Landslides susceptibility mapping based on geospatial data and geomorphic attributes (a case study: Pacet, Mojokerto, East Java)

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Abstract. The study of landslides for long time is studied by geomorphological approach. In the study of geomorphology, each and every spatial segment of the earth surface possesses some physiographic aspects. Its analysis enables us to predict an interrelationship between physical and cultural phenomena as a whole. Pacet is one of the most susceptible areas due to landslides in Mojokerto Regency, East Java. Pacet is located at mountainous area which the slope stability depends upon physical and chemical properties of the soil. Such condition is represented on the geomorphic properties, such as slope angle, slope aspect, profile curvature, TWI, TPI, SPI and lithological composition. To obtain a proper landslides susceptibility mapping, some data were derived from geospatial data such as slope angle, slope aspect, profile curvature, TWI, TPI and SPI. DEM extraction by GIS platform were used to obtain the data. Soil samples were collected from different landform unit. The spatial distribution of landslides data was processed using GIS Software. The result shows that landslides were influenced by slope, aspect, profile curvature, TWI, TPI, SPI and lithological composition in study area.

Keywords: Landslides, Mapping, Geospatial Data, Geomorphology

1. Introduction
The study of landslides for long time is studied by geomorphological approach. In the study of geomorphology each and every spatial segment of the earth surface possesses some physiographic aspects and the analysis of all the aspects enables us to predict an interrelationship between physical and cultural phenomena and as a whole. Nowadays, the analysis of landslides not only generated by geomorphological approach, but also the availability of geospatial data [1-4]

One of the most susceptible areas to landslides is Pacet. This study comprises a number of diversified physical aspects and there is a great diversity of forms and the complexity of interrelationships. The practical relevance of landslides can be recognized only by the systematic and thorough study of geomorphic attributes such as relief, geology, and soil.

Geologically, the landslides study area in Pacet owns 14 major lithological units with varying degree of resistance and intensity of landslides phenomena. The development of drainage network in the study area is the outcome of elevation and slope which are the ubiquitous elements of landscape, the structure and tectonic history of the area, and the existing humid climate.

This research used seven (7) parameters for analyzing the landslides susceptibility based on the geomorphic processes that occur in the study area. The seven parameters are factors that trigger landslides, namely: 1) slope angle, 2) slope aspect, 3) profile curvature, 4) TWI, 5) TPI, 6) SPI and 7) lithological composition [5-12]. The parameters used in this study were analyzed statistically to determine the susceptibility of landslides in Pacet District.

The development of statistics in analyzing a landslides event data is a modern method for making decisions. This method is used to predict the occurrence of landslides [13,14]. Frequency Ratio (FR) statistical analysis was used as one of the methods for detecting landslides susceptibility in this study.
Frequency Ratio was selected for the ability to identify the relationship strength between each class of landslides-causing factors and the rate of landslides events [15-17]. Besides, the FR in this research was used for constructing the landslides probability values. The estimation of FR value considers the pixel numbers of 1) the number of the affected area, 2) prevalent value in the study area, 3) landslide class and 4) areas affected by landslides [18-20].

2. Methods
This research was conducted by examining the relationship between landslides events and geomorphic processes based on regional physiographic conditions such as geology, morphology, and geomorphology. The research flow was divided into 3, namely: geomorphic attributes assessment based on geospatial data, landslides inventory data, and landslides susceptibility mapping.

2.1 Geomorphic Attributes Assessment based on Geospatial Data
The observation of geomorphic features such as the shape of the scarps, roughly the degree of slopes, the development of drainage pattern, shape of the valley and ridges, nature of exposed surface rock layers, were done by Simple Instruments (clinometer, abbey’s level, GPS), Topographical Map, Imagery and their photographs. On sight topographic observation and analysis helped to gain more information for preparing the various morphometric maps of the landslide susceptible areas. All of the step was determined success of geomorphologic research, especially on landslides susceptibility mapping [21,22].

The Geomorphic attributes to determine landslides susceptibility in this study include slope angle, slope aspect, profile curvature, TWI, TPI, and SPI which are topographic factors. Data processing for the topography analysis was held using DEM (Digital Elevation Model) ALOS PALSAR 12.5 meter spatial resolution. Lithological composition was generated by geological unit classification from 1:50.000 Geological Map of Pandaan published by PVMBG (Pusat Vulkanologi dan Mitigasi Bencana Geologi or Center of Volcanology and Geological Hazard Mitigation).

2.2 Landslides Inventory Data
Landslides inventory maps are able to identify landslides locations, types of landslides, and spatial and temporal patterns of landslides in an area (Figure 1). The landslides phenomenon distribution pattern is obtained through field investigations, landslides historical records, satellite imagery, and aerial photographs.

Landslides incident inventory at the research location was carried out using primary and secondary data. Primary data is obtained from collecting landslides point distribution in the field, while secondary data is obtained from geospatial data in the form of maps, images. Remote sensing analysis technique used is the classification of visual image observations. The image used is the worldview-2 image from 2017 to 2020 data acquisition. The obtained data is in form of landslides distribution points in the study area. There were 383 landslides points identified. Furthermore, all parameters are processed with the same pixel resolution into raster data for landslides modeling using a frequency ratio (FR).

2.3 Landslides Susceptibility Mapping
Landslides susceptibility mapping is important to assume that the spatial distribution of landslides is influenced by factors causing landslides [23,24]. Frequency Ratio (FR) is a quantitative method used for landslides susceptibility assessment and is very effectively for landslides susceptibility assessment [24-28]. Frequency Ratio (FR) is calculated using Equation 1.

\[ FR_1 = \frac{L_{VCi}/L_a}{AC_i/A_a} \]  

Where \( L_{VCi} \) is the pixel number of landslides events in each \( i \) class factors; \( L_a \) is the total pixel number landslides events in each class factors; \( AC_i \) is the total pixel of the research area.
Landslide susceptibility index (LSI) was obtained by calculating seven (7) parameters that had been converted to raster data types. Each of these parameters is a trigger and control factor for landslides. The equation applied is as follows:

$$LSI = FR_1 + FR_2 + FR_3 + \ldots + FR_n$$

3. Results and Discussion

Figure 1. Landslides Inventory Mapping and Field Observation

Figure 2. The Number of Landslides Distribution on Slope Angle, Slope Aspect, Profile Curvature, and TWI
The total number of landslides event points distributed in Pacet District was 383 points. Figure 2 and 3 show the number of landslides on each parameter. Parameter with high number of landslides distribution include: slope angle 16˚-35˚ (214 landslides); slope aspect North (126 landslides); profile curvature 0.0-0.13 (195 landslides); TWI 4.977-10.573 (202 landslides); TPI -1.504-0.390 (207 landslides); SPI 100-500 (223 landslides); and lithological composition Qvok (104 landslides). Meanwhile, the distribution of landslides events with a low number in each parameter of landslides events are: slope angle <2˚, 2˚-4˚ (0 landslides); slope aspect Flat (0 landslides); profile curvature -0.001-0.0 (23 landslides); TWI -0.617 (0 landslides); TPI -3.399 (0 landslides); SPI <100 (12 landslides); and lithological composition Qvlw3, Qvf3, Qvf8, Qvf, Qvf1 (0 landslides).

Figure 3. Distribution of Landslides Number at TPI, SPI, and Lithological Composition

Figure 4. Landslides Triggering Factors (a. Slope Angle; b. Slope Aspect)
3.1. Slope Angle Analysis

| Table 1. Slope Angle and Frequency Ratio (Landslides Probability) |
|---------------------------------------------------------------|
| Conditioning Factors | Classes | L vci | Ls   | A ci | As  | FR  |
|----------------------|---------|-------|------|------|-----|-----|
| Slope Angle          | <2      | 0     | 17048| 0    |     | 0   |
|                      | 2-4     | 0     | 5152 | 0    |     | 0.164653 |
|                      | 4-8     | 15    | 150953| 0.164653 |
|                      | 8-16    | 90    | 170472| 0.874804 |
|                      | 16-35   | 214   | 209487| 1.692692 |
|                      | 35-55   | 63    | 34183 | 3.053877 |
|                      | >55     | 1     | 957  | 1.731447 |

Source: Research Analysis (2020)

The slopes are classified into 7 (seven) classes based on Van Zuidam classification [29], namely < 2°, 2° – 4°, 4° – 8°, 8° – 16°, 16° – 35°, 35° – 55°, and > 55° (Figure 4a). The landslides occurred in Pacet district in slope class 4° to more than 55° (Table 1). Slope grade 35°-55° has the highest ratio frequency value, namely 3.0538. The landslides points are mostly distributed in areas with mountainous morphology (mountainous).

3.2. Slope Aspect Analysis

| Table 2. Slope Aspect and Frequency Ratio (Landslides Probability) |
|---------------------------------------------------------------|
| Conditioning Factors | Classes | L vci | Ls   | A ci | As  | FR  |
|----------------------|---------|-------|------|------|-----|-----|
| Slope Aspect         | Flat    | 0     | 471  | 0    |     | 0   |
|                      | North   | 126   | 144026| 1.449609 |
|                      | Northeast| 89   | 100420| 1.468557 |
|                      | East    | 54    | 55717 | 1.605932 |
|                      | Southeast| 16   | 15729 | 1.685544 |
|                      | South   | 1     | 6256  | 0.264865 |
|                      | Southwest| 6    | 34049 | 0.29199 |
|                      | West    | 19    | 105927| 0.297213 |
|                      | Northwest| 72   | 172034| 0.693489 |

Source: Research Analysis (2020)

Slopes with north, northeast, east, and southeast directions had the highest landslides occurrence ration frequency number of 1.4496, 1.4685, 1.6059, and 1.1685 (Table 2). The high value of the frequency ratio on the four slope aspects was influenced by the intensity of sunlight and high rainfall. This phenomenon has an impact on the decomposition of slope constituent material which results in erosion and weathering which affects the instability of a slope. [30,31]. While slope aspect flat, north, northeast, south, southwest, west and northwest has a low frequency ratio value so that the possibility of landslides is low.
3.3. Profile Curvature Analysis

### Table 3. Curvature and Frequency Ratio Profile (Landslides Probability)

| Conditioning Factors | Classes     | L_vci | Ls    | A_CI | As     | FR        |
|----------------------|-------------|-------|-------|------|--------|-----------|
| Profile Curvature    | -0.07 - (-0.001) | 165   | 275081|      |        | 0.993904 |
|                      | (-0.001) - 0  | 23    | 87706 | 634629 | 0.43453 |           |
|                      | 0.0 - 0.13   | 195   | 271842|      |        | 1.188609 |

Source: Research Analysis (2020)

Profile curvature in this study was classified into three classes (Figure 5a). Profile curvature is a parameter that shows the value of the slope gradient as a form of convex, flat, and concave. The curvature profile that has the highest frequency ratio is at a value of 0.0-0.13 (convex) with a FR value of 1.1886 (Table 3). The negative value of the profile curvature of a slope represents a concave, the zero value (0) represents flat, and the positive value represents the convex shape. Too high a positive or negative value of the curvature profile triggers the instability of a slope [31].
3.4. **TWI (Topographic Wetness Index) Analysis**

| Conditioning Factors | TWI Class | L_vci | Ls   | A_ci  | As    | FR      |
|----------------------|-----------|-------|------|-------|-------|---------|
| Topographic Wetness Index | < -0.617 | 0     | 17   | 0     | 0     |         |
|                      | -0.617 - 4.977 | 170   | 173139 | 1.626954 |
|                      | 4.977 - 10.573 | 202   | 383 | 412158 | 634629 | 0.812099 |
|                      | 10.573 - 16.168 | 10    | 44089 | 0.37583 |
|                      | 16.168 - 21.763 | 1     | 5226  | 0.317068 |

Source: Research Analysis (2020)

TWI indicates the level of saturation or wetness due to the water content of the material on a slope. The high TWI value illustrates the amount of water content stored in the slope constituent material which can affect slope instability. This is influenced by the drainage system and also the rainfall that occurs [39]. Based on five classes of TWI, the highest landslides susceptibility ratio frequency values occurred in class -0.617 - 4.977 and 4.977 - 10.573 with FR values of 1.6269 and 0.8120 (Table 4). The results showed a positive relationship between the TWI frequency ratio value, and the number of landslides points that existed. A total of 372 landslides points in Pacet District had a high TWI value where the frequency ratio value was also high.

3.5. **TPI (Topographic Position Index) Analysis**

| Conditioning Factors | TPI Class | L_vci | Ls   | A_ci  | As    | FR      |
|----------------------|-----------|-------|------|-------|-------|---------|
| Topographic Position Index | < -3.399 | 0     | 2281 | 0     | 0     |         |
|                      | (-3.399) - (-1.504) | 27    | 31296 | 1.429539 |
|                      | (-1.504) - 0.390 | 207   | 424473 | 0.808056 |
|                      | 0.390 - 2.285 | 131   | 165909 | 1.308346 |
|                      | 2.285 - 4.181 | 17    | 9744  | 2.890898 |
|                      | > 4.181    | 1     | 926   | 1.789411 |

Source: Research Analysis (2020)

TPI (Topographic Position Index) is the difference in elevation between one area on a certain slope and an area on another slope around it [32,33]. A positive TPI value indicates that the elevation of an area is higher than other areas around it (upper slope). Meanwhile, the negative TPI value indicates that the area has a lower elevation (lower slope), and if it is nearly zero, it indicates that the area tends to be flat [8].

The TPI value of Pacet District was classified into 5 (five) classes (Figure 6a). Of the five classes, the highest FR values for landslides susceptibility were 2.8908 and 1.7894 in the TPI class 2.285 - 4.181 and > 4.181 (Table 5). From this value, it can be seen that the landslides greatest frequency was located on the upper slope which can be identified based on the TPI value. The landslides were triggered by the large gravitational force, causing slope failure.
SPI (Stream Power Index) is one of the parameters used to analyze the potential for erosion due to surface runoff at a certain point. The intensity of this erosion will be closely related to the frequency of landslides. SPI Pacet District was classified into 4 (class) SPI which has a high frequency ratio to landslides occurs in classes 100 - 500, 500 - 1200, and > 1200 with FR values of 1.5716, 1.7211, and 1.2894 (Table 6). Areas that have SPI values tend to be on steep slopes, meaning that in this area the intensity of erosion and landslides tends to be high.

**Table 6. SPI (Stream Power Index) and Frequency Ratio (Landslides Probability)**

| Conditioning Factors | Classes | L vci | Ls   | A ci | As    | FR       |
|----------------------|---------|-------|------|------|-------|----------|
| Stream Power Index   | < 100   | 12    | 248978 | 0.079862 |
|                      | 100 – 500 | 223  | 235112 | 1.571633 |
|                      | 500 – 1200 | 383  | 118412 | 1.721197 |
|                      | > 1200  | 25    | 32127 | 1.28941 |

Source: Research Analysis (2020)
3.7. Lithological Composition Analysis

| Conditioning Factors | Lithological Composition | Class | L vci | Ls  | A ci | As  | FR     |
|----------------------|--------------------------|-------|-------|-----|-----|-----|--------|
| Qtw4                 | Qlw4                     | 4     | 6777  | 0   | 0.978011 |
| Qtw3                | Qvlw3                    | 0     | 2068  | 0   | 0   |
| Qvok                | Qvok                     | 104   | 158469| 1.087452|
| Qvw                 | Qvw                      | 40    | 224506| 0.295225|
| Qwp1                | Qvlp1                    | 26    | 17395 | 2.476681|
| Qvp2                | Qvlp2                    | 34    | 15646 | 3.600781|
| Qvlp3               | Qvlp3                    | 57    | 27301 | 3.459533|
| Qwlp4               | Qvlp4                    | 76    | 28369 | 4.439057|
| Qwp1                | Qvlp1                    | 16    | 18678 | 1.419419|
| Qvwp3               | Qvlp3                    | 57    | 27301 | 3.459533|
| Qvlp4               | Qvlp4                    | 76    | 28369 | 4.439057|
| Qvwp1               | Qvlp1                    | 16    | 18678 | 1.419419|
| Qvwp3               | Qvlp3                    | 57    | 27301 | 3.459533|
| Qvlp4               | Qvlp4                    | 76    | 28369 | 4.439057|
| Qvwp1               | Qvlp1                    | 16    | 18678 | 1.419419|
| Qvwp3               | Qvlp3                    | 57    | 27301 | 3.459533|
| Qvlp4               | Qvlp4                    | 76    | 28369 | 4.439057|
| Qvwp1               | Qvlp1                    | 16    | 18678 | 1.419419|
| Qvwp3               | Qvlp3                    | 57    | 27301 | 3.459533|
| Qvlp4               | Qvlp4                    | 76    | 28369 | 4.439057|
| Qvwp1               | Qvlp1                    | 16    | 18678 | 1.419419|

Source: Research Analysis (2020)

Pacet district has 14 geological units based on a 1: 50,000 scale geological map published by PVMBG (Pusat Vulkanologi dan Mitigasi Bencana Geologi or Center of Volcanology and Geological
Susceptibility Mitigation) (Figure 7). The Pacet area is geologically formed by volcanic activity of the Arjuno-Welirang and Anjasmara Volcanoes in the quaternary geological time period. Rock conditions found on the slopes of Mount Arjuno-Welirang are indicated by the presence of igneous, pyroclastic and clastic volcanic rocks that are Quaternary in age. The geological unit that affects the high landslides susceptibility ratio frequency is the Qvlp4 formation with a FR value of 4.4390 (Table 7), the lithology in this geological unit is dominated by conglomerates and volcanic breccias.

3.8. Landslides Susceptibility Mapping

![Figure 8. Landslides Susceptibility Map of Pacet District, Mojokerto Regency](image)

The landslides susceptibility level is divided into five classes, namely: very low, low, medium, high, very high (Figure 8). The forest area in Pacet District has a dominant high-very high landslides susceptibility class. The administrative areas such as: Wiyu, Kemiri, Sajen, Pacet, Padusan, Cepokolimo, Claket, and Cembor also have a high susceptibility class — a very high susceptibility class which is dominant. Meanwhile, in the Sumbersekar, Kembangbelor, Bendunganjati Nogosari, Kuripansari, and Mojokembang areas there are also areas with high landslides susceptibility class - very high, but with a lower ratio when compared to the total area of each. Areas that are relatively safer with a very low-medium susceptibility class include: Candiwatu, Warugunung, Pandanarum, Tanjungkenongo, Kasimtengah, Petak, and Kasimantengah. The presentation of the area of each landslide susceptibility classes in Pacet District is shown in Figure 9.
4. Conclusions
The Geomorphic attributes to determine landslides susceptibility in this study include slope angle, slope aspect, profile curvature, TWI, TPI, SPI, and lithological composition. Parameter with high number of landslides distribution include: slope angle 16˚-35˚ (214 landslides); slope aspect North (126 landslides); profile curvature 0.0-0.13 (195 landslides); TWI 4.977-10.573 (202 landslides); TPI 1.504-0.390 (207 landslides); SPI 100-500 (223 landslides); and lithological composition Qvok (104 landslides). Consecutively, the landslides susceptibility percentage in Pacet District was very high 30.1%, high 21.1%, medium 12.2%, low 12.6%, and very low 24.1%.

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