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WEST KALIMANTAN FOREST FIRE PROBABILITY MAPPING USING BINARY LOGISTIC REGRESSION

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ABSTRACT

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Forest fires, which occur almost annually, are common in West Kalimantan during the dry season. There is little question that the rate of regional development will slow down as a result of the huge effects this condition has on the social, economic, and environmental domains. Naturally occurring factors are one of the many potential causes of forest fires. The goal of this research was to identify the factors that significantly influence forest fires and to produce a map showing the likelihood of forest fires occurring in various West Kalimantan cities and districts. The analytical technique that enabled us to achieve our goal was logistic regression. The existence or absence of forest fires is one of the dependent variables being used. The temperature, geography, vegetation, and human influences are the independent variables during this time. The bulk of forest fires that occurred in West Kalimantan were caused by human activity as opposed to natural causes, per the study's findings. There are several reasons why humans set off forest fires, whether on purpose or accidentally, but one of them is the distance that people can go to conduct activities inside the forest. Beyond the variables listed above, there are two other criteria that can start a forest fire: the distance from the point to the road and the distance from the point to the air. Using logistic regression, it was discovered that the variable distance between the site and the river contributed thirty percent to the likelihood of forest fires.

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1. INTRODUCTION

The biodiversity that forests provide is an essential component of the living world. Specifically, this is because it serves as a reservoir for carbon dioxide, a habitat for animals, a preserver of soil, and an essential component of the earth's biosphere [1]. The forest serves as a reservoir of oxygen, which is the most crucial function for the survival of consumer creatures like humans and animals (Global Forest Watch, 2021). This function is analogous to the job that the lungs provide in both humans and animals [2].

According to Indonesia's Ministry of Environment and Forestry, the total forest area in 1950 was 162 million hectares. According to the Directorate General of Forestry Planning and Environmental Management (PKTL) KLHL, the results of monitoring Indonesia's forests in 2019 show that the remaining area of forested land throughout Indonesia's land area is 94.1 million hectares, which is equivalent to 50.1% of the total land area. This information is based on the monitoring activity's findings. The island of Kalimantan is home to one of the most extensive forests discovered in Indonesia.

The forests in the Kalimantan region suffered a drop rate of 490,540 hectares per year during the period of time spanning from 2000 to 2017. This resulted in a total of 8,400,000 hectares of forest. The annual decline in forest cover is primarily due to forest destruction [3]. There are two possible causes for this damage: natural occurrences and human activities. Conditions that are conducive to the occurrence of large-scale forest fires have been generated as a result of the rate of land clearing and drying in peatlands and forests [4]. Wildfires are one of the factors that contribute to the loss of forests as a result of human activities.

In 1982, the first forest fire of significant magnitude occurred in East Kalimantan, resulting in the destruction of around 3.6 million hectares of forest. As a result, approximately nine billion dollars in United States currency were lost (Forest Watch Indonesia, 2014). Forest fires directly result in the formation of acute respiratory diseases in the community, a reduction in work efficiency, and the emergence of international difficulties that cause material and immaterial losses in adjacent nations.

According to information obtained from the Karhutla Monitoring System, the number of hot spots in Kalimantan has continued to rise over the past five years. The number of hot spots in West Kalimantan continues to rise year after year, making it one of the provinces that continually experiences this trend [5]. The number of hot spots that were documented in this province in 2016 was limited from the middle of the year until the end of the year. However, after 2016, a hot spot was recorded in this province virtually every single month. In 2019, there were a total of 4,132 hot spots reported, with the exception of February, which did not have any hot spots whatsoever. According to Global Forest Watch (2021), it is highly unlikely that this increase in the number of hot spots will take place in a manner that sustains the environment.

Both natural and human forces contribute significantly to the increase in the number of hot spots. Extreme weather conditions, such as extended dry seasons, are examples of these natural forces [6]. In order to provide an explanation for the relationship between each element that significantly affects forest fires and the role that each factor plays, a quantitative study is required [7]. This is done in the context of fire prevention in order to lessen the damage that forest fires have on the surrounding area [8]. In the event that forest burning is permitted to continue unabated, the total area of forest will decline on an annual basis. As a result, this can lead to a decrease in forests' capacity to perform their role as the world's lungs, which can have an effect on the ecosystem in the surrounding area. According to [9], the fact that each location has its own unique environmental factors makes it necessary to conduct research that may serve as a reference for the purpose of successfully and efficiently suppressing forest fires.

The use of logistic regression is one approach that can be utilized to ascertain the locational features that have an impact on forest fires [10]. It is believed that this research's findings will provide an overview of the elements that significantly influence the occurrence of forest fires. Thus, it is hoped that these findings will provide input for associated parties in the process of developing policies.

2. METHODS

The initial stage of our investigation consisted of getting information about the locations of fires in West Kalimantan from satellite photographs taken over several years. When using logistic regression, the dependent variable is assumed to be binary. For this investigation, the dependent variable in the logistic regression model is the frequency of burning of land or forest, defined as either "burnt" or "not burned."

This study's independent variables can be classified into four groups: terrain, vegetation, anthropogenic factors, and climate. These categories can be utilized to define the variables. Multiple factors in each category were selected [11], [12], [13], [14], [15] based on previous research on forest fire occurrences that occurred overseas. The topographic parameters that might be considered are the slope class, elevation features, and the distance to bodies of water. In order to gather information on the vegetation and land cover, Landsat 8 satellite pictures were utilized. The term "anthropogenic elements" refers to the information about the proximity of flames to various infrastructure areas. It includes the distance to highways, population, settlements, and other destinations. In the meantime, the BMKG and weather monitoring stations in the West Kalimantan region will offer information on the climate and other climate data, such as the amount of rainfall and the length of the sunshine. Categorical variables can also function as independent variables.

Statistical analysis is a method that describes the relationship between a categorical dependent variable and one or more independent variables, which can be categorical or continuous [16]. Logistic regression is a method that describes the relationship. Success (coded 1) and failure (coded 0) are the only two categories included in the Bernoulli distribution used in the logistic regression model. The dependent variable follows this distribution. The probability distribution function can be expressed as [17]:

$$\boldsymbol{f(y_i) = [\pi(x_i)^{y_i}][1 - \pi(x_i)]^{1-y_i}} \tag{1}$$

where y_i is equal to 1, the probability of the occurrence is equal to; when y_i is equal to 0, the likelihood of the event is equal to; and y_i is the ith response variable, which has values of 0 and 1 with $i = 1,2,\cdots,n$. The expression for the likelihood of obtaining a "successful" result is denoted by the equation $P(y_i = 1) = \pi(x_i)$ where

$$\pi(x_i) = \frac{1}{1 + e^{-(\beta_0+\beta_1 x_i)}} \tag{2}$$

In the meantime, the chance of obtaining a "failure" result is denoted by the expression $P(y_i = 0) = 1 - \pi(x_i)$ with

$$1 - \pi(x_i) = \frac{1}{1 + e^{(\beta_0+\beta_1 x_i)}} \tag{3}$$

When conducting statistical modeling, it is frequently discovered that the value of a variable is affected by the values of other variables. The type of relationship that exists between these two variables is referred to as a basic linear regression model [18].

$$y_i = \beta_0 + \beta_1 x_i \tag{4}$$

In the context of statistical analysis, logistic regression is an intrinsic model, meaning it is a nonlinear model that can be transformed into a linear form. Obtaining this linear form requires performing a logit transformation, which is the ln form of the odds ratio [19]. This transformation involves comparing the probability of the event $y_i = 1$ and the likelihood of the event when $y_i = 0$. This comparison ensures that the following is true:

$$\frac{\pi(x_i)}{1 - \pi(x_i)} = e^{y_i} \tag{5}$$

Through the application of the logit transformation, it is achieved.

$$ln\left(\frac{\pi(x_i)}{1 - \pi(x_i)}\right) = \beta_0 + \beta_1 x_i \tag{6}$$

According to the logit model, the value of the outcome variable is represented by the equation $y_i = \pi(x_i) + \epsilon_i$. This equation assumes two possible outcomes: if y_i equals 1, the probability is $\pi(x_i)$, and if y_i equals zero, the probability is $1 - \pi(x_i)$. A table illustrating the link between ϵ_i and probability may be seen below. For further information, please refer to the table [20].

Table 1. The correlation between the likelihood and the value of ϵ_i

	ϵ_i	Probability
If $y_i = 1$	$1-\pi(x_i)$	$\pi(x_i)$
If $y_i = 0$	$-\pi(x_i)$	$1-\pi(x_i)$

As an illustration, let's consider the scenario where n independent experiments are conducted, denoted as $y_1, y_2, \cdots, y_n$ using the probability density function with the density function parameter β. The Maximum Likelihood Estimation Method is a technique that is employed to acquire estimations of the β parameter. This method is characterized by the approach of maximizing the likelihood function. It was reached as a result of the fact that the observations were carried out alone [21]:

$$L(\beta) = \prod_{i=1}^{n} [\pi(x_i)^{y_i}][1 - \pi(x_i)]^{1-y_i} \tag{7}$$

Estimating the regression coefficient (β) is accomplished by maximizing the equation presented above, which is based on the principle of maximum likelihood. One way to maximize this equation is to change the multiplication form to the addition form, which makes it simpler to perform. This resulted in the log-likelihood equation (Muse, 2021).

$$l = ln\big(L(\beta)\big) = \sum_{i=1}^{n} (y_i \ln \pi(x_i) + (1 - y_i) \ln(1 - \pi(x_i))) \tag{8}$$

By reducing the value of l about β and equating the derivative to zero, one can derive an approximated value for β. For the purpose of obtaining the value of β, the equation that is obtained is solved, ensuring that:

$$\frac{\partial l}{\partial \beta} = \begin{bmatrix} \dfrac{\partial l}{\partial \beta_0} \\ \dfrac{\partial l}{\partial \beta_1} \end{bmatrix} = \begin{bmatrix} 1 & 1 & \cdots & 1 \\ x_1 & x_2 & \cdots & x_n \end{bmatrix} \left(\begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{bmatrix} - \begin{bmatrix} \pi(x_1) \\ \pi(x_2) \\ \vdots \\ \pi(x_n) \end{bmatrix} \right) = \begin{bmatrix} 0 \\ 0 \\ \vdots \\ 0 \end{bmatrix} \tag{9}$$

or

$$\frac{\partial l}{\partial \beta} = \boldsymbol{X}^T (\boldsymbol{y} - \boldsymbol{\pi}(x_i)) \tag{10}$$

Because the equation presented above is not a linear function between β_0 and β_1, a different approach is needed to solve it, specifically the Newton-Raphson method [22].

In logistic regression, the goodness of fit is an attempt to determine how well a model fits the data, just like it is in linear regression [23]. After a "final model" has been chosen, it is common practice to apply it. The Wald test statistic is one of the goodness of fit criteria that are utilized in the analysis of logistic regression [24]. Similar to the t test in ordinary linear regression, the Wald test statistic in logistic regression is designed to examine the influence of the regression coefficient β on the model in a distinct manner. The hypothesis that is being tested is [25]:

$H_0: \beta_j = 0$

$H_1: \beta_j \neq 0; j = 1,2,\cdots,k$

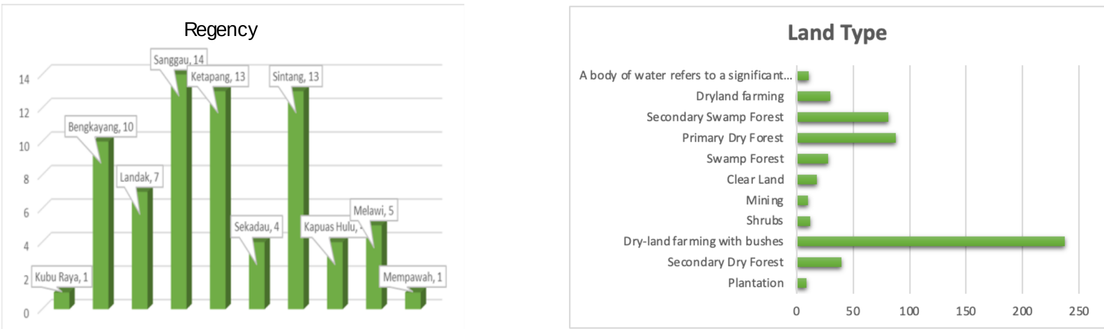
Afterwards is the formulation of the Wald test statistics:

$$W_j = \left(\frac{\hat{\beta}_j}{SE(\hat{\beta}_j)}\right)^2 \tag{11}$$

The chi-square distribution of this test statistic has a degree of freedom of 1, and the result is rejected if the $p - value < \alpha$ [26].

3. RESULTS

The information utilized in this study included information regarding forest fires in several districts in the West Kalimantan district. Bengkayang, Landak, Sanggau, Ketapang, Sekadau, Sintang, Kapuas Hulu, Melawi, and Mempawah are some of the districts that fall under this category. The variables observed in this study included the existence or absence of fire spots at each place, the slope, the distance from the point to towns, the distance from the point to the road, the distance from the point to the river, and the type of land. Additionally, the study sought to determine whether the forest burned out. As shown in Figure 1, the number of hotspots that were found in each district, as well as the types of land that were observed, are presented.



a) b)

Figure 1. Number of hotspots based on a) District b) Land type

The district with the most hotspots is Sanggau Regency, which has fourteen. Ketapang and Sintang Regencies come in second and third, respectively. On the other hand, the number of hotspots is a combination of dry land farming and shrubs when the land type is considered. Forest fires may take place on this sort of land because it is a form of terrain that is prone to burning. Figure 2 below will represent the locations of hotspots and non-fire hotspots according to the terrain type. In the meantime, Table 2 provides a comprehensive breakdown of the number of hotspots present in each place according to the type of land.

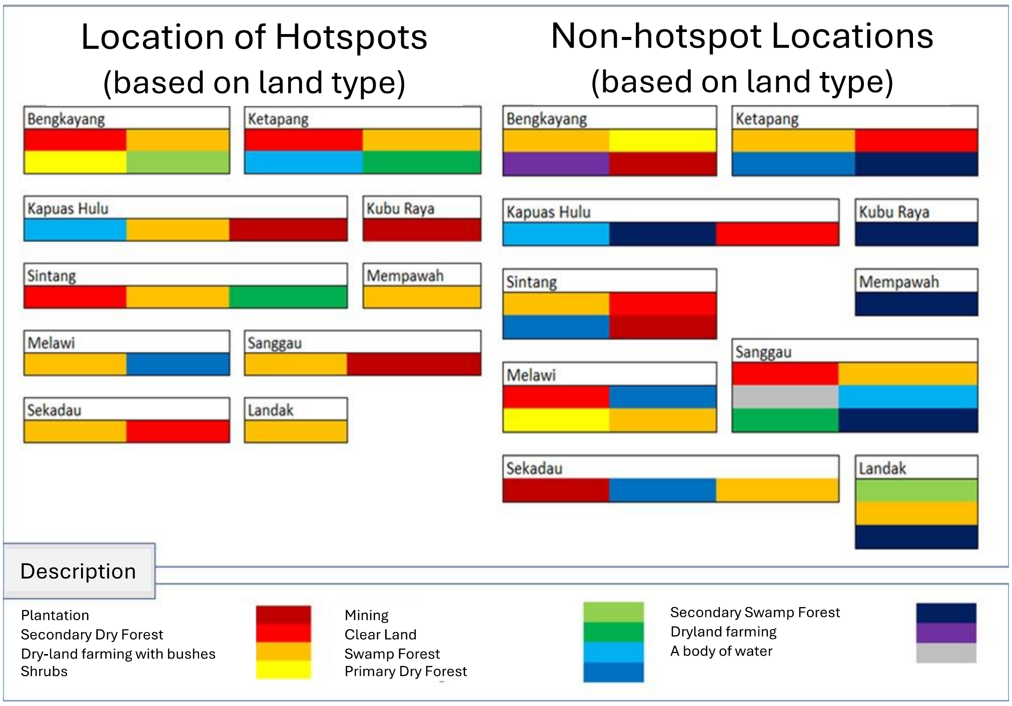


Figure 2. The distribution of fire hotspots and non-fire hotspots according to the kind of land

Table 2: The number of hotspots in each region, broken down according to the type of land

Regency/City	There are hotspots	Number of hotspots	There are no hotspots	Number of hotspots
Bengkayang	Secondary Dry Forest	1	Dry-land farming with bushes	5
	Dry-land farming with bushes	7	Shrubs	1
	Shrubs	1	Dryland farming	2
	Mining	1	Plantation	1
Kapuas Hulu	Swamp Forest	1	Primary Dry Forest	2
	Dry-land farming with bushes	2	Secondary Swamp Forest	1
	Plantation	1	Secondary Dry Forest	1
Ketapang	Secondary Dry Forest	3	Dry-land farming with bushes	4
	Dry-land farming with bushes	8	Secondary Dry Forest	5
	Swamp Forest	1	Primary Dry Forest	1
	Clear Land	1	Secondary Swamp Forest	3
Kubu Raya	Plantation	1	Secondary Swamp Forest	1
Landak	Dry-land farming with bushes	7	Mining	1
			Dry-land farming with bushes	5
			Secondary Swamp Forest	1
Melawi	Dry-land farming with bushes	2	Secondary Dry Forest	2
	Primary Dry Forest	3	Primary Dry Forest	1
			Shrubs	1
			Dry-land farming with bushes	1
Mempawah	Dry-land farming with bushes	1	Hutan Rawa Sekunder	1
Sanggau	Dry-land farming with bushes	10	Secondary Dry Forest	2
	Plantation	4	Dry-land farming with bushes	6
			A body of water refers to a significant expanse of water, such as a lake, ocean, or river.	1
			Swamp Forest	2
			Clear Land	1
			Secondary Swamp Forest	2
Sekadau	Dry-land farming with bushes	3	Plantation	1
	Secondary Dry Forest	1	Primary Dry Forest	1
			Dry-land farming with bushes	2
Sintang	Secondary Dry Forest	3	Dry-land farming with bushes	7
	Dry-land farming with bushes	9	Secondary Dry Forest	2
	Clear Land	1	Primary Dry Forest	3
			Plantation	1

Human activity is the primary cause of most of the forest fires in Kalimantan. Forest fires caused by human activities, whether purposeful or inadvertent, can be caused by several factors, one of which is the distance humans can travel to carry out activities within the forest. Additionally, the distance between points and highways and the distance between points and water are both factors that can spark forest fires between points.

The map depicting the distribution of hotspots and non-fire hotspots within the state of West Kalimantan in 2020 can be found below in Figure 3.

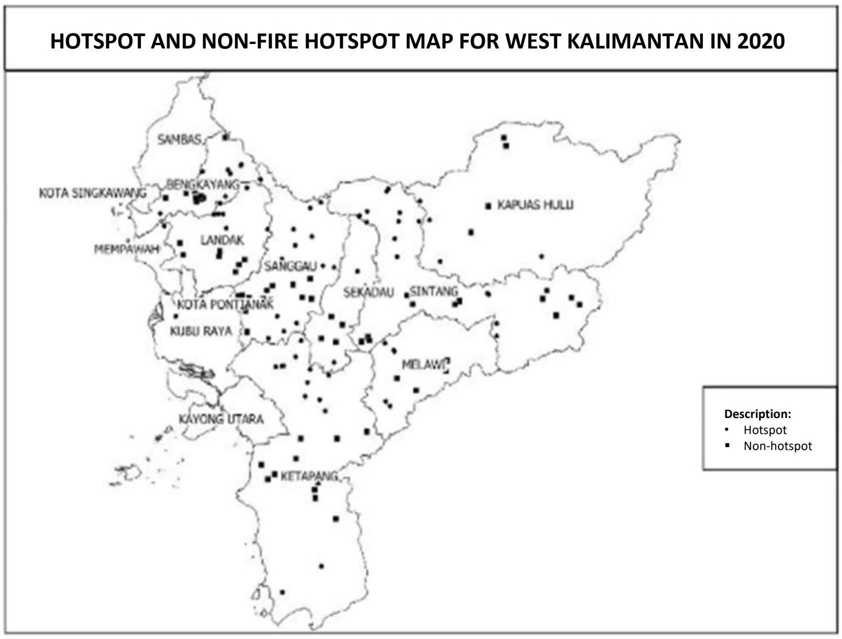


Figure 3. Map of 2020 West Kalimantan hotspots and non-fire hotspots

In West Kalimantan, the use of logistic regression analysis is employed to ascertain the elements that exert a substantial influence on the occurrence of forest fires. The dependent variable in the logistic regression model that was used in this investigation is the frequency of land and forest burning, which may be expressed as "a forest fire occurred" or "a forest fire did not occur." For the sake of this investigation, the independent variables can be classified into four distinct categories: terrain, vegetation, anthropogenic factors, and climate. Based on past research on forest fire incidents that occurred in other countries, several characteristics were chosen to be included in each category. The elevation parameters, slope class, and distance to water sources are all examples of topographic features of importance. Using Landsat 8 satellite imagery, vegetation and land cover were gathered. Factors that are caused by humans include information on the proximity of fires to different types of infrastructure, such as the distance to highways, the population, the distance to villages, and so on. Weather monitoring stations in the West Kalimantan region will be utilized by the BMKG to collect data on climate, which will include rainfall, the length of time that sunshine is present, and other climate-related information. Categorical variables can be used to describe some independent variables.

The steps in this research include estimating parameters in the logistic regression model, determining the logistic regression model, examining the influence of the independent variable on the dependent variable, and generating conclusions based on the analysis carried out. The results of the parameter estimation are presented in Table 3 below.

Table 3. Parameter Estimation

Variable	Parameter Estimation	Standard Error
Distance to river	-1.843	0.519
Distance to road	-0.010	0.072
Land type		
Land type (1)	21.215	40192.978
Land type (2)	20.711	40192.978
Land type (3)	20.671	40192.978
Land type (4)	19.333	40192.978
Land type (5)	19.720	40192.978
Land type (6)	21.121	40192.978

Variable	Parameter Estimation	Standard Error
Land type (7)	20.627	40192.978
Land type (8)	19.684	40192.978
Land type (9)	0.757	41781.442
Land type (10)	-1.297	46403.827
Constant	-19.556	40192.978

The next step is to conduct a test to determine whether the independent variable influences the variable being tested (the dependent variable). The outcomes of the tests are presented in Table 4.

Table 4. Partial test results

	Parameter Estimation	Sig.	Exp(B)
Distance to river	-1.843	.000	.158
Distance to road	-.010	.891	.990
Land type		.964	
Land type (1)	21.215	1.000	1634881276.905
Land type (2)	20.711	1.000	987928879.461
Land type (3)	20.671	1.000	948605154.278
Land type (4)	19.333	1.000	249108128.805
Land type (5)	19.720	1.000	366666571.306
Land type (6)	21.121	1.000	1487994877.517
Land type (7)	20.627	1.000	907928555.129
Land type (8)	19.684	1.000	353640806.988
Land type (9)	.757	1.000	2.131
Land type (10)	-1.297	1.000	.273
Constant	-19.556	1.000	.000

Just one variable affects the occurrence of forest fires: the distance from the point to the river, as shown in Table 4. It becomes apparent when looking at the data. Thirty percent of forest fires can be attributed to the distance separating the point from the river. The value of the Nagelkerke R Square has demonstrated this to be the case. In terms of factors that have a significant influence, the following are the best logistic regression models:

$$\pi(x) = \frac{\exp\left(0.914 - 1.954 \text{ distance to river}\right)}{1 + \exp\left(0.914 - 1.954 \text{ distance to river}\right)} \tag{12}$$

According to the conclusions that can be drawn from this model, there is a tendency for 0.142 forest fires to occur at a certain site whenever there is an increase of one kilometer in the distance between a point and the river.

4. DISCUSSIONS

Forest fires are a persistent problem in West Kalimantan, especially during the dry season due to the arid conditions. The social conditions, economic conditions, and environmental conditions of the region are all significantly impacted by these fires. The research was conducted to determine the primary elements that impact forest fires and develop a map that illustrates the possibility of forest fires occurring in several West Kalimantan cities and districts. According to the study's findings, most forest fires that occur in West Kalimantan cannot be attributed to natural reasons but rather to human activity. It is a very important observation because it brings to light the requirement for more strict precautions to be taken in order to prevent and control fires that humans cause. These fires are frequently caused by human activities such as clearing land for agricultural or plantation reasons, igniting by accident as a result of agricultural operations, and intentionally burning for the sake of land management. The research utilized logistic regression and concluded that the distance between a location and a river is responsible for around thirty percent of the likelihood of forest fires. According to this, regions further away from rivers are more likely to experience fires because fewer water sources are easily accessible for firefighting.

As the findings show, this research is majorly significant for controlling forest fires in West Kalimantan.

1. Enhanced Fire Prevention Measures: Implementing more stringent rules and enforcement to prevent human-caused fires, such as land clearance and agricultural activities that entail burning.
2. Enhanced Firefighting Capabilities: Ensuring that firefighting personnel have sufficient resources, especially a supply of water, to attack fires effectively.
3. The third step in the public awareness campaign process is to educate the general population about the perils of forest fires and the significance of responsible land use practices.

Taking action to address these variables will allow the region to lessen the frequency and intensity of forest fires, thereby lessening their negative effects on the environment, the economy, and society.

5. CONCLUSION

Human activity is the primary cause of most of the forest fires that take place in Kalimantan. Forest fires caused by human activities, whether purposeful or inadvertent, can be caused by several factors, one of which is the distance humans can travel to carry out activities within the forest. Additionally, the distance between points and highways and the distance between points and water are both factors that can spark forest fires between points (30%). It was discovered using logistic regression that the variable distance from the point to the river had a thirty percent influence on the occurrence of forest fires. The conclusion was reached after the analysis was made.

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