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Mapping of Forest Fire Vulnerability Using Information Value Model in West Kalimantan Province

Pemetaan Tingkat Kerawanan Kebakaran Hutan dan Lahan Menggunakan Information Value Model di Provinsi Kalimantan Barat

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ABSTRACT

Mapping forest fires became one of the efforts to reduce the fire vulnerability. Spatial model development for fire vulnerability could employ a GIS-based information value model (IVM) that excels in predicting vulnerability by leveraging hotspot inventory data. However, this model remained relatively unexplored. This research aimed to develop a fire vulnerability model of peatland-dominated areas in West Kalimantan Province and identify biogeophysical factors that significantly influence fire vulnerability in the research area. The IVM employed hotspots, accessibility, land cover, distance to settlements, distance to rivers, soil types, peat types, and Normalized Difference Vegetation Index (NDVI) parameters. The results revealed that the medium hazard class dominated forest and land fire vulnerability in West Kalimantan Province (272,663 ha). In addition, the average annual hotspot intensity from 2012 to 2022 negatively correlated with annual rainfall. Factors such as the brackish water topogen peat type, podzolic-cambisol soil type, accessibility, shrub land cover, and NDVI collectively contributed to the high level of vulnerability.

INTISARI

Pemetaan spasial kerawanan kebakaran hutan merupakan salah satu upaya untuk mengurangi tingkat kerawanan kebakaran. Pengembangan model spasial kerentanan kebakaran hutan dan lahan dapat dilakukan melalui information value model (IVM) berbasis Sistem Informasi Geografis. Metode ini memiliki keunggulan dalam memprediksi tingkat kerawanan berdasarkan data inventarisasi titik api, namun hingga saat ini penerapannya dalam kajian kebakaran hutan dan lahan belum banyak dieksplorasi. Penelitian ini bertujuan untuk mengembangkan model kerawanan kebakaran di Provinsi Kalimantan Barat yang didominasi oleh lahan gambut, dan mengidentifikasi kondisi biogeofisik yang berpengaruh signifikan. Metode IVM diterapkan dalam penelitian ini dengan parameter data hotspot, aksesibilitas, tutupan lahan, jarak ke pemukiman, jarak ke sungai, tipe tanah, tipe gambut, dan NDVI. Hasil penelitian menunjukkan bahwa sebaran kerawanan karhutla di Provinsi Kalimantan Barat didominasi oleh kelas bahaya sedang (272.663 ha). Rata-rata intensitas titik panas tahunan selama 2012–2022 berkorelasi negatif dengan tingginya curah hujan tahunan. Tingkat kerawanan yang tinggi dipengaruhi oleh jenis topogen gambut air payau, jenis tanah podsolik-kambisol, aksesibilitas, tutupan lahan semak, dan NDVI.

Introduction

Forest and land fire is a substantial threat, carrying a high risk of ecosystem damage, including the release of carbon emissions. This fire has the potential to profoundly change ecosystem structures, leading to impacts on biodiversity and contributing significantly to greenhouse gas emissions. The escalation of temperatures, changing weather conditions, and diverse topographical factors collectively promote fire incidence due to human activities, specifically in the Asian area (Reddy et al. 2019). For instance, Indonesia witnessed the adverse consequences of forest and land fires, resulting in significant societal losses, including reduced air quality, respiratory infections, and tragic fatalities (Hein et al. 2022). West Kalimantan, Central Kalimantan, South Sumatra, Riau, and Jambi became the five provinces that experienced a concentration of hotspots from 2016 to 2019 (Arisman 2020).

Fire occurrence depends on the convergence of heat sources, fuel availability, and oxygen, allowing the ignition stage. Yakub & Phuspa (2019) conveyed that human activities account for over 90% of forest and land fires in Indonesia. On the other hand, weather anomalies, which incorporate El Nino, profoundly influence fuel conditions, extending the duration of dry periods and causing drought conditions.

Mapping forest fire vulnerability is essential to furnishing spatial data, enabling local stakeholders to respond effectively to disasters and mitigate potential losses. This spatial model provides diverse levels of fire vulnerability, forming the foundation for regional monitoring efforts, particularly during dry seasons. However, vulnerability represents the cumulative outcome of exposure levels, impacts on ecosystems, and the adaptability of natural systems and human populations (Turner et al. 2003). The development of vulnerability-level models uses disaster-based Geographic Information Systems (GIS).

GIS has become integral to disaster research for mapping physical phenomena and understanding the social dimensions of disasters (Aguntar et al. 2022), providing knowledge-based disaster management and mitigation efforts (Durlević et al. 2021). The combination of GIS and remote sensing technology enables the analysis of various natural disasters, ranging from erosion and overflow floods to avalanches and forest fires (Lombardo et al. 2020; Sevieri et al. 2020). Various contexts show the use of the Information Value Model (IVM) in hazard mapping, including investigations of landslide vulnerability (Chen et al. 2014; Mansour et al. 2021) and endemic diseases (Nakhapakorn & Nitin 2005). Although numerous hazard research effectively uses GIS (Dicelebica et al. 2022; Humam et al. 2020), the application of the model in forest and land fire analysis still needs to be explored. The IVM indicates the predictive power within a dataset by comparing the distribution of feature values for the target variable (the variable to be predicted) with the distribution of feature values for the non-target variable (the variable not to be predicted). Furthermore, IVM assigns values to features from zero to infinity, with higher values indicating more robust predictive capability. This model also allows users to leverage information from inventory maps to statistically calculated parameters for predicting future disaster events (Chen et al. 2014).

Kubu Raya Regency in West Kalimantan Province is an area that frequently experiences forest and land fire (Rachman et al. 2020). The fire incidence in this area is relatively high, contributing significantly to global carbon emissions. From 2012 to 2022, Kubu Raya has recorded 1735 hotspots, averaging 173 hotspots per year (https://firms.modaps.eosdis.nasa.gov/). The dominant peat ecosystems pose an additional threat, as fire can release substantial carbon into the atmosphere. Based on the historical prevalence of fire and the clear advantages of IVM in disaster research. This research aimed to develop the IVM model and unveil the spatial distribution of forest fire vulnerability within the Kubu Raya Regency.

Methods

Research Area

This research focused on the Kubu Raya Regency administrative area, located within West Kalimantan Province, with geographical coordinates spanning from longitude 109° 02' 19.32" to 109° 58' 32.16" east and between latitude 0° 13' 40.83" north and 1° 00' 53.09" south. Geographically, the Natuna Sea bounded the west of this area. Simultaneously, Ketapang and Sanggau Regencies bordered it to the east, Mempawah Regency and Pontianak City to the north, and North Kayong Regency to the south (Figure 1). The Schmidt-Ferguson climate classification showed that Kubu Raya Regency experienced a very wet climate type, with an average of 0.4 dry months and 10.8 wet months within the 2012-2021 timeframe. The highest recorded rainfall was in 2016, with 4906 mm, while 2015 saw the lowest at 2672 mm (Figure 2). Kubu Raya Regency's forest consisted of 63% production forest and 37% protected forest (https://Sigap.Menlhk.Go.Id/ n.d.)

Data Collection

This research used secondary data from various sources, including the Kubu Raya Regency Geoportal website, Earth Explorer, and Fire Information for Resource Management System (FIRMS). The spatial data analysis used raster and vector formats within ArcMap software version 10.8 (Table 1).

Analysis and Design

The IVM modeling used a decade's historical hotspot data from 2012 to 2022 with a confidence level of 80%, complemented by biogeophysical factors. The hotspot analysis employed the Kernel density method to determine the clustering patterns within a given

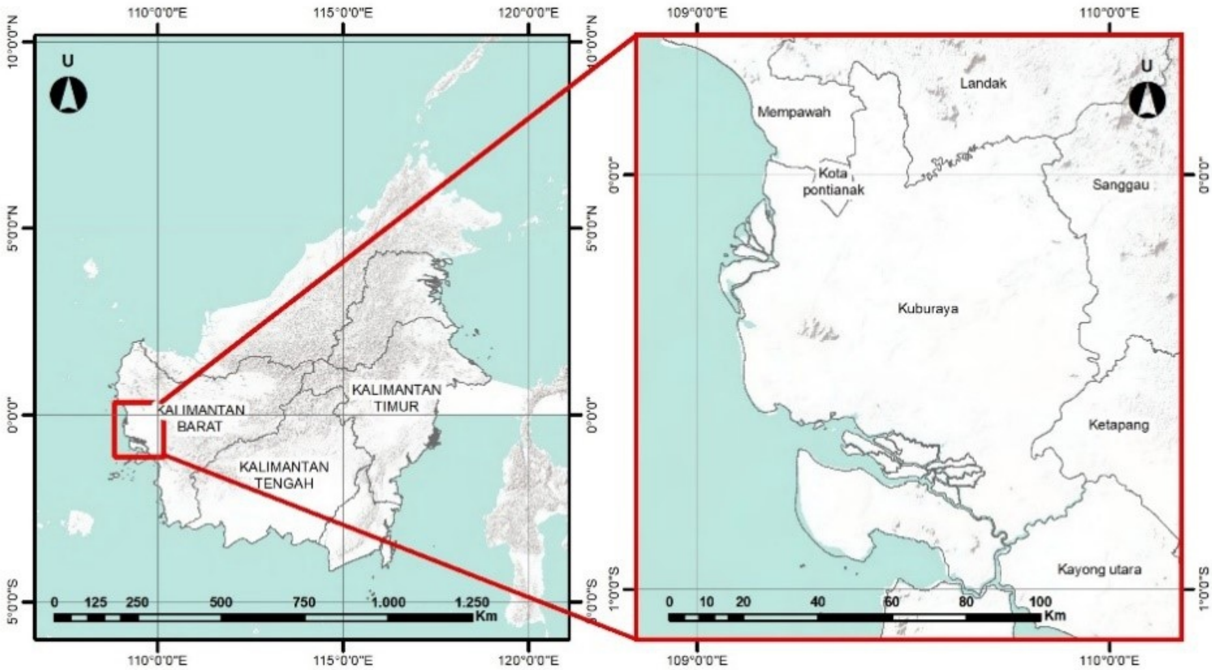

Figure 1. Location map of Tangkahan utilization zone between LPT and GLNP (Source: TNGL 2021)

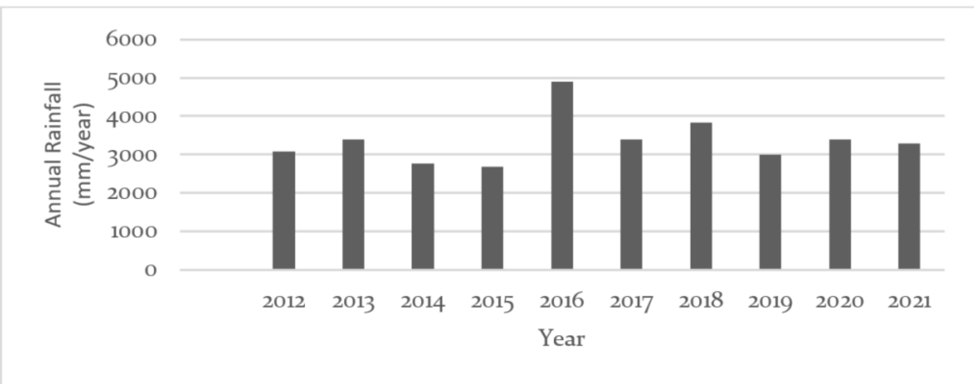

Figure 2. Annual Rainfall of Kubu Raya Regency

Table 1. Data Resources

Data	Source
Hotspot	FIRMS (https://firms.modaps.eosdis.nasa.gov/)
Road network, land cover, settlements, rivers, soil type, peat, and forest area boundaries	Kubu Raya Regency Geoportal (http://geoportal.kuburayakab.go.id/)
NDVI	Landsat 8 (Earthexplorer: https://earthexplorer.usgs.gov/)

phenomenon (Arisanty et al. 2021) and characterized spatial and temporal heterogeneity (Li et al. 2017). This research used kernel density to evaluate the likelihood of forest fire occurrences based on the historical hotspot distribution homogeneity. The outcomes of the kernel density analysis resulted in hotspot density, categorized into five distinct classes. Class intervals were determined using the natural breaks technique within ArcMap version 10.8 software. The two highest-density hotspots from this classification became the input for the subsequent IVM vulnerability modeling. These two highest-density classes corresponded to areas with the most concentrated hotspots. This classification was necessary to investigate the influence of each parameter on the vulnerability level. The parameters used in this research included hotspot density, distance to roads, distance to rivers, distance to settlements, land cover, soil type, peat type, and NDVI.

Forest and Land Fire Vulnerability Model, founded upon IVM, relied on a statistical analysis of parameter classifications that affected the occurrence of fire-related disasters. The resulting IVM model facilitated predictions regarding the spatial relationships between parameter classes and fire incidents. Furthermore, the IVM value for each parameter class was derived by summing the values of each class, producing a forest fire vulnerability value. The calculation of the model used the following formula

$$I(x_iH) = In\frac{S_i/N_i}{\sum S_i/\sum N_i} \quad \text{...} \quad (1)$$

Remarks:
H : Forest fire vulnerability probability
Si : The area of each parameter class
Σsi : Total mapping area
Ni : The area of each parameter class in the fire incident area
Σni : Total fire incidents (Kernel Density)

The overlays of the IVM values of each parameter resulted in the forest and land fire vulnerability map. The fuel sources analysis used the overlay of the vulnerability map and NDVI data. NDVI served as an essential index for assessing the distribution of vegetation, relying on the interpretation of reflectance disparities in near-infrared wavelengths. This index not only mapped the presence of vegetation based on pixel values but also quantified the amount or condition of vegetation within a given pixel (Wan et al. 2004). This research used Hong et al. (2010) equation to calculate NDVI.

$$NDVI = \frac{(NIR - R)}{(NIR + R)} \quad \text{..} \quad (2)$$

Remarks:
NDVI : Normalized difference vegetation index
NIR : Near infrared band value
R : Red band value

Results and Discussion

Hotspot Distribution

From 2012 to 2022, Kubu Raya recorded 1,735 or 173 hotspots/year. In 2020 there were only five fire hotspots, the lowest compared to previous years. Even though the fire hotspots reached 387 in 2018, the annual rainfall is not lower than rainfall in other years (Figures 2 and 3). There appeared to be no significant relationship between climate conditions and the occurrence of hotspots in Kubu Raya. Dicelebica et al. (2022) suggested that the elevated hotspot counts in 2018 attributed to the equatorial rain type characterized by an extended dry season. The results of the kernel density indicated that the hotspots had a significant concentration in the Rasau Jaya and Sungai Raya Regencies. Rasau Jaya Regency consistently witnessed hotspot occurrences in the 2012-2022 period. A more comprehensive understanding of

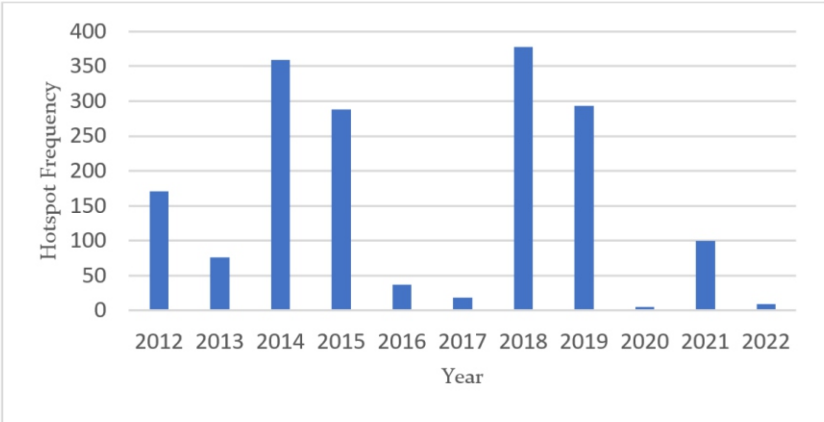

Figure 3. Hotspot Count in Kubu Raya Regency

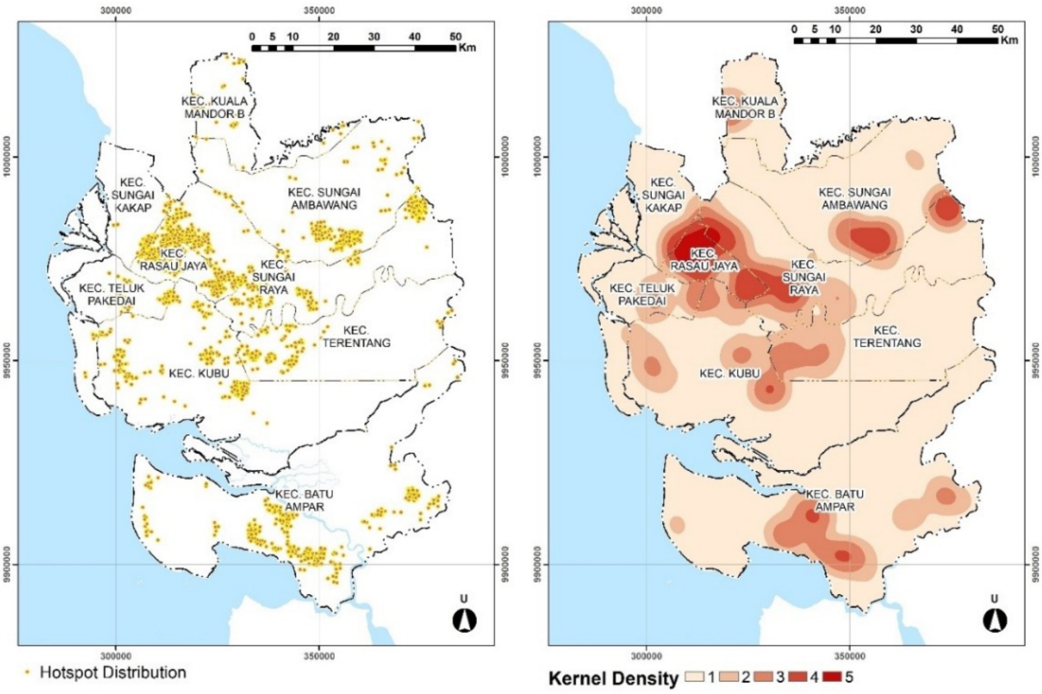

Figure 4. Hotspot distribution and Kernel Density

hotspot distribution required a thorough examination of the spatial distribution of biogeophysical parameters and fuel analysis.

Biogeophysical Parameters

This research used distance to the road networks, distance to rivers, distance to settlements, land cover, soil type, peat type, and vegetation density parameters (Figure 5). Brackish water topogen peat was the dominant peat type within Kubu Raya Regency, covering an extensive area of 193,958 ha, followed by a peat dome (187,619 ha), peat dome edge (130,448 ha), and swamp behind the meandering river (0.90 ha). Organosol soil prevailed, covering an area of 470,925 ha, followed by alluvial-gley humus soil types (187,597 ha), alluvial soil types (171,019 ha), podzolic soil types (21,591 ha), and podzolic-cambisol soil types (6,905 ha). Most areas in Kubu Raya had a low density, followed by medium, very low, dense, and very dense NDVI indices. The land cover of the regency was primarily dominated by jungle, accounting for an extensive area of 527,964 ha, while bare land constituted a smaller portion, measuring 6,39 ha (Table 2).

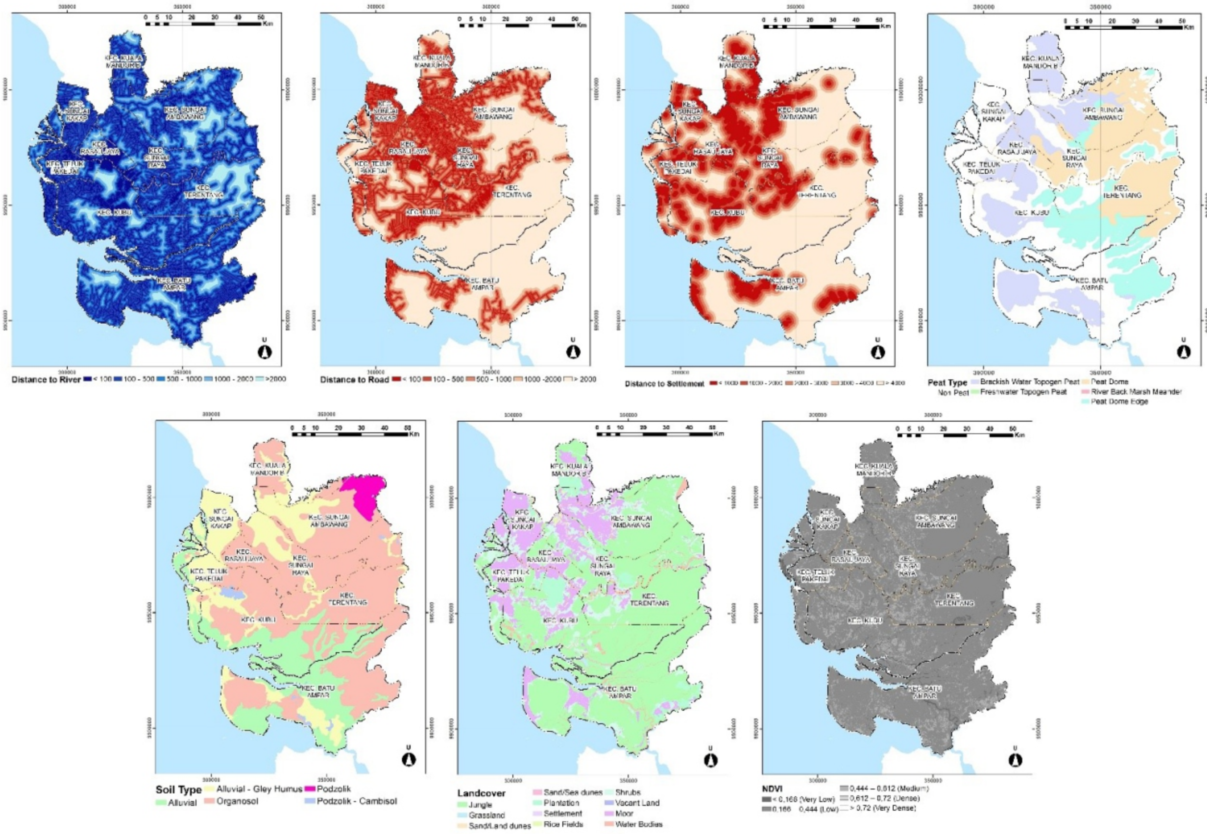

Figure 5. Forest and land fire parameter

IVM Distribution

Parameters with high IVM values indicated a propensity for forest and land fire within the parameter class. In contrast, values closer to zero or zero indicated a lower likelihood of fire incidents. A negative IVM value indicated an inverse relationship with forest and land fire, with smaller negative values corresponding to a decreased likelihood of fire occurrences (Table 2). Low IVM values were in the class of very low vegetation density, non-peat soil types, peat dome edge, alluvial soil, moor, settlements, grasslands, water bodies, locations with greater distances from roads and rivers, and locations that were very close orvery far from settlements.

Based on peat types, the brackish water topogen peat recorded the highest hotspots due to a substantial occurrence of forest and land fire in these areas, despite their fertility. Indigenous people practiced land clearing using fire through controlled burns for seasonal crop cultivation, contributing to the prevalence of fire in these peatlands (Goldstein et al. 2020). The brackish water topogen peat class had the highest IVM value, indicating a significant history or extensive coverage of forest fires. However, the formation of topogen peat typically occurs within the interior of coastal or river plains affected by tidal and flood runoff containing rich minerals (Agus 2014), and tends to be fertile and characterized by moderate thickness. In contrast, the peat dome edge experienced the fewest forest fire incidents due to their locations, which were typically close to cater bodies. The peat domes were less fertile and prone to fire. Consequently, the edge had fewer hotspots than the central peat dome areas.

Based on soil type, organosol soils had the highest number of hotspots due to their unique characteristics, including the low pH of approximately 4, poor nutrient content, and high acidity levels, rendering them susceptible to forest fire (Edwar et al. 2011). In contrast, the podzolic-cambisol soils had the lowest number of hotspots. Despite this low number of hotspots, cambisol soils had relatively high IVM and vulnerability values. These hotspots were

Table 2. Hotspot and IVM value for each class of parameter

Parameter	Code	Class	Hotspot Counted	Si	Ni	IVM
Distance to road (m)	1	0 – 100	275	112.646,79	22.103,28	0,42
	2	100 - 500	587	199.149,93	35.149,05	0,32
	3	500 - 1000	348	95.764,68	16.325,64	0,28
	4	1.000 – 2.000	208	96.477,21	12.996,54	0,05
	5	> 2.000	317	354.000,15	23.553,09	-0,66
Distance to river (m)	1	0 - 100	241	192.199,95	23.193,72	-0,06
	2	100 - 500	572	367.576,47	38.001,78	-0,22
	3	500 – 1.000	397	155.097,81	21.544,38	0,08
	4	1.000 – 2.000	403	105.898,77	20.221,83	0,40
	5	> 2.000	122	37.265,76	7.165,89	0,40
Distance to settlement (m)	1	0 – 1.000	194	160.233,30	18.561,06	-0,10
	2	1.000 – 2.000	296	119.966,31	19.638,72	0,24
	3	2.000 – 3.000	330	101.448,09	17.444,61	0,29
	4	3.000 – 4.000	285	86.209,74	14.287,77	0,26
	5	> 4.000	630	390.181,32	40.195,44	-0,22
Landcover type	1	Water Bodies	8	33.423,84	1.200,69	-1,27
	2	Jungle	1192	527.964,39	68.466,15	0,01
	3	Grassland	1	2.587,23	152,64	-0,78
	4	Sand/Sea dunes	0	219,96	0,00	0,00
	5	Plantation	116	3.3289,11	4.924,98	0,14
	6	Settlement	3	8.166,78	740,52	-0,35
	7	Shrubs	248	98.308,35	16.374,51	0,26
	8	Moor	166	15.2132,22	18.268,11	-0,07
	9	Sand/Land dunes	1	61,20	0,00	0,00
	10	Rice Fields	0	1.879,29	0,00	0,00
	11	Vacant Land	0	6,39	0,00	0,00
Soil type	1	Alluvial	33	171.019,08	2.808,99	-2,06
	2	Alluvial - Gley Humus	230	187.597,71	18.962,19	-0,24
	3	Organosol	1433	470.925,00	86.815,62	0,36
	4	Podzolic - Cambisol	11	6.905,70	1.540,80	0,55
	5	Podzolic	18	21.591,27	0,00	0,00
Peat type	1	Non Peat	205	346.010,85	21.522,15	-0,72
	2	Brackish Water Topogen Peat	804	193.958,64	45.125,37	0,59
	3	Freshwater topogen peat	0	130.448,97	10.353,78	-0,48
	4	Peat Dome	503	187.619,40	33.126,30	0,32
	5	Peat Dome Edge	203	0,00	0,00	0,00
	6	River Back Marsh Meander	0	0,90	0,00	0,00
NDVI	1	< 0,166 (Very Low)	21	30.592,80	1.958,85	-0,70
	2	0,166 – 0,444 (Low)	1422	731.333,34	93.656,16	0,00
	3	0,444 – 0,612 (Medium)	291	96.110,91	14.512,32	0,16
	4	0,612 – 0,72 (Dense)	1	1,62	0,27	0,26
	5	> 0,72 (Very Dense)	0	0,09	0,00	0,00

clustered in the relatively small areas of the podzolic-cambisol soils, resulting in high fire density as the input for the IVM calculation. In addition, podzolic soils are inherently prone to forest fire due to their low water-holding capacity, lack of nutrients, and acid reaction (Kartono et al. 2020). Moreover, most hotspots occurred within a distance of less than 500 m from rivers and roads. These areas often coincided with human traffic routes and activities, significantly contributing anthropogenic factors to forest and land fires (Cattau et al. 2016). Horton et al. (2021) revealed increased vulnerability in peatlands near rivers and roads.

IVM-Based Vulnerability Model

The IVM analysis resulted in six vulnerability classes. The very low, low, moderate, high, and very high vulnerability levels covered areas of 139,730 ha (16%), 69,093 ha, 272,663 ha (32%), 238,904 ha (28%), and 137,374 ha (16%), respectively. Almost all areas fell into high and very high vulnerability classes, particularly in the northern regions (Figure 6). The northern regions had relatively high NDVI values, indicating dense vegetation (Figure 7). This dense vegetation could serve as fuel and significantly

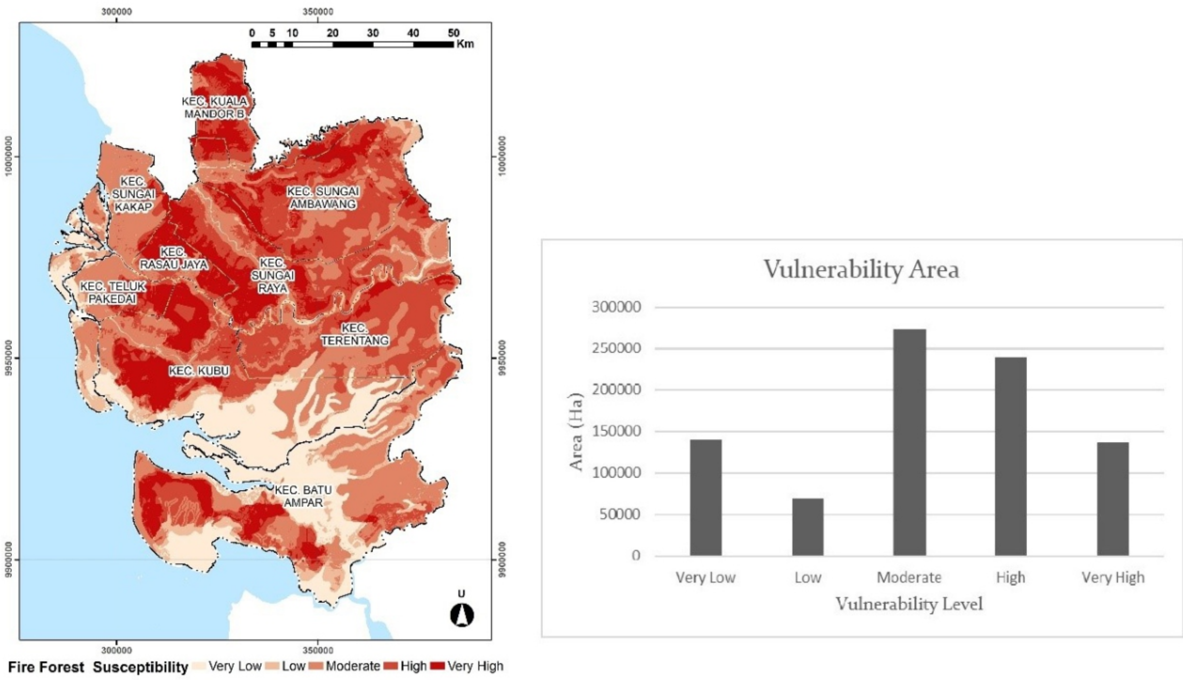

Figure 6. Vulnerability map and area of various vulnerability levels

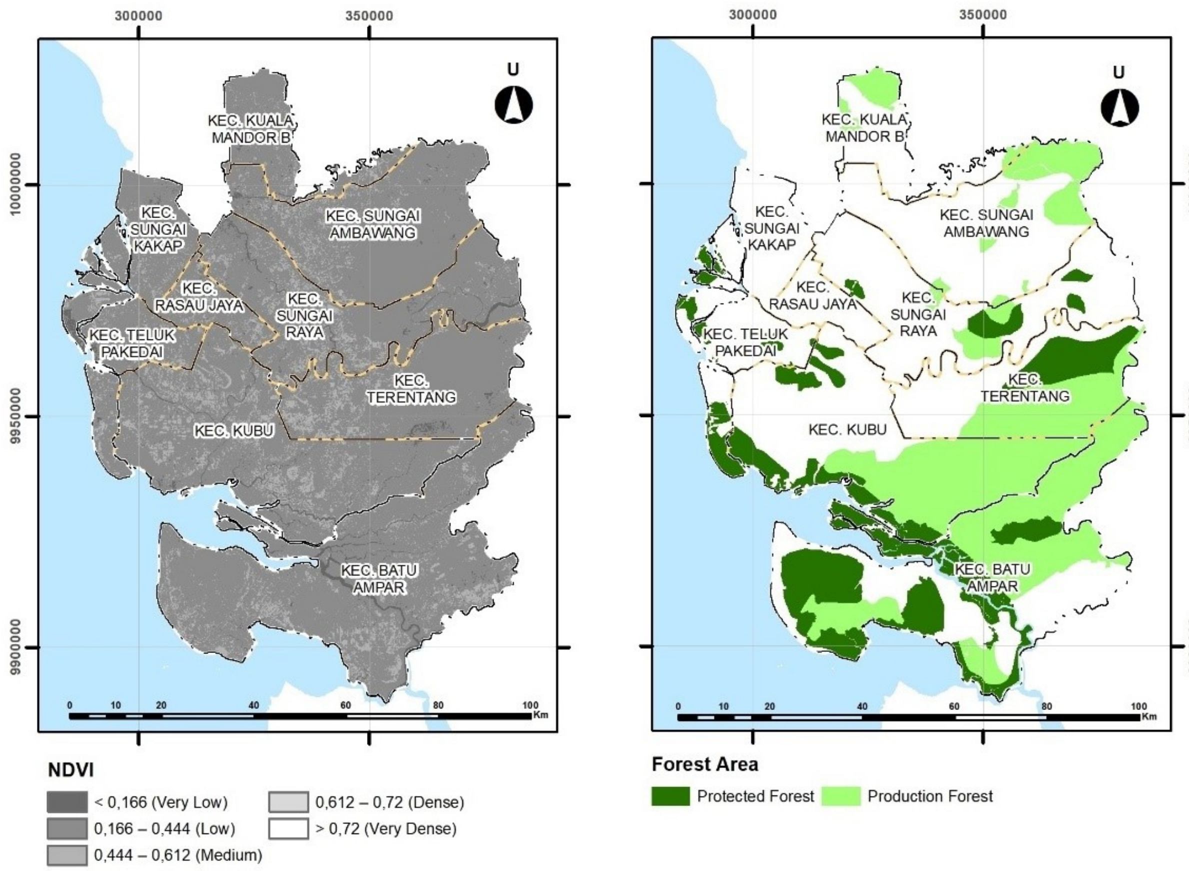

Figure 7. NDVI value map of Kubu Raya Regency and forest area map of Kubu Raya Regency

Table 3. Vulnerabilty area at each NDVI value

Vulnerability Level	Vulnerability Area at NDVI Value				
	< 0.166 (Very Low)	> 0.72 (Very Dense)	0.166 – 0.444 (Low)	0.444 – 0.612 (Medium)	0.612 – 0.72 (Dense)
High	1188.00	-	211021.92	26705.79	0.81
Low	9499.50	-	51212.52	8457.75	-
Moderate	3476.34	0.09	244135.26	25093.44	0.81
Very High	158.31	-	113035.23	24182.64	-
Very Low	16270.65	-	111928.41	11671.29	-
Total	30592.80	0.09	731333.34	96110.91	1.62

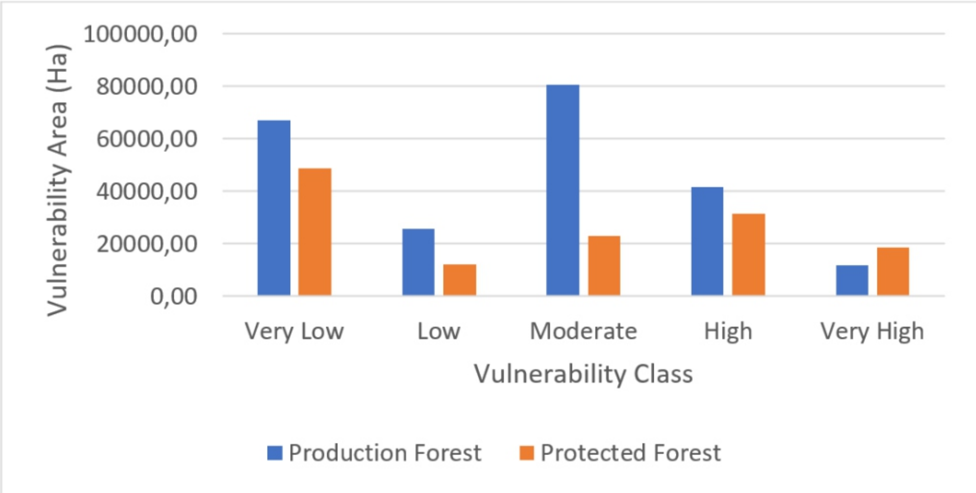

Figure 8. Forest area with high and very high vulnerability (ha)

contribute to an increased vulnerability to fire (Ya'Acob et al. 2022). In addition, high hotspot concentrations also occurred in the southern regions, coinciding with production and protected forest areas with relatively high NDVI values (Figure 7b). This dense vegetation could serve as fuel and significantly contribute to an increased vulnerability to fire (Ya'Acob et al. 2022).

The fire vulnerability tended to increase with higher NDVI values but decreased when the index fell within the medium range (Table 3). NDVI served as a representation of vegetation density concerning humidity levels, influencing potential fire occurrence. The results suggested that denser vegetation correlated with increased humidity and fire vulnerability. The observation was not in line with the analysis of (Astuti et al. 2021), indicating that peatlands with lower moisture levels were more susceptible to burning during dry seasons. While climatic factors, such as high humidity, could reduce fire hazards, the human factor significantly contributed to increased vulnerability (Fitria et al. 2021). In addition, the IVM values in the areas along the roads exhibited a direct proportional relationship with the rate of fire incidents. Areas with high IVM value near highways experienced elevated fire rates. Even in high-humidity forests, fire could occur when road networks allow access for people to engage in activities (Fitria et al. 2021). Areas with high vegetation density could be more susceptible to forest and land fire than those with medium and low vegetation density (Saputra et al. 2021; Abdo et al. 2022). High-density vegetation could experience higher fire incidence than medium and lower-vegetation-density areas. Forest and land fire contributed to vegetation degradation on peatlands, accompanied by reduced carbon biomass (Volkova et al. 2021). Biomass served as fuel for forest and land fires during dry seasons.

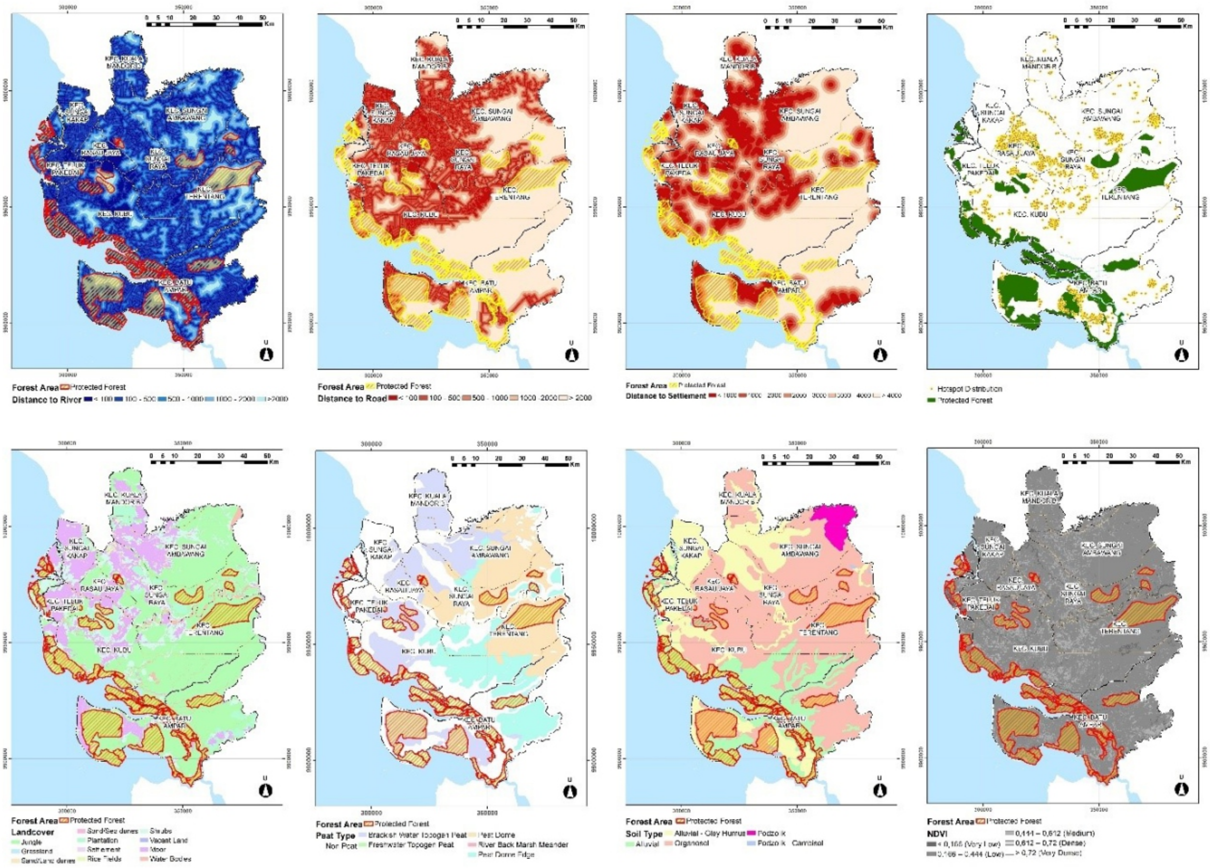

Figure 9. Protected forest area towards forest and land fire parameters

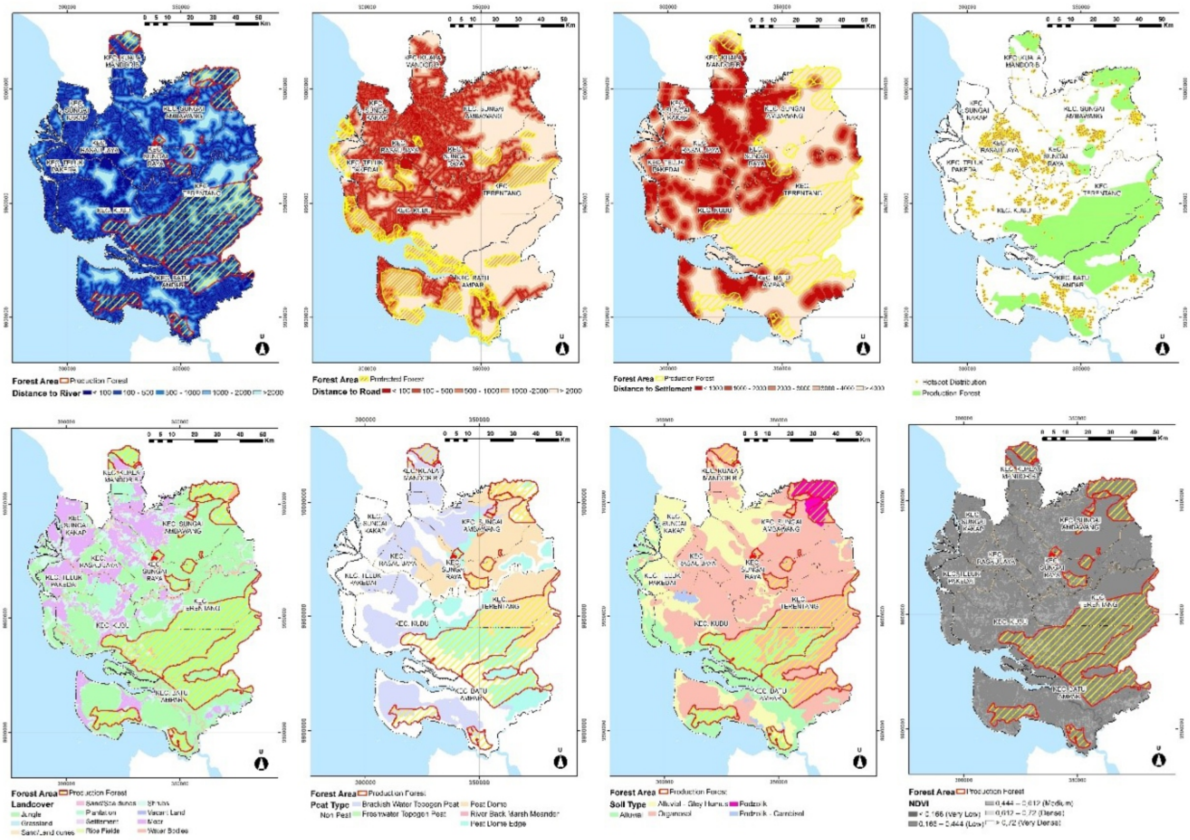

Figure 10. Production forest area towards forest and land fire parameters

The production forest area in the Kubu Raya Regency was larger than the protected forest (Figure 8). The protected forests tend to have low levels of vulnerability. However, the extent of areas with very high vulnerability in protected forests surpassed production forests. Several protected forest areas were near settlements and roads, allowing access for forest burning (Figure 9). In contrast, the production forest areas exhibited vulnerability levels ranging from very low to low. Most areas were relatively far from settlements and roads (Figure 10).

Conclusion

The occurrence of hotspots in Kubu Raya Regency did not consistently correlate with high annual rainfall due to the extended dry periods associated with equatorial rain patterns. The IVM model indicated that several factors significantly influenced the vulnerability level. These included the presence of brackish water topogen peat type, podzolic-cambisol, and organosol soil types, proximity to road networks and canals within a distance less than 500 m, distance to settlements ranging from 2000 to 4000 m, and areas characterized by dense NDVI values falling within the range of 0.612 to 0.72. Despite its limited coverage, the podzolic-cambisol soil type fell within the range of high fire density, resulting in a correspondingly high IVM value for this category. The proximity of hotspots to roads and rivers within 500 m suggested that easy accessibility served as a potential ignition source for fire. Moreover, the analysis of fuel sources underscored that areas with higher NDVI values were at increased anthropogenic fire risk. Forest areas with high vulnerability levels were primarily in permanent production forest areas. The results provided a valuable foundation for monitoring fire-prone areas, particularly within biogeophysical areas with elevated IVM values.

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