

Forest and Land Fire Susceptibility Mapping Using Kernel Density and Weighted Overlay Approaches in West Sumatra, 2021–2025

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Abstract

Forest and land fires are a recurring environmental disaster in Indonesia. Fire occurrence is influenced by various factors, including hotspot density, rainfall, and land cover. West Sumatra is classified as a region prone to forest and land fires, with characteristics that differ between areas. Therefore, susceptibility mapping is very important to support more effective mitigation efforts. This study aims to analyze the spatial distribution of hotspot density using the Kernel Density method and to develop a forest and land fire susceptibility index through the integration of hotspot density, rainfall, and land cover parameters using the Weighted Overlay method in a Geographic Information System (GIS). The data used include hotspots for the 2021–2025 period from NASA FIRMS, rainfall for the 2021–2025 period from CHIRPS, and 2024 land cover from Earthdata. The analysis was carried out at a spatial resolution of approximately 500 m using the Natural Breaks (Jenks) classification. Parameter weighting refers to previous research in Riau Province, with weights of 67.5% for hotspots, 25.7% for land cover, and 6.8% for rainfall. The results show that the highest hotspot density is concentrated in Pesisir Selatan Regency, while Dharmasraya and Pasaman Barat Regencies fall into the medium category. The resulting susceptibility map shows that Pesisir Selatan Regency falls into the very high class, with an index value of 3.2811–4.4760, while the Mentawai Islands fall into the very low class, with an index value of 0.9330–1.2942. Validation using 2024 burned area data shows that approximately 80.40% of the burned area falls within the high and very high susceptibility classes, indicating that the resulting susceptibility map has a fairly good spatial correspondence with actual fire occurrence. The results of this study can be used as supporting information for forest and land fire mitigation efforts in West Sumatra.

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INTRODUCTION

Forest and land fires (karhutla) have very broad impacts on ecological, public health, social, and economic aspects, making them one of the serious environmental problems in Indonesia [1]. Large-scale fire events have recurred repeatedly over the past decade. In 2015, approximately 2.6 million hectares of land burned, while in 2019 severe fires again occurred, producing widespread haze that disrupted community activities and the economy [2]. The extent of burned land showed annual fluctuations during the 2021–2025 period. According to data from the Ministry of Environment and Forestry, the burned area in Indonesia was recorded at 1,161,193 ha in 2023 [3]. For this reason, spatially based mitigation efforts are needed to identify areas with high forest and land fire

susceptibility, which can support the formulation of more effective prevention strategies so that susceptibility threats can be reduced.

Physically, forest and land fires are actually triggered by the interaction between the surrounding air, the type of ground surface, and a source of fire or heat. One of the most important factors is the water content of vegetation fuel. The drier the leaves or twigs, the easier they are to ignite, because the heat energy required to ignite them becomes smaller [4], [5]. On the other hand, low rainfall causes soil to dry out quickly and lose moisture. As a result, when sunlight hits the surface, the soil heats up faster and the surrounding conditions naturally become hotter, which clearly favors the occurrence of fire [6]. Land cover type also plays a role. Dense forest with a dark canopy tends to absorb more solar heat than open land. This can alter local temperatures and affect the water content of the surrounding vegetation [7]. Furthermore, large fires can also have a broader impact on climate, as the smoke and gases released into the atmosphere disturb the balance of the air [8]. These three factors are closely and physically interrelated; combining them in susceptibility mapping is not merely a technical step but also a concrete application of atmospheric physics and applied physics.

One indicator widely used to monitor forest and land fire incidents is the hotspot. A hotspot is a pixel in a satellite image with a temperature higher than the surrounding area, so it can be used as an early indication of burning activity [9]. Using the Kernel Density method to map hotspot density provides a clear spatial picture of fire concentration patterns, particularly for determining the most susceptible areas. However, the presence of hotspots cannot be used as the sole parameter in determining the level of forest and land fire susceptibility, because fire occurrence is also influenced by rainfall conditions and land cover characteristics [10].

West Sumatra is classified as a region susceptible to forest and land fires, with spatial characteristics that differ between areas. Previous research has shown that forest and land fires in West Sumatra tend to be concentrated in Pesisir Selatan Regency [11]. Other research has also shown that fire events in West Sumatra are mostly found in convertible production forest areas and shrub swamps, land cover types that are prone to fire [12]. These findings indicate that environmental factors play an important role in determining the pattern of forest and land fire occurrence, so an analysis integrating several parameters simultaneously is needed.

In addition to hotspots, rainfall is also a factor that affects the level of forest and land fire susceptibility. A decrease in rainfall reduces vegetation moisture and natural fuel, thereby increasing the potential for fire. Conversely, high rainfall increases environmental humidity and can inhibit fire spread. Therefore, rainfall is one of the important parameters in forest and land fire susceptibility analysis [13], [14].

On the other hand, land cover characteristics also significantly affect fire potential. Each land cover type has a different level of fire proneness. Shrubland, open land, and agricultural land are generally more prone to fire than forest areas with dense vegetation. Therefore, integrating the hotspot, rainfall, and land cover parameters is expected to produce a more comprehensive susceptibility map [12], [15].

Hotspots, rainfall, and land cover each make different contributions to forest and land fire occurrence. Hotspots are often used as the main indicator because they represent the location of thermal anomalies related to burning activity. Research by Sutopo et al. [16] showed that 83.8% of hotspots were located in high-vulnerability zones, so this parameter is considered to have a more direct relationship with fire occurrence. In addition, land cover plays a role in determining fuel availability that supports the ignition and spread of fire [16], [17]. Conversely, rainfall affects the moisture level of vegetation and surface fuel conditions, so a decrease in rainfall is generally followed by an increase in the number of hotspots [9], [18]. The different roles of each parameter indicate that their contribution to forest and land fire susceptibility is not always the same and needs to be taken into account in the susceptibility modeling process.

Although various studies have examined forest and land fire occurrence in West Sumatra, several limitations still need to be considered. Almegi et al. [11] analyzed the distribution of hotspots based on land cover in Pesisir Selatan Regency, but did not yet consider the rainfall factor that affects the level of vegetation dryness. Meanwhile, Fadly et al. [12] examined the distribution pattern and control strategy for forest and land fires in West Sumatra, but had not yet integrated the hotspot, rainfall, and

land cover parameters into a spatial susceptibility model. In addition, previous studies still used data from an earlier period. Therefore, this study integrates these three parameters using the latest data from the 2021–2025 period to produce more comprehensive and relevant spatial information on forest and land fire susceptibility to support mitigation efforts.

These three parameters have dynamic characteristics, so the level of forest and land fire susceptibility can change according to environmental conditions and time [19], [20]. Therefore, updating spatial information using the latest data is needed so that the resulting susceptibility map can represent current conditions and support more effective mitigation efforts. On this basis, this study combines the parameters of hotspot density, rainfall, and land cover to produce a forest and land fire susceptibility map using the weighted overlay method, using the latest 2021-2025 data so that the results are more accurate.

This study has two objectives: to analyze the hotspot density pattern using the Kernel Density method, and to map the level of forest and land fire susceptibility through the integration of the hotspot density, rainfall, and land cover parameters. The resulting information is expected to become a top priority for forest and land fire mitigation and control in West Sumatra.

RESEARCH METHODS

This study applies a quantitative approach through a descriptive spatial-temporal analysis. This approach is applied to identify hotspot distribution patterns and to map the level of forest and land fire susceptibility through the integration of the hotspot, rainfall, and land cover parameters using GIS.

1. Study Location

This study was conducted in West Sumatra Province, Indonesia. Geographically, this region is located at coordinates $0^{\circ}54' \text{ N} - 3^{\circ}30' \text{ S}$ and $98^{\circ}36' - 101^{\circ}53' \text{ E}$, with an area of approximately 42,297.30 km². West Sumatra Province is bordered by the Indian Ocean to the west, North Sumatra Province to the north, Bengkulu Province to the south, and Riau Province and Jambi Province to the east [21]. The study location is shown in Figure 1.

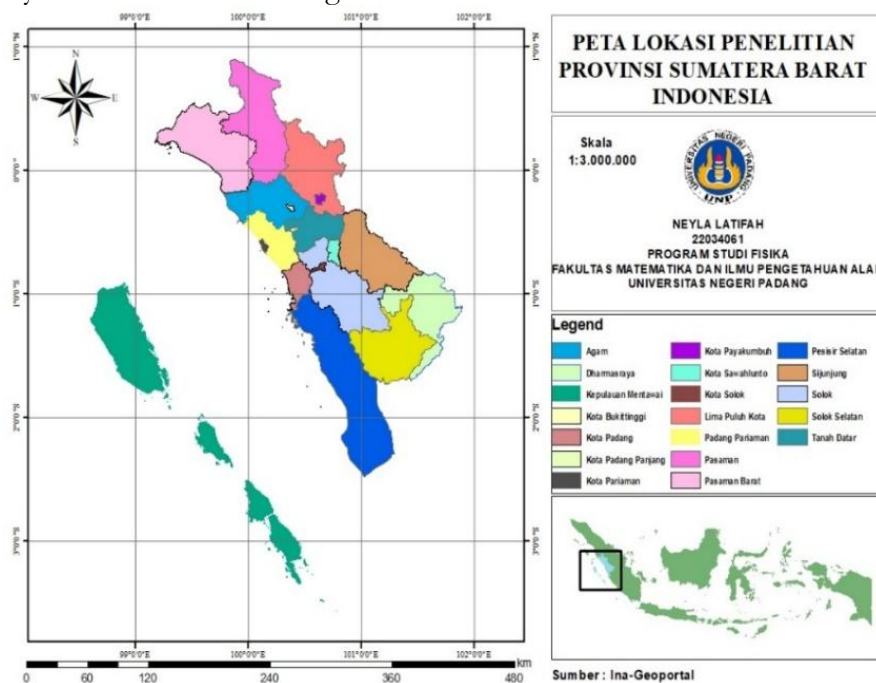


Figure 1. Map of the study location

2. Research Data

This study uses secondary data obtained from various official sources. The data used consist of MODIS hotspots, CHIRPS rainfall, and MCD12Q1 land cover from NASA Earthdata. The selection of CHIRPS and MCD12Q1 data was based on previous research showing that both products have an adequate level of accuracy for environmental and spatial analysis [22], [23]. Furthermore, all data

were processed to standardize the format, coordinate system, and area coverage before being analyzed using a Geographic Information System (GIS). Details of the data types and sources are presented in Table 1.

Table 1. Data Types and Sources

No	Data Type	Data Source
1	Hotspot data 2021–2025	NASA FIRMS
2	Administrative map of West Sumatra	Geospatial Information Agency (BIG)
3	Land cover map 2024	NASA Earthdata
4	Rainfall data 2021–2025	CHIRPS Climate Hazards Center

3. Data Analysis

Spatial analysis was carried out using GIS software to evaluate the level of forest and land fire susceptibility in West Sumatra. The analysis process began with calculating the hotspot density level (all confidence levels) using the Kernel Density method. This method is used to convert hotspot points into a continuous surface that describes the spatial concentration level of hotspots. The analysis was carried out using a bandwidth (search radius) parameter of 20 km, aimed at describing the distribution pattern at a regional scale. The selection of a 20 km radius was based on previous research showing that a bandwidth in the range of 15–20 km can provide a good balance between spatial detail and the model's ability to represent fire density patterns [24].

Next, hotspot density, rainfall, and land cover were each classified into several classes representing their respective characteristics. Overall, the analysis workflow consists of three main stages, namely scoring, weight normalization, and Weighted Overlay, which are explained in the following subsections.

a. Scoring

Each class was given a score based on its level of contribution to forest and land fire susceptibility. Classes with a greater contribution to fire occurrence were given higher scores, while classes with a lower contribution were given lower scores. The classification criteria and corresponding scores for each parameter are summarized in Table 2.

Table 2. Classification of Forest and Land Fire Susceptibility Parameters

No	Variable	Classification	Score	Susceptibility Class
1	Rainfall (mm/year)	<2000	6	Very Susceptible
		2000-2500	5	Susceptible
		2500-3000	4	Moderately Susceptible
		3000-3500	3	Medium
		3500-4000	2	Not Susceptible
		>4000	1	Very Not Susceptible
2	Hotspot Density	0.026605-0.069173	1	Very Not Susceptible
		0.069173-0.133025	2	Not Susceptible
		0.133025-0.220821	3	Medium
		0.220821-0.361828	4	Susceptible
		0.361828-0.675766	5	Very Susceptible
3	Land Cover	Savanna/Grassland	5	Very Susceptible
		Shrubland	4	Susceptible
		Plantation/ Agriculture	3	Medium
		Secondary dryland forest	2	Not Susceptible
		Forest	1	Very Not Susceptible

Source: Modified from [15], [25].

b. Weighting

The next stage involves assigning a weight to each parameter to represent its relative contribution to forest and land fire susceptibility. This weighting scheme was adopted from the research of Ramadhani et al. [25], which was adapted from the weighting approach carried out by Rosdiana [15]. These weights were then normalized so that their total equals 1. The original and normalized weights are presented in Table 3.

Table 3. Weights and Normalization Results of Forest and Land Fire Susceptibility Parameters

NO	Parameter	Initial Weight	Normalized Weight
1	Rainfall	0.063	0.068
2	Hotspot Density	0.630	0.675
3	Land Cover	0.240	0.257

Source: Modified from [15], [25]

Weight normalization was carried out using Equation (1) to obtain the proportional weight of each parameter so that the sum of all parameter weights equals one [26].

$$w'_i = \frac{w_i}{\sum w_i} \quad (1)$$

Where:

w'_i = normalized weight;

w_i = initial weight of parameter i;

$\sum w_i$ = total weight of all parameters.

c. Weighted Overlay

The final stage of the analysis uses the Weighted Overlay method to integrate the three parameters, namely hotspot density, rainfall, and land cover. Each parameter is multiplied by its normalized weight, and the weighted values are then summed to obtain the forest and land fire susceptibility index. The susceptibility index is calculated using equation (2)) [15].

$$K = (S_{CH} \cdot CH) + (S_H \cdot H) + (S_{PL} \cdot PL) \quad (2)$$

Where:

K = Susceptibility value;

S = normalized weight of each parameter;

CH = Rainfall;

PL = Land cover;

H = Hotspot.

RESULTS AND DISCUSSION

1. Hotspot

The annual fluctuation in the number of hotspots detected in West Sumatra during 2021–2025 is presented in Figure 2.

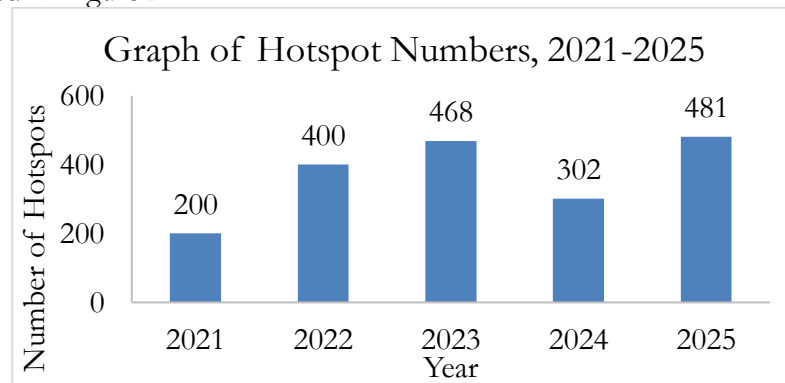


Figure 2. Graph of Hotspot Numbers, 2021-2025

Based on Figure 2, the number of hotspots in West Sumatra during 2021-2025 tended to change from year to year. The number of hotspots increased from 200 points in 2021 to 400 points in 2022,

then increased again to 468 points in 2023. In 2024, the number of hotspots decreased to 302 points, but increased again to 481 points in 2025, the highest number during the study period. The annual changes in the number of hotspots indicate that the dynamics of forest and land fires in West Sumatra are influenced by variations in environmental conditions. Rainfall can reduce vegetation moisture, thereby increasing the chance of hotspots appearing as an early indicator of forest and land fire occurrence [13], [14].

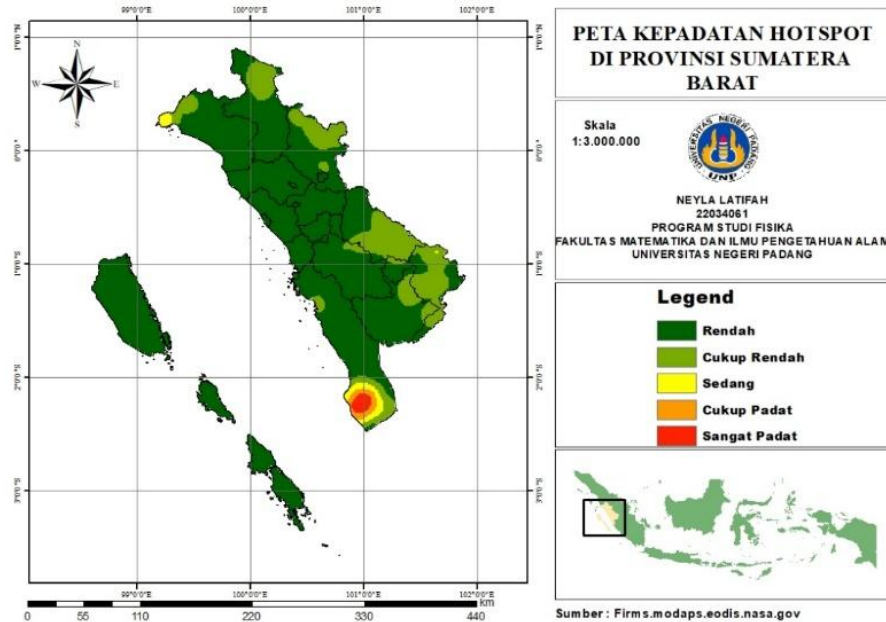


Figure 3. Map of Hotspot Distribution in West Sumatra, 2021-2025

Based on the results of the hotspot density analysis in Figure 3, most of the West Sumatra region falls into the low density class, covering an area of up to 79.04% of the total area. The fairly low class covers 18.01%, while the medium, fairly dense, and very dense classes cover only 1.40%, 0.87%, and 0.67%, respectively. Areas with fairly dense to very dense hotspot density are concentrated in Pesisir Selatan Regency, while medium-category density is found in Dharmasraya and Pasaman Barat Regencies. These results indicate that the distribution of hotspots in West Sumatra is uneven and tends to be concentrated in certain areas that have a higher potential for forest and land fire occurrence than other areas. These findings are consistent with previous research that identified Pesisir Selatan Regency as one of the areas with a high level of forest and land fires [11]. Therefore, the Kernel Density method effectively represents the spatial concentration of hotspots and can serve as an important basis for identifying priority areas for forest and land fire mitigation [27].

2. Rainfall

The annual fluctuation in the number of rainfall in West Sumatra during 2021–2025 is presented in Figure 3.

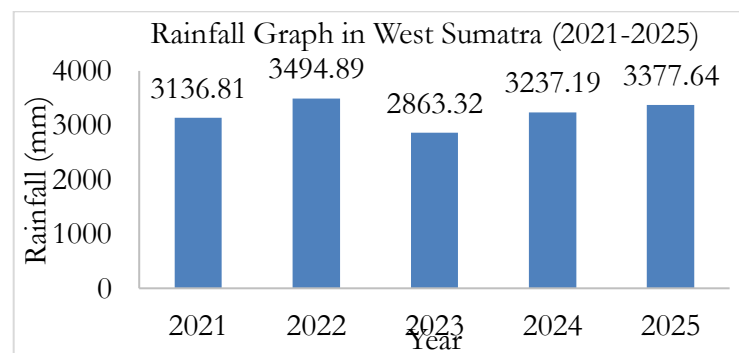


Figure 4. Rainfall Graph in West Sumatra (2021-2025)

Figure 4 shows the variation in annual rainfall across West Sumatra during the 2021-2025 period. The highest annual rainfall was recorded in 2022, reaching 3,494.89 mm, while the lowest value

occurred in 2023, at 2,863.32 mm. After the decline in 2023, annual rainfall increased to 3,237.19 mm in 2024 and 3,377.64 mm in 2025, although both values remained lower than those recorded in 2022. This variation indicates inter-annual climate fluctuations that can affect forest and land fire susceptibility. Lower rainfall generally reduces vegetation moisture, so that natural fuel conditions become drier and increase the likelihood of hotspots occurring as an early indicator of forest and land fires [13], [14].

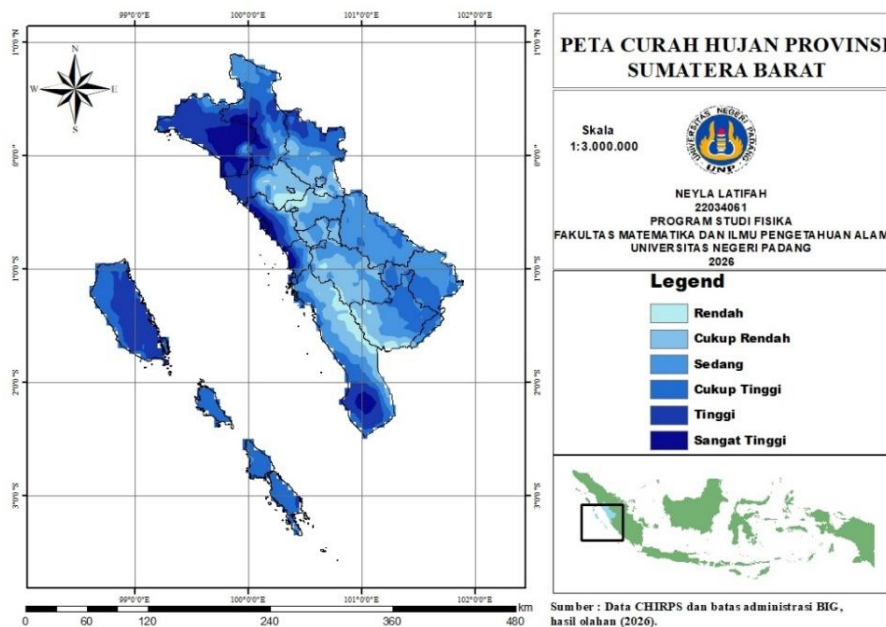


Figure 5. Map of Rainfall Distribution in West Sumatra, 2021-2025

The classification results show that West Sumatra is mostly covered by the 3,000-3,500 mm/year rainfall class, accounting for 42.63% of the total area. The 3,500-4,000 mm/year class is the second largest proportion (23.41%), followed by the 2,000-2,500 mm/year class (23.05%). Meanwhile, the 2,500-3,000 mm/year class accounts for 5.49%, the >4,000 mm/year class covers 4.70%, and the <2,000 mm/year class represents only 0.72% of the study area. The dominance of the relatively high rainfall classes indicates that most areas in West Sumatra maintain favorable moisture conditions, thereby reducing the potential for forest and land fires. Conversely, areas receiving lower rainfall tend to have drier vegetation, making them more prone to fire [28]. This finding is consistent with the rainfall distribution map, which shows that areas with low rainfall occupy only a small part of the province, while most of West Sumatra falls within the medium to high rainfall class.

3. Land Cover

The annual Land Cover Map for 2024 in West Sumatra is presented in Figure 2.

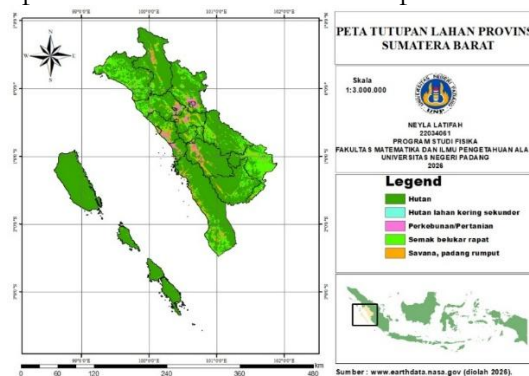


Figure 6. Land Cover Map for 2024 in West Sumatra

The land cover analysis in West Sumatra, as presented in Figure 6, shows that forest areas have the largest share, at 76.82%. Based on this land cover analysis, vegetation in West Sumatra can still be

classified as safe. The next land cover types are dense shrubland (16.42%), savanna and grassland (4.71%), and plantation or agricultural land (2.04%), and finally, the smallest, at 0.01%, is secondary dryland forest. Nevertheless, the presence of shrubland, savanna, grassland, and plantation or agricultural areas still needs attention, because these land cover types have a higher degree of flammability than forest areas. This finding is in line with previous research reporting that forest and land fire occurrences in West Sumatra are largely found in production forest areas and shrub swamps [12].

4. Forest and Land Fire Susceptibility

The forest and land fire susceptibility map was compiled by integrating three main parameters, namely rainfall, hotspot density, and land cover. Each parameter was first classified and given a score according to its level of influence on the potential for forest and land fire occurrence, then combined using the Weighted Overlay method based on the predetermined weights. This process produced a susceptibility index value, which was then grouped into five classes: very low, low, medium, high, and very high. Based on the analysis carried out in West Sumatra, a forest and land fire susceptibility map was obtained, as presented in Figure 7.

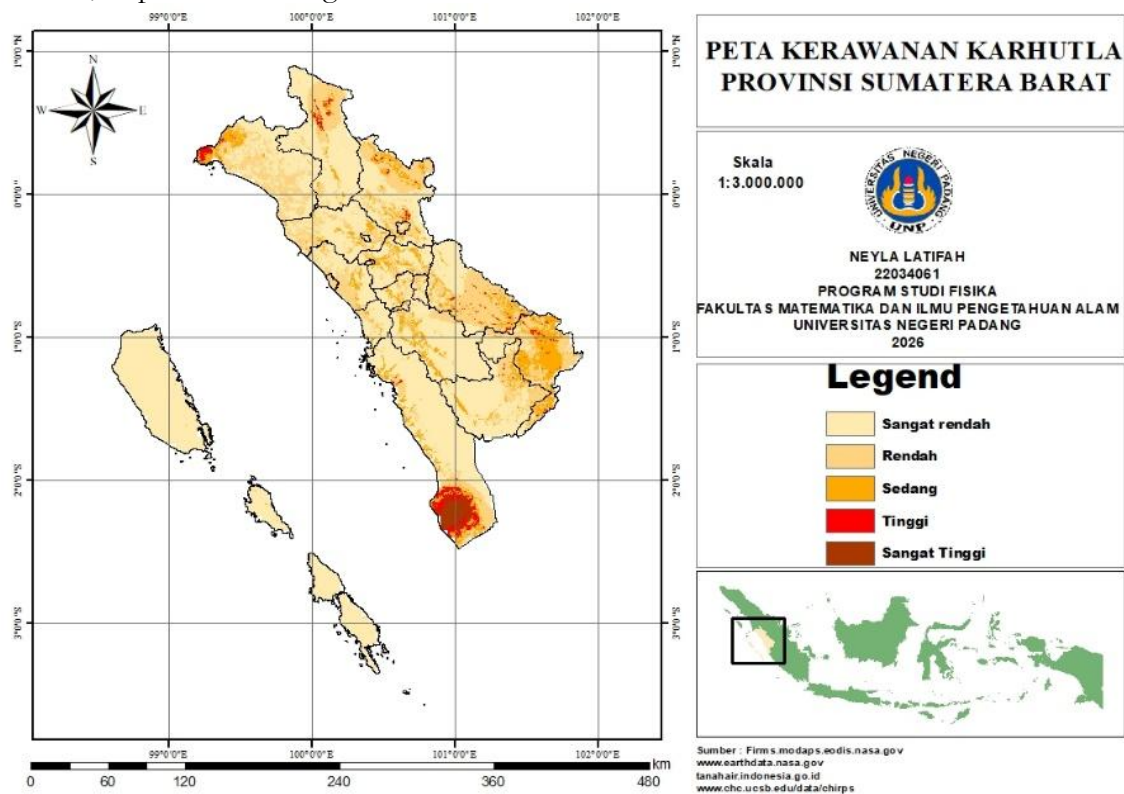


Figure 7. Forest and Land Fire Susceptibility Map of West Sumatra

Figure 7 shows that the level of forest and land fire susceptibility in West Sumatra is divided into five classes. This classification was compiled to provide a clearer picture of the variation in susceptibility levels across each region, so that areas requiring priority for prevention, monitoring, and mitigation activities can be identified more effectively. The value ranges that form the basis for grouping each susceptibility class are presented in Table 4.

Table 4. Classification of Forest and Land Fire Susceptibility

Susceptibility Class	Index Value Range	Area (%)
Very Low	0.9330–1.2942	63.15
Low	1.2942–1.9473	25.46
Medium	1.9473–2.5169	8.58
High	2.5169–3.2811	1.61
Very High	3.2811–4.4760	1.19

As shown in Table 4, the very low susceptibility class occupies the largest proportion in West Sumatra, covering 63.15% of the total provincial area. The remaining area is distributed among the low (25.46%), medium (8.58%), high (1.61%), and very high (1.19%) susceptibility classes. Most of West Sumatra falls into the very low and low susceptibility classes. This indicates that the potential for forest and land fire occurrence in these areas is generally still relatively low. Nevertheless, areas classified as having high and very high susceptibility require special attention, as they are the locations with the greatest potential for fire occurrence.

Areas classified as having high and very high susceptibility are mostly located in Pesisir Selatan Regency, with additional susceptible zones found in Pasaman Barat, Pasaman, Dharmasraya, Sijunjung, Lima Puluh Kota, and Solok Selatan. These areas show a combination of high hotspot density, relatively low rainfall during the dry season, and land cover types that are more prone to fire than other land cover categories [13], [14].

Pesisir Selatan Regency is the region with the highest susceptibility level in this study. This finding is consistent with the results of the hotspot density analysis, which shows that Pesisir Selatan Regency had the highest number of hotspots during the 2021-2025 period compared to other regencies and cities in West Sumatra. This high concentration of hotspots makes a major contribution to the resulting susceptibility index value. In addition, this region is dominated by plantation and agricultural land cover, which has a higher level of susceptibility to fire. Previous research has also reported that the hotspot ratio in both of these land cover types is relatively high. The risk of forest and land fire tends to increase when hotspots appear on agricultural land adjacent to plantation areas, especially during the dry season when vegetation moisture decreases [11].

In contrast, the very low and low susceptibility classes are mainly observed in the Mentawai Islands, along with parts of Agam, Solok, Tanah Datar, Bukittinggi, Padang Panjang, and Solok City. The relatively low susceptibility in these areas is associated with higher rainfall, forest cover dominance, and fewer recorded hotspots, all of which reduce the likelihood of forest and land fire occurrence [10], [19].

The susceptibility map produced in this study provides useful spatial information to support forest and land fire mitigation in West Sumatra. This map can help local governments and related institutions prioritize prevention, monitoring, and control measures according to the susceptibility level of each area [29]. Areas classified into the high to very high susceptibility classes, especially Pesisir Selatan, need to become the main focus of mitigation implementation. Efforts that can be made include increasing integrated patrols, regular hotspot monitoring through satellite data, strengthening early warning systems during the dry season, and conducting outreach to communities on land-clearing practices without burning. These measures are expected to reduce the potential for forest and land fire occurrence while minimizing the resulting environmental, social, and economic impacts.

Nevertheless, the resulting susceptibility mapping shows a pattern relatively similar to the hotspot density distribution. This condition is influenced by the dominance of the hotspot parameter weight of 67.5%, which is far greater than the rainfall weight (6.8%) and the land cover weight (25.7%). As a result, the contribution of hotspots to the final susceptibility value becomes more dominant, so that the resulting susceptibility pattern tends to follow the hotspot distribution pattern. This is evident in Pesisir Selatan Regency, which shows the highest hotspot density value while also falling into the very high susceptibility class. Thus, although integrating several parameters can provide a more comprehensive picture of susceptibility, the influence of rainfall and land cover in this model is relatively smaller than that of hotspots. Therefore, future research needs to re-evaluate the weighting scheme used, for example through the Analytical Hierarchy Process (AHP) method, expert judgment, and the ROC-AUC approach, to evaluate the model's ability to identify fire-prone areas more accurately [30].

5. Validation of the Susceptibility Map with Burned Area

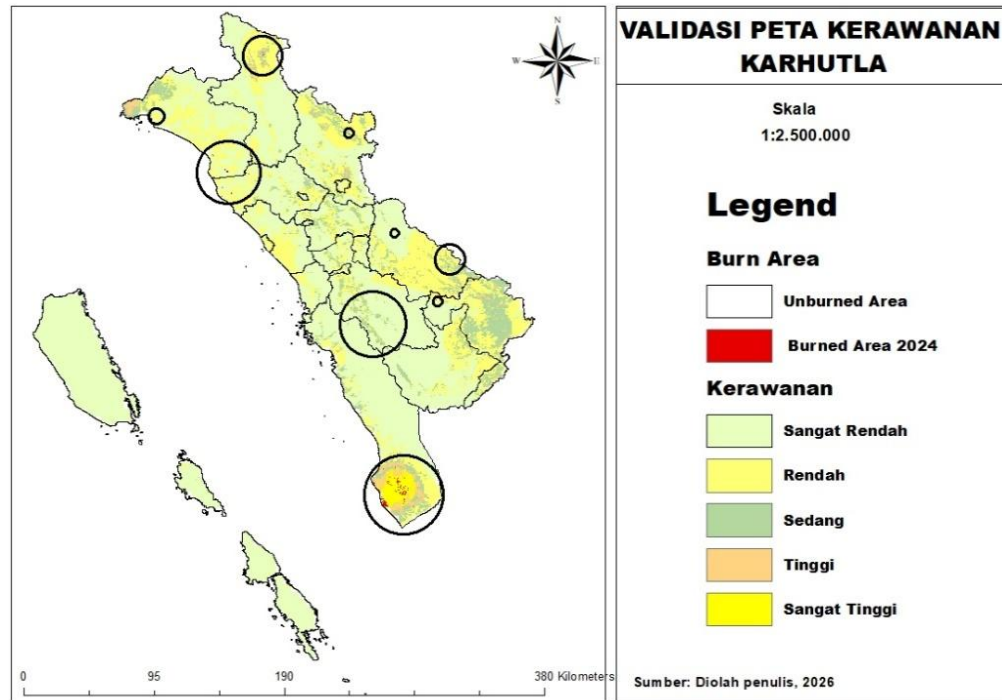


Figure 8. Validation Map of Forest and Land Fire Susceptibility with Burned Area

Validation of the susceptibility map was carried out using *burned area* (burned area) data for 2024 from MapBiomass Fire Indonesia (<https://fire.mapbiomas.id/id>) as a representation of actual fire occurrence. The validation results show that approximately 80.40% of the burned area falls within the high and very high susceptibility classes, while the remaining 19.60% falls within the very low to medium susceptibility classes. These results indicate that the resulting susceptibility map has a fairly good spatial correspondence in identifying areas potentially prone to forest and land fires.

Most of the burned area (66.68%) falls within the very high susceptibility class, indicating that the model is able to represent the spatial pattern of forest and land fire occurrence fairly well. However, the presence of burned areas within the low to medium susceptibility classes indicates that fire occurrence is not only influenced by the parameters used in this study. Other factors, such as soil moisture, surface temperature, human activity, and area accessibility, may also contribute to fire occurrence.

CONCLUSION

The hotspot density analysis shows that the distribution of hotspots in West Sumatra is uneven and tends to be concentrated in certain areas. Pesisir Selatan Regency has the highest hotspot concentration during the 2021–2025 period, followed by Dharmasraya and Pasaman Barat, which also show medium hotspot density. This condition indicates that these areas have a greater potential for forest and land fire occurrence than other areas in West Sumatra. Based on the susceptibility analysis results, Pesisir Selatan Regency falls into the very high susceptibility class, with an index value of 3.2811–4.4760. Meanwhile, the Mentawai Islands, together with parts of Agam, Solok, Tanah Datar, Bukittinggi City, Padang Panjang City, and Solok City, fall into the very low susceptibility class, with an index value of 0.9330–1.2942.

This study still has several limitations. The parameter weights used refer to previous research, so no specific adjustment or validation has been carried out for conditions in West Sumatra. The land cover map only uses 2024 data as a representation of land cover conditions during the study period. In addition, other parameters that could potentially affect forest and land fire occurrence, such as soil moisture, land surface temperature, soil type, elevation, population density, and area accessibility, could be added to make the resulting susceptibility mapping more accurate and representative.

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