Forest Fire Risk Mapping Using Analytical Hierarchy Process (AHP): A case of Malkangiri, Odisha, India

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Abstract: The risk of forest fires is affected by various factors such as vegetation density, topography, human activities, and climate patterns. These factors remain relatively constant over time, at least during the fire season. To manage forests and ensure protection against fires, fire-cycle analysis is performed which includes creating a map of potential fire ignition and preparing a vulnerability map that can assist in controlling the spread of fire. Accurate data is crucial for forest management, and geospatial technology provides reliable information. By providing accurate information, geospatial technology can help prevent and mitigate damage caused by forest fires, while also promoting sustainable land use practices. The study focused on assessing forest fire risk in the Malkangiri district of Odisha, India, using geospatial technology and the AHP method. The final risk map was categorized into five zones, namely very high, high, moderate, low, and very low, which can help guide forest management and firefighting efforts in the area. To validate these forest fire risk zones, the study used fire points data from the office of PCCF, Odisha from FIRMS. The results showed that the forest fire risk was high in the low to moderate elevation ranges, with most fire points overlapping in the very high-risk zones of the map. Anthropogenic activities have been a major cause of forest fires in tropical regions. Overall, the study demonstrated the effectiveness of using geospatial technologies and the AHP method for assessing forest fire risk. The results can help in developing strategies to prevent and mitigate the impact of forest fires, particularly in areas with high-risk zones, such as the Malkangiri district of Odisha, India.

Keywords: Forest Fire, AHP, Risk Map, GIS, Risk Zones

1. Introduction

1.1 Forest fire and Geospatial Technology

Forest fires pose a significant risk and threat to the forest ecosystem, whether they are caused by natural occurrences or human activity. These fires have resulted in a loss of biodiversity, forest degradation, and fragmentation. While forest and wild land fires can be considered vital natural processes that promote vegetation succession, their uncontrolled and improper use can have serious negative impacts on the environment and human society. In India, more than 2% of the total forest area is affected by fire each year, with an average of over 34,000 hectares of forest being burned annually (Farooq et al., 2022). While some of these fires may be incidental, the majority are deliberately caused. Fires are a frequent occurrence in forests worldwide, with both global ecological impacts and regional socio-economic challenges. They play a critical role in changing forest composition and structure but also pose environmental hazards that can negatively impact the atmosphere, infrastructure, and human well-being (Farooq et al., 2022). In India, forest fires contribute to black carbon emissions that changes surface albedo amount and increase snow melt from the Himalayan mountains (You & Xu, 2022). Forest managers, policy makers, climate modelers, and the scientific community are interested in evidence-based approaches to map forest fire susceptibility and understand the potentially fatal consequences of fires (Das et al., 2023). This information is crucial for regulating negative impacts on potentially affected groups and supporting conservation and restoration efforts. Accurate prediction of forest fire risk is very much important for promoting sustainable development, which will support resource allocation, early warning systems, emergency services, forest management and forest planning (Tuyen et al., 2021).

Remote sensing data and GIS techniques have been increasingly used in natural resource and forest management to provide accurate and meaningful information for decision-making. Satellite imagery and other remote sensing data offer specifics on topography, vegetation cover, and other environmental elements that influence fire risk (Michael et al., 2021). Models for forecasting the likelihood and intensity of fires in various locations can then be created by combining this data with other data, such as climatic patterns and human activity, using GIS techniques.

These predictive models can then be used to create management strategies that try to lower the risk of fire, like installing firebreaks, enforcing fire safety laws, or removing bushes from high-risk areas. Furthermore, firefighting teams can react swiftly and efficiently to contain and put out fires by using GIS techniques to track and monitor the spread of fires in real-time (Nikhil et al., 2021).

Understanding and controlling the risk of fire has been made much easier with the use of remote sensing data and GIS techniques in natural resource and forest management. These resources can support sustainable land use practices while preventing and lessening the harm caused by wildfires by offering precise and timely information.

1.2 Global Perspective:

Forest fires are becoming more commonplace worldwide, with Asia experiencing the majority of these incidents. In addition to posing a threat to human life, wildfires cause significant losses in terms of both people and property (Filkov et al., 2020). An important aspect of managing forest fires is the prediction of future flames. It is crucial to the allocation of resources, mitigation, and recovery efforts. As a result, many forest authorities have found that using forest fire risk assessment to help allocate and organize firefighting resources is very effective (Schinko et al., 2023). A fire risk assessment is also essential for preparing evacuations or calculating insurance costs. GIS and remote sensing techniques have been widely used to assess and forecast the frequency of fires, and satellite data can help detect forest fires in varied land uses.

1.3 Forest Fire in India:

21% of India is filled with forests and 53% of these forests are having very high and high risks of forest fire incidence (Milanović et al., 2021). The increase is not just in the incidence of forest fires but there’s also a very significant amount of increase in the area. In the last 13 years, over 7 lakh km^2 of our forest area has been affected due to fires (Gupta et al., 2022).

Many destructive forest fire incidents took place in our country. While the largest of all was the Bandipur incident, we chose Odisha as our target region for the pilot because, over the last three years, Odisha has consistently been recorded as the state with the highest number of fire alerts (Das et al., 2023).

1.4 Odisha and Its Forest

Almost one-third of Odisha contains forests which are about 51,968 km^2. Out of which, 538 km^2 are forests with a density more than 70 percent (high canopy density) and 23,656 km^2 come under the moderately dense category (Ashis Senapati, 2021). Odisha is a state with 4th highest forest cover in India, preceded by Madhya Pradesh, Arunachal Pradesh, and Chhattisgarh. Zooming into our study area, Malkangiri is a district in the southernmost region of Odisha. Almost 76 percent of the district area is filled with forests and only a selected amount of people live in the urban areas. The agricultural land is comparatively very low at only about 22 percent. Malkangiri has a very low literacy rate, lower than the national average of India since it’s underdeveloped and is not much urbanized.

Forest fire risk is influenced by factors such as vegetation density, topography, human activities, and climate patterns, which exhibit relative stability during the fire season (Parvar et al., 2024). Effective forest management employs fire-cycle analysis, encompassing the creation of ignition potential and vulnerability maps to control fire spread. Accurate data is crucial for this purpose, and remote sensing data and GIS techniques are instrumental (Tian et al., 2022). Satellite imagery provides insights into vegetation cover, topography, and environmental factors affecting fire risk. GIS integrates this information with data on human activities and climate patterns to formulate predictive models for assessing fire likelihood and severity in diverse areas. This information facilitates the development of management plans to mitigate fire risk through strategies like clearing high-risk areas, enforcing safety regulations, and establishing firebreaks (Naser et al., 2025). GIS techniques enable real-time monitoring of fire spread for swift response and containment. The synergy of remote sensing data and GIS techniques is pivotal in natural resource and forest management, offering precise information to prevent and mitigate damage from forest fires, thereby promoting sustainable land use practices.

In this context earth observation data can be play a very important role, specifically for derivation of the verity of spatial information related to the forest fire such as meteorological information, land use land cover and topography. At the same time multi criteria decision making (MCDM) can play an important role in this case to identify the risk zone, by using different variables that are responsible for forest fire along with by assigning weight to the variables, in this case methods such as logistic regression, artificial neural networks (ANN), analytical hierarchy process (AHP) can help to map and identify the forest fire risk area (Tien Bui et al., 2016; Chen et al., 2001; Satir et al., 2016). AHP and EO data can be combined together to create a map of the risk of forest fires (Eskandari & Miesel, 2017).

The study uses the AHP method and geospatial technologies to assess the risk of forest fires in the Malkangiri district of Odisha. The study's robustness can be increased by further validating the identified risk zones using fire point data from the Principal Chief Conservator of Forests (PCCF) office in Odisha. The current study investigates how the AHP method and multi-sensor geospatial technologies can be used to evaluate fire risk in the Malkangiri district of Odisha, India.

2. Study Area

Malkangiri District of Odisha covers of an area of 5,791 km^2 and lays between 17° 45’N to 18° 40’N latitudes and 81° 10’ E to 82° E longitude (Pattanaik et al., 2008) (Figure 1). The district is surrounded by

Koraput district, Visakhapatnam and East Godavari districts of Andhra Pradesh in the east, in the West Bastar district of Chhattisgarh, Koraput district of Odisha in the north and East Godavari and Khammam districts of Andhra Pradesh in the south respectively (Suchitra et al., 2014).

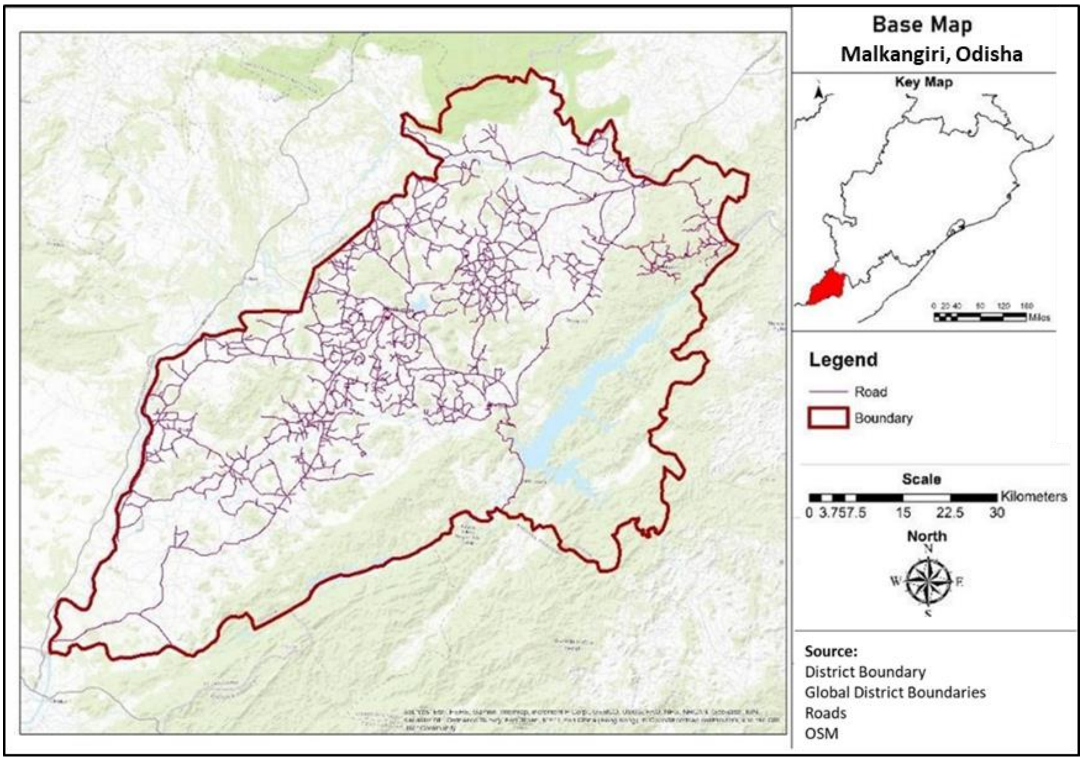

Figure 1: Malkangiri District, Odisha

The general topography of the district is broken mountain intercepted by riverbeds and water body present there while the elevation of the district ranges from 400 meters to 1200 meters near western side to eastern side respectively having numerous streams from the hills drain into major river such as Sabari, Sileru, Potteru, Kolab and Machhkund (Chintala et al., 2004). The soil of the study area is characterized by black soil, which is very rich in organic matter. The climatic condition of the area is directly influenced by variation of elevation (Pattanaik et al., 2011). In the winter the district experience average daily minimum temperature of 11.2º C and maximum temperature seldom touches 43℃ in summer during the summer (Pattanaik et al., 2011).

3. Dataset and Methodology

3.1. Dataset

Landsat 9 data was used for vegetation and temperature parameters. Four separate bands from the Landsat 9 sensor were presented in this study: red (Band 4), Near-Infrared (NIR) Band 5, Thermal Infrared (TIR) Bands 10 and 11, and also Shortwave Infrared (SWIR) Band 6. These groups selected several variables to extract in our next steps of research. The surface temperature of the study area was obtained by using TIRS-1, Thermal Infrared Sensor, data from band 10 of Landsat 9. Also, NDMI, Normalized Difference Moisture Index, and NDVI-Normalized Difference Vegetation Index were computed from that satellite dataset acquired from Landsat on standardized methodology (Lahmar & Akakba, 2024). All sets of data were collected by a reputable source platform known as United States Geological Survey USGS Earth Explorer. To develop elevation, slope, and aspect data, we utilised the Digital Elevation Model of Carto-DEM from NRSC-Bhuvan geoportal (https://bhuvan.nrsc.gov.in).

3.2. Methodology

The methodology of this study (Figure 2 used data from NDVI, NDMI, and LST as well as LULC that were downloaded from Landsat 9. In addition, Carto-DEM generated by Cartosat-1 satellite was utilized to extract elevation, slope, and aspects information. Meteorological support information including the wind speed product from ERA5 (Zhai et al., 2022) has also been used in this analysis. The AHP method which is one of the widely used techniques under the Multi-Criteria Decision Making (MCDM) methods has been employed to assess Forest Fire Risk Zoning over the study region.

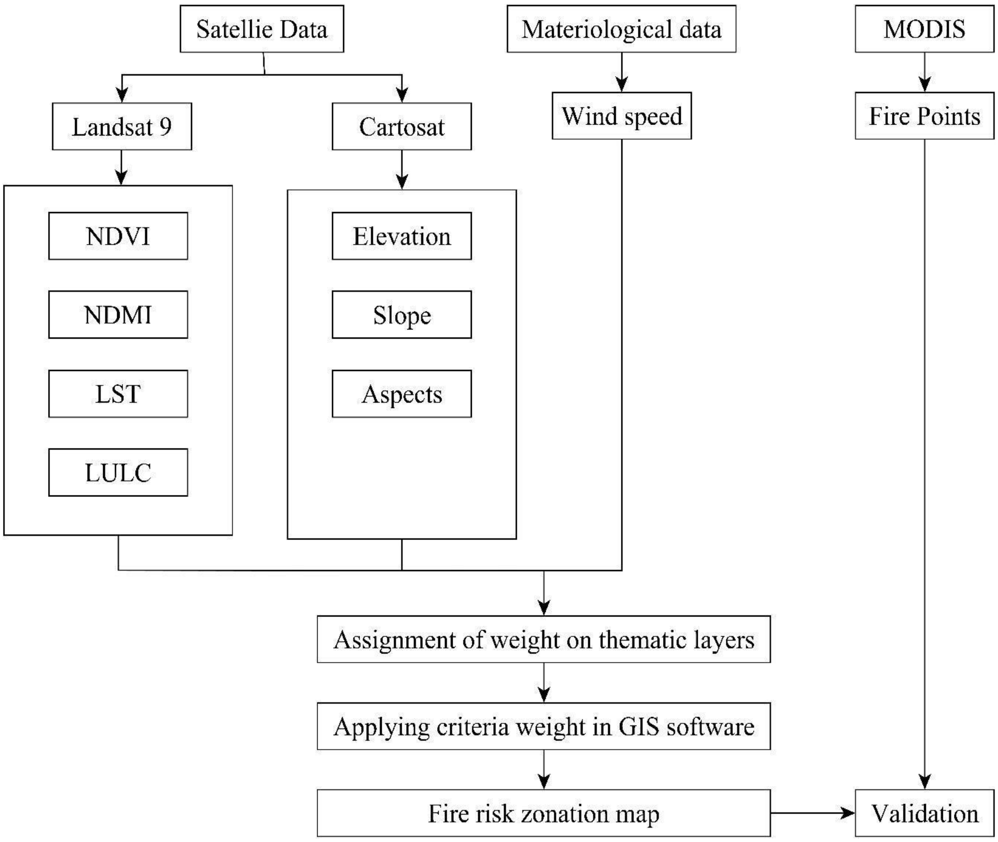

Figure 2: Methodology

At this stage of methodology development, these geodata layers have been normalized into five classes before taking up further analysis wherein Class 1 denotes low vulnerability to fire and Class 5 denotes high vulnerability to fire for each theme in consideration. The reclassification of layers into five classes helps segregate the data into some discrete form that helps meaningful comparison between layers and integration of various parameters for analysis.

Further, to comprehensively assess the influence of each factor on forest fire risk in the study area, weight values are assigned to indicate their relative importance. These weight values are determined through the pairwise comparison process proposed by Saaty in 1980 (Tavana et al., 2023). This systematic evaluation allows for a more rigorous understanding of each factor's contribution to the overall forest fire risk, facilitating the development of an effective risk assessment model (Kumari & Pandey, 2020).

It is crucial to recognise that different contributing factors have differing degrees of influence when conducting forest fire risk assessment. It is impossible to fully comprehend a region's forest fire risk by examining just one causative factor. Numerous factors, both natural and man-made, interact intricately to affect forest fires. Therefore, to properly assess and model forest fire risk, it is imperative to take into account all potential pertinent variables, such as vegetation, topography, climate, and human-induced factors. As described by (Shaban et al., 2001), an integrated approach is used to address this and ascertain the relative significance of each component. The rate factor is determined by adding the points that represent the effects of each factor, with one point being assigned for a major effect and half a point for a minor effect (Hammami et al., 2019).

Determining the decision problem is the first step in the Analytic Hierarchy Process (AHP). The second step involves creating a pairwise comparison matrix of the conditioning factors using Thomas L. Saaty's (1990) importance value scale. The significance of each factor in relation to the other factors it is paired with determines its arithmetic value, which ranges from 1 to 9. A value of 1 denotes equal significance, whereas a value of 9 indicates that the row factor is significantly more significant than the corresponding column factor (Table 1) (Veisi et al., 2022).

For pairwise comparisons, the suggested methodology uses an 8 × 8 matrix. The consistency of the pairwise comparison matrix is then evaluated using a numerical index known as the consistency ratio (CR). The AHP-based forest fire risk assessment model has a solid and reliable foundation for decision-making thanks to this methodical approach, which permits a thorough assessment of the relative importance of the various factors.

Table 1: Saaty Scale (1980)

Scale	Numerical rating	Reciprocal
Extremely importance	9	1/9
Very to extremely strongly importance	8	1/8
Very strongly importance	7	1/7
Strongly to very strongly importance	6	1/6
Strongly importance	5	1/5
Moderately to strongly importance	4	1/4
Moderately importance	3	1/3
Equally to moderately importance	2	1/2
Equally importance	1	1

Table 2: Random inconsistency indices

n	3	4	5	6	7	8	9	10
RI	0.58	0.9	1.12	1.24	1.32	1.41	1.45	1.49

The chosen criteria are arranged hierarchically in Table 3, which shows the relative significance of the different parameters. The importance of land use and land cover in relation to the other parameters indicated in the columns is highlighted in the top row. The Analytic Hierarchy Process (AHP) method is then used to normalise the weights that were obtained from this hierarchical analysis. A forest fire risk hazard map is then created by integrating the AHP-integrated model into a Geographic Information System (GIS), which aids in efficient decision-making and mitigation techniques (Stefanidis and Stathis, 2012).

The consistency ratio (CR) is calculated to assess the judgements' coherence (Wu et. al., 2020). A CR ratio greater than 0.1 would suggest that the decisions may be inconsistent and untrustworthy. On the other hand, total consistency in the decisions is indicated by a CR value of 0 (Elkhrachy, 2015). Using Eqs. (1) and (2), the consistency index (CI) is divided by the random inconsistency index (RI), where CI is the consistency index, RI is the random inconsistency index, n is the number of factors (Table 2), and λ is the average value of the consistency vector. This yields the CR.

$$CR = \frac{CI}{RI} \quad \text{Eq. (1)}$$

$$CI = \frac{(\lambda - N)}{(N-1)} \quad \text{Eq.(2)}$$

where λ is the consistency vector's average value and n is the number of factors (in this study, eight).

In this study, eight factors were examined individually for hazard area mapping. A thorough evaluation of each factor's importance and contribution to the overall forest fire hazard was ensured by the study's use of this scientific methodology. Accurate mapping and analysis of the forest fire hazard area are made possible by this methodological rigour, which provides important insights for efficient forest fire risk management and mitigation. After determining the final weights for each influencing factor, a weighted linear combination equation (Eq. 3) is used to create the hazard map.

To ensure the reliability of the analysis, the Consistency Ratio is computed and found to be 0.07, falling below the threshold of 0.1. This signifies a satisfactory level of consistency in the assigned weights. This rigorous evaluation of consistency ensures the robustness of the forest fire risk assessment model based on the Analytic Hierarchy Process (AHP), providing a scientifically sound basis for forest fire hazard management and decision-making.

$$Forest\ Fire\ Risk = NDVI \times 0.1645 + Temperature \times 0.3498 + Slope \times 0.0204 + Moisture\ Index \times 0.0725 + Elevation \times 0.2456 + Aspect \times 0.0401 + Wind\ Speed \times 0.0378 + LULC \times 0.0693 \quad \text{Eq.(3)}$$

Table 3: A matrix of pairwise comparisons of eight criteria for AHP

Matrix	NDVI	Temperature	Slope	Moisture Index	Elevation	Aspect	Wind speed	LULC	Normalized Principal Eigenvector
NDVI	1	1/5	8	3	1/3	5	7	4	**16.45%**
Temperature	5	1	9	5	2	6	7	5	**34.98%**
Slope	1/8	1/9	1	1/4	1/6	1/4	1/3	1/4	**2.04%**
Moisture Index	1/3	1/5	4	1	1/5	3	4	1/2	**7.25%**
Elevation	3	1/2	6	5	1	6	8	3	**24.56%**
Aspect	1/5	1/6	4	1/3	1/6	1	1	1/2	**4.01%**
Wind speed	1/7	1/7	3	1/4	1/8	1	1	1	**3.78%**
LULC	1/4	1/5	4	2	1/3	2	1	1	**6.93%**

4. Results and Discussion

Topographic and climatic conditions play a significant role in the ignition and spread of forest fire. The following sections offer an overview of topographic and climatic elements, including elevation, slope, aspect, land use, moisture, temperature, wind speed, etc., that contribute to forest fires in the study area.

4.1. Elevation:

The Malkangiri district of Odisha exhibits a substantial elevation variation from the Western side to the Eastern side, ranging from 400 meters to 1200 meters (Figure 3). This elevation gradient significantly influences the local climate. It has been observed that as elevation increases, there is a decreasing trend in forest fires (Tomar et al., 2021). The elevation factor is instrumental in regulating a spectrum of topographic, climatic, and hydrologic parameters that influence the spread and intensity of forest fires. These parameters comprise wind speed and direction, temperature, precipitation, humidity, and runoff. Additionally, elevation contributes to spatial variations in the spread of forest fires with respect to vegetation cover and soil properties. The presence of cooler temperatures and higher humidity at higher elevations reduces the likelihood of ignition and the subsequent spread of fires. Most fire incidents occur at lower and moderate elevations due to drier conditions (Rothermel, 1983).

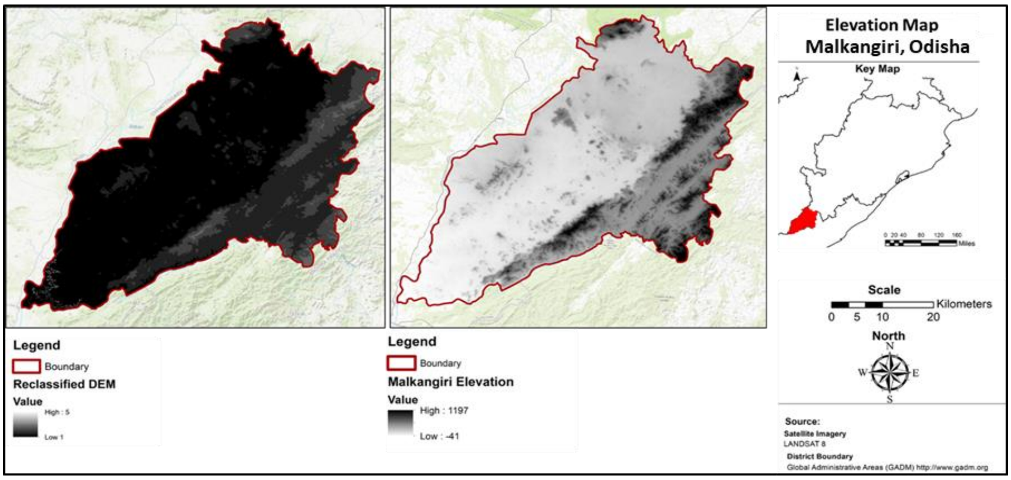

Figure 3: Elevation Map

4.2. Slope:

It functions as an indicator for the rate of elevation change (in degrees). Both the speed and direction of fire propagation are influenced by the slope. Fires generally advance more rapidly when moving uphill as opposed to downhill (Abedi Gheshlaghi, 2019). Upper slopes had drier fuel compared to lower slopes, contributing to the fire's propagation (Lamat et al., 2021). For Malkangiri, the slope ranges from high values in the hilly areas of the district to lower values in the water body areas. The slope map of the study area revealed varying degrees of incline, classified into four classes: low, moderate, high, and very high (Figure 4).

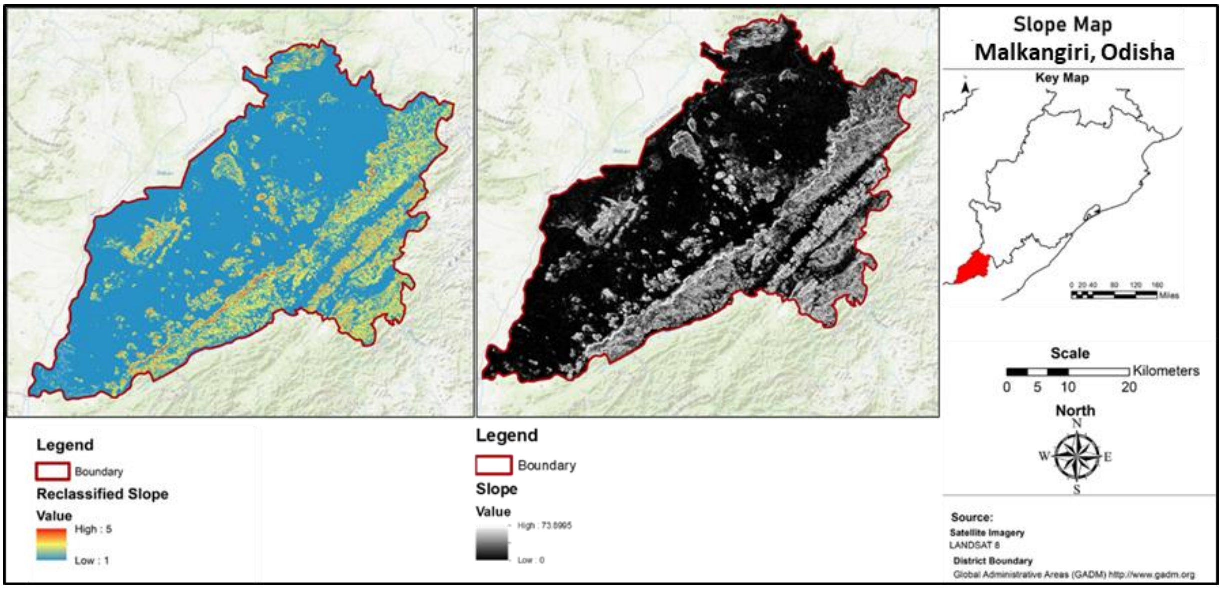

Figure 4: Slope Map

4.3. Aspect:

The slope of the terrain indicates the direction with the steepest change in elevation between adjacent cells. East-facing slopes receive direct sunlight earlier in the day compared to west-facing slopes, and south-facing slopes receive more intense direct heat from the sun, leading to drier vegetation and soil (Chang et al., 1996). Conversely, north-facing slopes receive less sunshine, influencing the moisture content of flora and soil. These factors play a significant role in shaping the microclimates and fire behaviour in different aspect of the landscape. The Aspect for the study area is shown in Figure 5.

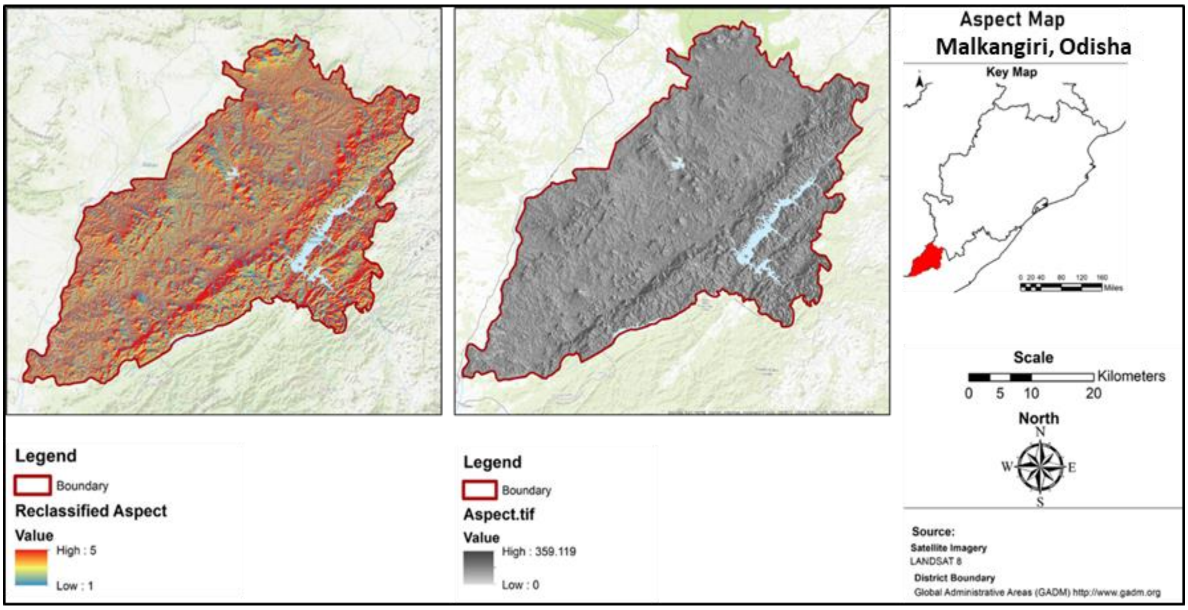

Figure 5: Aspect Map

4.4. LULC:

LULC dynamics, predominantly driven by human activities, have resulted in significant changes impacting forests and the environment's ecosystem. Evaluating fire risk in the study area was closely linked to land cover classes, reflecting fuel types and characteristics. Forest areas, especially very dense, dense, and open forests, were identified as highly susceptible to fire incidents, often stemming from slash-and-burn practices for cultivation (Vetrita &

Cochrane, 2020). Prudent management and conservation strategies are imperative to address the heightened fire risk in these vulnerable ecosystems. Forest and Agriculture is the two prominent LULC class for the study area. The spatial distribution of the LULC classes of the study areas is shown in figure 6 and corresponding area statistics is shown in Table 4.

Table 4: Area Statistics of different LULC classes of the study area

LULC Class	Area (sq-km)
Forest	3387.92
Water	217.98
Urban Areas	58.13
Agriculture	2152.77

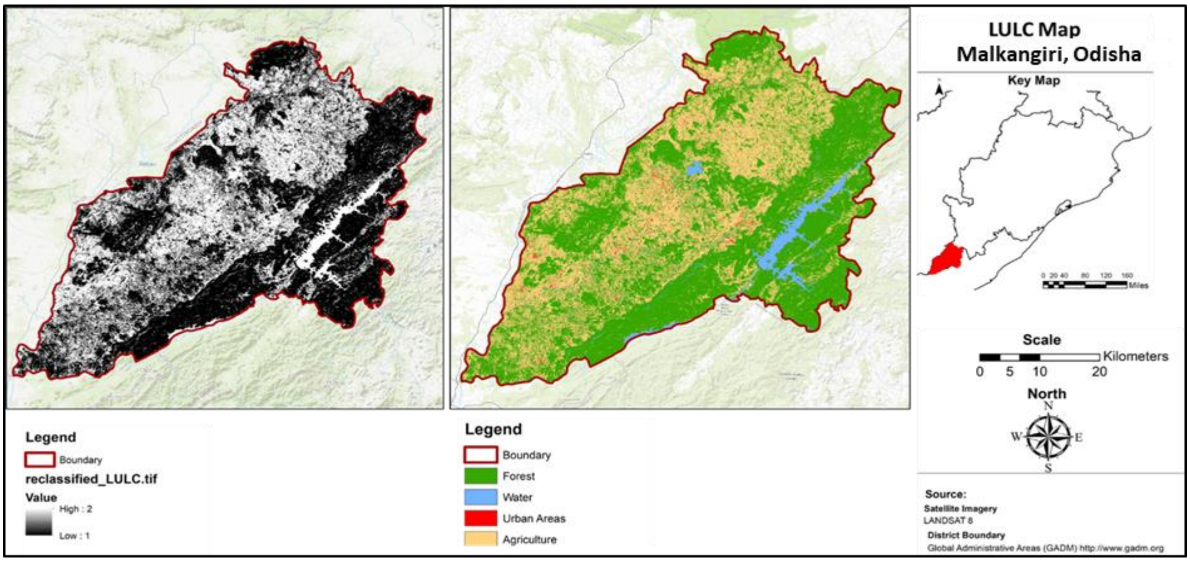

Figure 6: LULC Map

4.5. NDVI:
NDVI works as an indicator of water stress by detecting changes in vegetation's reflectance of near infrared and red wavelengths of light. During water stress, vegetation experiences reduced transpiration and increased evaporation, leading to decreased chlorophyll activity and a decline in NDVI values (Maselli et al., 2020). Lower NDVI values and higher water stress scalars indicate areas with drought-stressed vegetation, making them more susceptible to fire incidents, thereby assisting in fire danger assessment and proactive fire management strategies. Figure 7 displays the NDVI values' spatial distribution within the study area. The forest's low NDVI values have led to its reclassification as highly fire-prone.

4.6. NDMI:
The amount of moisture in an area has a significant impact on the likelihood of forest fires. Thermal band data from Landsat-8 satellite imagery is used to calculate the Normalised Difference Moisture Index (NDMI), which gives important information about the water content of vegetation (Figure 8). Because of the increased dryness, a declining moisture content in vegetation suggests a higher risk of forest fires. Analysis of the NDMI map for the Malkangiri district showed notable differences between the eastern and western sides, with the vegetation in the western section having a noticeably lower moisture content (Luo et al., 2019). These results highlight how crucial it is to keep an eye on moisture levels as a crucial metric for determining the risk of fire and possible fire incidents in various locations

4.7. Wind Speed:
One of the weather factors that significantly affects how quickly a fire spreads in any given area is wind speed. In the study area, wind speeds were generally low in high elevation ranges and high in low and moderate elevation ranges (Tomar et al., 2021). In the current study, the wind speed was higher in the upper portion of the study area than in the lower portion (Figure 9)

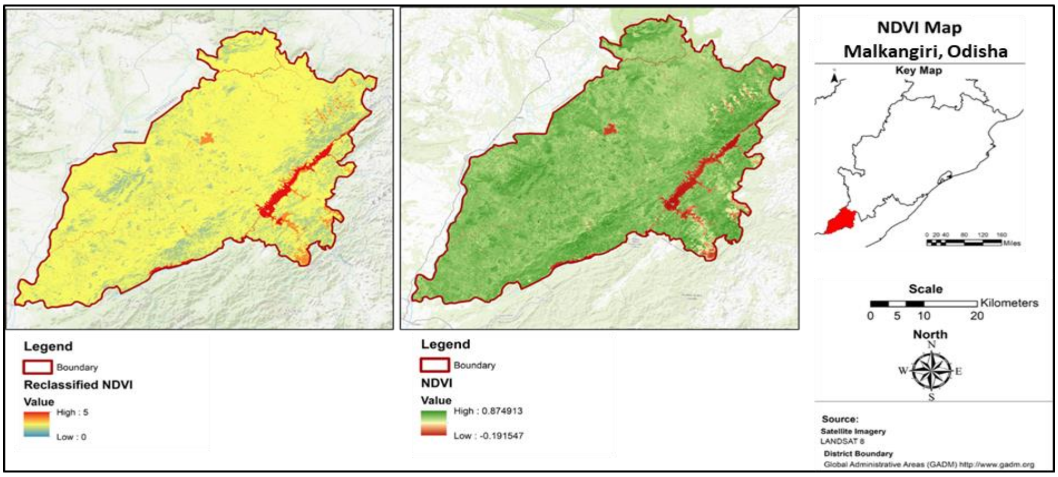

Figure 7: NDVI Map

4.8. Temperature:

Temperature plays a pivotal role in forest fires, exerting significant influence on fire behaviour through its impact on evapotranspiration rates. High temperatures facilitate rapid evapotranspiration, resulting in the seasonal desiccation of fuel materials like needles, leaves, twigs, and dead vegetation. These dry conditions create a conducive environment for fire ignition and propagation (Kumari & Pandey, 2020). The study area exhibited an average monthly temperature range of 17 to 32 °C, with elevated temperatures predominantly observed in the eastern regions of the district of Malkangiri (Figure 10). The direct correlation between temperature and fire outbreak underscores the role of rising temperatures in augmenting evaporation and transpiration, thereby desiccating flammable materials and heightening the risk and potential for forest fires (Tomar et al., 2021).

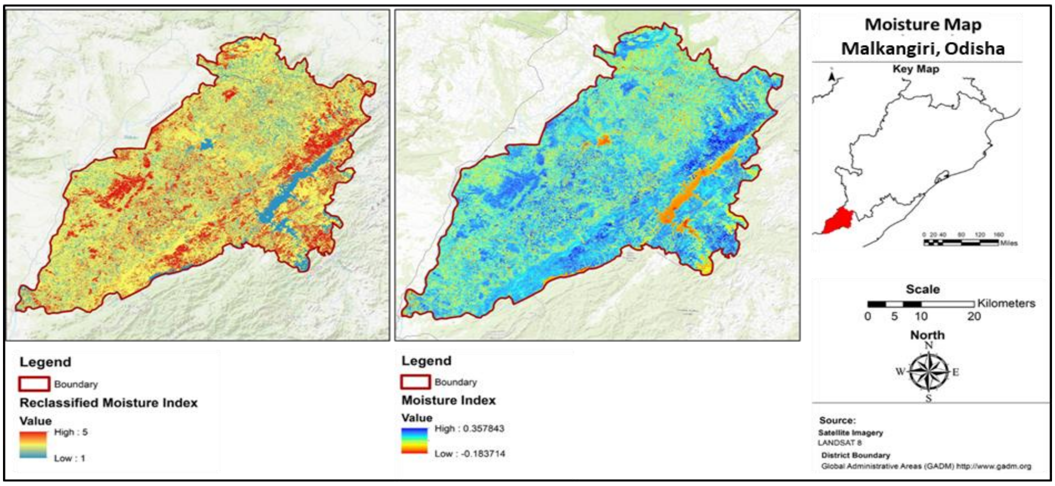

Figure 8: NDMI

4.9. Forest fire Risk map:

The research findings reveal a nuanced distribution of forest fire risk zones in the Malkangiri district of Odisha, India (Figure 11). The study categorizes the area into different fire risk zones based on the analysis of a total area of 5,496.8842 square kilometres. The greater percentage of the area under study, precisely 40.91%, falls within the very low fire risk zone hence indicating a lower probability for forest fires. The low fire risk zone embraces 33.06% of the area hence, further emphasizing moderate vulnerability levels in the areas. Some other 13.57% fall within a moderate risk that speaks volumes concerning some considerable potentials of such fire activities; this precarious high fire-risk zone covers 12.45% of the area and thus calls for immediate attention in strategic planning through effective forest management to mitigate such risks. Ideally, a meager portion of about 0.00075% in the real region is considered very high-risk and contains certain places with particular inclinations toward more intensive susceptibilities that have come out herewith; importantly, approximately only an average quarter part puts itself into middle-high categories which may be termed as vulnerable acreage lying under possible future fire incidents. Understanding the microclimate of these zones is paramount for effective prediction and the formulation of sustainable forest management strategies Remote sensing (RS) and Geographic Information System (GIS) emerge as indispensable tools in this context, providing advanced capabilities to analyze, model, and monitor environmental factors influencing fire risk. The integration of RS and GIS techniques enhances the accuracy of predictive models, aiding in the identification of vulnerable areas and facilitating informed decision-making for proactive fire prevention and containment measures. These results provide a nuanced understanding of the distribution of fire risk across the Malkangiri district, offering valuable insights for policymakers, forest management authorities, and firefighting teams to formulate targeted strategies for prevention and mitigation. The validation of forest fire risk zone was verified by the fire points obtained from the office of Principal Chief Conservator of Forest (PCCF), Odisha (Figure 12). The fire was very prone in low to moderate elevation ranges and most of the fire points overlaid in the map can be seen as very high-risk zones.

Forest fires due to anthropogenic regions have been a major problem across tropical regions. The final risk map was categorized into five zones as very high, high, moderate, low and very low. Although the AHP demonstrates potential for forest fire risk zonation using EO data, the integration of machine learning and other supervised models can offer a more robust alternative (Göltas et al., 2024; Banerjee, 2024). These data-driven approaches can enhance fire risk assessment by capturing complex, nonlinear relationships among multiple variables, thereby improving prediction accuracy and spatial mapping of fire-prone areas. The present study has primarily focused on environmental attributes; however, given that forest fires are often profoundly shaped by human actions, the results could be more informative by including human-induced elements. The integration of land use patterns, population density, distance to roads and settlements, and other human activity indicators would enhance the evaluation of forest fire risk.

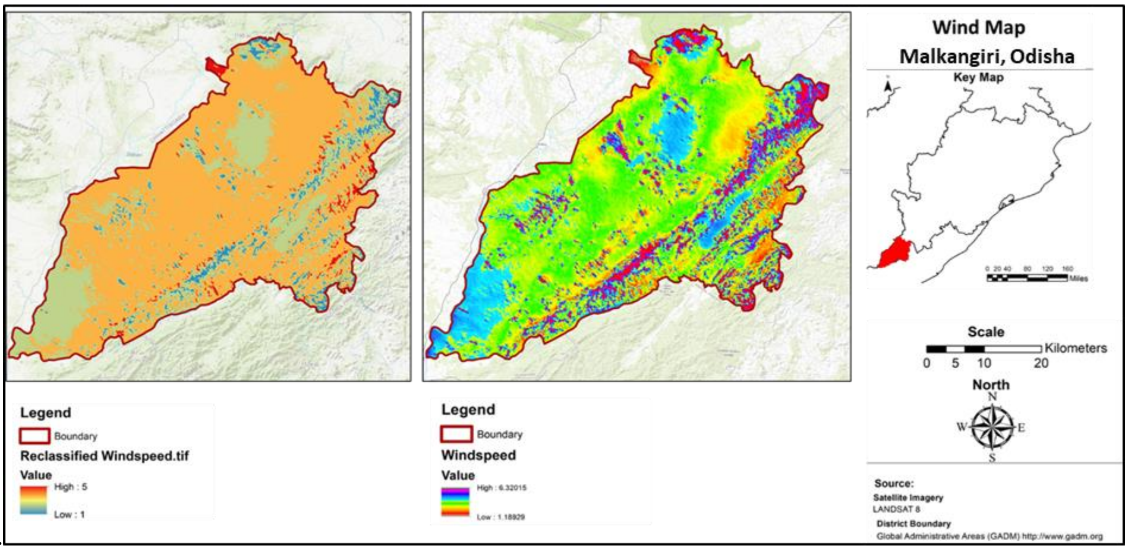

Figure 9: Wind Map

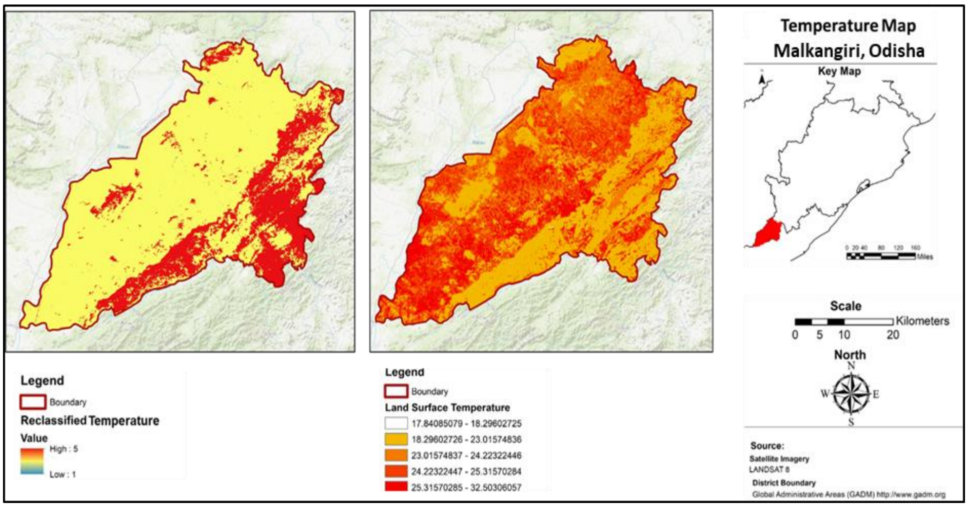

Figure 10: Temperature Map

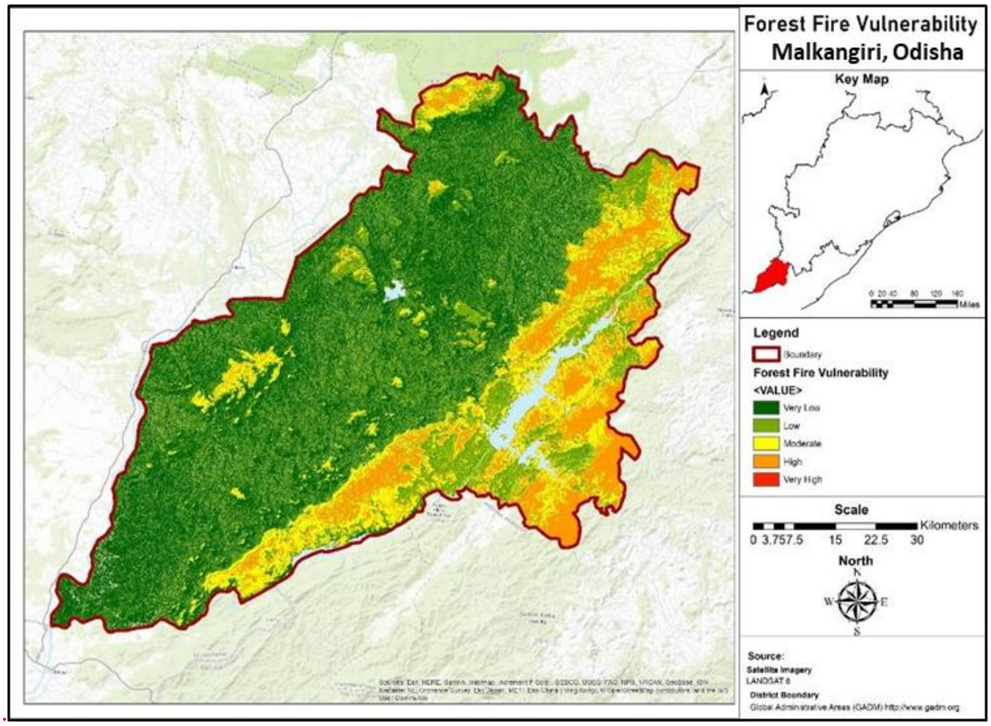

Figure 11: Forest Fire Risk Map

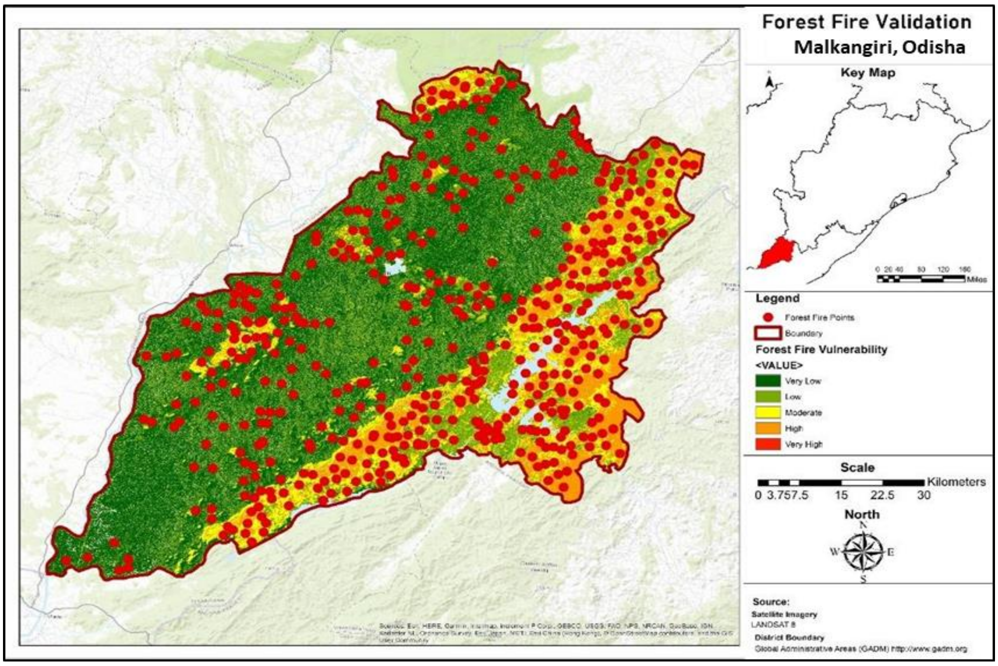

Figure 12: Validation Map

5. Conclusions

The objective of the work was to create an improved forest fire risk map based on geospatial and AHP methods. To analyze the influential factors of forest fire risk, we adopt geospatial technologies and satellite data, such as temperature, elevation, NDVI, the Moisture Index, LULC, wind velocity, slope, and aspect. A weighting matrix was created to weigh these factors and the weighted linear combination model was applied to develop a forest fire risk map. The results indicated that temperature was the most susceptible factor in the evaluation of forest fire. The study's forest fire risk map is extremely beneficial to the Malkangiri District's forest management and firefighting operations. These high-risk fire zones can support strategic plans to prevent forest fires and reduce their impact. The study also highlights the importance of the AHP approach for considering a range of environmental factors in a rational decision-making framework, which can improve the accuracy and objectivity of forest fire risk assessment. AHP's weighting of different influencing factors is essential for planning and resource allocation to reduce the risk of fires, in addition to ranking the most important causes of fire occurrence.

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