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RESEARCH PAPER

Mapping Forest Fire-affected Areas Using Advanced Machine Learning Techniques in Damoh District of Central India

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Abstract

Forest fires can cause calamitous damage to the forest ecosystems and may affect climatic parameters, such as temperature, evapotranspiration, and precipitation by catalyzing changes in the local ecology of the region. The main research objective of this work was to quantify the different indices as well as to identify the changes in years 2011 and 2020 in pre- and post-fire, these parameters, such as Normalized Difference Vegetation Index (NDVI), Land Surface Temperature (LST) and Normalized Burn Ratio Index (NBR), associated with the severity of forest fires in the Damoh district of Madhya Pradesh. An attempt has been also made to understand the interrelationship of these parameters to gauge how these may correlate to determine the sensitivity to forest fires. In this context, we have incorporated advanced GIS methods for the identification of the pre-post fires for 2011 and 2020 year from Landsat 5 and Landsat 8 OLI/TIRS level -1 and Random Forest (RF) model in the Google Earth Engine (GEE) platform. Land Use Land Cover (LULC) map was categorized into five classes based on the satellite data sets. Our findings indicate elevated Land Surface Temperature (LST) values in the Northern and Central regions of the study area, reaching 32.0°C before the fire event. Subsequently, following the fire incident in the year 2011, LST escalated to 39.0°C. Similarly, in the southern and south-eastern regions of the Damoh district, LST peaked at approximately 43.0°C coinciding with the onset of a forest fire in 2020. Furthermore, our analysis revealed a negative correlation between the Normalized Difference Vegetation Index (NDVI) and LST, whereas the Normalized Burn Ratio (NBR) displayed a positive correlation with LST. These results underscore the impact of LST on forest vegetation dynamics, with LST nearing 39.0°C indicating an increased risk of forest fires. The results of this study can be used by local administration to devise an efficient policy related to forest fire management.

Keywords: Forest Fire Mapping; Google Earth Engine; Land Surface Temperature; NDVI; NBR.

1. Introduction

Forest fires have become a significant global concern due to their profound impacts, particularly on climatic parameters and biodiversity. Annually, forest fires affect more than 50 million hectares of land worldwide [1]. Moreover, they contribute, on average, to a loss of approximately 38 ± 9% (range) of forest cover globally, alongside other factors influencing forest loss [2]. Additionally, forest fires are associated with a 0.15 K increase in surface temperature globally within the burnt areas a year following the fire incident [3]. This underscores the intricate relationship between forest dynamics and forest fires, particularly evident in wildfire-prone regions globally [2], [4]. According to the Global Forest Resource Assessment, about 55% of the forest cover in India, i.e. 3.73 Mha of forests, bears the brunt of fire each year [5].

Forest fires have caused unprecedented damage to different ecological processes and have also been detrimental in affecting the global carbon cycle as well as temperature rise; anthropogenic activities have exacerbated these effects even more by altering the climatic parameters [6], [7]. These effects include post-fire decay, decline in soil fertility, land use impacts, and post-fire trajectories of different plant species according to their relative carbon cycle appropriation capabilities [8]. To counteract and mitigate the effects stemming from forest fire regimes, land use, and forest fire management systems, which alter fuel characteristics and fire regimes, have been visualized as essential human intervention [9]. In addition to providing commodities and livelihoods, preserving biodiversity, and preventing soil erosion and degradation with a regulating climate by sequestering carbon that would have otherwise been added to greenhouse gases, forests are significant natural resources [10]. Therefore, efficient forest fire control is crucial for the efficient use of forest resources, environmental conservation, and upkeep of extensive ecological balances [11].

Numerous global ecosystems are predicted to experience adverse impacts of forest fires as a result of climate change[12], [13]. Additionally, some researchers have hypothesized that the rise in global temperature may have an impact on the spatial distribution of forest fires [14], [15], [16]. Hence, there is a need to research how climatic parameters are interrelated and contribute to the distribution of forest fires in any geographic setting. So, site-specific forest fire plans can be envisaged to mitigate the deleterious effects of forest fires. Because, the mismanagement and inefficient fire prevention strategies can lead to accent the effects of forest fires culminating in greater damage to natural resources, economic assets, and human wellbeing [17].

Surface temperature plays an important role in forest fire identification in present and future scenarios. Land surface temperature (LST) is a widely used parameter in the assessment and mapping of forest fires [18], [19], [20]. Damoh district in Central India is especially susceptible to change in a slew of climatic factors and a high frequency of forest fires. As Damoh is one of the rainfall deficit districts of Madhya Pradesh, people in this region are grappling with the scarcity of rainfall, the decline in crop productivity, and higher vulnerability to forest fire risks [21].

It is well known that fire causes wide damage to the forest ecosystem both quantitatively as well as qualitatively [15], [22]. Tropical biomass burning caused by forest fires affects the environment because it releases a lot of trace gases and aerosol particles and affects the chemistry of the troposphere and climatic anomalies [23]. Every year, valuable forest resources, including carbon-locked biomass, are lost due to forest fires [24], [25].

By utilizing the temperature contrast between burning fire and the backdrop and by evaluating the spectral signature of burn and non-burn areas, satellite-based remote sensing (RS) data have been widely employed since about the late 1970s to both detect active forest fires and map burned sites [26]. Because of their superior temporal, spatial, and spectral resolutions, RS data from satellites like Landsat [26], [27], [28], and more recently, the Sentinel-2 [29], [30], have been widely employed for precise estimation of the spatial extent of fire-affected areas and the fire severity at various scales (i.e. local, regional, and global).

Understanding the onset of forest fires, as well as post-fire vegetation dynamics, serves as a crucial foundation for devising effective planning strategies and post-fire resource management practices, along with implementing preventative measures against soil erosion. Research efforts aimed at identifying fire-affected areas have been conducted in various regions of India, demonstrating remarkable accuracy in predicting the spatial extent of forest fire impacts and assessing changes in post-fire vegetation using proxies such as the Normalized Difference Vegetation Index (NDVI). For instance, researchers observed a significant change between 2014 and 2018, indicating a 35.8% shift in average NDVI and a 14.69% variation in mean temperatures observed during the forest fire season in Tirupati, India [31].

In central India, which includes the Damoh district, forest fire incidences have been highly prevalent, with 70% of fires occurring during March and April from 2001 to 2020 [32]. Furthermore, warmer temperatures have been identified as exacerbating factors, leading to a doubling of forest fire occurrences during the forest fire season (February to May) between 2006 and 2020 [32]. Studies investigating the impact of forest fire frequency on vegetation in Central India have yielded varied conclusions. On one hand, researchers found that forest fire hotspots in central India exhibited comparatively lower tree density and dominance, indicating a negative effect on vegetation recovery [33]. Conversely, researchers reported non-linear trends in tree diversity in response to fire frequency, with fluctuations observed across different fire severity classes [34]. Specifically, researchers noted an increase in tree diversity and basal area in low-frequency zones, while medium and high-severity zones exhibited initial decreases in tree diversity followed by subsequent increases in high-severity zones [34]. These studies highlight the importance of comprehending the heterogeneous effects of forest fire occurrences on vegetation across various sites in central India, facilitating the implementation of site-specific mitigation strategies to counteract detrimental impacts.

India is a highly diverse country with varied forest types distributed across its confines. However, much focus on studying the burn areas due to forest fires and their resultant effects on vegetation has been confined to Himalayan Forest fires or the fires resulting from swidden agriculture in the north-eastern states of India, while forest fires in central India have received scant attention and there is a paucity of studies in this highly fire-prone region [32]. Hence, to bridge this gap, the present study has been conceptualized to understand the interrelationship between crucial climatic and vegetation indices to better understand the spatial distribution of forest fires in the Damoh district, Central India. NDVI and LST, which are used to signify the vegetation health and land surface temperature respectively, have been quantified to understand their relationship with NBR. Identification of climate change effect on LST was also done from the years of 2011 and 2020. In this study, we have combined the vegetation indices and land use land cover (LULC) datasets for the identification of pre-post fire mapping. Forest fire identification can help conceive an efficient forest fire management plan by deciphering the susceptibility of different areas to forest fires. The difference between the pre- and post-fire-based NDVI and NBR can further our understanding of the effects of forest fires on vegetation dynamics.

2. Study Area

Damoh district falls under the Bundelkhand region in Madhya Pradesh state of Central India (Figure 1). The district has a semi-arid climate and is characterized by severe drought-prone conditions, with drought frequency and intensity having increased in recent decades. The area of Damoh district is 7,306 km^2, of which 2630.16 km^2 area falls under forest. The average elevation of the district is 595 meters. Damoh experiences a subtropical climate with distinct seasons. Summers (March to June) are hot and dry, with temperatures often reaching high levels. Winters (November to February) are generally mild and pleasant. Geologically, it is a part of the Vindhyan rock system, which dates back several million years. Geomorphologically, the region is characterized by undulating landforms, with hills, plateaus, and valleys dotting the landscape. The annual precipitation of the region varies from 52 to 100 cm. The Tendu River and its tributaries, along with some other small streams, contribute to the water resources of the region. As per the researcher's revised classification of Indian forest types, the major forest type of the region is tropical dry deciduous forest [35]. The vegetation is characterized by dominant deciduous tree species like, Tectona grandis, Madhuca indica, Diospyros melanoxyon, Leucaena leucocephala, Buchanania lanzan, Lannea coromandelica, Terminalia bellirica, Terminalia chebula. The undergrowth is covered with tall dry grasses and invasive shrubs like Lantana camara;

which make the thick cover of dry leaf litter thus contributing to potential fuel for the surface fire. The surface fires frequently occur in the district, and these fires tend to spread very fast to vast areas covering deep valleys and rugged high hills.

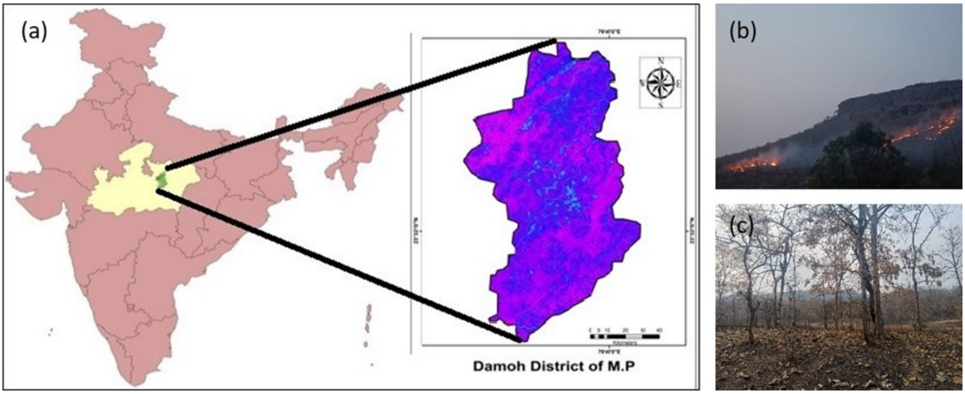

Figure 1: *Study area (a) Location of Damoh district in Madhya Pradesh (b) A picture of forest fire spreading over a vast area in Damoh (c) A post-fire photo of vegetation affected by surface fire.*

3. Methodology

Satellite images with atmospheric correction of the pre-and post-fire seasons were available on the GEE platform. In this study, Landsat 5 and Landsat-8 OLI satellite imagery (30m spatial resolution) were utilized in the land use land cover (LULC) mapping (refer to Tables 1 and 2); the classification of LULC mapping was conducted through the Random Forest (RF) algorithm. Change detection analysis from 2011 to 2020 was employed to observe changes in LULC, Land Surface Temperature (LST), and Normalized Difference Vegetation Index (NDVI). Maps of pre- and post-fire occurrences, NDVI, LULC, LST, and Normalized Burn Ratio (NBR) were generated using a machine learning (ML) approach with Landsat-5 and Landsat-8 satellite data (Figure 2).

Table 1: *Data Used and Methodology in year 2020*

Indices	Software	Satellite data	Source	Pre-Fire Season	Post fire Season	Bands
NDVI	ARC GIS	Landsat 8	USGS (Open Portal)	20-02-2020 to 10-03-2020	10-05-2020 to 25-05-2020	NIR and RED
LULC	GEE	Landsat 8	USGS (Open Portal)	20-02-2020 to10-05-2020		7 visible and near-infrared (VNIR) bands
LST	GEE	Landsat 8	USGS (Open Portal)	28-02-2020 to 03-03-2020	10-05-2020 To 25-05-2020	Band 10 and 11
NBR	ArcGIS	Landsat 8	USGS (Open Portal)	-	10-05-2020 to 25-05-2020	NIR and SWIR Band 5 and Band 7

The forest fire point data was sourced from the Forest Survey of India (FSI) website, depicting the locations of forest fires; FSI employs MODIS data for forest fire identification. LULC classification

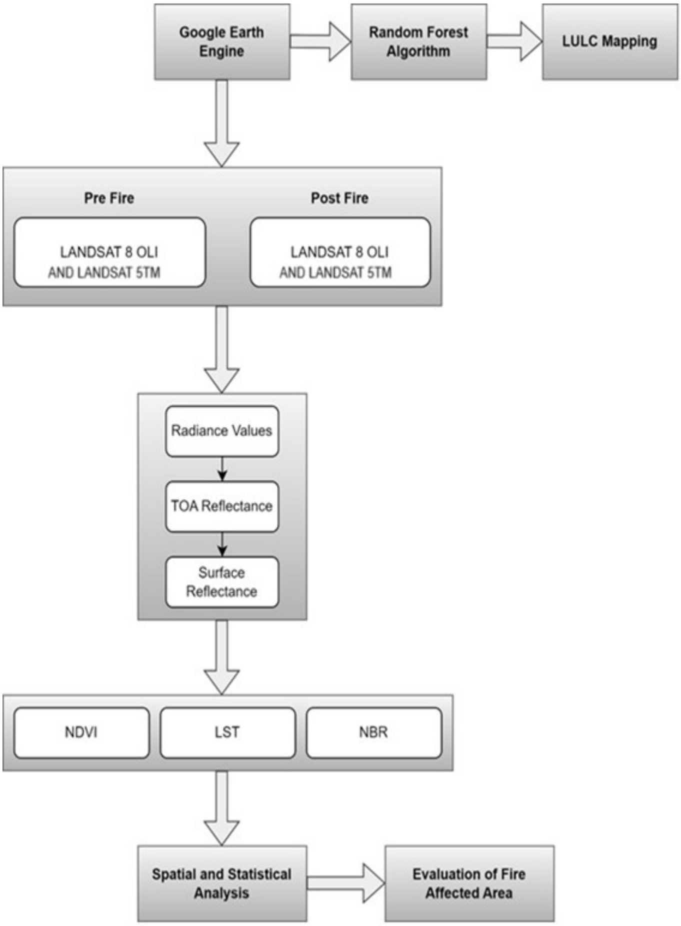

Figure 2: *The adopted methodology of this research.*

plays a crucial role in discerning features pre- and post-fire. NDVI was computed to assess current vegetation growth and quantify the impact of fire on vegetation. In 2020 Landsat-8 satellite data, bands 4 and 5 were utilized for NDVI computation. NBR was employed to calculate the burn ratio, with Landsat bands 5 and 7 serving this purpose. LST was calculated to ascertain the surface temperature at the onset of forest fire, utilizing band 10.

3.1 Google Earth Engine (GEE) and Random Forest Model

The Random Forest (RF) model is employed in this study due to its ability to construct an ensemble classifier for the identification of land use classes. Notably, the Random Forest algorithm is recognized for its capability to provide land use classification with a high degree of accuracy compared to alternative models [36]. Within the Google Earth Engine (GEE) platform, datasets can be obtained and subsequently processed using JavaScript application programming interface (API) and built-in algorithms. Consequently, following atmospheric correction and data analysis utilizing GEE's built-in algorithms, the time series data, facilitated by a cloud-based platform, can be utilized for quantifying desired parameters across various earth science applications [37], [38], [39].

The RF model, initially proposed by Breiman [36], offers several advantages for remote sensing applications [40], [41]. Widely popular in machine learning programming, the RF algorithm is renowned for its high accuracy in image classification. By amalgamating various types of tree classifiers, the RF algorithm enhances classification accuracy [42]. In this model, each tree node determines constraints by comparing predictor variables, enabling the model to utilize an ensemble of decision trees to generate classifications. Through the integration of outputs from multiple trees, classification results are consolidated and more accurate [43], [44].

3.2 Normalized Difference Vegetation Index (NDVI)

The NDVI index is a valuable tool for monitoring and understanding changes in vegetation [45], [46]. It is a numerical indicator commonly used in remote sensing and vegetation analysis to assess the health, density, and vigor of vegetation cover. It is particularly useful for monitoring changes in vegetation over a temporal scale and comparing vegetation health across different regions. NDVI was calculated to identify the condition of vegetation before the fire and after the fire. The index ranges from -1 to +1 and is calculated by the following formula:

$$NDVI = \frac{NIR - R}{NIR + R} \tag{1}$$

Where NIR (Near-Infrared) is the reflectance of the vegetation in the near-infrared spectrum (usually band 4 in satellite imagery), Red is the reflectance of the vegetation in the red spectrum (usually band 3 in satellite imagery).

Table 2: *Data Used and Methodology in year 2011*

Indices	Software	Satellite data	Source	Pre-Fire Season	Post fire Season	Bands
NDVI	ARC GIS	Landsat 5	USGS (Open Portal)	20-02-2011 to 10-03-2011	10-05-2011 to 25-05-2011	NIR and RED
LULC	GEE	Landsat 5	USGS (Open Portal)	20-02-2011 to 10-05-2011		7 visible and near-infrared (VNIR) bands
LST	GEE	Landsat 5	USGS (Open Portal)	28-02-2011 to 03-03-2011	10-05-2020 To 25-05-2020	Band 10 and 11
NBR	ArcGIS	Landsat 5	USGS (Open Portal)	-	10-05-2020 to 25-05-2020	NIR and SWIR Band 5 and Band 7

3.3 Land Surface Temperature (LST)

Land Surface Temperature (LST) refers to the temperature between the earth's surface and the surroundings as measured from a remote sensing perspective [47], [48]. It is the temperature of the physical land or ground, including natural surfaces like soil, vegetation, and water bodies, and human-made surfaces like buildings and roads. Remote sensing techniques, particularly those using satellites equipped with thermal infrared sensors, are commonly used to measure LST. These sensors detect emitted thermal radiation from the earth's surface, which is related to the temperature of the surface. The thermal infrared spectrum is typically in the range of 8 to 14 micrometers, also known as the "thermal window." The LST estimation was performed in the ArcGIS 10.8 version by using the raster calculator tool. For more details on the calculations of LST [49].

3.4 Normalized Burn Ratio (NBR) Index

The Non-Burn Ratio (NBR) index is a remote-sensing vegetation index used in the context of forest fire estimation and post-fire assessment. It is particularly useful for evaluating the severity and extent of forest fires and understanding the impact of the fire on the vegetation cover.

The NBR index is calculated using near-infrared (NIR) and shortwave infrared (SWIR) bands from remote sensing imagery, typically obtained from satellites equipped with multispectral sensors. The formula to compute the NBR index is as follows:

$$NBR = \frac{(\text{Band } 5 - \text{ Band } 7)}{(\text{Band } 5 + \text{ Band } 7)} \tag{2}$$

Where, NIR (Near-Infrared) is the reflectance in the near-infrared spectrum and, SWIR (Short-wave Infrared) is the reflectance in the shortwave infrared spectrum.

The NBR index compares the reflectance in the near-infrared and shortwave infrared portions of the electromagnetic spectrum. In healthy vegetation, the NIR reflectance is higher, while the SWIR reflectance is lower. However, after a forest fire, the vegetation is often burned or damaged, resulting in reduced NIR reflectance and increased SWIR reflectance. As a result, the NBR index values are positive after a fire event.

The NBR index can be used to assess the severity of forest fires and distinguish between different burn severity classes, such as low, moderate, and high severity. It is also helpful in mapping the extent of burned areas. By comparing pre-fire and post-fire NBR values, the changes in vegetation cover caused by the fire can be quantified.

4. Result

4.1 Land Use and Land Cover (LULC)

LULC mapping was obtained from Landsat 8 satellite images using a random forest (RF) model based on the GEE (Figure 3 and 4). Five land use classes have been classified based on the random forest model and GEE platform. The forest and agriculture accounted for the land use categories having maximum area, i.e., 36% and 34% respectively (Table 3).

Table 3: *LULC classes in study area.*

Sr. No.	Classes	(%) LULC area
1	Agriculture land	34.00
2	Built-up land	8.00
3	Waste land	12.00
4	Water body	10.00
5	Forest land	36.00

4.2 Normalized differentiate vegetation indices (NDVI)

Based on NDVI, an attempt was made to assess the current status of vegetation health in the study area from the years 2011 and 2020. In pre-fire season, NDVI in Damoh district ranged from 0.0975 to 0.996 (Figure 5), and in post-fire, it ranged from 0.0583 to 0.999 in 2011. Further, the difference between pre-post-fire NDVI results showed that 15.63% area was affected by forest fires in the 2011 summer in Damoh. In 2020 the pre-fire was -0.11 to 0.87 and the post-fire which was ranging in between 0.03 to 1. In 2020 20.84% area was affected.

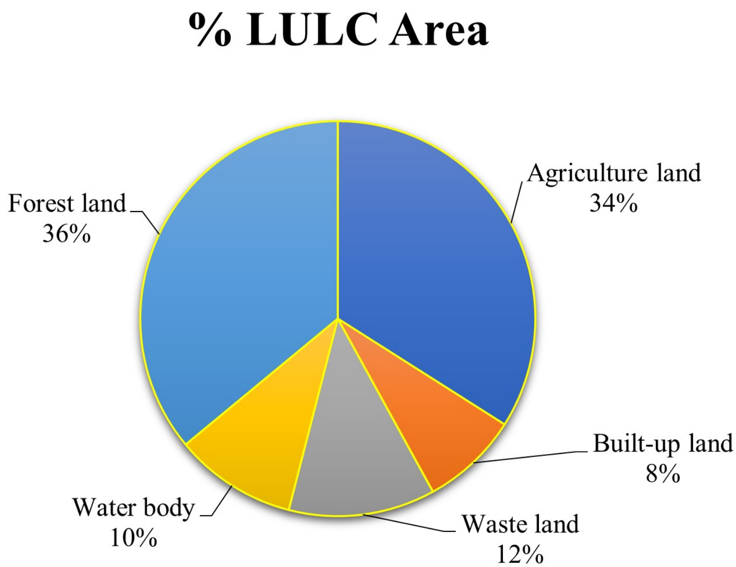

Figure 3: *Pie chart (%) of LULC area.*

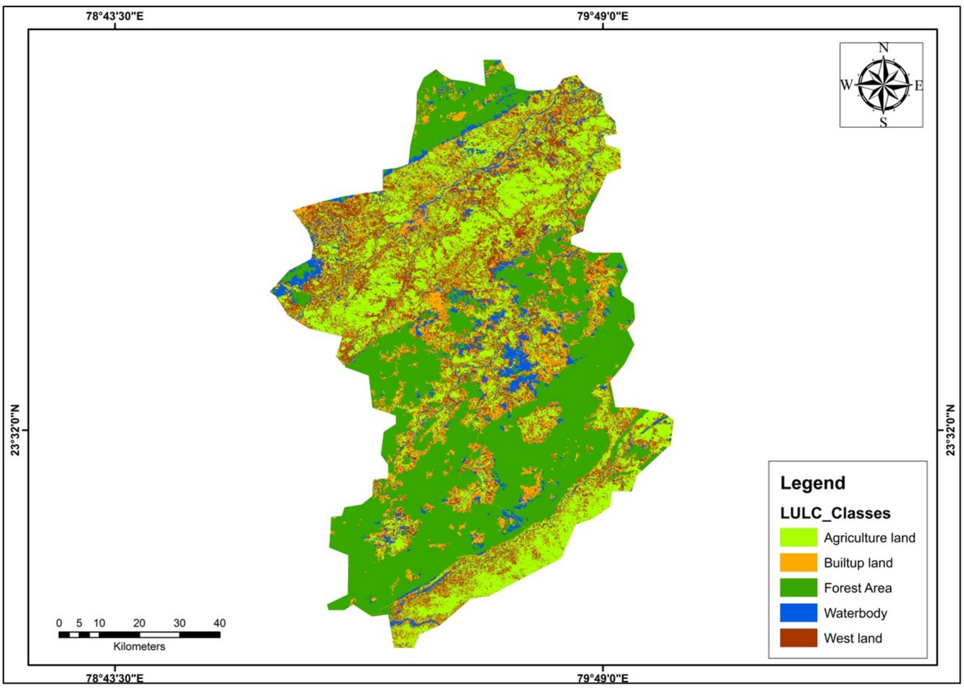

Figure 4: *LULC map of the study area.*

4.3 Land surface temperature

In 2011 the fire was started on 18/03/2011 based on FSI data. In 2011 the highest temperature was 390c and the lowest was 22.880c. The fire in Damoh started on 06/03/2020. Hence, the LST data

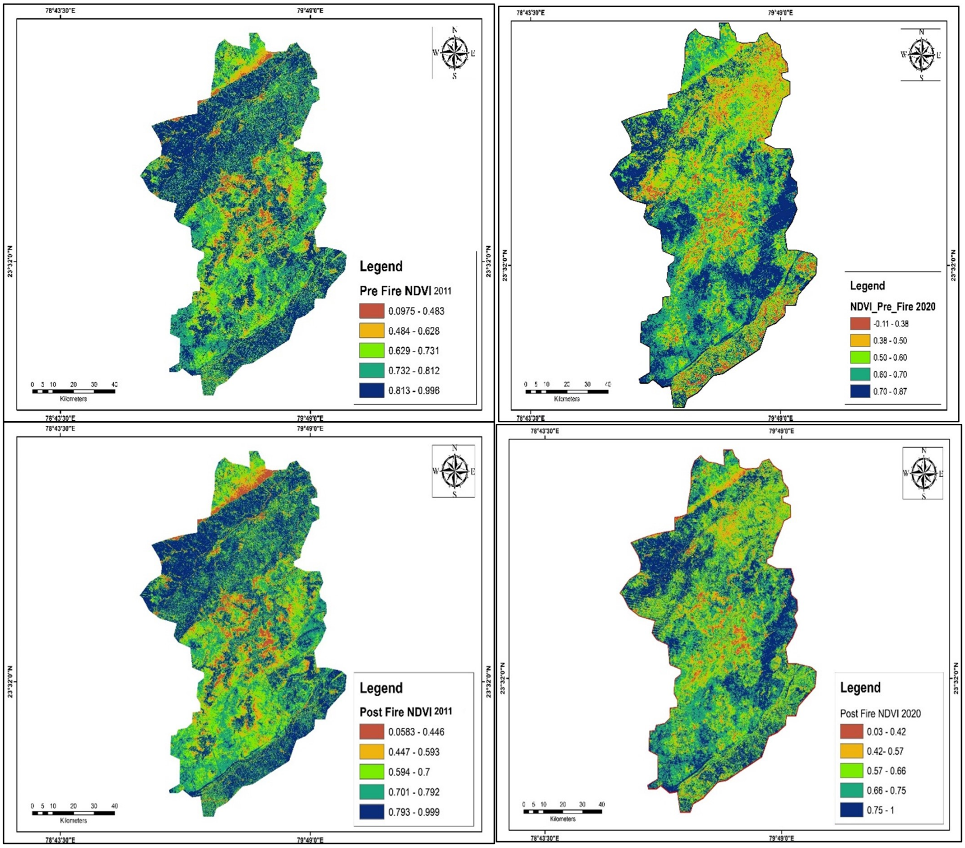

Figure 5: *Pre- and post-fire NDVI maps of the study area.*

was computed from 05/03/2020 (Figure 6). The LST in Damoh region varied from a minimum of 21.78 to a maximum of 43.25. However, the LST of fire points varied from 39.9 to 43.25. Hence, LST quantification indicated that when LST approached 390c, then there was an extreme possibility of forest fire. So, 390c can assumed to be the threshold value of LST for the onset of forest fire in Damoh district. By comparing both years the temperature was increased by about 40c which is in the following maps.

4.4 NBR

In NBR, the high value indicates the high severity of forest fire burn area while the low value shows the opposite. In the Damoh district, the NBR value ranged from 0.681 to 0.99. Hence, most of the area falls in moderate to high severity of forest fires. Although NBR values of forest fire points ranged from 0.72 to 0.99, most of the points fell above the NBR values of 0.8 (Figure 7).

4.5 Correlation between LST and NBR

There was a positive correlation between NBR and LST ($R = 0.56$, $P < 0.001$, $R2 = 0.31$, $df = 115$). When NBR approaches one then it indicates that there is a high severity of vegetation burn as high values of NBR indicate barren ground without vegetation. When LST increases, NBR also increases at the same time, hence the relationship between these two is directly proportional with each other (Figure 8).

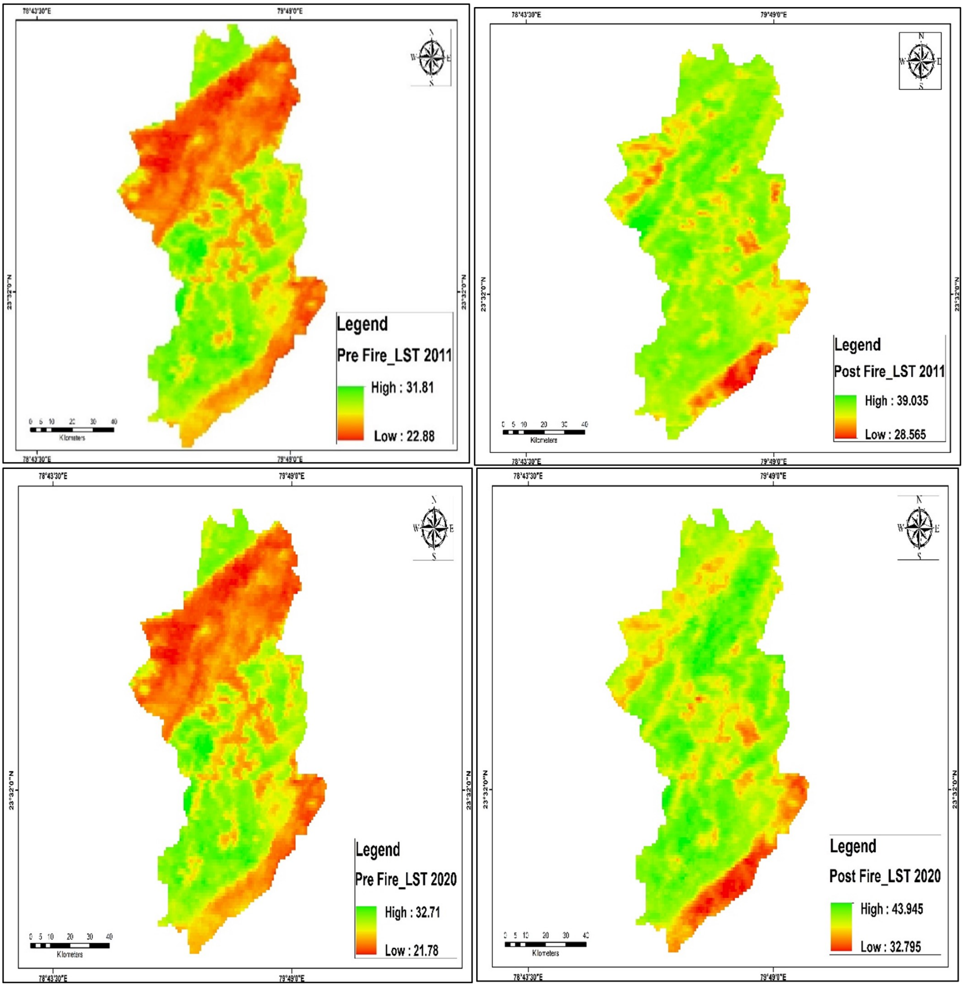

Figure 6: *Pre- and post-fire LST maps of the study area.*

4.6 Correlation between NDVI and LST

In the Damoh district, we found a negative correlation between LST and NDVI because the two have totally opposing changing trends ($R = -0.42$, $R^2 = 0.18$, $p < 0.0001$, $df = 115$). Higher values of NDVI indicate higher photosynthetic activity, i.e., good vegetation health; while on the contrary, high values of LST mean higher temperature which indicates poor vegetation or barren land due to the absence of vegetation. Hence, the relationship between these two is negative or inversely proportional (Figure 9).

5. Discussion

Our results demonstrate a moderate to high severity class of forest fires in the study area. The Damoh district is situated in the Bundelkhand region, characterized by tropical dry deciduous forests as a predominant forest type [35]. The climate of the Damoh district is dry due to low rainfall, and the presence of a compact rock body throughout the district, including sandstone, limestone, and shales. This compact nature contributes to higher storability and transmissivity, consequently affecting the forest type, resulting in dry deciduous forests. Such forests often accumulate dead leaves, branches,

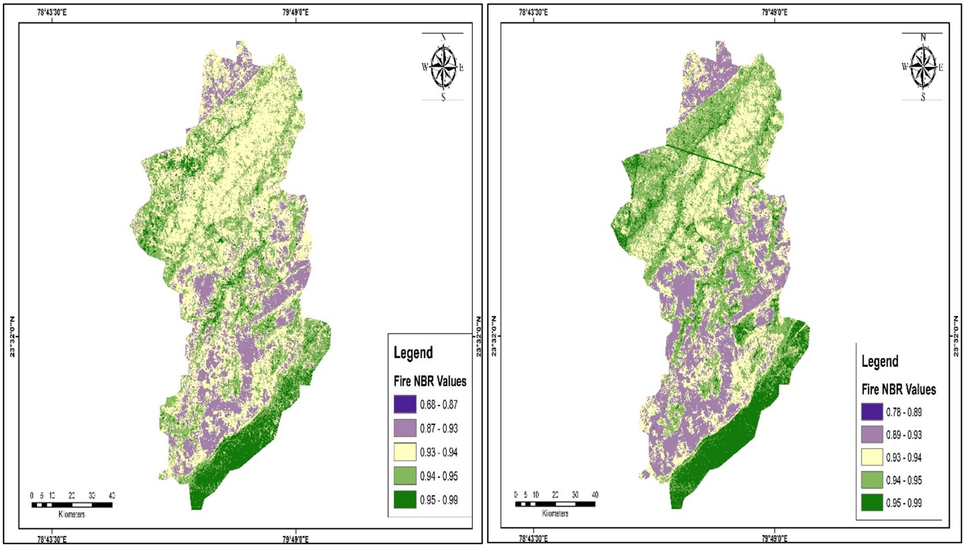

Figure 7: *NBR maps of the study area.*

and other plant material on the ground during the dry season. This accumulation increases fuel loads, rendering the forests more susceptible to ignition and fire spread. The presence of dry leaf litter from tree species such as Tectona grandis, Hardwickia binata, and Terminalia spp. in the Damoh district heightens the risk of forest fires during the summer season. Moreover, such surface fires tend to spread rapidly and intensely across vast areas, resulting in significant losses. The months of March and April typically mark the onset of forest fires. Elevated temperatures in this semi-arid region during this period, combined with the presence of dry leaf litter resulting from the shedding of leaves by dry deciduous tree species, further facilitate the initiation and spread of forest fires.

Climatological factors, such as temperature, precipitation, relative humidity, wind, seasonal variation, topography, and fuel moisture content all are known to have a role in influencing forest fires in deciduous forests [31], [50], [51], [52]. Elevated temperatures can increase the likelihood of forest fires by drying out vegetation and increasing evaporation rates. Higher temperatures may also influence the frequency and intensity of forest fire seasons, especially during periods of drought [32], [50]. Precipitation patterns, including the amount, frequency, and distribution of rainfall, can significantly impact forest fire risk. Below-average precipitation levels can lead to drier conditions, making forests more susceptible to ignition and fire spread [51]. Low relative humidity levels can contribute to dry conditions, making vegetation more prone to ignition and increasing the likelihood of fire spread. Conversely, higher humidity levels can inhibit fire activity by increasing moisture content in the air and vegetation [32]. Wind can accelerate the spread of forest fires by carrying smouldering fuel particles and flames to new areas. Strong winds can also fan flames, intensifying fire behaviour and making it more difficult to control [53]. Seasonal changes, such as the onset of dry seasons or periods of high winds, can significantly impact forest fire activity [32]. In deciduous forests, the timing of leaf senescence and leaf fall can influence fuel availability and fire behaviour [54]. The topography of the landscape, including slope, aspect, and elevation, can affect local weather patterns and fire behaviour [55], [56]. Steep slopes can create chimney effects that promote fire spread, while valleys can channel winds and exacerbate fire behaviour. The moisture content of vegetation, such as leaves, branches, and other forest fuels, directly influences their flammability. Dry vegetation ignites more easily and burns more intensely, contributing to the spread of forest fires [57], [58]. Understanding how these climatological factors interact with each other and with

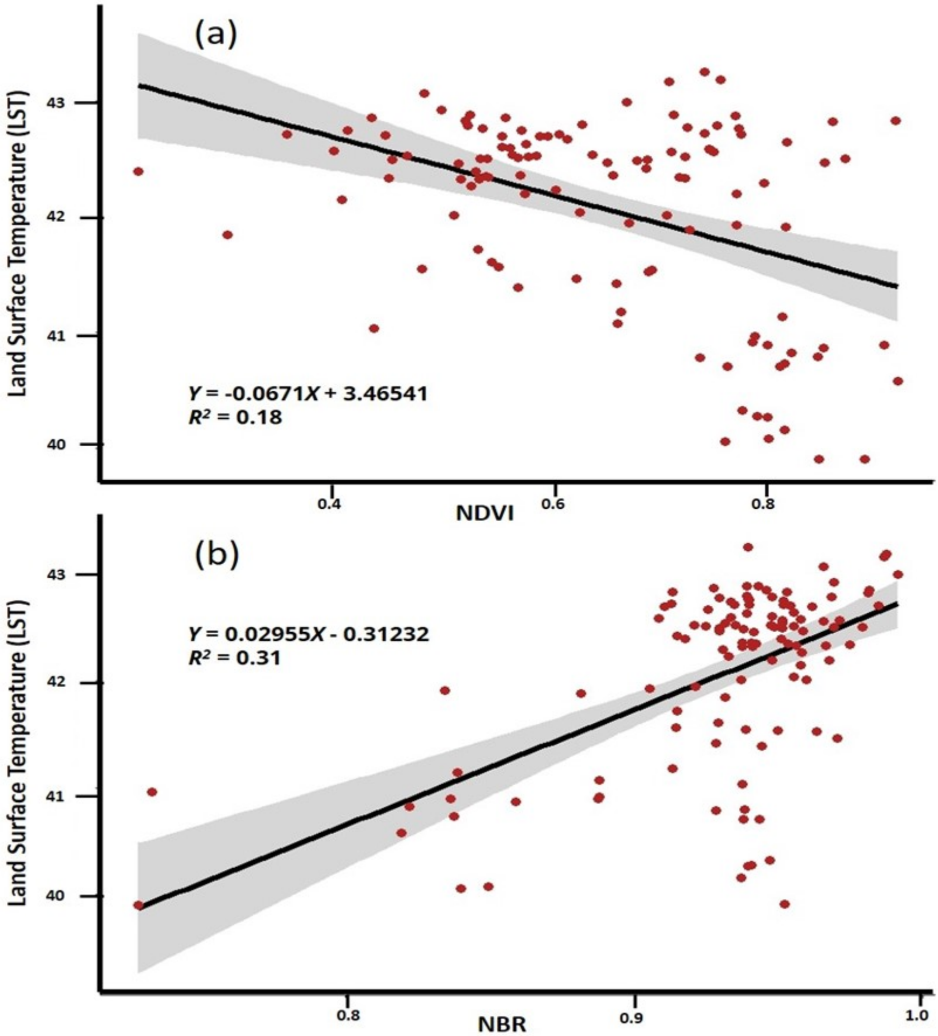

Figure 8: *The correlation plots depicting the relationship between (a) NDVI and LST and, (b) NBR and LST in 2020.*

local environmental conditions is essential for assessing and predicting forest fire risk in deciduous forests. Although all these factors have their importance in influencing forest fires, the temperature is arguably one of the most significant factors that affect forest fire behaviours, both long-term and short-term [59]. Hence, we have focused on the role of temperature in affecting the onset of forest fires in our study.

The correlation between indices $NDVI_{post}$ and LST_{post} may help in understanding forest fire risk mapping through their sensitivity to severity levels of forest fires. The changes in LST induced by forest fires are known to show seasonality, as LST increases abruptly postfire especially in the summer season when vegetation is dried out and the overall moisture content is low; it remains unchanged or consistent in the winter season [60]. Furthermore, the timing of fires may vary based on factors such as the onset of the dry season and human activities like agricultural burning. In addition, the magnitude of changes in LST post-fire compared to pre-fire are usually smaller, but

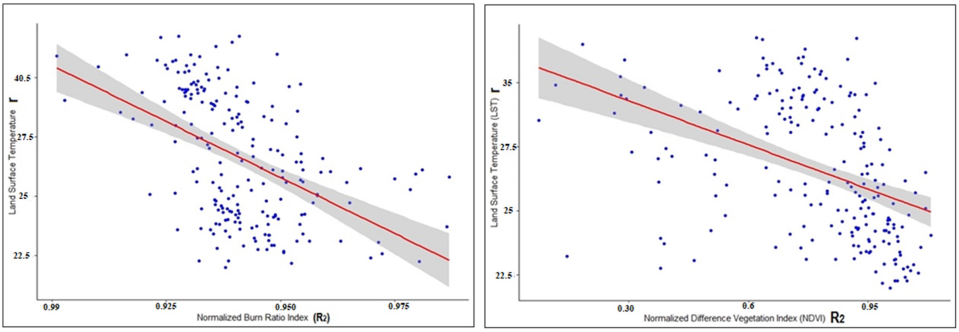

Figure 9: *The correlation plots depicting the relationship between (a) NDVI and LST and, (b) NBR and LST in 2011.*

the magnitude of increase in LST post-fire also depends upon LULC and fire burn severity class the region belongs to. In contrast, the magnitude of changes in vegetation postfire is large and these changes show clear contrast compared to pre-fire [60]. The results of our study, in the context of the sensitivity of $NDVI_{post}$ and LST_{post} to the fire severity levels, are congruent with other studies in the available literature as these studies report the inversely proportional relationship between NDVI and LST [31], [61], [62], [63]. In healthy vegetation, NDVI values are typically high, indicating abundant and vigorous plant growth [46], [64]. At the same time, LST in vegetated areas tends to be lower due to the cooling effect of transpiration and shading provided by the vegetation cover. Higher NDVI values are associated with lower LST values, as the presence of healthy vegetation can help regulate surface temperatures. Similarly, the results of our study, which elucidates a positive correlation between NBR and LST, align with many studies in the available literature [65]. As areas experience increased burn severity (higher NBR values), they tend to have elevated LST values. This is because the loss of vegetation covers due to the fire results in less transpiration and shading, leading to higher surface temperatures.

Researchers observed an abrupt rise of 10°C in LST post-fire in the burnt area of Tirupati Wildlife Sanctuary, India [31]. Furthermore, they observed that 19.86% area has been affected due to the forest fires in Tirupati and they found a strong negative relationship between NDVI and LST. Our results show that 15.63% of the total geographic area was affected by the forest fires in 2020 summer. Our results also posit that high values of LST were observed in fire-affected areas, this is similar to the findings of previous research carried out in this direction [62], [65], [66]. It has been observed that the range and difference size between severity categories differ as vegetation heterogeneity could be a factor affecting the severity classification across different regions and the response to forest fires could be different due to differences in vegetation [60], [67]. As the study was conducted in a relatively homogeneous coniferous forest, the range and size difference between several classes were large (for the same date) [67]. However, landscape heterogeneity and high vegetation diversity in a tropical deciduous forest compared to a boreal forest, could be a possible reason behind the small range size and small difference between forest fire severity classes.

Due to anthropogenic or natural processes, forest fire disaster is one of the primary reasons for the catastrophic degradation of forest ecosystems globally [68], [69]. Due to the growing influence of recent global warming, fire regimes are becoming progressively more prominent in many locations, with rising implications on human well-being resources and ecological function processes[70], [71]. The effects include land degradation and soil erosion, as well as impairment of soil ecology and water hydrology [72]. Hence, it is of paramount importance to understand the forest fire severity in high fire-prone areas and further, how vegetation responds to post-fire burn areas; vegetation indices like NDVI and burn ratio indices like NBR can act as a proxy to understand these responses.

This research examined a fire mapping framework based on the NDVI, LST, NBR, and land use datasets based on pre-post-fire Landsat 8 images. The main aim of this study was to investigate the correlation between NBR and NDVI with LST and what impact forest fires have on vegetation by quantifying the burn severity through the NBR index. Given the high frequency of forest fire events in the Damoh district, this study may be helpful for policymakers to envisage an efficient forest fire management plan for the region in the light of the results presented here so that the losses incurred due to forest fires, both economic and ecological, can be attenuated.

6. Limitations and Way forward for future research directions

Our research work elucidates the mapping of burnt areas with a change detection over a 10-year interval, specifically between 2011 and 2020. However, our study does not consider seasonal variations or other climatic factors that may influence forest fire susceptibility. Forest fires in tropical deciduous forests typically occur during the summer season, with minimal to no occurrences during winter. Therefore, seasonal variation is unlikely to significantly impact the findings of our study. However, it is important to note that changing climatic parameters over 10 years could potentially influence the occurrence of forest fires. Consequently, future research should incorporate these climatic parameters to gain a comprehensive understanding of their role in forest fire occurrence. In addition, future studies may benefit from incorporating a time-series analysis of forest fires in the area. By implementing suitable time intervals, future research maybe directed toward assessing vegetation recovery over a temporal scale and examining how it interacts with seasonal variations. This approach would provide valuable insights into the long-term effects of forest fires on ecosystem dynamics and resilience. By considering both climatic parameters and temporal dynamics, future research endeavors can enhance our understanding of forest fire ecology and inform more effective management strategies for mitigating their impacts on biodiversity and ecosystem health.

7. Conclusion

Our results show a positive correlation between LST and NBR, whilst a negative correlation between NDVI and LST. The results of this study could be useful in the planning and management for investigating and developing pre-post forest fire supervision and strategies for the Damoh district. In the study of Damoh district, as per LULC classification, forest is the predominant land use type. However, increasing anthropogenic pressures and changing climatic parameters, especially increases in temperature, may have a role in accentuating the frequency of forest fire events. Our results show that when LST nears 39, there is a big possibility of a forest fire, and LST has an inversely proportional relationship with NDVI which is a measure of vegetation health, and a positive relationship with NBR which is an indicator of fire burn severity. The results of our study can be used to undertake future research in this region to uncover how fire frequency and intensity in the dry deciduous forest impacts the established and unestablished regeneration rate of plant species. Remote sensing-based methods are continuously being developed and are operationally used but still these operational models need to be updated. More studies are required to develop early warning forest fire detection mechanisms for the semi-arid regions due to high temperatures during summer. The stratification conditions of pre- and post-fire environmental predictors (e.g., soil moisture, dry biomass, vegetation, topography, fire regime, organic, layer depth) need to be considered for improved accuracy in forest fire detection and prediction using high-resolution satellite data.

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