Forest Fire Susceptibility Mapping through Fuzzy Integration of Remote Sensing Indices, Climate Datasets and Historical Records

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ABSTRACT: Forest ecosystem is a fundamental resource which must be protected and conserved. The state of ecosystem equilibrium in the forest regions is collapsed frequently due to natural and anthropogenic induced fire events and other actions of deforestation. Bodi Reserve Forests in Theni Division (Tamil Nadu) is prone to about 100 fire events in the past decade (2010-2019) and faces ecological consequences and bio-diversity disruption. The present study tries to identify the hotspot zones of forest fire in Bodi Reserve Forests by utilizing remote sensing indices coupled with climate and forest fire database. The key factors used in this study includes terrain (elevation, aspect, slope, TWI, TPI and road proximity), meteorological (rainfall, LST, wind speed) and bio-physical (soil texture, NDVI, landcover) factors for forest fire susceptibility mapping through EVI, LST, GVI, SI and BSI. All the derived indices and datasets are integrated through fuzzy triangular membership function to tackle the problems of unequal contributions of each factor and to derive a composite index. The forest fire susceptibility index is compared with forest canopy density to observe the relationship and to understand the level of ecological destruction in Bodi Reserve Forests. The highly vulnerable zones are cross validated with the fire records and these identified zones are to be critically monitored with appropriate forest fire management strategies.

1. Introduction

Forest ecosystem is the significant natural resources that are responsible in serving life and renewable in nature which needs conservation for the sustainable environment (Zhang et al., 2019). However, forest fire is the major issue threatening the forest ecosystem around the world. It is very essential to continuous monitoring of such events in order to conserve the ecosystem and implementing better management strategies (Eugenio et al. 2016; Tian et al. 2013; pourghasemi et al., 2016). Accordingly, while evaluating the forest fire risk, monitoring the ecosystem that highly prone to fire risk is very crucial in the act of preventing its impairment (Chuvieco et al. 2010). In this case, it is most accepted thing that the man has no possibility in completely wiping out forest fire; hence its probable occurrences can be identified and monitored to reduce its intensity (Goleiji et al. 2017). Eventually, in the Western Ghats of India, markable events of forest fire are noticed in the recent times and especially in the Bodi North Reserve Forests of Theni district (Tamil Nadu). Where it is exposed to about 100 fire events in the past decade (2010-2019) and the forest fire in 2018 was wreaked havoc that lead to a death toll of nine tourists. After this hazard few studies attempted to this region and most of them extensively used remote sensing datasets as like novel studies of the past forest fire mapping (Chuvieco & Congalton 1989; Prosper-Laget et al. 1995;

Wulder & Franklin 2006). In the recent years, applications of GIS and Multi-Criteria Decision Analysis (MCDA) are widely used for analysing and mapping the regions vulnerable to forest fire events. Analytical Network Process and fuzzy logic have proved versatile methods with high accuracy to obtain the output techniques (Mosadeghi et al. 2013; Gheshlaghia et al., 2020) where its combined integration would bring influential approach to forest fire susceptibility mapping (Feizizadeh et al., 2015). Hence, in the present study, to identify vulnerable hotspot zones within the Bodi North Reserve Forests, remote sensing indices are coupled with climatic database and forest fire information. The factors influencing forest fires were analysed through fuzzy triangular membership function and compared with forest canopy density to quantify the amount of risk.

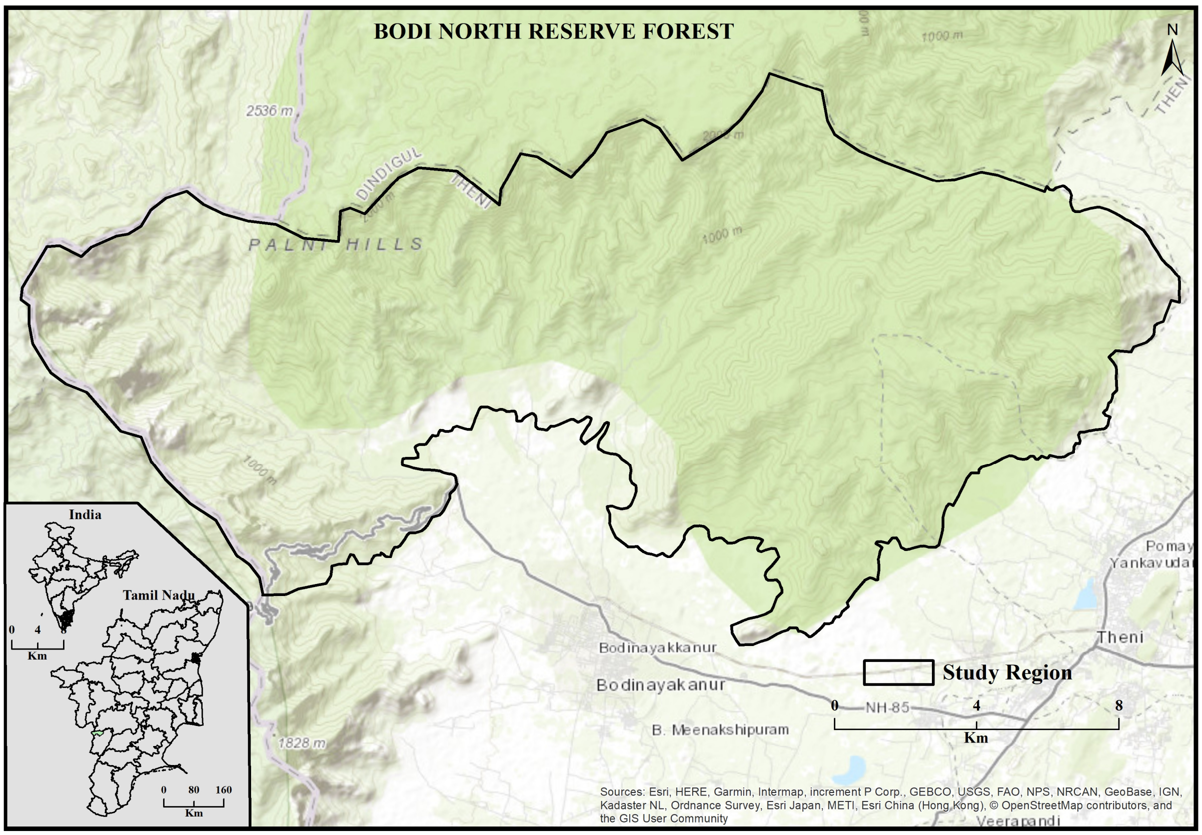

Figure 1: Study area of Bodi North reserve forest, western region of Tamil Nadu, South India

2. Study Area

Bodi North Hills Reserve Forest situated in the Western Ghats of Tamil Nadu India is selected as study region by considering frequent fire events recorded in the recent times. The selected study region is positioned in north western part of Theni district at 77º 29’57” to 77º 12’81” E longitudes and 10º 9’24” to 10º 0’39” N latitudes, bounded by Umaiyar hills reserve forest in the north, Cardamom hills reserve forest in the west, Bodinayakkanur in the south and Periyakulam in the east covering a total area of about 286 sq.km. The study region is bordered by Kottagudi, Agamalai and Bodi west hills reserve forests. The topography is rugged and the altitude anomalies ranges between 2539 and 237 m. The average temperature is 25ºC and average rainfall is 890 mm. Main river channels in the study region are Kottagudi river, Talaiyar river and Ulakkurutti river.

Major land uses are coffee, teak, silk cotton, cordamom and coconut plantations. A major road network (NH49) present in the south western tip of the study boundary.

3. Methodology

Multiple remote sensing data and ancillary datasets were utilised to compute 16 factors. The multispectral imagery of Landsat 8 OLI used to compute normalized difference vegetation index (NDVI), land surface temperature (LST), enhanced vegetation index (EVI), greenness vegetation index (GVI), bare soil index (BSI), shadow index (SI) and landcover. ALOS PALSAR DEM is used for extraction of slope, aspect, elevation, topographical wetness index (TWI) and topographical position index (TPI). Wind speed data is acquired from European global wind atlas (https://globalwindatlas.info/). SOI toposheets and google earth images are used to extract road network and monthly rainfall data is collected from the Indian meteorological department (IMD).

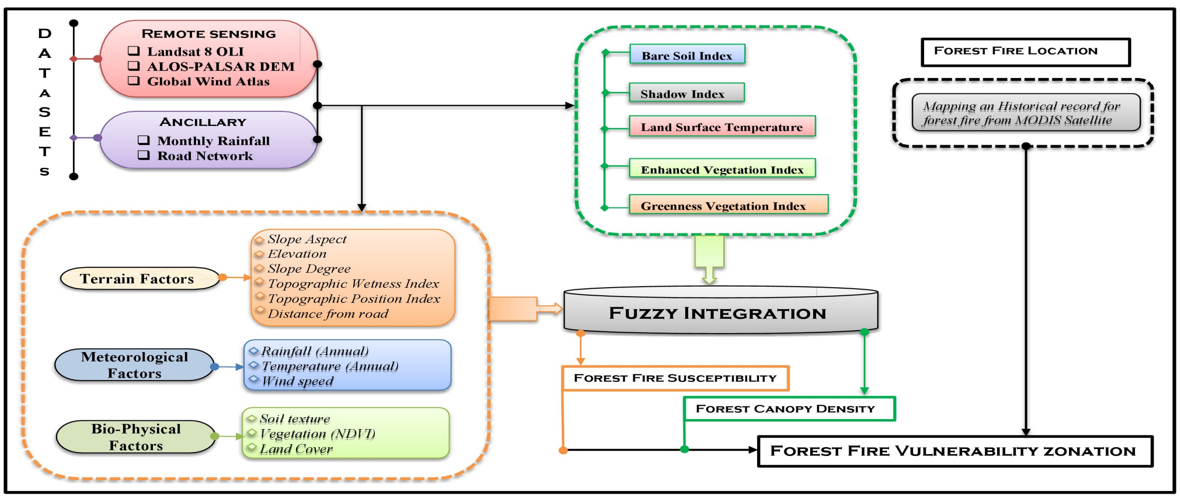

Figure 2: Methodological framework for forest fire mapping to assess the susceptibility map of forest fire and forest canopy density by utilizing remote sensing and ancillary datasets.

Based on the suggestions of past research works, Forest fire susceptibility (FFS) mapping was done with these essential terrain factors (slope, aspect, elevation, road proximity, topographical wetness index and topographical position index (Zhang et al., 2019; Venkatesh et al., 2020); meteorological (annual precipitation, annual temperature and wind speed) (Renard et al., 2012; Pourghasemi et al., 2016) and bio-physical (soil texture, normalized difference vegetation index and land cover) (Puri et al., 2011; Eugenio et al., 2016) factors. Simultaneously forest canopy density (FCD) (Sahana et al., 2015) was also mapped with five remote sensing indices such as enhanced vegetation index, greenness vegetation index, land surface temperature, bare soil index and shadow index for comparing the results. The forest fire historic data were used to validate the susceptibility map. The pairwise matrix was constructed for each sub factors and factors to assign the weights as shown in the Table 1. The factors and subfactors are individually weighted and ranked with the fuzzy triangular membership function and integrated through GIS platform to extract a composite index (FFS and FCD).

$$FFS = \sum_{i=1}^{n} \sum_{j=1}^{m} w_i \times n_j \ \& \ FCD = \sum_{j=1}^{n} w_i \times n_j \quad \text{where n \& m =1, 2,…n…………(1)}$$

The equation (1) is used to compute composite index of FFS and FCD, where the w_i is a global of i^{th} factors and n_i denotes an criteria weightage of j^{th} subfactor.

Table 1: Pairwise comparison matrix for sub criteria of FFS and FCD

Factors	Subfactors	Elevation	Aspect	Slope	TWI	TPI	Road	Global weightage (w_i)	Criteria weightage (n_j)
Terrain Factor	*Elevation*	*1*	*(1,2,3)*	*(1,2,3)*	*(3,4,5)*	*(2,3,4)*	*(4,5,6)*	0.401	0.412
	Aspect	-	*1*	*(1/3,1/2,1)*	*(1,2,3)*	*(1,2,3)*	*(2,3,4)*		0.162
	Slope	-	-	*1*	*(2,3,4)*	*(1,2,3)*	*(3,4,5)*		0.251
	TWI	-	-	-	*1*	*(1/3,1/2,1)*	*(1,2,3)*		0.048
	TPI	-	-	-	-	*1*	*(1,2,3)*		0.096
	Road	-	-	-	-	-	*1*		0.031
Meteorological Factor		***Rainfall***	***Temperature***	***Windspeed***					
	Rainfall	*1*	*(1/4,1/3,1/2)*	*(1/3,1/2,1)*	-	-	-	0.31	0.208
	Temperature	-	*1*	*(1,2,3)*	-	-	-		0.474
	Windspeed	-	-	*1*	-	-	-		0.319
Bio-Physical Factor		***Soil***	***Vegetation***	***Landcover***					
	Soil	*1*	*(1/5,1/4,1/3)*	*(1/4,1/3,1/2)*	-	-	-	0.289	0.161
	Vegetation	-	*1*	*(2,3,4)*	-	-	-		0.542
	Landcover	-	-	*1*	-	-	-		0.297
FCD	***(w_i)***	***EVI***	***GVI***	***SI***	***LST***	***BSI***			
	EVI	*1*	*(2,3,4)*	*(4,5,6)*	*(5,6,7)*	*(6,7,8)*	-		0.558
	GVI	-	*1*	*(2,3,4)*	*(4,5,6)*	*(5,6,7)*	-		0.268
	SI	-	-	*1*	*(1,2,3)*	*2,3,4)*	-		0.093
	LST	-	-	-	*1*	*(1,2,3)*	-		0.051
	BSI	-	-	-	-	*1*	-		0.030

3.2. Fuzzy Analytical Hierarchical Process (FAHP)

In this study, Fuzzy Analytical Hierarchical Process (FAHP) technique (Feizizadeh et al., 2015; Gheshlaghi et al., 2020) is adopted to derive weight and ranks for the factors and subfactors of forest fire susceptibility and forest canopy density. FAHP is one of the multi criteria decision making methods, introduced by Buckley, (1985) with integration of fuzzy set values with the AHP (Saaty, 1980). The geometric mean approaches in FAHP is employed for the study to tackle the problems of unequal contributions of each factor and subfactors. The following step describes the procedure for assigning fuzzy weightages.

In order to evaluate the individual criteria weightages and its relative importance, the pairwise comparison matrix of each criterion is constructed with the triangular fuzzy elements like eq (2). Where the values in the matrix indicating the opinions of decision maker regarding the relationship between each criterion and those value are be ranged from 1 to 9 based on the scale of relative importance (Saaty, 2008).

$$\tilde{A}_{ij} = (\tilde{a}_{ij})n \times n = \begin{pmatrix} (1,1,1) & (l_{12}, m_{12}, n_{12}) & (l_{1n}, m_{1n}, n_{1n}) \\ (l_{12}, m_{12}, n_{12})^{-1} & (1,1,1) & (l_{in}, m_{in}, n_{in}) \\ (l_{1n}, m_{1n}, n_{1n})^{-1} & (l_{in}, m_{in}, n_{in})^{-1} & (1,1,1) \end{pmatrix} \ldots\ldots\ldots\ldots\ldots\ldots (2)$$

The crisp numeric value converted into fuzzy elements through the eq (3)

$$\tilde{a}_{ij} = (l_{ij}, m_{ij}, n_{ij})^{=} \tilde{a}_{ij}^{-1} = \left(\frac{1}{n_{ij}}, \frac{1}{m_{ij}}, \frac{1}{l_{ij}}\right) \text{ where i, j=1, 2,…n and i} \neq \text{j.........(3)}$$

Fuzzy geometric mean of each criterion (a_{ij}) is determined using eq (4) (Buckley, 1985)

$$\tilde{r}_i = \left(\prod_{j=1}^{n} a_{ij}\right)^{1/n} \quad \text{Where, i= 1, 2,…..n……………………………………(4)}$$

With the equation 5, the fuzzy weightage ($\widetilde{w}_i$) for each criterion (a_{ij}) is computed

$$\tilde{w}_i = \tilde{r}_i \times \left(\tilde{r}_1 + \tilde{r}_2 + ...\tilde{r}_n\right)^{-1} \text{……………………………………………..(5)}$$

Further, the fuzzy weightage ($\widetilde{w}_i$) is de-fuzzified in crisp numeric values (w_i) through Centre of Area (COA) technique (Chou & Chang, 2008) eq (6)

$$w_i = \left(\frac{l\tilde{w}_i + m\tilde{w}_i + n\tilde{w}_i}{3}\right) \text{………………………………………………..(6)}$$

The normalization of non-fuzzy values (w_i) is done with the eq (7)

$$N_i = \frac{w_i}{\sum_{i=1}^{n} w_i} \text{……………………………………………………………(7)}$$

4. Result

4.1. Terrain Factors

Terrain factors play a key role in forest fire which includes elevation, slope, aspect, road proximity, TWI and TPI. Elevation refers to the altitudinal range, here most of the region falls under high and medium elevation, whereas the low elevation class is marked in mid portion and some parts in rim of eastern region. Steep slope is observed in high peak regions. South-east and West direction slope aspect covers the most portions. TWI, refers to the proportion of wetness, is showing low wetness in high altitude and high wetness in low altitude regions. TPI is exemplifying the position of valley, flat and ridge terrains where the results clearly show their positions in appropriate terrain with quantified values. Road proximity is analysed to quantify the risk of road activity on the natural phenomenon and is exhibiting that the western regions are at high risk when compared with the eastern regions.

4.2. Meteorological factors

Meteorological factors such as land surface temperature and wind speed (Figure 3) have immense capacity to accelerate the rate of forest fire. While surface temperature induces the fire, wind speed can intensify the spread of fire. However, the high rainfall regions are noticed with less fire accidents. The low values of LST are mainly found in the middle and north western parts whereas rest of the portions is found with a high surface temperature. Wind speed is predominantly high over the entire forest region. The highest rainfall is recorded in the north eastern portion and decreases towards the western region.

4.3. Bio-Physical Factors

Soil texture determines the amount of moisture held by the soil. The soils that quickly dries are severely prone to the fire accidents. A rock outcrop with loamy soil (class 1) is the dominant soil texture (Figure 3) and followed by clay loamy with moderately well drained soil (class 5). Similarly, a surface with more moisture content is least prone to occurrence of forest fire. In this study, Normalized Difference Vegetation Index (NDVI) measures the healthy vegetation distribution. Land cover is also a factor which determines the amount of natural vegetation in a region. The scrub land (SL) occupies a major portion which is prone to fire events; forest land (FL) is covered over high-altitude region and plantations (PL) are sparsely occupied throughout the study area.

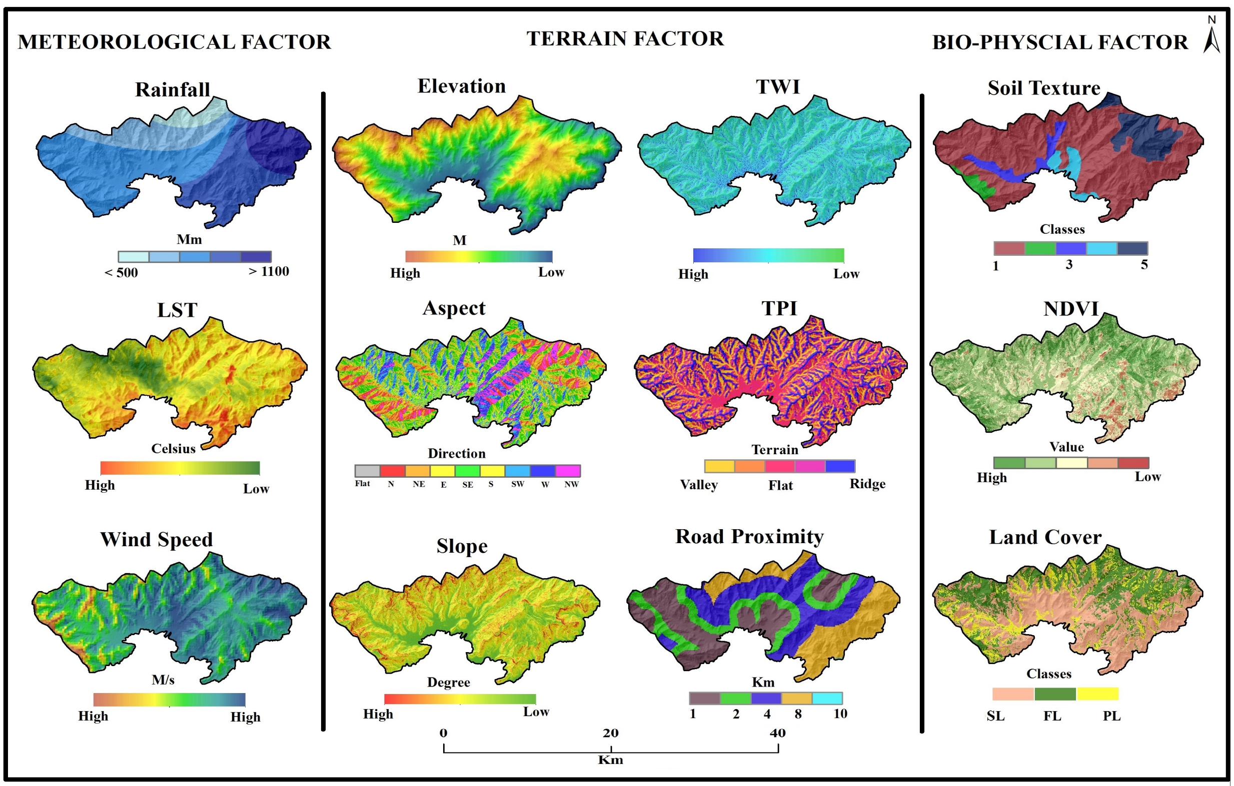

Figure 3: Spatial distribution of subfactors in forest fire susceptibility. The maps show various terrain, meteorological and bio-physical factors used for identifying forest fire susceptibility.

4.4. Forest Canopy Density (FCD)

The forest canopy is a measure of assessment of thickness of vegetation cover in a region. The forest canopy density has been estimated by integrating various indices such as Enhanced Vegetation Index, Land Surface Temperature, Greenness Vegetation Index, Shadow Index and Bare Soil Index. All the values of indices are categorised in to five classes as portrayed in the Figure 4. The EVI is high in the high-altitude region. The LST portrays the inverse phenomenon to

EVI, where most of the high-altitude region, especially the western portions, are exhibiting lower temperature. The values of GVI are consistent with the values of EVI with the minor variations. Shadow index is showing higher values throughout the study region except in the middle portions. The BSI is predominantly high in the middle and low altitude region. The integration of these indices shows that forest canopy density is very high throughout the study area especially in the northern uplands. The very low classes are concentrated in the middle low land portions of the study area.

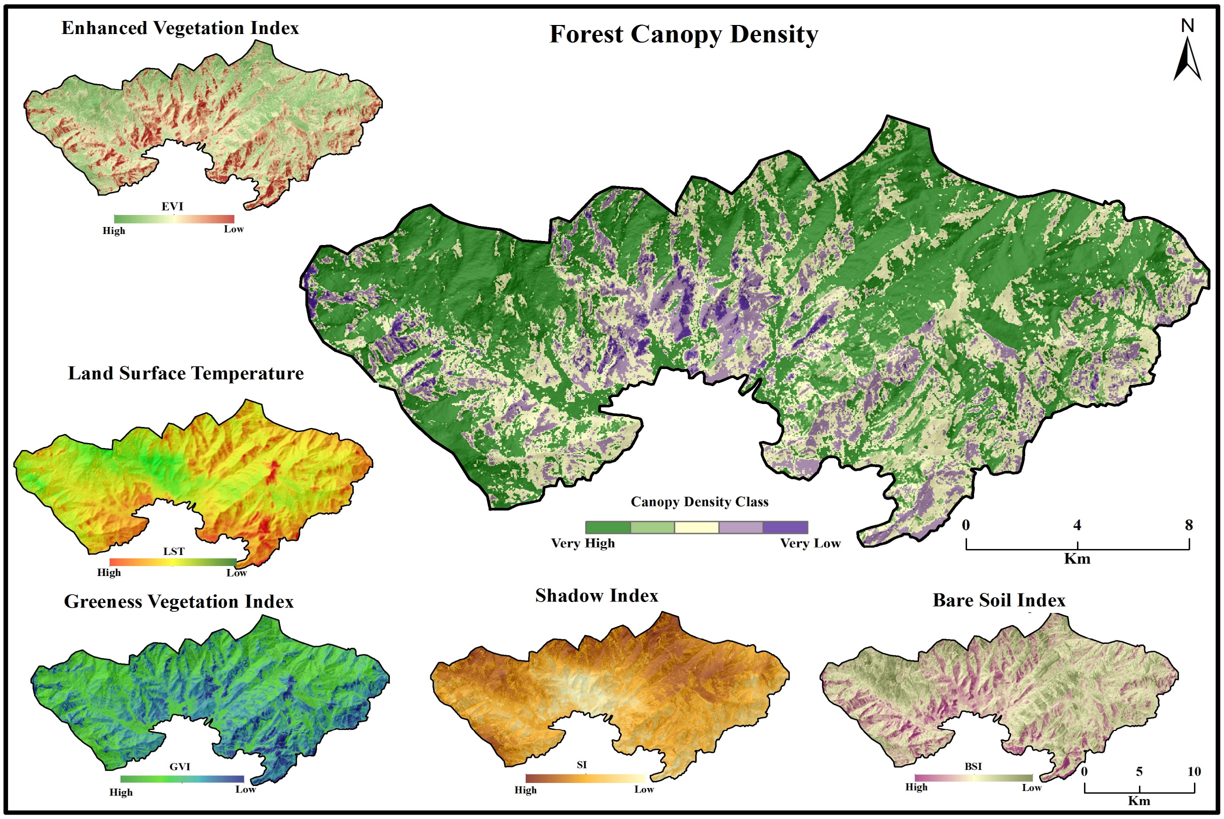

Figure 4: Spatial distribution of forest canopy density and its determining factors

5. Discussion

Forest fire susceptibility for the Bodi reserve forest region is segregated with the composite values acquired from the key factors such as the meteorological, terrain and bio-physical factors. The susceptibility of the forest fire is distinguished in five classes as very high, high, medium, low and very low as shown in the Figure 5. The very high classes are dominant in the highly elevated region and especially in the mid-eastern part of Bodi reserve forest where it is highly intensified. The high to medium class are mostly bordering the very high in every part of the study region and the low and very low class is distributed in the flat and low elevated regions.

Terrain factors are presenting very high classes, predominant over the elevated region (Figure 5), because of very low TWI (inverse relationship), high degree of slope and aspect direction (direct relationship). This imposing the complete dominant effect of terrain influence in the forest fire susceptibility, where the high vulnerable classes are distributed in elevated regions. Meteorological factors are exposing high class in the north eastern and mid portions of the study region as the LST is showing high values in the north eastern portion and wind speed is recorded high in the mid-portion, where the rainfall is exhibiting moderate class. As these meteorological factors are also intensifying high classes in the north eastern portion. It effects the susceptibility of high forest fire in the mid-eastern and north eastern portions. Bio-physical factors are mostly showing low class throughout the study site, where the high class is dominant over the north eastern, north western and south western regions. This is because of the extensive forest cover and healthy vegetation cover over the mentioned region. However, it is influencing the high forest fire susceptibility in the north western region of the study area.

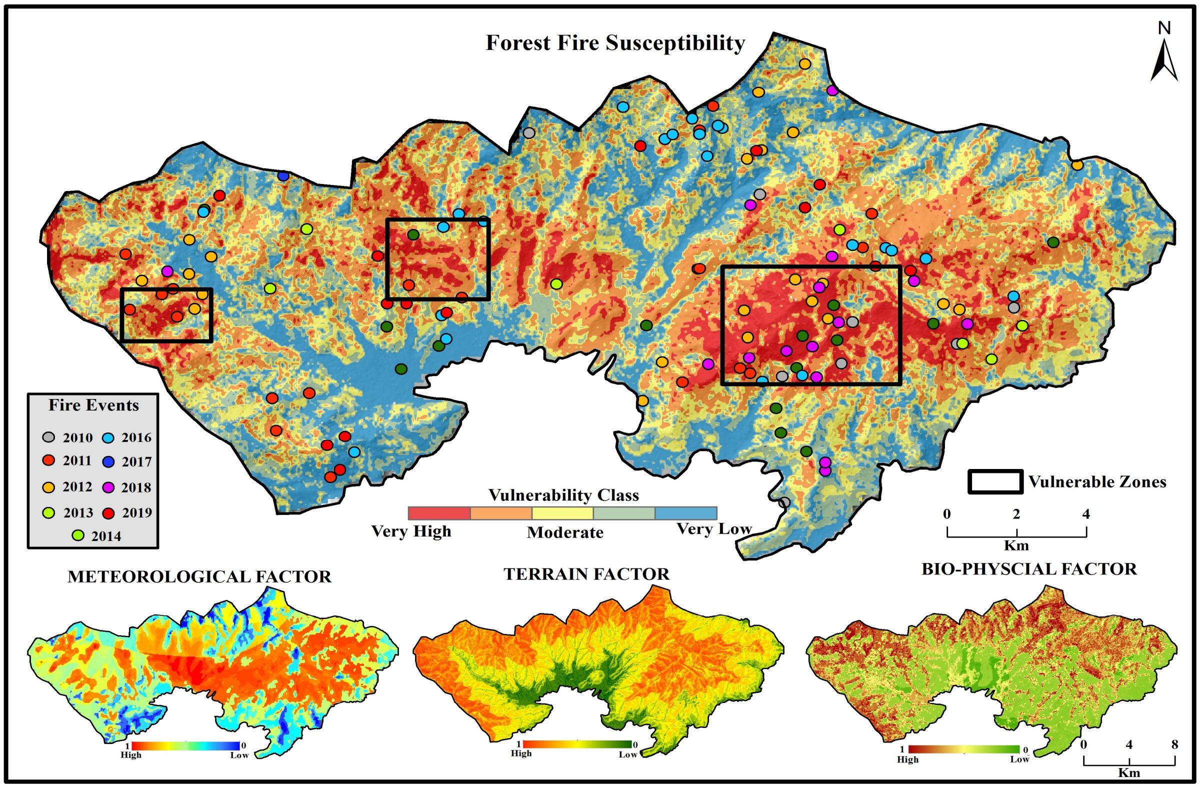

Figure 5: Forest fire susceptibility, its factors, Historical fire events and Vulnerable zones

The study also tries to compare and observe the relationship between forest fire susceptibility and the forest canopy density. It is identified that considerable extent of high canopy cover regions are exhibiting high susceptibility to forest fire. About 35 sq.km. area of high dense canopy covers out of 140 sq.km. area is susceptible to forest fire risks. However, in general, FFS and FCD exhibiting an uneven relation (Table 2).

The validation of forest fire susceptibility zones with historic fire events (2010 and 2019) show that most of the recent forest fire events are distributed well within the high susceptible zones. Based on the coincidence of present zonation and historic events, the hotspot region for forest fire is demarcated (Figure 5). The integration of all the results shows that the eastern part of Bodi reserve forest is highly vulnerable zone for forest fire.

Table 2: Geographical area of FCD and FFS classes

Classes	FCD		FFS	
	Pixel Count	*Area (Km^2)*	*Pixel Count*	*Area (Km^2)*
Very High	*156636*	*140.97*	*40175*	*36.16*
High	*16320*	*14.69*	*85838*	*77.25*
Moderate	*99736*	*89.76*	*66603*	*59.94*
Low	*39996*	*36.00*	*63264*	*56.94*
Very Low	*5316*	*4.78*	*62147*	*55.93*

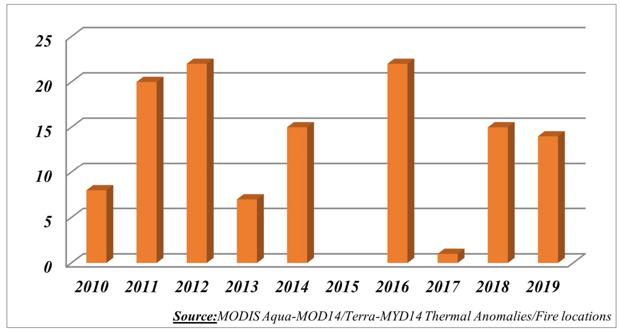

Figure 6: Forest fire events in the study area during 2010-2019

6. Conclusion

Forest ecosystem is encountered with the extreme fire events due to the global warming and extreme anomalies in climatic signs. Although its occurrences could not be wiped out with the human efforts, its intensity and effects can be reduced with the proper zonation and continuous monitoring. Hence, in the present study, forest fire susceptibility mapping of Bodi reserve forest region is attempted by utilizing remote sensing indices through fuzzy triangular membership function using GIS. The results representing that the moderate elevated region with high LST and low wetness is exhibiting high forest fire risk. These regions are also coinciding with the moderate to high forest canopy density which amounting to greater risks. The comparison of decadal forest fire records and composite forest fire index confirms that the exercised approach is very valid for forest fire susceptibility zonation. The identified hotspots of forest fire are to be critically monitored to mitigate the intensity of forest fire in future. The outcome of the study can be utilized to implement suitable planning measures and sustainable use of forest resources.

Reference

1. Buckley, J, J., 1985. Fuzzy hierarchical analysis. Fuzzy Sets and Systems, 17(3), pp.233-47. https://doi.org/10.1016/0165-0114(85)90090-9
2. Chou, S, W., & Chang, Y, C., 2008. The implementation factors that influence the ERP (enterprise resource planning) benefits. Decision Support Systems, 46(1), pp, 149-157. https://doi.org/10.1016/j.dss.2008.06.003
3. Chuvieco, E., Aguado, I., Yebra, M., Nieto, H., Salas, J., Martín, MP., Vilar, L., Martínez, J., Martín, S., Ibarra, P., Riva, J., Baeza, J., Rodríguez, F., Molina, J, R., Herrera, M, A., Zamora, R., 2010. Development of a framework for fire risk assessment using remote sensing and geographic information system technologies. Ecological Modelling, 221(1), pp. 46–58. https://doi.org/10.1016/J.ECOLMODEL.2008.11.017
4. Chuvieco, E., & Congalton, R, G., 1989. Application of remote sensing and geographic information systems to forest fire hazard mapping. Remote Sensing of Environment. 29, pp.147-159. https://doi.org/10.1016/0034-4257(89)90023-0
5. Eugenio, F, C., dos Santos, A, R., Fiedler, N, C., Ribeiro, G, A., da Silva, A, G., dos Santos, Á, B., Paneto, G, G., & Schettino, V, R., 2016. Applying GIS to develop a model for forest fire

risk: A case study in Espírito Santo, Brazil. Journal of environmental management, 173, pp. 65–71. https://doi.org/10.1016/j.jenvman.2016.02.021

6. Feizizadeh, B., Omrani, K., and Aghdam, F, B., 2015. Fuzzy Analytical Hierarchical Process and Spatially Explicit Uncertainty Analysis Approach for Multiple Forest Fire Risk. Journal for Geographic Information Science, 3, pp. 72-80. https://doi.org/10.1553/giscience2015s72
7. Gheshlaghi, H, A., Feizizadeh, B., & Blaschke, T., 2020. GIS-based forest fire risk mapping using the analytical network process and fuzzy logic, Journal of Environmental Planning and Management, 63, pp. 481-499. https://doi.org/10.1080/09640568.2019.1594726
8. Goleiji, E., Hosseini, S, M., Khorasani, N., & Monavari, S, M., 2017. Forest fire risk assessment-an integrated approach based on multicriteria evaluation. Environmental Monitoring and Assessment. 189, pp. 1-99. https://doi.org/10.1007/s10661-017-6225-7
9. Mosadeghi, R., Warnken, J., Tomlinson, R., & Mirfenderesk, H., 2013. Uncertainty Analysis in the Application of Multi-Criteria Decision-Making Methods in Australian Strategic Environmental Decisions. Journal of Environmental Planning and Management 56 (8), pp.1097–1124. https://doi.org/10.1080/09640568.2012.717886
10. Pourghasemi, H, R., 2016. GIS-based forest fire susceptibility mapping in Iran: a comparison between evidential belief function and binary logistic regression models, Scandinavian Journal of Forest Research, 31, pp.80-98. https://doi.org/10.1080/02827581.2015.1052750
11. Prosper-Laget, V., Douguedroitl, A., Guinot, J, P., 1995. Mapping the risk of forest fire occurrence using NOAA satellite information. European Association of Advance Remote Sensing Laboratories. 4 (3-Xll), pp. 30–38.
12. Puri, K., Areendran, G., Raj, K., Mazumdar, S., & Joshi, P, K., 2011. Forest fire risk assessment in parts of Northeast India using geospatial tools. Journal of Forestry Research 22, pp.641- 647 https://doi.org/10.1007/s11676-011-0206-4
13. Renard, Q., Pélissier, R., Ramesh, B.R., & Kodandapani, N., 2012. Environmental susceptibility model for predicting forest fire occurrence in the Western Ghats of India. International Journal of Wildland Fire, 21, 368-379. https://doi.org/10.1071/WF10109
14. Saaty, T, L., 1980. The analytic hierarchy process: planning. Priority setting. Resource allocation. MacGraw-Hill, New York City, pp. 287
15. Saaty, T, L., 2008. Decision making with the analytic hierarchy process. International Journal of Services Sciences. 1, pp. 83–98. https://dx.doi.org/10.1504/IJSSCI.2008.017590
16. Sahana, M., Sajjad, H. & Ahmed, R., 2015. Assessing spatio-temporal health of forest cover using forest canopy density model and forest fragmentation approach in Sundarban reserve forest, India. Model. Earth Syst Environ. 1, pp. 1-10 https://doi.org/10.1007/s40808-015-0043-0
17. Tian, X., Zhao, F., Shu, L., & Wang, M., 2013. Distribution characteristics and the influence factors of forest fires in China. Forest Ecology and Management, 310, pp. 460-467. https://doi.org/10.1016/J.FORECO.2013.08.025
18. Venkatesh, R., Abdul Rahaman, S., Jegankumar, R., & Masilamani, P., 2020. Eco-Environmental Vulnerability Zonation In Essence Of Environmental Monitoring And Management, Int. Arch. Photogramm. Remote Sens. Spatial Inf. Sci., XLIII-B5-2020, pp. 149–155, https://doi.org/10.5194/isprs-archives-XLIII-B5-2020-149-2020
19. Wulder M, A., Franklin, S, E., 2006. Understanding forest disturbance and spatial pattern: remote sensing and GIS approaches. Boca Raton (FL): CRC Press, pp. 246.
20. Zhang, G., Wang, M., & Liu, K., 2019. Forest Fire Susceptibility Modeling Using a Convolutional Neural Network for Yunnan Province of China. Int J Disaster Risk Sci 10, pp. 386–403. https://doi.org/10.1007/s13753-019-00233-1