Masters Program in Geospatial Technologies

LANDSLIDE SUSCEPTIBILITY ASSESSMENT IN KARANGANYAR REGENCY - INDONESIA

Comparison of Knowledge-Based and Data-Driven Models

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Dissertation

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--

If you are not a truly genius, do not conduct a research because of your ego, but because it is relevant, applicable and useful to society. No matter how simple it is.

AUTHOR'S DECLARATION

I hereby declare that this thesis is my original work and that I have not received any external assistance and only the sources cited were used. This thesis has never been submitted for any other degree program, and is submitted exclusively to the Universities participating in the Erasmus Mundus Master program in Geospatial Technologies.

Münster, 15 February 2011

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ABSTRACT

Disaster management requires spatial information as a backbone of preparedness and mitigation process. In that context, an assessment of landslide susceptibility becomes essential in an area that is prone to landslide due to its geographical condition. The Tawangmangu, Jenawi and Ngargoyoso Subdistric in Karanganyar Regency is the one of such areas, and is the area most frequently hit by landslides in the Central Java Province of Indonesia.

In this study, three different methods were applied to examine landslide susceptibility in that area: heuristic, statistical logistic regression and Artificial Neural Network (ANN). Heuristic method is a knowledge-based approach whereas the latter two are categorized as data-driven methods due to the involvement of landslide inventory in their analysis. Eight site-specific available and commonly used landslide influencing factors (slope, aspect, topographical shape, curvature, lithology, land use, distance to road and distance to river) were preprocessed in a GIS environment and then analyzed using statistical and GIS tools to understand the relationship and significance of each to landslide occurrence, and to generate landslide susceptibility maps. ILWIS, Idrisi and ArcGIS software were used to prepare the dataset and visualize the model while PASW was employed to run prediction models (logistic regression for statistical method and multi-layer perceptron for ANN). The study employed degree of fit and Receiving Operating Characteristic (ROC) to assess the models performance.

The region was mapped into five landslide susceptibility classes: very low, low, moderate, high and very high class. The results also showed that lithology, land use and topographical are the three most influential factors (i.e., significant in controlling the landslide to take place). According to degree of fit analysis applied to all models, ANN performed better than the other models when predicting landslide susceptibility of the study area. Meanwhile, according to ROC analysis applied to data-driven methods, ANN shows better performance (AUC 0,988) than statistical logistic regression (AUC 0,959).

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LIST OF ACRONYMS

ANN	Artificial Neural Network
ASCII	American Standard Code for Information Interchange
AUC	Area under Curve
Bakosurtanal	National Coordinating Agency for Surveys and Mapping
DEM	Digital Elevation Model
GIS	Geographic Information System
ILWIS	Integrated Water and Land Information System
LR	Logistic Regression
LSI	Landslide Susceptibility Index
LSM	Landslide Susceptibility Map
MLP	Multi-layer Perceptron
PASW	Predictive Analytics Software
ROC	Receiver Operating Characteristics
RS	Remote Sensing
SMCE	Spatial Multi Criteria Evaluation
SRTM	Shuttle Radar Topography Mission

CHAPTER 1 INTRODUCTION

1.1. Background and motivation

According to Crozier and Glade (2005), hazards are defined as processes and situation, which have potential to bring about damages, losses or other adverse effects to valued attribute of humankind. Hazards may cause losses of life or injuries, property damages, social and economic disruptions or environmental damages. One of the common natural hazards is landslide that is defined as "the movement of a mass of rock, debris, or earth down a slope" (Cruden, 1991). The movement happens because of natural occurrences, human activities or a combination of both that causes slope's instability.

As located in the equatorial area, which brings more than six months rainy season, diverse soil lithology characteristic and land cover, as well as diverse topographical relief, some parts in Indonesia could easily experience landslides. The statistical data from Indonesian National Agency for Disaster Management (BNPB) shows that in 2008, about 11% of the total disaster events in Indonesia were landslides that caused lots of damages (BNPB, 2008).

Figure 1. A landslide event in Legoksari Village, Tawangmangu, December 27th, 2010. (Sources: Kristijono et al., 2008)

Hadmoko et al. (2010) stated that during 1990–2005 there were 1.508 landslide occurrences that hit Java Island, the most mountainous and densest island in Indonesia. Those events damaged 8.682 houses, 3.017 hectares of agriculture areas, and 9.939 meters road. Economic losses were estimated around 18.040.450 euro. One of the most severe landslide occurrences was the one that hit 14 subdistricts in Karanganyar Regency, Central Java, in December 27th, 2007, caused 64 death tolls and damaged hundred houses and public facilities (PVMBG, 2007). Figure 1 shows one location of those events. The last landslide occurred on 22nd of July 2010 in Selomoro Village, Jenawi Subdistrict, which damaged a bridge, killed one person and wounded six people (Era Baru, 2010).

Regarding the aforementioned facts above, it is really important to reduce the risk of landslide event by doing preparedness, mitigation and risk planning in the region where historically known as the vulnerable area such as Karanganyar Regency. Those activities need landslide susceptibility assessment.

According to Fell et al. (2008), landslide susceptibility assessment is a quantitative or qualitative assessment of landslide spatial distribution that exists or potentially may occur in an area. This activity involves an analysis of environmental variables or factors that contribute to the events to take place, triggering factors that activate, and also a zoning process of susceptible area based on certain classifications. In short words, susceptibility is a function of landslide and its causative factors. Practically, in recent years landslide susceptibility assessment and mapping make use of statistical and geospatial tools e.g., Geographical Information System (GIS), Remote Sensing (RS), Global Positioning System (GPS) for handling spatial data in order to make better assessment (Van Westen et al., 2008).

There are many methods to assess landslide susceptibility. Ayalev et al. (2005) differentiate landslide susceptibility methods into three big groups: semi-qualitative, quantitative and hybrid. Examples of semi-qualitative methods are Simple Ranking and Rating and Analytical Hierarchy Process (AHP). Quantitative methods group could be divided into Process-based, Statistical (bivariate statistical analysis and multivariate statistical analysis: discriminant and logistic regression), and Training and Membership-based (Artificial Neural Network and Fuzzy). The last group, hybrid method, is a combination of the previous two groups e.g., the combination of bivariate statistical analysis and AHP.

The semi qualitative method is also known as heuristic method. According to Caniani et al. (2008), this method is categorized as knowledge-based assessment because it is leaning its semi-qualitative analysis based on literatures, expert opinions or previous researches to assess influencing factors. The factors are classified, integrated and weighted based on their importance using a decision rules mechanism (Lei and Jing-feng, 2006). One underlying assumption embedded to this approach is that the relationship between landslide susceptibility and the influencing factors has been recognized already. Although its limitation concerned the subjectivity, in areas where do not have a reliable landslide events record, this approach is useful. There were researchers who worked on this method e.g., Ruff and Czurda (2008), Abella and Van Westen (2008), Hadmoko et al. (2010), Wati (2010), and Wahono (2010), just to mention a few of many.

Accord with its name, quantitative methods applies more quantitative assessment. Commonly, quantitative methods use landslide inventory (i.e., records of landslide) in the analysis. This inclusion makes these methods are called data-driven methods. Two widely used methods are statistical method and artificial neural network (ANN).

Statistical methods lean their analysis based on numerical expressions of the relationship between influencing factors and landslides statistically. In bivariate analysis, it could be achieved by calculating landslide occurrence frequency or density. In multivariate analyses, for example in logistic regression, the correlation of all factors and the recorded landslide events is further elaborated by finding the coefficient and significance of each factors simultaneously. In this approach, the weights from density analysis could be treated as the value of predictor variables in logistic regression analysis (Lei and Jing-feng, 2006; Ayalew and Yamagishi, 2005). Dai et al. (2001), Borsevski (2001), Lee (2005), Muhiyudin et al. (2004), Pradhan (2010) are other several researches that used such analysis.

ANN is a relatively new approach in landslide susceptibility analysis (Lei and Jing-feng, 2006). One of its modules is multi-layer perceptron (MLP). This approach concerns towards interconnectivity among layers by creating hidden and output layers. It learns from experience via samples of past landslides; then performs forecast of events (Gomez and Kavzoglu, 2005). Nowadays, statistical programs (e.g., PASW, abbreviation of Predictive Analytics Software) also provide this kind of module and could give an importance value of each variable. This method was used by Caniani et al. (2008), Pradhan and Lee (2010), Chauhan et al. (2010), Nefeslioglu et al. (2008), and Melchiorre et al. (2008).

Fundamental concepts about landslide assessment are “the past and present are the keys to the future” (Carrara et al., 1991; Hadmoko et al., 2010), the main conditions that cause landslide can be identified, and the degree of susceptibility can be estimated (Chacon et al., 2006). Therefore, it is assumed that in some areas, which have landslides record in the past, the possibility of the events to take place again is bigger if the influencing or environmental factors (slope, curvature, geology and so forth) there are still similar or do not change significantly (Van Westen et al., 2006). In that context, data-driven methods, which include landslides inventory in their analyses, are really useful as prediction approach for landslide assessment.

In Karanganyar Regency, implementation of data-driven methods using landslide inventory to assess landside susceptibility, so far, not yet ever be applied. Though in the field work the occurrences were collected, Wati (2010) just produced landslide susceptibility map by using heuristic method (i.e., no involvement of landslide occurrences) because the main focus of her research was land capability assessment. Wati's study area was only confined to one sub district, Tawangmangu. Therefore, it is worthwhile to implement statistical logistic regression and ANN, as addition to heuristic method, in a comparative study.

These three methods–without disregarding to other methods–can represent three main variants of conceptual landslide susceptibility assessment. Although statistical method and ANN are the same quantitative method, these two methods have different approach to predict: the first is based on statistical relationship, whereas the latter is based on computational learning process in a network. By doing comparison of the processes and resulted models from these three methods, the drawbacks and eminences of every method will be assessed. Moreover, this study is expected not only to produce spatial information (i.e., the landslide susceptibility maps for land use planning) but also to investigate every model performance in the study area and show which can perform better.

1.2. Objectives

Based on the research background, the general objective of this research is to assess landslide susceptibility in the Tawangmangu, Ngargoyoso and Jenawi Subdistrict in Karanganyar Regency at medium scale using three different methods: heuristic, statistical and ANN. The objective could be specified as follows:

1. To generate landslide susceptibility model in order to know landslide susceptible areas distribution;
2. To analyze the factors/variables that influence landslides to take place;
3. To investigate the performance of the models based on success-analysis degree of fit and the cutoff-independent performance criteria's Receiving Operating Characteristic (ROC) curve;
4. To compare the methods descriptively based on their own characteristics and analyze the advantages and disadvantages of each.

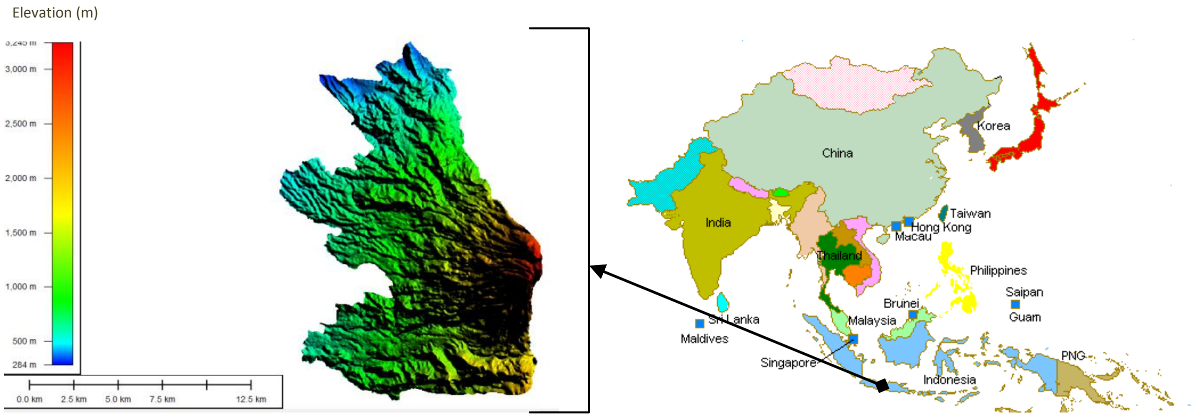
1.3. Research questions

To approach the objectives several research questions were proposed:

1. What are the factors used to build model?
2. How to assign weight for each factor?
3. What are the most influencing factors?
4. Which parts are susceptible in the study area?
5. How do degree of fit and ROC curve show model performance?
6. How do the methods interact with the datasets?

1.4. Study area

The study area is located in three subdistricts of Karanganyar Regency: Tawangmangu, Ngargoyoso and Jenawi in Central Java Province, Indonesia (Figure 2). It covers 174,13 km^2, within latitudes 70^{0}30’40”S to 70^{0}35’16”S and longitudes 111^{0}07’15”E to 111^{0}11’41”E. Based on historical records of landslide, those sub districts are the most often hit by landslide among 17 subdistricts inside Karanganyar Regency.



(a) (b)

Figure 2. Overview of the study area: (a) the scaled STRM 30m appearance of study area; (b) the unscaled map of Indonesia (source: Forensic Services, 2010)

The location is nearby Mount Lawu (3.265m above sea level), so some parts are hilly and mountainous–with the lowest altitude is 284m and the highest is 3.245m–the topographical situation that was presumed susceptible toward landslide occurrence (Figure 3). According to PVBMB (2007), there happens a large conversion from forest into agriculture areas, roads and settlements during the past 10 years. This activity affected soil capability to absorb rainfall, which potentially cause the movement of rock or debris down a slope.

Figure 3. Morphology of the study area (source: Kristijono et al., 2008)

1.5. Structure of thesis

The structure of thesis encompasses five chapters. Chapter 1 (Introduction) outlines the background, motivation, objectives, and study area. The second chapter (Data) is dedicated to explore landslide occurrences and the influencing factors of landslides. This chapter also works through their preparation and preprocessing to create ready-to-use datasets. Chapter 3 (Methodology) evaluates three employed methods and stages. In this chapter, the weighting process and importance of each factor are analyzed. Chapter 4 (Result and Discussion) presents the results and discusses the models and their performance. Finally, the fifth chapter (Conclusions and Recommendations) summarizes the work and limitation. It also gives necessary avenues for future study.

CHAPTER 2 DATA

This chapter describes the datasets and their preparation for use in the methods that follow.

2.1. Landslide inventory

Landslide inventory is a dataset about landslide occurrences in any certain area. It gives insight into landslide phenomena locations, date, type, volume and damages (Van Westen et al., 2008). Landslides are normally appeared as area or point forms. If there is an aerial photo or high resolution satellite imagery with respect to the occurrence time frame, landslides could be formed as areas because delineation process could be done. However, such materials are not available for the area of interest. It makes the presentation of landslide events is only in points, but next, for technical matter, becoming the buffered areas. In this study, landslides are spreading over 74 locations in three subdistricts (Figure 4).

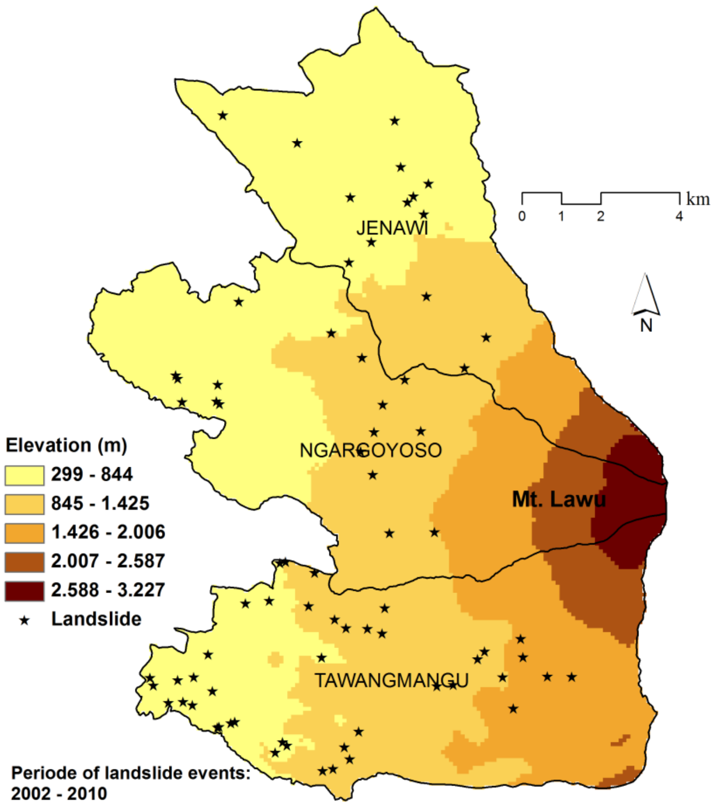


Figure 4. Distribution of the landslide occurrences in the study area at different elevation

Jenawi Subdistric has 14 occurrences (18,92%); Ngargoyoso has 18 occurrences (24,32%); Tawangmangu has 42 occurrences (56,76%). These occurrences are compilation from various sources: the field record from Wati (2010), reports from

PVMBG (2007) and local newspapers. The occurrences were the events that happened during a period from 2002 till 2010 (Annex 1).

There are several types of landslides: slide, topple, fall, spread, flow and complex (Highland and Bobrowsky, 2008). Slide occurs on surfaces of rupture from intense shear strain; its movement does not initially occur simultaneously. Topple occurs in forward rotations at a point or axis below the center of the displaced mass. It easily happens in the very steep slope. Fall happens in a material detachment along the surface on which little or no shear displacement has occurred. The occurrence is called flow if the movement is continuous. Flows often happen after slide happened. Spread is a subsidence of the fractured mass of cohesive material into softer underlying material. A landslide could be in complex type if it is a combination of the previous landslides. Landslide types are shown in Figure 5.

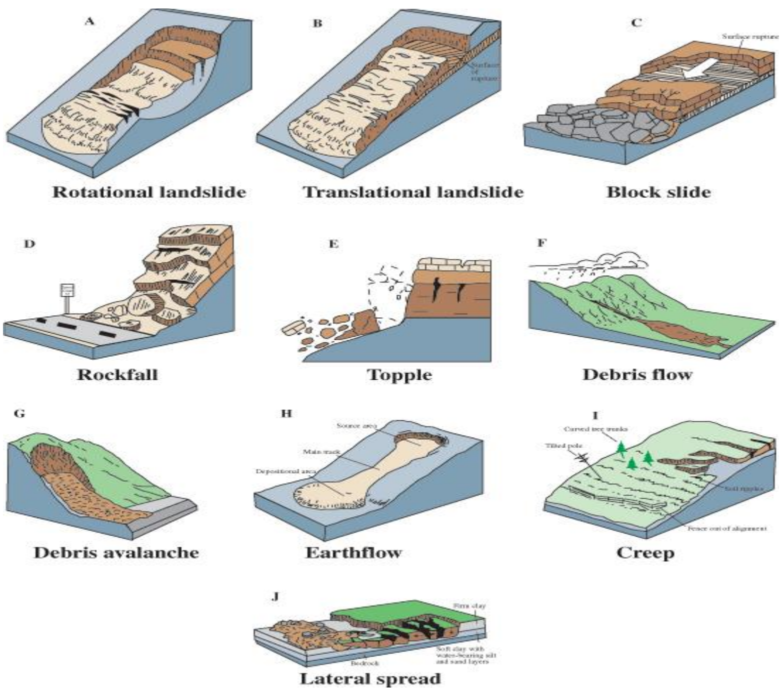


Figure 5. Landslide types (USGS, 2004)

The landslide inventory does not have landslides type differentiation. It makes this study considers that characteristics of each type in the analysis are similar. As result, there is no differentiation of events in model building process. According to Chacon et al. (2006), in regional scale assessment it is still acceptable as the required accuracy is not high, and the map is generally not aimed as an accurate predictive medium.

2.2. Influencing factors

Influencing factors (also called variables) are the causes of slope proneness in any certain area, which influence landslide to take place. According to Ayalew et al. (2005), in a GIS-based analysis, to choose influencing factors or variables one has to be sure that the selected factors are operational (have a certain degree of affinity with landslides), complete (fairly represented all over the study area), non-uniform (varies spatially), and measurable (have measurement level).

Practically, Soeters and Van Westen (1996) observed that there are five dataset groups that are commonly used to assess landslide susceptibility:

- Geomorphology, for instances geomorphological sub unit, land form
- Topography or morphology, for instances digital terrain model and its derivation (slope, aspect, curvature)
- Geology or engineering geology, for instances lithology, material of sequences
- Land use
- Hydrology, for instances proximity to drainage, catchment areas, temperature, evaporation, rainfall

Another classification, as proposed by Cruden and Varnes (1996), considered landslide influencing factors into four big groups:

- Geological factors such as weak material, sensitive material, sheared material, jointed or fissured material, aversely oriented structural discontinuity, weathered material;
- Morphological factors such as slope, angle, uplift (tectonic or volcanic), erosion (fluvial, glacial, wave), rebound;
- Physical factors such as intense rainfall, rapid snow melt, earthquakes, rapid draw down floods and tidal, volcanic eruptions;
- Human-induced factors such as excavation of slope, land use, land use/cover change (e.g., deforestation), loading, irrigation, mining.

Cruden and Varnes (1996) also regrouped factors into preparatory and triggering factors. Preparatory factors are usual causal factors as mentioned before. If the causes happen as the events that initiate landslides, they are called triggering factors. Heavy or prolonged rainfall, seismic activities such as volcano eruption and earthquake could be categorized as triggering factors. Normally landslides can have many causes but can only have one trigger.

The usage of factors can vary according to the specific conditions of an area (Jimenez-Peralvez, 2009). The area in this study is mountainous (not flat), so the availability of topography and morphology factors is important. Land use in the area is also heterogeneous, and there are many small rivers all over the area. As consequence, the factors related to human-induced and hydrology should be included.

Though not all related factors could be partaken because of unavailability matter, this study still employs some relevant factors that are scientifically important and universally used (Table 1):

- Slope, aspect, and curvature as the factors of topographical group;
- Topographical shape (land form) as a factor of geomorphologic group;
- Land use and distance to road as the factors of human-induced group;
- Lithology as a factor of geology group;
- Distance to river as a factor of hydrology group.

Table 1. Influencing factors in the study

No	Group	Factors	Source
1	Topographic	Slope	DEM extracted from the height information of Topographic Map at the scale of 1:25.000 (25K). Source: National Coordinating Agency for Surveys and Mapping (Bakosurtanal)
2		Aspect	DEM extracted from the height information of Topographic Map 25K. Source: Bakosurtanal
3		Curvature	SRTM 30m
4	Geomorpho-logic	Topographical shape	SRTM 30m
5	Geology	Lithology	Geology Map 100K Source: Indonesian Geological Research and Development Center
6	Human-induced	Land use	Land use layer from Topographic Map 25K Source: Bakosurtanal
7		Distance to road	Road layer from Topographic Map 25K Source: Bakosurtanal
8	Hydrology	Distance to river	River layer from Topographic Map 25K Source: Bakosurtanal

Slope is one of the most important factors and should be available. Almost all researches use this factor. Slope stability (or failure) is considered as the main cause that drives landslides. Because slope is derived from elevation, this study does not include elevation as its variable.

Lithology, same as slope, is the most universal determinant factor in most stability studies. By having lithology, general geologic conditions could be assessed as each class in a lithology map reflects unique material characteristics. Although lithology has the lowest scale (100K: the biggest available scale of Indonesian Geological Map in the study area) that could affect the discriminatory power, it is better to keep using it. The study area is located nearby Mount Lawu and much influenced by Lawu Land System. This situation makes the area has unique lithology condition.

Land use and distance to road are the most commonly used human-induced factors. Both are often used to assess susceptibility in the areas that have a lot of settlements. By having them in the analysis, this study also calculates the factual influence of human activities.

There are some other relevant factors such as soil type and distance to fault. As mentioned before, unfortunately there are no proper datasets regarding these factors available in the study area. Another missing factor is rainfall, a factor that is related with precipitation and often triggers landslides to occur. It is an important variable because, as shown in the landslide records database (Annex 1), landslides occurred more frequent in the rainy season from September to March, after heavy or prolonged rainfall. Without rainfall data, to involve the precipitation influence, this study still can use aspect as an indirect rainfall indicator. But, still the absence of rainfall makes this study cannot involve triggering factors to determine susceptibility, a condition that is also shown by other researches such as Wati (2010), Hadmoko et al. (2010), Wahono (2010), Ayalew and Yamagishi (2005), Gomez and Kavzoglu (2005).

In spatial modeling, it is generally true that the more factor the better model. Every single contribution of potential factors could be calculated to build the model. Nevertheless, the quantity is not always the case. Statistically, there are other conditions such as correlation and significance among factors that influence the quality. According to Soeters and Westen (1996), it may also not really necessary to include all causal variables because in nature landslides are actually caused only by several certain factors that being dominant in the area of interest. According to Kristijono et al. (2008), which assessed the December 2007's landslide events in Tawangmangu Subdistrict, land use and geology presumably behaved as the main factors.

During the period of occurrence, the influencing factors are considered constant or under the same condition throughout the study area and through time (i.e., not dependent on time). Because of no temporal engagement, this study is a non-temporal assessment.

The factors have two forms: discrete (nominal) and continuous. Lithology, land use and topographical shape are discrete variables whereas slope, aspect, curvature, distance to road and distance to river are continuous variables. As the way it is, heuristic method categorizes all factors into classes. Meanwhile, in data-driven methods, discrete variables are still categorized into classes but to maintain continuity, there is no categorization applied toward continuous variables (Van Den Eeckhaut et al., 2006; Lei and Jing-feng, 2007).

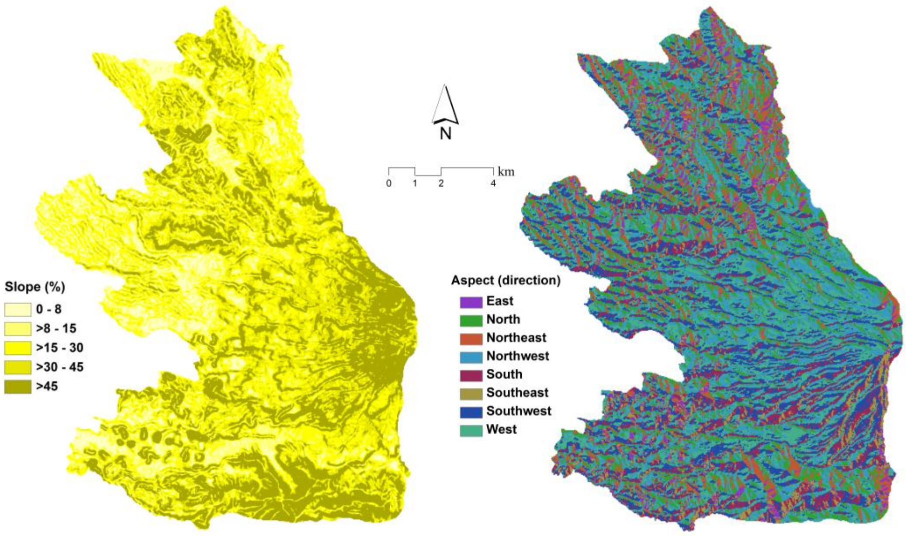
The following subsections describe preprocessing stages. Although the factors are multi scale and multi format, the final form of each factor is uniform: raster grid 30m following SRTM's grid size, WGS84 datum, and UTM 49S map projection. By using 30m grid, this study wants to keep the usage of high resolution "power" (as given by slope, curvature, topographical shape, aspect and land use) instead of reducing the grid size to approach lower resolution measure, which only belongs to lithology.

2.2.1. Slope

Slope is an angle between a location in the surface and the horizon. It could be expressed in degree or percentage at which 45^0 is equal with 100%. Dai et al. (2001) stated that slope or slope gradient is an essential influencing factor because foreknown that slope failure (instability) becomes the main reason of mass movement. Slope controls driving force (shear stress) and resisting force (shear strength) in an area. Wati (2010) mentioned that the higher the slope, the higher the shear stress, and so, the higher the chance of failure. It means landslides tend to occur more frequent on steeper slopes (Gomez and Kavzoglu, 2005).

Slope is derived from the raster interpolated/DEM extracted from the height information of 25K topographic map contour (12,5m interval and 4m accuracy). According to Land Info (2010), a DEM generated from 24K topographical map would have 1/3 arc second spatial resolution. It is better than STRM 30m that has 1 arc second spatial resolution.

Then, that raster grid file was converted into slope by assigning percentage as divider. The result indicates that the lower the slope value, the flatter the terrain; the higher the slope value, the steeper the terrain. Afterwards, in heuristic method, slope was reclassified into several categories using a classification schema from Research Center for Disaster, PSBA-UGM (2001). The classification categorizes slopes into five classes according to the gradients that represent terrain morphology: gently sloping (0–8%), undulating (>8–15%), moderately steep (>30–45%), steep (>30–45%) and very steep (>45%). Figure 6a illustrates the result. Table 2 shows that almost half of the area is occupied by steep and very steep slope, which preliminary indicates big chance for landslide to occur. For statistical and ANN, the continuous values from slope is going to be used in the process.



(a) (b)

Figure 6. Categorization of (a) Slope and (b) Aspect

Table 2. Tabulation of slope and aspect class in the study area

Factor	Class	Class name	Hectares	%
Slope	0-8	Gently sloping	4606,01	26,38
	>8-15	Undulating	1244,97	7,13
	>15-30	Moderately steep	3172,97	18,17
	>30-45	Steep	2188,81	12,54
	>45	Very steep	6247,36	35,78
Aspect	1	East	703,55	4,04
	2	North	2619,98	15,05
	3	Northeast	1696,20	9,74
	4	Northwest	3370,96	19,36
	5	South	1786,00	10,26
	6	Southeast	744,85	4,28
	7	Southwest	3157,36	18,13
	8	West	3334,22	19,15

2.2.2. Aspect

Aspect is expressed as horizontal direction to which a mountain or hill slope faces. Usually it is expressed clockwise, from 0^0 to 360^0. Aspect can influence a region's local climate (microclimate) due to the sun's ray incident to the faces. For instance, as the sun's rays are in the west at the hottest time of day in the afternoon, in most cases a west-facing slope will be warmer that a sheltered eat-facing slope. Because of that, aspect affects structural, soil and organic (e.g., vegetation distribution) of slope faces. Aspect also indirectly indicates a precipitation effect from rainfall as if rainfall has a pronounced directional component by influence of a prevailing wind, the amount of rainfall falling on a slope may vary depending on its aspect (Wieczorek et al., 1997). Hence, some faces become more stable than others. In short, it could be said that aspect has indirect influence on landsliding, related to other factors such as soil moisturizer, weathering and rainfall.

ArcGIS with its spatial analysis tool was applied to derive aspect. The aspect image shows eight categories excluding flat that are going to be used in heuristic method. Figure 6b and Table 2 shows the result. As so with slope, for statistical and ANN, no classification implemented so the original value from aspect is going to be used in the process.

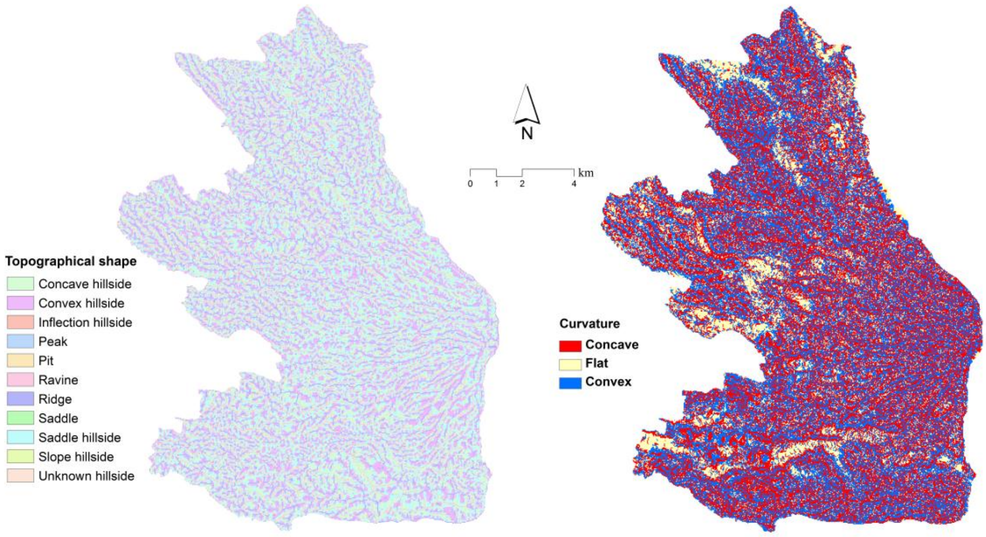
2.2.3. Topographical shape

It has already known that land form influences landslide occurrence. Hadmoko et al. (2010), reported that denudational and structural hill were more susceptible that plain/flat area (e.g., alluvial plain or flood plain). Another research, from Caniani et al. (2008), noted that hardly landslide happened in peak, flat and pit. Contrariwise, landslides were more often to occur in hillside.

The topographical shape is actually a specific surface land form, which is created automatically only in IDRISI software. The material, an ASCII file from SRTM 30m, was then converted into IDRISI raster format. The software classified the shape into 11 topographic features based on polynomial surface fitting of each 3x3 pixel area (Eastman, 2006). Figure 7a shows the result. Table 3 tabulates each class area.

2.2.4. Curvature

Curvature is the shape of surface. This study considers that negative curvatures value represent concave, around zero (-0.1 – 0.1) curvatures value represent flat and positive curvatures value represent convex surface (Pradhan and Lee, 2010). Concave and convex surfaces of the earth are more influential in boosting landslide to occur. SRTM 30m is used to create aspect. It has to be converted into ASCII in order to be processed. Then, after getting SRTM in raster grid, using spatial analysis facilities, curvature was created. The software uses fourth-order polynomial to calculate the area of 3x3 window. Figure 7b shows curvature categorization for heuristic method. Table 3 tabulates each class area. Data-driven methods use the original continuous value.



(a) (b)

Figure 7. Categorization of (a) Topographical shape and (b) Curvature

Table 3. Tabulation of topographical shape and curvature class in the study area

Factor	Class	Class name	Hectares	%
Topo shape	1	Concave hillside	4028,59	23,14
	2	Convex hillside	4355,88	25,01
	3	Inflection hillside	261,46	1,50
	4	Peak	0,59	0,003
	5	Pit	0,09	0,001
	6	Ravine	1772,55	10,18
	7	Ridge	1794,09	10,30
	8	Saddle	0,74	0,004
	9	Saddle hillside	4975,82	28,57
	10	Slope hillside	0,09	0,001
	11	Unknown hillside	223,40	1,28
Curvature	1	Concave	7379,80	42,38
	2	Flat	2769,82	15,91
	3	Convex	7263,68	41,71

2.2.5. Lithology

Lithology is a group of parent materials. In the study area, according to the geology map there are eight lithology classes (Table 4). These classes show the local geologic formations around Old and New Lawu Volcano, formed by volcanic activities in Pleistone and Holocene period (Wati, 2010). Each geological unit has own lithological characteristic. Each lithology has different materials. Its relation with landslides is located on the slippery degree of the materials toward erosion. For instance, hard and massive rocks are already known generally resistant to erosion (Anbalagan and Singh, 2001). It means the more massive the material the more potent its resistance.

Below the classification of those formations (Wati, 2010):

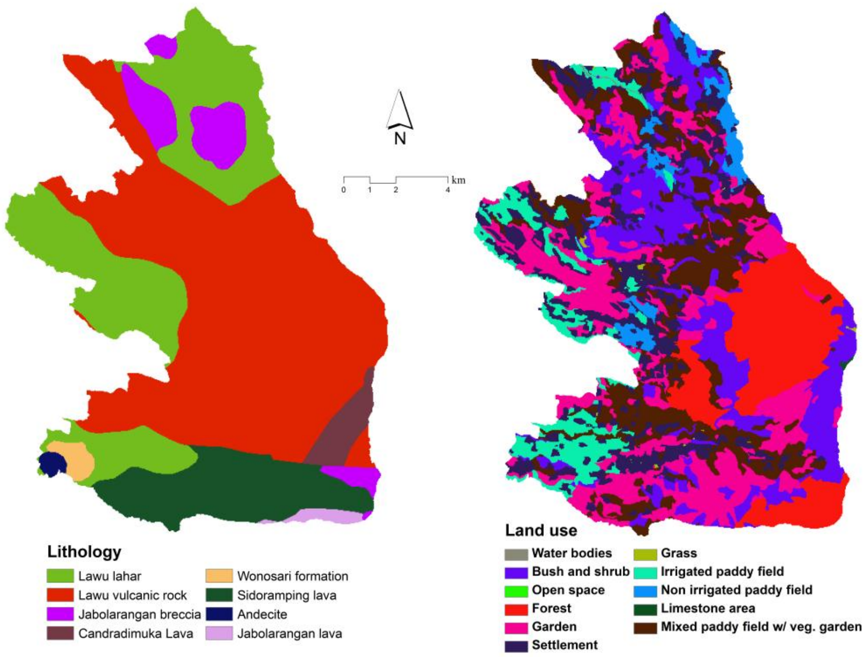
a. Lawu Lahar (Qlaa). This formation consists of andecite, basalt and minor fumice. Most of those minerals merge with volcanic sand. In the study area, Lawu Lahar formation spreads out in volcanic foot slope areas; it also forms several low hills.
b. Condrodimuko Lava (Qvcl). This formation is formed by andesitic lava from Condrodimuko Crater. It spreads out to southwest from the peak.
c. Lawu Volcanic Rock (Qvl). This formation is mostly composed by volcanic tuff and breccia inserted by andesitic lava. It is the largest formation in the area and extents out westward from the peak.
d. Jabolarangan Lava (Qvjl). This formation encompasses andesitic lava with andesine, quartz, feldfar and minor hornblende from Mount Jabolarangan (the peak of Old Lawu Volcano).
e. Sidoramping Lava (Qvsl). It contains dark grey andesitic lava from four old small mountains around Old Lawu (Mount Sidoramping, Mount Puncakdalang, Mount Kukusan and Mount Ngampiyungan). It is located in the southern part.
f. Jabolarangan Breccia (Qvjb). It is formed by volcanic breccia intercalated by andesitic lava, mostly located in slope 30-50%.
g. Wonosari Formation (Tmwl). This formation consists of reef limestone and calcarente inserted by conglomeratic limestone and marl. It formed several cone-shaped low hills.
h. Andecite (Tma). This formation is actually an intrusion rock with particular textures (porphyrictic, subhedral, and has 0,5 – 1 meter in size). Tma contains mostly andesine, and then orthoclase, small portion of quartz and plagioclase microlite, as well as 30% volcanic glass.

Because the data is ready-to-use data, it is only needed to be converted into raster grid. Figure 8a depicts the formations.

2.2.6. Land use

Land use could indirectly affect slope stability. Vegetation cover, for example, influences hydrological processes because of the hydraulic conductivity effect (Van Westen et al., 2008). Vegetable garden or sparse vegetation in steep slope could increase the susceptibility because such vegetation root could not bind the soil if rain fall down. As result, soil erosion could easily happen. Building construction nearby hill, which involved cut and fill activities, could enlarge pressure causing slope instability. According to the existing land use map, land use types are classified into 11 classes (Table 4).

Land use distribution in the study area principally depends on topographic condition. Lower part is intensively occupied for settlement area and agricultural activities (vegetable garden, paddy field, or mixed garden). But, in some undulating and hilly slope area, small village and agricultural activities are also found. Upper parts of Mount Lawu are dominated by dense protected forest. Bush and shrub are distributed everywhere mostly in between forest and agricultural field or settlement. The land use map then converted into raster grid format. Figure 8b shows the result.



(a) (b)

Figure 8. Categorization of (a) Lithology and (b) Land use

Table 4. Tabulation of lithology and land use class in the study area

Factor	Class	Class name	Hectares	%
Lithology	1	Andecite	77,84	0,45
	2	Candradimuka Lava	422,81	2,43
	3	Jobolarangan Breccia	1039,68	5,97
	4	Jobolarangan Lava	132,68	0,76
	5	Lawu Lahar	4537,24	26,06
	6	Lawu volcanic rock	9013,74	51,76
	7	Sidoramping lava	2026,20	11,64
	8	Wonosari Formation	163,13	0,94
Land use	1	Water bodies	10,27	0,06
	2	Bush and Shrub	3175,05	18,23
	3	Open space	1,41	0,01
	4	Forest	2701,27	15,51
	5	Garden	3903,75	22,42
	6	Settlement	2603,20	14,95
	7	Grass	23,41	0,13
	8	Irrigation paddy field	1229,43	7,06
	9	Non Irrigation paddy field	572,90	3,29
	10	Limestone Area	10,15	0,06
	11	Mixed paddy field w/ veg. garden	3182,46	18,28

2.2.7. Distance to road

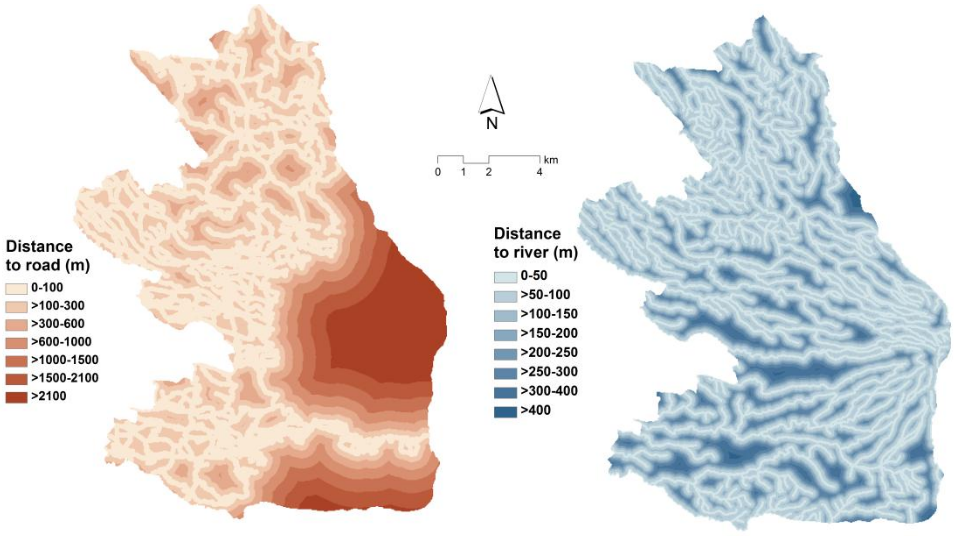
Road constructions in hilly or mountainous area are sites on anthropologically induced instability (Ayalew and Yamagishi, 2005). Road segments–according to hydrological perspective–may act as the barrier, sink or corridor of water flow that affect slope stability. Due to this reason, easy to find that landslides occurred above roads or nearby roads. The study area has more road networks in the western part rather than the eastern part where Mount Lawu exists.

To classify road network proximity, buffer analysis was applied. This study uses multiplied distance. The first 100 meters is assigned as the first class, the next 200 meters as the second class and so forth (Figure 9a). For accommodating data driven methods, distance analysis was used to assign values continuously. Table 5 shows distance to road classes' tabulation.

2.2.8. Distance to river

Rivers or streams drainage may induce river bank failure because of slope undercutting and stream erosion. There are a lot of small rivers in the study area. Two of them are the River Suwaluh and River Gembong that flow into the River

Bengawan Solo, the longest river in Java Island. With constant of distance 50 meters, multiple buffer analysis was applied to categorize this factor into classes (Figure 9b). For the purpose of data-driven methods, distance analysis was applied to create continuous values. Table 5 shows distance to river classes' tabulation.



(a) (b)

Figure 9. Categorization of (a) Distance to road and (b) Distance to river

Table 5. Tabulation of distance to road and distance to river class

Dist. to road	Class	Buffer distance (m)	Hectares	%
	1	0-100	6605,16	37,93
	2	>100-300	4767,16	27,38
	3	>300-600	2113,24	12,14
	4	>600-1000	1308,12	7,51
	5	>1000-1500	1342,37	7,71
	6	>1500-2100	1068,83	6,14
	7	>2100	208,42	1,20
Dist.to river	1	0-50	4400,50	25,27
	2	>50-100	7071,46	40,61
	3	>100-150	2184,28	12,54
	4	>150-200	1448,22	8,32
	5	>200-250	935,26	5,37
	6	>250-300	913,68	5,25
	7	>300-400	422,65	2,43
	8	>400	37,26	0,21

CHAPTER 3 METHODOLOGY

This chapter elaborates the methods used to conduct the analyses and build the landslide susceptibility models.

3.1. Knowledge-based: heuristic method

To assess landslide susceptibility using heuristic method there are two common approaches: direct and indirect method. The first method applies direct assessment to interpret susceptibility in the field on the basis of detailed maps (geomorphological maps, for instance). The latter does not assess directly in the field, but via data integration techniques in any particular software. This study uses indirect heuristic method.

As discussed in Chapter 1, heuristic approach is a semi-qualitative method. Besides uses knowledge properties (expert opinions, previous research results or literature recommendations), it also uses index-based procedures such as simple ranking and rating or analytical hierarchy process (AHP) in assigning weight and creating model. Concerning this, scoring and weighting process are crucial to build a model in heuristic approach.

3.1.1. Scoring

A scoring assessment is assigned to score every class. One class will have one score. Although there are many ways to rank each class, for most of the factors, this study uses scoring system from 1 to 5. Score 1 represents the lowest value and 5 represents the highest value (Table 6). Low values reflect low contribution.

Slope is scored based on its gradient classification. As discussed in Chapter 2, the higher slope the bigger landslide tendency to occur. As result, the lowest class gradient (0-8%) gains the lowest score and the highest class gradient (>45%) gains the highest score. Aspect in this study is scored based on the general characteristic in the equatorial area that the western or northern part of slope is commonly drier than others. Eight aspect classes are then categorized into five scored classes.

Curvature only has three classes. This study uses two values, 1 and 5, to score the classes because concave and convex surface are considered having the same influential condition toward landslides occurrence. Therefore, score 1 is assigned for the flat areas whereas score 5 for the concave and convex areas. In assigning topographical shape score, the surface land form such as flat and peak gain the lowest grade because landslides occur very sparsely on that area (Caniani et al., 2008). As contrary, according to the same research, the areas having most frequent landslides are saddle hillside, convex hillside and concave hillside. Eleven classes of topographical shape are then categorized into five scored classes.

Table 6. Score for each class

Influencing factor	**Class**	**Score**
Slope	0 – 8% (gently sloping)	1
	>8 – 15% (undulating)	2
	>15 – 30% (moderately steep)	3
	30% - 45% (steep)	4
	>45% (very steep)	5
Aspect	North (N), West (W), Northwest (NW)	1
	Northeast (NE)	2
	East (E), Southwest (SW)	3
	Southeast (SE)	4
	South (S)	5
Curvature	Concave	5
	Flat	1
	Convex	5
Topo. shape	Peak (Pk), Pit (Pt)	1
	Saddle (S), slope hillside (Sl Hs), unknown hillside (U Hs)	2
	Inflection hillside (I Hs)	3
	Ravine (Rv), Ridge (Rg)	4
	Concave hillside (Cv HS), convex hillside (Cx Hs), saddle hillside (S Hs)	5
Lithology	Andecite (Tma)	1
	Candradimuka Lava (Qvcl), Sidoramping Lava (Qvsl), Jabolarangan Lava (Qvjl), Wonosari formation (Twml)	2
	Jobolarangan Breccia (Qvjb)	3
	Lawu volcanic rock (Qvl)	4
	Lawu Lahar (Qlla)	5
Land use	Water bodies (WB), Limestone area (LA)	1
	Bush and Shrub (BS), Open space (OS), Grass (Gr)	2
	Irrigated paddy field (IPF), Non Irrigated paddy field (NIPF)	3
	Garden (Gd)	4
	Settlement (S), Mixed paddy field with vegetable garden (MFP)	5
Dist. to road	>1000 m	1
	>600 – 1000 m	2
	>300 – 600 m	3
	>100 – 300 m	4
	0 – 100 m	5
Dist. to river	>200 m	1
	>150 – 200 m	2
	>100 – 150 m	3
	>50 – 100 m	4
	0 – 50 m	5

A key concept to assign scores to lithology factor is resistance toward erosion. The resistance is determined by massiveness, or in the other side, brittleness. In this case, according to Wati (2010), andecite as massive rocks gain the lowest score. Jabolarangan breccias are more brittle than lava formations (Jabolarangan Lava, Sidoramping Lava, Candradimuka Lava) and Wonosari formation, due to the high amount of sand fragment. Lawu Lahar and Lawu volcanic rock that has volcanic sandstone (Kristijono et al., 2008) is more susceptible to landslide so both get high score.

Regarding land use, water bodies (lake), limestone area, and forest gain the lowest score; because lake area is normally flat, limestone area contains massive rocks, and forest has dense vegetation that could prevent erosion (Hadmoko et al., 2010). Garden is more susceptible than grass because of the lower pressure of grass. Relevant with the previous discussion in Subsection 2.2.5, settlement and mixed paddy field with vegetable garden (dryland agriculture) have the highest score.

As showed by Jadda et al. (2009), Ayalew and Yamagishi (2005), the scores for distance to road and distance to river are determined based on the proximity without considering road types. The possibility for landslides to occur becomes bigger nearby the feature. It causes the closer the buffer area to the feature, the higher the score.

3.1.2. Weighting process using SMCE ILWIS

Another important part in heuristic method is weighting process. Hadmoko et al. (2010), directly assigned weight for every contributing factor based on a checklist and give them a rank. To assign weight, this study does not use that method but uses Spatial Multi Criteria Evaluation (SMCE). SMCE is a module in ILWIS software that facilitates users in doing multi criteria evaluation in a spatial way. All datasets in advance must be converted into ILWIS raster format and surely have the same georeferences (coordinates, borders, and number of pixels).

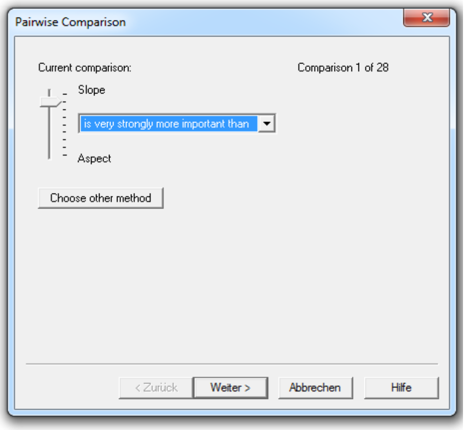


Figure 10. Pair-wise comparison tool in ILWIS

The first step to apply SMCE is creating a criteria tree. The criteria tree consists of root (main goal or final map) and leafs (criteria or influencing factors map). The factors cannot be straight off usable in weighting process unless had been standardized. The standardization has aims in order to make the factors comparable. This study uses maximum standardization by dividing them by the maximum value. Afterwards, to assign weight the software provides three tools: direct, pair-wise and rank ordering comparison. This study uses pair wise method that originally comes from analytical hierarchy process (AHP), a decision support method proposed by Saaty (1980).

Pair-wise method calculates the magnitude (importance) based on an appraisal to every unique pair of two factors qualitatively (Figure 10). To locate the factors according to a scale of importance (Table 7), this study refers to the previous researches that had used the same influencing factors and had given the significance value to each factor, for instance Hadmoko et al., 2010; Wati, 2010; Muhiyuddin et al., 2004; Ruff and Czurda, 2009. Slope, for example, was given higher weight than others; so this study adopts that result by placing slope more important than others.

Table 7. Scale of importance

Intensity	Definition
1	Is extremely more important than
2	Is very strongly more important than
3	Is strongly more important than
4	Is moderately more important than
5	Is equally important as
6	Is moderately less important than
7	Is strongly less important than
8	Is very strongly less important than
9	Is extremely less important than

However, still subjective opinion is needed to adjust exactly in which scale the degree of importance of one factor must be located comparatively with others, because there are nine detail options. There are 28 comparisons and to keep the quality, the software provides consistency value. The comparison process is considered having inconsistency if the value is bigger than 0.1. Weight for all factors is the final result. The bigger the weight value the bigger the contribution. The cumulative weight for all factors is equal with 1.

3.1.3. Heuristic modeling

A map from heuristic method is mathematically presented as:

$$LSI_h = (W_1*X_1)+(W_2*X2)+\ldots+(W_n*X_n) \qquad \text{(Eq.1)}$$

Where:

$LSIh$ = Landslide susceptibility index map from heuristic method
$W_{1\ldots n}$ = Weight of influencing factor
$X_{1\ldots n}$ = Predictor variable/influencing factor

ArcGIS raster calculator was used to generate the landslide susceptibility index (LSI) map by giving weights to each factor and calculating the model using Eq. 1. Afterward, LSI was classified into five susceptibility classes, i.e., very low, low, moderate, high and very high, to acquire land susceptibility map (LSM). Figure 11 illustrates the work flow.

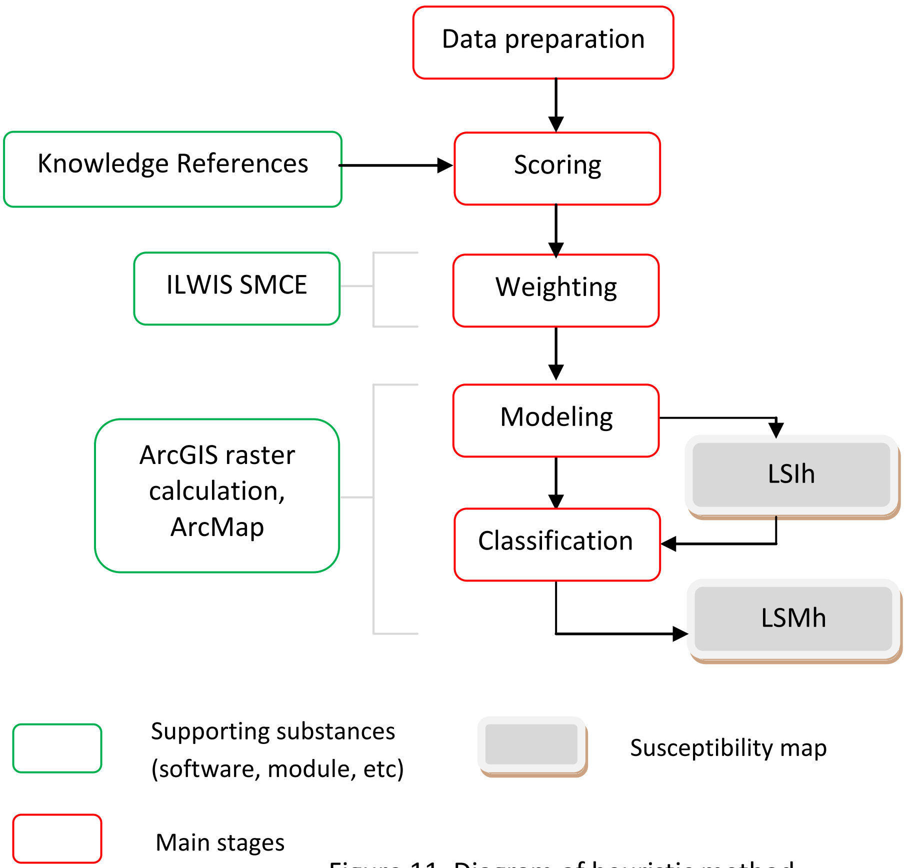


Figure 11. Diagram of heuristic method

To classify data, there are several methods. Four most common are natural breaks, equal interval, quantile, and standard deviation. By looking into data histogram, the most appropriate method can be decided. According to Ayalew and Yamagishi (2005), standard deviation method, which uses mean and standard deviation to break the class, is reliable to classify datasets that have normal distribution. Using this method, contrast of values above and below the mean is readily seen. Natural breaks (Jenks) is preferable if dataset does not show normal distribution, since this method can optimally assign data to classes such that the variances within all classes are minimized, and the variances among classes are maximized; so it can identify real classes inside the data. Equal interval method, which emphasizes the same interval size, is good to compare time series data, but it does not show real data characteristic. Quantile method that uses the same number to assign each class member is also good for time series data, but it tends to place widely different value in the same class so the classification does not show real data characteristic either.

3.2. Data-driven: statistical method

Statistical method in landslide susceptibility is actually about a quantitative analysis based on statistical analysis of factors and occurrences. Inside this concept, the relationship among influencing factors and between them and landslide occurrences is important to assess.

This study applies some processes to employ statistical method. First, it applies two bivariate assessments: pixel-based landslide density and weight of evidence (WoE). Generally, both aim to understand landslides distribution in every class of influencing factors. But, as landslide density gives the conditional probability that is going to be used as values for discrete variables, WoE gives weights that could be used to assess the relationship between landslide and a particular class (Barbieri and Cambuli, 2009).

Second, to have clearer understanding about datasets, this study conducts some explanatory analyses: descriptive analysis and Q-Q plots, bivariate pearson correlations and collinearity analysis. Q-Q plots is aimed to assess normality test graphically. The bivariate pearson correlation and collinearity show the correlation between predictor variables. Finally, this study applies binary logistic regression to build statistical model. The next following sections describe the processes.

3.2.1. Landslide density calculation

Landslide density analysis plays an important role in landslide studies because it shows clear representation about occurrences in a certain factor class. The representation roughly reflects the indication of which class that more sensitive than others. Before assessing density, it is necessary to create landslide inventory in the polygon format. Each point was buffered 50 meters with respect to the shortest used distance in distance to river factor. The process does not affect the quality because all points have the same treatment. Afterwards, using cross facilities in ILWIS, landslide inventory was overlaid with the factors to get information about which pixels inside the class are landslide pixels. This process needs separation for landside pixel and non-landslide pixels by giving attribute 0 for non-landslide and 1 for landslide pixels. After gaining the crossed table, the table needs to be modified to make it easy to read.

Landslide density can simply be defined as number of landslide pixels divided by the total number of pixels. To calculate landslide density within each class, the following formula is used (Lei and Jing-feng, 2006; Ayalew and Yamagishi, 2005):

$$Density = \frac{(Lpix_i / Tpix_i)}{\sum_{i=1}^{n}(Lpix_i / Tpix_i)} \qquad \text{(Eq. 2)}$$

Where:

$Lpix_i$ = landslide pixel number of *i* class in a certain factor

$Tpix_i$ = total pixel number of *i* class in a certain factor

3.2.2. Weight of evidence assessment

Weight of Evidence (WoE) method is first introduced by Bonham-Carter (1994) to assess mineral potential mapping. Nowadays, WoE is also implemented to assess landslide susceptibility (Lee et al., 2002; Neuhaser and Terhorst, 2007). This study uses this method to assess the correlation between a class and landslide occurrence. The idea of this method is originated from Bayesian probability using landslides presence and absence in a class. This method gives positive and negative weight of evidence (W_i+ and W_i-) assigned to each class in each factor. W_i+ is used to indicate the importance of presence, whereas W_i- is used to indicate the importance of absence. By subtracting W_i+ with W_i-, contrast (C) is gained as a basis to assess the spatial association between each factor class and landsides. Below the formulas to calculate weights (Barbieri and Cambuli, 2009).

$$W_i+ = \ln \frac{Lpix_i / TLpix}{NLpix_i / TNLpix} \qquad \text{(Eq. 3)}$$

$$W_i- = \ln \frac{Lpix_{others} / TLpix}{NLpix_{others} / TNLpix} \qquad \text{(Eq. 4)}$$

Where:

W_i+ = Positive weight

W_i- = Negative weight

$Lpix_i$ = Number of landslide pixel in i class

TLpix = Total number of landslide pixel (according to each factor)

$NLpix_i$ = Number of non-landslide pixel in i class

TNLpix = Total number of non-landslide pixel (according to each factor)

$Lpix_{others}$ = Number of landslide pixel in the other classes

$NLpix_{others}$ = Number of non-landslide pixel in the other classes

3.2.3. Logistic regression modeling

Logistic regression is a generalized linear statistical model that predicts the probability using a binary response (0 and 1 or true and false) and multicovariates (Hosmer and Lemeslow, 2000). The probability is fitted into a sigmoid logistic curve. Regarding to landslide susceptibility assessment, logistic regression aim is to find the best fitting model to describe relationship between the landslide (as a response variable) presence (1) and the absence (0) and influencing factors (as predictor variables). As all influencing factors are used in one-time analysis, this method is categorized as multivariate analysis.

Statistical logistic regression is applicable in landslide susceptibility assessment as the usage of binary response is fit with landslide situation (occurred and not occurred). It also could manage both continuous and discrete variable, so the subjective discretization of continuous variables could be avoided.

In logistic regression the relationship among predictor variables and response variable can be expressed as below:

$$Pr(event) = 1/(1+e^{-z}) \quad \text{(Eq. 5)}$$

Where:

Pr (event)	= the estimated probability of landslide occurrence (varies from 0 to 1: nearby 0 reflects low and near 1 reflects high probability).
e^{-z}	= exponential function, where e is a number (approximately 2.718281828)
and z	= the linear combination expressed as:

$$z = B_0+B_1X_1+B_2X_2\ldots+B_nX_n \quad \text{(Eq. 6)}$$

Where B_0 is the intercept; B_1, B_2,…,B_n are the coefficient (or weight) for each predictor variable indicating its contribution; X_1, X_2,…, X_n are the predictor variables.

Each class of discrete predictor variables then is given value from its density. This process can solve the problem about how to assign numeric value for discrete variables that are originally nominal data. According to Lei and Jing-feng (2006) and Carrara (1983), this process is beneficial as it allows the consideration about the so-called “previous knowledge” of landslide susceptibility.

In the prediction process, training dataset size of response variable is important because it determines the resulted model. One of the recommendations is to use the equal number size of landslide and non-landslide pixel (Dai and Lee, 2002;

Ayalew and Yamagishi, 2006). This study picks the response variables in two ways. First, takes all landslide pixels but randomly selects the non-landslide pixels. Second, still takes all landslide pixels but selects non landslide pixel smoothly to the whole area, also in equal proportion between landslide and non-landslide pixels. Each withdrawal was done three times to get the best result. This approach gives opportunity to choose the best datasets based on model summary and overall percentage correct.

Logistic regression analysis is conducted in PASW software. Landslide inventory and all influencing factors must be converted from grid raster format into ASCII file (.txt). It is also necessary to do cleaning process, because the ASCII files from conversion still have original header information and a blank area value (-9999) that should be omitted. At the same time, the file must be restructured to order variable values in one single column.

Basically, there are three forms of logistic regression module: enter, forward inclusion and backward elimination. In the first module, all predictor variables are directly calculated in one step whereas in the second, all predictor variables are initially excluded and then some are included in the next steps until the requirements are achieved (García-Rodríguez, et al., 2008). This study uses the latter type: backward elimination (Backward Likelihood Ratio) approach to run logistic regression analysis. In this approach, the software predicts the probability using all predictor variables at the initial iteration, and then after several steps the final result shows the remaining variables that fulfill the significance requirement (maximum likelihood-ratio). It becomes an advantage: there are elimination and selection during the process, so the analysis can give the variables that are statistically important to build the model.

The result also gives intercept and the coefficient for each predictor. Using those values, Eq. 5 and 6 were calculated using raster calculator ArcGIS to build the landslide susceptibility index map. Similar with the heuristic method, the index map was classified into classes by considering the distribution. Figure 12 illustrates the work flow.

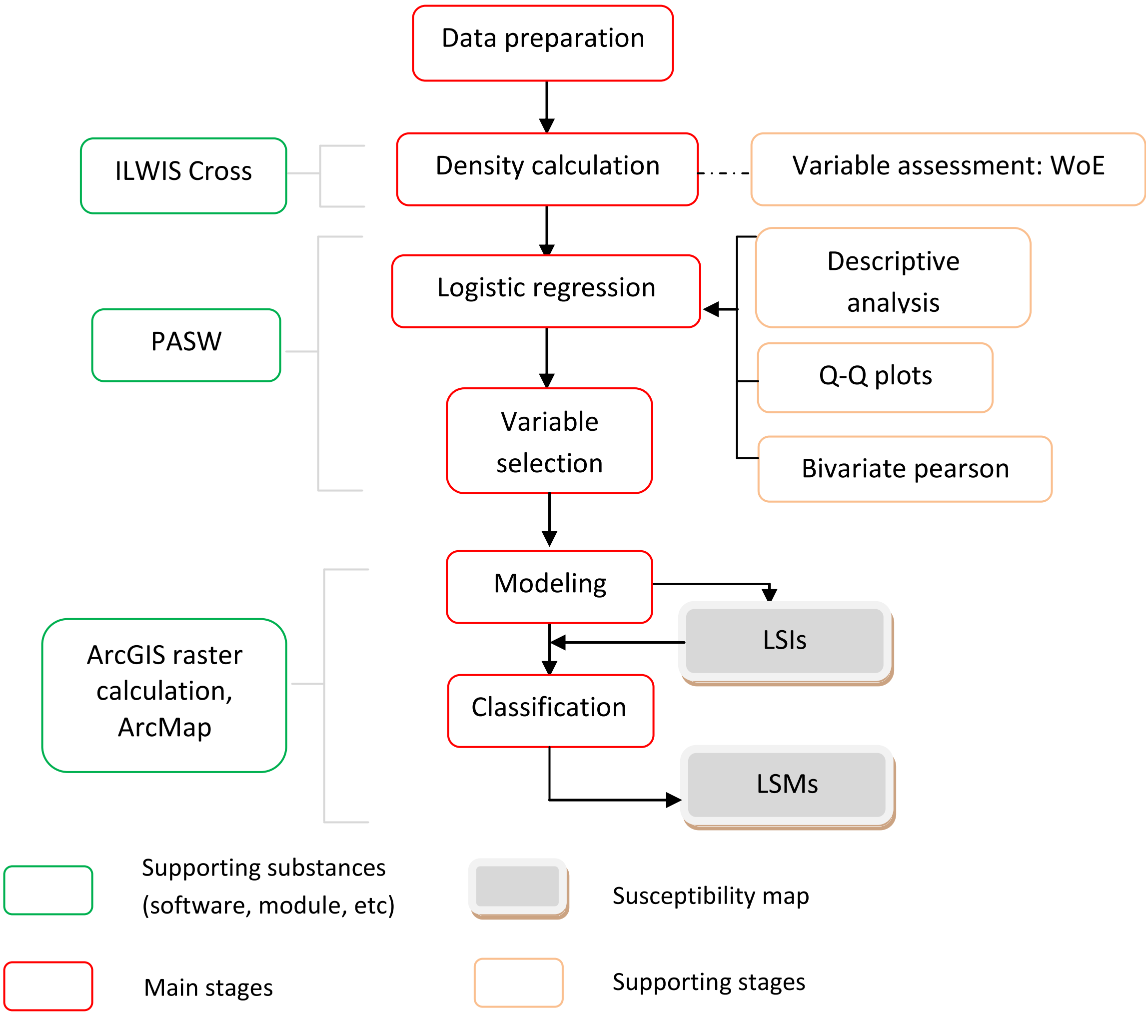


Figure 12. Diagram of statistical method

3.3. Data-driven: artificial neural network

Artificial neural network is a computational model that attempts to mimic biological neural networks or human brain mechanism in making prediction (Gomez and Kavzoglu, 2005). ANN is an adaptive model. It can learn or update the system internal representation as responses to the stimuli in iteration processes, so that the performance of a specific task is improved. Its learning process is function of learning algorithm that can define how network synaptic weights (interneuron connection strengths) are adjusted between successive training cycles. The network is outlined as layers and interconnection (Figure 13).

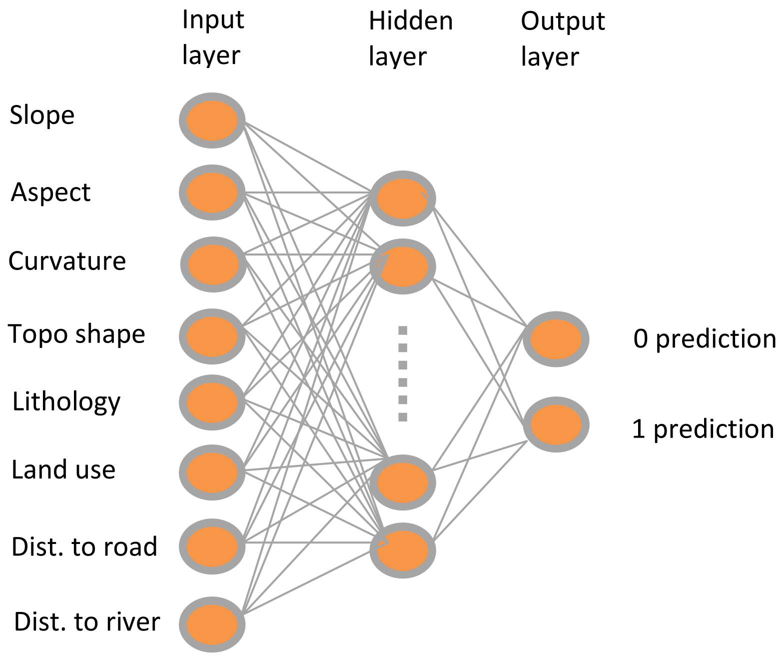


Figure 13. Neural network schema in landslide susceptibility assessment

The input layer contains the predictors (influencing factors). The hidden layer contains unobservable nodes, or units whose values are some functions of the predictor given by the process. The output layer contains responses. Each output unit is some function of the hidden units. In neural network procedures, the form of the function depends in part upon the network type and in part upon user-controllable specifications (SPSS Technical Support, 2010).

There are two common ANN architecture or topology viz. feed-forward and recurrent neural network (Rios, 2010). In feed-forward architecture**,** connections in a network flow forward from input layers to output layers without any feedback loops whereas there are loops in a recurrent neural network. This study uses feed-forward Multi-layer Perceptron (MLP).

MLP consists of multiple layers of nodes. One layer is connected to the next. MLP utilizes a supervised learning technique. As explained by Rios (2010), it means the network is trained by providing it with input and matching output patterns. The pattern can be created by an external teacher, or provided by the system/software (self-supervised). The technique itself is called back-propagation as an abbreviation of backwards propagation of error. In this propagation, the iteration has two basic movements (Gomez and Kavzoglu, 2005): forward movement that will present the input pattern and backward error correction movement that will deliver back the error from the output toward input via intermediate layers in order to adjust the synaptic weight and reduce the error. It means the process tries to find the model that has minimum error, or the error has achieved the acceptable level between the desired and actual output values. This level can be set by iteration times or threshold value.

Regarding landslide susceptibility assessment, multi-layer perceptron (MLP) is more appropriate than single layer perceptron because of the existence of intermediate (or hidden) layers in between input layers and output layers. Hidden layers can accommodate non-linearity so the model can solve the nonlinear classification.

Basically, there are two phases in artificial neural network: training and testing phase (Pradhan and Lee, 2010). Before running MLP on those two phases, there are some parameters that must be set up in order to complete the model architecture. Those parameters are composition of training set and testing set, number of hidden layers, activation function, type of training, initial learning rate, momentum, stopping rules and iteration times. The training set is used in the training phase to train the network and produce internal weight. The testing set is a set used to track prediction error during training in order to prevent overtraining (SPSS Technical Support, 2010). The testing set is not the same with the training sets, and the sofware can choose them differently. A testing phase is also called a classification phase.

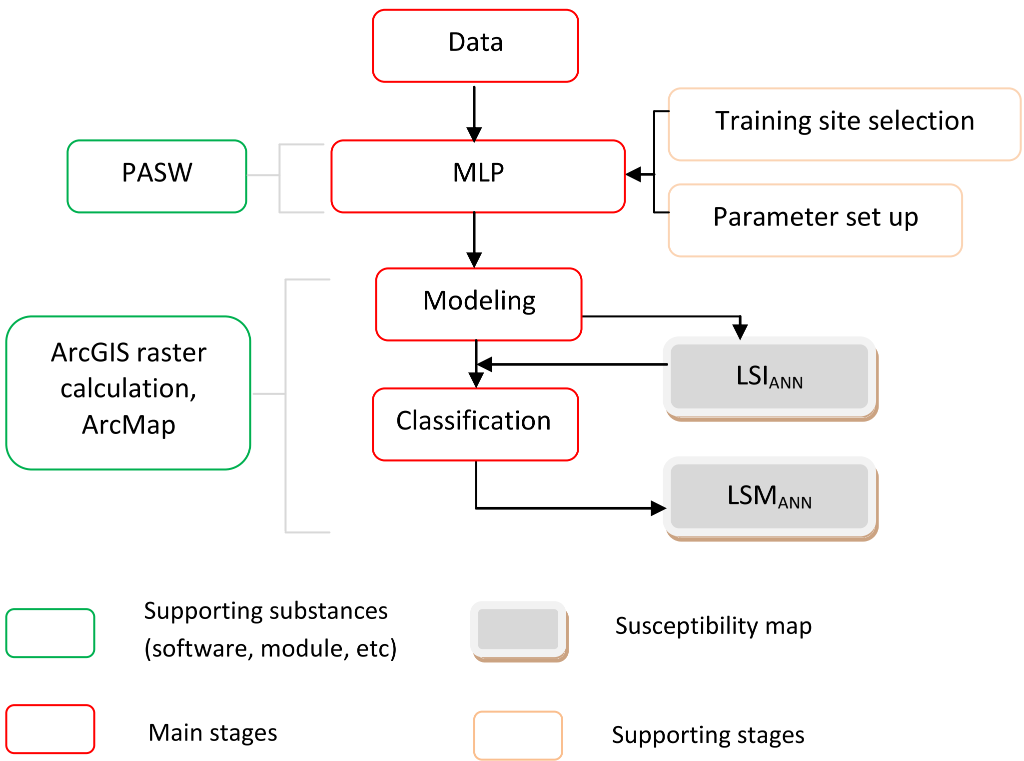


Figure 14. Diagram of artificial neural network

To conduct MLP analysis, this study applies PASW. Besides giving a classification table for each categorical response variable, ANN process also gives pseudo-probabilities values for each dependent variable category, and the importance of predictor variables (SPSS, 2009). Lee et al. (2003) used the pseudo-probabilities, whereas Pradhan and Lee (2010), Chauchan et al. (2008) used the importance to develop landslide susceptibility index. This study employs both and then selects one that could give better result.

LSI map was created in ArcGIS. Then, the ANN LSI map was classified using the same procedure with heuristic and statistical methods. Figure 14 illustrates the work flow.

3.4. Performance analysis

The next step after gaining landslide susceptibility models is to evaluate their performance by measuring prediction accuracy, which is achieved by analyzing the agreement between the results and the observed data/landslide occurrences (Fratinni et al., 2010).

There are two basic concepts to assess models performance: using success analysis and predictive analysis. As mentioned by Van Den Eeckhaut et al. (2010), success analysis uses the same landslide occurrences (often called as calibration set) with the ones used to build the model. It makes this analysis is occasionally called as calibration analysis. Another one, predictive power analysis, uses the different landslide occurrence dataset (often called as validation set) with the one that is used to build models. Because of that, in some literatures, it is called validation analysis. This study only implements success-performance analysis because the number of landslide occurrence is small and cannot be divided into two different sets, i.e. calibration and validation set.

However, there is a special case for heuristic method. This method does not involve landslide occurrence dataset in its analysis. It makes a condition that the performance test using landslide occurrence dataset in this method could be categorized as a validation analysis too.

This study applies degree of fit for all methods and goes deeper by conducting Receiving Operating Characteristic (ROC) analysis for data-driven methods. Degree of fit analysis compares or crosses landside inventory with LSM (Fernandez et al., 2003; Jimenez-Peralvarez et al., 2009) by following the Eq. 2. In some sense, degree of fit is similar with density analysis but it is applied toward each class of susceptibility map and is not toward each class of influencing factor. Degree of fit analyses was conducted by means of ILWIS. Regarding this, the LSM must be exported into ASCII file (.asc) in order to be read.

ROC analysis is one of the most common approaches used to assess landslide susceptibility model performance, such as explored by Frattini et al. (2010), Jadda et al. (2009), Van den Eeckhaut et al. (2006), Mancini et al. (2010). The technique evaluates the performance of classification schemes in which there is dependent variable with two categories by which subjects are classified (based on a cutoff value). Because of that, this technique is appropriate to be applied for statistical logistic regression and ANN, the methods that using binary response in their classification. ROC analysis gives area under curve (AUC) that can be used as a metric to assess the overall quality of a model (Frattini et al., 2010). Larger AUC indicates better performance. Graphically, it is showed by the curve closer to the upper-left corner.

ROC analysis was applied by means of PASW. In statistical logistic regression, landslide inventory dataset (as state variable) is “compared” with the predicted probability (as test variable, a derivative result from logistic regression analysis). For ANN, the software calculates ROC curve using pseudo-probabilities values that are derived from the prediction process. These values are based on the combined training and testing samples used to build the model.

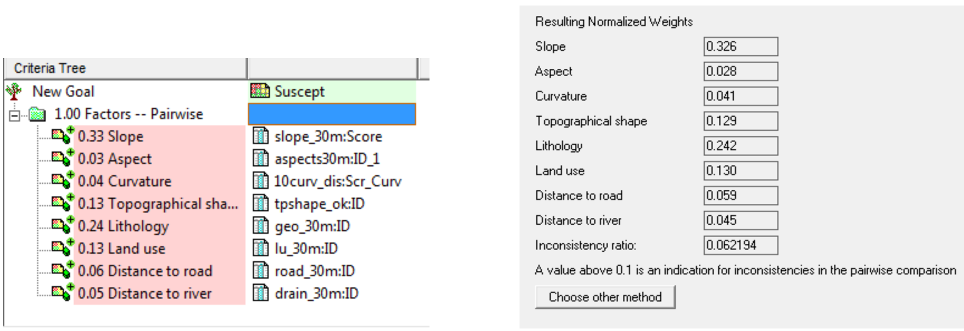
ROC analysis can give an explanatory power of a model using two operating characteristics in the contingency test of binary classifier: TPR and FPR (Fawcett, 2004). TPR (True Positive Rate) or sensitivity shows the correct classifying positive instances among all positive cases. FPR (False Positive Rate), on the other hand, defines how many incorrect positive results occur among all negative cases available during the test. FPR is calculated based on the specificity, a measure of negative proportion that are correctly identified (FPR = 1 – specificity). Hence, ROC curve is a graphical plot of sensitivity and (1 – specificity).

CHAPTER 4 RESULTS AND DISCUSSION

This chapter presents and discusses the results from the methods described in the previous chapter.

4.1. Heuristic model

The weighting judgment process in pair-wise comparison gives a weight for every influencing factor (Figure 15b). From the calculation, the final criteria tree (with weight in 2 digits) was created as shown in Figure 15a. Bigger weights indicates that the pertinent factor gives bigger influence toward the model. Slope has the biggest contribution (0,326), followed by lithology and land use with value 0,242 and 0,130, respectively. On the other side, the lowest contribution is given by aspect (0,028), followed by curvature (0,041) and distance to river (0,045). No negative weights in heuristic method. The inconsistency value is 0,062194: smaller than 0,1. It means, according to SMCE validation, the choosing process is consistent. No improper stage while positioning the factor based on its importance to another.



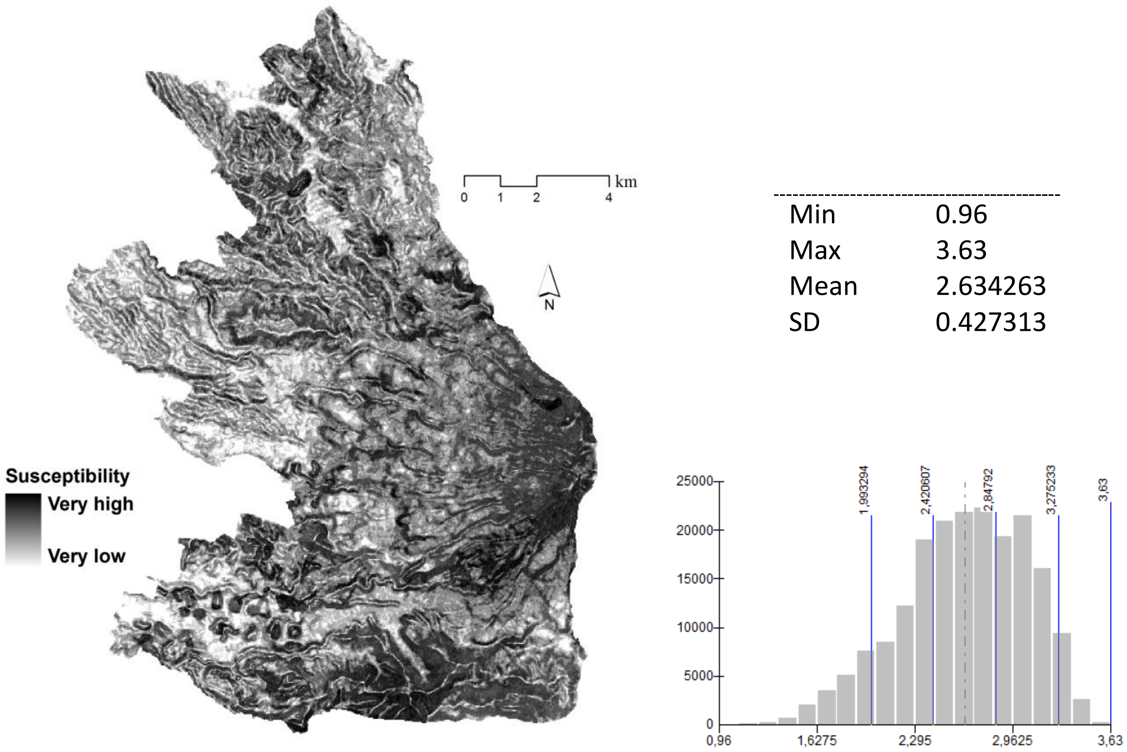
(a) (b)

Figure 15. Pair wise comparison in ILWIS (a) Criteria tree with input (spatial factors) and resulted weight; (b) Weighting process result containing the inconsistency value

Those values could be interpreted as an indication of possibility. If there is an area close to the river or road, but situated at gently slope, the possibility for landslide to occur is lower than another area where is distant to the road but has steep slope.

Following Eq. 1, LSI is calculated and mathematically modeled as below and presented in Figure 16a.

$LSI_h = 0{,}326slo+0{,}028asp+0{,}041curv+0{,}129tpshp+0{,}242lit+0{,}130lu+0{,}059d.road+0{,}045d.river$



(a) (b)

Figure 16. (a) Landslide susceptibility index of heuristic model (LSIh), and (b) Histogram of the map

The index map has the highest value 3,63 showing the highest susceptibility and the lowest is 0,96 showing the lowest susceptibility. As shown in Figure 16b, the histogram depicts near normal distribution indicated by near bell-shaped curve, which means values near the mean (dashes line type) occur more often. This condition, as discussed earlier in the Chapter 3, gives consequences for the usage of standard deviation as better option method to classify. As result, there are five classes that are divided based on the mean of each class. Figure 17 depicts the final landslide susceptibility map from heuristic method.

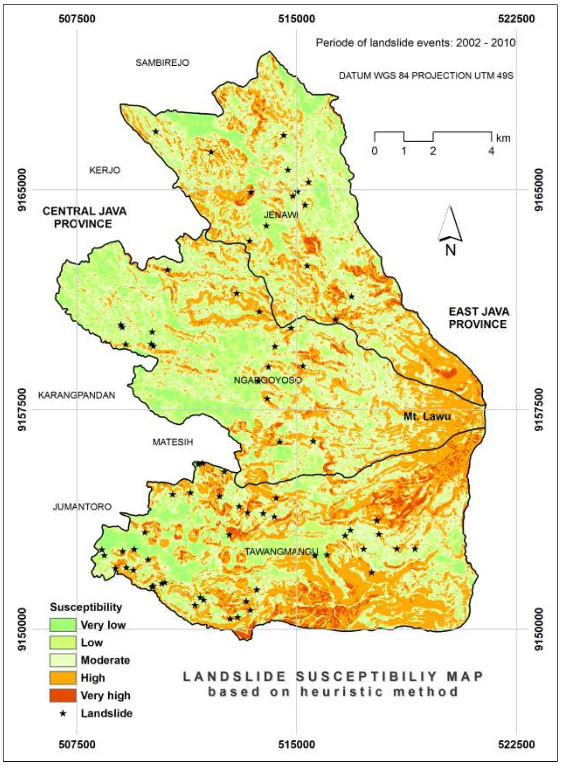


Figure 17. Landslide susceptibility map of heuristic method (LSMh)

Range values for each susceptibility class is 0,96 – 1,99 (very low), 2 – 2,24 (low), 2,43 – 2,85 (moderate), 2,86 – 3,27 (high), and 3,28 – 3,63 (very high).

Table 8. Area of LSMh class

No	Class	Hectares	Km^2	%
1	Very low	1466,98	14,67	8,45
2	Low	3596,77	35,97	20,73
3	Moderate	6357,07	63,57	36,64
4	High	5264,02	52,64	30,34
5	Very high	666,53	6,67	3,84

Table 8 resumes that the largest susceptibility area is moderate class, followed by high, low, very low and very high respectively. Most areas under high class consist of steep slope e.g., the area nearby Mount Lawu in the eastern part. Very high classes are located in very steep slope areas, gardens and mixed paddy fields with vegetable gardens, and Lawu Lahar formation. High class areas are also mostly located in steep and very steep slope, but with lower scored factor class such as forest. Moderately class as the majority is distributed smoothly. Low and very susceptibility classes are mostly located in the gently slopes, andecites, forests and paddy fields.

4.2. Statistical model

The analyses in statistical method give density and contrast (C), explanation about normality, correlation and significance of influencing factors, and probability calculation.

4.2.1. Landslide density

Landslide density that locates the existing occurrences into each class can reveal the relation between each class and landslide: which class having many events (i.e., the densest class or denser class) and which class having no events. Landslide density can indicate which area or class that is historically sensitive to earth failure. However, in this study, the density is not considered as the weight. It means the density is not applied directly to gain each factor contribution in modeling process, as had been done by other researches (Wahono, 2010; Van Westen, 1993; Memarian et al. 2006). As discussed earlier in Chapter 3, landslide density values are used as values for discrete variables while doing logistic regression and ANN analysis.

As shown in Table 9, the landslides spread across classes. In slope factor for example, most events occurred in steep class (>30 – 45%) and least in undulating class (>8 – 15%). Density of aspect is almost equal for each class. In this factor, north becomes the densest class and southeast is the least dense. Inflection hillside class is becoming the densest class (28,47%) in topographical shape. Meanwhile, for curvature, concave and convex class acquire 71,61% of occurrences. The densest class in lithology, land use, distance to road, distance to river is Wonosari formation, irrigated paddy field, 0-100 meter buffer distance class and class >100-150 meter, respectively. There are some classes that do not have landslide occurrences such as pit (Pt) in topographical shape, limestone area (LA) in land use factor, and > 1000 meter classes in distance to road factor.

4.2.2. Weight of evidence

The density just shows up the relationship between landslide occurrences and any classes positively because it just calculates the presence, whereas WoE assessment steps further by also considering the absence. While Pearson analysis is done mainly aimed to statistically assess dependency between two predictor variables based on covariance, WoE is aimed to assess the association based on the evidences (occurrences). So, in this assessment, statistical description such as covariance and standard deviation is not put into attention.

Table 9. Density and WoE tabulation

Name	**Density**	**Lpix$_i$**	**Lpix$_{others}$**	**TLpix**	**NLpix$_i$**	**NLpix$_{others}$**	**TNLpix**	**W+**	**W-**	**C**
Slope (%)										
0-8	0,1822	49	183	232	45973	144160	190133	-0,1352	0,0395	-0,1748
>8-15	0,0611	5	227	232	14006	176127	190133	-1,2291	0,0547	-1,2838
>15-30	0,2397	49	183	232	34939	155194	190133	0,1392	-0,0342	0,1734
>30-45	0,3161	47	185	232	25401	164732	190133	0,4163	-0,0830	0,4993
>45	0,2008	82	150	232	69814	120319	190133	-0,0381	0,0215	-0,0596
Aspect										
E	0,1122	8	230	238	7633	185198	192831	-0,1635	0,0062	-0,1697
N	0,1921	52	186	238	28960	163871	192831	0,3749	-0,0838	0,4587
NE	0,1018	18	220	238	18932	173899	192831	-0,2609	0,0247	-0,2856
NW	0,1087	38	200	238	37443	155388	192831	-0,1957	0,0419	-0,2376
S	0,1339	24	214	238	19184	173647	192831	0,0135	-0,0015	0,0150
SE	0,0770	6	232	238	8341	184490	192831	-0,5399	0,0187	-0,5586
SW	0,1582	51	187	238	34510	158321	192831	0,1801	-0,0440	0,2241
W	0,1160	41	197	238	37828	155003	192831	-0,1299	0,0293	-0,1592
Tp shape										
Cv Hs	0,1639	62	176	238	44733	148355	193088	0,1173	-0,0382	0,1555
Cx Hs	0,0979	40	198	238	48327	144761	193088	-0,3982	0,1041	-0,5023
I Hs	0,2847	7	231	238	2908	190180	193088	0,6693	-0,0147	0,6840
Pk	0,0000	0	238	238	6	193082	193088	INFINITY	0,000031	INFINITY
Pt	0,0000	0	238	238	1	193087	193088	INFINITY	0,000005	INFINITY
Rv	0,1323	22	216	238	19667	173421	193088	-0,0970	0,0104	-0,1075
Rg	0,1432	24	214	238	19818	173270	193088	-0,0177	0,0020	-0,0197
S	0,0000	0	238	238	8	193080	193088	INFINITY	0,000041	INFINITY
S Hs	0,1780	83	155	238	55162	137926	193088	0,1994	-0,0924	0,2919
Sl Hs	0,0000	0	238	238	1	193087	193088	INFINITY	0,000005	INFINITY
U Hs	0,0000	0	238	238	2457	190631	193088	INFINITY	0,0128	INFINITY
Curvature										
Cv	0,3260	114	124	238	81417	110194	191611	0,1198	-0,0988	0,2186
Fl	0,2838	33	205	238	32407	159204	191611	-0,1987	0,0360	-0,2347
Cx	0,3901	91	147	238	77787	113824	191611	-0,0599	0,0390	-0,0989
Lithology										
Qlla	0,0485	66	202	268	55198	138007	193205	-0,1485	0,0537	-0,2022
Qvl	0,0401	99	169	268	100007	93198	193205	-0,3374	0,2679	-0,6053
Qvjb	0,0181	3	265	268	6715	186490	193205	-1,1330	0,0241	-1,1571
Qvcl	0,0347	4	264	268	4677	188528	193205	-0,4836	0,0095	-0,4931
Tmwl	0,4059	18	250	268	1781	191424	193205	1,9860	-0,0603	2,0462
Qvsl	0,1278	71	197	268	22471	170734	193205	0,8232	-0,1841	1,0074
Tma	0,3249	7	261	268	867	192338	193205	1,7614	-0,0220	1,7834
Qvjl	0,0000	0	268	268	1489	191716	193205	INFINITY	0,0077	INFINITY

Table 9 (continued)

Land use										
WB	0,0000	0	237	237	111	192294	192405	INFINITY	0,0006	INFINITY
BS	0,0845	22	215	237	34067	158338	192405	-0,6457	0,0974	-0,7432
OS	0,0000	0	237	237	195	192210	192405	INFINITY	0,0010	INFINITY
F	0,0000	0	237	237	29992	162413	192405	INFINITY	0,1695	INFINITY
Gd	0,1558	52	185	237	43645	148760	192405	-0,0333	0,0096	-0,0429
S	0,3110	64	173	237	26876	165529	192405	0,6592	-0,1643	0,8235
Gs	0,0000	0	237	237	693	191712	192405	INFINTY	0,0036	INFINTY
IPF	0,5004	16	221	237	13983	178422	192405	-0,0737	0,0056	-0,0793
NIPF	0,0000	0	237	237	6467	185938	192405	INFINITY	0,0342	INFINITY
LA	0,0000	0	237	237	119	192286	192405	INFINITY	0,0006	INFINITY
MPF	0,2990	83	154	237	36257	156148	192405	0,6198	-0,2223	0,8421
Dist to road (m)										
0-100	0,4484	160	78	238	72447	117477	189924	0,5667	-0,6352	1,2019
>100-300	0,1809	46	192	238	51688	138236	189924	-0,3422	0,1029	-0,4451
>300-600	0,1196	14	224	238	23805	166119	189924	-0,7565	0,0733	-0,8298
>600-1000	0,2510	18	220	238	14574	175350	189924	-0,0145	0,0012	-0,0157
>100-1500	0,0000	0	238	238	15009	174915	189924	INFINITY	0,0823	INFINITY
>1500-2100	0,0000	0	238	238	12227	177697	189924	INFINITY	0,0665	INFINITY
>2100	0,0000	0	238	238	174	189750	189924	INFINITY	0,0009	INFINITY
Dist to river (m)										
0-50	0,1910	48	152	200	47457	131924	179381	-0,0974	0,0328	-0,1303
>50-100	0,2762	96	104	200	65586	113795	179381	0,2722	-0,1988	0,4710
>100-150	0,2840	39	161	200	25917	153464	179381	0,2999	-0,0609	0,3607
>150-200	0,1591	12	188	200	14246	165135	179381	-0,2804	0,0209	-0,3012
>200-250	0,0897	5	195	200	10528	168853	179381	-0,8534	0,0352	-0,8886
>250-300	0,0000	0	200	200	10432	168949	179381	INFINITY	0,0599	INFINITY
>300-400	0,0000	0	200	200	5047	174334	179381	INFINITY	0,0285	INFINITY
>400	0,0000	0	200	200	168	179213	179381	INFINITY	0,0009	INFINITY

Note: Apprehension about $Lpix_i$ and other abbreviations can be seen in Subsection 3.2.2.

Table 9 shows the calculation results from Eq. 3 and 4. The W+ (positive weights), which explain importance of presence, can have a positive or negative value. A positive value means the presence of a class is favorable for the landslide occurrence. The larger W+ is, the higher the positive correlation is. On the other way, if the W+ gives negative value it means the class is not favorable.

The W-, negative weights that deal with absence, also has positive and negative value. Positive W- means the absence of the factor is favorable for the occurrence, whereas negative W- means the absence for the class is unfavorable. Another important issue is about the nearness to 0. If a class has value around 0, that class could be considered has no or less relation with the occurrences. In contrary, if a class has big value, that class it is more related with the occurrences.

Bonham-Carter (1994) also noted that subtraction of W+ with W- would give Contrast (C), a measure of correlation. This notation shows spatial association between a class and landslide occurrence. Positive contrast draws positive association (positively correlated) and negative contrast draws negative association (negatively correlated). If W+ = W- = 0 means there is no correlation between the class and occurrence (Neuhauser and Terhorst, 2007). In a positive correlation, it is assumed if the area of the class increase, number of landslide occurrences also increase. Otherwise, in negative correlation, if the area increases, number of occurrences decrease. If there is no occurrence in a class ($Lpix_i$ = 0), then it causes W+ becomes undefined/infinity, for example for water bodies class in land use factor or classes with buffer more than 2.100m in distance to road factor. In the case of C analysis, that value gives no indication of correlation.

In slope, moderately and steep class have positive correlation with landslide, but gently slope, undulating and very steep class have negative correlation. Settlement area has positive correlation with landslides, which could be interpreted that the increasing number of settlement area can influence landslides to occur more often. All classes with positive C are the crucial causative classes and are likewise possible indicators for future landslides. On the other side, WoE analysis also shows that locally in this study, there some classes that are uncorrelated to landslide occurrences.

To deepen the discussion, it is also relevant to assess the relative importance of a factor i.e., positive C of a factor (not a class). Hence, the sum of all positive weight values (no matter from W+ or W-) is subtracted with the sum of all negative weight values (Neuhauser and Terhorst, 2007). As result, slope has C = 2,1909; aspect 2,6855; topographic shape 1,7737; curvature 0,5522; lithology 7,3024; land use 2,5760; distance to road 2,6422; and distance to river has C = 2,2412. These values conclude that based on WoE assessment, lithology is the most influencing factor, followed by aspect, distance to road, land use, distance to river, slope, topographic shape and the least is curvature.

4.2.3. Normality test result

The straightforward assessment of skewness (measures of symmetry) and kurtosis (measures of flatness of the distribution) from all predictor variables shows a situation that the datasets are generally not following the ideal traditional condition of normal distribution at which skewness is 0 and kurtosis is 3 (Table 10). A Q-Q plot (quantile-quantile plot) was done to show a more convenient assessment graphically. This plotting compares a quantile of dataset from normal target. If skewness is > 0 (positive skew) the tail of the histogram extends to the right; the mass of the distribution is concentrated on the left of the figure. Lithology factor shows this situation, for example; and the Q-Q drives the point eminently. On the other way, as shown by land use variable, the skewness is < 0 (negative skew), means the tail tends to the left and the mass of the distribution is concentrated on the left. Annex 2 explains this deeper.

Table 10. Descriptive analysis of the predictor variables (using original values)

Predictor	N	Minimum	Maximum	Mean	Std. Deviation	Skewness		Kurtosis	
						Stat	S.E	Stat	S.E.
Slope	177596	,0410404	287,742300	35,2014288	24,791978496	1,910	,006	7,641	,012
Aspect	177596	,0009087	359,995800	224,3941658	100,51940587	-,862	,006	-,309	,012
Curvature	177596	-20,85386	15,7820400	,0055026773	1,0059974917	-1,032	,006	26,226	,012
Toposhape	172153	,00000	,63920	,2557415	,21363775	1,167	,006	-,476	,012
Lithology	172153	,00000	,405921	,06115611	,051386602	4,151	,006	22,390	,012
Landuse	172153	,00000	,500414	,18298872	,143569028	,485	,006	-,552	,012
Dist to road	177634	,00000	4890,00000	676,3035062	994,58549180	1,860	,006	2,768	,012
Dist to river	170958	,00000	948,68330	126,7420920	109,38623615	1,423	,006	2,754	,012

4.2.4. Correlation

This study uses bivariate pearson correlation to check interdependence among the predictor variables. Generally, independence intuitively means that the occurrence of one event makes it neither more nor less probable than the other occurrences. The departure is shown by degree of correlation, and in Pearson analysis, it is called Pearson coefficient/correlation (Pearson product-moment correlation coefficient). The coefficient shows a linear relationship.

The analysis works by dividing the covariance of two variables by the product of their standard deviation. This study uses 2-tailed probabilities in the significance test because the direction of association is not known in advance. If the value approaches 0, there is less of relationship (closer to uncorrelated or closer to be independent). Value 1 shows a perfect positive correlation; and -1 shows a perfect negative correlation. It means the value between -1 and 1 indicates the degree of correlation. The closer the value to either -1 or 1, the stronger the correlation is. If the significance level (p-value) is relatively large (more than the given limit, usually

0,05) then correlation is not significant or it shows the independency between the two variables.

Table 11. Result of bivariate pearson analysis

		Slope	Aspect	Curva-ture	Topo-shape	Litho-logy	Land use	Dist toroad	Dist toriver
Slope	Pearson Correlation	1	-,058**	,002	,003	,072**	-,223**	,338**	,005
	Sig. (2-tailed)		,000	,407	,248	,000	,000	,000	,081
	N	177596	177596	177596	122540	122540	122540	177140	121615
Aspect	Pearson Correlation	-,058**	1	-,006*	,003	-,101**	-,038**	,114**	,008**
	Sig. (2-tailed)	,000		,017	,353	,000	,000	,000	,007
	N	177596	177596	177596	122540	122540	122540	177140	121615
Curva ture	Pearson Correlation	,002	-,006*	1	-,005	,003	-,009**	,006*	,001
	Sig. (2-tailed)	,407	,017		,065	,311	,001	,011	,721
	N	177596	177596	177596	122540	122540	122540	177140	121615
Topo shape	Pearson Correlation	,003	,003	-,005	1	,010**	-,009**	-,003	,010**
	Sig. (2-tailed)	,248	,353	,065		,000	,000	,334	,000
	N	122540	122540	122540	172153	172153	172153	122483	164963
Litho logy	Pearson Correlation	,072**	-,101**	,003	,010**	1	,081**	-,165**	,020**
	Sig. (2-tailed)	,000	,000	,311	,000		,000	,000	,000
	N	122540	122540	122540	172153	172153	172153	122483	164963
Land use	Pearson Correlation	-,223**	-,038**	-,009**	-,009**	,081**	1	-,451**	,068**
	Sig. (2-tailed)	,000	,000	,001	,000	,000		,000	,000
	N	122540	122540	122540	172153	172153	172153	122483	164963
Dist toroad	Pearson Correlation	,338**	,114**	,006*	-,003	-,165**	-,451**	1	-,027**
	Sig. (2-tailed)	,000	,000	,011	,334	,000	,000		,000
	N	177140	177140	177140	122483	122483	122483	177634	121476
Dist Toriver	Pearson Correlation	,005	,008**	,001	,010**	,020**	,068**	-,027**	1
	Sig. (2-tailed)	,081	,007	,721	,000	,000	,000	,000	
	N	121615	121615	121615	164963	164963	164963	121476	170958

**. Correlation is significant at the 0.01 level (2-tailed).
*. Correlation is significant at the 0.05 level (2-tailed).

Table 11 shows statistically that some pair of predictor variables are dependent and the correlation is significant, for example between slope and land use, aspect and lithology, lithology and distance to road and others that are signed. On the other side, there are also pairs that show insignificant relations (means independent) such as slope and curvature, aspect and topographical shape, topographical shape and distance to road, and the others that do not have signs.

The existing significance correlation or highly correlated condition (having multicollinearity) makes difficulties to identify the unique contribution of each variable in predicting the dependent variable because the highly correlated variables are predicting the same variance in the dependent variable. Because of that, the steps taken to handle this problem might be removing one of the highly correlated variables, creating "composite" of those variables, or leaving as is by considering that in the regression the most important is the overall result of combined predictors, not the unique effect of each predictor. The highly correlation is indicated by value above 0,75 or 0,80.

In addition to bivariate pearson, this study also conducts collinearity test by assessing tolerance and VIF (Variance Inflation Factor, the reciprocal of tolerance). Multicollinearity exists when tolerance is below 0,1 and VIF is greater than 10 or an average much greater than 1. In the same sense, tolerance close to 1 shows little multicollinearity, whereas close to 0 suggests that multicollinearity may be a threat (Williams, 2009b).

Table 12. Collinearity analysis

Predictor variable	Collinearity statistics	
	Tolerance	VIF
Slope	,868	1,152
Aspect	,965	1,036
Curvature	1,000	1,000
Toposhape	,999	1,001
Lithology	,911	1,098
Landuse	,763	1,311
Disttoroad	,676	1,478
Disttoriver	,998	1,002

Table 11 shows that the highest pearson correlation is 0,451 which belongs to the relationship between land use and distance to road. The highly correlation is proved also by the tolerance value of those two (0,763 and 0,676 as the two lowest) in Table 12. The values there are still below the highly correlation threshold, which indicates no threat of multicollinearity from the usage of all predictor variables. Therefore, in this study multicolliearity is not an issue.

4.2.5. Logistic regression model

From the normality test that had been done before (Subsection 4.2.3), the datasets shows non-normal distribution. As the theory mentions that normal datasets will behave better and show better properties, the original values of continuous variables was transformed by using formula: (data)-mean (data)/standard deviation(data).

As discussed before in Chapter 3, this study tests two dataset samples and chooses one as the best model for logistic regression. There are 448 cases (224 landslide pixels and 224 non-landslide pixels). Below the test summary and the complete results can be seen in Annex 3 (for dataset 2).

Table 13. Model summary of datasets

Model summary				
Dataset	-2 Log likelihood	Cox & Snell R Square	Negelkerke R Square	Overall percentage correct
1	303,042	0,508	0,678	83,7
2	235,256	0,577	0,770	90,4

Dataset 1 = non landslide pixel is randomly selected by software
Dataset 2 = non landslide pixel is smoothly distributed

In Table 13, the deviance (-2 Log Likelihood) measures how poor the model predicts the decisions: the smaller the statistic the better the model fits the data (William, 2009a). R square is the square of correlation between the model's predicted values and the actual values. The value ranges from 0 to 1. The bigger the value resulted, the greater the magnitude of correlation, regardless of whether the correlation is positive or negative (UCLA Academic Technology Services, 2008). The magnitude of correlation shows how good the prediction model created.

The overall percentage correct is an overall success rate, calculated based on the sensitivity of prediction (the correct prediction of event did occur) and the specificity of prediction (the correct prediction of event did not occur). This gives the percent of cases for which the dependent variables was correctly predicted (how good the agreement between observed and predicted). The higher the percentage exists, the better the prediction runs. Based on those criteria, dataset 2 is opted

Table 14 shows logistic regression process results. Constant or intercept is the value of z when the value of all predictor variables is zero. B value (coefficient of the constant) is the indicator of contribution embedded to each predictor variable that is going to be used in linear combination (z in Eq. 6). The coefficient could have negative, zero or positive value. A positive regression coefficient explains that the predictor variable increases the probability, while a negative regression coefficient asserts that the variable decreases the probability. A large value, which does not matter positive or negative, shows that the factor strongly influences the probability. Cases for this are lithology, land use and topographical shape. A near-zero coefficient indicates that the causal factor has little influence on the probability.

Table 14. Result of backwise LR

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1	Aspect	-,274	,174	2,473	1	,116	,761
	Slope	-,566	,232	5,970	1	,015	,568
	Disttoroad	,197	,228	,748	1	,387	1,218
	Disttoriver	-,398	,185	4,620	1	,032	,672
	Lithology	13,754	3,533	15,156	1	,000	940665,829
	Landuse	3,562	1,589	5,023	1	,025	35,220
	Curvature	2,697	,363	55,158	1	,000	14,835
	Toposhape	-3,251	,790	16,944	1	,000	,039
	Constant	,151	,568	,070	1	,791	1,163
Step 2	Aspect	-,246	,170	2,096	1	,148	,782
	Slope	-,510	,220	5,365	1	,021	,600
	Disttoriver	-,384	,183	4,404	1	,036	,681
	Lithology	12,745	3,218	15,686	1	,000	342754,390
	Landuse	3,068	1,473	4,337	1	,037	21,491
	Curvature	2,665	,363	53,984	1	,000	14,372
	Toposhape	-3,189	,785	16,487	1	,000	,041
	Constant	,294	,541	,295	1	,587	1,342
Step 3	Slope	-,503	,218	5,308	1	,021	,605
	Disttoriver	-,393	,183	4,634	1	,031	,675
	Lithology	13,487	3,168	18,118	1	,000	719695,188
	Landuse	3,355	1,460	5,281	1	,022	28,642
	Curvature	2,620	,359	53,211	1	,000	13,731
	Toposhape	-3,220	,784	16,868	1	,000	,040
	Constant	,201	,536	,140	1	,708	1,222

S.E. = Standard errors associated with the coefficients

df = This column lists the degrees of freedom for each of the tests of the coefficients

Exp(B) = The odds ratios for the predictors

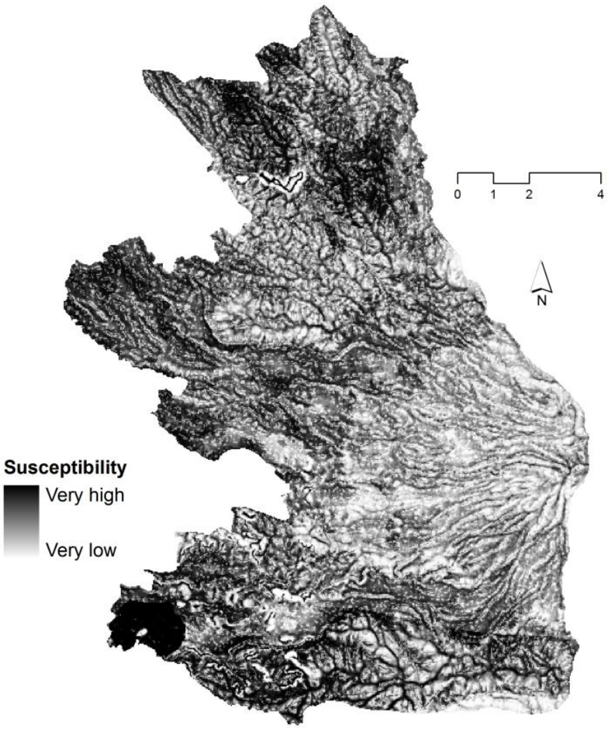
Wald and Sig. = The Wald chi-square value and 2-tailed p-value

At the moment, there were three steps in the backwise LR method. In first two steps, there was elimination process for variables that have significance (sig.) higher than 0,05 limit (critical p-value). In the step 2, distance to road was eliminated and in the step 3, aspect was eliminated. Therefore, at the end of the process, there are six selected predictor variables that give significant influence to the model. Those are slope, curvature, topographical shape, lithology, land use, and distance to river. Based on their significance values, slope, land use, and distance to river have low significance. However, the calculation still includes these variables to build model.

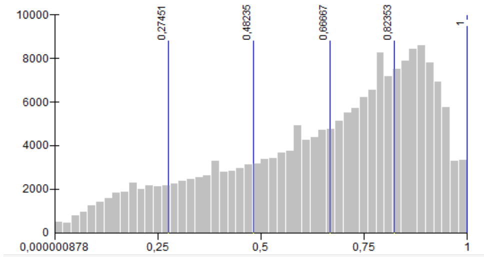
This selection leads the usage of only six factors in statistical logistic regression model. Based on the coefficient from step 3, z (Eq. 6) was calculated as follow:

$$z = 0{,}201 + 0{,}503slo + 2{,}620curv - 3{,}220tpshp + 13{,}487lit + 3{,}355lu - 0{,}393d.river$$

Then, p was calculated using Eq.5 and the LSIs is shown in Figure 18a:



Min	0
Max	1
Mean	0,64781
SD	0,24522



(a) (b)

Figure 18. (a) Landslide susceptibility index of statistical model (LSIs), and (b) Histogram of the map

The LSIs histogram (Figure 18b) shows that the dataset is not normally distributed so this study uses natural breaks (Jenks) method to classify into five classes. The LSMs is shown in Figure 19. Range value for each susceptibility class is 0 - 0,27451 (very low), 0,27452 - 0,48235 (low), 0,48236 - 0,66667 (moderate), 0,66668 - 0,82353 (high), and 0,82354 - 1 (very high).

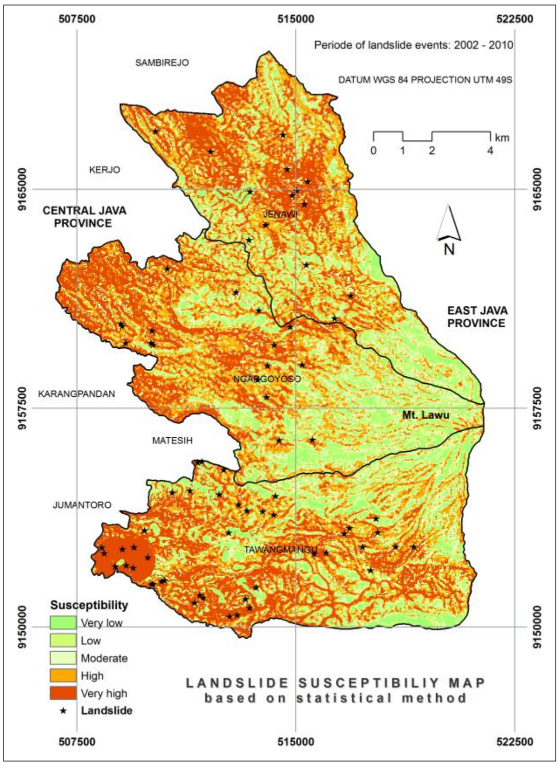


Figure 19. LSM based on statistical method

Table 15. Area of LSMs class

No	Class	Hectares	Km^2	%
1	Very low	1853,55	18,53	10,68
2	Low	2489,67	14,89	14,35
3	Moderate	3273,39	32,73	18,87
4	High	4374,41	43,74	25,21
5	Very high	5360,36	53,60	30,89

According to the result (Table 15), very high susceptibility area occupies 30,89% and becomes the largest area. With high class (25,21%), both covers more than half of the whole area. Very low class becomes the smallest area with 18,53 km^2 (10,68%). It is clear, as shown in Figure 19, that areas where landslides did not take place, such as in nearby Mount Lawu, the susceptibility is low or very low. Most susceptible areas are mainly located in the western and northern part following the recorded landslides distribution.

4.3. Artificial Neural Network model

ANN uses the same sample dataset with the one that had been chosen in logistic regression. The original and normalized dataset (by formula (data)-mean (data)/standard deviation (data)) were tested in advance. As result, the normalized dataset give better outcome (based on percent correct prediction), so it was chosen in the process.

Prior setting up of parameter must be determined while running ANN. To get optimum result, which is indicated by correct classification value, the setting process was done three times by changing the partition and the order of predictor variables. In its training process, ANN is sensitive to variable order because every different order gives different pattern of initial synaptic values, which can affect the whole process. Table 16 shows the neural network setting in this study.

Table 16. ANN setting

Partition	50% training (6) 33,3% test (4) 16,67 holdout (2)
Type of training	Batch
Optimization Algorithm	Scaled conjugate gradient
Training:	
- Initial Lambda	0,00000005
- Initial Sigma	0,00005
- Interval center	0
- Interval offset	+-0,5
Stopping rules:	
- Max training epoch	Automatically
- Max training time	15 minutes
- Min rel. change in train error	0,0001
Data to use computing pred. error	Automatically

ANN could divide samples into training, testing and holdout partition. A network will generally be most efficient if testing samples are smaller than training samples. Because of that, this study implements the partition architecture as shown by Table 16. The third dataset, holdout partition, is an independent dataset. It gives the "honest" estimate of predictive ability, as holdout data is not used to build the model in the previous steps. Small percentage of holdout incorrect prediction indicates that the network provides better result.

This study applies batch training module when employing information from all records in the training dataset. The module updates the synaptic weights after passing all training data record. It is preferred because it directly minimizes the total error and can update the weights many times until the stopping rule is met. For the usage of big dataset, batch training method is not really appropriate because of time consuming process. However, this study only uses small dataset, so batch method is more useful rather than online (use one record at a time) or mini-batch (use group record at a time). The online method is useful for large dataset whereas mini-batch is for "medium-size" dataset. ANN PASW names discrete variables as factors and continuous variables as covariates (Table 17).

Table 17. Network information

Input Layer	Factors	1	Lithology
		2	Landuse
		3	Toposhape
	Covariates	1	Slope
		2	Aspect
		3	Curvature
		4	Disttoroad
		5	Disttoriver
	Number of Units[a]		24
	Rescaling Method for Covariates		Normalized
Hidden Layer(s)	Number of Hidden Layers		1
	Number of Units in Hidden Layer 1[a]		5
	Activation Function		Hyperbolic tangent
Output Layer	Dependent Variables	1	Landslide
	Number of Units		2
	Activation Function		Softmax
	Error Function		Sum of Squares

a. Excluding the bias unit

While using pseudo-probability values in determining landslide susceptibility, the whole area or the whole pixels should be fed into the network using the same architecture (i.e., repeat running the model again). The acquired pseudo-probability values are two values, for example (0,002; 0,998) for each pixel. The first values represent no-landslide pseudo-probability and the second values represent landslide pseudo-probability. The first values were subtracted from the second to gain susceptibility values. Those values then were converted into raster grid to build map. However, the result is poor (Annex 4). The susceptibility index map seems "insensible" because it only gives two values (near 1 = very high class and near 0 = very low class). Because this network uses all pixels, probably the usage of so-unbalanced numbers of landslide and non-landslide pixels has big impact in the ANN modeling.

Considering the situation above, this study then uses the network that employs sample dataset (equal number of landslide and non-landslide case) and its variable importance to build landslide index. As shown in Table 18a (and then, in Figure 21), according to this network, the model shows more sensible result. The hold out samples incorrect prediction is 7,6%, which means the total correct prediction is 92,4%. Holdout accuracy for non-landslide pixels is 97%, whereas for landslide pixels is 89,1% (Annex 5). Table 18b displays values that show the importance/contribution of every predictor variable.

Table 18. Results of ANN process (a) Model summary; (b) Predictor importance

(a)

Training	Sum of Squares Error	15,228
	Percent Incorrect Predictions	1,4%
	Stopping Rule Used	1 consecutive step(s) with no decrease in error[a]
	Training Time	00:00:00,326
Testing	Sum of Squares Error	20,517
	Percent Incorrect Predictions	5,5%
Hold out	Percent Incorrect Predictions	7,6%

Dependent Variable: Landslide

a. Error computations are based on the testing sample.

(b)

Predictor	Importance	Normalized Importance
Lithology	,163	54,9%
Landuse	,120	40,7%
Toposhape	,185	62,4%
Slope	,102	34,5%
Aspect	,049	16,7%
Curvature	,296	100,0%
Disttoroad	,045	15,2%
Disttoriver	,040	13,6%

In GIS modeling, the interval of predictor variables was determined by their five classes' natural break and given sequential value from 1 to 5. This approach has an advantage in the term that the process did not subjectively discretize the variable (still in the concept "data-driven"). Because ANN does not have specific formula to predict real probability that can connect directly to a GIS environment such so in logistic regression (i.e., Eq.5), the model is created based on a linear equation modeling/overlay model in GIS (summing up all weighted layers).

To model the formula in correct way, the values of distance to river and distance to road variables need to be inversed. It is due to a situation that landslides potential occurrences are not following the increasing distance measure but the decreasing proximity measure. Hence, the closest class was given value 5, the next was 4, and so forth. This process is crucial to be done. Otherwise, the result will be misleading.

From the analysis, could be seen that curvature is the most important variable with importance value 0,296; then followed by topographical shape (0,185), lithology (0,163), and so forth (Table 18b). Following Eq. 1, ANN model could be mathematically presented as below and the index map is shown in Figure 20a:

$$LSI_{ANN} = 0{,}102slo+0{,}049asp+0{,}296curv+0{,}185tpshp+0{,}163lit+0{,}120lu+0{,}045d.road+0{,}040d.river$$

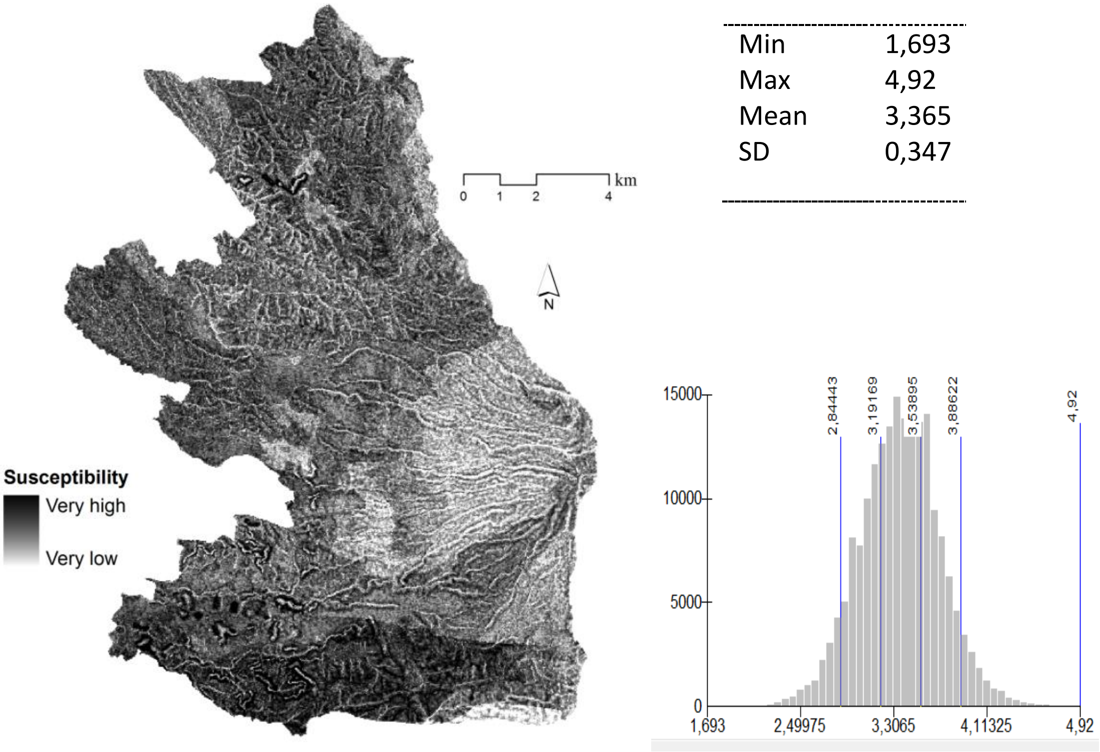


Figure 20. (a) Landslide susceptibility index of ANN model (LSI_{ANN}), and (b) Histogram of the map

LSI_{ANN} histogram in Figure 20b displays that the dataset is normally distributed so this study uses standard deviation method to classify the map into five classes. The LSM_{ANN} can be seen in Figure 21. According to ANN (Table 19), very high susceptibility areas occupy 6,08% of the area and become the smallest class. Together with high class (24,16%) that becomes the second largest area, both cover around 30,24%. The largest area 69,08 km^2 (7,88%) is moderate class. Very low class is the second smallest class, occupies 6,67% of the area. Most susceptible areas are mainly located in the southern part following the landslides distribution.

The result also shows that lithology formation density is influential. As can be seen in Figure 21, some high and very high classes (in the southern part) are located in

Sidoramping Lava and andecite formation. From the density analysis, already known that andecite is the densest class and Sidoramping Lava is the third densest class.

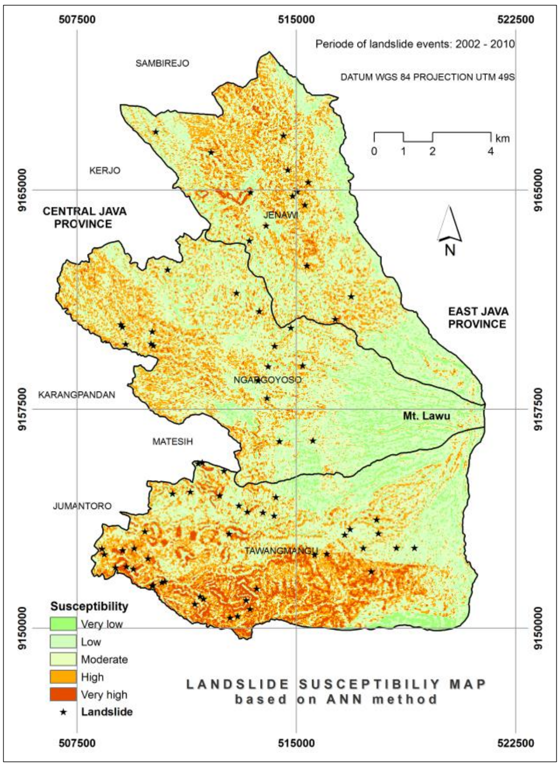


Figure 21. LSM based on ANN method

Table 19. Area of LSM_{ANN} class

No	Class	Hectares	Km^2	%
1	Very low	1156,49	11,56	6,67
2	Low	4039,79	40,39	23,28
3	Moderate	6908,06	69,08	39,81
4	High	4191,31	41,91	24,16
5	Very high	1055,72	10,55	6,08

4.4. Comparison

After getting result for all used methods, it is apparent that these three methods give different result quantitatively. One reason for this is due to the difference of contribution of each variable. Therefore, it is good to compare the results, the contribution of variables, as well as the characteristic of each method that inevitably casts on the difference.

4.4.1. Results comparison

Based on Table 8, Table 15, and Table 19 about LSM result tabulation, a column chart was created and shown in Figure 22.

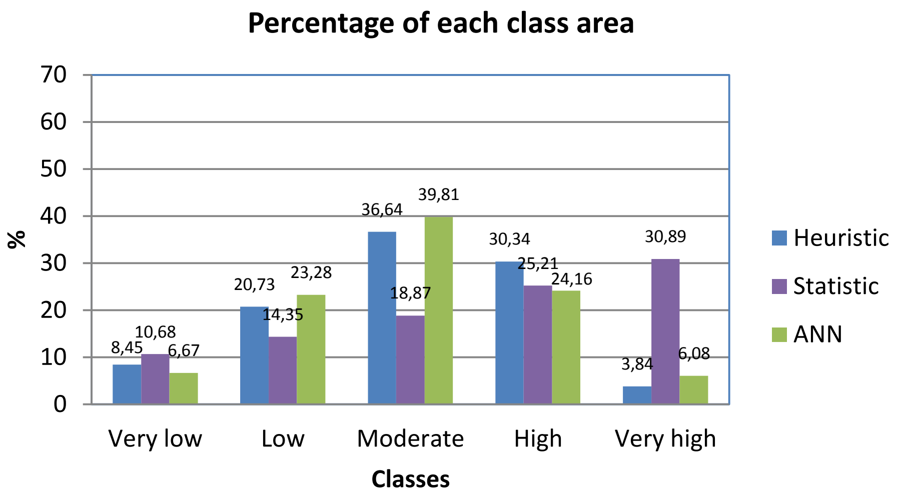


Figure 22. Comparison of each class from three methods

The figure shows the results difference, for example, the largest area in very low class comes from statistical logistic regression; in high class the largest area comes from heuristic method. However, it does not demonstrate superiority. Although the statistical logistic regression has the largest area for high and very high class (25,24 + 30,89 = 56,13%), that outcome does not automatically state that the method is the best in prediction. The percentage just explains that the process has found out that 56,13% of the study area is high and very high susceptible according to heuristic method.

Some visual findings could be discussed about the effect of landslide inventory usage. It seems clear that in data-driven method results (Figure 19 and Figure 21), landslide occurrences give significant effect: the less the landslides in any certain areas the less susceptible such areas to be. For example, in the area near Mount Lawu's peak where almost no landslide took place, the susceptibility class is largely low or very low. It is different to the outcome from heuristic method (Figure 17). Since there is no involvement of landslide occurrence, no clear indication about landslide record influence in the map. Different from the other two, according to heuristic method, the area near Mount Lawu in fact belongs to high and very high susceptibility class. That outcome is logical because such area has steep and very steep slope gradient, and specifically for heuristic method slope becomes the most influential factor. A visualization from landslide susceptibility maps in single frame, which is using the SRTM 30m aspect and elevation as background, could be seen in Annex 6.

The variable importance also could be compared. However, in statistical logistic regression, because the modeling equation is different and not like the other methods that have all contribution values equal with 1, its importance could not be compared quantitative-graphically with the others. The importance only could be compared by ranking sequentially.

Table 20. Importance ranking of variables

Ranking based on importance of contribution	Heuristic	ANN	Statistical logistic regression
1	Slope	Curvature	Lithology
2	Lithology	Topo shape	Land use
3	Land use	Lithology	Topo shape
4	Topo shape	Land use	Curvature
5	Distance to road	Slope	Slope
6	Distance to river	Aspect	Distance to river
7	Curvature	Distance to road	Aspect**
8	Aspect	Distance to river	Distance to road*

*Omitted in the first step
**Omitted in the second step

Table 20 resumes that variables ranking in each method is not the same. According to heuristic method, statistical logistic regression, and ANN, respectively the most significance variable is slope, lithology and curvature. These dominant factors give the highest effect to the model. In heuristic method for example, as seen in Figure 23 and Figure 17, slope influence is clearly appearing. The area having high slope gradient such as the one nearby the mountain, mostly belong into high or very high susceptibility class.

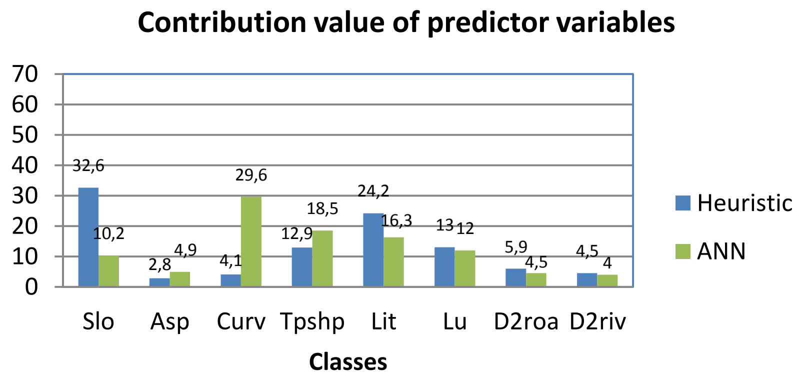


Figure 23. Variables comparison between Heuristic and ANN method

Although each method gives different importance order, there is a trend of importance. As instance, lithology and topographical shape always exist in the top positions whereas aspect and distance to river always being in the bottom. To assess them completely but without looking at the original value, a simple weighting process was done by giving them sequential values: 8 for the 1st rank and 1 for the lowest rank (8th), and then summing the same variables up. The variable having highest value is considered as the most influential variable while the variable having small value as the less influential variable. As result, lithology becomes the most influential, followed by land use and topographical shape (both have the same score), slope, curvature, distance to road, distance to river, and aspect, respectively. Furthermore, by looking back to the result from WoE analysis that also specifically examines the influence using landslide inventory (see Subsection 4.2.2), this study also finds out that lithology is being the most influential factor.

4.4.2. Methods comparison in landslide susceptibility assessment

Heuristic method limitation is situated on its subjectivity. It is certainly known that heuristic method contains subjectively approach when applying techniques to score and rank. Because of that, results from many researchers could be different one another, depend on their references, expertise and knowledge. It brings a consequence that in order to get finer result, a clear understanding of causal factors' natural behavior and additional module (e.g., the decision support analysis) is necessary. Another thing, for an intensive heuristic research, an advisable reference is the one that bears similar geo-environmental condition with the area of interest. Otherwise, the information about causal factors could be bias in part.

Concerning data availability, heuristic method has benefit in flexibility because it still could be applied even if there are no landslide records in the area of interest. If an area has representative landslide records, the better option is using statistical and artificial method as these methods are more quantitative than heuristic method.

In landslide susceptibility assessment, because landslide inventory map as a response variable is showing dichotomic phenomena (landslide and non-landslide), logistic regression is appropriate. Statistical logistic regression has additional but convincing eminence concerning variable assessments: sturdy methods to assess the variables' behavior (e.g., normality, collinearity), a clearance process of variable selections, and its capacity to select the variables based on significance. It makes this method more robust than heuristic method in one side, but also less flexible on the other side because it needs a rigorous statistical basis to run the analyses. In case this statistical basis assessment is not fulfilled, the results could be not optimum. That sense makes an understanding, to get better results from statistical logistic regression, a statistically proper data treatment is important.

Statistical logistic regression and ANN can handle discrete and continuous data or both at the same time without any problem. In that case, heuristic method can only deal with discrete data, so continuous variables should be discretized into categories.

ANN is flexible in term that it can determine the form of relationship between predictor variables and response variables during the learning process. If a linear relationship is appropriate, the result should closely approximate that of the linear regression model. If a non-linear relationship is more appropriate, the network will automatically approximate the "correct" model structure (SPSS Technical Support, 2010). However, because of that flexibility, ANN also has trade-off about model interpretability. Its synaptic weights and error propagation, as well as how it determines the relationship between landslide influencing factors and landslide occurrences are not easily interpretable. Thus, in this context, it would be more reliable to use statistical model if the interpretability is necessary to explain. If one just wants to obtain optimum model more quickly, ANN is reliable.

In this study, ANN employs the variable importance derived from the network, in a linear equation model when creating landslide susceptibility map. It makes the process behaves more closely to heuristic model rather than to logistic regression that has its own equation (sigmoid) for calculating probability. In some sense, it could be considered that the process is not generally following the ANN prediction schema that, following its activation function, could produces end result as 0 to 1 values. Nevertheless, in other sense, it is sensible because it uses "the influence value" of every variable in building the model, and specific in this study, as another approach it could improve the performance.

All methods could be implemented to all scale. However, according to Dai et al. (2002), there is a particular scale range that susceptibility mapping process using data-driven methods could be more advantageous. The range is 1:10.000 – 1:50.000. On that scale, it is possible to map out the occurrences of past landslides in detail and to collect sufficient information from supporting materials and activities such as from high resolution imagery and field surveys. To make the description more compact, Table 21 lists some equality and distinction.

Table 21. Comparison of each method

No	Characteristics	Heuristic	Statistical logistic regression	ANN
1	Analysis	Expert-driven	Data-driven	Data-driven
2	Weighting	Could be qualitative or semi-qualitative, trial and error	Quantitative	Quantitative
3	Scale	Applied in all scale, the detail depends on the smallest mapping unit	Applied in all scale. But more advantageous in 10.000 – 50.000 mapping scales (Dai et al. 2002)	Applied in all scale. But more advantageous in 10.000 – 50.000 mapping scales (Dai et al. 2002)
4	Landslide occurrences involvement	Does not require landslide occurrences record in modeling	Need landslide occurrences record as response variable	Need landslide occurrences record as response variable
5	Data treatment	Discretization of continuous variable into classes	Could handle continuous and discrete	Could handle continuous and discrete
6	Modeling (equation)	GIS model	Statistical model	GIS model (in PASW)
7	Coverage	Applied to all area coverage	Applied to all area coverage	Applied to all area coverage
8	Factor selection	Not applicable	Applicable, based on significance	Applicable (but, PASW does not provide the module)
9	Factor correlation	Not assessed	Assessed	Not assessed
10	Easiness	Easy to understand the process, but need expertise in scoring and weighting process to make the analysis reasonable	All process and contribution of each factor are reasonable and could be followed	Difficult to follow the internal process within the hidden layers (black-box nature)
11	Normality issue	Not really matter for traditional GIS. SMCE Ilwis applies normalization	Influential	Influential
12	Probability issue	Not applied	Applied completely	Could be applied as pseudo-probability

4.5. Success-performance

As discussed earlier in Section 3.4, this study uses degree of fit and ROC analysis to assess model performance. According to its characteristic, degree of fit is a spatial-based analysis (analyzing based on spatial matching between the resulted map and landslide events) while ROC is called a probability/statistical-based analysis (analyzing based on statistical classification).

Degree of fit analysis explains model performance by assessing relative error: the summation value of low and very low susceptibility class; and assessing relative success rate: the summation value of high and very high susceptibility class. The smaller relative error and the higher relative success rate, the higher the quality of the susceptibility map.

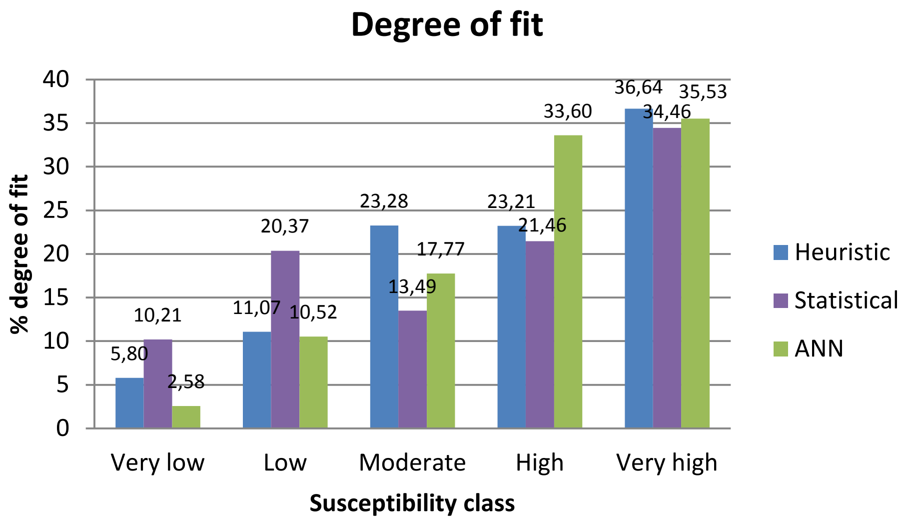


Figure 24. Degree of fit result

Figure 24 indicates that the relative error for heuristic, statistical and ANN is 16,87%; 30,58%; and 13,10%. The relative success rate is 59,86%; 55,92% and 69,13% respectively for heuristic, statistical and ANN. These values shows that, based on degree of fit, ANN performs better as it gives the lowest relative error and the highest relative success rate.

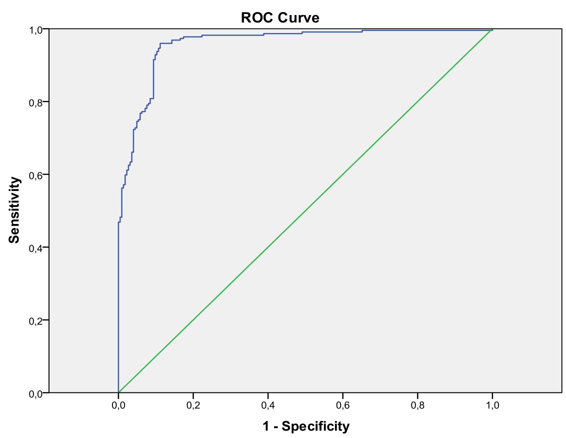


Figure 25. ROC curve plot of logistic regression

Table 22. ROC AUC of logistic regression

Area Under the Curve

Test Result Variable(s):Predicted probability

Area	Std. Error[a]	Asymptotic Sig.[b]	Asymptotic 95% Confidence Interval Lower Bound	Asymptotic 95% Confidence Interval Upper Bound
,959	,009	,000	,941	,976

a. Under the nonparametric assumption
b. Null hypothesis: true area = 0.5

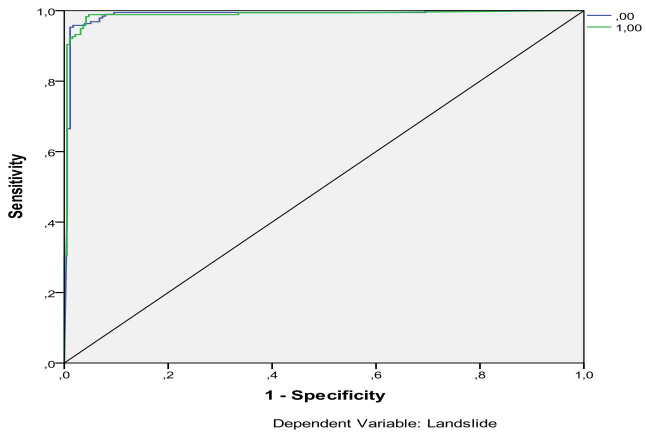


Figure 26. ROC curve plot of ANN

Table 23. ROC AUC of ANN

Area Under the Curve

		Area
Landslide	,00	,988
	1,00	,988

As discussed earlier in Section 3.4., and then shown in Figure 25 and Figure 26, to acquire ROC curve, the sensitivity is plotted against “1 – specificity”. Area under curve can serve as global accuracy statistic of a model. Its value can range from 0,5 to 1. Value 0,5 shows random prediction, represented by the diagonal straight line and value 1 shows a perfect prediction. The closer the value to 1 the better the model. The AUC results (Table 22 and Table 23) demonstrate that ANN model performs better than statistical logistic regression model. Its line is closer to upper-left corner and its AUC value is higher (0,988) than logistic regression (0,959). This value can be interpreted that ANN model has 98,8% all possible pairs of cases are assigned correctly, whereas logistic regression has 95,9%.

ROC analysis strengthens the earlier findings from degree of fit. From the result given by degree of fit and ROC analysis, this study shows that the ANN Multi-layer Perceptron model performs better than the other methods.

4.6. Additional discussion

After gaining the results, although previously there is discussion in the end of every result, it is going to be good to have critical and specific discussion about some substances.

In data-driven methods, the condition of landslide inventory affects the results. Figure 4 visualizes landslide events distribution in the study area. The figure depicts that in the area near Mount Lawu’s peak (the western part), no data available about landside occurrences. The area is located on high elevation part. A critical question could be promoted regarding this: are there really no landslides or the landslides are simply not recorded? This is important because if the latter becomes the case, the results could have a systematical error. In the field, the area is covered by dense forest. Naturally, very scarce landslides take place over dense forest. On the other side, the area is a remote area; no human access (i.e., roads or settlements) there. If landslides occur, probable nobody could record them. Therefore, this study could only assume that possibly there are events but because they are small, infrequently and inaccessible, there are no written record on them. It could be one source of the uncertainty in this study.

The next thing that must be noticed is about the sample size. By having only 74 events under the area 174,13 km^2, this study could be categorized as rare-event landslide susceptibility assessment. Rare-event data makes a situation that binary dependent variables dozens to thousands of times fewer 1s than 0s. As noted by Van den Eeckhaut et al. (2006), when modeling the events probably a factual result could not be reached, because of overestimation for example.

This rare-event case makes this study cannot conduct predictive-power analysis on data-driven methods in assessing model performance. Hence, the assessment of model performance is not really optimal. As consequence, the sense “better model” cannot be globally generalized and should be framed inside the concept of how well or successful the models describe the phenomena (i.e., the available landslide events) that happened locally in the study area and at the corresponding time. In other circumstances (e.g., different area of interest, different landslide event time frame) which model gives better performance probably different.

Regarding causal factors, Fell et al. (2008) mentioned that at least there were two aspects that might be affecting the results: the usage of factors that in nature change in time but for practical matter had been assumed stabile, and dataset detail level. This study just takes a look for static land use, although in fact a dynamic condition (i.e., land use change) is more influential.

Dataset detail level (i.e., scale or resolution) can affect results, in case of discriminatory power. So, especially in a GIS-based spatial modeling circumstance, datasets having same detail degree are more favorable. That issue is devised in this study. Only lithology has lower scale than others. Spatially, lithology will have bigger mapping unit than others. In some sense, related with spatial-matching analysis (e.g., density and WoE), probable that situation affects the analysis result.

Another thing that could be discussed is about normalization process. Since the datasets come from different unit of measurement, normalization becomes an important part in this study. Besides as an effort to make data closer to normal so they can behave better in the modeling, this process also makes all data more comparable. Although it has been recognized that logistic regression and ANN can compromise with normality issue, this study has proven that it is a matter in getting better model performance, especially to logistic regression that more sensitive to datasets behavior. For example, in degree of fit analysis using the original datasets, logistic regression model gives poor result: relative error 44,42% and relative success 32,71%. Then, the normalization was applied. Although the result shows there are several factors remain not normal, the normalization effort takes effect because some datasets are closer to normal than before. As result, the relative error decreases to 30,58% and relative success increases to 55,92%. But, still this method is less competitive than the others because its statistical basis causes a less flexibility requirement of normality than the others (i.e., it demands normal data to perform better).

Based on what have been discussed before, although many efforts have been conducted to improve the quality (e.g., AHP implementation, multicollinearity test to avoid overfitting, normalization, three times withdrawal of equal-number binary response samples, and withdrawal of more training cases in multi-layer perceptron) it seems clear that the datasets are naturally embedded with uncertainty and characteristics that make the results could have imperfect part. This study does not deal much with the uncertainty of the datasets and analyses–or its solution, but for further study, this matter could be an important consideration.

CHAPTER 5 CONCLUSIONS AND RECOMMENDATIONS

Landslide susceptibility assessment and susceptibility zoning actually are just one part of disaster management. As a preventive medium to minimize landslides risk in the threatened area, these processes could be continued by other steps such as landslide risk mapping (which involve the life loss and property loss assessment) and its integration with land use planning and regional development. The susceptibility assessment in the Tawangmangu, Jenawi and Ngargoyoso Subdistrict in Karanganyar Regency using knowledge-based heuristic method and data-driven methods (statistical logistic regression and ANN) conclude some points as below:

1. The methods are applicable. The objectives of this study, which are formulated by a set of research questions, are fulfilled. Using eight influencing factors (slope, aspect, curvature, topographical shape, lithology, land use, distance to road and distance to river), each method applies specific way to assign weight and build the model. Heuristic method uses SMCE analysis, statistical logistic regression uses Backward LR, and ANN uses MLP back-propagation approach. As result, the most influencing factor in heuristic method, statistical logistic regression, and ANN is slope, lithology, and curvature, respectively. Totally, the most influential factor is lithology.
2. The study area was mapped into five landslide susceptibility classes: very low, low, moderate, high and very high class. According to heuristic method, the largest area is moderate (36,64%), followed by high (30,34%), low (20,73%), very low (8,45%) and very high class (3,84%). Logistic regression displays that the largest area is very high class (30,89%), followed by high (25,21%), moderate (18,87%), low (14,35%) and very low class (10,68%). ANN exhibits that moderate class (39,81%) became the largest area, followed by high (24,16%), low (23,28%), very low (6,67%) and very high class (6,08%).
3. Degree of fit analysis showed that ANN performs better that the other methods. The second is heuristic and the third is statistical logistic regression. According to ROC analysis, which is applied to data-driven methods, ANN (AUC 0,988) shows better performance than statistical logistic regression model (AUC 0,959).
4. Each method has its own characteristics, eminences and limitations. In short, heuristic method has more flexibility concerning free requirement of landslide inventory dataset, but also has limitation in its subjectivity. Data-driven methods are more robust in their analyses, but at the same time require more preliminary treatments for the variables. Some considerations could be implemented to improve the quality, such as proper references

basis and involvement of more quantitative weighting mechanism specific for heuristic method, correlation assessment, normalization, well-defined neural network setting, and proper selection of cases sample.

5. The models and their contribution value cannot be extrapolated or used to other regions because the methods use site-specific information to make prediction (zoning).

This study contains some limitations and drawbacks, which generally regard to data availability and uncertainty. Hence, continuing what have been discussed in Section 4.6, for further research below are some recommendations.

1. The involvement of more and time series of causal and triggering factors. Recognized that triggering factor (e.g., rainfall) is important; as noticed that landslide frequency becomes bigger in the rainy season (October-March). This factor may function not only as a complement for hydrological group but also as a way to add some temporal analyses. More factors, such as soil and its characteristic (type, depth, textures, and permeability) and fault proximity, would be beneficial because by having more comprehensive factors, the study could reckon all possible contribution from the factors.
2. It is recommended to have bigger number of landslides. Besides help avoiding uncertainty, more cases can deliver validation set to fulfill the need to assess not only model's success but also predictive-performance for data-driven models.
3. High resolution satellite imageries (SPOT 5, Quickbird, IKONOS, and so forth) from the corresponding years could be used in the further study as supporting materials to acquire the polygon form of landslide events. Landslides in original polygon feature are better than they are in point feature as polygon form could depict the real affected area.
4. Landslides have various types in nature; each type has its specific characteristics, material, and movement style (e.g., avalanches and flows advance at high speed and cover a wider area, while creep is so local and slow in speed). As consequence, the most representative models are the ones that assess every type individually. Hence, it is recommended to have various landslide types in landslide inventory map.
5. One common characteristic of individual grid-based analysis and small mapping unit is class dispersion. The same susceptibility classes are not always flocking together in the same area, so for further application such as land use planning, a generalization is indispensable and suggested. The generalization can be processed by following the most dominant class according to the desirable mapping scale.

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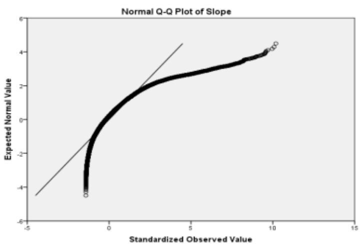
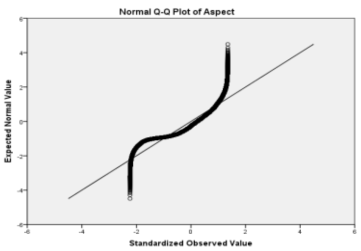
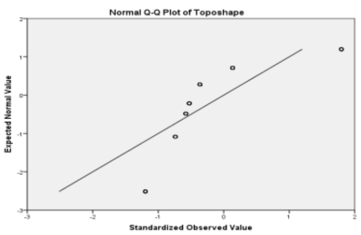
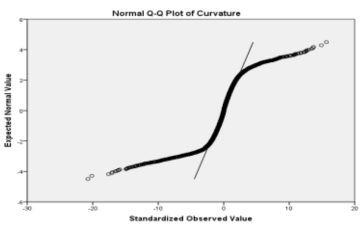
ANNEX 1. List of landslide events 2002 – 2010 in the study area

No	Subdistrict	Village	Time	Effects
1	Tawang mangu	Tawang mangu	Dec 26, 2007	37 died and 17 damaged houses
2		Ledoksari	Dec 26, 2007	Twelve damaged houses
3		Tengklik	Dec 26, 2007	Damaged agricultural land
4		Tengklik	Feb, 2009	33 damaged houses and damaged road
5		Sepanjang	Dec 26, 2007	Four damaged houses
6		Sepanjang	Dec 26, 2007	Seven damaged house and damaged road
7		Sepanjang	March 17, 2009	Damaged house
8		Sepanjang	Feb27, 2009	Damaged road
9		Sepanjang	Dec 2006	Damaged land (shrub and bush)
10		Sepanjang	Nov 18, 2009	Damaged agricultural land (mixed garden
11		Sepanjang	Nov 15, 2009	Damaged road
12		Sepanjang	2008 (no info about exact date)	Damaged agricultural land
13		Sepanjang	2007 (no info about exact date)	Damaged agricultural land
14		Plumbon	Feb, 2007	Damaged building
15		Plumbon	Feb, 2007	Damaged road retaining wall
16		Plumbon	Dec, 2007	Three damaged houses
17		Plumbon	Dec, 2008	Damaged land (shrub and bush)
18		Plumbon	Jan, 2009	Damaged land (shrub and bush)
19		Karanglo	March, 2008	Damaged road
20		Kalisoro	August 12, 2009	Damaged agricultural land
21		Kalisoro	June 2009	Damaged land (pine plantation)
22		Bandardawung	March, 2009	Damaged agricultural land (mixed garden)
23		Bandardawung	2009 (no info about exact date)	Damaged road
24		Bandardawung	2008 (no info about exact date)	Damaged agricultural land (mixed garden)
25		Bandardawung	2009 (no info about exact date)	Damaged road
26		Bandardawung	2009 (no info about exact date)	Damaged agricultural land (mixed garden)
27		Bandardawung	2009 (no info about exact date)	Damaged agricultural land (mixed garden)
28		Bandardawung	2009 (no info about exact date)	Damaged agricultural land (mixed garden)
29		Bandardawung	2009 (no info about exact date)	Damaged agricultural land (mixed garden)
30		Gondosuli	Dec 4, 2005	Damaged land (shrub and bush)
31		Nglebak	2006 (no info about exact date)	Damaged road

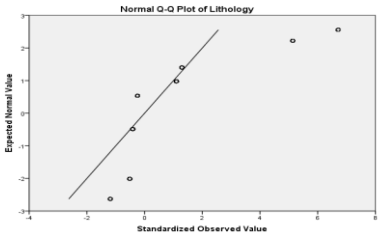
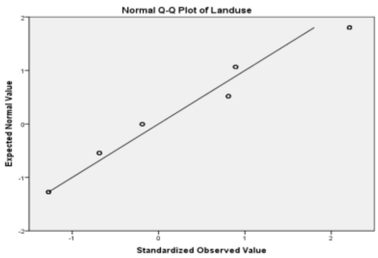
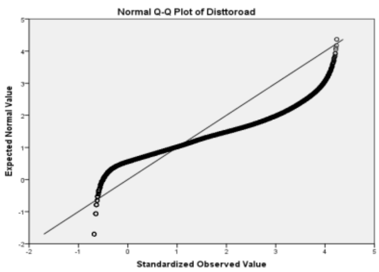
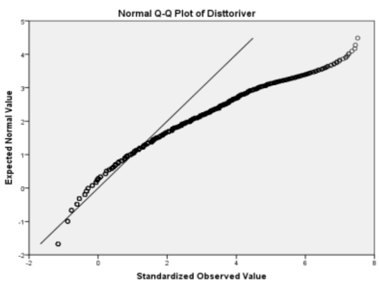
Annex 1 (continued)

32		Tengklik	Nov 15, 2009	Damaged agricultural land
33		Tengklik	2006 (no info about exact date)	Damaged mixed vegetable garden
34		Bandardawung	2006 (no info about exact date)	Damaged land (shrub and bush)
35		Tawangmangu	Oct 2007	Damaged land (shrub and bush)
36		Tawangmangu	2006 (no info about exact date)	Damaged land (shrub and bush)
37		Sepanjang	Nov 19, 2009	Damaged houses, land (shrub and bush)
38		Tengklik	May 27, 2008	Damaged road
39		Tengklik	Nov 15, 2009	Damaged houses
40		Blumbang	Jan 21, 2010	Damaged houses
41		Blumbang	June 15, 2010	4 died, damaged bridge and road
42		Blumbang	Jan 18, 2005	Damaged houses
43	Ngargoyoso	Nglegok	Dec 12,2002	Damaged houses, land (shrub and bush)
44		Nglegok	Dec 26, 2007	Damaged houses, land (shrub and bush)
45		Berjo	Mar 28, 2008	Damaged houses, land (shrub and bush)
46		Nglegok	Jan 23, 2009	Damaged houses, land (shrub and bush)
47		Nglegok	Jan 23, 2009	Damaged mixed vegetable garden
48		Nglegok	Jan 30, 2009	6 died, damaged 2 houses.
49		Gondosuli	Nov 21, 2005	Damaged land (shrub and bush)
50		Berjo	Mar 5, 2007	Damaged houses
51		Ngargoyoso	Jan 6, 2010	1 died, damaged house
52		Ngargoyoso	Feb 19, 2010	Damaged houses
53		Kemuning	Jan 21, 2010	Damaged 3 houses
54		Kemuning	Jan 21, 2010	Damaged houses, land
55		Nglegok	Jan 30, 2009	Damaged houses, land (shrub and bush)
56		Kemuning	Feb 19, 2010	Damaged houses
57		Kemuning	Feb 19, 2010	Damaged houses land (shrub and bush)
58		Ngargoyoso	Feb 19, 2010	Damaged land (shrub and bush)
59		Girimulyo	Feb 19, 2010	Damaged land (shrub and bush)
62		Girimulyo	Feb 19, 2010	Damaged houses
61	Jenawi	Balong	Jan 12, 2009	Damaged houses
62		Balong	Jan 12, 2009	Damaged houses
63		Balong	May 22, 2009	Damaged houses, land (shrub and bush)
64		Trengguli	Jan 3, 2008	Damaged houses, land (shrub and bush)
65		Seloromo	Dec 27, 2007	Damaged 51 houses
66		Balong	May 22, 2009	Damaged houses, land (shrub and bush)
67		Balong	May 22, 2009	Damaged houses, land (shrub and bush)
68		Sidomukti	Jan 21, 2010	Damaged houses, land (shrub and bush)
69		Trengguli	Feb 21, 2010	Damaged houses, land (shrub and bush)
70		Jenawi	Feb 21, 2010	Damaged houses, land (shrub and bush)
71		Lempong	Feb 4, 2010	Damaged houses
72		Seloromo	July 22, 2010	1 died, 6 wounded, damaged bridge
73		Argamanis	Nov 15, 2009	Damaged houses, land (shrub and bush)
74		Gumeng	Nov 15, 2009	Damaged houses, land (shrub and bush)

ANNEX 2. Q-Q plot of variables

Plot	Explanation
Slope 	*Positive skew* (1,910) The right tail is longer; the mass of the distribution is concentrated on the left of the figure.
Aspect 	Left end of pattern is below the line; right end of pattern is above the line. Short tails at both ends of the data distribution. *Negative skew (-,862):* The left tail is longer; the mass of the distribution is concentrated on the right of the figure.
Topographical shape 	Starting below the target line (or to the right), arching across it and then back to finish below (or to the right of) the line again. Skewed to the right/positive skew (1,167): The right tail is longer; the mass of the distribution is concentrated on the left of the figure.
Curvature 	*Negative skew (-1,032)* Left end of pattern is above the line; right end of pattern is below the line. Short tails at both ends of the data distribution but the left tail is longer; the mass of the distribution is concentrated on the right of the figure.

Annex 2 (continued)

Lithology 	*Skewed to the right/positive skew (4,151):* The result is a Q-Q plot that resembles the left hand top of an arch, starting below the target line (or to the right if you prefer), arching across it and then back to finish below (or to the right of) the line again (i.e., it has a long right hand tail).
Land use 	*Positive skew (0,485)* : The right tail is longer; the mass of the distribution is concentrated on the left of the figure.
Distance to road 	*Positive skew (1,860):* The mass of the distribution is concentrated on the left of the figure.
Distance to river 	*Positive skew (1,423)* : The right tail is longer; the mass of the distribution is concentrated on the left of the figure.

ANNEX 3. Logistic regression prediction results

Notes

Output Created		04-Jan-2011 19:03:40
Comments		
Input	Data	D:_THESIS\DATA\Variables\continuous\cont_ascii\dataset3_egual_ori_normalized.sav
	Active Dataset	DataSet1
	Filter	<none>
	Weight	<none>
	Split File	<none>
	N of Rows in Working Data File	448
Missing Value Handling	Definition of Missing	User-defined missing values are treated as missing
Syntax		LOGISTIC REGRESSION VARIABLES Landslide /METHOD=BSTEP(LR) Aspect Slope Disttoroad Disttoriver Lithology Landuse Curvature Toposhape /SAVE=PRED /CRITERIA=PIN(0.05) POUT(0.10) ITERATE(20) CUT(0.5).
Resources	Processor Time	00:00:00,047
	Elapsed Time	00:00:00,100
Variables Created or Modified	PRE_2	Predicted probability

[DataSet2] D:_THESIS\DATA\Variables\continuous\cont_ascii\dataset2_egual_ori_normalized.sav

Case Processing Summary

Unweighted Cases[a]		N	Percent
Selected Cases	Included in Analysis	448	100,0
	Missing Cases	0	,0
	Total	448	100,0
Unselected Cases		0	,0
Total		448	100,0

a. If weight is in effect, see classification table for the total number of cases.

Dependent Variable Encoding

Original Value		Internal Value
dimension0	,00	0
	1,00	1

Block 0: Beginning Block

Classification Table[a,b]

Observed			Predicted		
			Landslide		Percentage Correct
			,00	1,00	
Step 0	Landslide	,00	0	224	,0
		1,00	0	224	100,0
	Overall Percentage				50,0

a. Constant is included in the model.
b. The cut value is ,500

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 0	Constant	,000	,094	,000	1	1,000	1,000

Variables not in the Equation

			Score	df	Sig.
Step 0	Variables	Aspect	4,388	1	,036
		Slope	53,534	1	,000
		Disttoroad	50,245	1	,000
		Disttoriver	5,853	1	,016
		Lithology	28,953	1	,000
		Landuse	59,740	1	,000
		Curvature	210,688	1	,000
		Toposhape	193,652	1	,000
	Overall Statistics		269,870	8	,000

Block 1: Method = Backward Stepwise (Likelihood Ratio)

Omnibus Tests of Model Coefficients

		Chi-square	df	Sig.
Step 1	Step	388,608	8	,000
	Block	388,608	8	,000
	Model	388,608	8	,000
Step 2[a]	Step	-,732	1	,392
	Block	387,876	7	,000
	Model	387,876	7	,000
Step 3[a]	Step	-2,072	1	,150
	Block	385,804	6	,000
	Model	385,804	6	,000

a. A negative Chi-squares value indicates that the Chi-squares value has decreased from the previous step.

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	232,452[a]	,580	,773
2	233,184[a]	,579	,772
3	235,256[a]	,577	,770

a. Estimation terminated at iteration number 7 because parameter estimates changed by less than ,001.

Classification Table[a]

	Observed		Predicted: Landslide ,00	Predicted: Landslide 1,00	Percentage Correct
Step 1	Landslide	,00	203	21	90,6
		1,00	25	199	88,8
	Overall Percentage				89,7
Step 2	Landslide	,00	203	21	90,6
		1,00	24	200	89,3
	Overall Percentage				90,0
Step 3	Landslide	,00	203	21	90,6
		1,00	22	202	90,2
	Overall Percentage				90,4

a. The cut value is ,500

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	Aspect	-,274	,174	2,473	1	,116	,761
	Slope	-,566	,232	5,970	1	,015	,568
	Disttoroad	,197	,228	,748	1	,387	1,218
	Disttoriver	-,398	,185	4,620	1	,032	,672
	Lithology	13,754	3,533	15,156	1	,000	940665,829
	Landuse	3,562	1,589	5,023	1	,025	35,220
	Curvature	2,697	,363	55,158	1	,000	14,835
	Toposhape	-3,251	,790	16,944	1	,000	,039
	Constant	,151	,568	,070	1	,791	1,163
Step 2[a]	Aspect	-,246	,170	2,096	1	,148	,782
	Slope	-,510	,220	5,365	1	,021	,600
	Disttoriver	-,384	,183	4,404	1	,036	,681
	Lithology	12,745	3,218	15,686	1	,000	342754,390
	Landuse	3,068	1,473	4,337	1	,037	21,491
	Curvature	2,665	,363	53,984	1	,000	14,372
	Toposhape	-3,189	,785	16,487	1	,000	,041
	Constant	,294	,541	,295	1	,587	1,342
Step 3[a]	Slope	-,503	,218	5,308	1	,021	,605
	Disttoriver	-,393	,183	4,634	1	,031	,675
	Lithology	13,487	3,168	18,118	1	,000	719695,188
	Landuse	3,355	1,460	5,281	1	,022	28,642
	Curvature	2,620	,359	53,211	1	,000	13,731
	Toposhape	-3,220	,784	16,868	1	,000	,040
	Constant	,201	,536	,140	1	,708	1,222

a. Variable(s) entered on step 1: Aspect, Slope, Disttoroad, Disttoriver, Lithology, Landuse, Curvature, Toposhape.

Model if Term Removed

Variable		Model Log Likelihood	Change in -2 Log Likelihood	df	Sig. of the Change
Step 1	Aspect	-117,456	2,459	1	,117
	Slope	-119,472	6,491	1	,011
	Disttoroad	-116,592	,732	1	,392
	Disttoriver	-118,648	4,844	1	,028
	Lithology	-126,778	21,104	1	,000
	Landuse	-118,775	5,098	1	,024
	Curvature	-167,149	101,845	1	,000
	Toposhape	-124,220	15,988	1	,000
Step 2	Aspect	-117,628	2,072	1	,150
	Slope	-119,488	5,792	1	,016
	Disttoriver	-118,893	4,602	1	,032
	Lithology	-127,032	20,880	1	,000
	Landuse	-118,777	4,369	1	,037
	Curvature	-167,626	102,069	1	,000
	Toposhape	-124,362	15,541	1	,000
Step 3	Slope	-120,466	5,676	1	,017
	Disttoriver	-120,048	4,841	1	,028
	Lithology	-129,756	24,257	1	,000
	Landuse	-120,294	5,332	1	,021
	Curvature	-167,719	100,182	1	,000
	Toposhape	-125,549	15,843	1	,000

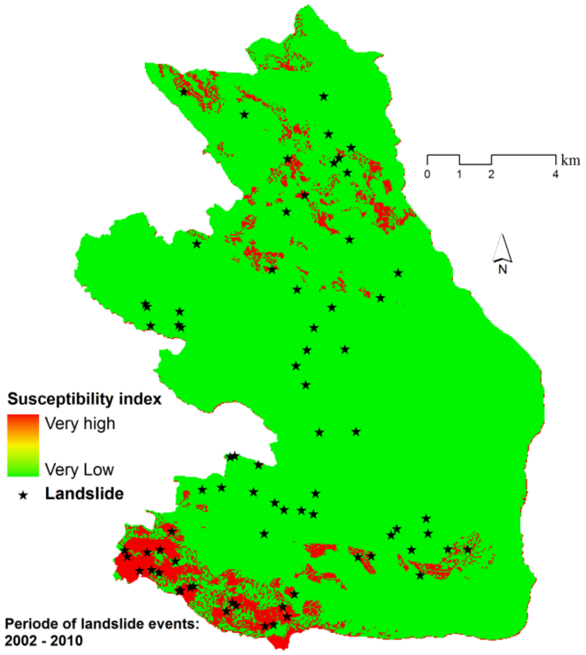
Variables not in the Equation

			Score	df	Sig.
Step 2[a]	Variables	Disttoroad	,750	1	,386
	Overall Statistics		,750	1	,386
Step 3[b]	Variables	Aspect	2,114	1	,146
		Disttoroad	,350	1	,554
	Overall Statistics		2,838	2	,242

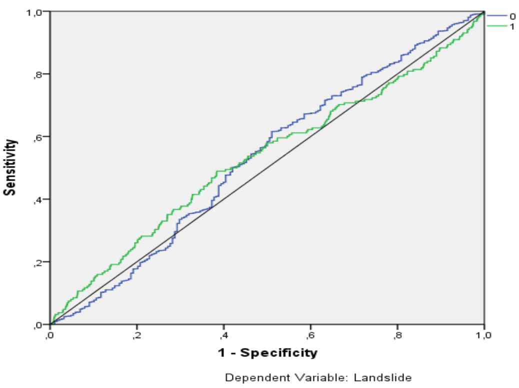
a. Variable(s) removed on step 2: Disttoroad.

b. Variable(s) removed on step 3: Aspect.

ANNEX 4. LSI using pseudo-probabilities



ANN model performance from ROC AUC analysis:



Area Under the Curve

		Area
Landslide	0	,531
	1	,531

ANNEX 5. ANN used in this study

```
*Multilayer Perceptron Network.
MLP Landslide (MLEVEL=N) BY Lithology Landuse Toposhape WITH Slope Aspect Curvature
Disttoroad Disttoriver
 /RESCALE COVARIATE=NORMALIZED
  /PARTITION  TRAINING=6  TESTING=4  HOLDOUT=2
  /ARCHITECTURE   AUTOMATIC=YES (MINUNITS=1 MAXUNITS=50)
  /CRITERIA TRAINING=BATCH OPTIMIZATION=SCALEDCONJUGATE
LAMBDAINITIAL=0.0000005 SIGMAINITIAL=0.00005 INTERVALCENTER=0 INTERVALOFFSET=0.5
MEMSIZE=1000
  /PRINT CPS NETWORKINFO SUMMARY CLASSIFICATION IMPORTANCE
  /PLOT NETWORK
  /STOPPINGRULES ERRORSTEPS= 1 (DATA=AUTO) TRAININGTIMER=ON (MAXTIME=15)
MAXEPOCHS=AUTO ERRORCHANGE=1.0E-4 ERRORRATIO=0.0010
 /MISSING USERMISSING=EXCLUDE .
```

Multilayer Perceptron

Notes

Output Created		18-Nov-2010 16:20:35
Comments		
Input	Data	D:_THESIS\DATA\Variables\continuous\cont_ascii\dataset3_egual_ori_normalized.sav
	Active Dataset	DataSet1
	Filter	<none>
	Weight	<none>
	Split File	<none>
	N of Rows in Working Data File	448
Missing Value Handling	Definition of Missing	User- and system-missing values are treated as missing.
	Cases Used	Statistics are based on cases with valid data for all variables used by the procedure.
Weight Handling		not applicable
Syntax		MLP Landslide (MLEVEL=N) BY Lithology Landuse Toposhape WITH Slope Aspect Curvature Disttoroad Disttoriver /RESCALE COVARIATE=NORMALIZED /PARTITION TRAINING=6 TESTING=4 HOLDOUT=2 /ARCHITECTURE AUTOMATIC=YES (MINUNITS=1 MAXUNITS=50) /CRITERIA TRAINING=BATCH OPTIMIZATION=SCALEDCONJUGATE LAMBDAINITIAL=0.0000005 SIGMAINITIAL=0.00005 INTERVALCENTER=0 INTERVALOFFSET=0.5 MEMSIZE=1000 /PRINT CPS NETWORKINFO SUMMARY CLASSIFICATION IMPORTANCE /PLOT NETWORK /STOPPINGRULES ERRORSTEPS= 1 (DATA=AUTO) TRAININGTIMER=ON (MAXTIME=15) MAXEPOCHS=AUTO ERRORCHANGE=1.0E-4 ERRORRATIO=0.0010 /MISSING USERMISSING=EXCLUDE .
Resources	Processor Time	00:00:00,889
	Elapsed Time	00:00:00,902

[DataSet1] D:_THESIS\DATA\Variables\continuous\cont_ascii\dataset3_egual_ori_normalized.sav

Model Summary

Training	Cross Entropy Error	15,228
	Percent Incorrect Predictions	1,4%
	Stopping Rule Used	1 consecutive step(s) with no decrease in error[a]
	Training Time	00:00:00,326
Testing	Cross Entropy Error	20,517
	Percent Incorrect Predictions	5,5%
Holdout	Percent Incorrect Predictions	7,6%

Dependent Variable: Landslide
a. Error computations are based on the testing sample.

Network Information

Input Layer	Factors	1	Lithology
		2	Landuse
		3	Toposhape
	Covariates	1	Slope
		2	Aspect
		3	Curvature
		4	Disttoroad
		5	Disttoriver
	Number of Units[a]		24
	Rescaling Method for Covariates		Normalized
Hidden Layer(s)	Number of Hidden Layers		1
	Number of Units in Hidden Layer 1[a]		5
	Activation Function		Hyperbolic tangent
Output Layer	Dependent Variables	1	Landslide
	Number of Units		2
	Activation Function		Softmax
	Error Function		Sum of Square

a. Excluding the bias unit

Classification

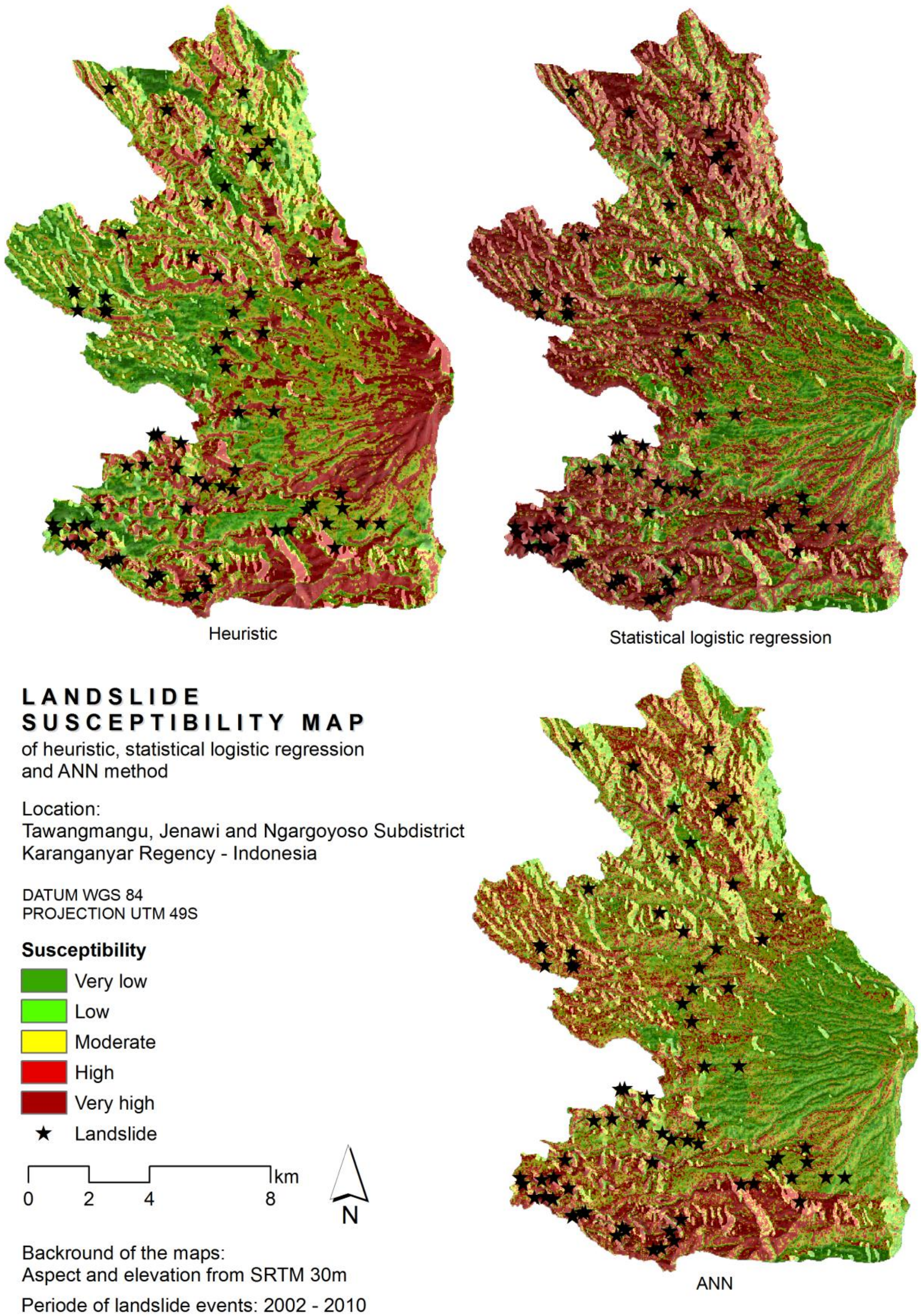
Sample	Observed	Predicted		
		,00	1,00	Percent Correct
Training	,00	110	2	98,2%
	1,00	1	109	99,1%
	Overall Percent	50,0%	50,0%	98,6%
Testing	,00	74	5	93,7%
	1,00	3	64	95,5%
	Overall Percent	52,7%	47,3%	94,5%
Holdout	,00	32	1	97,0%
	1,00	5	41	89,1%
	Overall Percent	46,8%	53,2%	92,4%

Dependent Variable: Landslide

Independent Variable Importance

	Importance	Normalized Importance
Lithology	,163	54,9%
Landuse	,120	40,7%
Toposhape	,185	62,4%
Slope	,102	34,5%
Aspect	,049	16,7%
Curvature	,296	100,0%
Disttoroad	,045	15,2%
Disttoriver	,040	13,6%

ANNEX 6. Landslide susceptibility maps



Masters
Program
in **Geospatial**
Technologies

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