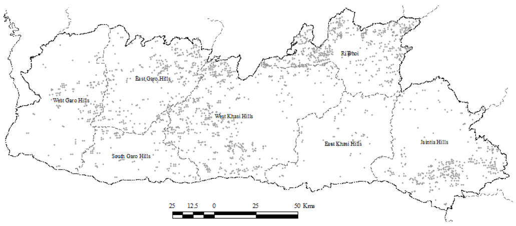
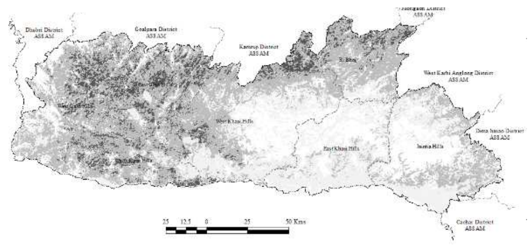
FOREST FIRE OCCURRENCE, DISTRIBUTION AND RISK MAPPING USING GEOINFORMATION TECHNOLOGY: A CASE STUDY IN THE SUB-TROPICAL FOREST OF THE MEGHALAYA, INDIA

Graphical Abstract:

Distribution of Fire points, 2021



Fire prone Map



Abstract:

The study focuses on Meghalaya, the North Eastern State of India, for forest fire occurrence, distribution, and risk mapping using the different geospatial techniques is validated using different decision-making techniques such as MCDM, Space Time Cube Analysis (STC), and Emerging Hot Spot (EHS) Analysis. The archive data of Moderate Resolution Imaging Spectroradiometer (MODIS) near real time (NRT) fire data has been considered for this study. Fire points were obtained from Fire Information for Resource Management System (FIRMS), a web service provided by NASA. Using two decadal data, a NetCDF file was created which can store four-dimensional data. Based on this NetCFD file, forest fire trend and future prospect has been foreseen. After analyzing these points, a relationship with other fire triggering factors such as Human settlement, Roads, Climate, Elevation, Slope, Aspect, Forest Type, Forest Canopy density, Soil Moisture, Wind Speed, and Forest Health has been established. Forest risk map with four classes (extreme, severe, moderate, and mild) is also generated. These results are very effective for the managers, planners, and other stakeholders for disaster management. The suggested methodology can be implemented for the preparedness of forest fire management. The policy makers must act quickly to protect the Himalayan region with the highest biodiversity by adopting focused interventions and the strategic allocation of scarce resources in effective areas.

Keywords: Forest Fire, Geospatial, MCDM, EHS, STC, FIRMS, NASA, NetCDF, MODIS, NRT, Disaster Management, Biodiversity, Fire Risk Mapping

1. Introduction

Forests are the vital global resource that humans depend on for pure air, fire wood as fuel, recreation, and many other uses. They also serve as habitats for millions of floras and fauna. Forest fire is the primary cause of deforestation worldwide. Research shows that climate change results in extremely hot and dry conditions, which is the triggering factor in rising of wildfire in different regions of earth (Yue, et al., 2013). A recent study concluded by the Forest Survey of India shows that almost 36% of the country's canopy cover is prone to fires, and of this, more than 10% are at high risk (Ghosh, et al., 2019). Forests encounter several interferences that adversely affect their health and, as a result, cannot provide goods and ecosystem services. In 2015 earth lost 98 million hectares of forest due to forest fire (Food and Agriculture Organization, 2020). Thus, persistent protection, monitoring and mapping are very crucial in fire-prone forests (Chand, et al., 2006). According to Bobsien & Hoffmann, 1998, the fire has had a massive impact on ecology, the economy, and socio-culture on a local, regional, and worldwide scale. Fire-related aerosol can raise cloud condensation nuclei concentrations in the atmosphere by order of magnitude, impacting cloud microphysics, rainfall, and atmospheric circulation (Ramanathan, et al., 2001; Andreae, et al., 2004). Many researchers, fire managers, and fire management agencies believe that due to climate change, the forest will confront increasingly challenging fire weather conditions, longer fire seasons, and large fire to a very large fires, (IUFRO, 2018; Sankey, 2018; David, et at., 2021; Jolly, et al., 2015). The significant reason that leads to forest fires is warming due to the increase in the earth's average temperature. A steep slope provokes forest fires, high summer temperatures, high wind velocity, and abundant flammable materials in the forest, all of which contribute to significant damage and widespread fire (Rothermel, 1983; Roy, 2003).

Forest fire protection and control schemes emphasize adopting modern techniques and equipment to prevent and manage forest fire incidents. Several researches suggest how satellite remote sensing can be used to map, monitor, and prevent forest fires. (Jain et al., 1996). Potić et al., 2018; Ahmad et al., 2018, found that Geospatial Analytics using GIS and Remote Sensing is a potent tool for estimating risk and trend for a forest fire. India has a geographical area of 328 million ha, of which 72 million hectares are covered by forest, accounting for 22% of the total area (FSI, Indian State of Forest Report, 2021). However, India lacks adequate data on several aspects of fire, such as the area burned, loss of ecological and economic assets, and regeneration status (Bahuguna & Singh, 2002). Forest depletion due to natural causes such as forest fires and infestations or human activities such as clear-cutting, burning, land conversion, and monitoring forest health and growth for successful commercial exploitation and conservation are the key concerns facing forest management (Bhatta, 2008). Since the adoption of the Indian Forest Act in 1927, which made the forest fire a penal offence, all forest-dependent people have been required to help prevent and manage fires. Forest fire protection was also emphasised in the National Forest Policy of 1988 (Gupta, et al., 2018)

In our research, fire influencing factors (vegetation, landscape, climate and hydrology, and human interference) were taken from various portals. The satellite images of Sentinel 2 MSI and MODIS C6.1 were processed and used in Google Earth Engine, the cloud computing platform. The thermal anomaly science quality data was collected from FIRMS, NASA.

Several studies were carried out to examine the spatiotemporal dynamics of forest fire in India and abroad. The fire prone regions or the spatial distribution were identified in different researches of Lamat, et al., 2021; Achu, et al., 2018,2021; Veena, et al., 2017; Bhusal & Mandal, 2020; Prasad, et al., 2008; Ahmad, et al., 2018; Joseph et al., 2009. The summer months were discussed as fire prone month in different studies by scholars like Lamat, et al., 2021. Bhusal & Mandal, 2020; Sannigrahi, et al., 2020 found the month of April and May as fire prone months. Ahmad, et al., 2018 found, in Arunachal pradesh the month of march and april experience most (73%) forest fire incidents. Mc Cullum, et al., (2022) depicted that how fire influencing factors are related with fire.

This research further progresses the earlier efforts by offering a novel analysis of spatiotemporal dynamics, where twelve fire influencing aspects were considered, two decadal data of fire were studied. This study evaluates different factors to identify fire prone regions, space-time performance and its co-relation using remotely sensed data.

The present study aims to identify the spatiotemporal dynamics of forest fire in Meghalaya. The state is a part of the global biodiversity hotspot, which is now feeble. The region tolerates jhum cultivation by its inherent and burning jungle is the easier approach to clear the land for agriculture. The current research will assess (1) The *temporal window* (2) The *spatial distribution* of forest fire, and (3) The correlation between fire-influencing factors with MODIS fire points. Thus, fire managers can understand, monitor, foresee and take drastic decisions.

2. Study Area

The research was carried out in Meghalaya, one of India's seven sister states, which is located between 26°05' 27.2039" N, 89°47' 47.8038" E and 25° 01' 28.5122" N, 92° 48' 22.1359" E. The State encompasses 22,429 square kilometres, or 0.68 percent of the country's total land area. Meghalaya share an international border with Bangladesh in the south and west direction and State Assam in the east and north. (Figure 1)

The Khasi, Garo, and Jaintia hills, which make up Meghalaya's three geographical sub-regions, are among the world's wettest parts, with clouds lingering in various parts virtually all year (Meghalaya means "abode of the clouds" in Sanskrit). In terms of forest diversity, orchids, Angiosperms, and faunal richness, Meghalaya is one of India's richest states. It is often regarded as a gold mine for taxonomists from several fields, as seen by the regular discovery of new specie in orchids, butterflies, and amphibians (Meghalaya Biodiversity Board, 2016). The majority of Meghalaya is part of the 'Indo-Burma' global biodiversity hotspot (Myers, 2003). The State is drained by several rivers, including Sanda, Someshwari, Umngot and Myntdu.

Meghalaya has a population of 2.96 million people, accounting for 0.24 percent of India's total population, according to the 2011 census. The rural and urban populations are 79.93 percent and 20.07 percent. The State's population density is 132 people per square kilometre, which is significantly lower than the national average.

The region enjoys a humid subtropical climate. The average annual rainfall of Meghalaya is about 202.2cm, the lowest rainfall observed in January is 0.8 cm, and the highest rainfall observed in July is 43.8cm. The average annual maximum temperature is 21°C, and the average annual minimum temperature is 13°C (Meteorological Centre, Shillong)

The soils in the states originated from gneissic complex parent materials; the colour of the soil varies from dark brown to dark reddish-brown. The region has soil depth that varies from 50cm to 200cm. The texture varies from loamy to fine loam. The soils are very rich in organic carbon. The pH of the soil is found to range from 4.5 to 6.0. Soils found at the higher altitude under the high rainfall zone (above 2000 mm) are strongly acidic due to excessive leaching of topsoil.

The primary forest species of the study area were Schima Wallichii (needlewood), Pinus Kesiya (Khasi pine), Shorea robusta (Sal), Bambusa vulgaris (bamboo), Thysanolaena (broom grass), Arundinaria or cane (FSI, Forest Types of India, 2020).

According to the 2011 census, 71 percent of the inhabitants of this region worked in agriculture, where the traditional method of shifting cultivation was the prevalent form of practice, as indicated by (Sarma, 1981), and as a result, roughly 2.38 million hectares of land were lost in India, with the north eastern states contributing the most (Satendra & Kaushik, 2014).

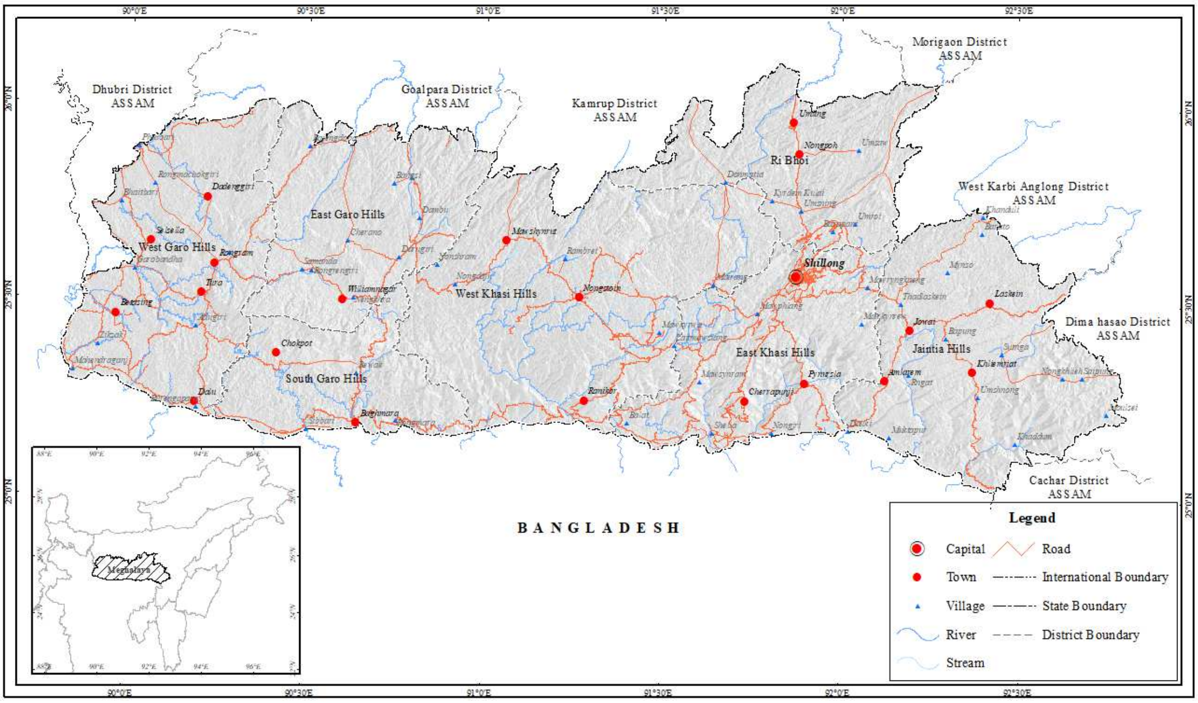


Figure 1: Study area, Meghalaya.

Meghalaya is a prosperous forest State. Forests play a crucial role in the socioeconomic and sociocultural life of rural people in this largely tribal state. In contrast to other states, Meghalaya's forest is mostly under community and private ownership. The State Forest Department has direct jurisdiction over only 1,113 square kilometres of forest in Reserved Forests, Protected Forests, National Parks, and Sanctuaries (FSI, Indian State of Forest Report, 2019) Sacred Groves are areas of virgin forest that have been left unspoiled by locals and are safeguarded by them owing to their culture and religious beliefs. Sacred Groves, estimated to number over 400 in the state, have been historically safeguarded by tribal peoples such as the Khasi, Jaintia, and Garo since time immemorial (Meghalaya Biodiversity Board, 2016).

3. Methodology

To identify the fire-prone regions, the fire-causing factors were identified. These factors were broadly classified into Vegetation, Landscape, Climate, and Human Interference. The individual factors, such as Vegetation class then subclassified into Forest Health, Forest Type, and Forest Canopy Cover. The landscape is further segregated into Elevation, Slope, and Aspect. Climate and Hydrology is further parted in Temperature, Precipitation, Wind speed, and Soil moisture. The last fire prompting factor is Human Interference which contains Distance from the Habitation patch and Distance from the Road network.

Forest Health has been extracted from Sentinel-2 MSI data. The Landscape information was extracted using SRTM (Shuttle Radar Topographic Mission) void-filled Data of 1 arc-second for elevation, slope, and aspect. Climate and Hydrology information was gathered from WordClim 2.1, where temperature and precipitation are available at 30 arc seconds, and soil moisture data from Copernicus Climate Change Service, 2018 (C3S). The Human Interference data, such as the Habitation patch collected from SEDAC and Road information collected from Open Street Map. These Forest fire triggering factors were collected from different portals, pre-processed those layers, and masked with the boundary of the Meghalaya state. The processed layers were kept in a geodatabase, which is further used for weighted overlay analysis. They performed Multiple Criteria Decision-Making techniques based on weightage given to individual factors. The resultant fire-prone map was classified into five fire intensity classes extreme, severe, moderate, mild, and non-forest. On the other hand, MODIS thermal anomaly data were downloaded from FIRMS (Fire Information for Resource Management System), masked with the study area polygon, and selected points correlated with fire triggering factors to understand the relationship between those variables. MODIS two decadal points were also inspected how those are related to time and space. Emerging hot spot analysis using forest fire data has been carried out to understand how fire points behave.

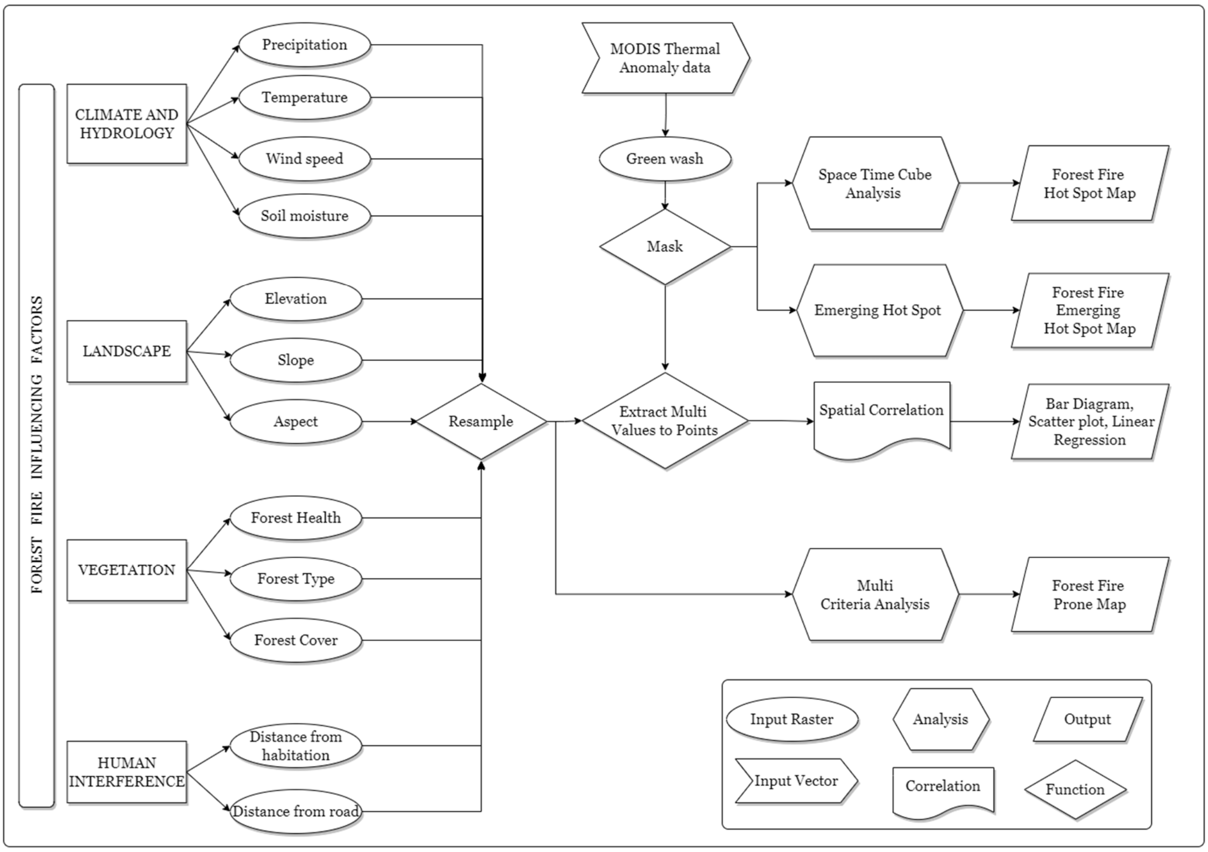


Figure 2: Flow chart

Forest fire data has been downloaded from FIRMS, which is NASA'S land, atmosphere near real-time capability for Earth Observation System. Forest fire data from 2000 onward are available in this portal. MODIS NRT (near real-time) data has been used in this study. The data is of thermal anomaly observed by MODIS represents the location of the midpoint of 1sq km pixel.

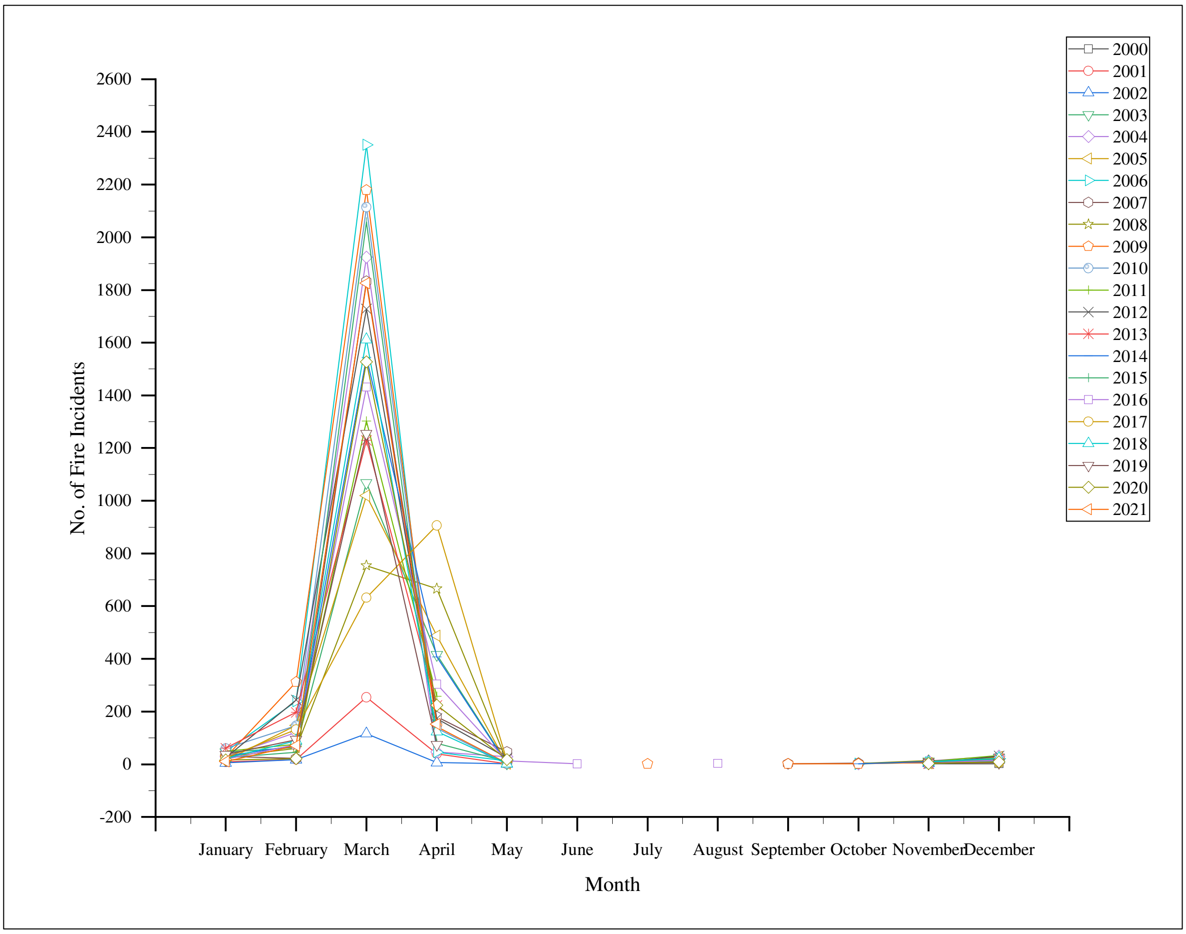


Figure 3: Yearly distribution of forest fire in Meghalaya

The MODIS fire points represent thermal anomaly which may be caused due to forest fire, agriculture stubble burn, or excessive heat generated by industries. The total number of MODIS points falling in Meghalaya from 2000 to 2021 is 39,314. After masking those points from the greenwash layer of Meghalaya, the number became 38,414. After analysing those points (Table 1), it has been observed that the fire season is from February to April every year. More than 90% of forest fire incidents took place in these three months, from offset of winter to pre-monsoon. The month of March is the most vulnerable in Meghalaya as 77.46% of fire incident is observed only in this month, followed by April 13.25% and February 5.88% (Figure 3). The year 2006 marked the highest fire alerts (2725), whereas the minimum was observed in the year 2002, which is 164.

Table 1: Distribution of forest fire in Meghalaya

YEAR	JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	OCT	NOV	DEC	GRAND TOTAL
2001	8	18	254	39	1								**320**
2002	5	17	116	6	1						3	16	**164**
2003	46	64	1068	416	4						11	25	**1,634**
2004	28	121	1924	47	29					1	13	31	**2,194**
2005	14	147	1019	488	2						4	27	**1,701**
2006	48	239	2351	46	13					1	6	21	**2,725**
2007	30	22	1833	180	47				2	4	5	15	**2,138**
2008	28	60	754	666	11					3	14	7	**1,543**
2009	26	312	2179	142	4		1		1	1	6	20	**2,692**
2010	60	146	2114	137	2						2	12	**2,473**
2011	49	76	1303	258							11	33	**1,730**
2012	25	244	1728	173	24						2	31	**2,227**
2013	61	197	1229	223							3	21	**1,734**
2014	31	71	1544	408	1					1	10	20	**2,086**
2015	24	45	2058	80	11						8	19	**2,245**
2016	19	74	1431	304	12	1		3			4	16	**1,864**
2017	24	131	632	906	14						4	6	**1,717**
2018	23	89	1612	124	2						8	23	**1,881**
2019	37	93	1255	74							4	6	**1,469**
2020	16	21	1527	224	17						3	9	**1,817**
2021	11	71	1826	152									**2,060**
GRAND TOTAL	**613**	**2,258**	**29,757**	**5,093**	**195**	**1**	**1**	**3**	**3**	**11**	**121**	**358**	**38,414**

The yearly change of the fire count depicts the number of forest fires is decreasing with the progress of time, and the change curve is rising and falling that is because the number of fire incidents is higher in one year compared to the next year, or we can say in every alternate year the case of forest fire is rising (Figure 4). In the year 2021, the total 2,060 number of fire incidents were observed; hence we can anticipate that in the year 2022 the count will be rather less than 2021. One of the reasons may be in decline in forest fire incidents with the time is the decline in forest cover in the state. The state has a forest cover of 17,119 sq. km and 17,046 sq. km as per (FSI, Indian State of Forest Report, 2019; FSI, Indian State of Forest Report, 2021). It has been observed that the forest cover of the state is constantly declining as per figure published by FSI from 2010 onwards (Figure 5).

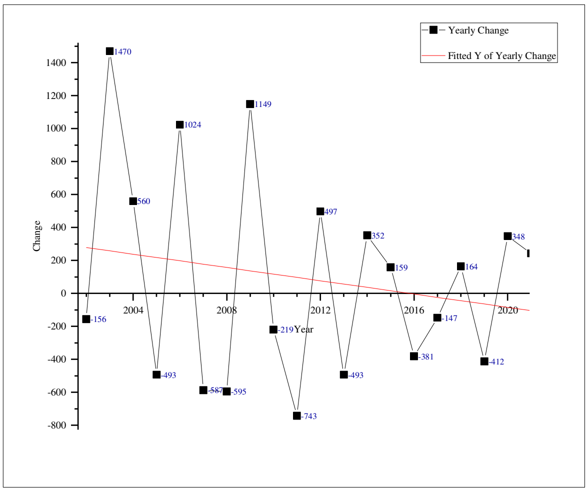


Figure 4: Trend of yearly forest fire count.

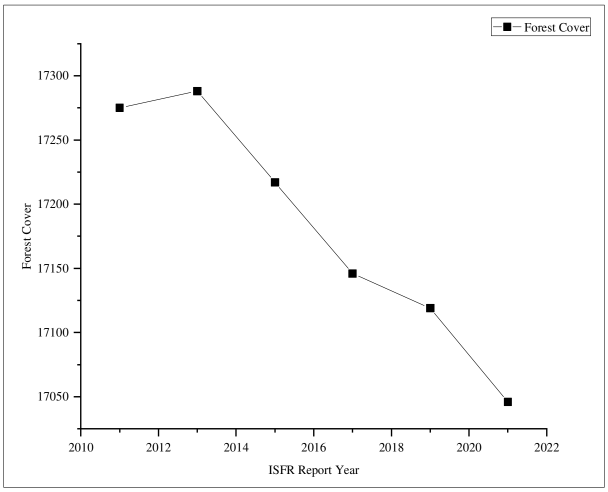


Figure 5: Forest Cover of Meghalaya

The fire points of two decades have depicted that in March, the incident is at its peak; hence an analysis for March with two decadal data found that during the first ten days and last ten days, the fire incident is less than the two decadal averages of March, but from 10th day to 20th day of the March month registered higher numbers of fire incidents (Figure 6), from the figure it can be identified.

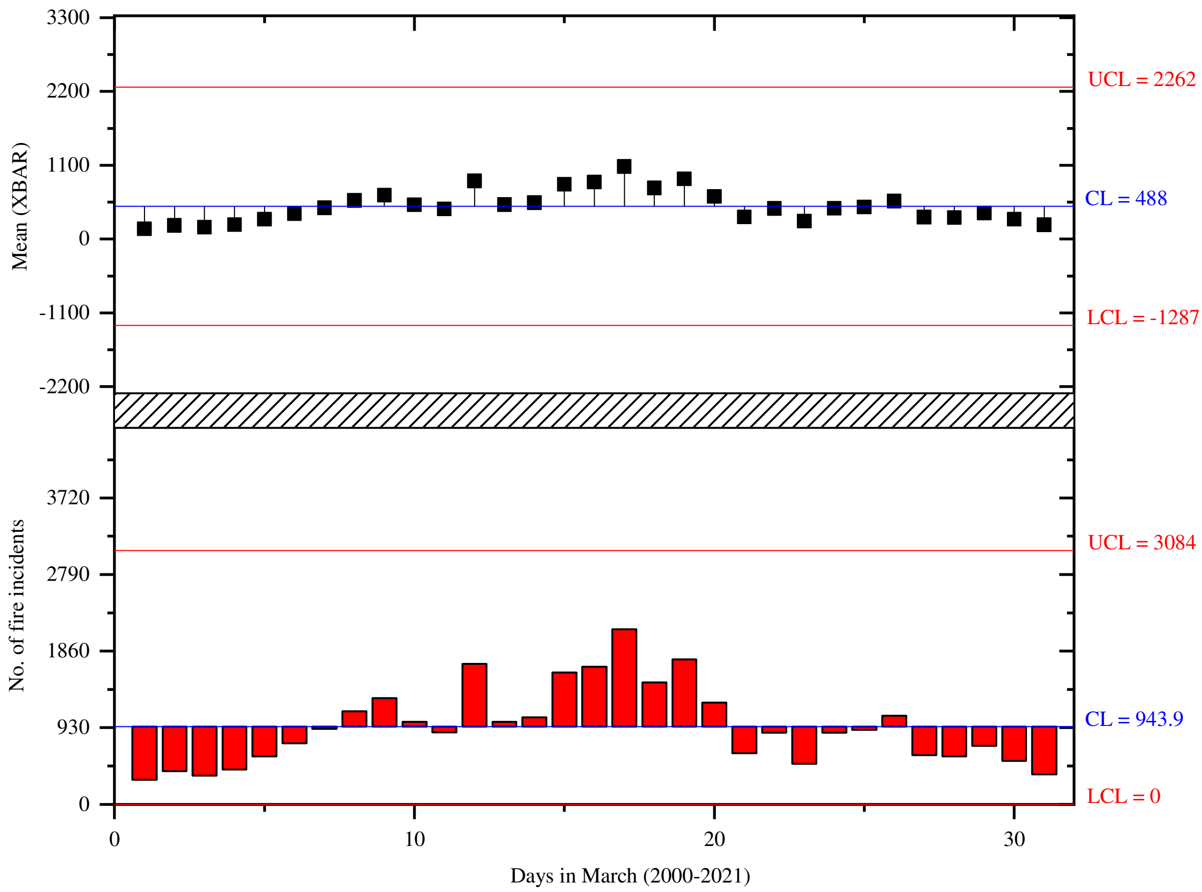


Figure 6: Total Forest fire for the month of March (2000-2021)

4. Exploratory analysis

4.1. Vegetation

4.1.1. Forest Health and Forest fire

To identify the health of the vegetation in the fire-prone month of March, a study of the forest health of entire Meghalaya has considered, using GEE (Georelick, et al., 2017). A Sentinel 2 composite was created for the entire state of Meghalaya, there are seven Sentinel-2 scenes covering the state. Sentinel-2, Level-2A orthorectified atmospherically corrected surface reflectance data provided by European Union/ESA/Copernicus, available from March 2017 onwards. For the convenience of the study, we made a composite while keeping in mind that all the selected scene which has less than 15% cloud cover were selected for three-time period T1 (1st March to 15th March 2021), T2 (15th March to 30th March 2021) and T3 (1st April to 15th April) was only selected.

Using the above said composites, the normalized difference has been calculated. After the computation that has been downloaded for further analysis, after downloading the NDVI of the three-time period, a

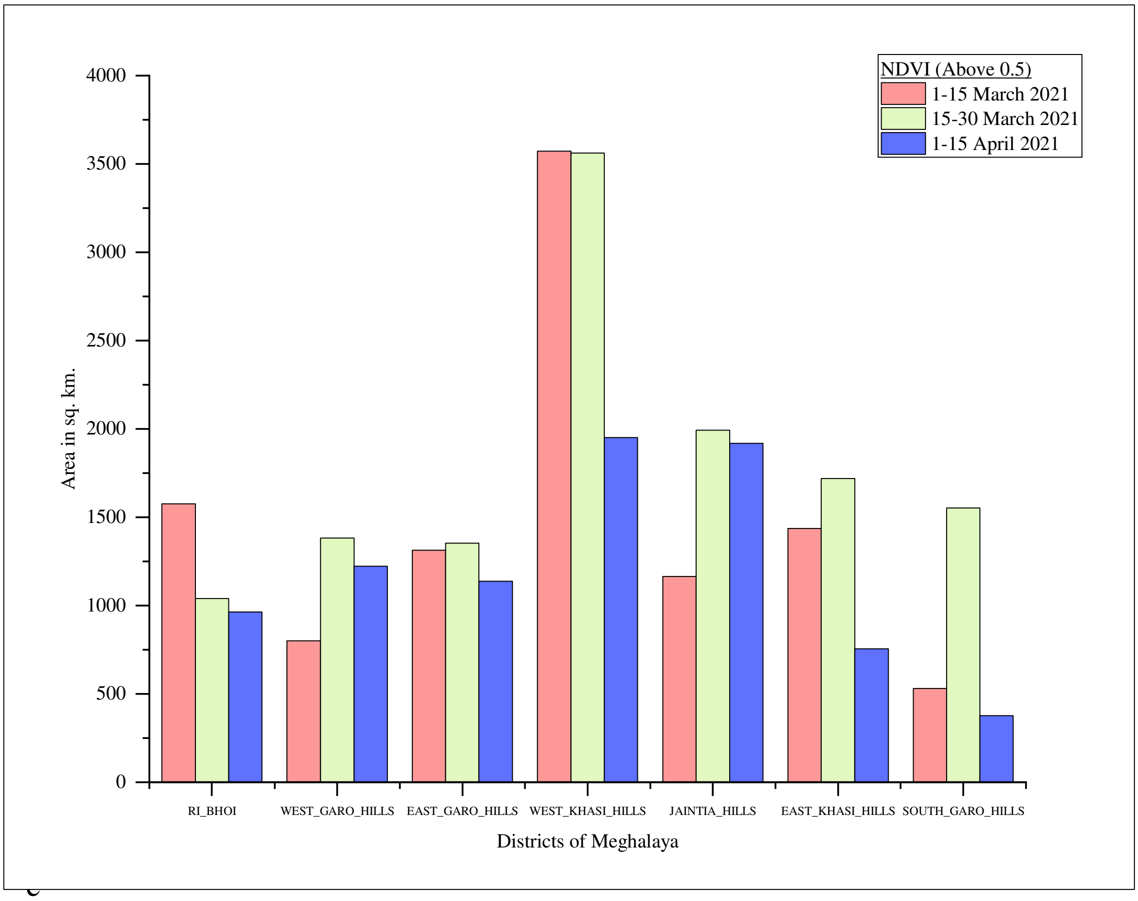


Figure 7: District wise distribution of forest health.

n done where the density classes were classified as Very Low, Low, Moderate, and High based on the NDVI value less than -0.5, -0.5 to 0, 0 to less than 0.5 and above 0.5 respectively (Figure 17).

The reclass NDVI files were added with an area column. By executing the tabular summary with the respective district file of the state, it has been observed that in the NDVI of T1 composite for the district, Ri Bhoi has healthy vegetation above 1500 sq. km However, in the T3 composite, the health of vegetation has fallen below 1000 sq. km in the high-density class of classified NDVI. This decreasing trend of NDVI value is observed in West Khasi Hills and East Khasi hills. It has been noted that fire incidents in these districts are higher (Figure 7),

4.1.2. Forest Type and forest fire

Vegetation parameters such as forest type and cover play a vital role in fires' ignition, spread and dispersal (Prasad, et al., 2008). hence the forest type of Meghalaya is collected, where the forests are broadly classified into 16 major

types (Champion & Seth, 1968) of these, the tropical forests occupy 80% of the forested area. In particular, the tropical moist and dry deciduous forests, which are frequently affected by the forest fire, and account for 64% of the total forest area in the state (FSI, Indian State of Forest Report, 2003).
The forest type is one of the triggering factors of forest fire, as in the state there are nine forest types that are Cachar tropical evergreen forest(1B/C3), Pioneer Euphorbiaceous scrub (1/2S1), Assam alluvial plains semi-evergreen forest (2B/C1a), Secondary moist bamboo brakes (2/2S1), Khasi hill sal (3C/C1a(ii)), East Himalayan moist mixed deciduous forest (3C/C3b), Khasi Subtropical wet hill forest (8B/C2), Assam subtropical pine forest (9/C2) and Assam subtropical pine savannah (9/C2/DS1) as published by (FSI, Forest Types of India, 2020) in its Atlas (Figure 16), based on Champion and Seth classification. (Accessed from - http://vanagniportal.fsiforestfire.gov.in/fsi_fire/fire.html).

Global forest type is also available at Copernicus Global Land Service (Buchhorn, et al., 2018), with six forest type classes (Six types: Evergreen, needle leaf forest (ENF), Evergreen, broad leaf forest (EBF), Deciduous, needle leaf forest (DNF), Deciduous, broad leaf forest (DBF), Mixed, Unknown / Other with 1km resolution, hence in this study FSI, Forest Type of India, 2019 was utilised.

Table 2: Distribution of forest fire in different forest type in Meghalaya

Forest Type	Code	East Garo Hills	East Khasi Hills	Jaintia Hills	Ri Bhoi	South Garo Hills	West Garo Hills	West Khasi Hills	Total Fire Point	Area	% of FA	% of GA
		A	*B*	*C*	*D*	*E*	*F*	*G*	*H=sum(A:G)*	*I*	*J=(I/Total area*100)*	*K=(I/GA*100)*
Pioneer Euphorbiaceous scrub	1/2S1	196	138	242	231	35	163	600	1,605	485	2.63	2.16
Cachar tropical evergreen forest	1B/C3	-	172	523	-	102	-	872	1,669	1,515	8.22	6.76
Secondary moist bamboo brakes	2/2S1	108	3	60	735	28	27	296	1,257	376	2.04	1.67
Assam alluvial plains semi-evergreen forest	2B/ C1a	-	-	-	-	173	-	-	173	129	0.70	0.58
Khasi hill sal	3C/C1a(ii)	723	-	-	386	290	385	259	2,043	1,177	6.38	5.25
East Himalayan moist mixed deciduous forest	3C/C3b	6,064	-	67	6,274	2,206	2,953	5,475	23,039	8,692	47.14	38.76
Khasi subtropical wet hill forest	8B/C2	129	510	2,567	367	1	92	763	4,429	3,593	19.49	16.02
Assam subtropical pine forest	9/C2	-	192	407	101	-	-	139	839	1,169	6.34	5.21
Assam subtropical pine savannah	9/C2/DS1	-	34	270	-	-	-	81	385	720	3.90	3.21
TOF/Plantation	TOF	405	282	404	375	147	604	596	2,813	581	3.15	2.59
Total		**7,625**	**1,331**	**4,540**	**8,469**	**2,982**	**4,224**	**9,081**	**38,252**	**18,438**		

MODIS Fire points of 2021 were analysed as per forest types of state Figure 20 *b*, The East Himalayan Moist Mixed Deciduous Forest (3C/C3 b) is the most vulnerable forest type (Achu, et al., 2018,2021; Janzen, 1988; Murphy & Lugo, 1986) which covers 8,692.38 sq. kms in the state followed by Khasi Sub

Tropical Wet Hill Forest (8B/C2) and Cachar Tropical Evergreen Forest (1B/C3). In the year 2021 number of fire points falling in East Himalayan Moist Mixed Deciduous Forest is 1419 which is more than 65% of the total fire points. The said forest type is then analysed with 20 years of available MODIS forest fire data and the results were quite similar, East Himalayan Moist Mixed Deciduous Forest are generally found in the outer Himalayan range and it is found in East Garo Hills, Jaintia Hills, Rihboi, West Garo Hills, South Garo Hills and West Khasi Hills. Dominant tree species under East Himalayan moist mixed deciduous forests are *Schima wallichii, Haldina Cordifolia, Lagerstroemia parviflora, Aglaia spectabilis, Gmelina arborea etc. Bamboos like Bambusa tulda, Dendrocalamus hamiltonii, Bambusa pallida*. 23,039 numbers of Forest fire alert have been sent in this forest type from 2001 onward.

4.1.3. Forest Canopy Cover

The Forest cover map (FCM) for the year 2019 of Meghalaya state, has been analysed with the fire points. The FCM was used to classify tree cover into four classes, namely very dense forest (VDF), moderate dense forest (MDF), open forest (OF) and scrub, based on the crown density of above 70 percent, 40 to 70 percent, 10 to 40 percent and below 10 percent respectively. The occurrence of fire mostly has been observed in the open forest density class as this density class is dominant in the periphery of forest boundary where cattle grazing, settlement and roads exist (Figure 15). More than 1700 fire points were in open forest density class, the moderate density class has also endured above 1400 fire incidents, followed by scrub (Figure 20 *c*).

4.2. Landscape

4.2.1. Elevation and forest fire

The effect of terrain on forest survival following wildfire has been analyzed by (Prasad, et al., 2008; Kushla & Ripple, 1997). The relation between elevation and forest fire is analyzed in the Meghalaya state.
The Digital Elevation Model is obtained from Earth Explorer, SRTM (Shuttle Radar Topographic Mission) void-filled Data of 1 arc-second (approximately 30 meters) is available at Earth Explorer, 2022; Global Land cover Facility, 2022) at coarser scales. The Digital Elevation Model data has been classified into three broad classes (i) Below 500 meters, (ii) 500-1500 meters and (iii) Above 1500 meters (Figure 12).

Prasad, et al., 2008 observed that elevation is one of the crucial predictors of fire in the Deccan plateau, attributed to slash and burn agriculture practiced by indigenous people in hilly regions. The Meghalaya state has 86.15% tribal (ST) people in total population (Census of India, 2011) and the slash and burn are practiced in almost all the hilly districts. Fire points were analysed with the classified elevation data and observed that the lower altitude classes are fire-prone, and there is significantly less to almost zero in the higher altitude class (Figure 20 *d*).

4.2.2. Slope with forest fire

Slope angle influences fire intensity, since pre-heating of materials and rate of spread are greater on steeper slopes, while fire flows upslope (Mc Cullum, et al., 2022; Weise & Biging, 1996). The Forest fire is caused by the upward flowing hot air resulting in moisture loss and high temperature in the upper region. It has been observed that the presence of Isolated trees at higher altitudes and scrubs at lower altitudes readily catch fire due to less moisture content and presence of high flammability of the coniferous vegetation (Gupta, et al., 2018). Additionally, rolling and burning forest material promote and reignite fire at new locations down the slopes (Landmann, et al., 2015).

It has been observed that in Meghalaya, 70 percent of the area falling within 30-degree slope and fire points accounts over 95 percent in this region (Figure 13). Generally, Forest fire in a mountainous terrain spread uphill very rapidly but in the state forest fire is mostly due to traditional method of shifting cultivation (Ramkrishnan, 1993; Tomich & Lewis, 2002; Joseph, et al., 2009; Stolle, et al., 2003) and they prefer the gentle slope, as in gentle slope tribal can practice agriculture easily (Figure 20 *e*).

4.2.3. Aspect with forest fire

The slope aspect is another component that effects the quantity of solar radiation and moisture content, as well as the nature and movement of forest fires through vegetation composition and density (Ebel, 2012; Estes, et al., 2017; Mc Cullum, et al., 2022) In general, the northern hemisphere's south-facing slopes receive more sunlight and have higher evaporation rates from the surface (Thornbury, 1954) , making the land surface drier and more prone to forest fires. After overlay of fire points on the aspect file, it has been observed that the east and northwest aspects of the hill face more forest fire compared to others (Figure 20 *f*). The least forest fire was observed in the northeast direction (Figure 14).

4.3. Climate and Hydrology

It has been observed by (Parry, et al., 2007) that, the last two decadal data show the increasing intensity and spread of forest fire in Asia were primarily related to temperature rises and decline in precipitation in combination with increasing land-use intensity. Hence, an analysis of impact of climate on forest fire of the state's forest fire incident has been done.

World climate data is available from 1970 onward at WorldClim 2.1 at http://worldclim.org, The data represent average monthly climate data. The spatial resolution is approximately 30 arc seconds (~1 km) (Fick & Hijmans, 2017), The data was downloaded and processed to extract information such as monthly total precipitation and monthly average temperature to learn its behaviour with forest fire.

4.3.1. Temperature with forest fire

The earth's Land Surface Temperature (LST) is provided by the MODIS sensor of NASA's Terra satellite. It represents the temperature of the earth's skin (up to 1 mm) on the land surface during the daytime and nighttime. It is also mentioned by (NASA, 2018) that in the forest canopy, LST represents canopy temperature. The canopy temperature may be used to estimate sensible heat fluxes between forests and the lower atmosphere. In this study, the annual average temperature was downloaded from WorldClim 2.1, which is based on the MODIS average of night and daytime land surface temperatures (LST mean) and top-of-atmosphere incident solar radiation calculated by (Fick & Hijmans, 2017). The annual average temperature was classified in three classes (Figure 9). A positive relationship has been established between the annual average temperature and the forest fire incidents (Sayad, et al., 2019) (Figure 20 *g*).

4.3.2. Precipitation with forest fire

The state receives the highest rainfall compared to other parts of the country, and Mawsynram, a village that is almost 60 km away from its capital Shillong, gets the highest rainfall in India, and it is the wettest part of the world. It is in the Guinness Book of World Records for its whopping 26,000 mm of rain received in 1985.

The amount of rainfall influences the forest fire; a good amount of rain increases the vegetation growth, which becomes fuel for fire during the dry season (Mc Cullum, et al., 2022). In the state, we got an almost similar result; as the precipitation increases, the fire incident during the fire season is also increases (Figure 20 *h*). In Figure 8, the annual average rainfall for the month of march has been shown.

4.3.3. Wind speed on forest fire

Wind speed data is readily available at WorldClim 2.1, but the resolution is course hence data from (Global Wind Atlas 3.0, 2019) was used for this study, the wind speed with a unit of meter per second with 250-meter spatial resolution.

The speed of the wind is a massive influencing factor on the intensity of fire spread in any region (Adab, et al., 2013; Schoennagel, et al., 2004; Keeley, 2004)

The wind speed of the region varies from 1 - 6 m/s, it is also observed that more than 85% of the region is facing wind speed below 4 m/s. we observe a positive relation with wind velocity and forest fire incidents (Figure 20 *i*). The wind speed map (Figure 10) has been prepared.

(Byram, 1954) suggested that there are certain wind profiles which are linked with blow-up forest fire and jet streams is also linked with wildfire by (Schaefer, 1957)

4.3.4. Soil moisture and forest fire

Soil moisture gridded data of the study area has been collected from (Copernicus Climate Change Service, 2018). The C3S provide information to increase the knowledge base to support policies on adaptation to and mitigation of climate change.
Data were available 0.25°x0.25° resolution of the entire globe, the temporal resolution is varying from daily, 10-day and Monthly with Network Common Data Form (NetCDF) file format. The soil moisture data were created by using SCATTEROMETER and RADIOMETER. The Volumetric soil moisture is calculated by measuring content of liquid water in a surface soil layer of 2 - 5 cm depth expressed as cubic meter of water per cubic meter soil (Figure 11).
It has been observed that volumetric soil moisture above 0.04 m^3/m^3 is dominant in the study area, this zone covers more than 80% of the geographical area. The fire points have a positive relation with high soil moisture zone compared to low (Figure 20 *j*).

4.4. Human Interference

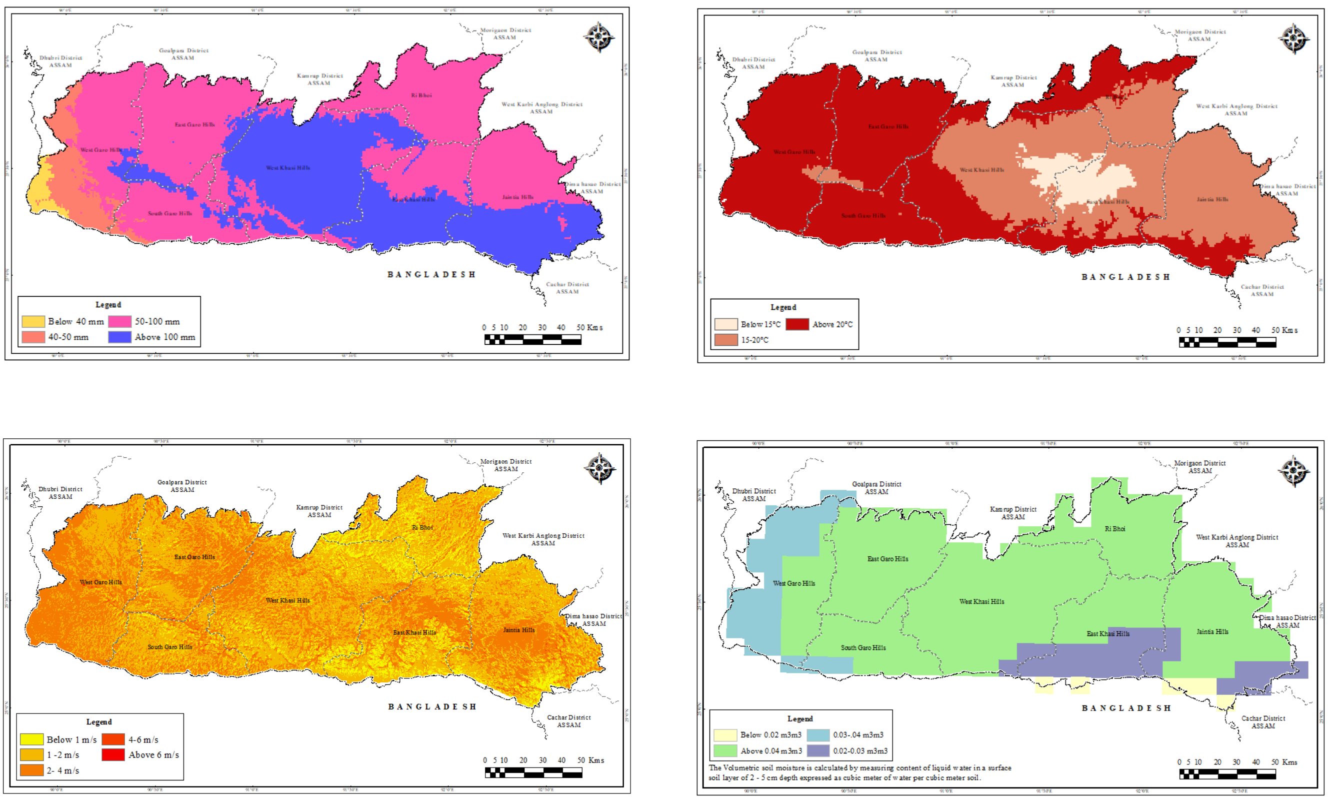
Population of rural Meghalaya were largely depending on valuable forest and mineral resources. The minerals like coal and limestone are predominant apart from them occurrence of apatite, china clay, copper, lead-zinc, silver, titanium, felspar, magnetite, quartz etc were available in different district of the state, Indian Minerals Yearbook, 2016. The state falls under Obvious Geological Potential area for all minerals declared by Geological survey of India. All these minerals beneath ground are covered by vegetation on the surface, hence the vegetation has to suffer. The tribal method of agriculture is practiced here, forest fringe villages and proximity to road considered influencing the factor in forest fire.

4.4.1. Distance from Habitation patch

The spatial distribution of habitation was collected from Socioeconomic Data and Applications Centre (Balk, et al., 2019) SEDAC, NASA, where Indian population as per census 2011 in gridded estimation based on official tabulations of population and settlement type and remotely sensed of habitation is derived from the Global Human Settlement Layer, (Balk, et al., 2019). Occurrence of Forest fire is higher in places closer to habitation and vice versa (Figure 20 *k*)., this pattern also observed by (Sowmya & Somashekar, 2010) in their study of Bhadra Wildlife Sanctuary. Distance from habitation was classified in five categories, Habitation i) Below 2km, ii) 2-5km, iii) 5-10km, iv) 10-15km and v) Above 15km. out of these the maximum fire has occurred in those forest which are within 10km from habitation (Figure 19).

4.4.2. Distance from Road network

Almost all fire incident in the study area is human induced hence road plays a vital road, Accessible places of forest by road is always prone to forest fire, author like (Bhusal & Mandal, 2020; Veena, et al., 2017; Jacob, et al., 2014) also observed the same. The distance from road was classified in 5 categories, distance i) Below 2 Kms., ii) 2 – 5 Kms. iii) 5-10 Kms, iv) 10-20 Kms and v) Above 20 Kms (Figure 18). In the study area forest fire activities were high in those forest which were within 10 kms of road (Figure 20 *l*).



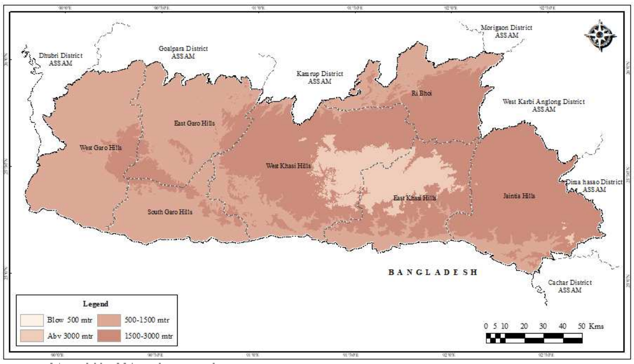


Fig 12: Elevation.

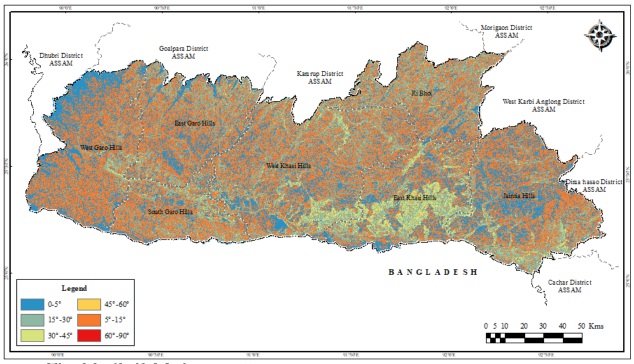


Fig 13: Slope.

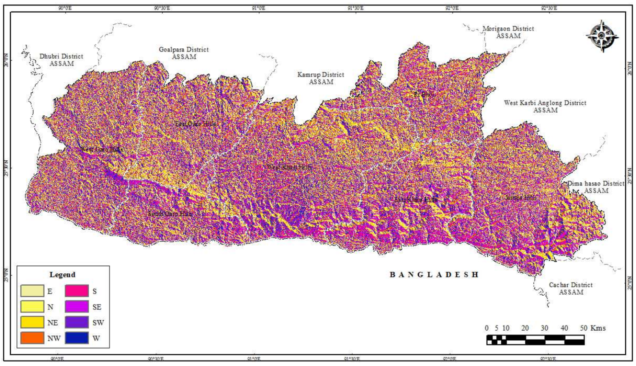


Fig 14: Aspect of slope.

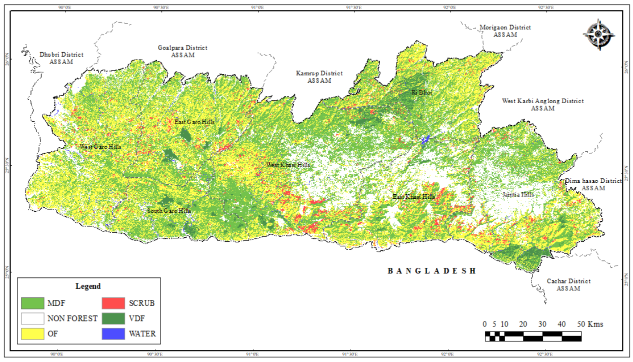


Fig 15: Forest Cover Map, 2019

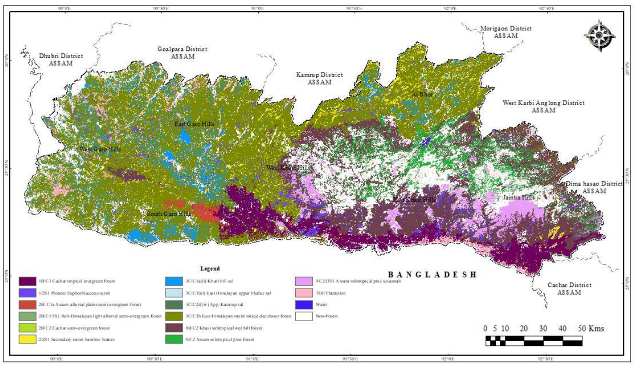


Fig 16: Forest Type Map, 2019

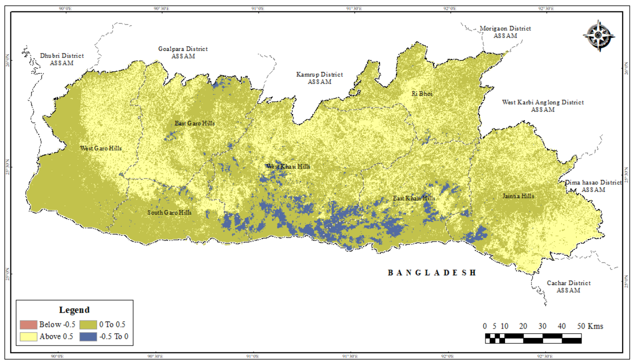


Fig 17: NDVI for the month of march, 2021.

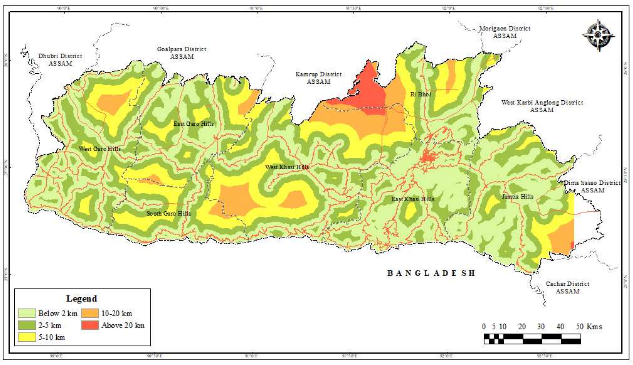


Fig 18: Distance from road.

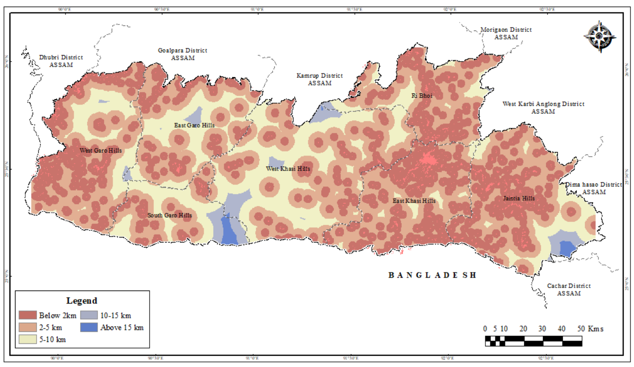
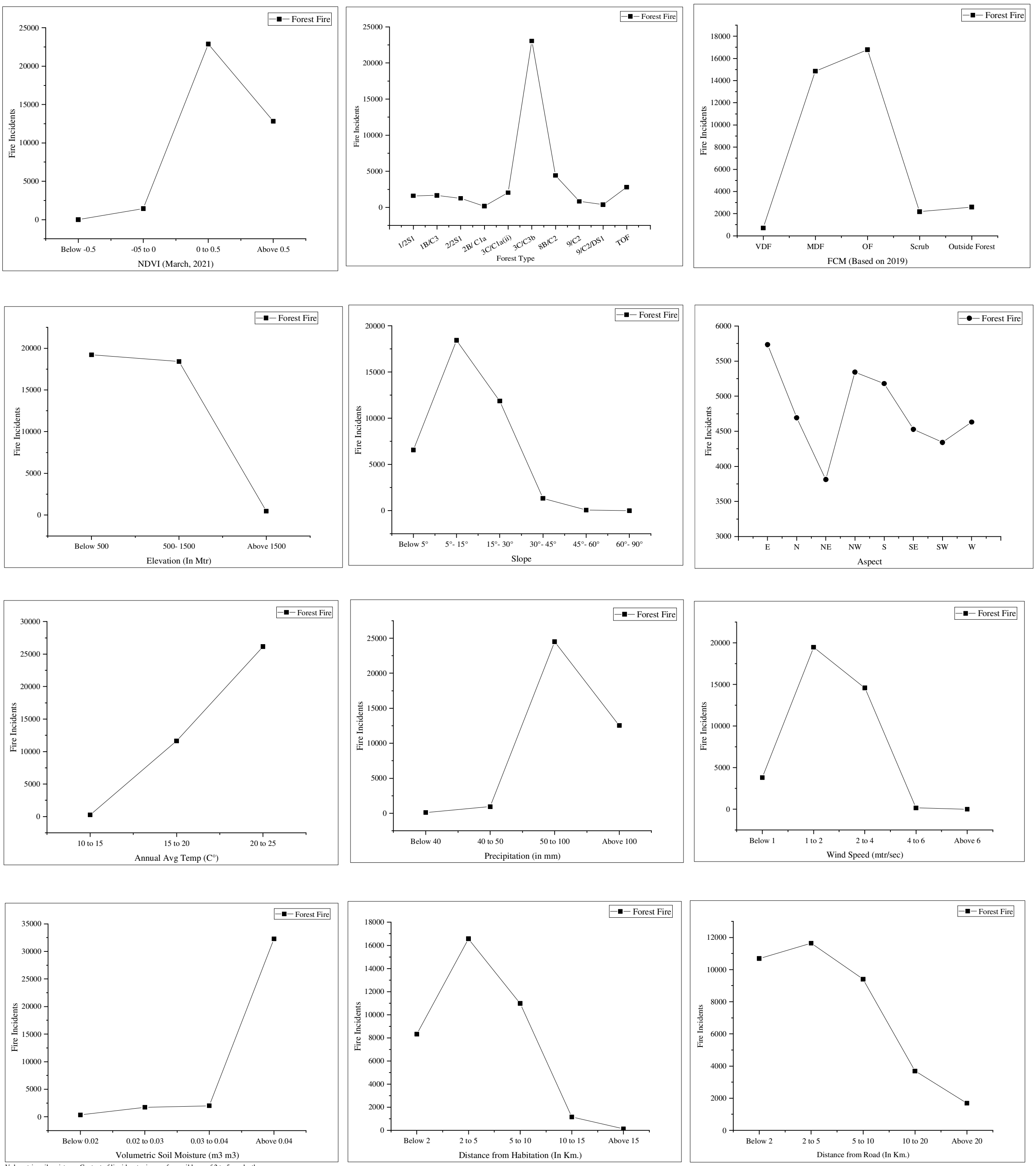


Fig 19: Distance from habitation.



Volumetric soil moisture - Content of liquid water in a surface soil layer of 2 to 5 cm depth expressed as m3 water per m3 soil.

Figure 8: Correlation of forest fire with respect to a) NDVI values, b) Forest type, c) Forest cover, d) Elevation, e) Slope, f) Aspect, g) Annual average temperature, h) Annual average Precipitation i) Wind speed, j) Soil moisture, k) Distance from habitation and l) Distance from road.

5. Result and Discussion:

5.1. Emerging Hot Spot Analysis

The analysis required NetCDF (Network Common Data Form) file as input as this file type can store multidimension data such as location (x,y), count (z) and time(t).

The Hot Spot Analysis calculates the Getis-Ord Gi* statistic (pronounced as G-i-star) Ord & Getis, 1995, for each fire point in MODIS fire dataset. Each feature is within the proximity of another feature.

$$G_i^* = \frac{\sum_{j=1}^{n} w_{i,j}x_j - \bar{X}\sum_{j=1}^{n} w_{i,j}}{S\sqrt{\frac{\left[n\sum_{j=1}^{n} w_{i,j}^2 - \left(\sum_{j=1}^{n} w_{i,j}\right)^2\right]}{n-1}}}$$

Where,

x_j is attribute value for feature j

$w_{i,j}$ is the spatial weight between feature i *and* j

n is the Total number of features.

$$\bar{X} = \frac{\sum_{j=1}^{n} x_j}{n}$$

$$S = \sqrt{\frac{\sum_{j=1}^{n} x_j^2}{n} - (\bar{X})^2}$$

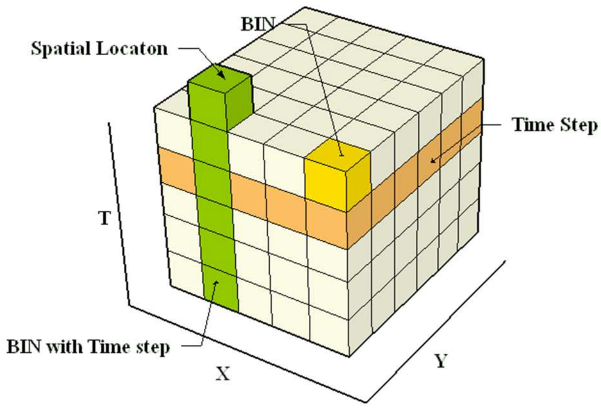


Figure 9: Bin Time Series

The analysis was carried out using input as NetCDF that will create a cube (Figure 21) where all the information will be stored, based on that information the data will be classified in several classes.

High feature value may be interesting, but they may not represent statistically significant hot spots. A feature must have a high value and be surrounded by other feature with high values to be statistically significant. The total of all features is compared proportionally to the local sum for a feature and its neighbours. The Positive and negative Gi* statistic refers to cluster of fire points with high and low number of fire event (Manepalli, et al., 2011).

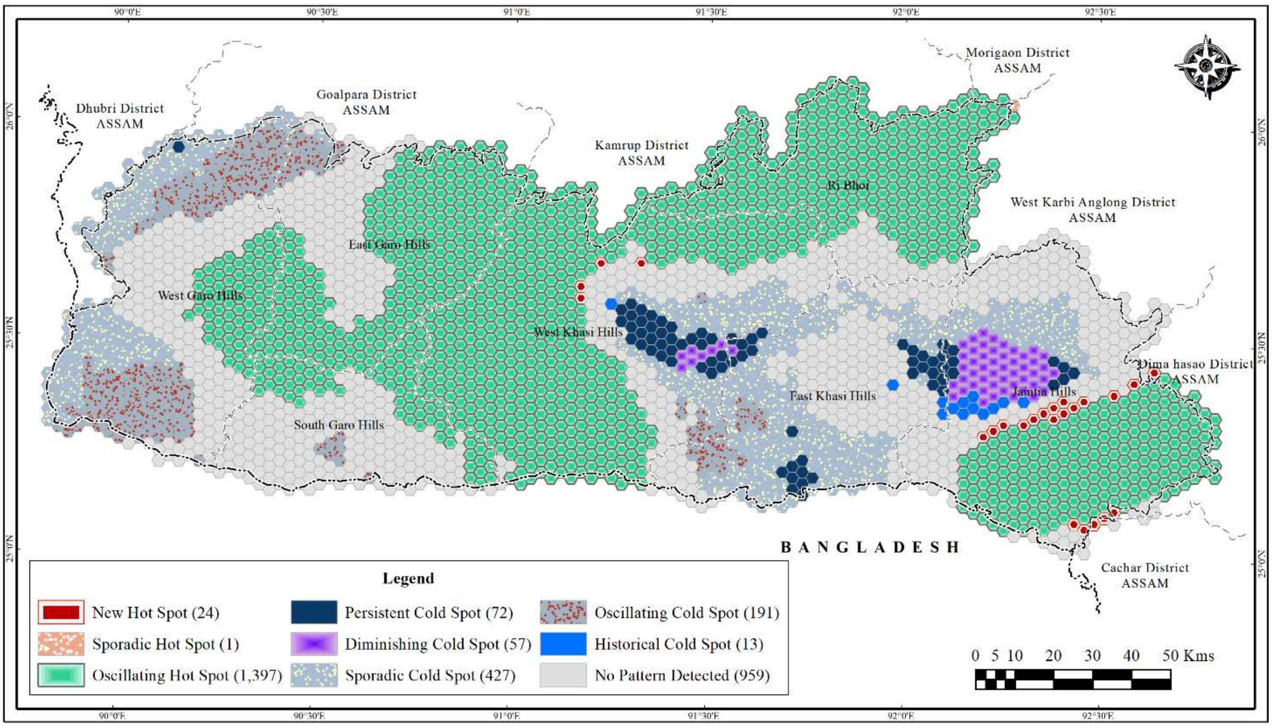


Figure 10: Emerging Hot Spot Analysis.

The result of Gi* statistics in forest fire points of Meghalaya is self-explanatory, a four months of time lap was given in two decades of MODIS fire data, the result was classified in nine classes such as i) *Oscillating Hot Spot* which refers as in recent time the region is fire prone but it has a history of been cold spot, followed by ii) *No Pattern Detected* zone which consists of primarily built up and non-forest region, iii) *Sporadic Cold Spot* tells us that these region never being a hot spot and less than 90% of time step the region was cold spot. iv) *Oscillating Cold Spot*- the region is currently cold spot but it has a history of being a hotspot, less than 90 percent of time step this region is a cold spot. v) *Persistent Cold Spot*- at least 90% of the time step intervals are cold, with no trend up or down. vi) *Diminishing Cold Spot* – The region experiences at least 90% of the time step intervals are cold, and becoming less cold over time intervals. vii) *New Hot Spot*- Those regions which are most recent cases of forest fire. viii) *Historical Cold Spot* - The most recent time period is not cold, but at least ninety percent of the time-step intervals have been statistically significant cold spots. ix) *Spordic Hot Spot*- forest fire location that is an on-again, off-again hot spot. Less than 90% of the time-step intervals were statistically significant hot spots, and none of the time-step intervals were statistically significant cold spots (Figure 22).

5.2. Space Time Cube Analysis

A Space Time cube Analysis has been done to further understand the trend of forest fire in Meghalaya, The NetCDF file containing x, y, z and t which refers to locational data, count and time. This analysis creates a space-time bin which is a three-dimensional cube as shown in Figure 8.

Each bin in the cube has location, a time step of 4 month and count value, the count value represent number of fire points that occurred at the associated location within the associated time step interval.

This study has been done in Meghalaya state and the result can be seen in the map (Figure 23) where West Khasi Hills, Ri Bhoi and Jaintia hills districts were most prone to forest fire, it is also observed that nearly half of the state's tree cover is fire prone. However, it is also observed that the due to human induced fire there is a particular pattern in this fire activities, the tribal people use to burn the forest every alternate year.

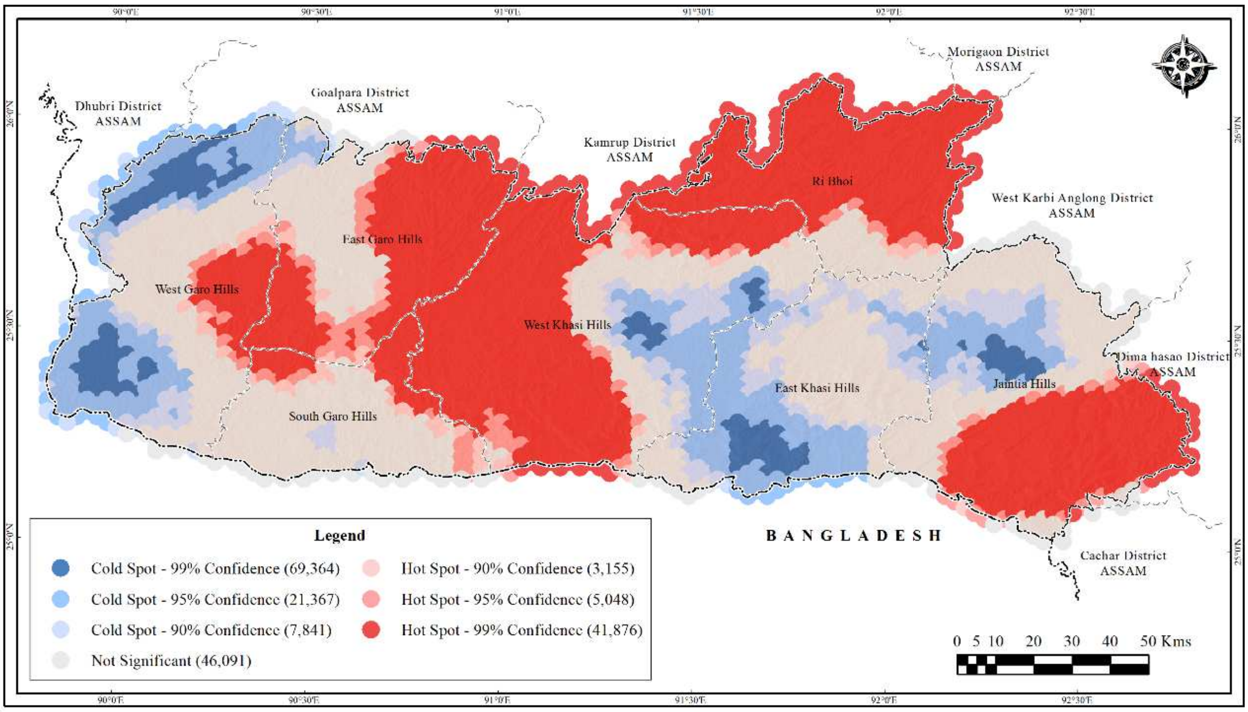


Figure 11: Space Time Cube Analysis

5.3. Multiple Criteria Decision Making

A Multiple criteria analysis has been executed using twelve influencing forest fire factors, all raster files were converted into discrete integer raster with equal pixel spacing. MCA is very helpful in finding the suitable site with given parameters. user needs to specify the weightage of every single layer which were influence forest fire. By using Weighted Overlay (MCA) all the input raster files were reclassified into a common scale, which may be based on suitability or preference, in this case an evaluation scale of 1 to 9, where 1 represent the lowest suitability and 9 the highest, furthermore all the pixel values were multiplied with the weight of importance, in each layer a weightage has been assigned, for forest fire prone region the higher weightage is given to Distance from Road, Distance from Habitation, Forest Type, Annual Average Temperature and Annual Average Precipitation all these were explained in the Table 3 the sum of all layer's weightage is 100 percent. Finally, all resulting cell values from input raster files were added to produce the Fire risk prone map (Figure 24).

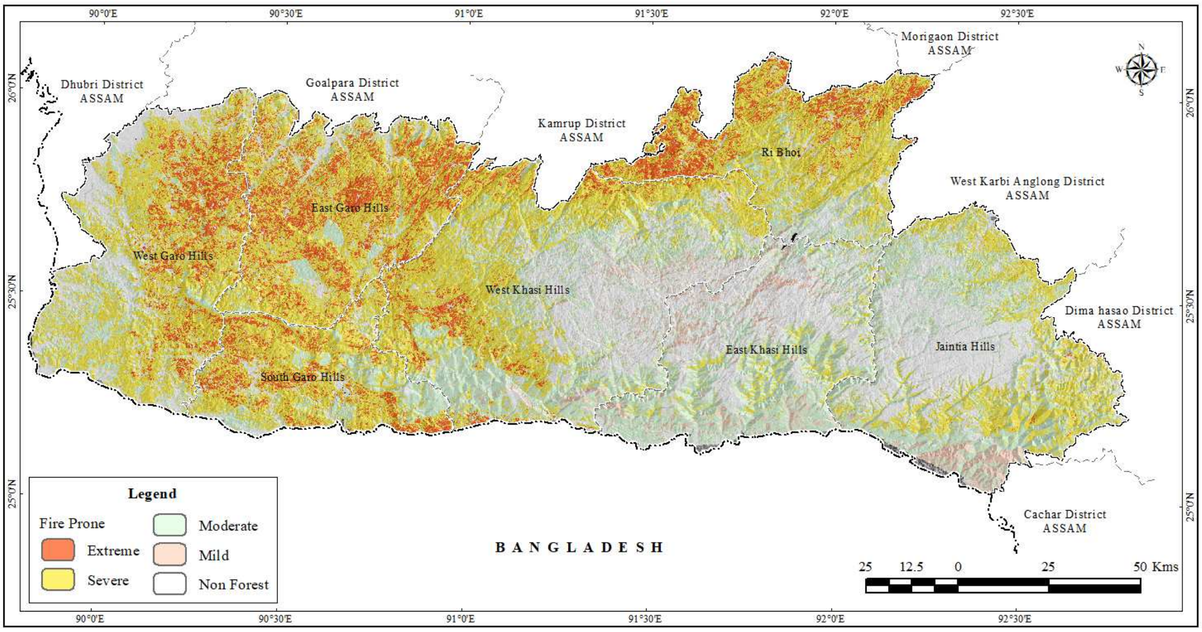


Figure 12: Forest Fire Prone Map.

Table 3: Fire influencing variables with Weightage value.

Sl. No.	**File**	**Influence**	**Field**	**Weightage Value (1-9)**	**Sl. No.**	**File**	**Influence**	**Field**	**Weightage Value (1-9)**
1	Wind Speed	5	Below 1	3	**8**	Distance from Habitation	12	Below 2 kms	5
			1 to 2	9				2 To 5 kms	9
			2 to 4	7				5 To 10 kms	7
			4 to 6	1				10 To 15 kms	3
			Above 6	1				Above 15 kms	1
2	Soil Moisture	8	Below 0.02	3	**9**	Aspect	5	N	5
			0.02 to 0.03	5				NE	1
			0.03 to 0.04	7				E	9
			Above 0.04	9				SE	5
3	Slope	5	0 to 5	5				S	7
			5 To 15	9				SW	3
			15 To 30	7				W	5
			30 To 45	3				NW	7
			45 To 60	1	**10**	Annual Avg. Temp	10	Below 15 °c	5
			60 To 90	1				15 To 20°c	7
4	NDVI 1 to 15 march	5	Below -0.5	1				Above 20°c	9
			-0.5 To 0	3	**11**	Annual Avg. Precipitation	10	Below 40 mm	3
			0 To 0.5	7				40 To 50 mm	5
			Above 0.5	9				50 To 100 mm	9
5	Tree Cover-2019	8	VD	3				Above 100 mm	7
			MD	5	**12**	Forest Type	12	1/2S1	1

			Open	9	1B/C3	1
			Scrub	7	2/2S1	3
			Water	Restricted	2B/ C1a	1
			NF	Restricted	3C/C1a(ii)	5
6	Elevation	8	Below 500	9	3C/C3b	9
			500 To 1500	7	8B/C2	7
			1500 To 3000	3	9/C2	1
7	Distance from Road	12	Below 2 kms	7	9/C2/DS1	1
			2 To 5 kms	9	TOF	1
			5 To 10 kms	5		
			10 To 20 kms	3		
			Above 20 kms	1		

6. Conclusions

We discussed a very severe issue that endangers both our ecosystem and our lives in this research. Thousands of hectares of forest are burned by fire each year all around the world (Food and Agriculture Organization, 2020). In addition to destroying the structure and composition of forests, these fires also harm biodiversity, expose forests to invasive species, disturb water cycles and soil fertility, and disrupt the lives of those who live in the vicinity of forests. Hence, for better management of this kind of disaster in state we have applied Geospatial technology, utilizing this technique entire state has been analysed to identify the hotspots and by analysing MODIS thermal anomaly data fire prone month with most fire prone dates were identified. These

Figure 13:Ground verification photographs of Forest Fire on 25th March 2021 (Laskein, Jaintia Hills)

results were very effective for the managers,


Figure 14: Ground verification photographs of Forest Fire on 25th March 2021 (Laskein, Jaintia Hills)

planners, and other stakeholders. Strict rules and regulations can be introduced based on spatiotemporal distribution of forest fire.

In this research twelve forest fire triggering variables were analysed to identify the forest prone regions, using MCA all files were assigned a weightage in percentage, higher influencing factor were assigned higher value and vice versa. The output discreate raster files with value from 1 to 9, where 9 is most prone and 1 is least. The fire prone regions were also validated with ground verified data. A fire hotspot map from MODIS data was also being developed for comparing with the output of multi criteria analysis and found a good result. In this state as almost all the fire were human induced, the month of March has been identified as most forest fire prone month, the same has been recognised different researchers (Matin, et al., 2017; Prasad, et al., 2008; Ahmad, et al., 2018). Every year from 10th day to 20th day of the month can be classified as extreme fire prone.

In India forest fire alert system was pioneered by the Forest Survey of India in early 2000, where thermal anomaly data were forest masked to identify forest fire. The author's proposed approach analysed forest fire influencing factors to forecast forest fire. Meghalaya is a state where indigenous people were relaying their ancestors' legacy in the forest fire. This study has discovered a temporal window where a forest fire is frequently observed. Forest management committees can use this to initiate awareness campaigns during the detected time interval. The shifting cultivation is practiced mainly for the livelihood of inhabitants. With the collaboration of forest dwellers, the governing bodies and local administrations can establish joint forest management; thus, dependence on forest resources can be lowered to a vaster extent.

The future work is to create a forest fire alert system where all fire persuading factors discussed and archived MODIS and SNPP NRT data will be analysed to forecast the forest fire.

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8. Contributions:
   Tapan Dhar: Conceptualization, Methodology, Software, Data curation, Writing - Original draft preparation. Dr. Sengalvarayan Aravindan: Supervision. Dr. Basudeb Bhatta: Validation, Writing-Reviewing and Editing.

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