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Evaluating Forest Fire Risk in the Sathyamangalam Forest, Erode District, Tamil Nadu, India: An Analytical Hierarchy Process (AHP) Approach

Mr. S. Stephen Jayaseelan¹ Mr P. Raju²

Research Scholar, Department of Geography, University of Madras, Guindy campus, Chennai, Tamilnadu, India

ABSTRACT: In this study, we assess forest fire risk in the Sathyamangalam Forest, Erode District, Tamil Nadu, India, by considering various environmental factors such as land use, elevation, slope, aspect, temperature, relative humidity, and wind force. Through an analytical approach, we create a hazard identification map that classifies areas into different risk levels. The moderate forest fire risk class stands out, impacting the largest area (40.35% of the total), possibly due to more frequent or severe fires driven by environmental conditions like high temperatures and low humidity. The high and low risk classes also pose significant concerns, potentially linked to different environmental conditions or human activities. The very low and very high-risk classes have the smallest affected areas, with varying degrees of fire severity and frequency. Importantly, the high-risk class benefits from a more extensive dataset, making its forest fire density results more reliable. This study highlights the need for systematic risk assessment to inform mitigation and management strategies for forest fire protection in the region.

KEYWORDS: Forest Fire, AHP Analysis, GIS and Remote Sensing.

I. INTRODUCTION

Forest fires indeed present a significant ecological and societal challenge, with their ramifications extending across ecosystems and human populations (Pyne, 1997). The assessment and comprehension of factors contributing to forest fire risk play a pivotal role in formulating effective strategies for mitigation and management (Calkin et al., 2015). This study, therefore, seeks to offer a comprehensive framework by identifying critical factors and their associated parameters, an endeavor rooted in an exhaustive examination of existing literature related to forest fire risk assessment (Cohen et al., 2016). The incorporation of these factors and parameters into forest fire risk analysis offers a multifaceted view of the multitude of variables influencing the probability and severity of forest fires. Such a multifaceted understanding is instrumental in shaping customized risk management approaches, aimed at reducing the impact of forest fires and securing both human and ecological communities from their deleterious effects (Abt et al., 2019). This research endeavor aligns with the broader objective of enhancing our grasp of forest fire dynamics and bolstering the resilience of susceptible regions against these natural disasters (Moritz et al., 2014).

II. METHODOLOGY

The forest fire risk assessment into this study involves an expansion of the existing physical climate and environmental variables. Raster-based analysis remains the cornerstone of multi-criteria decision analysis (MCDA), effectively amalgamating a broad array of datasets. To initiate this process, the pertinent data, which now encompasses forest fire risk factors, is transformed into a raster format. This conversion is executed through techniques such as interpolation, raster calculator, and raster-to-vector conversion. Subsequent to the transformation, data resampling is undertaken to establish uniform pixel dimensions, thereby enabling the execution of raster overlay analyses, including methods like the Analytic Hierarchy Process (AHP) and the Weighted Sum Method. In the context of forest fire risk, critical data layers incorporating physical climate and environmental variables are generated, culminating in the creation of a pairwise comparison matrix. This matrix, along with the AHP table weights, serves as a crucial tool for quantifying the impact of each factor and its seamless integration into the overlay analysis, thus facilitating a comprehensive decision-making framework that accounts for forest fire risk alongside other relevant criteria.

III. DATA USED FOR FOREST FIRE RISK ANALYSIS

A comprehensive approach was undertaken, encompassing four primary parameters: Topography, Land Cover, Climate, and social factors. Within these categories, 11 sub-parameters were meticulously employed as part of the Analytic Hierarchy Process (AHP) analysis. This methodological choice aimed to ensure the robustness and reliability of the results, contributing to a more comprehensive assessment of forest fire risk.

In the weighted sum tool to use a scaled raster that has been resampled with the same pixel and a value assigned using the reclassification approach in terms of 1 to 5, with 1 being the least important and 5 being the most important. According to the weighted sum analysis the input which can be any positive or negative decimal value then output result will be floating value. So that for assigning weighted sum is done with based on the saaty scale (1977). For evaluation of satty scale pairwise comparison method has been used to derive weighted sum value to apply weighted overlay analysis.

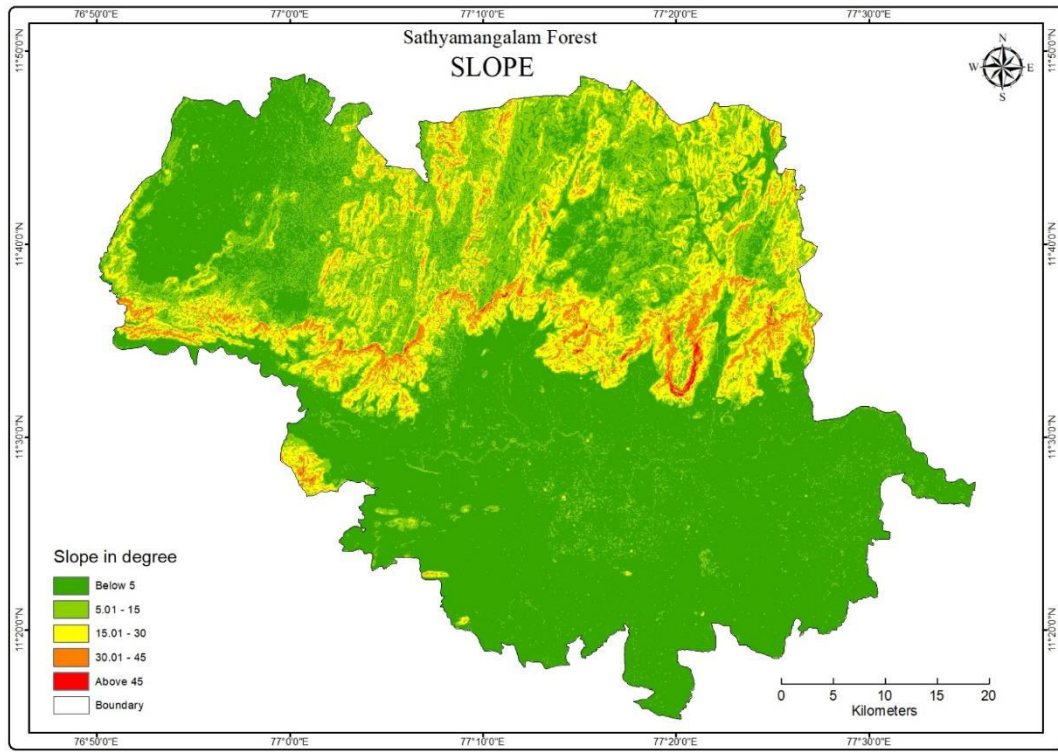
Slope:

The angle of the slope can also have a significant impact on fire behavior. As the slope angle increases, the fire's intensity and rate of spread also increase (Agee, 1993). Steeper slopes increase the amount of radiant heat and decrease the amount of convective heat, causing the fuel to preheat more quickly and ignite more easily.

The angle of the slope can also affect the fire's ability to move against the wind. On a steep slope, the fire may be able to move uphill against the wind due to the increased draught caused by the slope. while on a gentle slope, the wind may prevent the fire from moving uphill. (Cruz et al., 2003; Riley et al. 2020).

Slope in degree	Area in Km ²	Percentage	weightage
0 to 5	1685.73	58.55	1
5 to 15	631.36	21.93	2
15 to 30	451.44	15.68	3
30 to 45	106.35	3.69	4
Above 45	4.06	0.14	5

Slopes in the range of 0 to 5 degrees represent the largest expanse, accounting for 58.55% of the total area and assigned a weightage score of 1, signifying their lower susceptibility to forest fires. Areas characterized by slopes falling within the 5.01 to 15-degree range occupy 21.93% of the total area, with a weightage score of 2, indicating a moderate vulnerability to forest fires. Regions with slopes spanning 15 to 30 degrees encompass 15.68% of the total area, receiving a weightage score of 3, denoting a moderate vulnerability level. In contrast, areas with slopes ranging from 30.01 to 45 degrees constitute merely 3.69% of the total area but are assigned a weightage score of 4, signifying a heightened vulnerability to forest fires. Notably, areas with slopes exceeding 45.01 degrees are the least extensive, covering just 0.14% of the total area; however, they bear the highest weightage score of 5, indicative of their heightened susceptibility to forest fires. Consequently, areas with slopes between 30.01 to 45 degrees and those exceeding 45.01 degrees demand heightened attention and focused management to proactively prevent and mitigate the impact of forest fires.



Elevation:

Elevation exerts its influence on fire dynamics by modifying factors such as precipitation patterns, wind exposure, and seasonal fuel drying (Agee, 1993; Cruz et al., 2003). In lower elevation areas, the combination of higher temperatures and reduced precipitation leads to the earlier drying of fuels in the year. Conversely, at higher elevations, fuels tend to retain moisture for a longer duration (Agee, 1993). Additionally, elevated regions are more susceptible to lightning strikes (Cruz et al., 2003), which can subsequently trigger wildfires (Moritz et al., 2014).

Elevation in (m)	Area in Km ²	Percentage	Weight
79 - 335	264.94	9.20	5
335.1 - 616	328.73	11.42	4
616.1 - 829	701.44	24.36	3
829.1 - 1032	202.38	7.03	2
1032.1 - 1647	1381.44	47.98	1

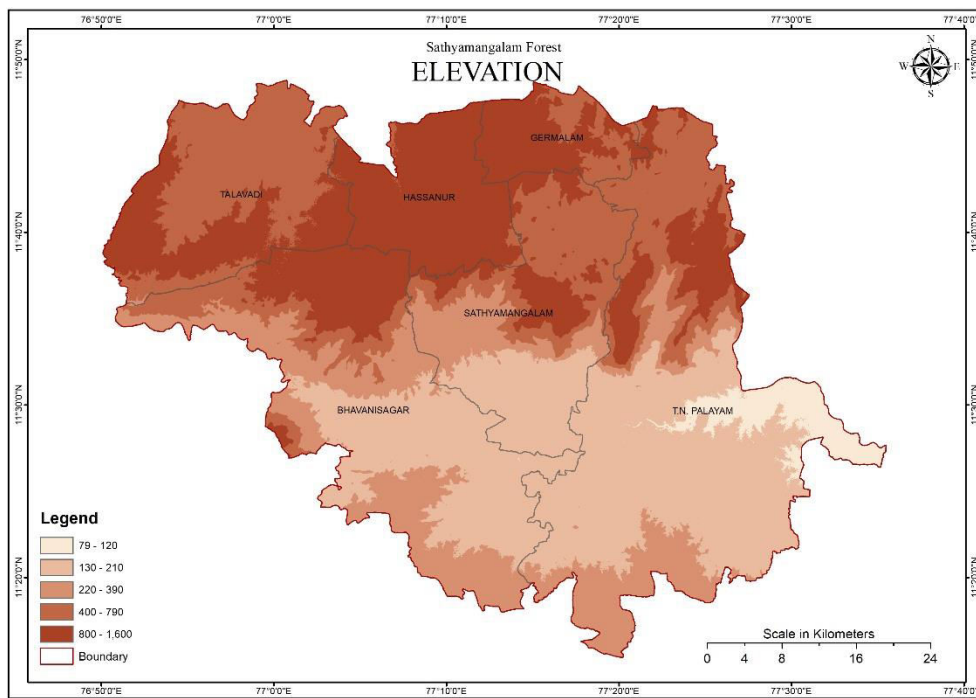
The provided table delineates the relationship between elevation levels and their corresponding susceptibility to forest fires. This tabulation is partitioned into five distinct elevation ranges, each accompanied by its respective weightage, percentage coverage, and total area. These elevation ranges commence at 79 meters and extend to 1647 meters, with weightages ranging from 1 to 5, where 5 signifies the highest vulnerability and 1 represents the lowest vulnerability to forest fires.

Specifically, areas falling within the elevation range of 79 to 335 meters encompass 264.94 square kilometers, constituting 9.20% of the overall area. These areas carry the highest weightage of 5, indicative of their heightened vulnerability to forest fires. Elevation spans of 335.1 to 616 meters encompass 328.73 square kilometers, accounting for 11.42% of the total area, with a weightage of 4, denoting a substantial vulnerability to forest fires.

In the elevation between of 616.1 to 829 meters, an area of 701.44 square kilometers is covered, representing 24.36% of the total expanse, and it assigned weightage of 3, signifying a moderate vulnerability to forest fires. Areas within

the 829.1 to 1032 meters elevation range encompass 202.38 square kilometers, equivalent to 7.03% of the total area, and they bear a weightage of 2, indicating a lower vulnerability to forest fires.

The largest contiguous area, spanning elevations from 1032.1 to 1647 meters, covers 1381.44 square kilometers, accounting for 47.98% of the total area. These areas are associated with the lowest weightage of 1, underscoring their minimal vulnerability to forest fires. In summary, the table highlights the inverse relationship between elevation and forest fire vulnerability, with lower elevation areas exhibiting higher susceptibility and higher elevation areas enjoying a reduced vulnerability. This pattern can be attributed to factors like increased humidity and cooler temperatures at higher elevations, which diminish the likelihood of forest fire initiation and propagation.



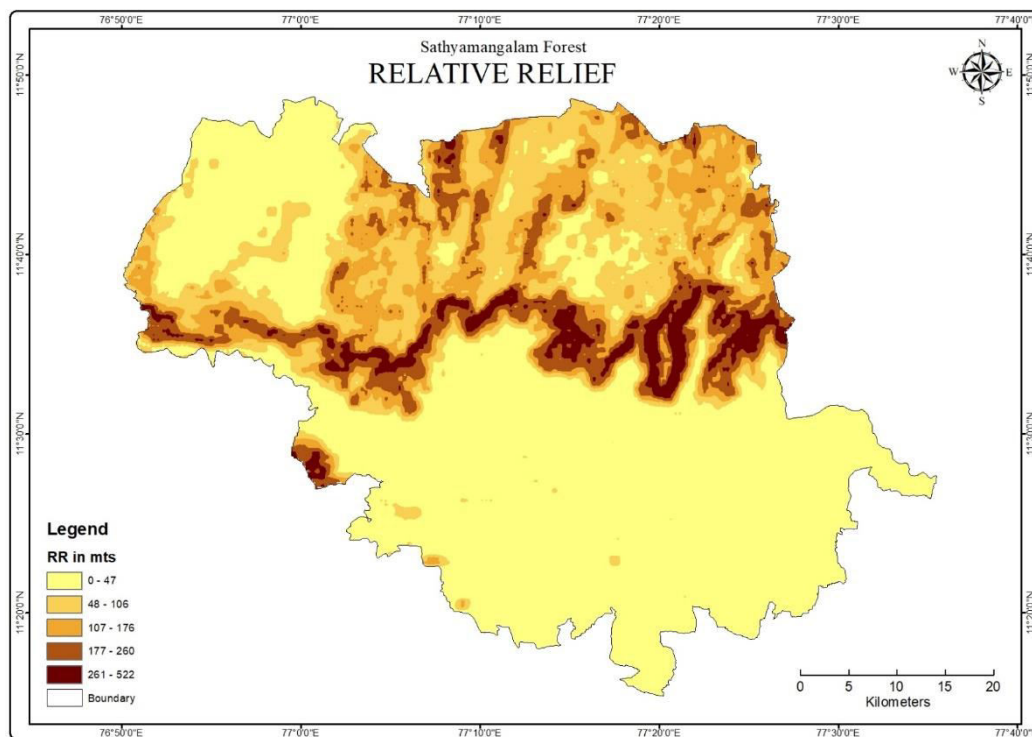
Relative relief:

The relative relief, describing the actual change in altitude over an area in relation to its local base level, plays a significant role in fire risk assessment (Pausas & Ribeiro, 2013). In the context of forest fires, high relative relief areas may have a lower risk of fire, primarily due to their steeper slopes, which may limit the rapid spread of fires. These areas may also benefit from cooler temperatures and higher humidity levels, reducing the overall risk of ignition and fire spread. Conversely, lower relative relief areas, characterized by flatter terrain, may face a higher risk of fire as they facilitate the easier spread of fires. Such areas often possess more combustible fuel, including dry vegetation, and may experience hotter and drier conditions, increasing the susceptibility to ignition and fire propagation (Cruz et al., 2003; Pausas & Ribeiro, 2013).

Class	RR in Meters	Area in km2	Percentage	Weightage
Very high	261 - 522	109.80	3.81	5
High	177 - 260	251.81	8.75	4
Moderate	107 - 176	396.96	13.79	3
Low	48 - 106	508.66	17.67	2
Very low	0 - 47	1611.70	55.98	1

The Relative Relief (RR) value indicates the difference in altitude between high and low points within a specific area. A higher RR value indicates greater elevation differences or undulated terrain, while a lower value indicates lower altitude differences.

Areas with a very low RR range (261-522 meters) cover 109.80 km², which is 3.81% of the total area, and have a weightage of 5, indicating high vulnerability to forest fires. Areas with a low RR range (177-260 meters) cover 251.81 km², which is 8.75% of the total area, and have a weightage of 4, indicating a high vulnerability to forest fires. Moderate RR range (107-176 meters) covers 396.96 km², which is 13.79% of the total area, and has a weightage of 3, indicating moderate vulnerability to forest fires. High RR range (48-106 meters) covers 508.66 km², which is 17.67% of the total area, and has a weightage of 2, indicating a low vulnerability to forest fires. The largest area, with a very high RR range (0-47 meters), covers 1611.70 km², which is 55.98% of the total area, and has the lowest weightage of 1, indicating the least vulnerability to forest fires



. Overall, the table shows that areas with very low RR have the lowest vulnerability to forest fire, while areas with very high RR have the highest vulnerability to forest fire.

Topographic Wetness Index:

The index is determined by the slope as well as the amount of upstream contributing area per unit width orthogonal to the flow direction. The index value is highly associated with various soil characteristics, including horizon depth, silt percentage, organic matter concentration, and phosphorus (Moore et al., 1993). The primary difference between methods of computing this index is how the upslope contributing area is determined. Similarly, output from the Topographic Wetness Index (TWI) indicates that a higher value represents higher runoff-contributing areas, while a lower value indicates upslope areas with lower runoff (Beven & Kirkby, 1979). Therefore, based on the runoff, topographic wetness can be determined and utilized as one of the factors in assessing forest fire risk

TWI	Area in Km ²	Percentage	Weightage
6.09 - 12.28	485.59	16.87	5
12.29 - 13.48	804.63	27.95	4
13.49 - 14.5	944.15	32.80	3
14.51 - 16.15	562.51	19.54	2
16.16 - 20.58	81.47	2.83	1

The topographic wetness index formula was applied to DEM data to obtain it. It's a useful model for predicting where water will concentrate in an area with varying elevations. It is determined by the slope and the area contributing upstream.

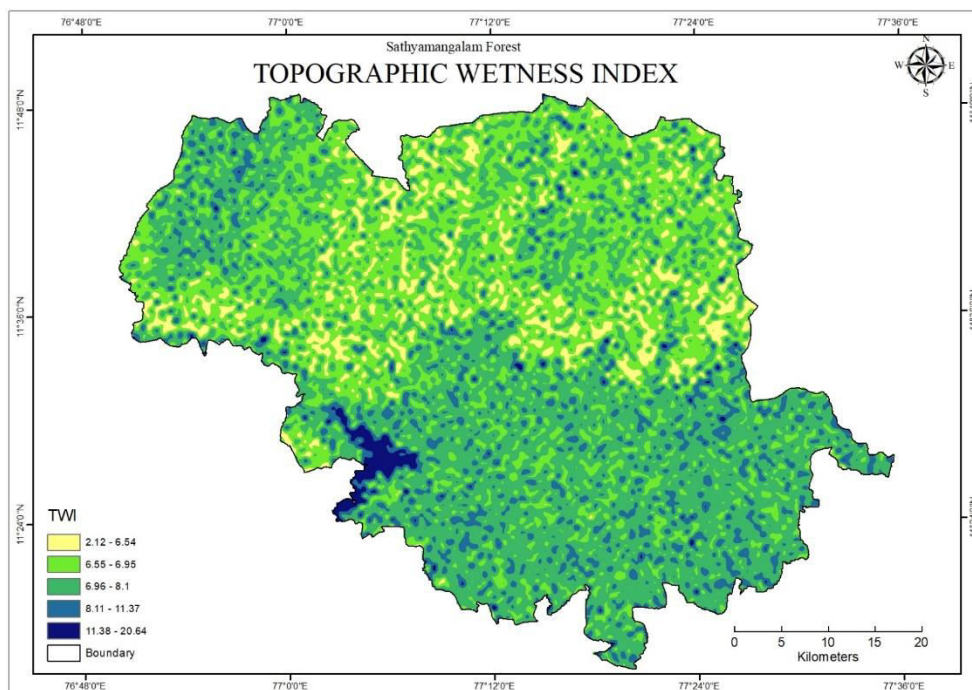
$$TWI = \ln \frac{a}{\tan b}$$

Where:

a = upslope contributing area (m²)

b = slope in radians

The TWI ranges from 6.09 to 20.58. Areas with TWI between 6.09 and 12.28 cover 485.59 km², which is 16.87% of the total area, and have a weightage of 5, indicating the highest vulnerability to forest fires. Areas with TWI between 12.29 and 13.48 cover 804.63 km², which is 27.95% of the total area, and have a weightage of 4, indicating a high vulnerability to forest fires. Areas with TWI between 13.49 and 14.5 cover 944.15 km², which is 32.80% of the total area, and have a weightage of 3, indicating a moderate vulnerability to forest fires. Areas with TWI between 14.51 and 16.15 cover 562.51 km², which is 19.54% of the total area, and have a weightage of 2, indicating a low vulnerability to forest fires. Areas with TWI between 16.16 and 20.58 cover 81.47 km², which is 2.83% of the total area, and have the lowest weightage of 1, indicating the least vulnerability to forest fires. Therefore, areas with lower TWI values are less vulnerable to forest fires, while areas with higher TWI values are more vulnerable to forest fires due to their higher moisture content.

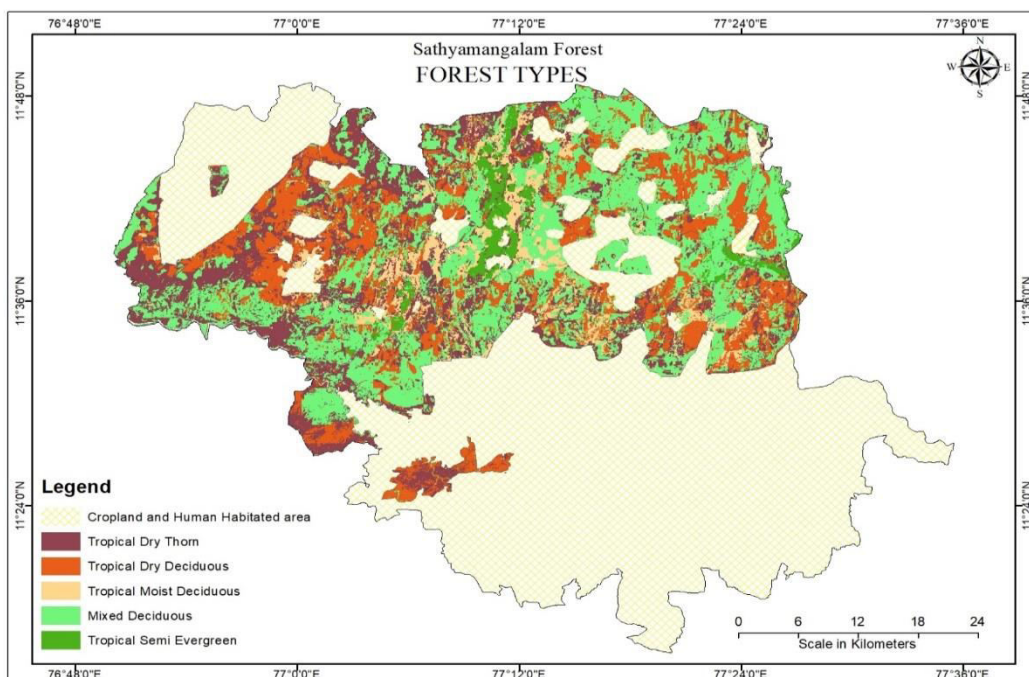


Forest type: (Fuel type)

Vegetation characteristics play a pivotal role in fire susceptibility. Different vegetation types exhibit varying fuel properties (Pyne, 1997). Vegetation with higher density and lower moisture content tends to be more susceptible to fire, as opposed to vegetation with higher moisture content and lower density. Additionally, the extent of dry fuel accumulation in an area significantly influences the likelihood of ignition and the duration of fire propagation. Dry fuel areas are particularly prone to ignition and sustained fire spread when fuel moisture decreases and prolonged periods of warm, dry weather prevail (Taylor et al., 2006). Uncontrolled combustion or burning of vegetation in natural settings, such as grasslands or bush/scrub areas, is contingent upon the availability of natural fuels and is influenced by prevailing environmental conditions (Gill, 1975).

S. No	Forest Types	Area in Km ²	Percentage	Weight
1	Mixed Deciduous	543.24	38.33	3
2	Tropical Dry Deciduous	348.11	24.56	4
3	Tropical Dry Thorn	372.36	26.27	5
4	Tropical Moist Deciduous	103.23	7.28	2
5	Tropical Semi Evergreen	50.48	3.56	1

Among the diverse forest types examined, the "Tropical Dry Thorn" forest stands out with an expansive coverage of 372.36 km² and a high weightage score of 5, signifying its extreme susceptibility to forest fires due to arid conditions and high temperatures. Closely trailing is the "Tropical Dry Deciduous" forest, spanning 348.11 km² with a weightage of 4, indicating a substantial vulnerability to forest fires. The "Mixed Deciduous" forest, encompassing 543.24 km² and assigned a weight of 3, represents a moderately vulnerable category. In contrast, the "Tropical Moist Deciduous" forest, covering a smaller area of 103.23 km² and bearing a weight of 2, indicates a lower level of susceptibility. Lastly, the "Tropical Semi Evergreen" forest, occupying 50.48 km² and with a weight of 1, is deemed less prone to forest fire occurrences. This analysis provides valuable insights into the diverse forest types' varying levels of vulnerability to forest fires based on their characteristics and environmental conditions.



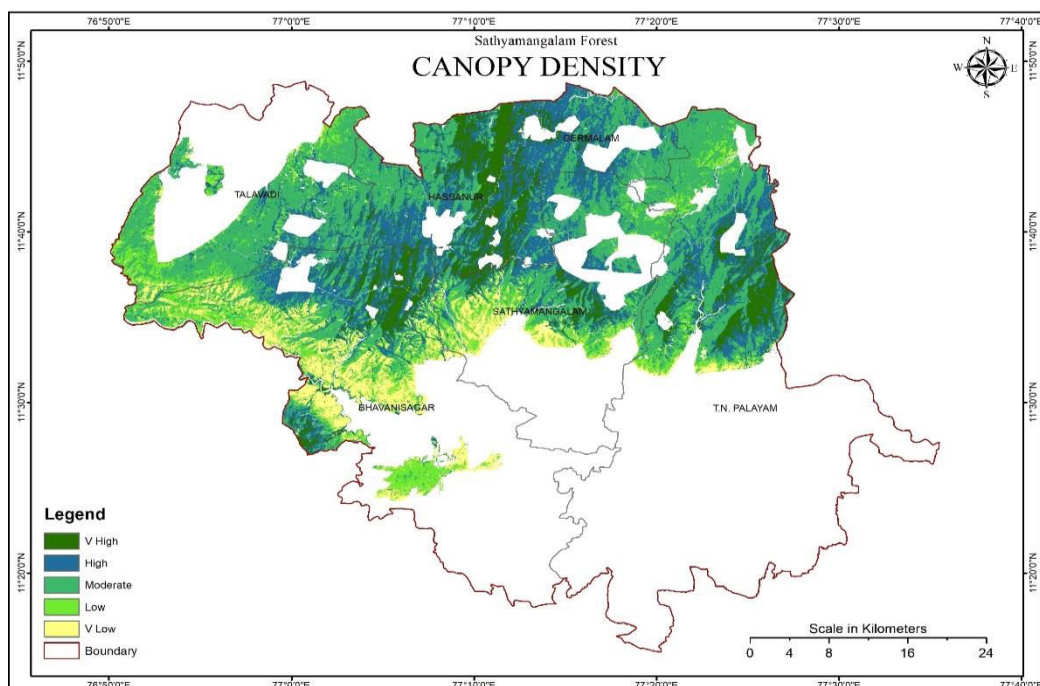
Forest Canopy density

Forest density plays a critical role in influencing forest fire dynamics. High forest density, characterized by closely spaced trees and dense underbrush, can lead to increased fuel loads, making areas more susceptible to intense and destructive forest fires (Stephens et al., 2018). Forest canopy density model selected for to understand density of forest, model describes 0 to 100 percentage of forest density. The data has been extracted based on FCD model superimposed with the year of 1991, 2001, 2011 and 2021.

Percentage	Classes	Area in Km ²	%	Weight
< 10	scrub	367.40	25.96	5
11-40	Moderately dense	381.79	26.98	4
41-70	Dense forest	186.06	13.15	3
Above 70	Very dense forest	479.79	33.91	2

Class 1, which represents vegetation categorized as scrub and covers less than 10% of the total area, covers 25.96% of the total area. This class has a weighted value of fire risk of 5, indicating a high risk of fire. Class 2, which represents moderately dense vegetation covering 11-40% of the total area, covers 26.98% of the total area. This class has a weighted value of fire risk of 4, indicating a high risk of fire. Class 3, which represents dense forest covering 41-70% of the total area, covers 13.15% of the total area. This class has a weighted value of fire risk of 3, indicating a moderate risk of fire. Class 4, which represents very dense forest covering above 70% of the total area, covers 33.91% of the total area. This class has a weighted value of fire risk of 2, indicating a low risk of fire.

The distribution of vegetation types in the area is relatively balanced, with each class covering between 13.15% and 33.91% of the total area. However, the risk of fire varies significantly between vegetation classes. Scrubs and moderately dense forest, which cover just over half of the total area, have the highest weighted values of fire risk, indicating a high risk of fire. In contrast, dense and very dense forest, which cover just under half of the total area, have lower weighted values of fire risk, indicating a moderate to low risk of fire. This information could be useful for forest management and fire prevention efforts. It is particularly relevant in areas where the risk of fire is most significant and preventative measures are most effective.



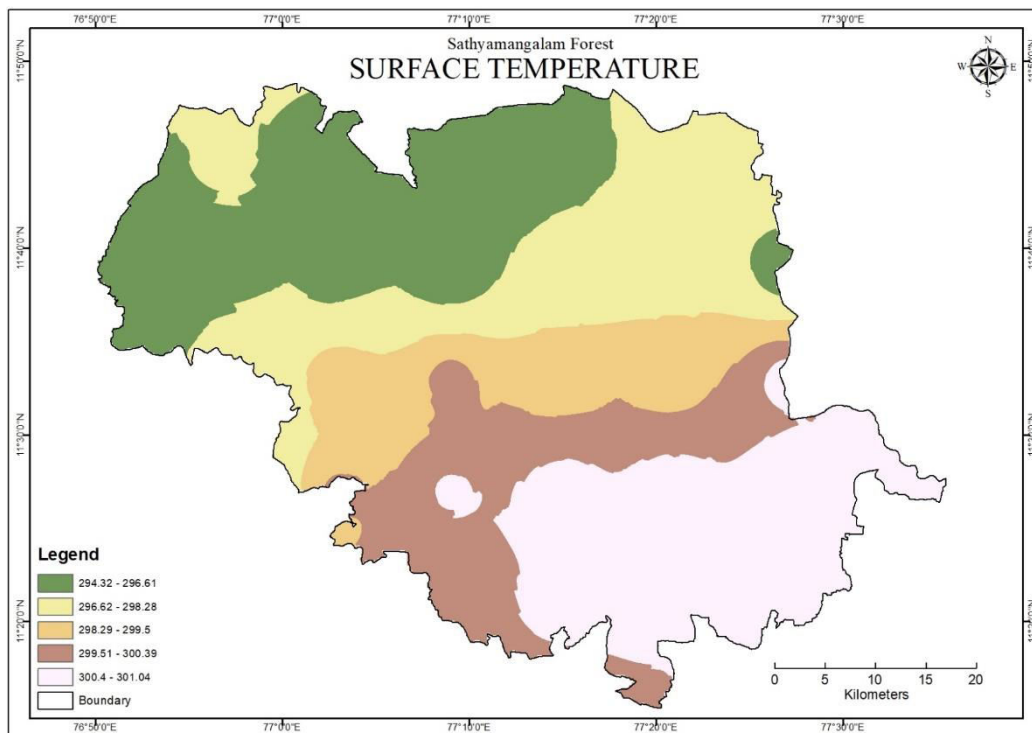
Land Surface temperature:

Throughout the Earth's climate system, the Land Surface Temperature (LST) is a significant variable. Among the processes described are the exchange of energy and water between the land surface and the surrounding atmosphere. It also has an impact on the rate and duration of plants growth. So, rising surface temperatures, cause more moisture to escape from the ground, causing the soil to dry up and plants to become more flammable.

Data downloaded from Geovanni 4.7 (MODIS-Terra MOD11C3 v006) data set, spatial resolution (0.05*0.05 degree), 10 years (2011 - 2021). The surface air temperature is recorded in kelvins, with values ranging from 294.32 to 300.39.

Surface temperature	Area in Km ²	Percentage	Weighted value
294.32 - 296.61	749.36	26.03	1
296.62 - 298.28	659.8 2	22.91	2
298.29 - 299.5	380.49	13.22	3
299.51 - 300.39	442.16	15.36	4
300.4 - 301.04	647.12	22.48	5

The surface temperature was determined using data obtained from Geovanni during the summer season using an average of 10 years. Data transformed with the help of applying the method of data conversion, and it carried out interpolation using IDW. the data were categorized using the natural breaks approach.



Surface air Temperature:

Climate change exacerbates the conditions conducive to ideal fire situations. Lower precipitation and increasing air temperatures contribute to the drying of forests and vegetation (Abatzoglou & Williams, 2016). The surface air temperature, often measured 2 meters above the ground surface, is a crucial indicator of these temperature changes and their impact on fire risk.

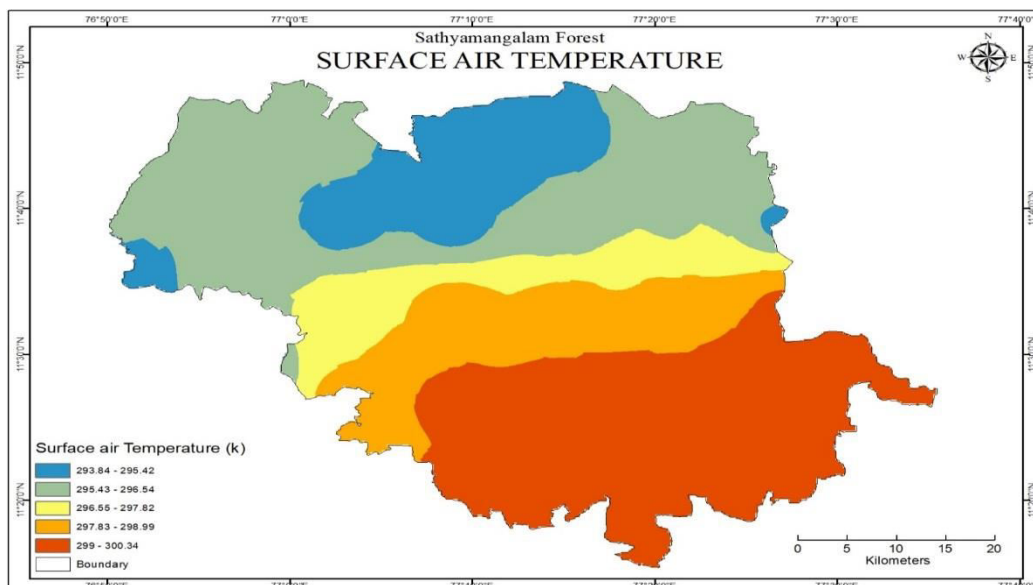
Data downloaded from Geovanni 4.7 (FLDAS NOAA01 C GL M v001) data set, spatial resolution (0.01*0.01 degree), 10 years (2011 - 2021). The surface air temperature is recorded in kelvins, with values ranging from 293.84 to 300.34.

Data processed with using the conversion method and it performed interpolation of IDW. Data classified in the method of Natural breaks to understand spatial distribution in the study area. Surface and surface air temperature variations are similar in terms of spatial variation. Significant temperature changes have been seen, particularly in mountainous areas. The southern part of the study area is plain terrain, and human habitations are densely clustered here. As a result, the temperature in this location is 5 degrees higher than in the forest.

Surface air Temperature (k)	Area in Km ²	Percentage	Weight
293.84 - 295.42	394.4922	13.70551	5
295.43 - 296.54	869.8173	30.21933	4
296.55 - 297.82	280.6834	9.734174	3
297.83 - 298.99	421.2682	14.63576	2
299 - 300.34	912.5866	31.70523	1

The above represents the weightage forest fire vulnerability of different areas based on surface air temperature levels. The table categorizes the areas based on specific temperature ranges and assigns them a weightage ranging from 1 to 5, with 1 being the least vulnerable and 5 being the most vulnerable. The percentage column represents the proportion of the total area that falls within each temperature range.

The area with a surface air temperature range of 299-300.34 K have the highest percentage of 31.70% and the lowest weight of 1. This implies that these areas are the least vulnerable to forest fires since high surface air temperature levels reduce the risk of fire occurrence. Conversely, areas with a surface air temperature range of 293.84-295.42 K have the highest weight of 5, indicating that they are the most vulnerable to forest fires due to low surface air temperature levels. Overall, the table indicates that surface air temperature is a critical factor in determining the vulnerability of a forest to fires. Areas with higher surface air temperatures are less vulnerable to fires, while those with lower temperatures are more vulnerable. Therefore, monitoring and maintaining surface air temperature levels within a safe range could be a useful strategy for reducing forest fire risk. Additionally, the weightage assigned to each temperature range could be used to prioritize resources for fire prevention and management efforts in the most vulnerable areas.





Humidity:

Humidity is defined as the ratio of moisture in the air to the moisture required to saturate the air at the same temperature and pressure (Scott, 1998). This concept is crucial in the context of forest fire behavior, as dead forest fuels and the surrounding air continually exchange moisture. When humidity levels are low, these fuels tend to absorb moisture from the air, and conversely, when humidity is high, the fuels release moisture into the air. Light fuels, such as grass and pine needles, display rapid absorption and loss of moisture in response to humidity fluctuations, rendering them highly sensitive to environmental conditions. Consequently, when humidity decreases, fire behavior intensifies due to the rapid drying of fine fuels. In contrast, heavy fuels exhibit a slower response to changes in humidity. Substantial increases in heavy fuel moisture typically necessitate significant moisture inputs, often derived from precipitation events (Albini, 1979).

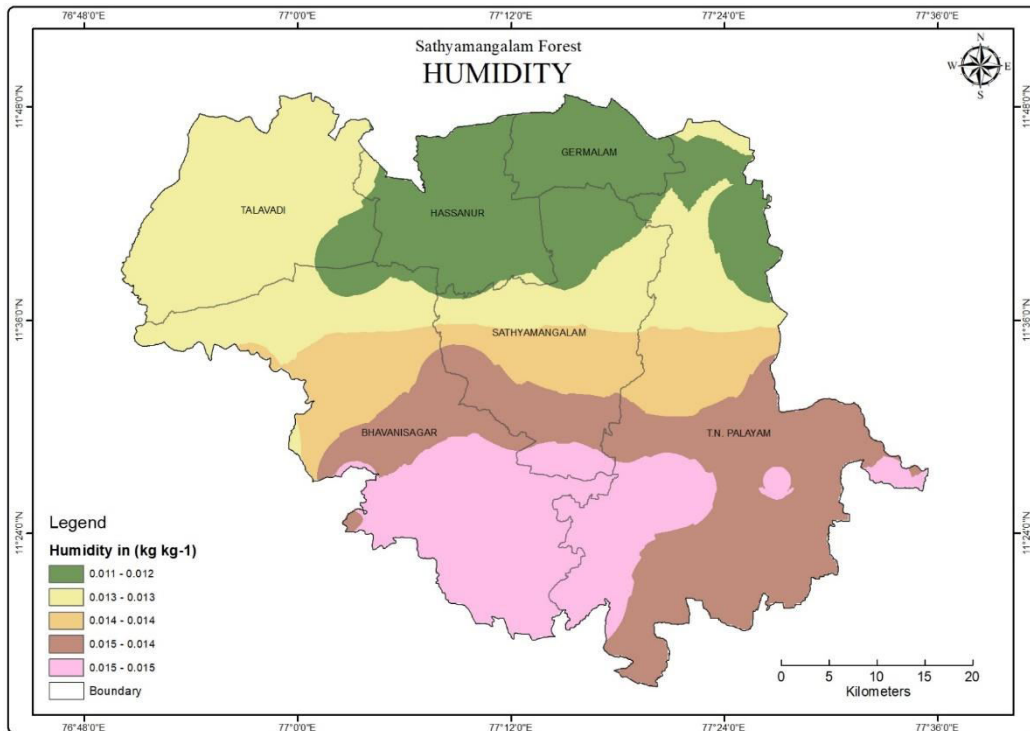
Humidity (kg kg-1)	Area	Percentage	Weight
0.011 - 0.012	478.9	16.64	5
0.012 - 0.013	790.36	27.46	4
0.013 - 0.014	240.88	8.37	3
0.014 - 0.015	379.81	13.2	2
0.015 - 0.016	988.4	34.34	1

Precipitation has a direct influence on fire prevention since moisture reduces the probability of a wildfire spreading. When the air gets saturated with moisture, the moisture is released in the form of rain. Rain and other precipitation increase the quantity of moisture in fuels, preventing possible wildfires. The northern portion of the study area has a lower vulnerability to fire than the southern part of the study area. Because a large portion of the northern part of the study area is covered by a dense forest canopy, relative humidity is increasing in the northern part of the study area. Data downloaded from Geovanni 4.7 (FLDAS_NOAH001_G_CA_D v001) data set with the resolution of (0.01*0.01 degree) spatial resolution 10 years (2011 - 2021)., The measurement for humidity is the amount of water or moisture present in one kilogram of air.

the weightage forest fire vulnerability of different areas based on humidity levels. The humidity is measured in kg kg-1, and the areas are categorized based on specific humidity ranges. The weight column represents the importance or significance of each range in determining the vulnerability of the forest to fire.

Humidity range of 0.015-0.016 kg kg-1 have the highest percentage of 34.34% and the lowest weight of 1. This means that these areas are the least vulnerable to forest fires as the high humidity levels reduce the risk of fire occurrence. Conversely, areas with a humidity range of 0.011-0.012 kg kg-1 have the highest weight of 5, indicating that they are the most vulnerable to forest fires due to low humidity levels.

Based on the result data shows that humidity levels play a crucial role in determining the vulnerability of forests to fires. The lower the humidity, the higher the vulnerability, and the higher the weightage assigned to that category. Therefore, monitoring and maintaining humidity levels within a safe range could be a useful strategy for reducing forest fire risk.



Proximity to human habituated area:

Due to the high mobility of houses and people around the village, there is some chance of wildfires. Wildfires can occur when various ignition sources, such as naked flames, cigarettes, electric sparks, vehicles, or other potential sources of ignition, come into contact with flammable materials (Moritz et al., 2014).

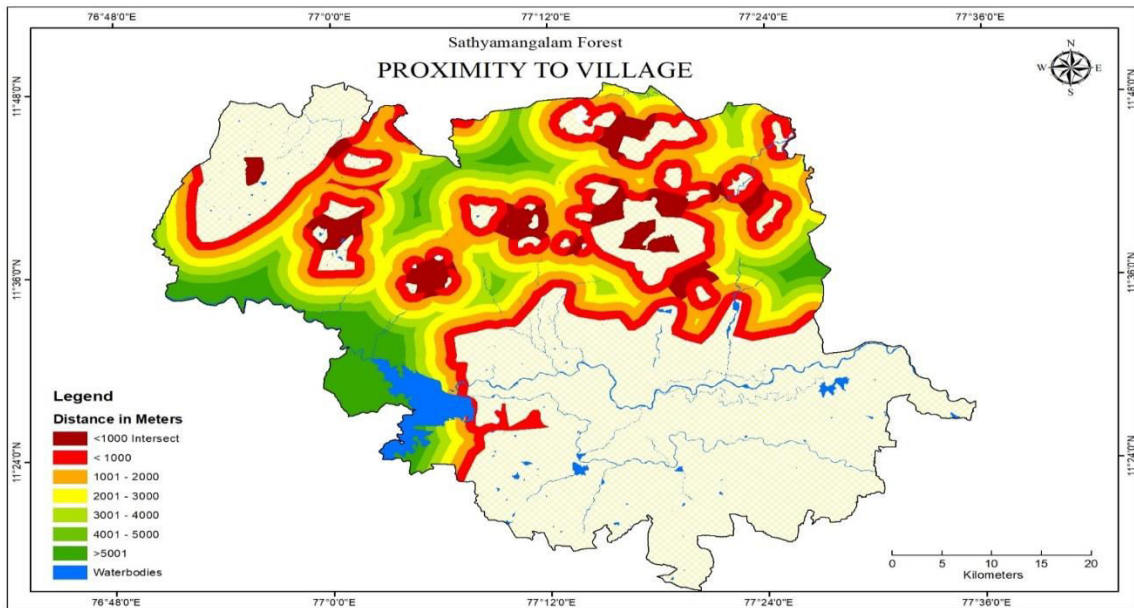
Proximity (in meters)	AREA	percent	weight
< 1000 Intersect	125.06	8.31	5
< 1000	338.23	22.47	4
1001 - 2000	346.46	23.02	4
2001 - 3000	259.65	17.25	3
3001 - 4000	169.65	11.27	2
4001 - 5000	110.73	7.35	1
> 5001	154.84	10.29	1

The above given table proximity analysis done with the distance high class is defined that where the buffer intersect in near village has assigned higher risk. Accordingly, buffer area created with the 1000-meter interval. This proximity has been calculated from the edges of the human habituated area.

The table represents the weightage forest fire vulnerability of different areas based on the proximity of settlements to the forest. Forest fires can have a significant impact on settlements and communities located near or adjacent to forests. The distance of these settlements from the forest is an important factor in determining their vulnerability to fires.

the areas based on specific proximity ranges and assigns them a weightage ranging from 1 to 5, with 1 being the least vulnerable and 5 being the most vulnerable. The percentage column represents the proportion of the total area that falls within each proximity range.

Based on the data, areas located within 1000 meters of settlements have the highest weight of 5, indicating that they are the most vulnerable to forest fires. This vulnerability decreases as the distance from the settlements increases, with areas beyond 5001 meters having the lowest weight of 1, suggesting that they are the least vulnerable to forest fires.



The data shows that human habituated areas have the highest percentage of 47.73% and the low weighted value of 1, indicating that they are the least vulnerable to forest fires. This is likely due to the presence of infrastructure and resources that can be used to prevent and manage fires in these areas.

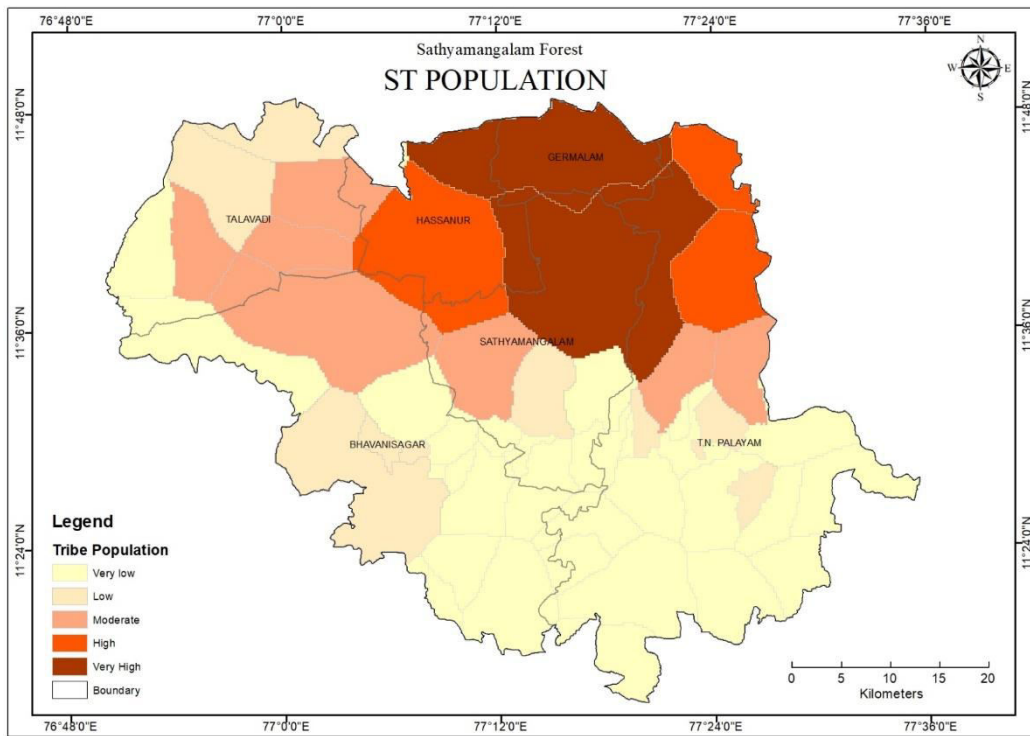
It is a critical factor in determining the vulnerability of a forest to fires, with areas closer to settlements being more vulnerable than those further away. The weightage assigned to each proximity range could be used to prioritize resources for fire prevention and management efforts in the most vulnerable areas. The data on human habituated areas could be used to inform policies and strategies intended at reducing the impact of forest fires on communities and settlements located near forests.

Population:

In this study, the local population is recognized as one of the most influential factors affecting forest fires (Bowman et al., 2017; Mistry et al., 2016). Given that the study area encompasses a protected forest and Tiger reserve with restricted access to outsiders, the focus here is on extracting the Scheduled Caste and Scheduled Tribe (SCST) population data independently to assess the level of fire susceptibility.

. As one of the critical parameters, the Scheduled Tribe (ST) population is ascertained based on the 2011 census data, classifying it into five distinct categories ranging from "very high" to "very low."

Population density Class	Area in km ²	Percentage	Weightage
Very low	1141.76	39.66	1
Low	410.53	14.26	2
Moderate	526.85	18.30	3
High	313.61	10.89	4
Very High	486.17	16.89	5
	2878.9	100	



The villages of Gudiyatham and Thingalur have the highest population density in a zone of extremely high susceptibility. followed by the villages of Hasannur, Kothampalayam, and Gundri, which have a greater level of risk. The population density is lower in the Thalamalai, Neithal puram, Iggalore, and Chikarampalayam villages, which are located in the northwestern and southern forest regions. In the southern half of the forest are villages with a low Vulnerability.

The highest population considered high prone and lower population is considered low prone area. in this regard numerical weightage is assigned accordingly 1 to 5 respectively low to high in five classes.

IV. AHP ANALYSIS

In Analytic Hierarchy Process (AHP) analysis, the calculation of priorities involves two key components: row averages and original judgments. Row averages are computed by taking the average of the values within each row of the pairwise comparison matrix, representing the relative importance of each criterion or factor in relation to others. These row averages offer insights into the initial prioritization of the criteria. The original judgments, on the other hand, represent the pairwise comparisons made by experts or decision-makers to establish the relative importance of criteria or alternatives.

Pairwise comparisons table as Normalised Matrix

S.N	Item Description	1	2	3	4	5	6	7	8	9	10	11
1	Slope	1.0	3.0	2.0	4.00	5.00	6.00	7.00	8.00	9.00	8.00	1.00
2	Elevation	0.3	1.0	0.5	3.00	4.00	5.00	6.00	7.00	8.00	9.00	9.00
3	Surface Temperature	0.5	2.0	1.0	4.00	5.00	6.00	7.00	8.00	9.00	9.00	8.00
4	Topographic wetness index	0.2	0.3	0.2	1.00	2.00	3.00	4.00	5.00	6.00	7.00	8.00
5	Vegetation types - Fuel type	0.2	0.2	0.2	0.50	1.00	2.00	3.00	4.00	5.00	6.00	7.00
6	Forest canopy density	0.1	0.2	0.1	0.33	0.50	1.00	2.00	3.00	4.00	5.00	6.00
7	Relative relief	0.1	0.1	0.1	0.25	0.33	0.50	1.00	2.00	3.00	4.00	5.00



8	Surface air Temperature	0.1	0.1	0.1	0.20	0.25	0.33	0.50	1.00	2.00	3.00	4.00
9	Humidity	0.1	0.1	0.1	0.17	0.20	0.25	0.33	0.50	1.00	2.00	3.00
10	Distance to the human	0.1	0.1	0.1	0.14	0.17	0.20	0.25	0.50	0.50	1.00	2.00
11	Population	1.0	0.1	0.1	0.13	0.14	0.17	0.20	0.25	0.33	0.50	1.00
12	sum	3.9	7.4	4.7	13.7	18.5	24.4	31.2	39.2	47.8	54.5	54.0

Calculation of priorities: row averages & original judgments and priorities

The provided table represents a pairwise comparison matrix used in the Analytic Hierarchy Process (AHP), a systematic decision-making technique applied to assess the relative importance of various factors in the context of forest fire risk analysis. Each row and column in the matrix correspond to a specific factor associated with forest fire risk, with values within the matrix indicating the relative significance or preference of one factor over another. Values greater than 1.00 signify a preference for the factor in the row over the one in the column, while 1.00 suggests equal importance.

S.No	Item Description	1	2	3	4	5	6	7	8	9	10	11	1
1	Slope	0.25	0.40	0.42	0.29	0.27	0.25	0.22	0.20	0.19	0.15	0.12	0.08
2	Elevation	0.08	0.13	0.11	0.22	0.22	0.20	0.19	0.18	0.17	0.17	0.17	0.17
3	Surface Temperature	0.13	0.27	0.21	0.29	0.27	0.25	0.22	0.20	0.19	0.17	0.15	0.12
4	Topographic wetness index	0.06	0.04	0.05	0.07	0.11	0.12	0.13	0.13	0.13	0.13	0.13	0.09
5	Vegetation types - Fuel type	0.05	0.03	0.04	0.04	0.05	0.08	0.10	0.10	0.10	0.10	0.10	0.07
6	Forest canopy density	0.04	0.03	0.04	0.02	0.03	0.04	0.06	0.08	0.08	0.09	0.11	0.05
7	Relative relief	0.04	0.02	0.03	0.02	0.02	0.02	0.03	0.05	0.06	0.07	0.09	0.03
8	Surface air Temperature	0.03	0.02	0.03	0.01	0.01	0.01	0.02	0.03	0.04	0.06	0.07	0.02
9	Humidity	0.03	0.02	0.02	0.01	0.01	0.01	0.01	0.01	0.02	0.04	0.06	0.02
10	Distance to the human habituated area	0.03	0.01	0.02	0.01	0.01	0.01	0.01	0.01	0.01	0.02	0.04	0.05
11	Population	0.25	0.01	0.03	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.02	1.62

These judgments are typically converted into a consistent set of priorities using mathematical techniques like the eigenvector method. Together, the row averages and original judgments contribute to the final priority scores, aiding in decision-making processes by offering a systematic and informed way to rank and assess criteria within the AHP framework.

CI and CR worksheet:

The calculation of priorities through row averages and original judgments, the Consistency Index (CI) and the Consistency Ratio (CR) worksheet play a crucial role in evaluating the consistency of the decision-making process. The below table pairwise comparisons are, with lower values indicating greater consistency. The CR, which is derived by comparing the CI to a predefined threshold, helps assess the reliability of the decision matrix.

S.No	Item Description	1	2	3	4	5	6	7	8	9	10	11	W-SUM
1	Slope	0.070	0.413	0.095	0.027	4.029	0.011	0.007	0.005	0.003	0.139	0.030	4.831
2	Elevation	0.023	1.240	0.024	0.021	3.224	0.010	0.006	0.004	0.003	0.157	0.270	4.980
3	Surface Temperature	0.035	0.620	0.048	0.027	4.029	0.011	0.007	0.005	0.003	0.157	0.240	5.182
4	Topographic wetness index	0.017	3.720	0.012	0.007	1.612	0.006	0.004	0.003	0.002	0.122	0.240	5.744
5	Vegetation types - Fuel type	0.014	4.959	0.010	0.003	0.806	0.004	0.003	0.002	0.002	0.104	0.210	6.117
6	Forest canopy density	0.012	6.199	0.008	0.002	0.403	0.002	0.002	0.002	0.001	0.087	0.180	6.898
7	Relative relief	0.010	7.439	0.007	0.002	0.269	0.001	0.001	0.001	0.001	0.070	0.150	7.950
8	Surface air Temperature	0.009	8.679	0.006	0.001	0.201	0.001	0.001	0.001	0.001	0.052	0.120	9.071
9	Humidity	0.009	9.919	0.005	0.001	0.161	0.000	0.000	0.000	0.000	0.035	0.090	10.221
10	Distance to the human habituated area	0.009	11.159	0.005	0.001	0.134	0.000	0.000	0.000	0.000	0.017	0.060	11.386
11	Population	0.070	11.159	0.006	0.001	0.115	0.000	0.000	0.000	0.000	0.009	0.030	11.390

A lower CR suggests a more consistent set of judgments, enhancing the overall robustness of the AHP analysis. These tools ensure that the decision-making process aligns with rational and consistent criteria, ultimately leading to more effective and reliable decision outcomes.

Saaty's CIr values	Random Consistency (CIr)	Weighted Sum	Priority	Result
1	0	4.83	0.28	17.39
2	0	4.98	0.17	29.88
3	0.58	5.18	0.23	23.00
4	0.90	5.74	0.09	61.22
5	1.12	6.12	0.07	91.66
6	1.24	6.90	0.05	147.75
7	1.32	7.95	0.03	246.01
8	1.41	9.07	0.02	404.05
9	1.45	10.22	0.05	206.89
10	1.49	11.386	0.95	12.01
		11.390	1.62	7.04

The above table saaty CI value and Random consistency index for to analyse the priority and result from the below given formula

$C.I. = (\lambda_{max} - n) / (n - 1)$	Count	9
	lambda max	10.44
	CI	0.144991
	CR	0.1
	constant	1.45



The result of AHP Result table provided offers insights into the consistency of pairwise comparisons conducted using the Analytic Hierarchy Process (AHP), a valuable technique for multi-criteria decision-making. It reveals that there are a total of 9 criteria being compared, and the lambda max, which signifies the maximum eigenvalue of the matrix, is determined to be 10.44. A key indicator of the reliability of these comparisons, the Consistency Index (CI), stands at 0.144991, implying a degree of consistency in the judgments made. The Consistency Ratio (CR), often used to assess the acceptability of consistency, is measured at 0.10, indicating that the level of consistency in the comparisons is generally acceptable. These results suggest that the pairwise comparisons in this AHP analysis exhibit a reasonable level of consistency, making them reliable for further decision-making processes.

Analysis of weighted sum:

The Weighted Sum Process (WSP) is indeed a multi-criterion decision-making method used to assess various factors and determine the optimal parameter based on their relative importance in multiple criteria (Saati et al., 2008; Mardani et al., 2015). This approach involves assigning weights to each criterion to reflect their significance and aggregating the criteria to make informed decisions or evaluations. The weighted value assigned to each criterion is derived from the Analytic Hierarchy Process (AHP) Worksheet, reflecting their significance in the decision-making process (Saati et al., 2008; Mardani et al., 2015).

Description	Selected factors (Resampled Raster with value field)	Weight
Topography	Slope	1.43
	Elevation	0.14
	Relative relief	1.25
	Topographic wetness index	0.26
Land cover	Vegetation types - fuel type	1.96
	Forest canopy density	1.03
Climate	Surface Temperature	2.65
	Surface air Temperature	0.51
	Humidity	0.31
Social	Distance to the human habituated area	3.52
	Population	0.36

Before using the weighted sum tool to combine the raster the input raster has been assigned different weights to each respectively.

In the weighted sum tool to use a scaled raster that has been resampled with the same pixel and a value assigned using the reclassification approach in terms of 1 to 5, with 1 being the least important and 5 being the most important. According to the weighted sum analysis the input which can be any positive or negative decimal value then output result will be floating value. So that for assigning weighted sum is done with based on the saaty scale 1977.

For evaluation of satty scale pairwise comparison method has been used to derive weighted sum value to apply weighted overlay analysis.

Forest fire Risk:

The land use, elevation, slope, aspect, temperature, relative humidity, and wind force that are carried out are all characteristics that might increase the likelihood of a forest fire. In order to accurately portray the danger posed by forest fires in the area, the hazard identification map was created by combining eleven different forest fire risk criteria and then performing map weighted overlay analysis. The areas shown in red represent the highest risk, whilst the areas denoted in yellow is moderate level of risk and green represent the lowest probability of risk. Forest fires are a natural phenomenon and play an important role in maintaining the health and diversity of ecosystems. However, when they occur too frequently or with too much intensity, they can cause widespread damage and have lasting effects on the environment.

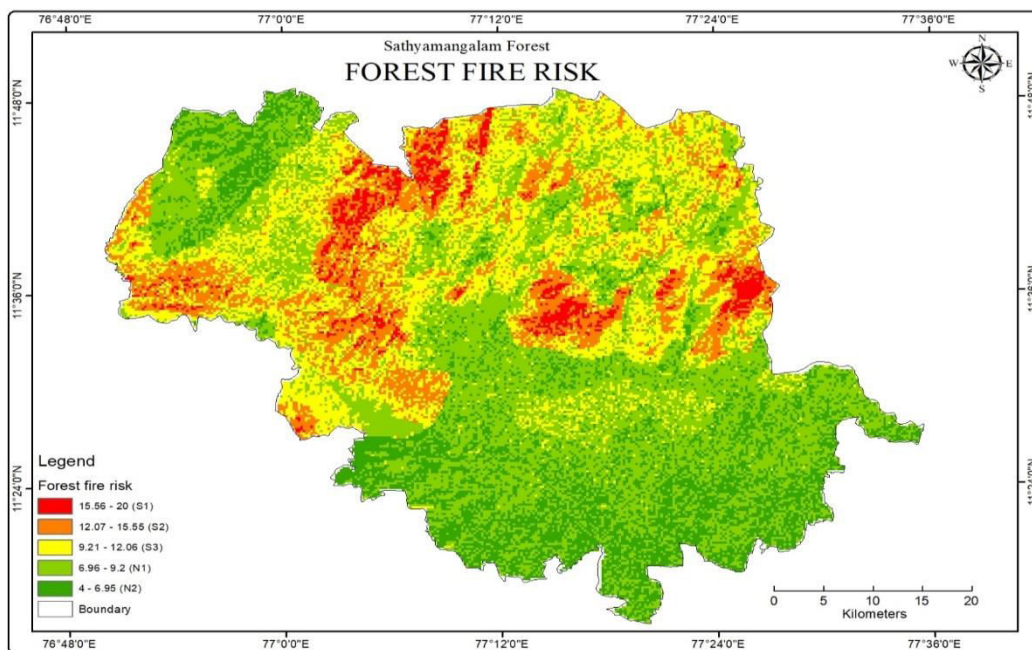
The result shows that forest fires in the Moderate class have caused the most damage in terms of area affected, with 571.35 square kilometres, accounting for 40.35% of the total area affected by forest fires. This suggests that fires in this class are more frequent and/or more severe than fires in the other classes. The Moderate class may be associated with environmental conditions, such as high temperatures, dry weather, or low humidity, that make it more prone to fires.

Forest fire Classes	Area in Km ²	Area in Percentage	fire data 2001 to 2020
Very Low	63.55	4.49	0
Low	317.89	22.45	0
Moderate	571.35	40.35	5
High	366.08	25.86	8
Very High	96.94	6.85	16
Total	1415.8	100	28

The Low and High classes follow the Moderate class closely in terms of the area affected by forest fires, accounting for 22.45% and 25.86% of the total area, respectively. This indicates that fires in these classes are also a significant issue that needs to be addressed. The Low and High classes may be associated with different environmental conditions or human activities, such as deforestation or land-use changes, that increase the risk of fires.

The Very Low and Very High classes have the smallest areas affected by forest fires, accounting for 4.49% and 6.85% of the total area, respectively. Fires in the Very Low class may not be as severe as those in the other classes, while fires in the Very High class may be less frequent, but more intense and difficult to control.

When examining with the evident that the number of past fire data available for the Low Forest fire class is only two, while the High Forest fire class has seven past fire data available. This suggests that there is a greater abundance of past fire data available for the High Forest fire class in comparison to the Low Forest fire class. As a result, the forest fire density results for the High class may be considered more reliable.

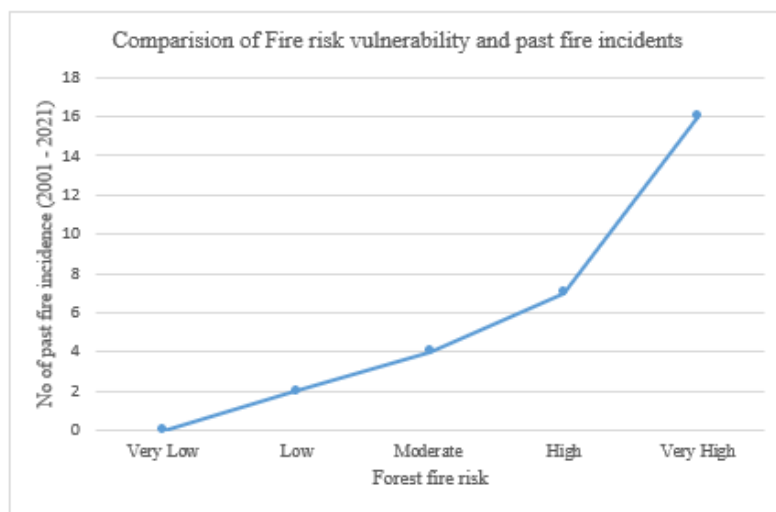


Validation with past fire incidents

Forest fire result table represents the increased number of past fire data available for the High Forest fire class may indicate a higher level of reliability for forest fire density results in that forest fire result classes mentioned.

The comparison referred to in this statement involves a comparison of forest fire classes and the number of fire incidents. The results of this comparison are presented in a graph, which displays the data in a clear and concise manner. The purpose of the graph is to show the reliability of the data that has been compared with past data.

By comparing the forest fire classes and the number of fire incidents, it is possible to gain insights into the patterns and trends that may be present in the data. This can be useful for identifying potential areas of concern, such as areas with a high incidence of forest fires, or areas that are particularly susceptible to fire.



The forest fire result compared with the past forest fire data were downloaded from Fire Information for Resource Management System (FIRMS) 2000 to 2020. Collected fire data is taken the confidence level of 80 to 100 from the data. Table no shows that number of incidents are covered in each category shows that very high area has highest number of incidents and low and very low has there is no incidents are recorded in this time

Summary:

The level of fire vulnerability in each factor, such as the type of vegetation, slope, aspect, altitude, distance from human habitation, land usage, humidity, air temperature, and surface temperature, were used to create rating classes that were incorporated in the creation of a forest fire risk map.

By assigning rating classes to each factor, experts can create a more comprehensive assessment of the overall fire risk in a particular area. These rating classes are then incorporated into the creation of a forest fire risk map, which provides a visual representation of the potential fire risk in a given location.

The forest fire risk map is typically created using evaluation classes, which are based on the combined rating classes of each individual factor. These evaluation classes may be assigned different weightages depending on the importance of each factor in contributing to the fire risk.

The creation of a forest fire risk map is an important tool for assessing and managing the risk of forest fires in a particular area. By taking into account multiple factors that can influence the likelihood and severity of a forest fire, experts can make more well-versed decisions about how to prevent and respond to forest fires, and ultimately help to protect communities, wildlife, and natural resources.

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