

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



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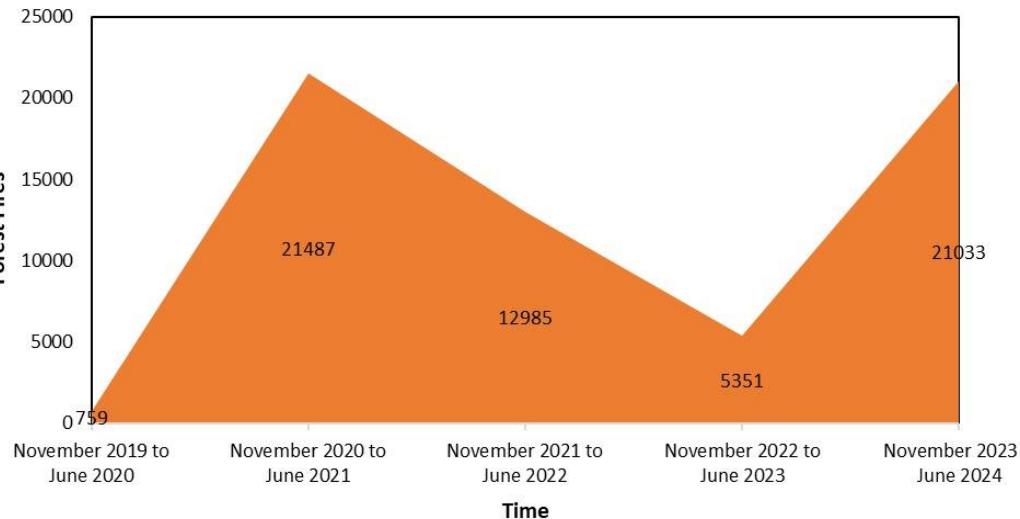
Forest Fire in Nainital

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:

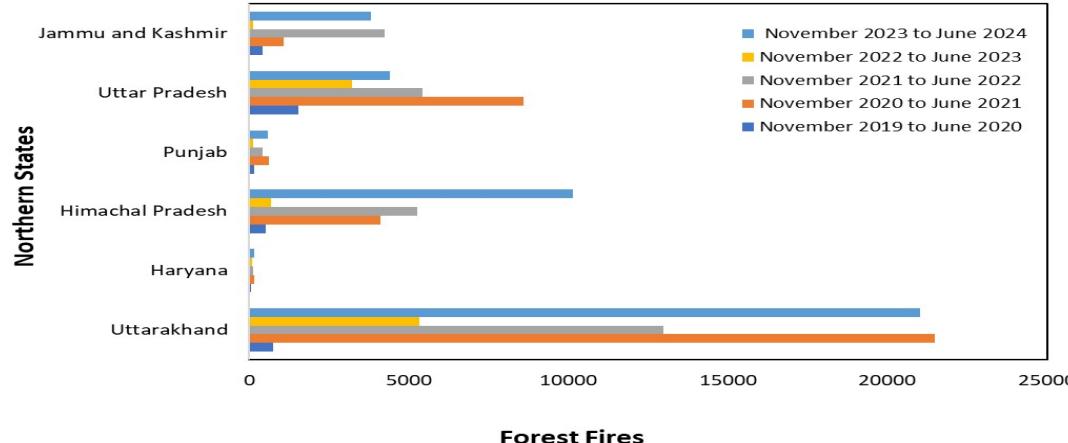
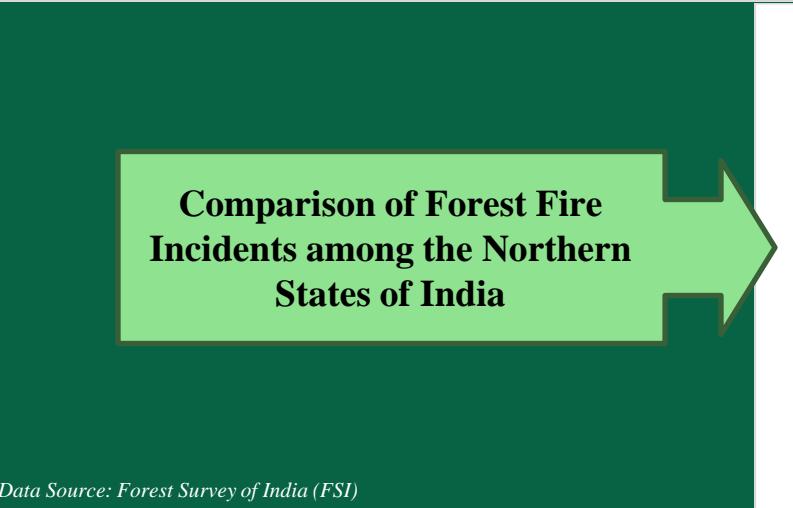
- Rising Temperatures**
- Prolonged Dry Spells**
- Human Activities such as Tourism and Deforestation**

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**





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.

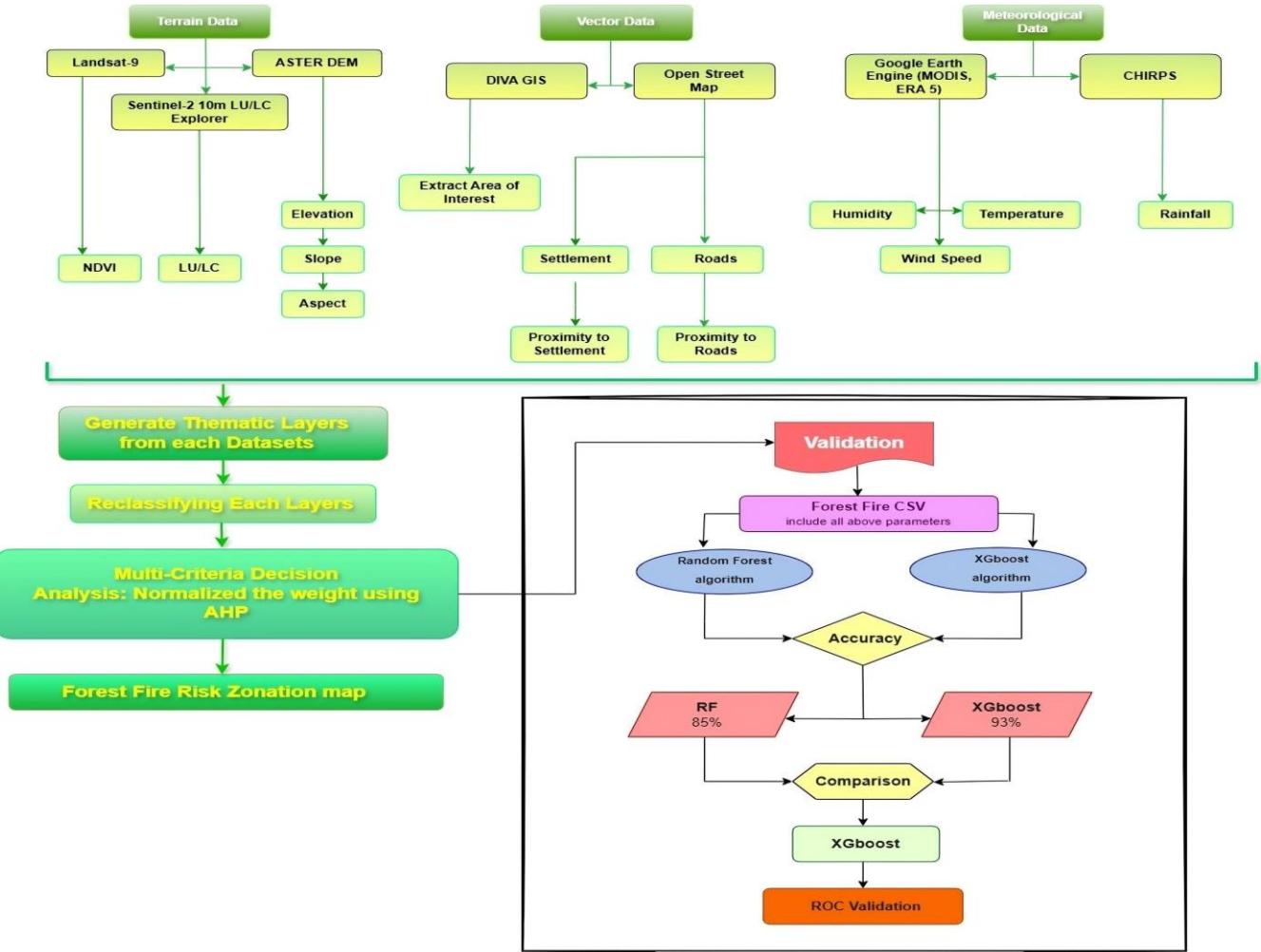
⌚ Future Wildfire Prediction

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

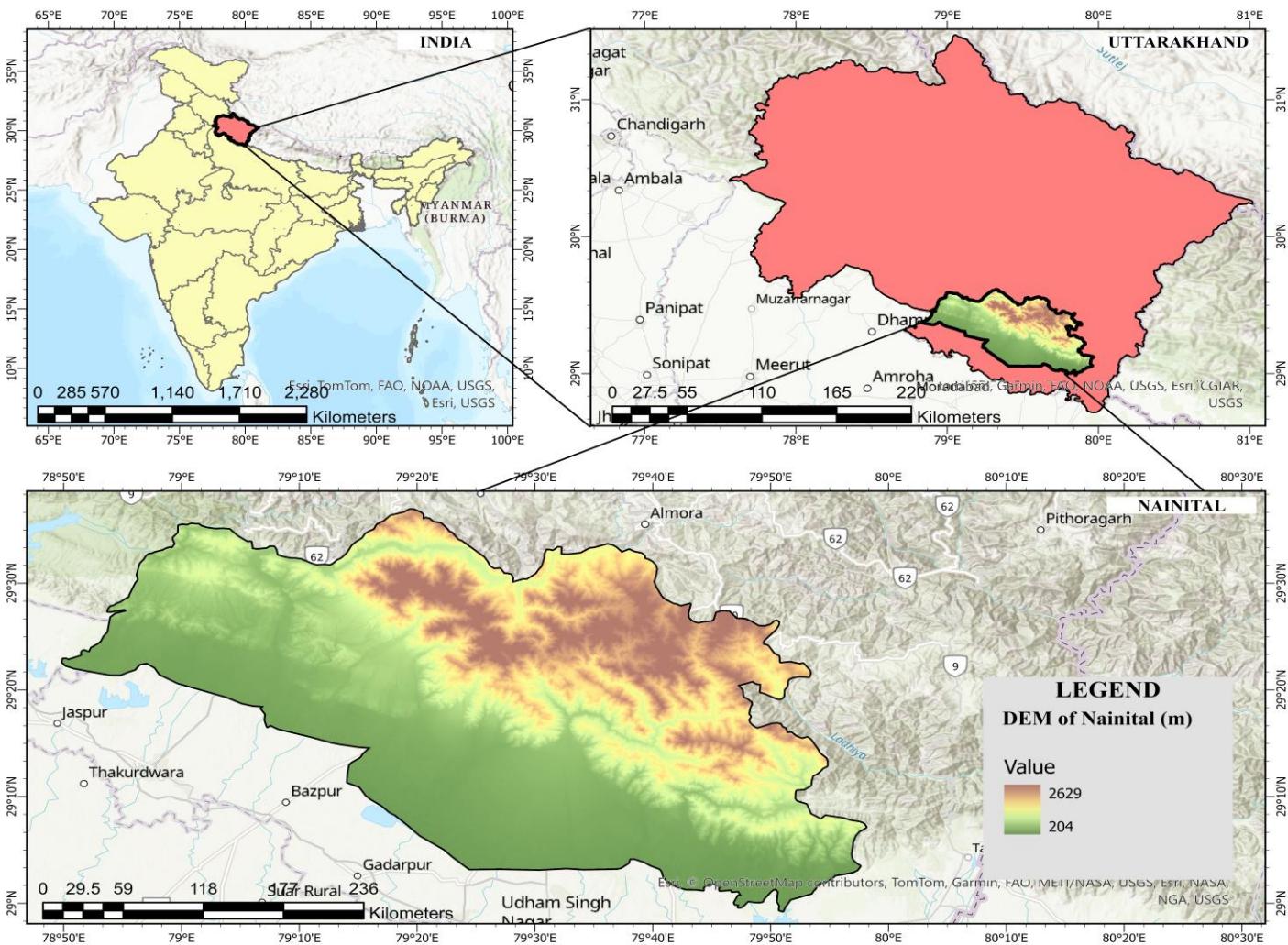
Datasets

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/	

Methology



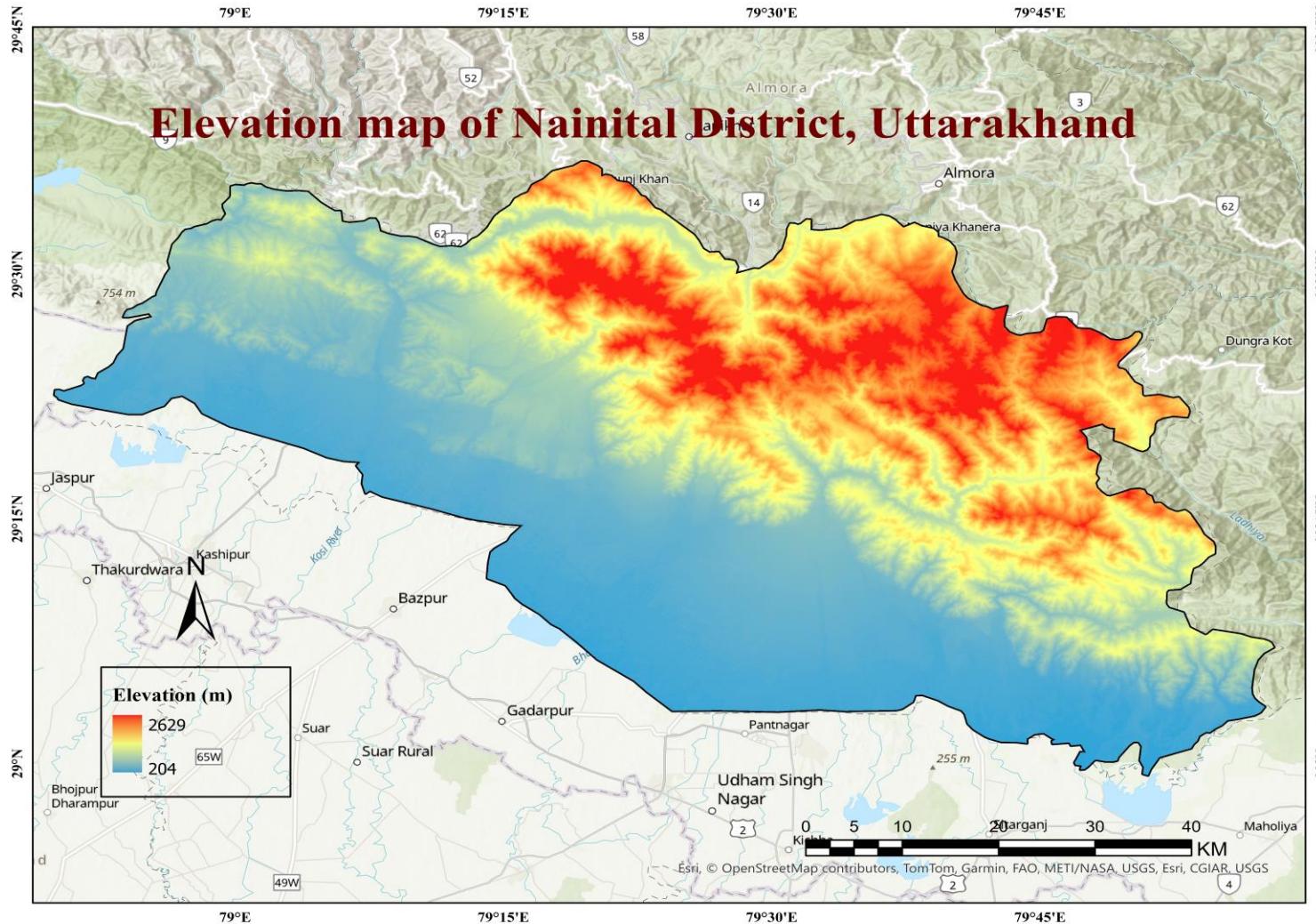
Study Area Map



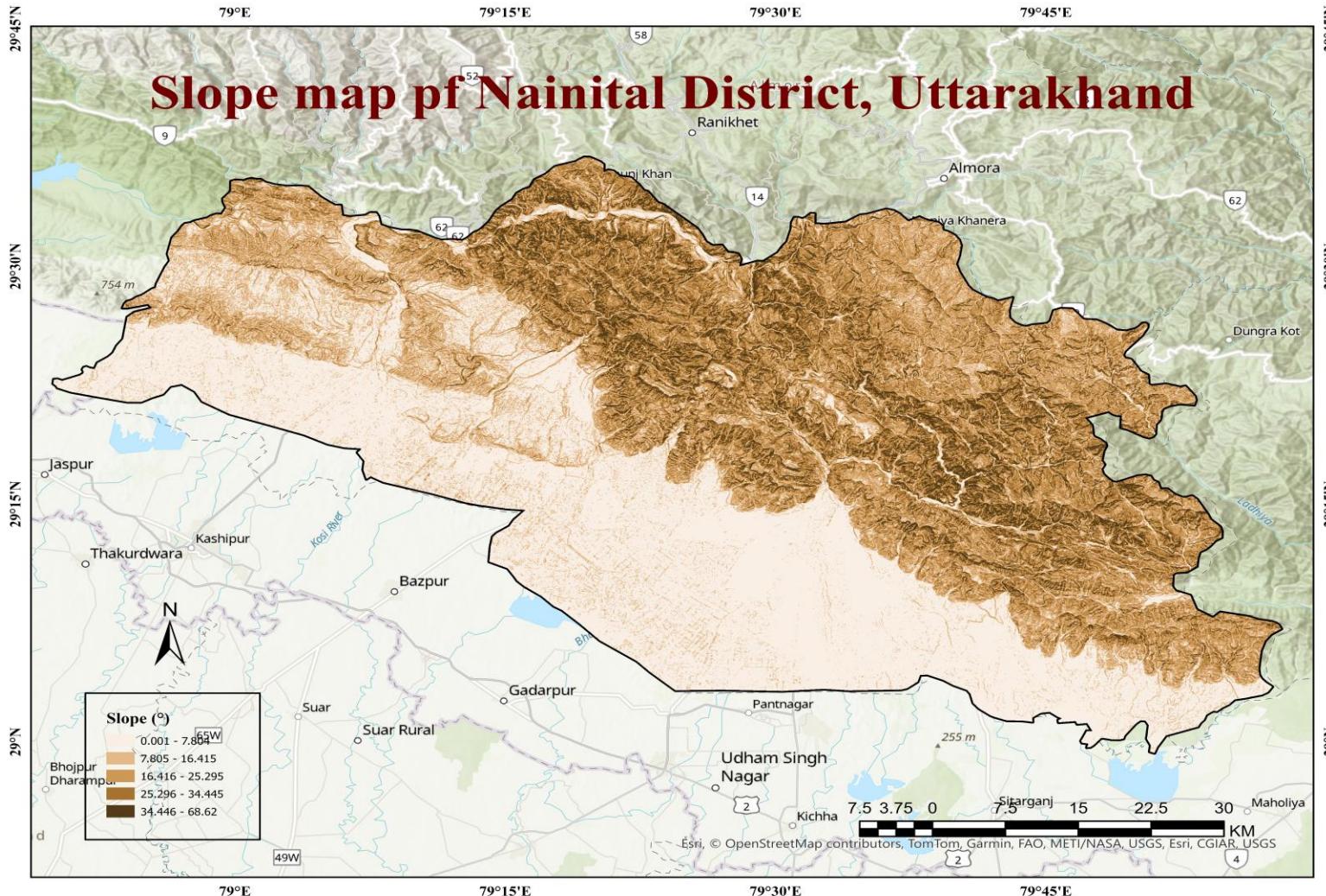
A photograph of a forest fire. In the foreground, there are green plants and moss-covered rocks. In the background, tall trees stand amidst thick smoke and bright orange flames. A yellow rectangular frame surrounds the title text.

Determinant Factors for Forest Fire Occurrences

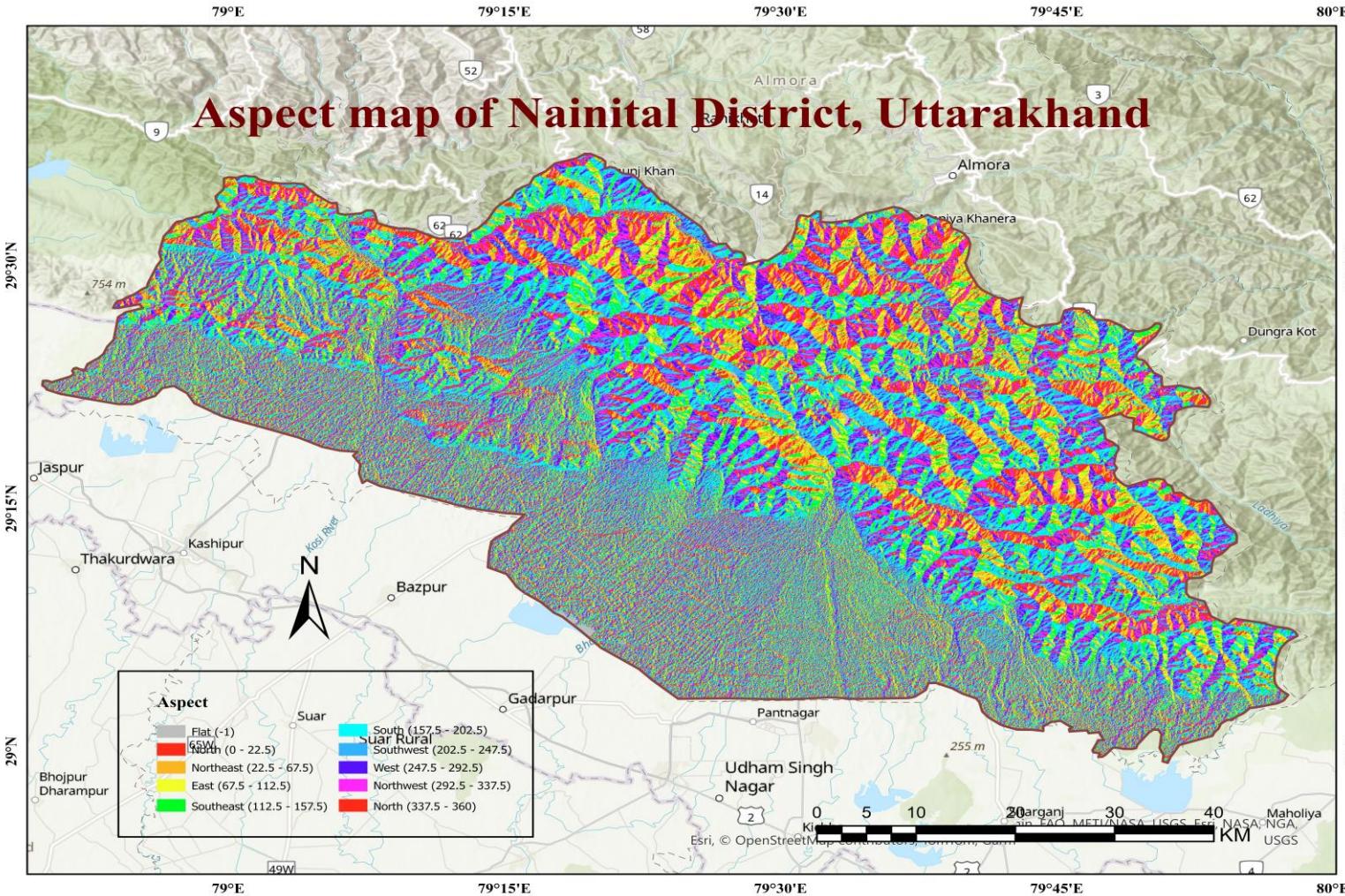
Elevation Map



Slope Map

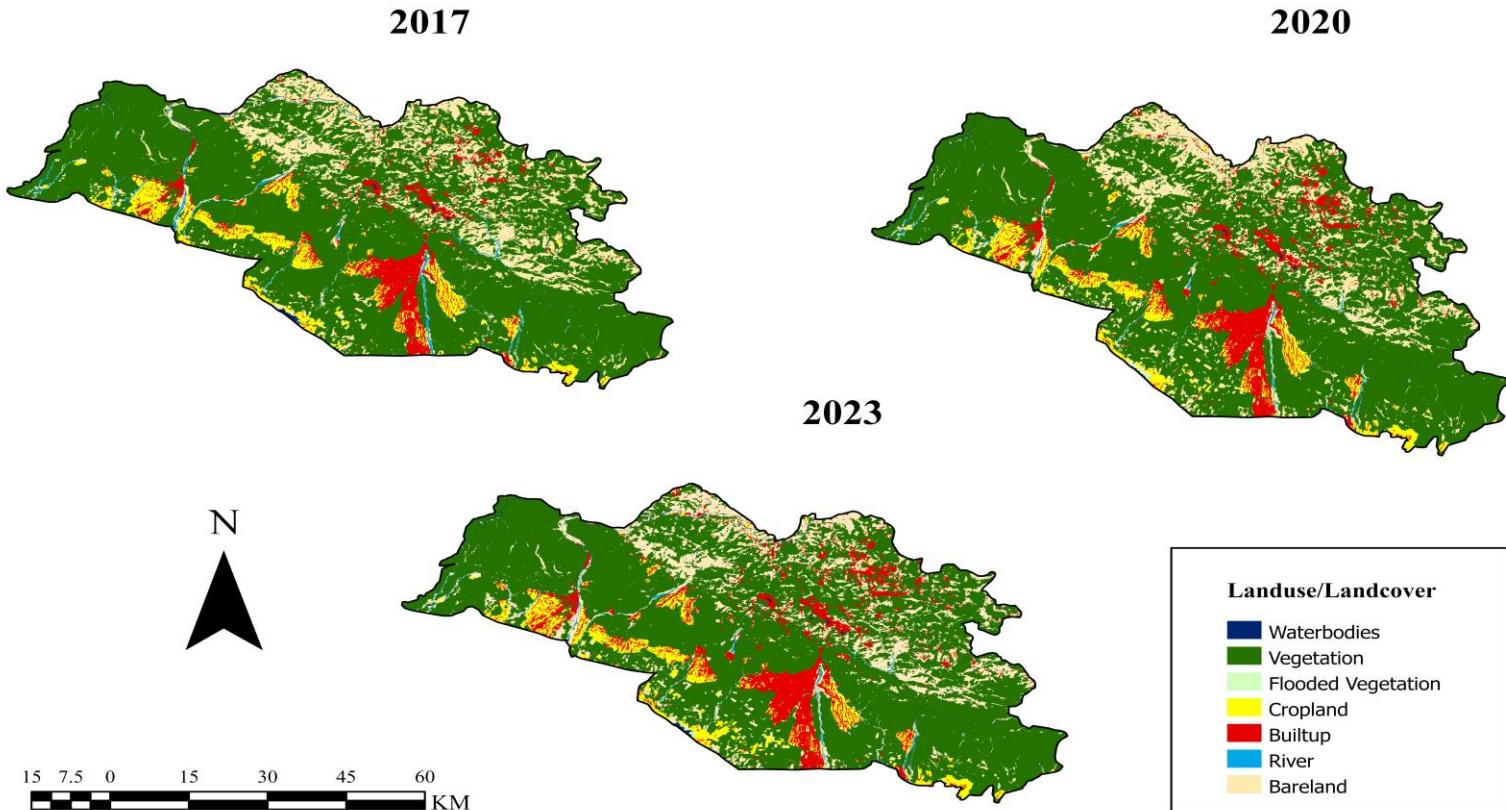


Aspect Map



Land Use/Land Cover Map

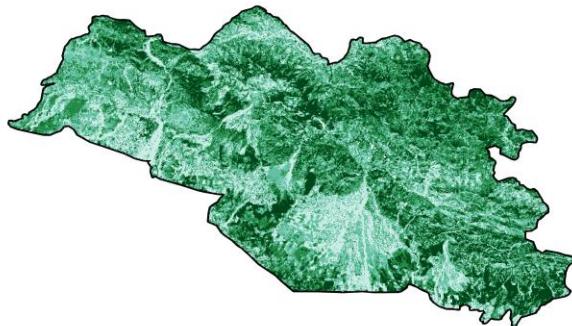
LULC highlighting spatiotemporal variations between 2017 to 2023



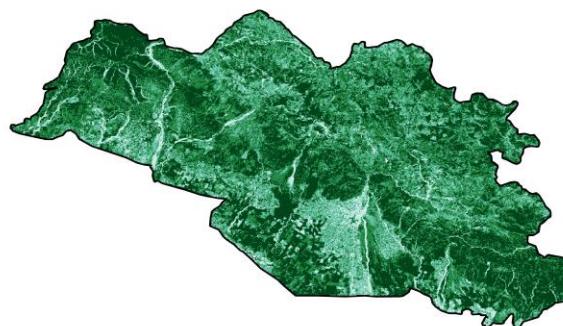
Normalized Difference Vegetation Index Map

NDVI highlighting spatiotemporal variations between 2017 to 2023

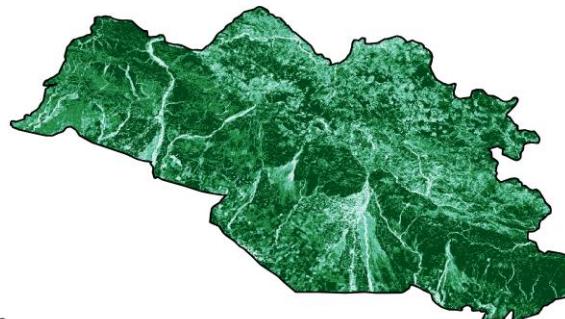
2017



2020



2023



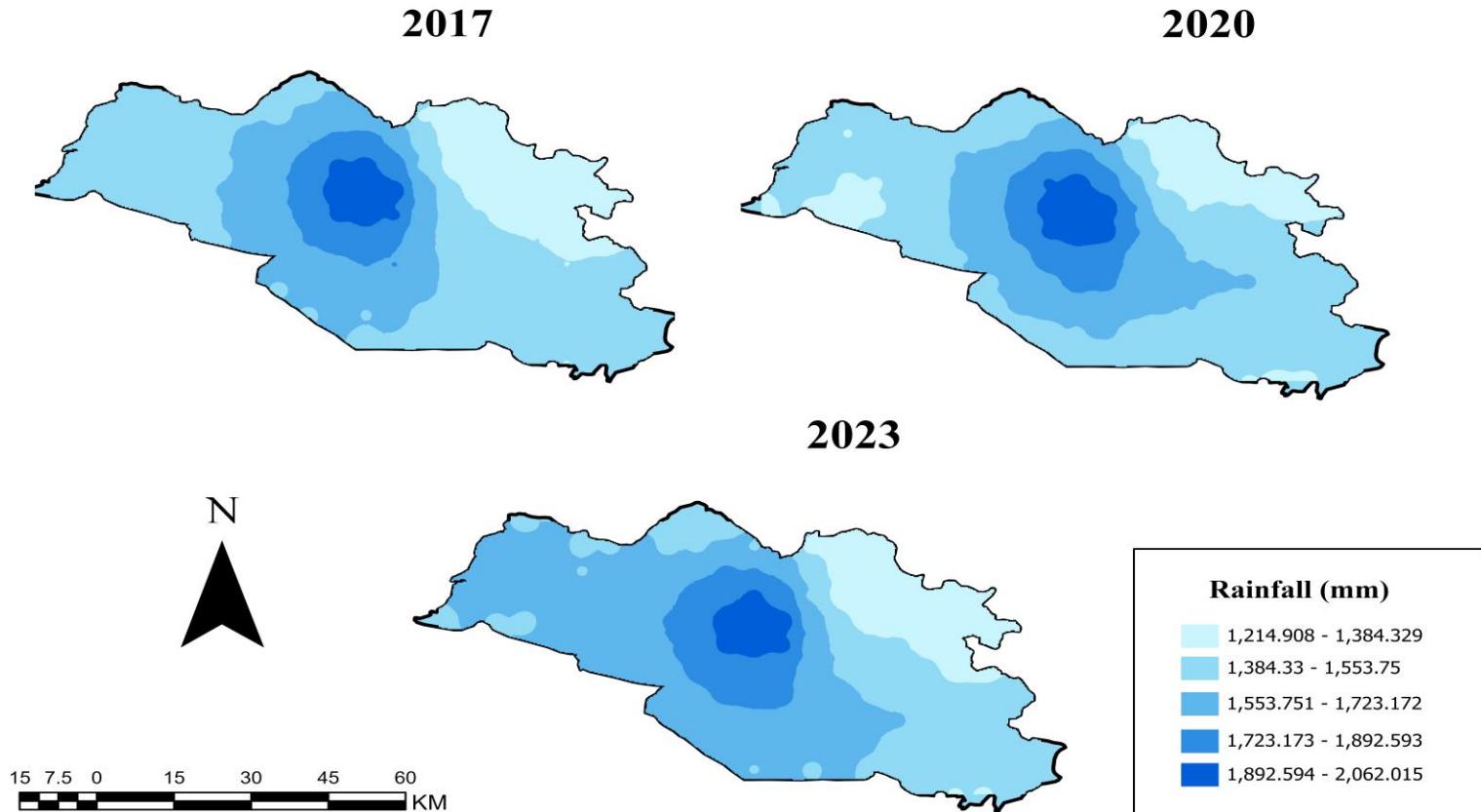
20 10 0 20 40 60 80 Kilometers

NDVI

-0.999 - -0.255
-0.254 - 0.294
0.295 - 0.522
0.523 - 0.702
0.703 - 1

Rainfall Map

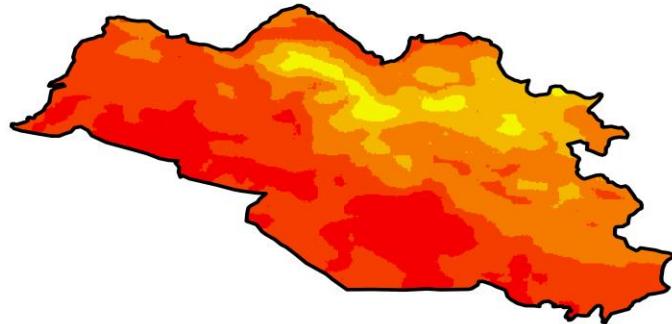
IDW showing Rainfall Variations between 2017 to 2023



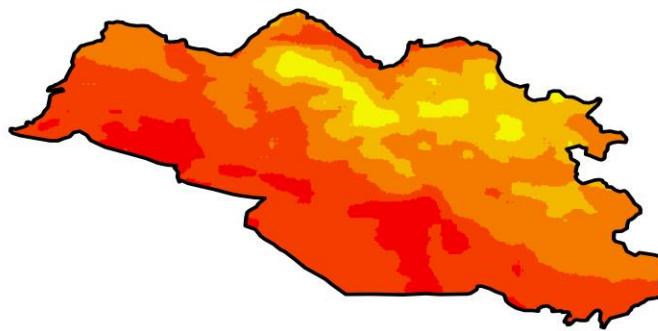
Temperature Map

IDW showing Temperature Variations between 2017 to 2023

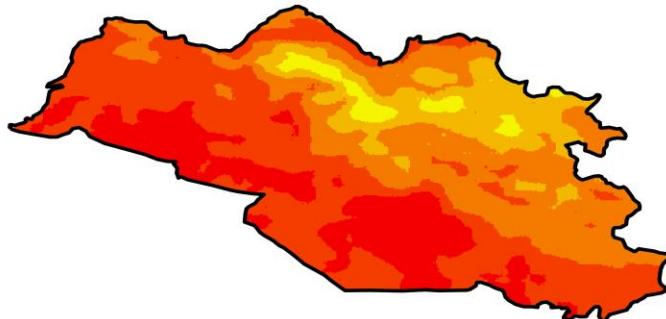
2017



2020



2023



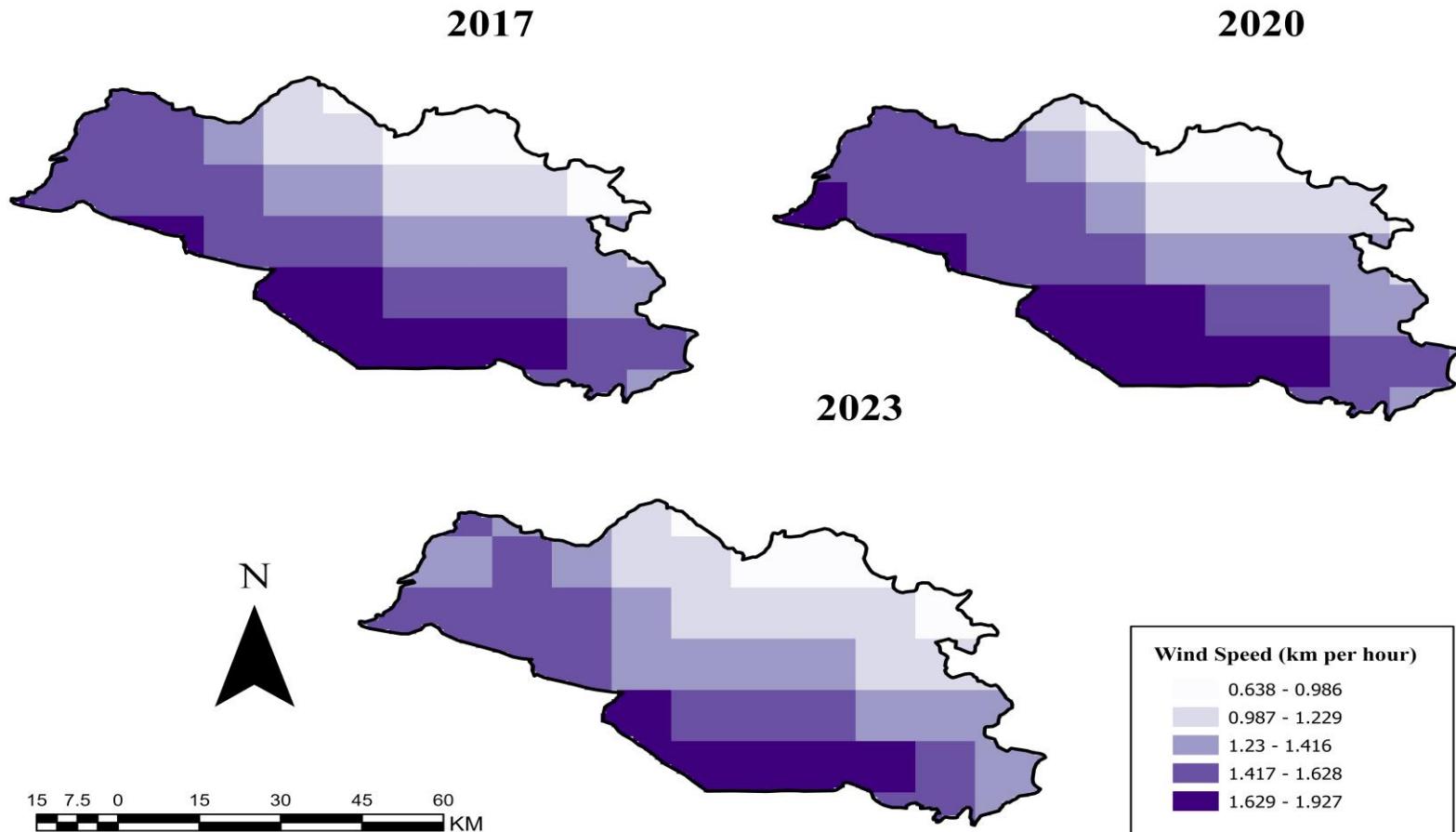
16 8 0 16 32 48 64 KM

Temperature (°C)

16.948 - 19.752
19.753 - 22.556
22.557 - 25.361
25.362 - 28.166
28.167 - 30.971

Wind Speed Map

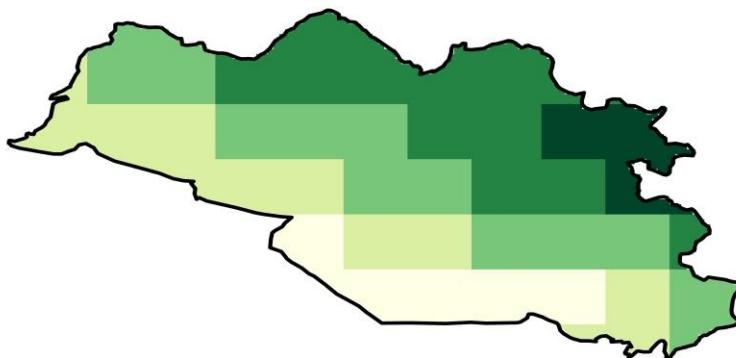
Wind Speed Variations between 2017 to 2023



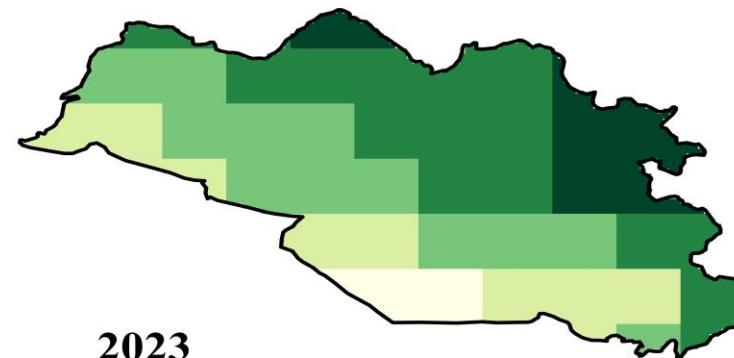
Relative Humidity Map

Relative Humidity Variations between 2017 to 2023

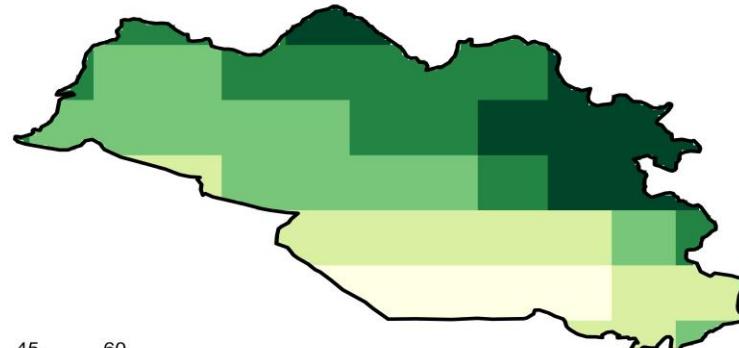
2017



2020



2023



N



15 7.5 0 15 30 45 60 KM

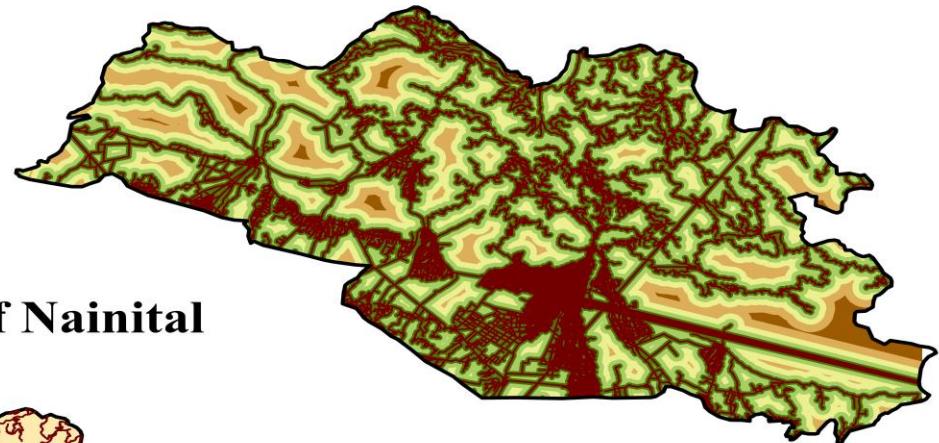
Relative Humidity (%)

65.997 - 68.514
68.515 - 70.935
70.936 - 72.872
72.873 - 75.148
75.149 - 78.344

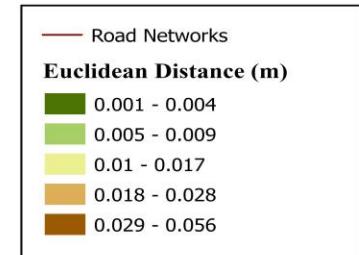
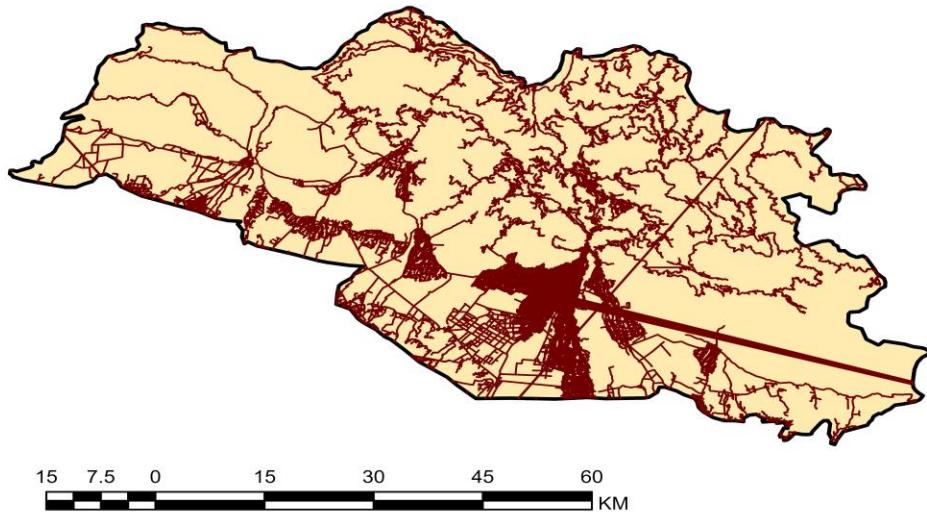
Proximity to Roads Map



Euclidean Distance for the Road Networks



Road Networks Map of Nainital

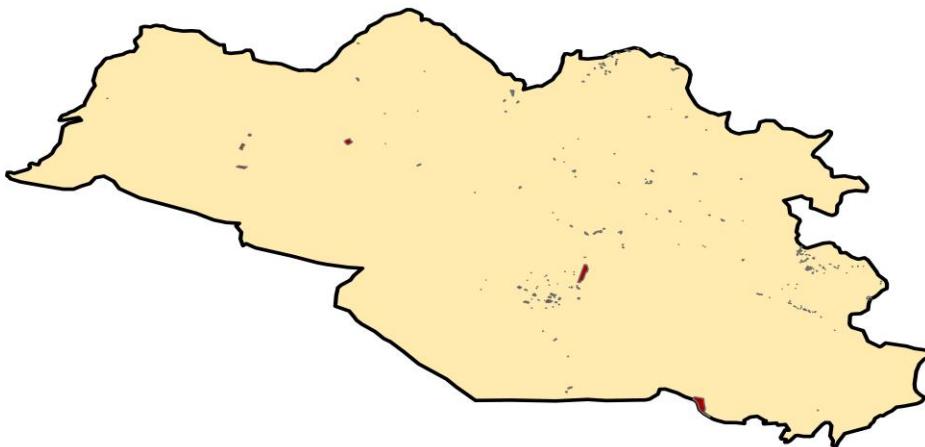
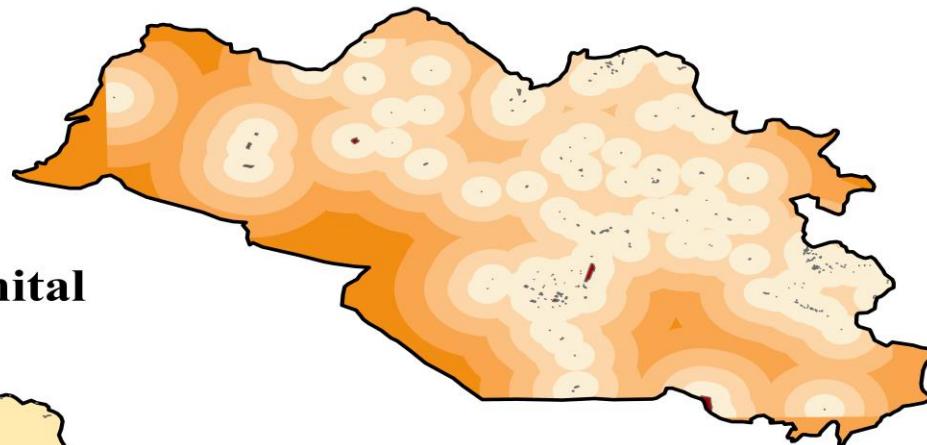


Proximity to Settlements Map

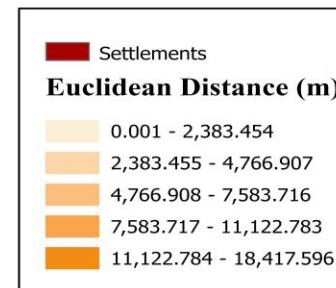
Euclidean Distance for the Settlements



Settlements Map of Nainital



15 7.5 0 15 30 45 60
A scale bar at the bottom left of the map, ranging from 0 to 60 Kilometers (KM) in increments of 7.5.



A photograph of a forest fire. In the foreground, there are green mossy rocks and some low-lying green plants. The background is filled with tall, thin trees, many of which are engulfed in bright orange and yellow flames. Thick smoke rises from the fires. A large, semi-transparent yellow rectangular box is overlaid on the center of the image, containing the title text.

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	1.00	100.0	12.50

Percentage Weight	lemda
28.01	lemda
17.03	MMULT(array1, array2)
12.58	
10.17	12.04
10.10	12.12

To Calculate Lemda (λ), for NDVI,
 $\lambda = \text{MMULT}(\text{1st row of Pair-wise comparison Matrix, Criteria Weights column}) / \text{criteria weight of NDVI}$

CI	Random Index	CR
0.150430228	1.51	0.09962267

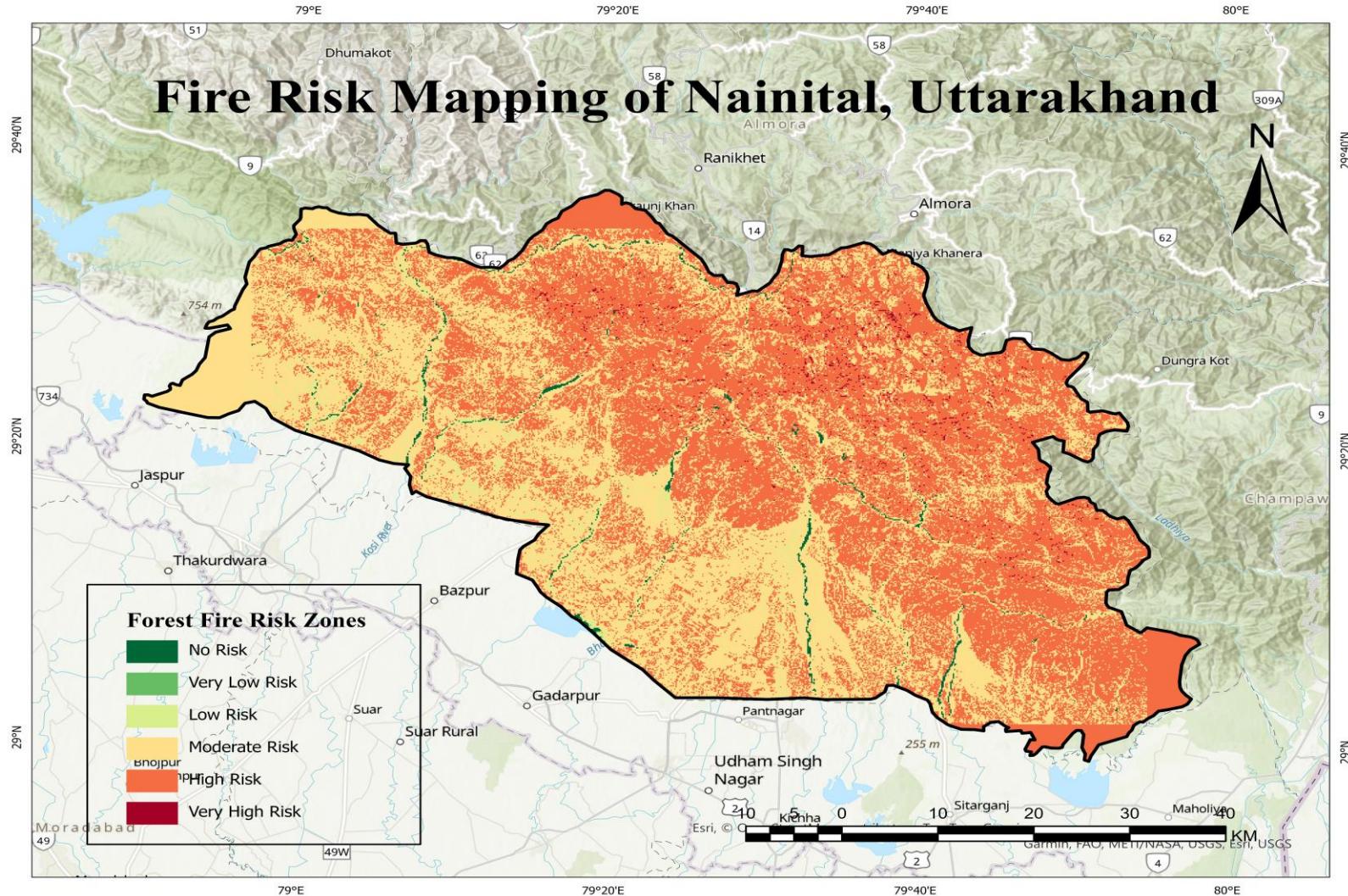
Consistency Index (CI) =
 $(\lambda_{\max} - n) / (n - 1)$

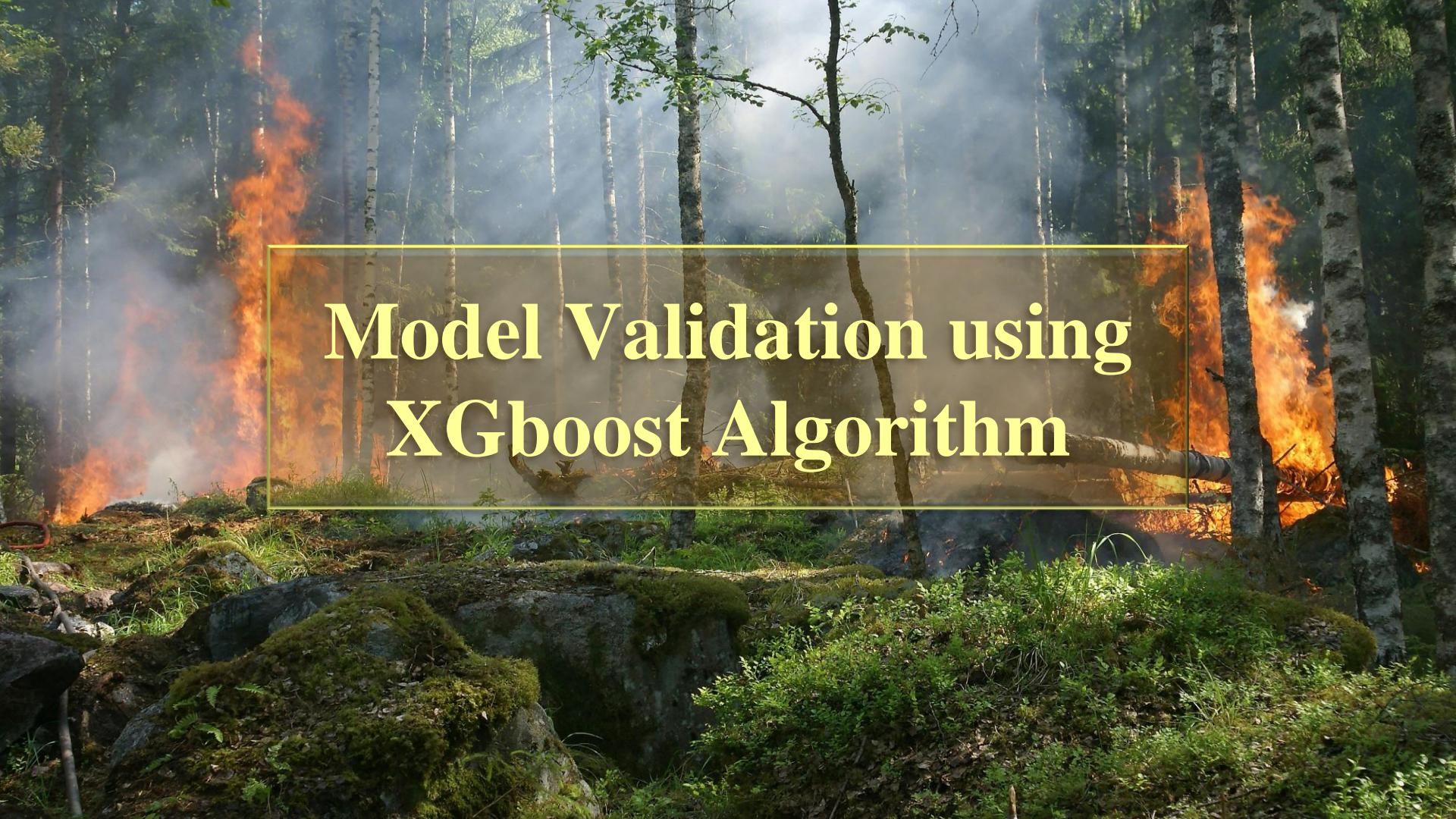
Consistency Ratio =
Consistency Index / Random Index

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

```
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'])

# 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()
```

Scaling the Dataset

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

Training and Testing

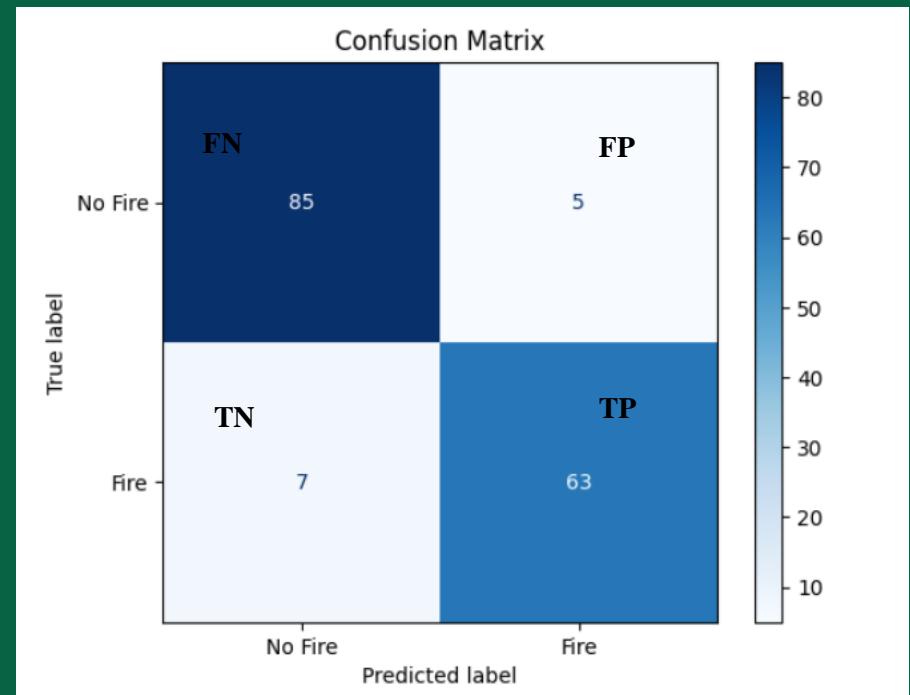
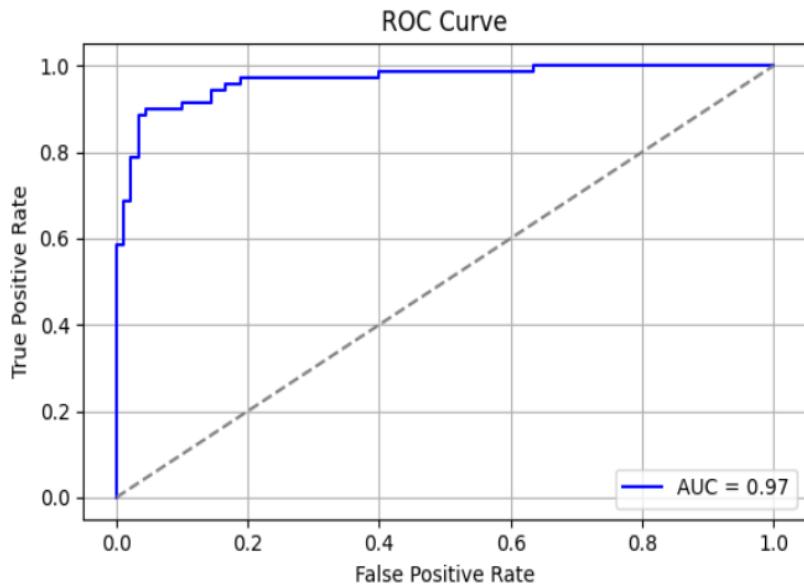
```
# Train-test split
X_train, X_test, y_train, y_test = train_test_split(
    X_scaled, y, test_size=0.2, random_state=42
)

# 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)
```

Accuracy Testing and ROC Curve generation

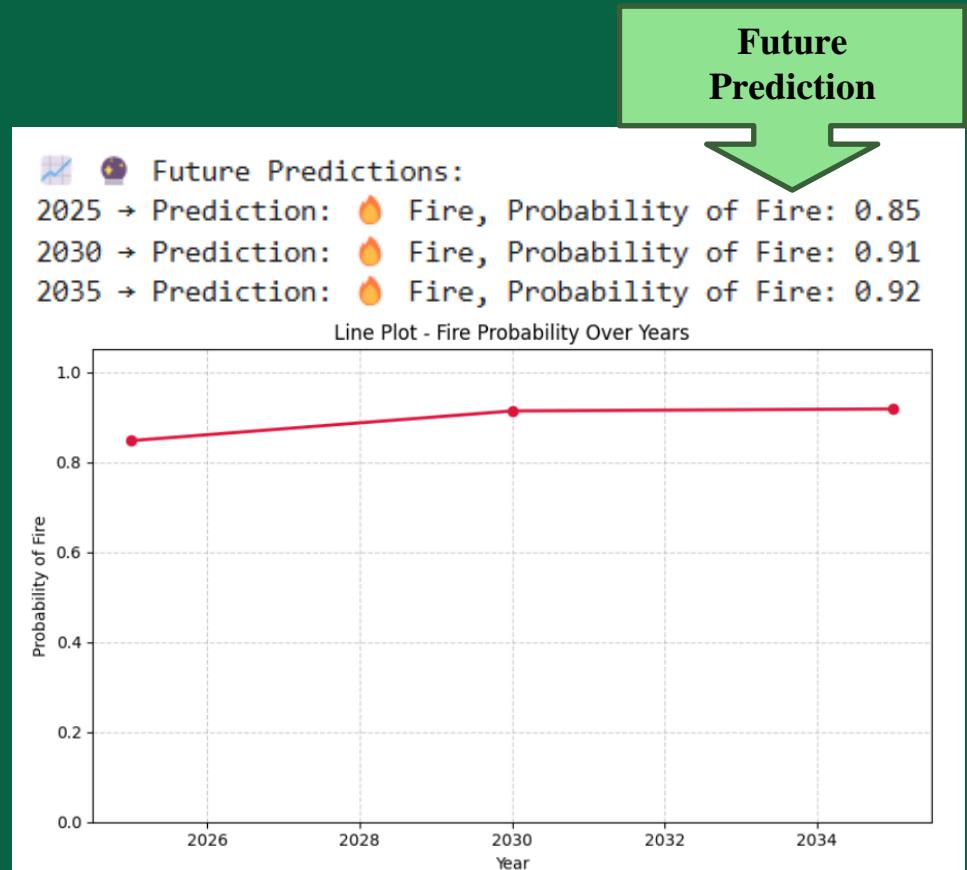
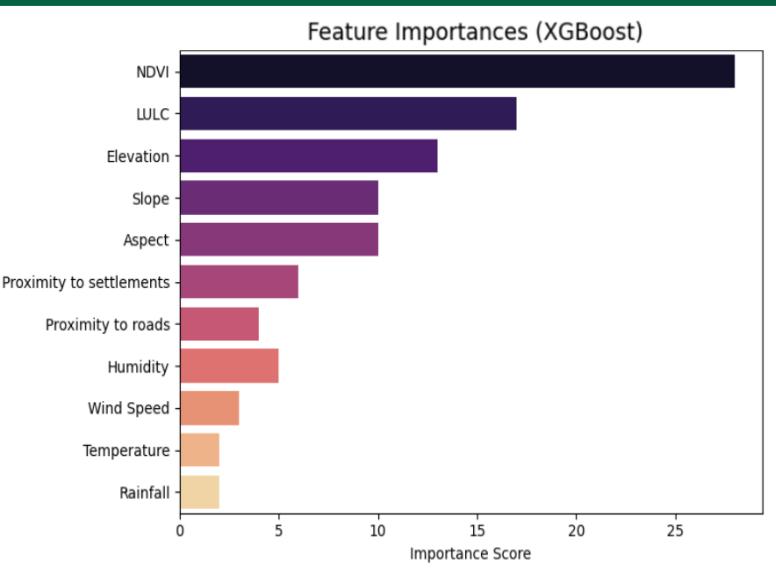
Model Validation

✓ Accuracy: 0.93
✓ ROC AUC Score: 0.97





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

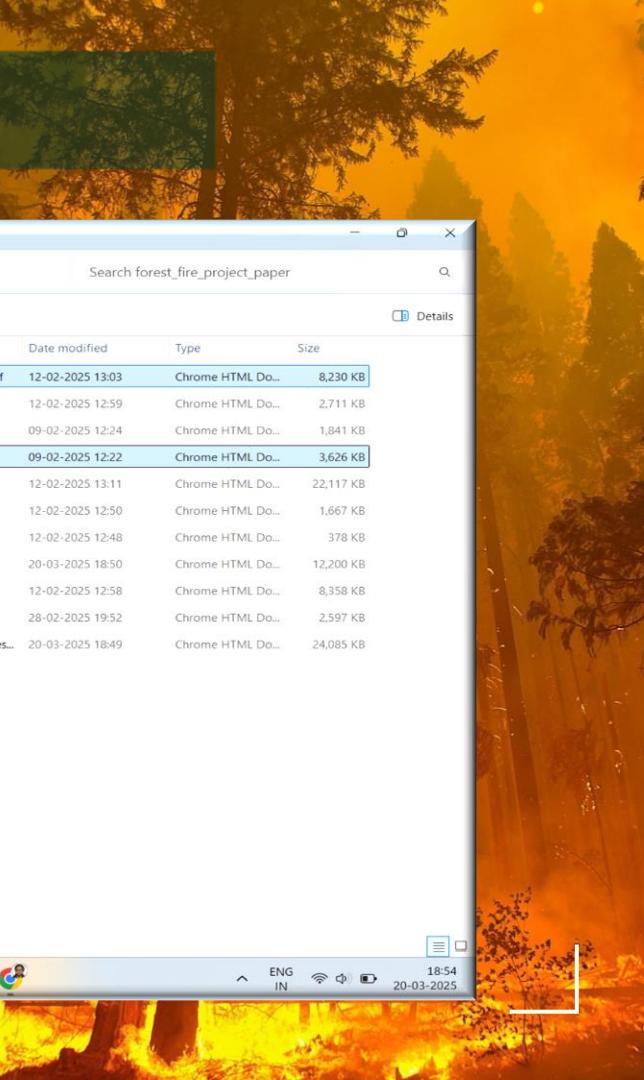


Conclusion

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



A screenshot of a Windows file explorer window titled "forest_fire_project_paper". The window shows a list of PDF files related to forest fire risk mapping. The left sidebar shows the folder structure under "This PC". The taskbar at the bottom displays the date and time as 18:54, 20-03-2025, along with weather information (34°C, mostly sunny) and various system icons.

Name	Date modified	Type	Size
Application of GIS and AHP Method in Forest Fire Risk Zone Mapping a Study of the Parambikulam Tiger Reserve, Kerala, India.pdf	12-02-2025 13:03	Chrome HTML Do...	8,230 KB
Evaluation of Forest Fire Risk with GIS.pdf	12-02-2025 12:59	Chrome HTML Do...	2,711 KB
Forest Fire Risk Mapping by using GIS Techniques and AHP Method A Case Study in Bodrum (Turkey).pdf	09-02-2025 12:24	Chrome HTML Do...	1,841 KB
Forest fire risk mapping using GIS and remote sensing in two major landscapes of Nepal.pdf	09-02-2025 12:22	Chrome HTML Do...	3,626 KB
FOREST FIRE RISK MAPPING USING GIS SPATIAL ANALYSIS IN ALPINE AREA.pdf	12-02-2025 13:11	Chrome HTML Do...	22,117 KB
FOREST FIRE RISK ZONE MAPPING FROM SATELLITE IMAGERY AND GIS A CASE STUDY.pdf	12-02-2025 12:50	Chrome HTML Do...	1,667 KB
Forest fire risk zone mapping from satellite imagery and GIS.pdf	12-02-2025 12:48	Chrome HTML Do...	378 KB
Harnessing geospatial tools to map the forest fire Risk zonation in Pauri Garhwal, Uttarakhand.pdf	20-03-2025 18:50	Chrome HTML Do...	12,200 KB
Mapping Forest Fire Risk—A Case Study in Galicia (Spain).pdf	12-02-2025 12:58	Chrome HTML Do...	8,358 KB
Mapping_forest_fire_affected_areas_using_advanced_machine_learning_techniques_in_Damoh_district_of_Central_India.pdf	28-02-2025 19:52	Chrome HTML Do...	2,597 KB
Prediction of forest fire susceptibility applying machine and deep learning algorithms for conservation priorities of forest resources...	20-03-2025 18:49	Chrome HTML Do...	24,085 KB



A photograph of a lush green forest with tall evergreen trees. Sunlight filters through the dense canopy, creating bright highlights and deep shadows. A large, solid dark green rectangular overlay covers the middle portion of the image, containing the text "Thank You".

Thank You