plt.plot([0, 1], [0, 1], linestyle='--', color='gray')
plt.xlabel("False Positive Rate")
plt.ylabel("True Positive Rate")
plt.title("ROC Curve")
plt.legend()
plt.grid(True)
plt.tight_layout()
plt.show()
```

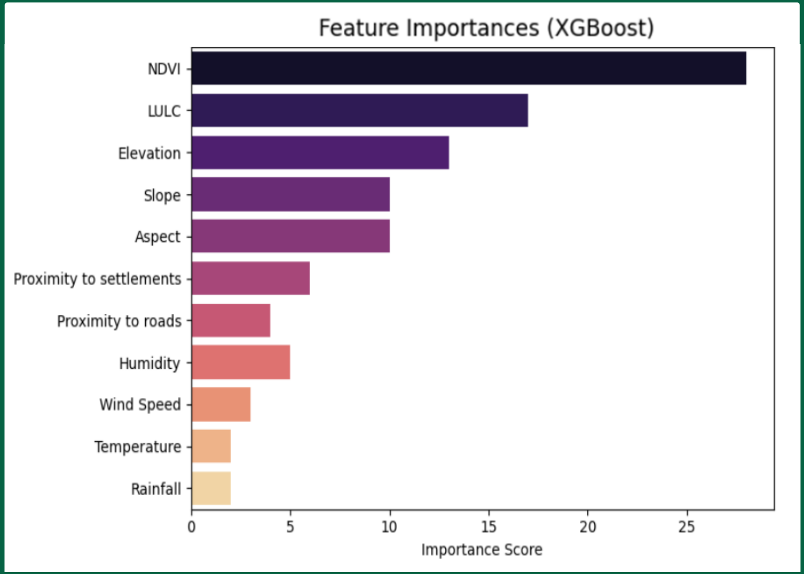
Accuracy Testing and ROC Curve generation

Model Validation



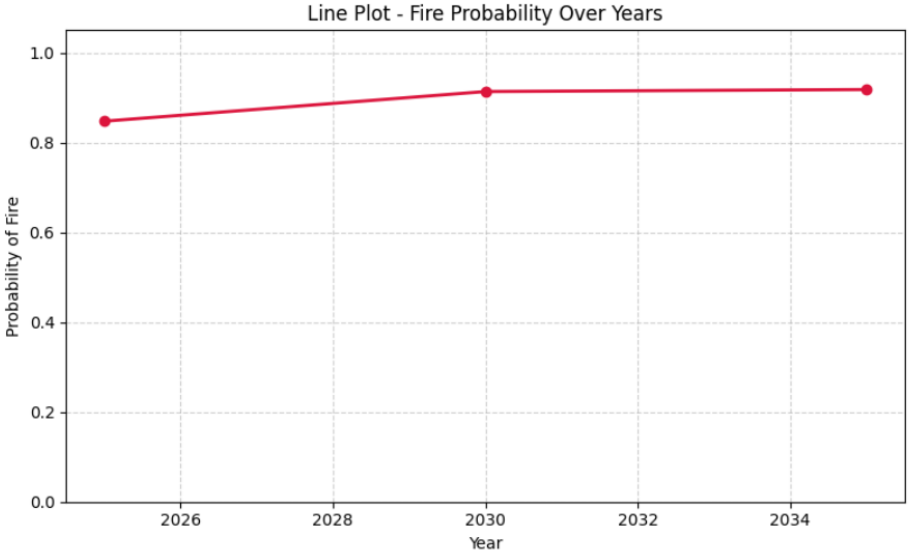



Future Prediction for the
Year 2025, 2030, 2035 using
XGboost Algorithm



Future Prediction

📈 🔮 Future Predictions:
2025 → Prediction: 🔥 Fire, Probability of Fire: 0.85
2030 → Prediction: 🔥 Fire, Probability of Fire: 0.91
2035 → Prediction: 🔥 Fire, Probability of Fire: 0.92



Conclusion

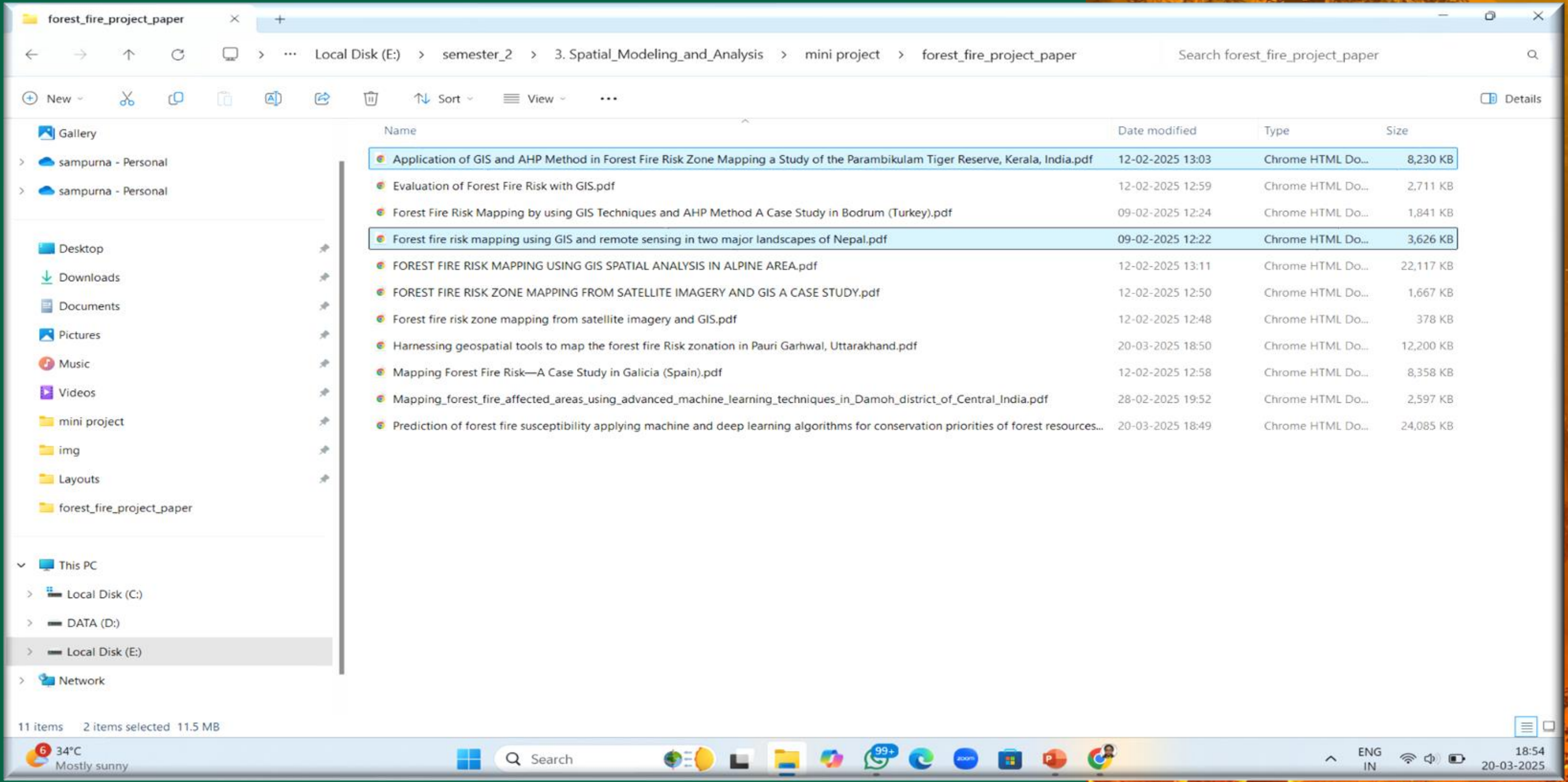
1. We used 11 determinants to generate our forest fire risk zones. After generating the AHP model, it was concluded that NDVI happens to be the major determining factor for the forest fire occurring in Nainital District.

2. Through our weighted overlay map, we generated the fire risk map of Nainital and it was conceived that northeastern part of the district is prone to forest fire coming within the range from moderate to very high-risk zone, whereas southern and eastern part of the district has more inclination towards moderate risk.

3. With the help of XGboost Algorithm we generated the ROC curve with an accuracy of 0.97, thus validating our model and also the confusion matrix further strengthen the validation.

4. Finally, through XGboost we conducted future prediction for the year 2025, 2030 and 2035. The line graph generated showed that the forest fire which was 0.85 in 2025 would reach to 0.92 by 2035.

Master Reference Papers




Thank You