Forest Fire Susceptibility Mapping of the Western Ghats, India Using Remote Sensing, GIS, and Machine Learning.

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ABSTRACT:

Forest fires pose a serious threat to ecological stability, biodiversity, and human livelihoods, particularly in biodiversity hotspots such as the Western Ghats of India. This study presents an integrated forest fire susceptibility (FFS) assessment using Remote Sensing (RS), Geographic Information Systems (GIS), and Machine Learning (ML) techniques. A Random Forest (RF) model was developed using 20 fire ignition conditioning factors grouped into topographic, climatic–hydrologic, vegetation, and anthropogenic categories. Forest fire inventory data (2012–2022) were obtained from the FIRMS database and used to train (70%) and validate (30%) the model. Feature selection was performed using Pearson correlation and multicollinearity (VIF) analysis. The resulting susceptibility map classifies the Western Ghats into very low, low, moderate, and high fire-prone zones. Results indicate that approximately 33,709.82 km² of the region is susceptible to forest fires, with high susceptibility concentrated in northern parts (Maharashtra) and parts of Karnataka, while coastal and southern regions show low susceptibility. Climatic variables (AET, rainfall, soil moisture), vegetation indices (NDVI, NDMI), and anthropogenic proximity factors were identified as dominant contributors. The study demonstrates the effectiveness of RF-based susceptibility modelling and provides valuable insights for forest management, fire mitigation planning, and climate adaptation strategies.

Key Words:

Forest fire susceptibility, Random Forest, Remote Sensing, GIS, Machine Learning.

1. INTRODUCTION:

One of the primary natural resources that serve as a safeguard for the sustainability of human civilisation and the ecological balance of the planet is the forest. According to a report by the Food and Agriculture Organisation (FAO), forests cover 4.06 billion hectares, or 30.06 percent of the earth's surface. Every year between January and September 2024, wildfires destroyed about 12 million hectares of the Amazon, or 2.8% of the biome. In 2024, 62,131 wildfires detected by the Global Wildfire Information System (GWIS) burnt an estimated 46101798 hectares (113920020 acres) of tropical wetland worldwide. Forest fires are a common occurrence worldwide, causing ecological harm on a global scale as well as socioeconomic difficulties on a local to regional level. They also have a significant role in altering the composition and structure of forests as well as environmental dangers that have an adverse effect on infrastructure, the environment and human health. Maps are of importance to forest managers, climate modellers, policymakers, and the scientific community in order to understand the lethal impacts of fire and future scenarios of fire-prone areas. the susceptibility of forests to forest fires using an evidence-based methodology. In the modern era, search information is crucial because it controls adverse effects on groups that may be impacted and supports conservation and restoration efforts. This helps the corresponding agencies plan and manage forests, emergency services, early warning systems, and resource distribution. Improving fire mitigation strategies and more accurately predicting the likelihood of forest fires are top priorities for promoting sustainable development. However, based solely on high confidence alerts, 13072 VIIRS fire alerts have been reported in India thus far in 2024. Compared to prior years dating back to 2012, this amount is low. In 2021, there were 23388 fires, the most ever recorded in a single year.

The creation of numerous prediction models that have focused on elucidating spatiotemporal patterns associated with various factors [topography, climate, vegetation indices, and disturbances] related to arson wildfires has necessitated this. Geographic information systems (GIS) and remote sensing offer ways to work with spatial data about the factors that influence the occurrence of forest fires for generations on the forest fire susceptibility map. Using a geospatial database, Alca Sena et al. investigated how to optimize prescribed fire allocations for creating ecosystems that are resistant to fire. Search researchers like Proughasemi and others use geospatial techniques and machine learning to assess forest fire hazard, susceptibility, and risk mapping.

In this region forest fire susceptibility map represent northern (Maharashtra) part mostly susceptible, Karnataka and karela north part moderate susceptibility and south part of map and costal part non susceptibility area. Western Ghat in India susceptibility map (91349.24 sq km) area is non-Susceptibility and (33709.82 sq km) area is susceptible.

2. MATERIALS AND METHODS

2.1 Study Area:

The Western Ghats known as the Sahyadri, is a mountain range that stretches 1600 km along the western coast of the Indian peninsula. Covering a surface area of 160000 km2 (795315 ha), located between the 8°10′N To 20°45′N, 73°00′E To 77°30′E Western Ghats is distributed in six states- Tamil Nadu, Kerala, Karnataka, Maharashtra, Goa, and Gujarat. From the Tapti River to Swamithoppe in Kanyakumari district at the southernmost tip of the Indian peninsula, the Deccan plateau's western side is home to an essentially continuous mountain range. Before going south, the western and eastern ghats converge at the Nilgiris. The climatic conditions change annual temperatures are most likely to be between 26.8 °C and 27.5 °C in the 2030s. The average annual rainfall and the temperature increase in the 1970s will be between 1.7 and 1.8 degrees Celsius. will be about 20 cm to 250 cm. It has a rich Tropical evergreen forest found in the western part of the Western Ghats, there are three types of forest in this region. Western Ghats are mostly covered by forest in Karnataka Forest cover (37.4%), Maharashtra (25.9), Kerala (17%) and Tamil Nadu (13.6%). This region's elevation is 2695 meters (8842 feet).

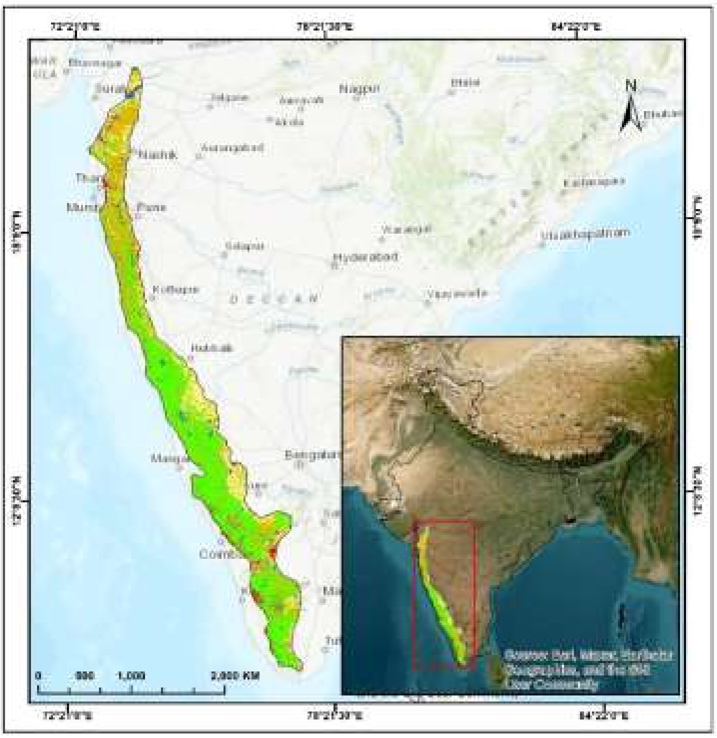


Fig – 1: Location Map of Western Ghat

It has been determined that around 60% of the study area's total forest cover is extremely vulnerable to forest fires. In 90 years, 35% of the forest in the Western Ghat was lost. According to a recent study by the Indian Space Research Organization's (ISRO) National Remote sensing Centre in Hyderabad, the Western Ghats, which are regarded as one of the hotspots for biodiversity worldwide, have lost 33579 square kilometres of forest cover, or 35.3%, of the entire forest over the past 90 years, making it a vulnerable ecosystem.

Western Ghat famous Forest List:

Serial No	Forest Name	Stats	Cover Area (sq. km)	Forest type
1.	Silent Valley National Park	Kerala	89.52	Undisturbed tropical rainforest and biodiversity.
2	Kudremukh National Park	Karnataka	600	shola forests and grasslands
3	Anamalai Tiger Reserve	Tamil Nadu & Kerala	958	tiger and elephant conservation.
4.	Periyar Tiger Reserve	Kerala	925	deciduous and evergreen forests.
5.	Agasthyamalai Biosphere Reserve	Tamil Nadu & Kerala	3500	its high endemism in flora and fauna.
6	Bhimgad Wildlife Sanctuary	Karnataka	190	subtropical evergreen forests
7.	Nilgiri Biosphere Reserve	Tamil Nadu & Kerala & Karnataka	5520	Mudumalai, Wayanad, and Bandipur forests.
8	Koyna Wildlife Sanctuary	Maharashtra	423	Tiger Reserve, featuring evergreen and semi-evergreen forests.

Table – 1: list of western Ghat Impotence Forest in India.

2.2 Data Used:

This Table displays the multi-source data set that was impo sed by the particular driving forces in this investigation. USGS Earth Explorer (SRMT Sensor) provided a digital elevation model (DEM) (https://earthexplorer.usgs.gov/(accessed in December 2023) was used to derive the topical factor. Topographic data include elevation, slope, curvature, aspects, drainages, Topographic Wetness Index (TWI), Land use And Land cover (LULC) and Forest Type. And Hydrologic data such as temperature, wind speed, soil moisture, relative humidity, rainfall, solar radiation and Actual Evapotranspiration (AET)gate in Terra climate (https://www.climatologylab.org/terraclimate.html) (accessed in 2001 – 2023). The Normalised Difference Water Index (NDWI), Normalised Difference Vegetation Index (NDVI), and Normalised Difference Moisture Index (NDMI) spatial distribution data collected from the (https://modis.gsfc.nasa.gov/data/dataprod/mod13.php) (accessed in 2001 – 2023). The Anthropogenic interface data such as Distance to settlement, Distance to Road, and Distance to Strems, this data obtained from the Open Street Map (https://www.openstreetmap.org/#map=5/21.84/82.79). Other forest health data such as Forest Conservation Fund (FCF) data downloaded from Hansen Global Forest Change (https://developers.google.com/earth-engine/datasets/catalog) (accessed in 2001 vs 2023).

Using interpolation techniques, the spatial distribution of the factor related to the anthropogenic interface was mapped at a resolution of 30 meters. Road distance data in the India Governorate made it possible to track how the road network affected the likelihood of forest fires. At a resolution of 30 meters, the distances to the road network, settlement, and strims were mapped using Euclidean distance tools. These data were entered and processed in the GIS environment (ArcMap 10.8.2) at a resolution of 30 meters using a variety of analytic tools, including resampling, Euclidean distance, interpolation, tabulation, conversion, Map algebra, and reclassification tools. Using information from multiple sources, particularly remote sensing, a thematic layer depicting the causes of forest fires was created in a GIS environment. maps of elevation, slope, profile curvature, aspects, and drainage network were created using the projected DEM, which had a resolution of 30 meters. Equation was used to map the Topographic Wetness Index (TWI) spatial distribution.

TWI = Ln (Flow Accumulation / Tan Slope).

Vegetation indices other three thematic layers are creating purpose take Landsat 8 Satellite Image.

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

$$\boldsymbol{NDMI = (SWIR - Red)/(SWIR + Red)}$$

$$\boldsymbol{NDWI = (NIR - SWIR)/(NIR + SWIR)}$$

where SWIR stands for the short-wave infrared band and NIR for the near-infrared band. Normalization indicators that range from -1 to +1 are the NDVI, NDMI, and NDWI.

The LANCE (Land, Atmosphere Near real-time Capability for EOS) fire detection system (https://firms.modaps.eosdis.nasa.gov) and GEE-based FIRMS were used to collect data for the forest fire inventory producing map from 2012 to 2022 in this study region. There were over 28,000 forest fires in India's western Ghat region. Inventory values of 0 and 1 denote no fire and fire, respectively, in accordance with the forest fire susceptibility model. The sample number was divided for validation and tasting at a 70% to 30% ratio.(https://firms.modaps.eosdis.nasa.gov).

Sl.no	Sub Classification	Factors	Data Sources
1	Topographical	Elevation	https://earthexplorer.usgs.gov/
2		Slope	
3		Aspect	
4		TWI	
5		LULC	
6		Profile Curvature	
7		Forest Type	
8	Climate Hydrologic	Temperatures	https://www.climatologylab.org/terraclimate.html
9		Wind Speed	
10		Soil moisture	
11		Rainfall	
12		AET	
13		Solar Radiation	
14	Vegetation Indices	NDVI	https://modis.gsfc.nasa.gov/data/dataprod/mod13.php
15		NDWI	
16		NDMI	
17	Fire location	Fire location Point	https://firms.modaps.eosdis.nasa.gov
18	Anthropogenic interface	Distance from Settlement	https://earthexplorer.usgs.gov/
19		Distance from Road	https://www.openstreetmap.org/#map=5/21.84/82.79
20		Distance from Streams	https://earthexplorer.usgs.gov/

Table -2: In Paper Using Factors and their Source.

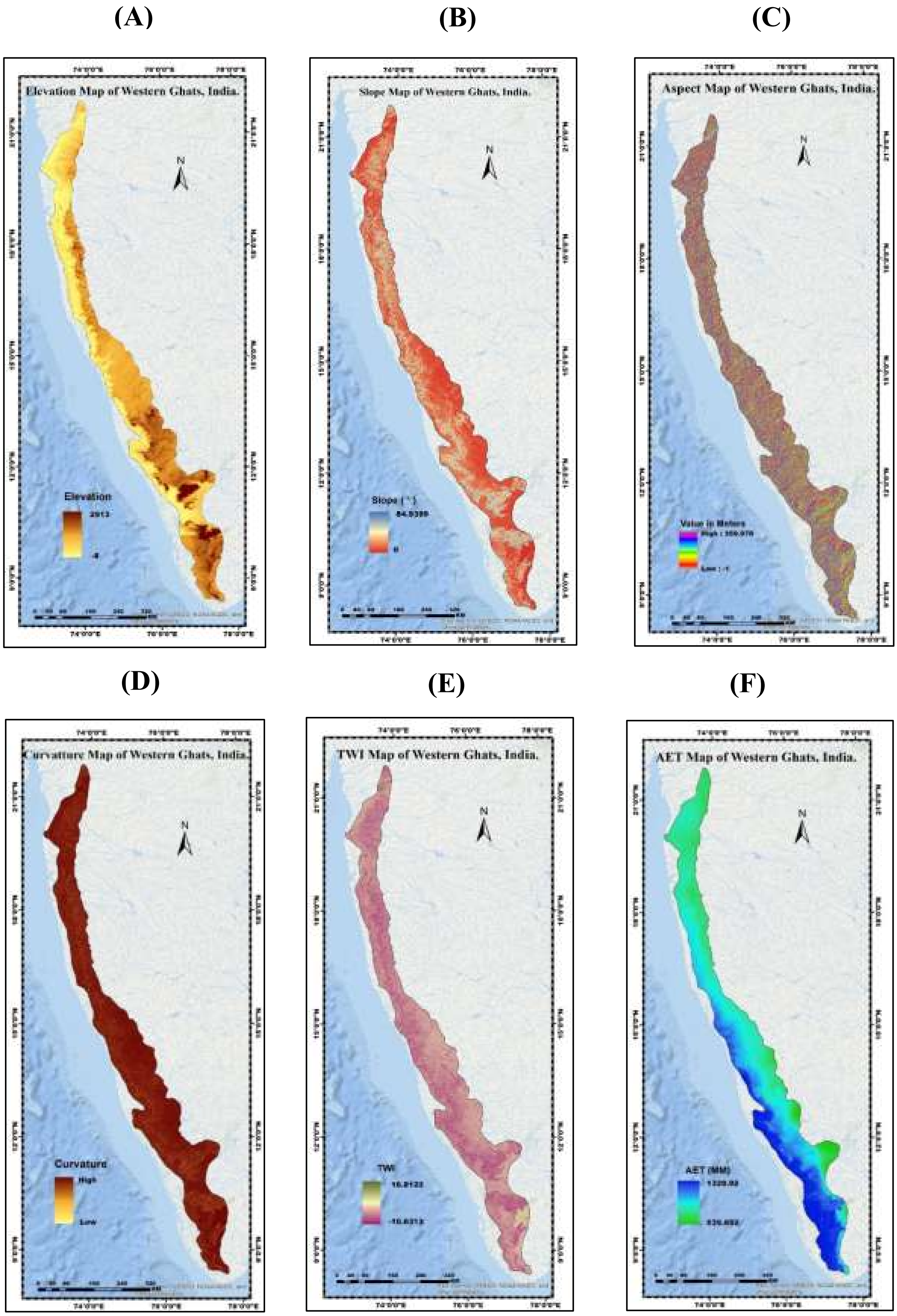
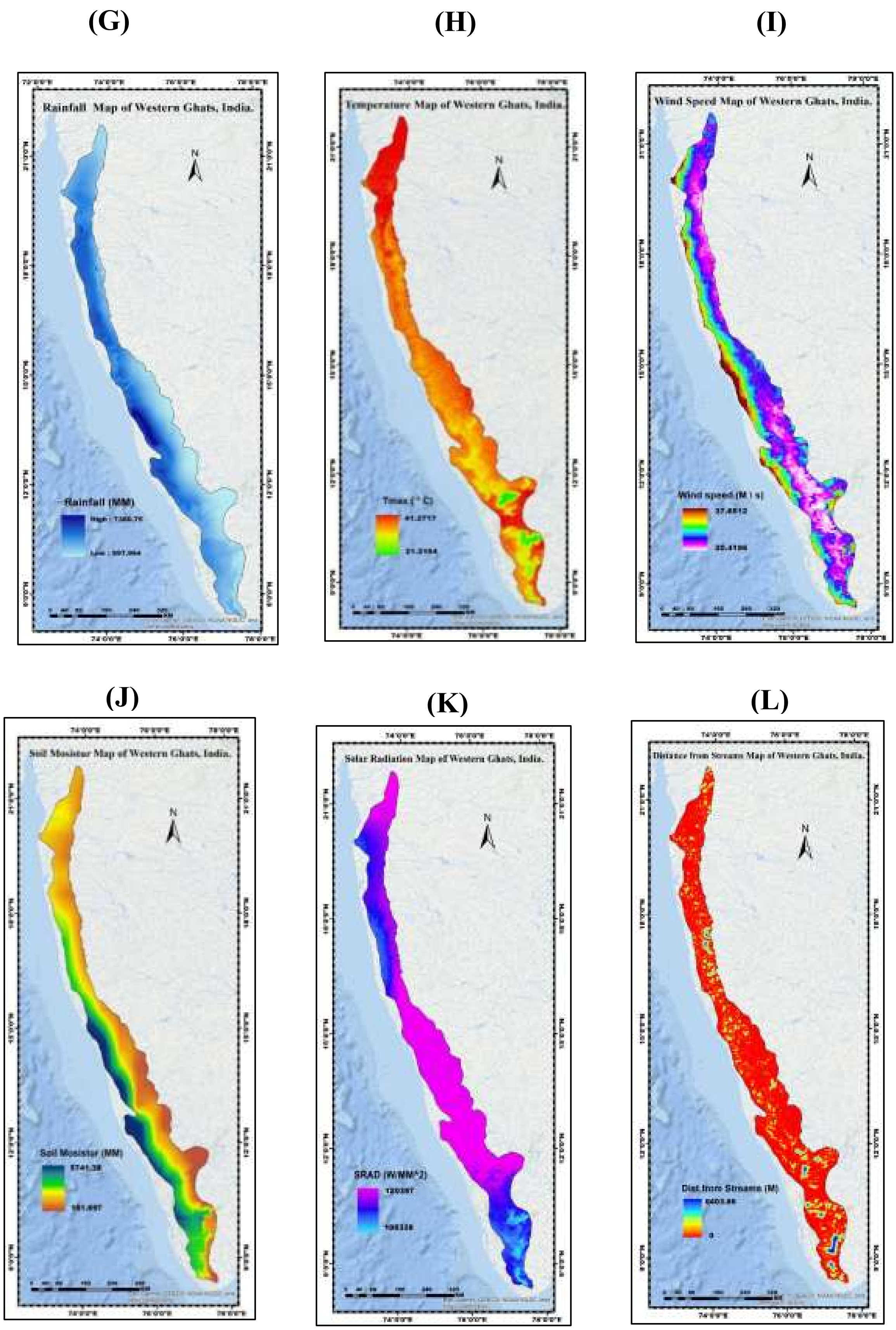


Fig – 2: Factor- (A- Elevation, B- Slope, C- Aspect, D- Curvature, E- TWI, F – AET)



<u>Fig – 3: Factor- (G- rainfall, H- Temperature, I- Wind Speed, J- Soil Moistures, K- Solar Radiation, L – Distance from Streams).</u>

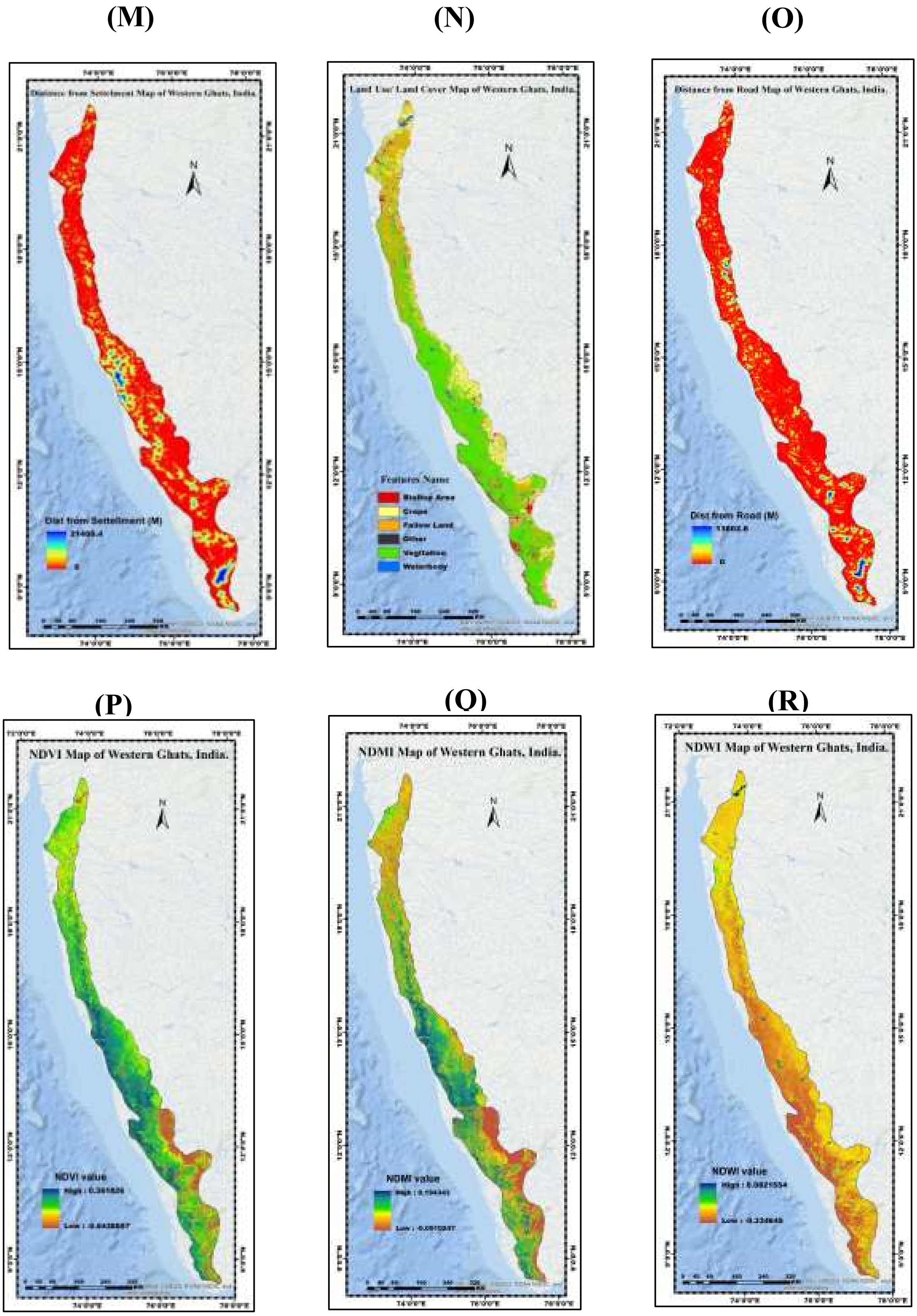


Fig – 4: Factor- (M- distance from settlement, N- LULC, O- distance from road, P- NDVI, Q- NDMI, F – NDWI)

2.3 Methodology:

There are three steps in the methodology's workflow. In order to confirm that both fire conditioning elements were evaluated using multi-collinearity tests, Pearson correlation, and ordinary least squares (OLS), a raster layer mapping fire ignition locations was first made using the GEE platform. In the final step, the final forest fire susceptibility map was predicted using Machine Learning (ML) algorithms (RF).

2.3.1 Forest Fire Inventory Map:

The LANCE (land, Atmosphere Near real-time Capability for EOS) fire detection system, in combination with GEE-based FIRMS, was used to gather data on the forest fire inventory in this research region between 2012 and 2022. The number of forest fires in the western Ghat region of India was approximately 28,000. Inventory numbers (0) indicate no fire and 1 indicate fire, using the forest fire susceptibility model. The sample amount for taste and validation was divided in a 70% to 30% ratio.

2.3.2 Ordinary least square and multicollinearity test:

The Ols method was used to estimate the coefficients and perform a linear analysis of the chosen fire ignition parameters. The degree of correlation between two variables using this method was evaluated using the variance inflation factor. The multicollinearity method identifies factors from independent factors it gives the subject base what factor how much importance.

2.3.3 Machine Learning Model application:

Definition of machine learning. With the use of deep learning and neural networks, machine learning (ML), a branch of artificial intelligence, allows a system to learn and grow on its own without explicit programming by consuming vast volumes of data. The following subsections provide descriptions of the ML models under consideration.

2.3.4 Random Forest (RF):

With its foundation in decision tree methodology, the Randon forest algorithm is a potent instrument for knowledge acquisition and producing precise forecast-based data. a machine learning algorithm that generates classifications and predictions by combining several decision trees. It is particularly good at building models that show intricate connections between input and output variables. The brand's sections show the dependent mess in our particular situation. To provide a final, accurate forecast, Rf builds many decision trees, each trained on a different sample of the data. These decision trees then average their forecasts or cast votes. The only information required is the number of candidates for each split, the number of trees required for system implementation, and user-defined hyperparameters.

Methodology Chat:

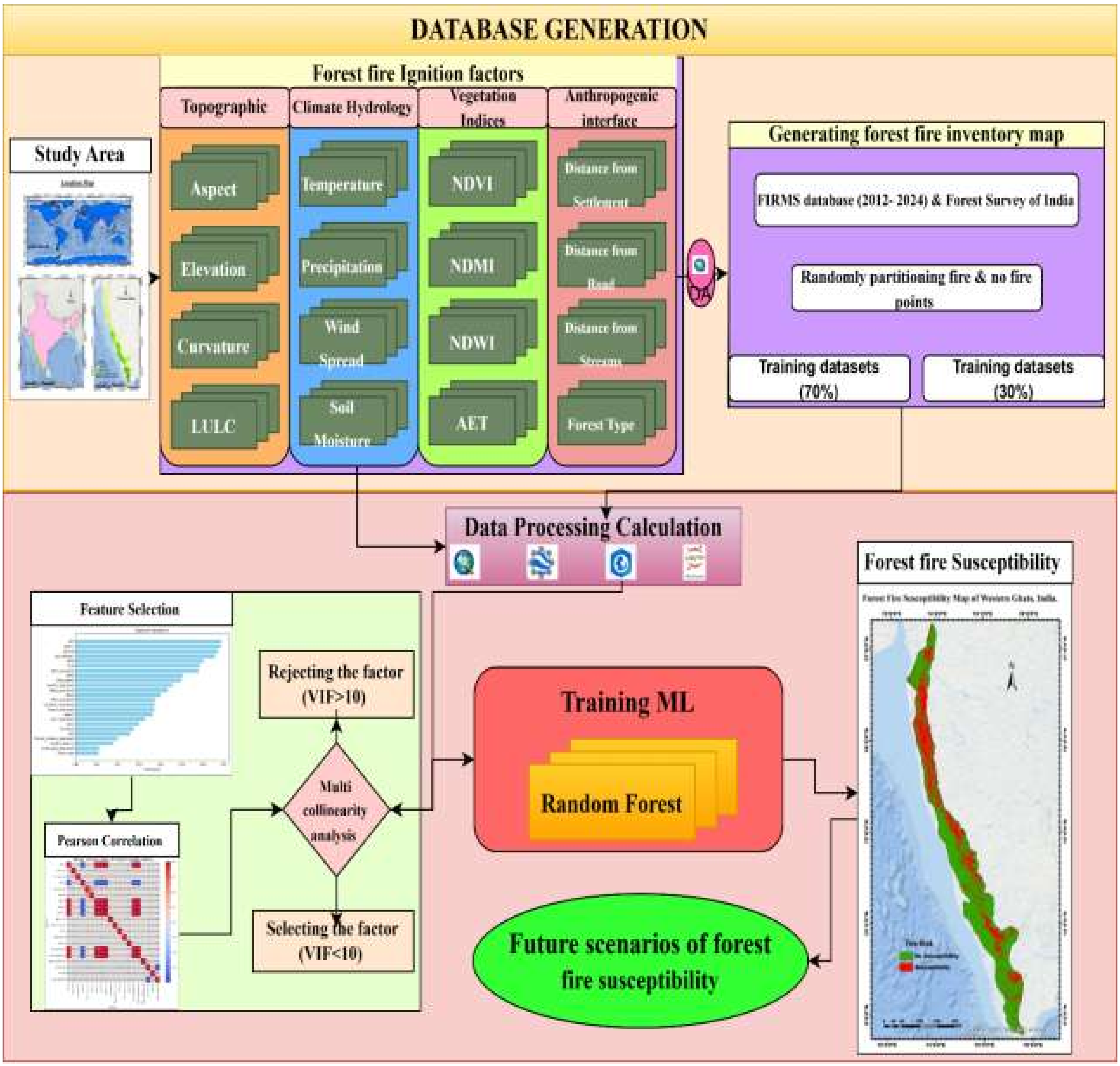


Fig – 5: details workflow methodology for the FFS Modelling.

3. RESULTS & DISCUSSION:

3.1 Generating forest fire inventory map:

Highlights of the spatial distribution of fire events displayed in your inventory map for the Western Ghat region of India. Discuss patterns such as cluster formations in specific regions or proximity to topography. (high region and low region). Mention that the inventory data was sourced from the FRAMS website and processed using geospatial techniques. Discuss the significance of fire-prone zones in terms of land use, vegetation, and climatic factories. Mention how the western ghats region exhibits varying fire densities across ins northern (Maharashtra) central (Karnataka) and southern parts (Kerala) Fire located. There red point located forest fire point (2012 to 2022).

In India, most forest fires happen because of human activity. Humans develop industries and increase agricultural land or settlements that create fire in forests.

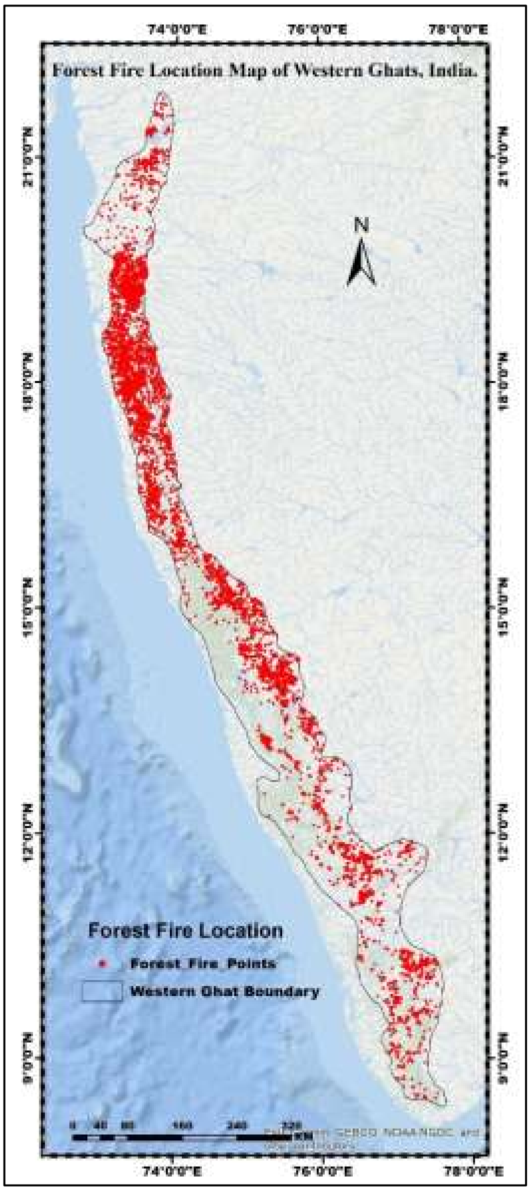


Fig – 6: Forest Fire inventory map

3.2 Pearson correlation:

To determine the best features for forest fire susceptibility models, a study of the dependent variables' meanings has been carried out btable-3, this table numerically displays the Pearson correlation coefficients between pairs of variables. There is always 1 as it represents the self-correlation of each factor. Higher absolute values (closer to 1 or -1) indicate a strong positive or negative relationship. For instance, NDVI and NDMI show a robust positive correlation (~1) and DEM and AET have a strong negative correlation (~ 0.9996), or values closer to 0 suggest little to no linear relationship.

Factors	AET.tif	Aspect.tif	Curvature	DEM1.tif	FCF.tif	Forest_Ty	LULC.tif	NDMI.tif	NDVI.tif	NDWI1.ti	Rainfall.ti	Road_dis	Settelmen	Slope.tif	Soil_Moi	Solar_Ra	Stream_d	Tem_Max	TWI1.tif	Wind_speed.tif
AET.tif		0.09895	0.01371	-0.9996	-0.0138	0.05961	0.01809	0.99999	0.99999	0.99999	0.01973	0.01501	0.01343	-0.073	0.99992	0.99991	0.02989	-0.0229	0.0252	0.022959884
Aspect.tif	0.09895		0.00876	-0.0982	-0.0125	0.07196	0.028	0.09895	0.09895	0.09895	0.01995	0.01271	0.00528	-0.044	0.09897	0.09896	0.02372	-0.023	0.024	0.023029307
Curvature.tif	0.01371	0.00876		-0.0136	-0.0136	0.06811	0.02308	0.01371	0.01371	0.01371	0.01909	0.01654	0.0043	0.02162	0.01362	0.01369	0.02051	-0.0198	0.0206	0.019748171
DEM1.tif	-0.9996	-0.0982	-0.0136		0.01373	-0.0595	-0.0182	-0.9996	-0.9996	-0.9996	-0.0197	-0.015	-0.0134	0.07309	-0.9996	-0.9997	-0.0299	0.02286	-0.0251	-0.02288839
FCF.tif	-0.0138	-0.0125	-0.0136	0.01373		-0.0334	-0.0139	-0.0138	-0.0138	-0.0138	-0.0015	-0.0094	-0.007	-0.0094	-0.0138	-0.0138	-0.0132	0.01528	-0.0136	-0.01525569
Forest_Type.tif	0.05961	0.07196	0.06811	-0.0595	-0.0334		0.41628	0.05961	0.05961	0.05961	0.06933	0.03362	0.05186	0.06343	0.0596	0.05961	0.05458	-0.0697	0.06679	0.06966717
LULC.tif	0.01809	0.028	0.02308	-0.0182	-0.0139	0.41628		0.01809	0.01809	0.01809	0.02346	0.0102	0.01513	0.01942	0.01811	0.01809	0.02037	-0.0208	0.01911	0.020739151
NDMI.tif	0.99999	0.09895	0.01371	-0.9996	-0.0138	0.05961	0.01809				0.01973	0.01501	0.01343	-0.073	0.99993	0.99992	0.02989	-0.0229	0.0252	0.022959884
NDVI.tif	0.99999	0.09895	0.01371	-0.9996	-0.0138	0.05961	0.01809				0.01973	0.01501	0.01343	-0.073	0.99993	0.99992	0.02989	-0.0229	0.0252	0.022959884
NDWI1.tif	0.99999	0.09895	0.01371	-0.9996	-0.0138	0.05961	0.01809				0.01973	0.01501	0.01343	-0.073	0.99993	0.99992	0.02989	-0.0229	0.0252	0.022959884
Rainfall.tif	0.01973	0.01995	0.01909	-0.0197	-0.0015	0.00933	0.02346	0.01973	0.01973	0.01973		0.01383	0.00972	0.02059	0.01973	0.01973	0.0201	-0.0223	0.02111	0.022310312
Road_distance.tif	0.01501	0.01271	0.01654	-0.015	-0.0094	0.03362	0.0102	0.01501	0.01501	0.01501	0.01383		0.01676	0.02951	0.01502	0.01501	0.03089	-0.0097	0.01477	0.00973372
Settelment.tif	0.01343	0.00528	0.0043	-0.0134	-0.007	0.05186	0.01513	0.01343	0.01343	0.01343	0.00972	0.01676		0.02482	0.01339	0.01344	0.00542	-0.0181	0.01887	0.018124889
Slope.tif	-0.073	-0.044	0.02162	0.07309	-0.0094	0.06343	0.01942	-0.073	-0.073	-0.073	0.02059	0.02951	0.02482		-0.073	-0.073	0.00897	-0.0231	0.03011	0.02305024
Soil_Mositur.tif	0.99992	0.09897	0.01362	-0.9996	-0.0138	0.0596	0.01811	0.99993	0.99993	0.99993	0.01973	0.01502	0.01339	-0.073		0.99988	0.0299	-0.0229	0.0252	0.022929898
Solar_Radiation.tif	0.99991	0.09896	0.01369	-0.9997	-0.0138	0.05961	0.01809	0.99992	0.99992	0.99992	0.01973	0.01501	0.01344	-0.073	0.99988		0.0299	-0.0229	0.02521	0.022963222
Stream_distance.tif	0.02989	0.02372	0.02051	-0.0299	-0.0132	0.05458	0.02037	0.02989	0.02989	0.02989	0.0201	0.03089	0.00542	0.00897	0.0299	0.0299		-0.0195	0.01848	0.019458162
Tem_Max.tif	-0.0229	-0.023	-0.0198	0.02286	0.01528	-0.0697	-0.0208	-0.0229	-0.0229	-0.0229	-0.0223	-0.0097	-0.0181	-0.0231	-0.0229	-0.0229	-0.0195		-0.0259	-0.99912596
TWI1.tif	0.0252	0.024	0.0206	-0.0251	-0.0136	0.06679	0.01911	0.0252	0.0252	0.0252	0.02111	0.01477	0.01887	0.03011	0.0252	0.02521	0.01848	-0.0259		0.02588245
Wind_speed.tif	0.02296	0.02303	0.01975	-0.0229	-0.0153	0.06967	0.02074	0.02296	0.02296	0.02296	0.02231	0.00973	0.01812	0.02305	0.02293	0.02296	0.01946	-0.9991	0.02588	

Table – 3: chart of Pearson correlation.

Fig No…. This heatmap visualizes the same data, making it easier to spot trends. In colour, Red signifies a strong positive correlation, blue signifies a strong negative correlation, and neutral shades indicate weak or no correlation. Other patterns said observation factors, like soil_moistur and solur_Radiation, have a near-perfect positive correlation.

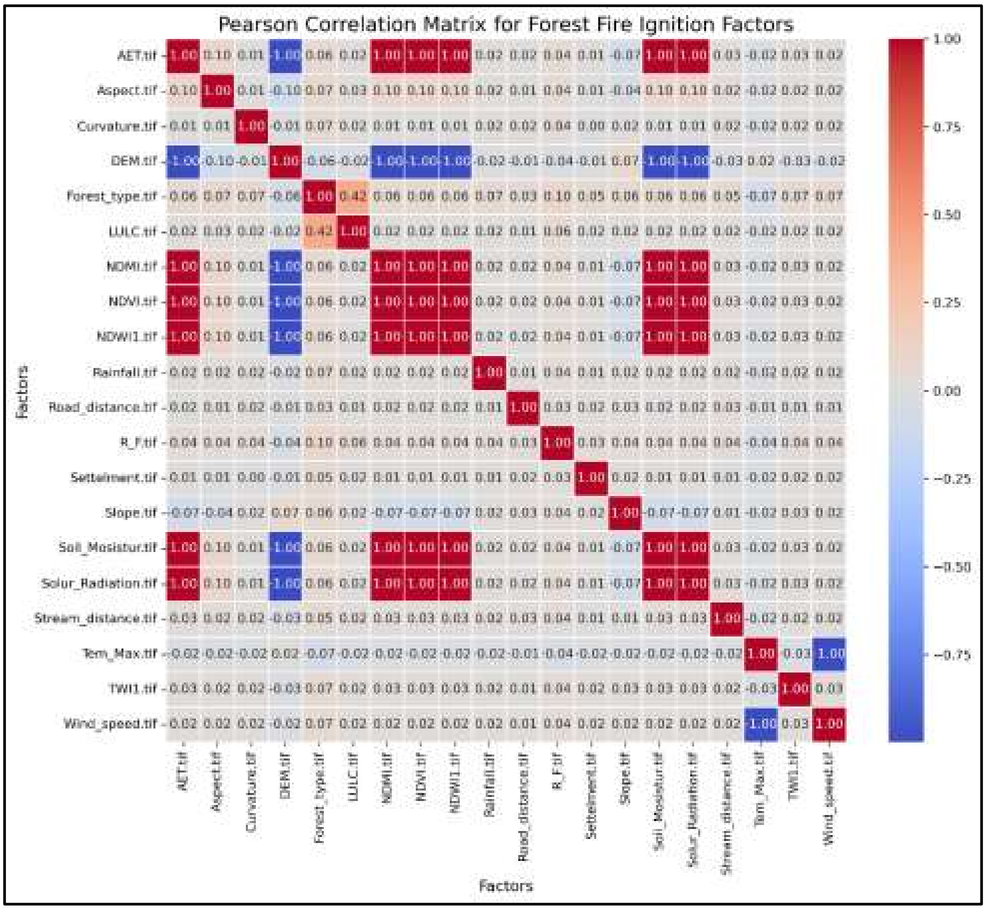


Fig – 7: Pearson Correlation Matrix for Forest Fire Factors.

3.3 Multi-collinearity evaluation:

An analysis of the signification of dependent variables was conducted to identify optimal features for forest fire susceptibility models. ………….. Fig- this table numerically displays the multi-collinearity. AET, NDVI, Rainfall, soil moisture, and NDWI, are the most important factors in predicting forest fire susceptibility. DEM, Wind speed, slope, and TWI, maintain moderate impotence, reflecting the potential benefits of spatial resolution adjustment: Curvature, Aspect, Forest type FCF low importance for the forest fire susceptibility.

Variable	VIF
AET.tif	1.179267
Aspect.tif	1.126578
Curvature.tif	1.027768
FCF.tif	1.009445
Forest_Type.tif	2.286531
LULC.tif	2.032217
Rainfall.tif	1.0306
Road_distance.tif	1.016554
Settelment.tif	1.017968
Slope.tif	1.090698
Stream_distance.tif	1.029569
Tem_Max.tif	1.034169
TWI1.tif	1.035741

Table 4: Chat of Multi collinearity

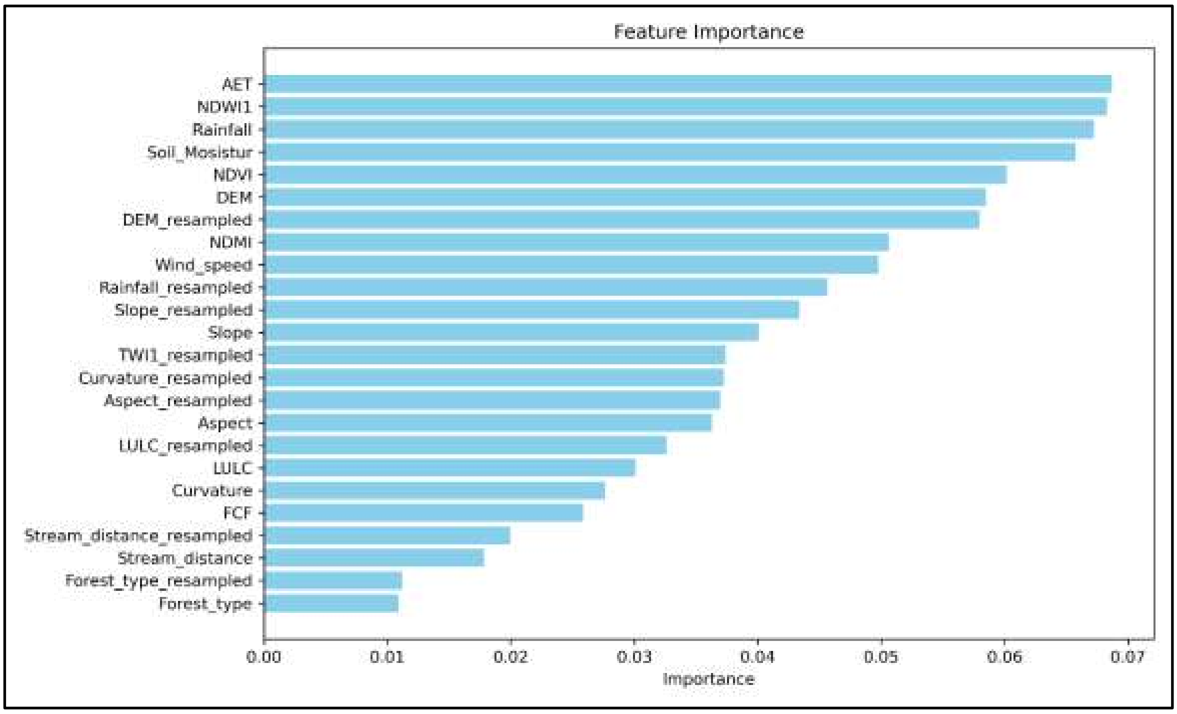


Fig 8: Multi collinearity analysis for forest fire ignition factors importance.

3.4 Forest fire susceptibility:

in this result, the forest fire susceptibility map highlights the spatial variation in forest fire susceptibility across the Western Ghats. Areas marked in indicate regions with high susceptibility, while green represents areas with susceptibility. High susceptibility areas are prominently located along the mid to upper elevations (mostly part of Maharashtra, Karnataka, a little bit of Kerala and Tamil Nadu) of the Western Ghats, coinciding with regions of dense vegetation and anthropogenic activities. Low susceptibility regions dominate coastal and lowland zones, likely due to differences in vegetation cover, moisture content and climatic conditions. Approximately (33709.82 sq.km Area) of the Western Ghats region is identified as susceptible to forest fires. These areas are hotspots for forest fire occurrences. Influenced by both natural factors (dry climate, steep slopes) and human-induced activities (Agricultural, resource extraction). Role of Environmental Factors, steeper slopes and rugged terrains show a higher correlation with fire susceptibility, as these have drier microclimates and are less accessible for fire suppression. Forested regions with mixed vegetation types and plantations are more prone to fire, emphasizing the need for sustainable management practices. Seasonal dryness and high temperatures in these zones contribute significantly to fire risk. In forest fire susceptibility Discussion, the susceptibility map can serve as a critical tool for forest management authority. It aids in prioritizing high-risk areas for preventive measures, such as creating firebreaks, monitoring human activities, and improving accessibility for firefighting operations. Human activities Such as shifting cultivation deforestation, and accidental fires, play a substantial role in exacerbating fire susceptibility. The clustering of high-risk zones near population or agricultural areas indicates the need for awareness campaigns and stricter enforcement of fire prevention regulations. The western

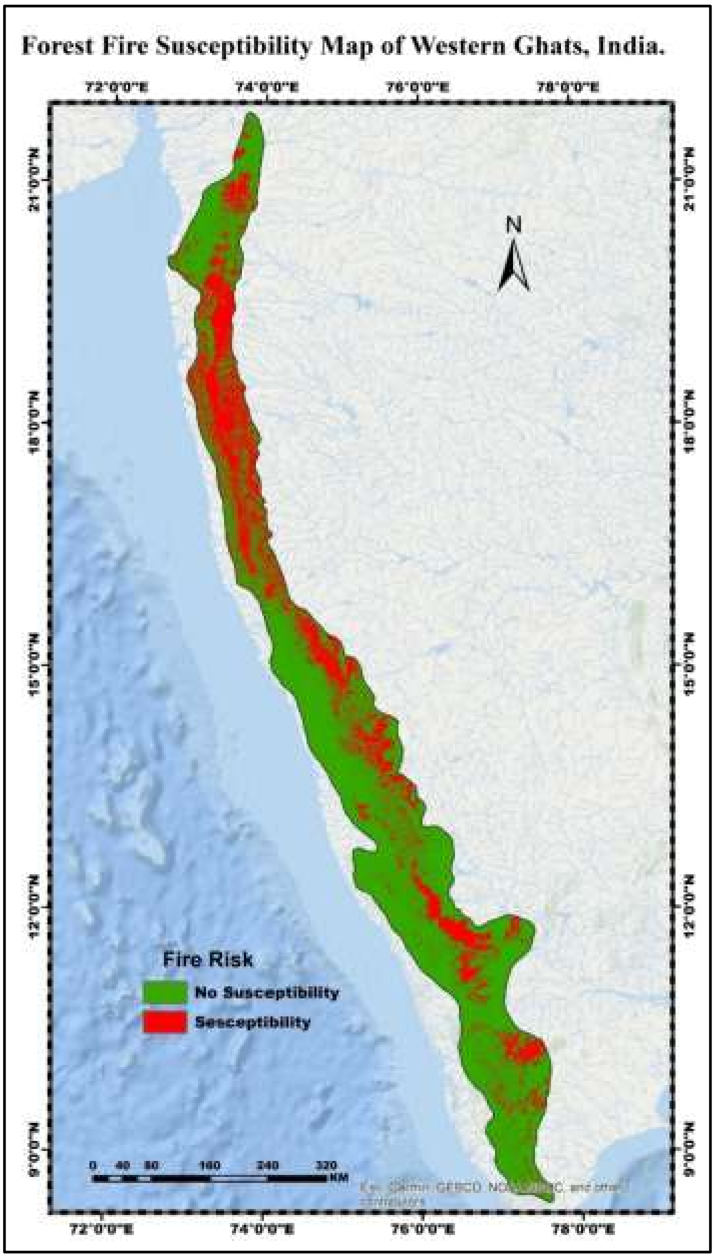


Fig – 9: Forest fire susceptibility map

ghats a biodiversity hotspot, houses numerous endemic species that are vulnerable to habitat destruction caused by fires. Protecting high-susceptibility areas is critical to preserving the ecological balance and preventing biodiversity loss. The findings highlight the necessity to incorporate climate change scenarios into fire susceptibility models. Increasing temperatures and rainfall patterns will likely expand high-risk zones in the coming decades, requiring adaptive management strategies. While the current model provides a robust analysis, further refinement can be achieved by incorporating additional variables like real-time meteorological data, soil moisture levels, and socio-economic factors. Validation using historical fire occurrence data can also enhance the reliability of the susceptibility predictions.

4. CONCLUSION:

This study examines of the significant effects in forest fires on India's western Ghat, highlighting the depletion of biodiversity and essential resources. Twenty ignition elements were grouped into four categories and FFS maps were produced using Random Forest ML models. After extensive training and testing, the models reliably determined that the Western Ghat in India had a high risk of forest fires in the north, a moderate risk in the centre, and a very low risk in the south or coastline region.

This research highlights the urgent need for sustainable forest management in the Western Ghats in India, focusing on high-susceptibility zones to mitigate the risk of forest fires. Integrating geospatial tools, RS, and ML provides a powerful framework for identifying vulnerable Ares and guiding resource allocation for fire prevention and mitigation strategies.

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