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Evidence-Based Landslide Hazard Mapping in Purworejo using the Information Value Model

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Abstract. Purworejo District, which is located in Central Java, Indonesia, is prone to landslides. These are a natural hazard that often occur in mountainous areas, so landslide hazard analysis is needed to develop mitigation strategies. This paper elaborates on the use of an evidence-based statistical approach using the Information Value Model (IVM) to conduct landslide hazard mapping. The parameters of slope, aspect, elevation, rainfall, NDVI, distance from rivers, distance from the road network, and distance from faults were employed for the analysis, which was conducted based on a raster data environment, since the pixel is the most appropriate means to represent continuous data. Landslide evidence data were collected by combining secondary data and interpreting satellite imagery to identify old landslides. The IVM was successfully calculated by combining factors related to disposition to landslides and data on 19 landslide occurrences. The results helped produce a landslide susceptibility map for the northern and eastern parts of Purworejo District.

Keywords: landslide, hazard, Information Value Model.

Abstrak. Kabupaten Purworejo adalah salah satu daerah rawan longsor di Indonesia. Tanah longsor adalah bencana alam yang sering terjadi di daerah perbukitan atau pegunungan. Analisis spasial untuk pemetaan bahaya bencana alam diperlukan untuk mitigasi yang tepat. Penelitian ini menggunakan *Information Value Model* (IVM) berbasis bukti untuk melakukan pemetaan bahaya tanah longsor. Ada delapan parameter yang digunakan dalam penelitian ini, yaitu kemiringan lereng, arah hadap lereng, elevasi, curah hujan, *Normalized Difference Vegetation Index* (NDVI), jarak dari sungai, jarak dari jaringan jalan, dan jarak dari patahan. Analisis dilakukan menggunakan data raster karena piksel adalah cara yang paling tepat untuk merepresentasikan data kontinyu. Data kejadian longsor dikumpulkan dengan menggabungkan data sekunder dan menginterpretasikan citra satelit untuk mengidentifikasi longsor lama. IVM berhasil dihitung dengan menggabungkan faktor-faktor predisposisi tanah longsor dan 19 data kejadian tanah longsor. Kalkulasi IVM tersebut menghasilkan peta kerentanan longsor di bagian utara dan timur Kabupaten Purworejo.

Kata kunci: tanah longsor, bahaya, *Information Value Model*.

1. Introduction

Landslides are a natural hazard that can cause casualties, property loss and environmental damage, and which occur mostly in mountainous areas (Devkota *et al.*, 2013). Although categorized as a natural hazard, landslides are not only a natural phenomenon, but are also caused by human land-based activities. They are one of the many natural hazards that frequently occur in Indonesia, especially in Purworejo, Central Java (Hadmoko *et al.*, 2017a). Based on data provided by the National Agency for Disaster Management (BNPB), there were 97 landslide occurrences in Purworejo in the period 2000 to 2017, which resulted in many casualties.

Spatial analysis can be used as a landslide hazard mitigation strategy (BNPB, 2017).

As disaster knowledge develops into a Disaster Risk Reduction (DRR) paradigm, geospatial data is urgently needed (Kerle *et al.*, 2009). Generally, DRR is divided into four stages, and each stage needs such data (GTZ, 2004). Hazard maps are essential to DRR, since knowledge of a hazard zone can be used to determine the mitigation process. Furthermore, many risk transfer scenarios could be implemented by conducting analysis based on the risk map which results from the hazard and vulnerability maps.

Landslide hazard mapping has been subject to long and strenuous efforts by previous researchers, with various methods applied (Hadmoko *et al.*, 2010; Nugraha *et al.*, 2015, Saputra *et al.*, 2016). A new method for landslide hazard mapping, called Information Value Model, has recently been proposed by Sharma *et al.* (2015), although it has not been widely implemented in Indonesia yet. The results show that the Information Value Model could produce accuracy of up to 81.8% (Ba *et al.*, 2017). It is a data-driven method and can be applied to assess landslide susceptibility. Therefore, there is a possibility to implement the new method in Purworejo.

The rapid advances in geospatial technology have provided many opportunities in the mapping process; for example, the ubiquitous remote sensing nowadays could provide an opportunity to explore the world on an appropriate scale. Moreover, the Geographic Information System (GIS) has also been extensively used in geospatial research. Both technologies can provide great data and analysis capability in DRR studies, since natural disasters have geospatial properties.

2. Study Area

Purworejo is a district located in the southern part of Java Island, about 65 kilometers west of Yogyakarta City (Figure 1). The area is 1.034 km^2 and consists of 16 sub-districts. The northern and eastern areas are dominated by mountains, where landslides frequently occur. The southern area is dominated by fluvial planes and is mostly used as paddy fields. Purworejo has a tropical climate, with an annual average temperature ranging from 19°C to 28°C, and humidity of 80% to 90%. The highest rainfall usually occurs in December, up to 311 mm/month, which corresponds to the occurrence of landslides.

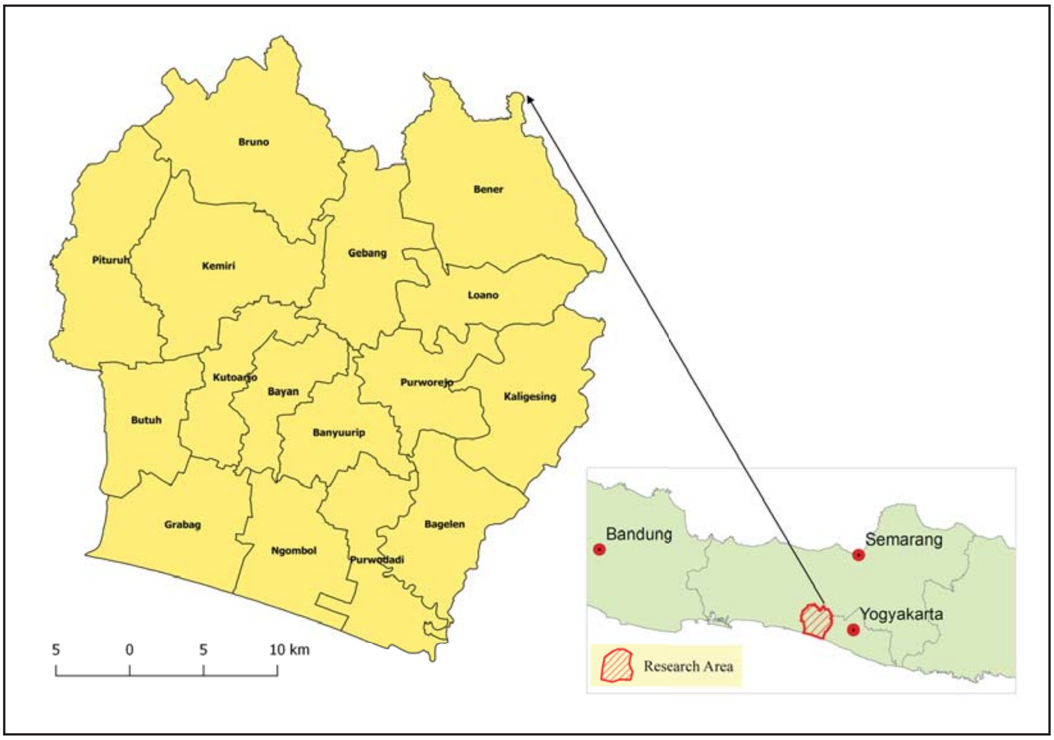

Figure 1. Research area shown by red hatched area and detailed view of subdistricts.

3. Research Method

3.1. Landslide Data Inventory

Previous landslide data were provided by the Regional Disaster Management Agency (BPBD) and satellite imagery. Landsat 8 imagery was used to identify old landslides based on visual interpretation, and data from BPBD were used as an initial indicator of old landslide locations. Table 1 shows the total number of landslide occurrences in Purworejo by sub-district. Fieldwork was conducted in some landslide locations to assess the accuracy and reliability of the data. A drone survey was also conducted to capture samples of the current condition of the landslide area.

Table 1. Landslide occurrences in Purworejo District 2014-2017.

No	Subdistrict	Number of Landslides				Total
		2014	2015	2016	2017	
1	Bagelen	17	19	6	24	66
2	Banyuurip	0	0	2	0	2
3	Bayan	0	0	0	0	0
4	Bener	18	73	33	56	180
5	Bruno	9	10	10	19	48
6	Butuh	0	0	0	0	0
7	Gebang	20	1	6	94	121
8	Grabag	0	0	0	0	0
9	Kaligesing	25	14	42	60	141
10	Kemiri	3	16	7	6	32
11	Kutoarjo	0	0	0	0	0
12	Loano	2	8	40	17	67
13	Ngombol	0	0	0	0	0
14	Pituruh	13	7	4	5	29
15	Purwodadi	0	0	0	0	0
16	Purworejo	9	3	23	6	41
Total		116	151	173	287	

Source: PPID Purworejo District

3.2. Predisposition to Landslide Factors

In this research, we used eight factors related to predisposition to landslides to construct the landslide susceptibility model. These were slope, aspect, elevation, rainfall, Normalized Difference Vegetation Index (NDVI), distance from rivers, distance from road network, and distance from faults. All the data were prepared in the raster format, as the analysis was raster based.

Elevation strongly correlates with physical aspects such as rainfall, hydrologic features, geology and soil. These physical aspects combine with slope gradient, which plays an important role in landslide hazard occurrence. Elevation, slope and aspect were derived from Shuttle Radar Topographic Mission (SRTM) imagery, which has a spatial resolution of 30 meters.

High rainfall intensity can be considered as a landslide triggering factor. Monthly cumulative rainfall data were used, since these represent annual rainfall intensity. Distance from the hydrographic network, faults and road network were added, as suggested by Ba *et al*. (2017). Theoretically, dense vegetation may stabilize slopes during intense precipitation. In this research, vegetation density is represented by NDVI values based on Landsat 8 imagery. Figure 2 shows the methods employed to obtain the factors related to predisposition to landslides.

3.3. Information Value Model (IVM)

The IVM was developed from information theory to perform statistical analysis. Based on this model, the information value of landslide predisposition factors will be used for the landslide modelling. The formula follows the expression of the information value $I(x_i, H)$ of each landslide predisposition factor x_i (I = 1,2,3,….,n).

$$I(x_i, H) = ln\frac{N_i/N}{S_i/S} \tag{1}$$

In this case, H denotes the possibility of landslide occurrence, S is the total of mapping units, and N is the total area of landslides in the research area. S_i is the number of mapping units with the presence of a predisposing factor x_i, while N_i is the total area of landslides with the presence of a predisposing factor x_i.

The total information (I) of each mapping unit can be calculated by adding together

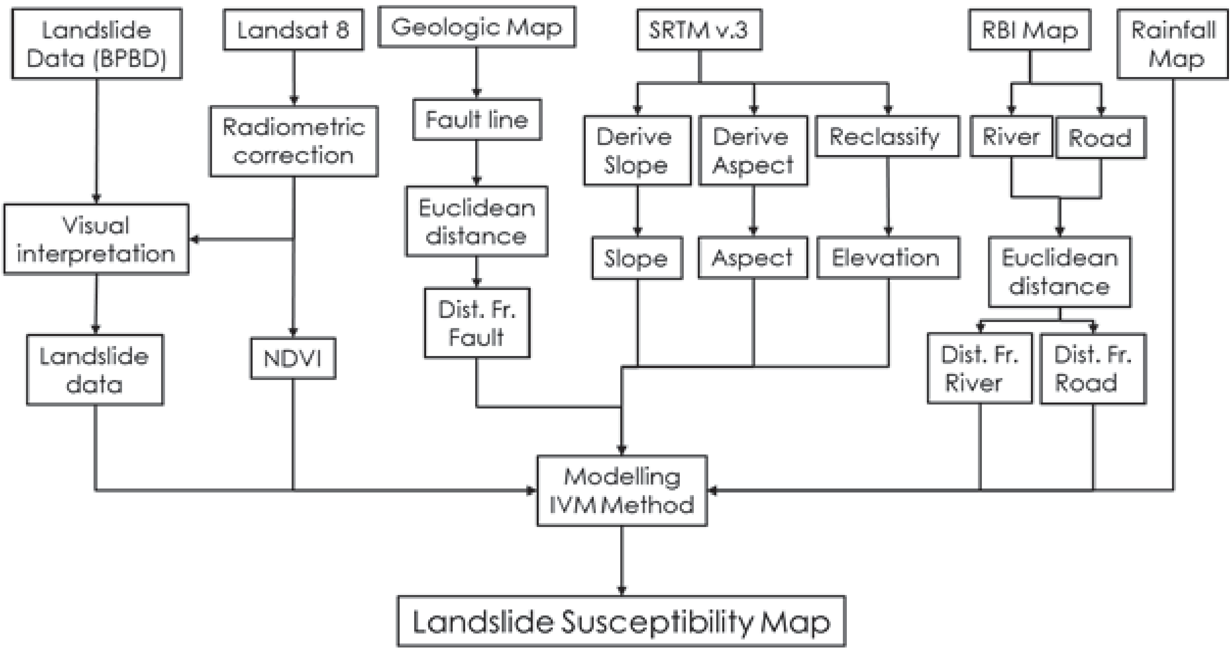

Figure 2. Landslide predisposition factor extraction methods.

the information values of all predisposing factors. The resulting value may be positive or negative, with the following class: if $I < 0$, the possibility of landslide is lower than average; if $I = 0$, the possibility of landslide is equal to the average; and if $I > 0$, the possibility of landslide is higher than average (Ba *et al*., 2017). The higher the information value, the higher the probability of landslide occurrence.

4. Results and Discussion

Identification of landslide events that have occurred is challenging, since over time the location experiences changes such as rehabilitation. The reference data in Table 1 show a large number of landslide events, but the data is not completed by other attributes such as location or area to facilitate the identification. However, 19 landslide locations were successfully identified using Landsat 8 imagery, most of which were recent events. Figure 3 shows some examples of landslide areas.

The identified landslides were then processed using IVM (Formula 1). Nine landslide predisposition factors were used to calculate the IVM value; Table 2 shows the results of the IVM calculation. Landslides are often referred to as slope instability, which is caused by geomorphological factors, especially slope angles (Aman *et al*., 2014). Generally, a steep slope is more susceptible to landslides because the overland flow velocity is high, and able to move soil material to a lower area due to gravity. The SRTM image show that the southern part of Purworejo Regency has an altitude of <100 meters above sea level (asl), with a gentle slope of <5°. Meanwhile, the northern area is mountainous, with an elevation of more than 400 m asl and a steep slope between 10-35° (Figures 4a and 4b).

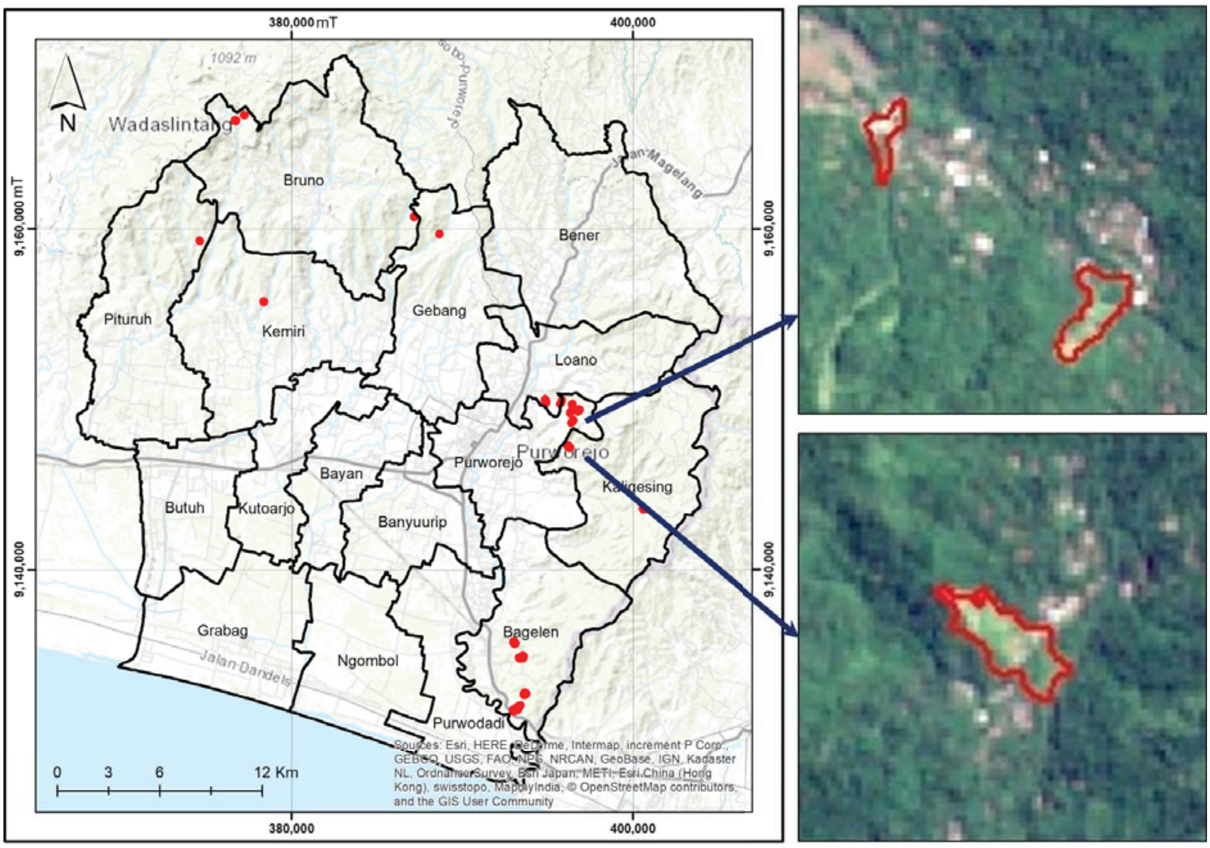

Figure 3. Landslide identification using Landsat 8 imagery.

Table 2. Information Value Model calculation.

Factor	Class	S	Si	N (m^2)	Ni (m^2)	IVM
Elevation	<100	1,205,224	630,621	238,500	110,700	-0.11983
	100-200		139,058		57,600	0.73868
	200-300		132,843		38,700	0.38672
	300-400		126,226		11,700	-0.75843
	>400		176,476		19,800	-0.56745
Slope	<5	1,205,223	607,228	238,500	9,000	-2.59163
	5-10		165,254		46,800	0.35845
	10-20		283,239		116,100	0.72821
	20-35		138,556		62,100	0.81752
	>35		10,946		4,500	0.73115
Aspect	Flat	1,205,224	11,048	236,204	0	0
	North		125,031		29,700	0.19231
	Northeast		113,211		30,600	0.32147
	East		136,562		36,900	0.32115
	Southeast		158,404		32,400	0.04273
	South		174,603		32,400	-0.05463
	Southwest		175,078		20,700	-0.50537
	West		168,312		32,400	-0.01794
	Northwest		142,975		30,600	0.08805
Distance from river	<1000	1,205,385	1,010,764	236,204	161,100	-0.20658
	1000-2000		145,442		77,400	0.99906
	2000-3000		39,958		0	0
	3000-4000		9,221		0	0
	>4000		0		0	0
Distance from fault	<600	1,205,836	83,205	236,204	49,500	1.11089
	600-1200		84,245		0	0
	1200-1800		78,100		98,100	1.85823
	1800-2400		76,549		4,500	-1.20362
	>2400		883,737		0	0
Rainfall (mm/month)	<30	1,205,212	4,257	236,204	0	0
	30-60		48,573		4,500	-0.74928
	60-90		250,449		58,500	0.17548
	90-120		782,993		87,300	-0.56406
	>120		118,940		88,200	1.33070
Distance from road network	<200	1,205,887	806,890	236,204	195,300	0.21162
	200-400		269,660		9,900	-1.67435
	400-600		86,113		4,500	-1.32131
	600-800		28,689		21,600	1.34645
	>800		14,535		7,200	0.92779
NDVI	<0,55	1,207,274	249,048	236,204	69,300	0.35222
	0,55-0,65		96,985		11,700	-0.48354
	0,65-0,75		183,102		31,500	-0.12863
	0,75-0,85		528,412		105,300	0.01836
	>0,85		149,727		20,700	-0.34726

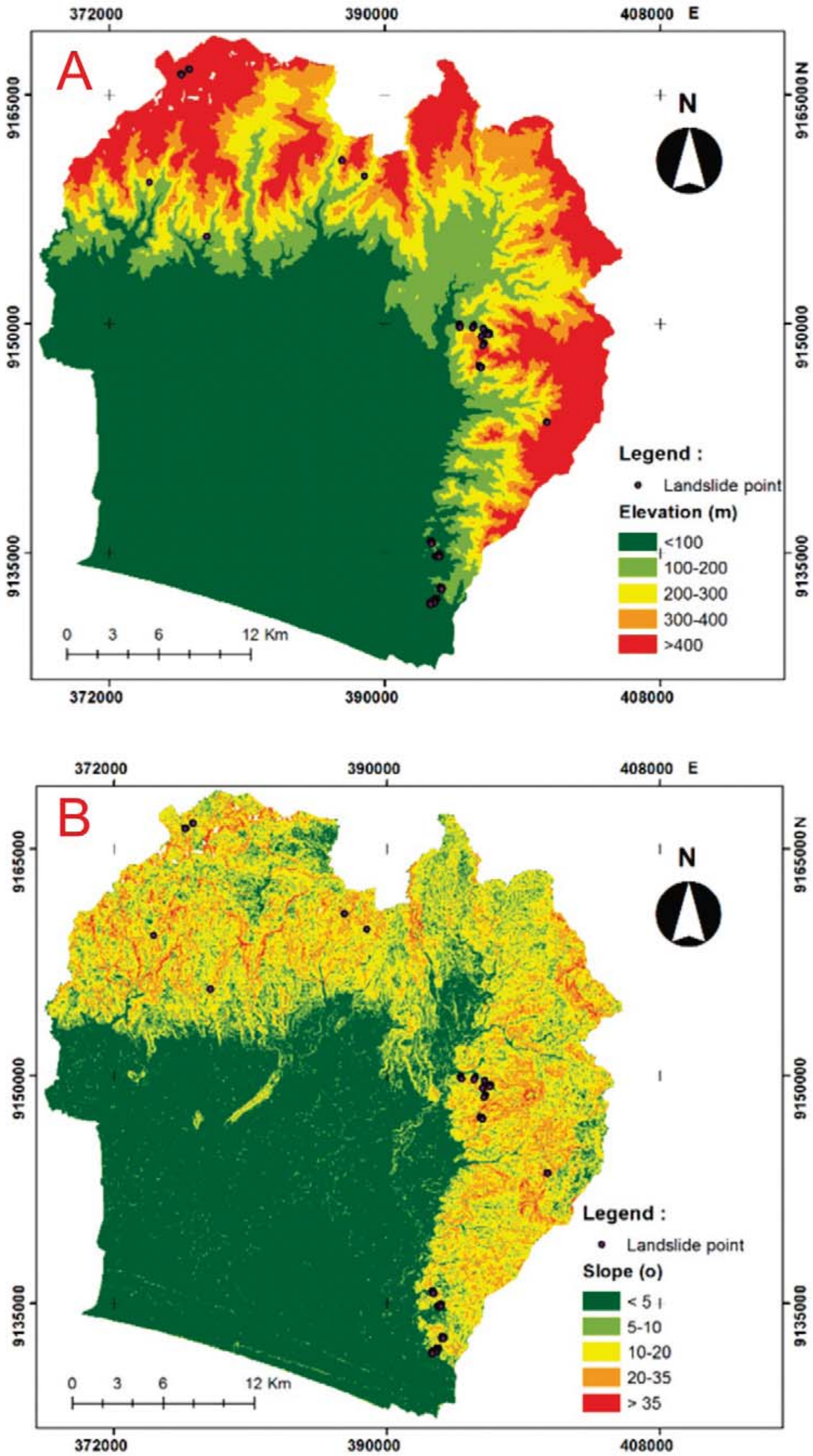

Figure 4 (a) elevation and (b) slope of research area.

The slope map shows that the frequency of landslide events in Purworejo increases with slopes up to 35° and then decreases with steeper slopes greater than 35°. In the highest slope class, i.e greater than 35°, the majority of landuse is shrubs, which have less weight than wood or water. This could be the reason why the steepest slope class has a lowest number of events. Moreover, the areas of the steepest slopes are also the smallest. The highest IVM value can be found in the fourth class of slope (20° - 35°), which has a value of 0.8. The positive value means that it has high landslide susceptibility. With regard to elevation, the number of landslide points at elevations of <100, 100-200, 200-300, 300-400 and > 400 are 122, 64, 45, 13, 21 respectively. The incidence of landslides decreases at an altitude of 300 meters to more than 400 meters. Surprisingly, a higher elevation does not imply a more susceptible area. This fact is supported by the negative IVM value for the top two elevation classes; a negative IVM value indicates that the level of landslide susceptibility is very low. The domination of andesite rocks that may have not experienced intensive weathering in high elevation areas in Purworejo gives a plausible explanation of why the possibility of landslides is low there. Overall, the distribution of landslide points in Purworejo Regency is dominated by slopes of 20°-35°, which are distributed on the north and east sides and dominated by mountainous areas.

The landslide event points in Purworejo are dominated by slopes facing north, northeast and east, with the number of occurrences 33, 46 and 36 respectively. The IVM calculations show a weight range of -0.50 to 0.32. The highest values are for east and northeast facing slopes. Slopes that face south tend to have longer sun exposure, so the air temperature is higher, which increases erosion (Rajakumar *et al.*, 2007; Quan & Lee, 2012). The IVM results from this study area do not completely agree with previous findings, since most of the landslide data refer to the western part of Menoreh Hill. Aspect map can be found in Figure 5a.

The aspect of a slope determines the duration of sunlight on it. This is considered to be one of the landslide predisposition factors because it affects soil moisture, vegetation cover and soil strength (Hadmoko *et al.*, 2017b). If a slope faces the sun's radiation for a long period of time, there will be a high possibility of more vegetation cover as there will be more light for photosynthesis. Based on this fact, it is assumed that the denser the vegetation, the lower the possibility of a landslide occurring. It is important to note that this assumption is an independent point of view with regard to landslide predisposition factors. Figure 5a shows the slope aspect in Purworejo district, which is dominated by southeast, south and southwest facing slopes. Areas with dense vegetation cover tend to be able to withstand soil loads, even though some landslide events are caused precisely by the weight of the surface objects, including vegetation. The vegetation data are represented by NDVI, which is conceptually related to vegetation density (Figure 5b). Low-density vegetation with an NDVI value of less than 0.55 has a high level of landslide susceptibility. However, that with a high-density value of 0.75 to 0.85 also has a high level of landslide susceptibility, with an IVM value of 0.018362.

Rain is the main driving factor for landslides because it can directly or indirectly reduce the strength of the rock to resist soil loads (Hadmoko *et al.*, 2017b). The higher the rainfall, the higher the potential for landslides. Areas that have more than 120 mm/month rainfall have a high level of landslide susceptibility, with an IVM value of 1.330703. A rainfall map of the research area is presented in Figure 6a.

The distance from faults, rivers and roads affects the level of landslide susceptibility (Figure 6 and Figure 7). However, the IVM value indicates a nonlinear relationship due to the limitations of the landslide data. From the calculations, it was found that the area 1200-1800 meters from a fault had the highest IVM value (1.85823), followed by a distance shorter than 600 meters (1.110898). There should be a strong correlation between faults and landslides, as suggested by Gokceoglu and

Aksoy (1996). The high IVM value of distances shorter than 600 meters from faults supports previous research. In addition, the highest IVM value based on distance from faults in this study area gives a new perspective that not all the landslides which have occurred in the study area have been the result of the existence of faults. Other distance classes have a lower level of landslide susceptibility.

The data related to distance from roads show that the lowest level of susceptibility is an area that has a distance of 200-600 meters from a road. This has a negative IVM value, while other distance classes have a positive value. Regions that are 1000-2000 meters distant from a river have the highest vulnerability value, at 0.999068, whereas areas that are under 1000 meters from a river have a lower landslide susceptibility level, with an IVM value of -0.20658. Many researchers have used distance from roads as a factor in landslide hazard assessment because the natural conditions of a slope might be damaged by road construction (Wu *et al*., 2017).

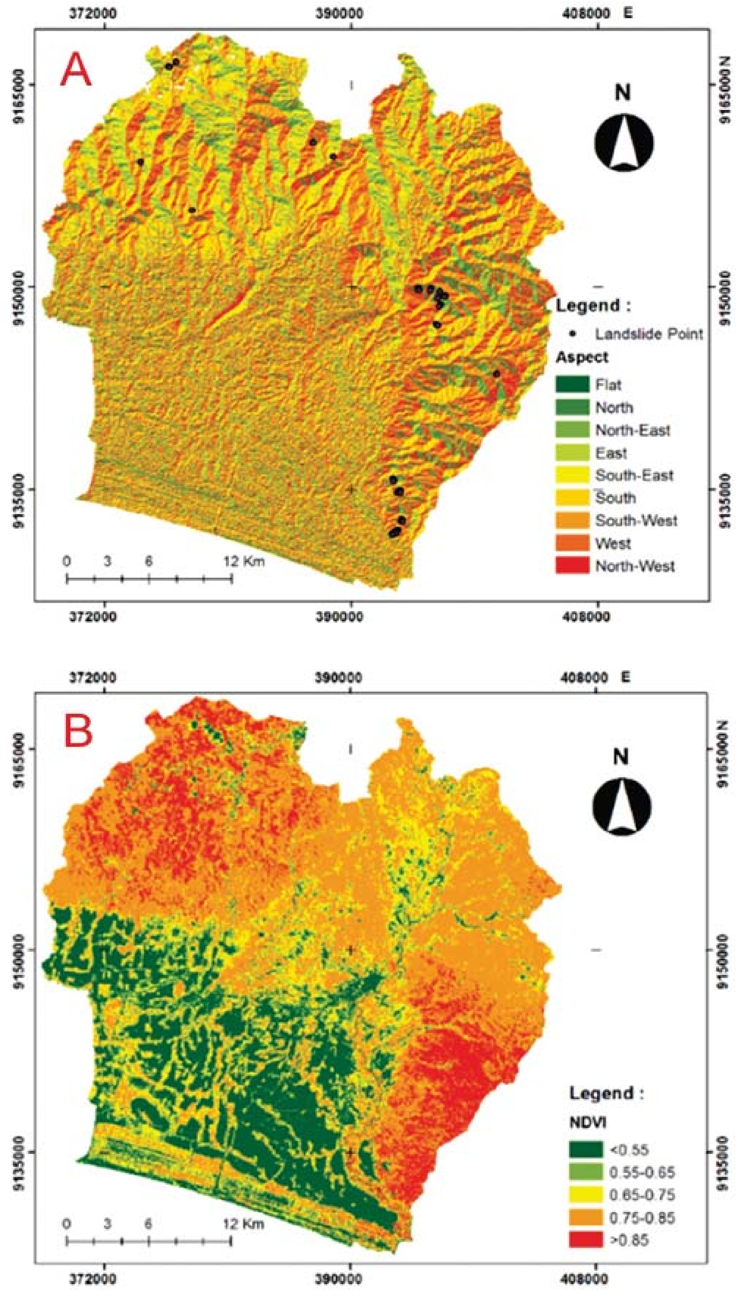

Figure 5 (a) aspect map and (b) NDVI results of research area.

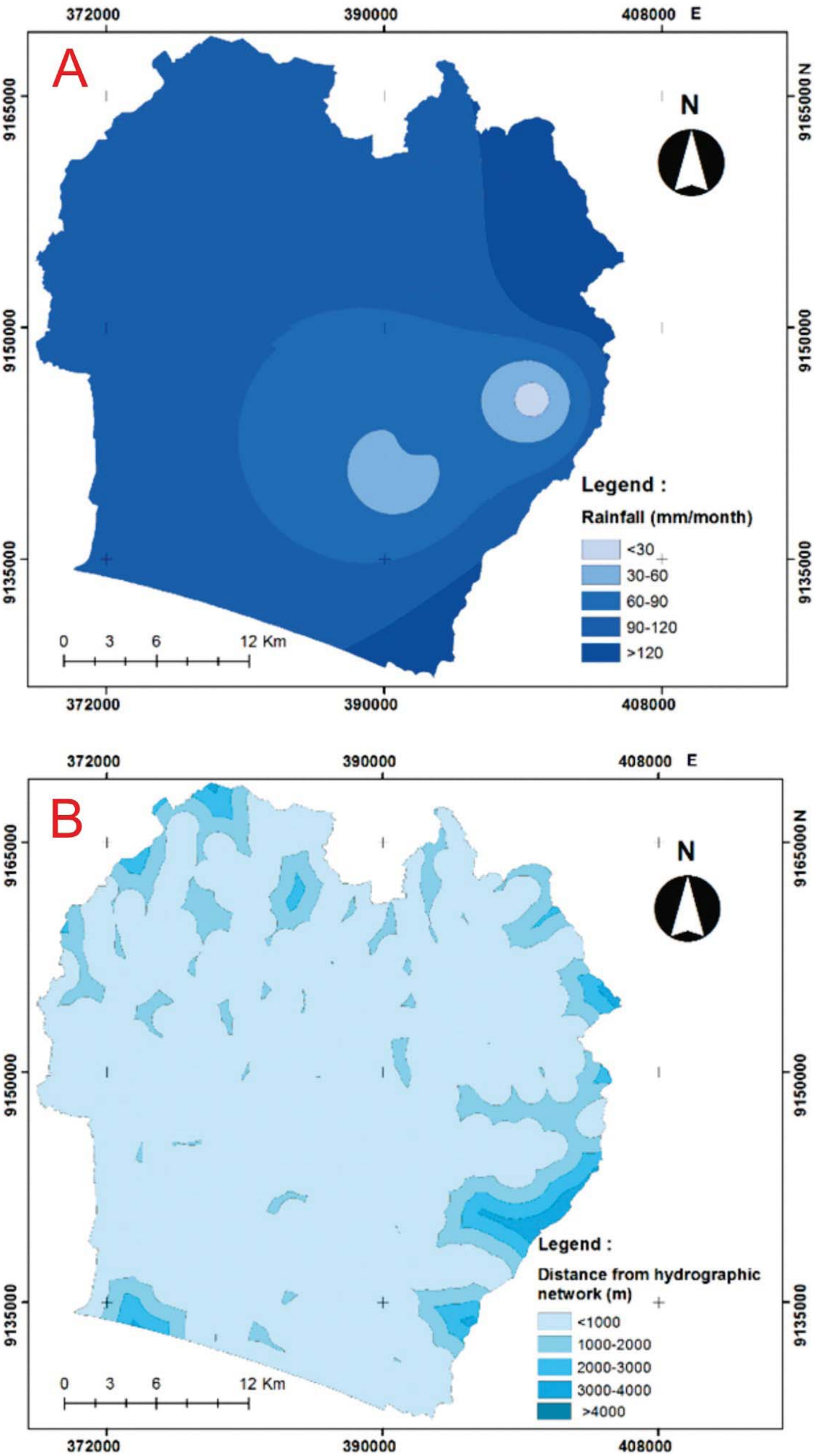

Figure 6 (a) rainfall and b) distance from river.

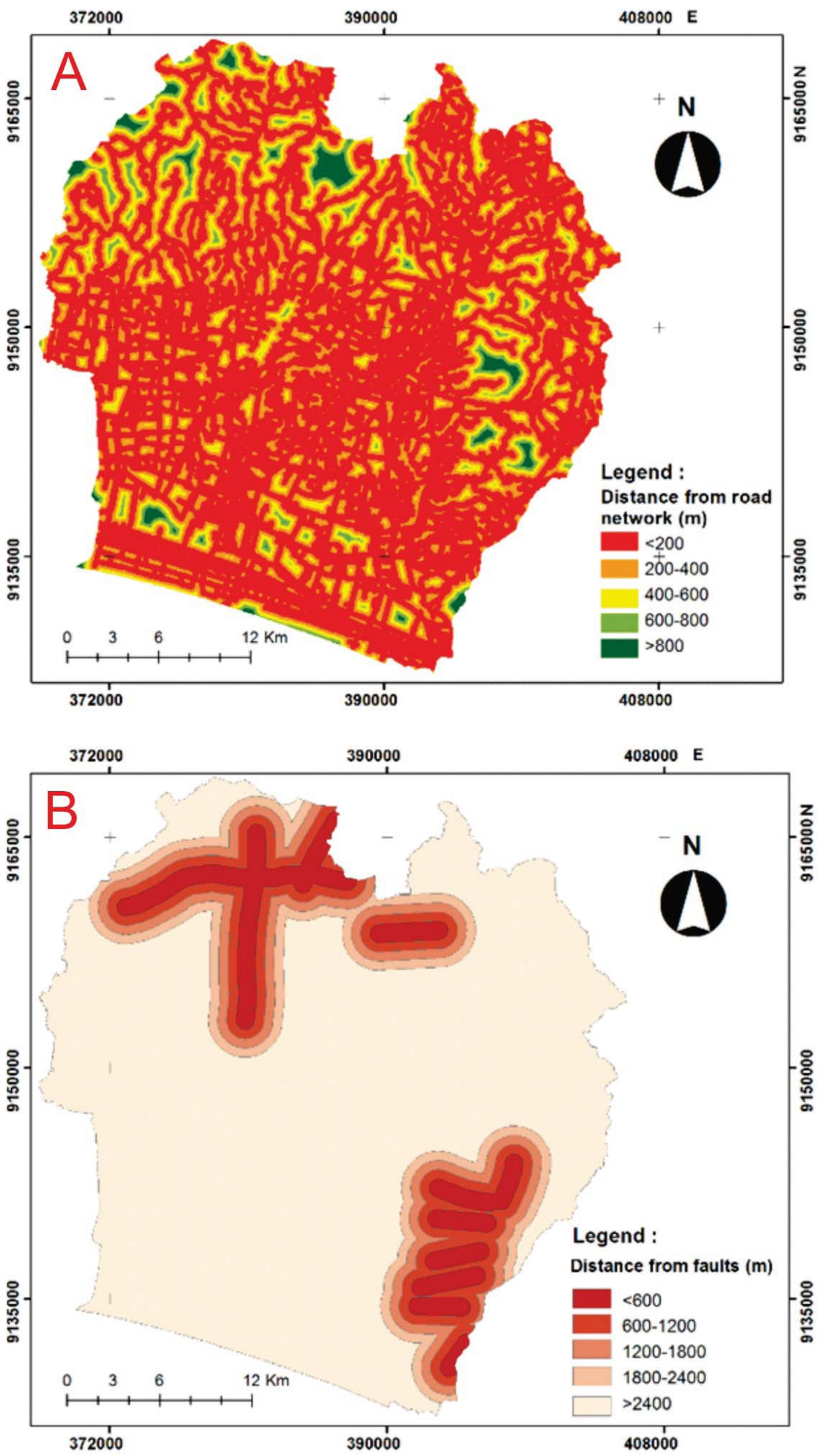

Figure 7 (a) distance from road network and b) distance from faults.

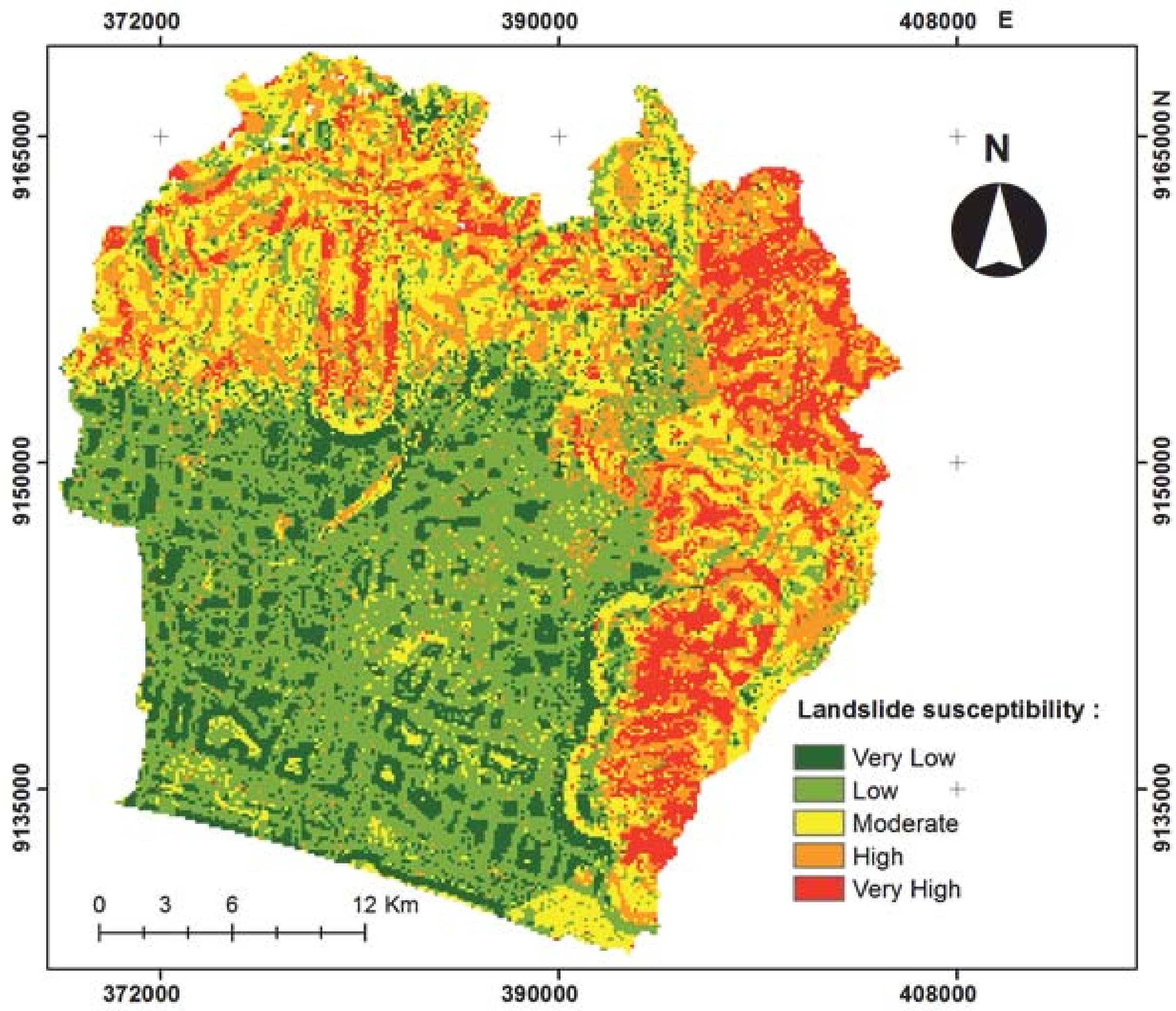

Figure 8. Landslide susceptibility model using IVM method.

Figure 8 shows the landslide susceptibility map using the IVM method. The eastern side of Purworejo is dominated by a very high level of susceptibility; the northwest is dominated by moderate to high levels; while the south is dominated by low levels of landslide susceptibility. The level of susceptibility is categorized based on the total IVM value held. This total is the sum of the IVM of each parameter without a weighting multiplication factor. The lowest total IVM value is -7.5 while the highest is 6.3. The higher the IVM value, the higher the level of landslide susceptibility in an area, and vice versa. The distribution of landslide susceptibility levels is consistent with the distributions of slope, aspect, elevation and distance from roads. The Information Value Model (IVM) method does not include weighing in its calculation, so all parameters have the same level of equality. This is one of the weaknesses of the method, because each parameter might have a different level of impact on landslide susceptibility.

4. Conclusion

The results of the spatial modelling using the IVM method were able to describe the spatial distribution of landslide susceptibility levels in Purworejo District. Although it is known that in general the northern and eastern parts of Purworejo Regency are very prone to landslides, more detailed knowledge is needed for use in landslide disaster mitigation strategies. Collaboration between stakeholders in reducing landslide disasters is necessary so that disaster mitigation is effective.

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