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SPATIAL ASSESSMENT OF PEAT-LAND FIRES UTILIZING BINARY LOGISTICS REGRESSION IN WEST KALIMANTAN

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ABSTRACT

This study contributes to the understanding of forest fire susceptibility by applying a binary logistic regression model combined with a Geographic Information Systems (GIS) to map hotspot vulnerability in West Kalimantan, Indonesia, an approach not extensively explored in previous research. Forest fire is one of the environmental problems. In West Kalimantan, land fires are a routine disaster that is experienced almost every year. In this paper, a binary logistic regression model was used to identify land fire in west Kalimantan. In addition, mapping of confidence of hotspot susceptibility was carried out in West Kalimantan. The data used were 72 hotspots spread across in seven districts of West Kalimantan in 2020. The independent variables used were land cover, slope, topography, distance of hotspots to rivers, distance of hotspots to roads and distance of hotspots to settlements. While the dependent variable was the point which was classified into hotspots and non-hotspots. Results showed that the method identified that the variables significantly influencing land fires include the distance of the points to the river and the distance of the points to the road. The Binary Logistic Regression model of the land fire in West Kalimantan has a classification accuracy rate is 84.03%. From the results of weighting and visualization using GIS shown that the area that has a very high level of vulnerability is the city of Pontianak (42.97%). Meanwhile, areas that have a moderate level of vulnerability include Kayong Utara, Kubu Raya, Mempawah, Sambas, Sanggau, Sekadau and Sintang districts. Kubu Raya and Kayong Utara districts in the medium vulnerability level have the largest forest fire districts (43.70% and 41.25%). Meanwhile, districts that are in the very low vulnerability level are Bengkayang, Singkawang, Landak and Melawi districts.

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1. INTRODUCTION

West Kalimantan is one of the provinces in Indonesia which has a direct land border with other countries. The area of West Kalimantan is 146,807 km or 7.53% of the total area of Indonesia. This area is a volcano-free area but there are many environmental problems such as clean water problems, forest fires, floods and landslides. Research on statistical modeling for clean water problems and forest fires has been carried out, including [1], [2], [3], [4], [5], [6], [7], [8] and [9]. The forest fires that occur in West Kalimantan has direct impacts, including the emergence of acute respiratory infections for the community, reduces work efficiency when large-scale forest fires occurred, animal habitat loss, and smoke pollution [10]. Forest fires can be caused by several factors, such as natural (biophysical) and environmental factors. Biophysical factors that influence the occurrence of forest fires include weather and topography. Environmental factors that cause forest fires are the distance to the river, the distance to the road and the distance to settlements. Forest fires then have a lot of impact on the environment.

Using binary logistic regression, this study model probability of fire-prone areas based on hotspot data [11]. Binary logistic regression is a regression analysis used to find the relationship between the dependent variable, which is binary or dichotomous on a nominal scale with more than one independent variable [12]. Its novelty lies in the combined use of spatial and non-spatial variables within a region-specific context, which is rarely a forest fire vulnerability map using a GIS-based scoring and overlay method, offering a valuable decision-support tool for fire prevention and environmental management. This integrated approach advances the application of statistical modeling in regions facing complex ecological challenges like West Kalimantan Province.

2. RESEARCH METHODS

2.1. Data Collection and Analytical Procedures

The data used in this study were hotspot data spread across West Kalimantan Province and this data was obtained from MODIS satellite imagery (Moderate Resolution Imaging Spectroradiometer). The data obtained was in the form of points made and launched by NASA which was taken from https://firms.modaps.eosdis.nasa.gov. Sampling was carried out using simple random sampling [13]. The population used was the number of hotspots with a confidence level $\geq$ 80%, namely 252 points spread across several regions of West Kalimantan. 72 samples of hotspots used in this study were obtained which were spread across 10 regencies in West Kalimantan Province.

This study also used non-hotspot data, which were selected from coordinate points located at a considerable distance from confirmed hotspot locations. However, the selection process did not employ a formal spatial algorithm or defined distance threshold; instead, non-hotspot points were subjectively chosen to ensure they were spatially separated from known fire points. It is important to note that the detection of a fire point does not always confirm the occurrence of an actual forest fire [14]. To balance the dataset, the number of non-hotspot samples was matched to the number of hotspot samples using Propensity Score Matching. The dependent variable—forest fire occurrence—was binary (hotspot = 1, non-hotspot = 0), while the independent variables included a combination of nominal and ordinal types. The sequential stages of the analysis conducted in this study are illustrated in Fig. 1.

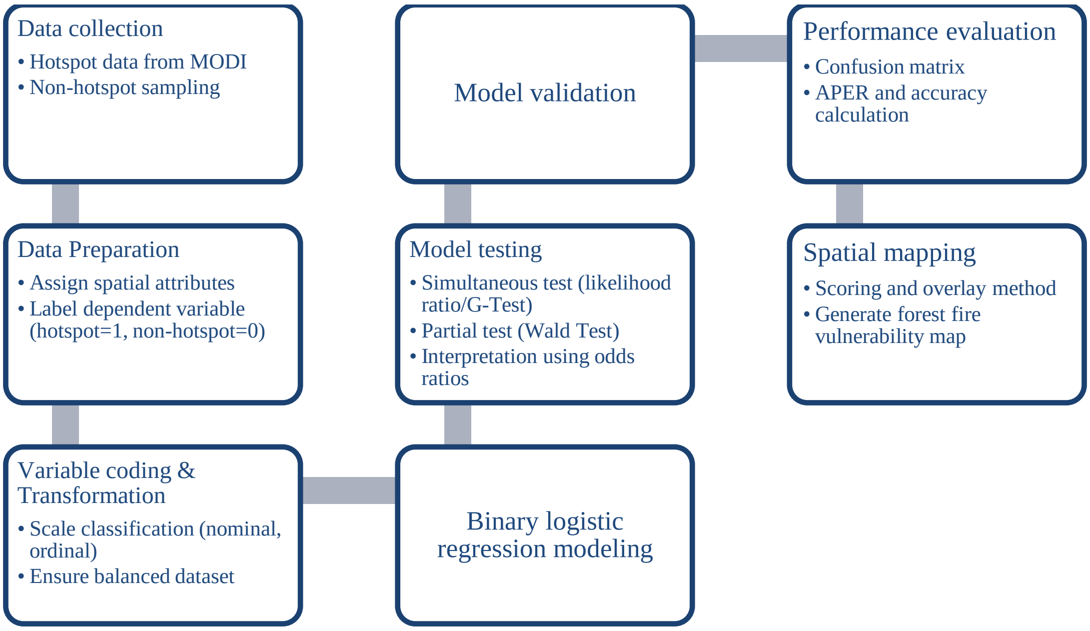

Figure 1. Stage of Analysis

2.2. Binary Logistic Regression

Binary logistic regression is a statistical analysis used to analyze the dependent variable ($\boldsymbol{Y}$) and the independent variable ($\boldsymbol{X}$) [15]. The dependent variable produces two categories, namely 0 and 1 with a nominal scale, while the independent variable has an interval or categorical measurement scale (nominal and ordinal scale). The binary logistic regression equation is shown in Eq. (1) [12].

$$\pi(x) = \frac{\exp(\beta_0 + \beta_1 x_1 + \cdots + \beta_p x_p)}{1 + \exp(\beta_0 + \beta_1 x_1 + \cdots + \beta_p x_p)}, \tag{1}$$

where $\boldsymbol{\pi(x)}$ is the probability of the event of interest in a binary logistic regression model. To complement Eq. (1), Eq. (2) introduces the logit transformation, expressing the model as the natural logarithm of the odds [16]:

$$g(x) = logit\big(\pi(x)\big) = \ln\left(\frac{\pi(x)}{1 - \pi(x)}\right) = \beta_0 + \beta_1 x_1 + \cdots + \beta_p x_p, \tag{2}$$

where $g(x)$ represents the log-odds of the event occurring. β_0 is the intercept (constant term), β_j ($j = 1,2,\cdots,p$) are the coefficients associated with each independent variable x_j, and p is the total number of independent variables in the model. This form highlights that binary logistic regression models the log-odds of the probability of the event occurring (i.e., $Y = 1$) as a linear combination of the predictor variables. Including Eq. (2) is essential for interpreting coefficients in terms of odds ratios.

The estimation method used in estimating the parameters of the binary logistic regression model was Maximum Likelihood Estimation (MLE) [15]. This method estimates β coefficients by maximizing the likelihood function based on the assumption that the response variable follows a Bernoulli distribution. The resulting likelihood function, constructed from the product of individual Bernoulli probabilities, is given in Eq. (3) [17] [18].

$$l(\beta) = \prod_{i=1}^{n} f(x_i) = \prod_{i=1}^{n} p_i^{y_i}(1 - p_i)^{1-y_i}, \tag{3}$$

where the success probability p_i for observation i is modeled as:

$$p_i = \frac{1}{1+\exp\left(-(\beta_0+\beta_1 x_1+\cdots+\beta_p x_p)\right)}.$$

The likelihood function is constructed under the assumption that the observations are independent and that the relationship between the log-odds of the dependent variable and the independent variables is linear. To estimate, the log of the likelihood function known as the log-likelihood function is taken, as shown in Eq. (Eq. ((4) [17].

$$l(\beta) = \ln l(\beta) = \sum_{i=1}^{n}\{y_i \ln[p_i] + (1 - yi)\ln[1 - p_i]\}. \tag{4}$$

In Eqs. (3) and (4), $l(\beta)$ is a likelihood function and a $L(\beta)$ *is log-likelihood* function. In logistic regression, the *likelihood ratio test* was used to assess the overall significance of the model. The likelihood ratio test can also be called the G test statistic. The simultaneous test hypothesis is as follows [16]:

H_0 : $\beta_1 = \beta_2 = \cdots = \beta_p = 0$;
H_1 : there is at least one value of $\beta_p \neq 0$, for $p = 1,2,\dots,p$;

where the test statistic used is [12]:

$$G = -2\ln\left(\frac{LL_U}{LL_R}\right), \tag{5}$$

where G is the likelihood ratio test, LL_U is the likelihood model which only consists of β_0, and LL_R is the likelihood model which consists of p independent variables. In this test, the decision-making criteria H_0 is rejected if the value $G > \chi^2$ or p-value < α [19].

Partial test was conducted to determine the effect that was partially significant in this logistic model using the Wald test. The partial test hypothesis is as follow:

H_0 : $\beta_j, = 0$;
H_1 : $\beta_j, \neq 0$, for $j = 1,2,\cdots,p$.

The test statistic used is as follow [20]:

$$W = \left(\frac{\hat{\beta}_p}{se(\hat{\beta}_p)}\right)^2, \tag{6}$$

where W is the Wald test, β_0 is the value of the p-regression coefficient and $se(\hat{\beta}_p)$ is the value of the standard error of the p value regression coefficient. The decision-making criterion used is H_0 is rejected if the value $W > \chi^2_{a.1}$ or p-value $< \alpha$.

The interpretation of the parameter coefficients in the binary logistic regression model was carried out in the form of odds ratios. Odds ratio is a comparison between the probability of a successful event and the probability of failure. To determine the odds ratio, see Eq. (7) [16] [21].

$$\theta = \left[\frac{\pi(1)/(1-\pi(1))}{\pi(0)/(1-\pi(0))}\right]. \tag{7}$$

The model feasibility test was used to determine whether a model without insignificant variables is the best model. The test used to test the feasibility of the binary logistic regression model was the Hosmer-Lemeshow test. The hypothesis used is as follows:

H_0 : Compatible models;
H_1 : Incompatible models.

The test statistics used is as follow [19]:

$$\hat{C} = \sum_{p=1}^{g} \frac{(O_p - n'_p\pi_p)^2}{n'_p\pi_p(1-\pi_p)}, \tag{8}$$

where g is the number of groups, O_p is the frequency of observations of the p-group, π_p is the estimation of the averaging subjective probability of the group, and n'_p is the total frequency of observations of the p-group, with $p = 1,2,\cdots,p$. The decision-making criteria used H_0 is accepted if $\hat{C} < X^2_{a.p-1}$ or p-value $> \alpha$ [18].

Classification measurement was performed using the confusion matrix. The confusion matrix is a measure used to measure classification performance. The dependent variable that has two classes has four possible prediction results for different classifications, namely true positive (TP), true negative (TN), false positive (FP) and false negative (FN) [22], [23]. The confusion matrix is presented in Table 1.

Table 1. Confusion Matrix

Observation Result	Predictions		Total
	Positive	**Negative**	
Positive	True Positive (TP)	False Negative (FN)	TP+FN
Negative	False Positive (FP)	True Negative (TN)	FP+TN
Total	TP + FP	FN + TN	TP+FN+FP+TN

To determine the accuracy and results of the classification, it is necessary to test the accuracy of the classification. To determine the accuracy of the classification can be done by calculating the APER value. The formula for calculating APER is as follows [24] [25] [26].

$$\text{APER}(\%) = \frac{FN+FP}{TP+FP+TN+FN}, \tag{9}$$

$$\text{Classification Accuracy} = \frac{TP+TN}{TP+FP+TN+FN}. \tag{10}$$

3. RESULTS AND DISCUSSION

In this research, the descriptive analysis for the variables of land cover, slope, and topography were presented in the form of maps, while for the variables of distance of hotspots to rivers, distance of hotspots to roads, and distance of hotspots to settlements, were presented in the form of bar charts.

Fig. 2 (a) reveals that both hotspots and non-hotspots are predominantly concentrated in areas of high vulnerability, particularly those characterized by land cover types such as swamp shrubs, dryland agriculture, and mixed shrub-agriculture mosaics. This spatial clustering suggests that such land cover types may contribute to or coincide with environmental conditions favorable to fire ignition or spread. In Fig. 1 (b), the moderate vulnerability class contains the highest density of both hotspots and non-hotspots. Notably, this class is associated with relatively steep slopes, indicating that topographic factors mays influence fire susceptibility possibly by affecting drainage, vegetation density, or human accessibility. These spatial patterns imply that fire risk is shaped by the interaction between land use and terrain, rather than vulnerability level alone [27].

From Fig. 2 (c), it is known that the hazard class that had the most hotspots and non-hotspots was the moderate vulnerability class. Topographical factors had a strong influence on the occurrence of fires. The area which had a height of two meters with a flat topography and could be accessed was the main reason for people to burn. From Fig. 2 (d), it is found that the areas with the most hotspots was at high vulnerability and non-hotspots at low vulnerability. Forest areas that were more open to public access to forest areas would increase the number of hotspots which was relatively high compared to other areas that could not be accessed by the community.

In Fig. 2 (e), it was found that the hazard classes that had the most hotspots and non-hotspots were very high hazard ($> 4000m$) and low hazard ($1000m - 2000m$). The closer the river is to the point of fire, the faster the process of extinguishing forest fires, and vice versa. This is supported by the parameter estimation result for the variable distance from point to the river, which has a coefficient (β) of -0.994. By applying the formula $\exp(\beta)$, the odds ratio for this variable is $\exp 9 - 0.994) \approx 0.370$. This means that for each unit increase in distance from the river, the odds of a fire hotspot decrease by approximately 63%, emphasizing that proximity to rivers facilitates quicker response and extinguishing of fires. As well as Fig. 2 (f), hotspots appear in areas that have a high level of vulnerability, and the most non-hotspots appear at low vulnerability. The existence of road access will make it easier for the community to carry out interactions that have a negative impact so that it can trigger forest fires. Parameter estimation is performed on six independent variables. The results obtained are presented in Table 2.

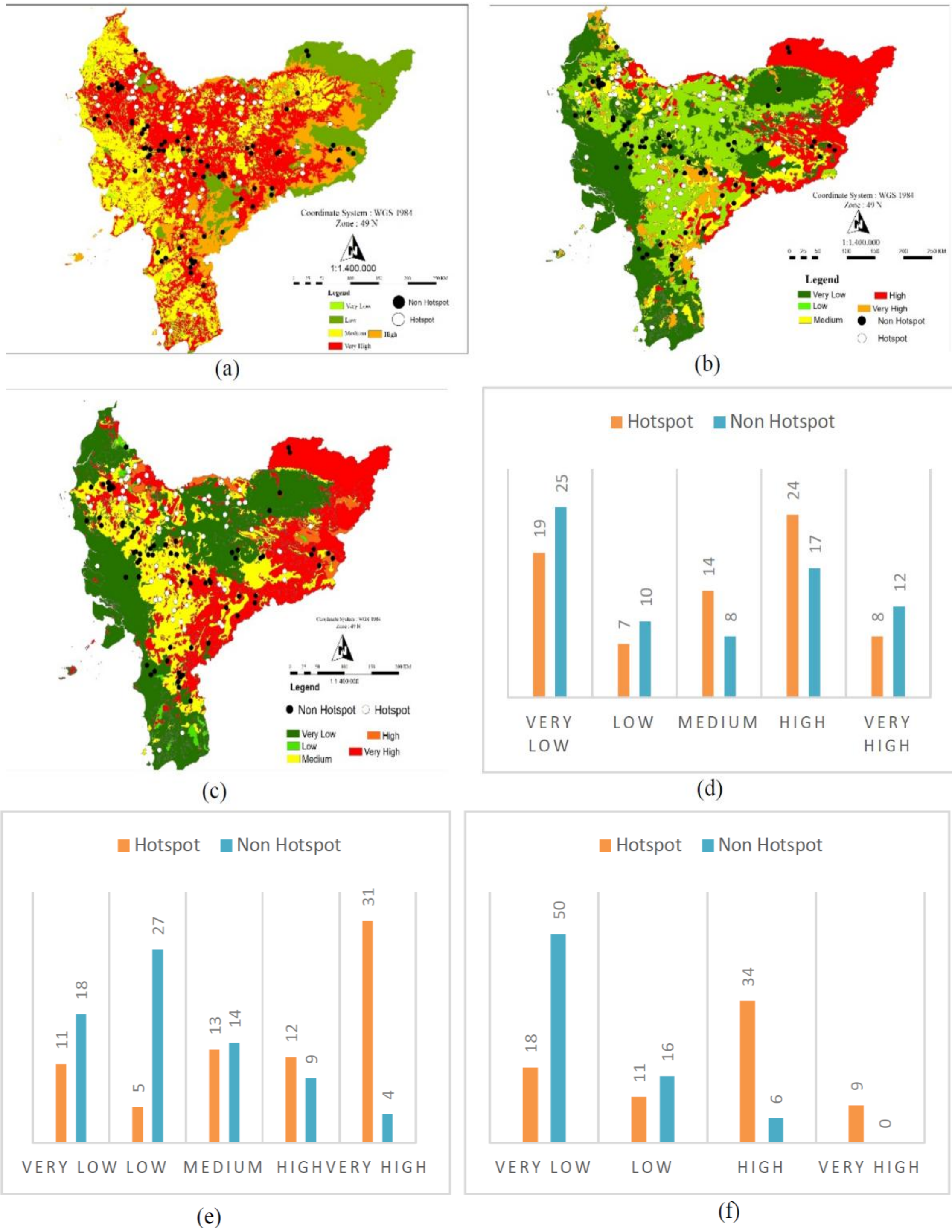

Figure 2. Distribution of (a) Points to Land Cover, (b) Points over the Topography, (c) Points on Slope, (d) Points to Settlement Distances, (e) Points to the Distance of the River, (f) Points to the Distance of the Road.

Table 2. Parameter Estimation Results

Variable	Coefficient
Constant(β_0)	6.414
Land Cover(β_1)	-0.051
Slope(β_2)	-0.064
Topography(β_3)	0.288
Distance From Point to the Settlement (β_4)	0.029
Distance From Point to the River (β_5)	-0.994
Distance From Point to the Road (β_6)	-1.915

Based on Table 2, the initial binary logistic regression equation is obtained as follows:

$$\pi(x) = \frac{\exp\,(6{,}414 + -0{,}051(X_1) - 0{,}064(X_2) + 0{,}288(X_3) + 0{,}029(X_4) - 0{,}994(X_5) - 1{,}915(X_6))}{1 + \exp\,(6{,}414 + -0{,}051(X_1) - 0{,}064(X_2) + 0{,}288(X_3) + 0{,}029(X_4) - 0{,}994(X_5) - 1{,}915(X_6))}.$$

Simultaneous test results obtained a significance value of $0.000 < 0.05$ and $86.424 > X^2_{0,05;6}(12.592)$ so it can be concluded that H_0 was rejected. This means that the independent variables simultaneously influenced the presence or absence of forest fires in an area.

Table 3. Partial Test Results

Variable	S.E.	Wald	df	Sig	$X^2_{0,05;1}$
Land Cover(β_1)	0.029	0.059	1	0.808	3.814
Slope(β_2)	0.159	0.164	1	0.685	3.814
Topography(β_3)	0.358	0.643	1	0.422	3.814
Distance From Point to the Settlement (β_4)	0.375	0.017	1	0.897	3.814
Distance From Point to the River (β_5)	0.215	21.311	1	0.000	3.814
Distance From Point to the Road (β_6)	0.221	26.106	1	0.000	3.814

From Table 3, the statistical value of the Wald test $W > X^2_{\alpha:1}$ and p-value $< \alpha$. Then it can be concluded that H_0 was rejected. Based on the Table 3, there are two independent variables that have a significant effect on the dependent variable, namely the variable distance from the point to the river and the distance from the point to the road. The final binary logistic regression equation that is formed is as follow:

$$\pi(x) = \frac{\exp\,(6.414 - 0.994X_5 - 1.915X_6)}{1 + \exp\,(6.414 - 0.994X_5 - 1.915X_6)}.$$

Binary logistic regression model after carrying out $\pi(x)$ logit transformation as follow:

$$g(x) \;=\; 6.414 - 0.994(X_5) - 1.915(X_6)$$

The magnitude of the influence of each significant independent variable can be explained based on the odds ratio values as presented in Table 4.

Table 4. Odds Ratio Results

Variable	Odds Ratio
Distance From Point to the River	0.370
Distance From Point to the Road	0.147
Constant	610.385

Based on Table 4, the odds ratio value of the point to river distance variable was 0.370, which means the odds ratio value was < 1. The conclusion obtained is that the point to river distance variable tended to reduce the risk of forest fires by 0.370 times and provides a preventive effect occurrence of forest fires.

The odds ratio value of the point-to-road distance variable was 0.147, which was < 1. The conclusion obtained is that the point-to-road distance variable also tended to reduce the risk of forest fires by 0.147 times and had a preventive effect on forest fires. The results of the model feasibility test calculations show the Chi-Square value $5.490 < X^2_{(0.05;8)}$ (15.507) and a significant value of $0.704 > 0.05$. So that H_0 was accepted. This means that the regression model formed was able to predict the value of observations well.

Table 5. Classification Accuracy Results

Observation of Forest Fire	Prediction of Hotspot: Hotspot	Prediction of Hotspot: Non-Hotspot
Hotspot	61	11
Non-Hotspot	12	60

$$\text{APER}(\%) = \frac{11 + 12}{61 + 12 + 11 + 60} = 15.97\%,$$

$$\text{Classification Accuracy} = 100\% - 15.97\% = 84.03\%.$$

Based on the calculation of APER and Accuracy, it is found that the APER value (misclassification) was 15.97% while the percentage of accuracy or accuracy of classification was 84.03%. It can be concluded that the classification of forest fires based on hotspots and non-hotspots [9], [14] in the binary logistic regression model had good criteria. Based on the results of the analysis using the binary logistic regression method, the variables that had a major influence on the occurrence of forest fires were the variable distance from the point to the road and the distance from the point to the river. The weight value given to each influential variable is as follows:

Table 6. Weighting Variables that are Significant to Forest Fire Vulnerability

No	Variable	Weighting (%)
1	Distance From Point to the River	51
2	Distance From Point to the Road	49
	Total	100

Based on [4], this study used five classes of forest fire vulnerability levels in the Province of West Kalimantan. The following is the classification value of the level of vulnerability to forest fires in Table 7.

Table 7. Interval Class Level of Vulnerability to Forest Fires

No	Vulnerability Value (x)	Forest Fire Vulnerability
1	$1 \leq x < 1.702$	Very Low
2	$1.702 \leq x < 2.404$	Low
3	$2.404 \leq x < 3.106$	Medium
4	$3.106 \leq x < 3.808$	High
5	$3.808 \leq x < 4.51$	Very High

After obtaining the classification value of the level of vulnerability to forest fires, an overlay analysis was carried out and produced a mapping of forest fire vulnerability in West Kalimantan Province. Based on the overlay results, the districts in West Kalimantan Province that had the following levels of vulnerability to forest fires were obtained as follow:

Table 8. Forest Fire Vulnerability by District

District/City	Forest Fire Vulnerability in West Kalimantan Province					
	Very Low	Low	Medium	High	Very High	Total
Bengkayang	35.11%	22.65%	32.37%	6.41%	3.55%	100%
Kapuas Hulu	45.83%	20.47%	29.89%	2.25%	1.56%	100%
Kayong Utara	30.45%	15.09%	41.25%	5.86%	7.35%	100%
Ketapang	30.40%	19.17%	36.31%	7.17%	6.95%	100%
Pontianak City	0.00%	3.47%	36.35%	17.21%	42.97%	100%
Singkawang City	32.15%	15.49%	23.60%	9.89%	18.86%	100%
Kubu Raya	28.02%	14.83%	43.70%	6.21%	7.24%	100%
Landak	39.24%	23.69%	29.13%	4.81%	3.13%	100%
Melawi	36.08%	22.96%	31.38%	5.55%	4.04%	100%
Mempawah	26.31%	18.23%	34.97%	9.79%	10.69%	100%
Sambas	19.74%	17.38%	36.52%	12.63%	13.73%	100%
Sanggau	25.37%	21.19%	37.67%	8.04%	7.73%	100%
Sekadau	21.57%	21.38%	33.70%	10.20%	13.16%	100%
Sintang	31.81%	19.39%	33.39%	7.71%	7.71%	100%

Based on Table 8, Pontianak City falls into the very high forest fire vulnerability category, with 42.97% of its area classified as such the highest among all districts and cities in West Kalimantan Province. This figure indicates that Pontianak is particularly prone to forest fires, far exceeding other regions in terms of risk level. Singkawang city also shows a relatively high percentage in the very high vulnerability class (18.86%), while districts such as Kayong Utara, Ketapang, and Kubu Raya display a more balanced distribution across all vulnerability levels yet still reflect notable proportions in the high and very high categories.

On the other hand, seven districts such as Sanggau, Sintang and Mempawah are predominantly classified under the medium vulnerability level, indicating a moderate but still significant risk of forest fires. In contrast, four districts, including Kapuas Hulu and Landak, show the highest percentages in the very low vulnerability category, with 45.83% and 39.42% respectively. This variation in vulnerability across the province highlights the geographical and ecological diversity of West Kalimantan and suggests the need for region-specific forest fire mitigation strategies. Strengthening community-based forest management and raising public awareness about fire risks could enhance local resilience. Additionally, integrating satellite monitoring and localized climate data may help improve predictive capabilities for future fire events. [28]

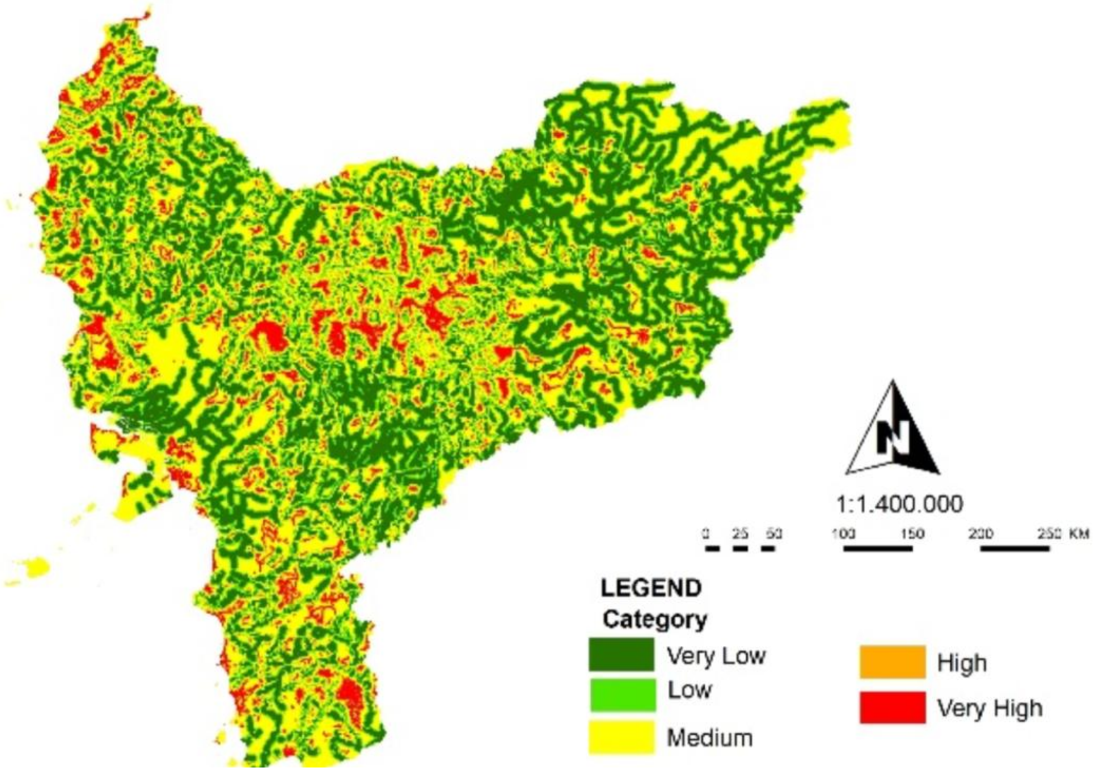

Figure 3. Map of Forest Fire Prone Areas in West Kalimantan Province

From Fig. 3, the data on areas prone to forest fires in West Kalimantan Province was obtained. With the acquisition of this data, it is possible to take steps to prevent forest and land fires by disseminating early warnings through local media (print and radio). This warning may be disseminated to the community and is anticipated to assist them, particularly during prolonged dry seasons that may precipitate fires. Early warning systems can inform farmers and plantation workers, prompting them to implement safer methods during high-risk seasons. This preventive measure can monitor activities in forested and land areas, particularly those susceptible to wildfires, through daily patrols, disseminate information regarding the prohibition of burning, prepare and train all personnel and the public in fire suppression efforts, enforce strict penalties for violations of established regulations, and extinguish fires promptly upon detection of a fire source. Furthermore, educational initiatives aimed at schools and local communities can enhance understanding regarding the significance of fire prevention and the ecological and economic ramifications of forest fires. Partnerships between local governments, non-governmental organizations, and corporate sector companies can enhance fire prevention initiatives by consolidating resources and knowledge. Advanced technology, such satellite photography and drone surveillance, can be connected to deliver real-time data, facilitating expedited detection and reaction. By implementing a holistic strategy, these methods not only aid in the prevention of extensive forest fires but also promote sustained environmental preservation and the welfare of residents.

4. CONCLUSION

Based on the results of the analysis, it can be concluded that the variables that affect forest fires are the distance from the point to the road and the distance from the point to the river. The binary logistic regression model formed has a classification accuracy rate of 84.03% and an APER value of 15.97%. This means that the classification of forest fires based on hotspots and non-hotspots in the binary logistic regression model has good criteria. Areas prone to forest fires in West Kalimantan Province in 2020 which are included in the very high-class category are Pontianak City with an area of 42.97%. Areas that are in the moderate vulnerability class include Kayong Utara, Kuburaya, Mempawah, Sambas, Sanggau, Sekadau, and Sintang Regencies. Kubu Raya District and North Kayong District are in a moderate level of vulnerability, having the largest area of forest fires, namely 43.70% and 41.25%. The districts that are in the very low vulnerability class include Bengkayang Regency, Singkawang City, Landak, and Melawi. There is not a single district that has a low or high level of vulnerability to forest fires.

Author Contributions

Naomi Nessyana Debataraja: Conceptualization, Methodology, Writing - Original Draft, Software, Validation, Writing - Review and Editing. Dadan Kusnandar: Investigation, Resources, Writing - Original Draft. Martina Simanjuntak: Data curation, Formal analysis, Visualization. All authors engaged in discussions about the findings and contributed to the preparation of the final version of the manuscript.

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Declarations

The authors declare no competing interest.

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