GOOGLE EARTH ENGINE BASED TEMPORAL ANALYSIS OF INDICES USED FOR FOREST FIRE STUDY IN MIZORAM, INDIA

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ABSTRACT:

Forest fires would be a global disaster if they were not addressed seriously? From 2015 to 2021, the number of forest fires in India nearly tripled. According to FSI, the North Eastern Himalayas, one of UNESCO's 36 Biodiversity Hotspots, account for 36% of forest fires in India. This state is dominated by tribal population which practices shifting agriculture. It's 76.01% of total forest cover is highly prone to Forest fires. Despite this, there hasn't been any time-series research on forest fires in this region. The Normalized Difference Vegetation Index (NDVI), Normalized Difference Moisture Index (NDMI), Normalized Burnt Ratio (NBR), Aerosol Free Vegetation Index (AFRI 1600), and Land Surface Temperature may all be linked to forest fires (LST). For Mizoram, India, random samples were taken every 16 days using Landsat 8 satellite data across different land cover types, including dense forest, sparse forest, farmland, and bare land etc. The study was conducted on a bimonthly basis from January 2016 to June 2021. The findings of this work show that an automated temporal analysis utilizing GEE may be used successfully over a wide range of land cover types, providing critical data for future monitoring of such threats.

1. INTRODUCTION

There has been a progressive increase in temperature and decrease in precipitation in recent years as a result of global warming, which has resulted in an increase in forest fire incidences(Vilar et al., 2016). The most visible effect of climate change in the last decade has been the increase in the number of forest fires around the world(Krikken et al., 2021) . Forest fires have become a serious environmental hazard in many nations throughout the world as a result of changing climates and concomitant local and regional warming (Zhang-Turpeinen et al., 2020). As a result, forest fires have wreaked havoc on flora and fauna, as well as on the human life and infrastructure(Vega Hidalgo et al., 2013) .

Tropical forests serve as a natural conservation area and play an important function in balancing carbon dioxide levels in the atmosphere (Bonan, 2008; Nuthammachot and Stratoulias, 2021).Despite their importance, tropical forests are rapidly disappearing(Abdullah and Nakagoshi, 2007; Sánchez-Azofeifa et al., 2001). Forest fires, developmental activities, a fast growing population, and other anthropogenic activities were the main causes of deforestation in the recent decade(Uusivuori et al., 2002). Shifting agriculture is still widely practised by indigenous people in many tropical parts of the world. Shifting cultivation, also known as 'slash and burn' and 'bush fallow,' is performed all over the world and is known as Ladang in Indonesia, Kaingin in the Philippines, and Ray in the Philippines. Ray in Vietnam, Brazil, the Congo's Masole, and Central Africa, as well as the Manchurian highlands, Korea, and southwest China(Layek et al., 2018) and Jhum cultivation in North East India. As forest fires are harmful to the ecosystem, so adequate preventive and mitigating measures, as well as the development of forest fire sensitive zones, are becoming a necessity for minimising the ever-increasing threat of forest fires (Kale et al., 2017).

Because most forest fires occur in remote areas, they go undetected. As a result, India lacks complete statistical data on active forest fire incidences. As a result, remotely sensed satellite data is an excellent alternate source for forest fire research. Nowadays, remote sensing is becoming an indispensable technique for monitoring large-scale events in terms of both area and time, particularly in distant locations such as forests(Sobrino et al., 2019). Furthermore, Landsat satellites offer the free of cost, best resolution and spectral efficiency for tracking occurrences such as forest fires (Konkathi and Shetty, 2021). Remotely sensed satellite data is used to create indices that serve as indicators for many aspects of the earth's surface, such as vegetation, temperature, and humidity. The Normalized Difference Vegetation Index (NDVI) is one of the oldest and most important indexes for assessing vegetation vigour and its potential as a source of forest fire fuel (Long et al., 2019). This indicator has also been used in studies on forest fires to detect burnt areas and changes in flora as a result of the fire. Since the last two decades, the Normalized Burnt Ratio (NBR), a comparatively newer metric than NDVI, has been frequently and successfully utilised in forest fire studies(Lozano et al., 2007). Other indices, such as the Normalized Difference Moisture Index (NDMI) and the Aerosol Free Vegetation Index (AFRI), are also examined to support the findings. The environmental variable Land Surface Temperature (LST) was also investigated in relation to forest fires (Ermida et al., 2020).

Additionally, temporal analysis of forest fire creates a large volume of data that is difficult to pre-process and evaluate using standalone computer system. Google Earth Engine, a cloud computing platform with access to a massive collection of satellite data, has changed study in this field in recent years. Furthermore, it significantly improves practically any geo-computation regime used in time series or spatial analysis (Wagle et al., 2020).

Forest fires in India have gotten a lot of attention in recent years because of its ecological, economic, social, climatic, and political implications(Vadrevu et al., 2010) . Forest fires are also becoming a major cause of forest degradation, particularly in tropical areas with dry deciduous forests, such as Madhya Pradesh, Odisha, and Chhattisgarh (Chandra and Bhardwaj, 2015). It is a significant contributor to changes in forest structure and function. As a result, there has been an increase in data gathering for forest fires. As a result, multiple studies on

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forest fires have been conducted in various parts of India(Srivastava et al., 2019; Tiwari et al., 2021). Although forest fires can occur naturally, over 90% of forest fires in India are caused by humans(Roy, 2003) . Due to the age-old practise of shifting cultivation and the spread of fires from jhum fields, the North-eastern Himalayas, UNESCO's one of the richest biodiversity hotspots, is badly impacted by forest fires (Puri et al., 2011). 90% of the population of Mizoram, a state in North East India, is tribal ("Census of India Website : Office of the Registrar General & Census Commissioner, India,"), and most of them engage in shifting cultivation (Sati and Rinawma, 2014). However, it is paradoxical that, despite having some of the world's greatest flora and fauna in North East forest and ranking second only to central India in terms of fire proneness, comparatively few research had been conducted(Ahmad et al., 2018) . These findings influenced our decision to study in north-eastern India.

All previous forest studies in North Eastern India are at least 7 years old. As a result, many investigations lacked either high-resolution Landsat 8 data or effective cloud-based geo-computing platforms such as Google Earth Engine(Puri et al., 2011). Apart from that, it's worth noting that, according to the Forest Survey of India (FSI), the total forest cover of Mizoram has been divided into the following five classes based on their fire proneness: Extremely fire prone 29.91 percent, very highly fire prone 38.46 %, highly fire prone 24.64 %, moderately fire prone 5.35 %, and less fire prone 1.64 % (IFSR 2019). This clearly reveals that more than 90% of Mizoram's forest area is at risk of fire. Furthermore, while India's total forest cover has increased in the last two years, it has decreased in the north eastern states (IFSR, 2019). According to the Mizoram government's Fire and Emergency Services Department, there were 69 forest fires in 2016, 46 in 2017, 56 in 2018, and 82 in 2019 ("Fire & Emergency Services Department, Mizoram"). In April 2021, there were also numerous serious forest fire incidents, according to news reports. All of this inspired us to conduct study on forest fires in Mizoram in North East India.

Furthermore, no temporal analysis of forest fire indices has been conducted for Mizoram in the last fifteen years. Forest fire studies must also be reanalysed utilising current technology and high-resolution data due to significant changes in the environment over the last decade. This would allow us to improve the accuracy of the data collected and gauge the impact of forest degradation. This could be used for a variety of forest fire-related investigations, such as identifying forest fires, mapping forest fire zones, evaluating the ecological and economic impact of forest fires, and so on.

Thus, in this work, we investigated indices such as NDVI, NBR, NDMI, AFRI, and LST for the Mizoram state of India between 2016 and 2021 using Landsat 8 data on Google Earth Engine platform. Furthermore, the temporal analysis using GEE provided valuable insights into vegetation phenology, which will aid in the development of critical phenological criteria for forest fire. The study's main goal is to do a temporal analysis of forest fire-related indices and see the land surface temperature variance.

2. STUDY AREA, DATASET AND METHEDOLOGY

2.1 Study Area

The state of Mizoram lies between 21°56' N to 24°31' N latitude and 92°16' E to 93°26' E longitude covering an ares of 21,081 sq km. The state's geography is primarily mountainous, with rocky and steep slopes creating deep valleys that lead to a

number of streams and rivers in the lowlands. Almost all of the hill ranges are in north-south orientation. When compared to the western portion of the state, the eastern part has a higher elevation. In south-eastern Mizoram, the tallest mountain, Phawngpui, stands at 2,165 m. Hill ranges, on the other hand, have an average height of roughly 920 metres. In the state, there are 15 major rivers, seven of which flow north and the rest flow south or west.

Mizoram is a monsoon-rich state, with annual rainfall ranging from 2,100 to 3,500 mm and yearly temperatures ranging from 11°C to 24°C during the winter months of November to January, and 18°C to 29°C during the summer months of March and April. It rains heavily during the monsoon season, which runs from May through September. According to ISFR 2019, Mizoram has a forest cover of 18,005.51 sq km, accounting for 85.41 % of the state's entire geographical area, making it the state with the greatest forest proportion out of the total geographical area in the country. The major types of forest in the state are tropical semi-evergreen (71.94%), tropical moist deciduous (27.4%), subtropical broad leaved (0.04%), and subtropical pine forests (0.62%).

Mizoram has a population of 1.09 million people, according to the 2011 census and a population density of 52 people per sq km, which is significantly lower than the national average of 382 people per sq km. The rural population accounts for 47.89% population, while the urban population accounts for 52.11%. The tribal population accounts for 94.43% population. However, the state's literacy rate is 91.33%.
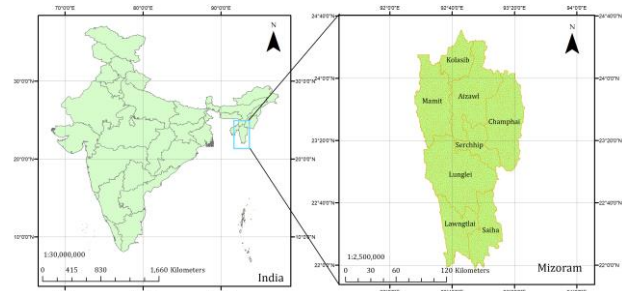

Figure 1: Map drawn using ArcMap showing the study area of Mizoram, North East India.

2.2 Dataset

The LANDSAT/LC08/C01/T1-SR and LANDSAT/LC08/C01/ T1-TOA dataset from the USGS Landsat series of Earth Observation satellites is used in this study. The study area falls in path 135/136 and row 43/44/45 which makes the whole set of the image collection. The atmospherically corrected surface reflectance of 5 visible and near-infrared (VNIR) bands, 2 short-wave infrared (SWIR) bands, and 2 thermal infrared (TIR) bands are used (Hislop et al., 2018). Tier 1 Landsat scenes are appropriate for temporal analysis because they have the best data quality available for free.

2.3 Methodology

The workflow was broken down into three sections namely data gathering and pre-processing, data processing, and time series analysis are all steps in the process.

Data Gathering and pre-processing:

The Landsat 8 surface reflectance images were selected from the image collection on GEE for the study area. The image collection was filtered based on the study location, time period and minimum cloud percentage. After that, cloud masking was applied to remove the errors caused by cloud covers and cloud shadows in the filtered images. Then mosaicking was done for the same dates and the study area was clipped from the image.
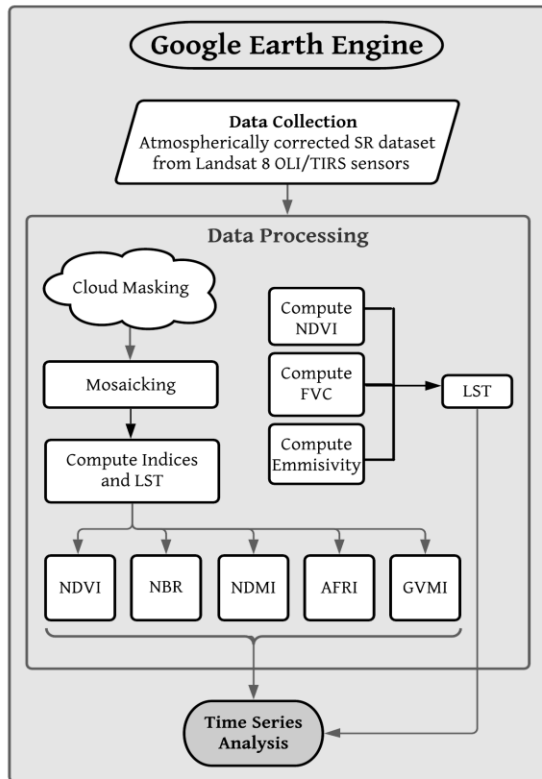

Figure 2: Methodology used for time series analysis of Indices calculated for the Mizoram region

Calculating Indices:

On the extracted satellite images many indices were calculated for the requisite time period. The NDVI, NDMI, NBR (Lozano et al., 2007), and AFRI were calculated using the below mentioned formula,

$$NDVI = \frac{(NIR - RED)}{(NIR + RED)} \tag{1}$$

$$NDMI = \frac{(NIR - SWIR1)}{(NIR + SWIR1)} \tag{2}$$

$$AFRI = NIR - 0.66 * \frac{(SWIR1)}{(NIR + 0.66 * SWIR1)} \tag{3}$$

$$NBR = \frac{(NIR - SWIR2)}{(NIR + SWIR2)} \tag{4}$$

LST was also calculated from using the formula given below (Ermida et al., 2020).

$$LST = Ai * \frac{Tb}{\varepsilon} + Bi * \frac{1}{\varepsilon} + Ci \tag{5}$$

Time series Analysis:

The total forest cover of Mizoram is highly prone to forest fires, yet, there hasn't been any time-series analysis on forest fires in this region. Further the effect of land use practices on forest fires is not analyzed yet. Hence in this work, 30 random samples were taken on different land cover types, including dense forest, sparse forest, farmland, and bare land at every 16 days using Landsat 8 satellite data. The study was conducted on a bimonthly basis from January 2016 to June 2021. All the indices as mentioned above were calculated for these points and for representation their mean value was considered. The basic statistical analysis for these indices derived for above mentioned classes is shown in table 1. Points depicting burned areas/scars of recent forest fires in Mizoram were collected using Google Earth Pro for the purpose of validation and estimating the forest fire extents.

3. RESULTS

The temporal graph of NDVI for different classes like dense forest, sparse forest and bare land shows that the value of NDVI starts increasing from May, reaches near peak value in mid-June and maintains a high value above 0.8 for almost 5 months and then starts decreasing from mid-November and reaches a minimum value of around 0.6 sometime in April end. This behaviour is seen to be repetitive for all the years showing the phenological pattern of the vegetation growth in the area. Almost same behaviour is seen for other indices and LST was found to be higher at the fire incidents.
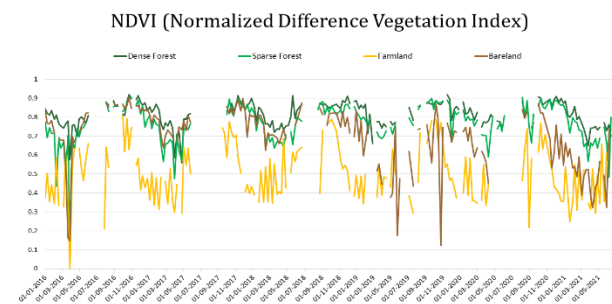

Fig. 3: Mean NDVI for 30 random points taken in each land cover class of Mizoram area from year 2016-2021.

The average NDVI values for sparse forest, farmland and bare terrain were determined to be 0.77, 0.51 and 0.70, respectively. The NDVI for the dense forest region is around 0.8 on average, with highest values reaching 0.9 having standard deviation of 0.06. The farmland and bare land show a minimum value of 0 and 0.12 and maximum value of 0.8 and 0.9 with a similar standard deviation of 0.15. The maximum value of NDVI is reached in the month of October 2016 for the bare land region and in the month of September 2016 for the farmland region.

Interestingly, around March 28, 2016, the NDVI reaches its lowest point which can be seen from the figure 3, with a value of 0 for farmland, 0.12 for bare terrain and 0.18 for sparse forest. Also, the minimum value of NDVI for dense forest points is around 0.56, which corresponds to 6 April 2016, as

shown in figure 3, implying that there is a likelihood of a forest fire at that time.

Similarly, during March 2021, low NDVI values in the dense, sparse forest and bare land region is observed that indicates the presence of some fire events during that time. This was validated with the news reports and the high-resolution satellite image of that time period.
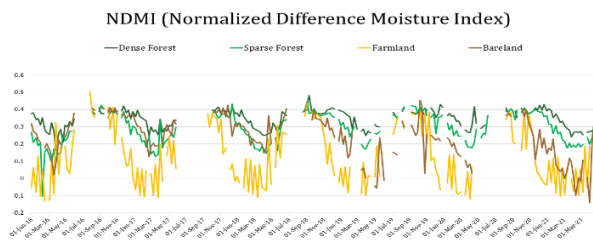

Fig. 4: Mean NDMI for 30 random points taken in each land cover class of Mizoram area from year 2016-2021.

According to the data, the average NDMI for the dense forest region is 0.34, with a maximum of 0.48 and a standard deviation of 0.05. The minimum NDMI of dense forest points is around 0.16, which corresponds to March 28, 2016, showing that there may have been a dip in moisture content due to a fire occurrence at that time. In the sparse forest region, the NDMI has an average value of 0.45 while the minimum value for the sparse forest zone, which corresponds to February 9, 2016, indicating reduced moisture content at that time means there is high chance of some event of forest fire. (Figure 4). Minimum NDMI value for the farmland was found to be -0.13 around 05

Index	Statistical Parameter	Dense Forest	Sparse Forest	Farm land	Bare land
NDVI	Min	0.56	0.18	0.00	0.12
	Max	0.92	0.91	0.84	0.91
	Avg.	0.82	0.77	0.51	0.70
	Std. Dev	0.07	0.10	0.15	0.15
NDMI	Min	0.16	-0.10	-0.13	-0.14
	Max	0.48	0.45	0.52	0.45
	Avg.	0.34	0.29	0.12	0.24
	Std. Dev	0.05	0.09	0.17	0.12
AFRI	Min	2024.01	1684.00	792.00	1333.00
	Max	5210.34	5643.60	9575.00	6976.01
	Avg.	3006.81	3411.05	2726.92	3410.41
	Std. Dev	657.57	749.01	733.83	837.82
NBR	Min	0.40	0.05	0.02	-0.01
	Max	0.75	0.75	0.71	0.76
	Avg.	0.64	0.58	0.35	0.51
	Std. Dev	0.06	0.10	0.19	0.16

Table1: Statistical estimates for various indices for different land cover types gathered from 2016 to 2021.

March 2016 shows these months to have registered some event (Figure 4). Similarly, on 29 May 2021 the NDMI value for bare land reaches a minimum of -0.14 indicating very low vegetation moisture content.

The average value of AFRI in sparse and dense forested region is 3411 and 3007 with the standard deviation of 749 and 658 respectively (Table 1). While the average AFRI for bare land and farmland is 3410 and 2727 with the standard deviation of 838 and 734 respectively.

The lower values of AFRI for the farmland is observed in April 2016; July 2019 and May 2021 while that for bare land is observed in January 2017. However, for dense and sparse vegetation the lowest AFRI value is seen around January and February 2016, that matches with the time period when other indices are also low suggesting that these are the months of degradation in vegetation health, most probably due to forest fire events. The peak shown in the figure 5 might be the outlier.
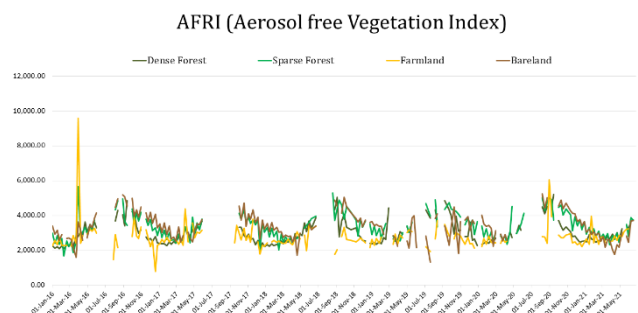

Fig. 5: Mean AFRI for 30 random points taken in each land cover class of Mizoram area from year 2016-2021.

There are days when many indices are lower and it is expected that there must have been some forest fire indices. Hence to corroborate that, NBR was calculated using equation 4. The temporal variation of mean NBR is shown in figure 6. The maximum value of NBR for all the land cover types is around 0.71-0.75 and except dense vegetation the minimum value of NBR for other land cover types is near 0. The average NBR value for farmland and bare land region is 0.35 and 0.51, while that for sparse and dense forest in 0.58 and 0.64 respectively. The standard deviation for bare land farmland, sparse forest, dense forest regions is 0.16, 0.19, 0.10, 0.06 respectively (Table 1).

It can be seen that farmland and bare land attains minimum value around mid-March 2016 and beginning of April 2021 (Figure 6). The value of NBR for bare land region reaches its lowest value to -0.01 on 11th April 2021, and that for farmland the minimum value is observed 1st April 2020 (Figure 6). Thus, the April of 2016 and 2021 seems to be the time when forest fire had occurred which led to decrease in NBR value in farmland and bare land. Similarly, for the sparse forest regions, during mid-April 2016 and for dense forest regions, during the end of March 2016, the NBR values are minimum indicating the occurrence of forest fire event. This is also be validated by local media coverage.
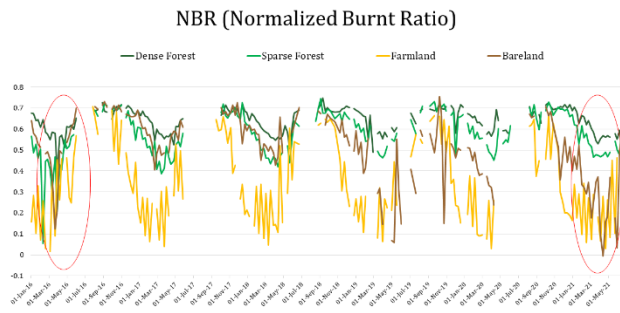
NBR (Normalized Burnt Ratio)

Fig. 6: Mean NBR for 30 random points taken in each land cover class of Mizoram area from year 2016-2021.

These incidents when we expect that forest fire had occurred, would led to increase in the temperature of the surrounding area and so we calculated the LST for those points in different land cover types. During different time periods, we didn't get the LST values because of presence of clouds at that time. The results showed that the effect of fire events has indeed increased the temperature which can be seen in the temporal graph shown below.

In general, the maximum temperature of the study area is around 27°C and that in forested areas is few degrees lower. But the land surface temperature for May 2016, 2020 and 2021 was higher than this value. But during March 2016, 2019, 2020 the temperature for sparse forest is more than even 30°C (Figure 7). In general, the LST for the farmland was found to be maximum in May (Figure 8). Many fire events have occurred during this time period of March - May mainly due to slash and burn agricultural practices (jhum cultivation). However, these results needed more detailed analysis to converge to exact time frame for estimation of forest days based on LST values. But for the initial work, we obtained sufficiently good results.
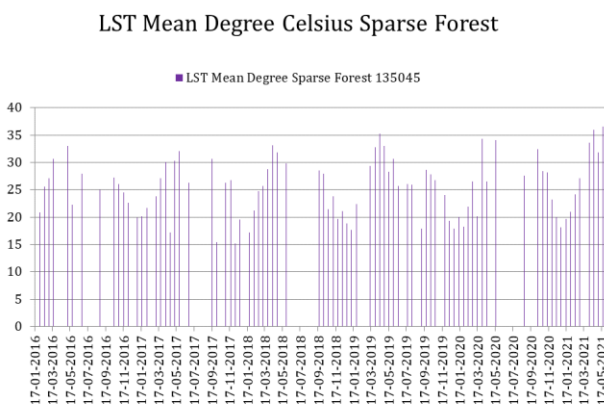
LST Mean Degree Celsius Sparse Forest

Fig. 7: LST Mean Degree Celsius for Sparse Forest region from year 2016-2021 in Mizoram region
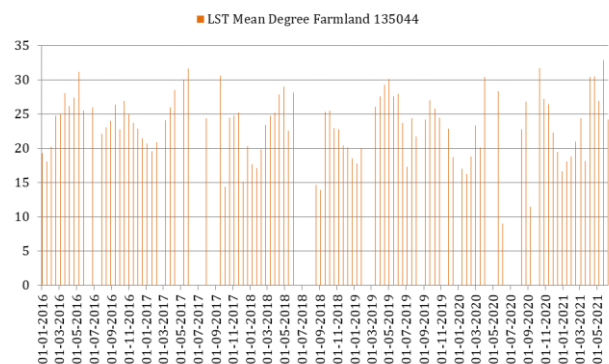
LST Mean Degree Celsius Farmland

Fig. 8: LST Mean Degree Celsius for Farmland region from year 2016-2021 in Mizoram region

We found that the NBR gives better results and to validate those results, we marked the burnt areas for 2021 on Google Earth Pro. There were many big fires in the months of March-April, 2021 in Mizoram, so those locations were marked in GE pro manually. Then for these points NBR was calculated for the whole-time frame. Due to cloud masking many data points were not obtained, as we got gaps in the data as shown in figure 9. The minimum, maximum and the mean values of NBR value for all those burnt areas were plotted (Figure 9). It is interesting to observe that during 2021 the NBR value for those burnt pixels/ areas dropped significantly. The maximum value of NBR also was very low during the period of forest fire in between March to May 2021. It's vital to remember that these fire points are from the fire outbreak in March and April of 2021. When we see the NBR graph for other land cover types in figure 6, we observe lower values in 2016 which seems to be due to forest fire events in 2016 and indeed some event had happened in 2016 in Mizoram. Thus, NBR gives good proxy for estimating the forest fire areas. More detailed work is required to estimate and define the threshold for NBR corresponding to forest fire events.
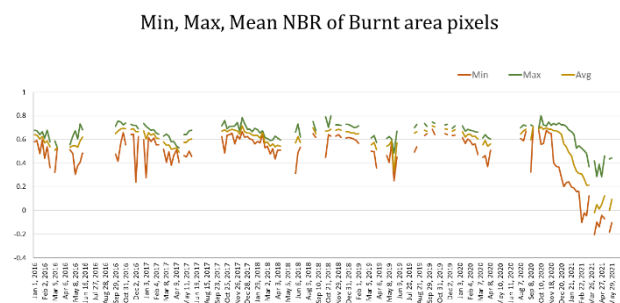
Min, Max, Mean NBR of Burnt area pixels

Figure 9: Min, Max, and Mean NBR of the burnt area points taken from Google earth pro in the Mizoram region.

4. DISCUSSION

Forest fires are most common in tropical climates during the long, dry summer season. They have a significant impact on atmospheric chemistry, biogeochemical cycle, and ecosystem structure. This feedback relationship may be increased during these times of rapid change in environmental conditions. As a

result, it's critical to analyse, interpret, and explain the findings of this research work.

Mizoram is a monsoon-rich state, with monsoon season beginning in May and ending in September. As a result, the majority of the vegetation blooms at this time, increasing the NDVI value around September-October and falling NDVI values throughout the hot months of March-April. In addition, Mizoram's forest cover accounts for more than 85% of the state's total land area. Dense forests have high NDVI values, often greater than 0.8, whereas sparse forests have mean NDVI values that range between 0.6 and 0.8. In both dense and sparse forest, the maximum and minimum NDVI values were found in September-October and March-April, respectively. Paddy is the major food crop grown in Mizoram's shifting cultivation dominated topography due to abundant rain (Wapongnungsang and Tripathi, 2018). It is planted at the beginning of the Kharif season, in May-June, and harvested in October-November. In September-October, the paddy sapling grows into a green plant. This is supported by high NDVI values for farmlands in September, followed by a drop in NDVI due to harvesting in October and November. Farmers often grow vegetables such as cabbage, cauliflower, beans, and other similar crops during the Rabi season, which begins in November and lasts 45-60 days. Furthermore, during the Rabi season, the NDVI values show a lot of zig-zag patterns with brief cycles. This trend could be attributable to a number of factors. Additionally, the spectral characteristic of farmland fluctuates greatly during the year. When harvested or tilled, it resembles a burned-out field. The values of NDVI of farmlands also drop sharply after ripening and before harvesting (Long et al., 2019).

As NDVI, NDMI and NBR are all normalised indices with the same NIR band, the relative behaviour of all three indices are nearly identical across all land use groups. Despite the fact that the AFRI was not a normalised index, it behaved similarly to the NDMI because its calculation included NIR and SWIR 1. Due to the presence of the SWIR band, a comparative analysis of the graphs of different indices clearly demonstrates that the NBR index is more capable of identifying fire conditions than the other indices(Hislop et al., 2018). Similar to NBR, NDMI outperformed NDVI in capturing changes in vegetation moisture and fire-like conditions. The presence of SWIR bands, which at least penetrate thin clouds, could explain the higher performance of NBR and NDMI(Lozano et al., 2007). NDMI is also more useful in detecting water stress areas that are susceptible to forest fire since it is more susceptible to moisture levels in crops and trees (Tian et al., 2013).

In general, the estimated mean Land Surface Temperature (LST) for various land cover classes displays the yearly highest values in March and April. This corresponds to the actual situation. The LST values were also found to be significantly higher than the respective month's average maximum temperature on the days that had chances of forest fire events. This is also consistent with the results of the other indices, and it concord the real data.

As the revisit time of Landsat 8 satellite is of 16 days so it becomes challenging to identify active fire points. But still, if more sample points would have been selected in each of the land use classes then results would have been much better. Thus the findings of this work show that an automated temporal analysis utilizing GEE may be used successfully over a wide range of land cover types, providing critical data for future monitoring of such threats.

5. CONCLUSION

- The time series analysis of these indices revealed that, in general, all indices increased during the monsoon season, peaked around September, and then began to decline, reaching a minimum value in April.

- Furthermore, all indices deviated from the general trend in a few instances, which could be related to a few forest fire events. In addition, the majority of fire accidents were discovered to occur in the month of March, with few outliers for winter events.

- NBR captures the forest fire events more prominently than other indices and hence could be used as proxy to forest fires.

- The general behaviour and anomalies were adequately described, and the results were consistent with real-world settings and incidents of forest fire.

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