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GIS-BASED METHOD IN DEVELOPING WILDFIRE RISK MODEL
(Case Study in Sasamba, East Kalimantan, Indonesia)

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ABSTRAK

Analisis pemetaan lengkap (Cemplete Mapping Analysis) yang berbasis sistem informasi *geografis (SIG) digunakan untuk melakukan pembobotan terhadap nilai "vulnerability" dari faktor-*faktor resiko dalam rangka membangun suatu model dan memetakan kelas-kelas resiko kebakaran liar. Ada dua faktor utama, yaitu faktor lingkungan fisik dan aktifitas manusia yang sangat mempengaruhi terjadinya kebakaran hutan. Model yang ditemukan pada saat ini memperlihatkan bahwa kelembaban relatif adalah faktor terpenting diantara faktor lingkungan fisik, sementara jarak terhadap pusat-pusat pemukiman merupakan faktor terpenting diantara faktor aktifitas manusia. Diketahui juga bahwa, terjadinya kebakaran liar lebih banyak dipengaruhi oleh faktor aktifitas manusia daripada faktor lingkungan fisik. Pada studi ini, wilayah resiko kebakaran liar dibagi atas 3 kelas, dimana ditemukan bahwa kelas resiko kebakaran tertinggi mendominasi lokasi penelitian, selanjutnya diikuti dengan kelas resiko sedang dan rendah. Berdasarkan hasil verifikasi, model hanya berhasil menduga kelas resiko tinggi yaitu sebesar 76,05%, sementara gagal dalam menduga resiko kebakaran sedang dan rendah (lebih rendah dari 40%).

INTRODUCTION

Reports within the past two decades have evidently showed that forest and land fire had increased severely and for longer periods. Normally, fires occur every year but a prolonged and extremely severe fire season occurred in years of unusually long drought associated with the El-Niño-Southern Oscillation (ENSO). Wildfires in Indonesia are almost always human caused; Dennis (1999) noted that smallholders clearing land for cultivation were primarily blamed for starting fires that rapidly spread out of control.

Fire losses often make it impossible to reach sustainable forest management; therefore in order to have an effective and efficient sustainable forest management, the fire prevention should be considered as high priority because it is the key to solving the fire

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problem. Furthermore, the focus on this principal problem should not be on fire fighting, but in identifying major factors and interactions among them that contribute to wildfires.

A wildfire risk model can serve as an early warning system to predict the severity level of future fire risks which significant for wildfire prevention and fighting strategies. In addition, a GIS method is able to use information from many different sources, in many different forms, as well as be able to analyze such information in a quick and more efficient manner. The map of wildfire risk zone provides information for identifying the critical areas, and supports the control of large fire risk areas. Information for fire risk areas is essential to define corrective measure, which act on the existing environment and to implement defensive infrastructures that will prevent high incidence of fire ignition.

The main goal of this study is to use a GIS application to develop a wildfire risk model through the study of the spatial dimensions of interacting factors associated with the likelihood of wildfires. The specific objectives are:

1. To assign and analyze the physical-environmental and human activity factors those are associated with the location of fire starting in the study area.
2. To map the severity class of wildfire risk.

MATERIALS AND METHODS

Site Description

The study was conducted within the Integrated Economic Development Zone (KAPET) of Sasamba, East Kalimantan, Indonesia, during the period of January to July 2001. The study area is approximately 249,516 hectares or 79 % of the total area of Sasamba. It is situated in equatorial area between 116º43´30´´ and 117º18´30´´ East Longitude and –0º33´30´´ and –1º13´30´´ South Latitude. This area is dominated with forest-protected area. It was chosen because of the availability of data as well as this zone is being developed to enhance the development in hinterland's prime sectors for supporting the growth of East Kalimantan. Approximately 219,487 hectares or 87.96 % of the study area was fire affected during the great fires in 1997/98.

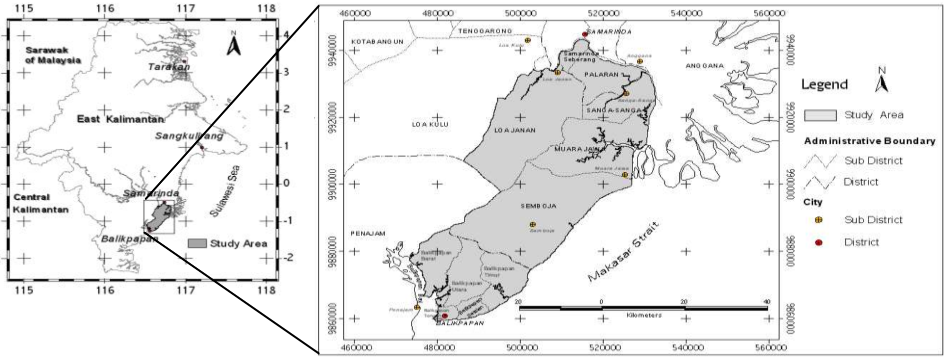

Figure 1. Map of the study area, Sasamba region, East Kalimantan, Indonesia

Materials and Tools

Maps and supporting data were collected from several agencies in Indonesia such as BAKOSURTANAL (National Coordinating Agency for Surveys and Mapping of Indonesia), GTZ Samarinda Office (Integrated Forest Fire Management Project: IFFM), and BPPT (Agency for the Assessment and Application of Technology). The collected data included topographic maps, weather data, and thematic maps in both digital and hard copy format. The PC ARC/INFO 3.5.1 software was used for inputting data, while data manipulation and analysis was implemented the using the ArcView GIS Version 3.1.

Research Method

A GIS-based method of CMA was used to determine the severity level of a wildfire risk zone in terms of wildfire vulnerability mapping by assessing the relative importance between wildfire factors and the location of fire ignition. The general flow of the research activities is shown in Figure 2.

Data Manipulation

The wildfire risk factors were grouped into two major groups, i.e. physical-environmental and human activity factors (Table 1). A DEM dataset was interpolated in order to derive slope and aspect dataset. All of the weather data that was associated with the El-Niño-Southern Oscillation (ENSO) were collected for the May 1997 to May 1998 period. Afterwards, the data was transferred to an ArcView GRID dataset using the Kriging interpolation method. The buffer function was used to generate buffer zones ranging from 1 km up to 2 km from the human activity features. The vegetation and land cover type factor was placed under the human activity factor because it was not directly related to the fire starting, but was strongly associated with the use of land by humans in the study area.

All of the dataset were converted into 1-hectare gird cell size in ArcView Grid format. A grid cell size of 1 hectare was assigned because the Hot Spots was recorded as a point feature, thus the number of Hot Spots in the grid format must be considered. The result showed that the comparison of the number of Hot Spot between original data and grid dataset is exactly the same.

Defining the Wildfire Risk Factors

The sub-factors or categories of each factor were classified on the basis of the rank of data value and original data (Table 1). However, the classifications of sub-factors were modified to adjust the vulnerability score.

Table 1. Classification of sub-factor for wildfire risk factors

Wildfire Risk Factor	Sub-factor
Average daily maximum temperatures	< 30, 30-31, 31-32, > 32 Degree Celsius
Total daily rainfall	< 800, 800-900, > 900 millimeters
Average daily 1300 relative humidity	< 60, 60-70, > 70 %
Average daily maximum wind speed	< 10, 10-12, > 12 knots
Agro-climatic zone	D1: wet month 3-4, dry month < 2 E1: wet month < 3, dry month < 2 E2: wet month < 3, dry month 2-3
Slope steepness	0-8 %, 3-8 %, 8-15 %, 15-30 %, > 30 %
Aspect	Flat, North, Northeast, East, Southeast, South, Southwest, West, Northwest
Distance to village center	0-1 km., 1-2 km., > 2 km
Distance to road network	0-1 km., 1-2 km., > 2 km
Distance to river network	0-1 km., 1-2 km., > 2 km
Vegetation and land cover type	Open land, Alang- alang, Brush land Lowland Dipterocarp forest Mangrove Forest Nipa Forest Swamp forest Degraded secondary and plantation forest Settlement area

Analysis for the wildfire vulnerability value

In this study, the actual burnt area was not chosen for analyzing wildfire vulnerability value because the study area was mostly (87.96 %) affected by the 1997/98 fires. The composite vulnerability value of wildfire starting was calculated using the following equation:

$$V = \left(E \sum w_i x_i + H \sum y_i z_i \right)$$

Where: $E + H$ = 1 and
V = the composite vulnerability value
E = weight of all physical-environmental factors related to all human activity factors
H = weight of all human activity factors related to all physical-environmental factors
w_i = weight of each physical-environmental factor related between them
y_i = weight of each human activity factor related between them
x_i = vulnerability score of physical-environmental sub-factors
z_i = vulnerability score of human activities sub-factors

The relationship of the sub-factor within each factors were determined based on the percentages of Hot Spots in each sub-factor. All scores were scaled between 0 and 100. The vulnerability score of the sub-factor was described by the following two equations:

$$x_i \text{ and } z_i = \left[\frac{o_i}{e_i}\right] \times \frac{100}{\sum\left[\frac{o_i}{e_i}\right]} \;;\; e_i = \left[\frac{T \times F}{100}\right]$$

Where: x_i = vulnerability score of the physical-environmental sub-factors
z_i = vulnerability score of the human activity sub-factors
o_i = number of observed Hot Spots in each sub-factor
e_i = number of expected Hot Spots in each sub-factor
T = total number of observed Hot Spots
F = the percentage of area in each sub-factor

The weighing score of both physical-environmental and human activity factors were calculated using the following two equations:

$$w_i = \frac{M_i}{\sum M} \;;\; y_i = \frac{N_i}{\sum N}$$

Where: w_i = weight of each physical-environmental factor related to all the environmental-physical factors.
y_i = weight of each human activity factor related to all human activities factors
M_i = average of the percentage of Hot Spots for each physical-environmental factor.
$\sum M$ = total average percentage of Hot Spots from all physical-environmental factors.
N_i = the percentage of Hot Spots within buffer zone 1 km for each human activity factor.
$\sum N$ = total percentage of Hot Spots within buffer 1 km from all human activity factors.

In this study area, it was assumed that the location of Hot Spots inside the 1 km buffer zone was more influenced by human activity factors, while the location of Hot Spot outside the 2 km buffer zone was more influenced by physical-environmental factors. In other words, Hot Spots outside the 2 km buffer zone had a lower probability of being influenced by human activities. The relative weighting score of both factors were estimated using the two equations below:

$$E = \left[\frac{\left(\frac{o_{(>2km)}}{e_{(>2km)}} \right)}{\left(\frac{o_{(>2km)}}{e_{(>2km)}} \right) + \left(\frac{o_{(1\ km)}}{e_{(1\ km)}} \right)} \right] \quad ; \quad H = \left[\frac{\left(\frac{o_{(1\ km)}}{e_{(1\ km)}} \right)}{\left(\frac{o_{(>2km)}}{e_{(>2km)}} \right) + \left(\frac{o_{(1\ km)}}{e_{(1\ km)}} \right)} \right]$$

Where:

E = weight of all physical-environmental factors related to all human activity factors

H = weight of all human activity factors related to all physical-environmental factors

$o_{(>2km)}$ = number of observed Hot Spots outside the 2 km buffer zone

$e_{(>2km)}$ = number of expected Hot Spots outside the 2 km buffer zone

$o_{(1km)}$ = number of observed Hot Spots inside the 1 km buffer zone

$e_{(1km)}$ = number of expected Hot Spots inside the 1 km buffer zone

Mapping the wildfire risk model

The map of wildfire risk zone was created from the dataset of composite vulnerability value. The zone was grouped into 3 severity classes of wildfire risks i.e., low, moderate, and high, using the equal interval range as class breaks (that means, the 33.33% of the lowest values were put in the first class, the next 33.33 % in the second class and so on), using the following equation.

$$\text{Level of wildfire risk} = \frac{\text{Maximum} - \text{Minimum value of the composite vulnerability}}{3}$$

Accuracy Assessment of the Model

The burnt scar map was used as the reference dataset to evaluate the accuracy of wildfire risk model. This model assessment used the relationship between the burnt scar map and each wildfire risk class. Overlaying the burnt scar map onto map of wildfire risk did a basic verification of the wildfire risk model. To check the coincided value (CV), the following equation (Boonyanuphap, 1998) was used:

$$CV = \frac{2 \times S \times 100}{(R + F)}$$

Where:

CV = the Coincided Value of each fire risk class as compared with the burnt area (0-100 %)

R = the area of burnt scar in 1997/98

F = the area of each class of fire risk

S = the coincided area of burnt scar and each class of fire risk

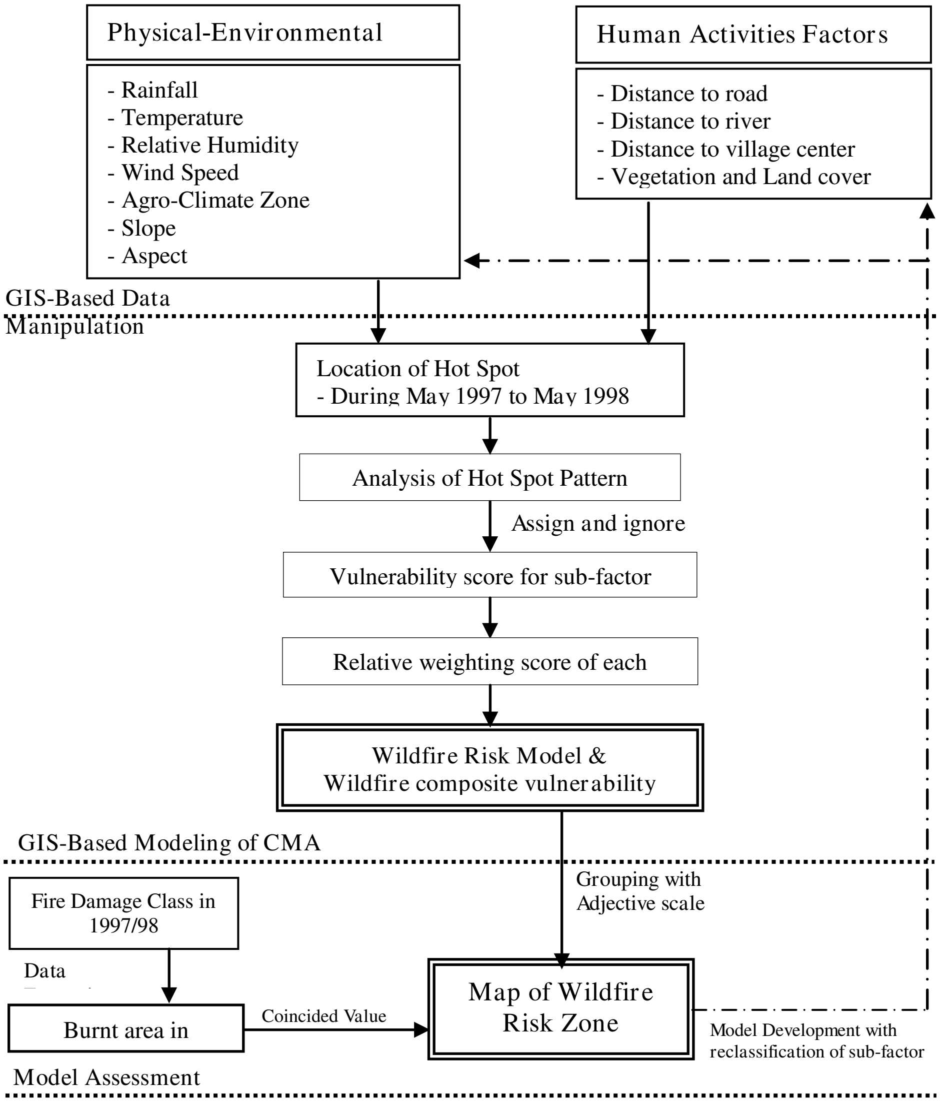

Figure 2. General flow of research activities

RESULTS AND DISCUSSIONS

Hot Spot pattern and Relative vulnerability scores of each sub-factor

The Hot Spot pattern simply depicted the relationship between the sub-factors of each wildfire factor and the percentage of Hot Spots occurrences. The high percentage of Hot Spot occurrences expressed a higher probability of fire ignition. In addition, the vulnerability score of the sub-factors strongly relate to the percentage of Hot Spot occurrences in each factor (Table 2).

It was found that the average daily maximum wind speed, aspect and river network factors had an illogical relationship between percentage of Hot Spot and each sub-factor. These factors conflict with former research study literatures (Heikkilä et al., 1993). Normally, the probability of wildfire occurrence increases when the wind speed increases to produce a successful ignition. This study shows that it decreases with the increasing of wind speed. For the aspect, the areas generally get heat and drying from the sun and wind in the afternoon were easier to start a fire than areas that get heat only in the morning. In this study area, the southern aspect has the highest percentage of Hot Spot occurrences; followed by area on east and northeast aspects. Moreover, the Hot Spot pattern of river network had no relationship between the percentage of Hot Spot occurrences and the distance from rivers. It seems to be different from the other human activity features (village center and road), the area with more than 2 kilometers away from river network has the lowest percentage of Hot Spots occurrence.

Table 2. The percentage of number of hot spots and vulnerability scores of all factors

a)

Temperature (Celsius)	% of Hot Spot	Score (xi)
< 29	0.389	18
30-31	0.487	23
31-32	0.548	26
> 32	0.719	34

b)

Rainfall (Millimeter)	% of Hot Spot	Score (xi)
< 800	0.643	46
800-900	0.530	38
> 900	0.237	17

c)

Relative humidity (Percent)	% of Hot Spot	Score (xi)
< 800	0.643	46
800-900	0.530	38
> 900	0.237	17

d)

Slope (Percent)	% of Hot Spot	Score (xi)
0-3	0.567	29
3-8	0.568	29
8-15	0.552	28
15-30	0.326	14
> 30	0.000	0

e)

Distance to Village Center (Km)	% of Hot Spot	Score (xi)
0-1	0.604	36
1-2	0.567	34
> 2	0.491	29

f)

Distance to Road Network (Km)	% of Hot Spot	Score (xi)
0-1	0.601	39
1-2	0.598	39
> 2	0.351	23

g)

Wind speed (Knots)	% of Hot Spot	Score (xi)
< 8	0.630	-
10-12	0.561	-
> 12	0.318	-

h)

Agro-climate zone	% of Hot Spot	Score (xi)
D1	0.431	27
E1	0.576	36
E2	0.596	37

i)

Aspect (Percent)	% of Hot Spot	Score (xi)
Flat	0.000	-
North	0.499	-
Northeast	0.589	-
East	0.603	-
Southeast	0.538	-
South	0.622	-
Southwest	0.581	-
West	0.556	-
Northwest	0.527	-

j)

Vegetation and Land cover type	% of Hot Spot	Score (xi)
Open land, Alang-alang, Bush land	0.737	18
Lowland Dipterocarp Forest	0.428	10
Mangrove Forest	0.533	13
Nipa forest	0.815	19
Peat Swamp Forest	0.759	18
Secondary and Plantation Forest	0.592	15
Settlement Area	0.254	6

k)

Distance to River Network (Km)	% of Hot Spot	Score (xi)
0-1	0.561	-
1-2	0.509	-
> 2	0.719	-

Hot Spot pattern of physical-environmental and human activity factors

The relative effects of the distance from human activity factors and the physical-environmental factors suggested that the human activity factors had a higher percentage of Hot Spots occurrences than the physical-environmental factors (Table 3).

Table 3. The number of hot spots inside 1 km and outside 2 km buffer zones

Buffer Interval (km)	Total Cell	Number of Hot Spot	% of Hot Spots
0-1	188,717	1126	0.597
1-2	35,690	208	0.583
Outside 2	25,125	76	0.302

Relative weight of the physical-environmental and human activity factors

From Table 4, the average daily 1300 relative humidity gave the highest weight, while the slope factor gave the lowest influence of all physical-environmental to start a fire. The percentage of Hot Spots within the 0-1 km buffer zone from village and road network factors was used for calculating the weighting score of each human factor. The result showed the location of village center was the most important factor to probability of starting fire.

Table 4. Weighting score of each physical-environmental and human activity factor

Physical-environmental Factor	Weight (w_i)	Human Activity Factor	Weight (y_i)
Daily 1300 Relative Humidity	0.23	Village center	0.34
Daily Maximum Temperature	0.21	Road network	0.33
Agro-Climatic Zone	0.21	Vegetation and Land Cover Type	0.33
Total Daily Rainfall	0.19		
Slope Class	0.16		

Relative weight between the physical-environmental and human activity factors

The relative weighting score of physical-environmental and human activity factors as shown in Table 5, evidently showed that the human activity factor had greater influence than physical-environmental factor in causing wildfire.

Table 5. Weighting score of environmental physical and human activity factors

Factor	Weight
Physical environmental (E)	0.34
Human activity (H)	0.66

Analysis of the wildfire vulnerability values

The final vulnerability and weighting scores for each sub-factor and factor were then entered in the equation of the wildfire vulnerability model as follows:

$$V = \{[0.34\ (0.21\ x_1 + 0.19\ x_2 + 0.23\ x_3 + 0.21\ x_4 + 0.16\ x_5)] + [0.66\ (0.34\ z_1 + 0.33\ z_2 + 0.33\ z_3)]\}$$

Where:

V = the composite wildfire vulnerability value
x_1 = vulnerability score of sub-factors in average daily maximum temperature
x_2 = vulnerability score of sub-factors in total daily rainfall
x_3 = vulnerability score of sub-factors in average daily 1300 relative humidity
x_4 = vulnerability score of sub-factors in agro-climatic zone
x_5 = vulnerability score of sub-factors in slope
z_1 = vulnerability score of sub-factors in location of village center
z_2 = vulnerability score of sub-factors in road network
z_3 = vulnerability score of sub-factors in vegetation and land cover type

The composite wildfire vulnerability values had a range from 21.40 to 33.76, in which the higher values of wildfire vulnerability expressed the higher probability of the fire starting. This vulnerability value also forecasts the wildfire risk level and assesses the susceptibility in wildfire.

Mapping the wildfire risk model

The wildfire vulnerability value was then grouped into 3 severity classes i.e., low, moderate, and high. As shown in Table 6 and Figure 3, the area of low wildfire risk zone was 30,709 hectares or 12.31 % of the study area. This zone was mostly found in flat or almost flat and undulating terrain, which was covered by the area of lowland dipterocarp forest. The major portion of this wildfire risk zone was outside the area dominated by human activities. The moderate wildfire risk zone covered approximately 59,422 hectares or 23.81 % of the study area, which was mostly spread out in the lowland dipterocarp