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Landslide Susceptibility Mapping of Pagsanjan–Lumban Watershed using GIS and Analytical Hierarchy Process

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ABSTRACT

Landslide is one of the most destructive natural calamities that poses great threat to both human lives and properties especially in developing countries like the Philippines. Due to these reasons, many techniques such as Landslide Susceptibility Mapping (LSM) have been developed to reduce the adverse impacts of such phenomenon. This study was conducted to develop a landslide susceptibility map of the Pagsanjan–Lumban Watershed by integrating the Analytical Hierarchy Process (AHP) and Geographic Information System (GIS).

The study considered seven factors (elevation, slope, rainfall, soil texture, land cover, fault lines and roads) in generating the susceptibility map. Results from AHP showed that experts from various fields have different perspectives on the level of importance of factors that resulted to the variability in judgments. Among the different factors, slope (23.18%) and rainfall (21.50%) had the highest relative weights while road (8.70%) and elevation (6.61%) had the lowest relative weights. Based on the weighted overlay analysis, the Landslide Susceptibility Index (LSI) of the watershed was observed between 1.43 and 3.65. About 13.82% (6,280 ha) of the area had classification of high susceptibility while 5.51% (2,502 ha) fell under the very high susceptibility level. Furthermore, Lucban (2,648.57 ha) and Lumban (1,956.96 ha) were found to have the largest areas with high to very high susceptibility while Mauban (1.20 ha), Liliw (1.20), Sampaloc (13.49 ha) and Magdalena (28.90 ha) generated low susceptibility levels. The findings of the study can contribute in the effective management of the Pagsanjan–Lumban Watershed.

Keywords: Analytical Hierarchy Process, Geographic Information System, landslide, landslide susceptibility mapping, pair–wise comparison matrix

INTRODUCTION

The Philippine archipelago has a total land area of approximately 30 million ha with almost 75% considered as watersheds (Saplaco *et al.* 2001). A watershed is a "topographically delineated area where rainwater is drained as surface run–off via a specific stream or river system to a common outlet which may be a dam, an irrigation system or a municipal water supply take off point, or where the stream/river discharges water into a larger water body" (ERDB 2011).

Philippine watersheds are naturally prone to environmental disasters due to the presence of several active faults, steep slopes, rugged topography and poor vegetation cover (ERDB 2011). These are further exacerbated by anthropogenic activities such as logging, *kaingin*, charcoal making and the like. Among the problems besetting the country, landslide is one of the most catastrophic environmental disasters in upland areas. Landslide is a phenomenon usually triggered by earthquake or rainfall, and can cause significant damage not only to the watershed continuum but also to life and properties. For these reasons, various scholars and experts have formulated several techniques to identify risk areas and develop strategies for these areas to reduce or even prevent adverse effects of landslides. One of these techniques is landslide susceptibility mapping. Nowadays, with the advent of the state–of–the art technologies such as remote sensing and geographic information system (GIS), landslide hazard mapping has become a very effective way in management planning. These technologies are being used by experts worldwide to develop landslide maps, hazard maps, risk maps, susceptibility maps and vulnerability maps. In many studies, the selection of factors and weights provided for each criterion are based solely from one field of expertise. This study therefore aimed to capture the development of a landslide susceptibility model that incorporates various fields of expertise. One of the approaches that can accommodate such kind of analysis is the Analytical Hierarchy Process (AHP).

AHP is a well–known semi–quantitative method developed by Thomas L. Saaty in 1971 (Saaty 1987). Saaty (1980) created this tool to refrain from making simplified assumptions not only to suit quantitative models but to reflect the complex situations. To be realistic, Saaty says that the model must include and measure all tangible and intangible, qualitative and quantitative factors. The use of pair–wise comparison judgment in AHP as inputs allows one to cope with factors which, in the main stream of application, have not been effectively quantified. This then gives values to each factor depending on the level of its influence.

Over the years, AHP was used by many experts from simple decision making as choosing the computer model to buy to complicated decisions as redesigning the Higher Education in Malaysia (Yusof & Salleh 2013).

AHP has become a very useful tool in the fields of environmental science and management particularly in planning, decision making, and hazard mapping. Many landslide susceptibility studies have been conducted using this tool (Mezughi *et al.* 2012; Moradi *et al.* 2012; Phukon *et al.* 2012,

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Mondal & Maiti 2012; Feizizadeh & Blashcke 2013; Pourghasemi, Moradi 2013). AHP was also applied with other methods such as fuzzy logic to further increase the accuracy of the results (Gorsevski *et al.* 2006).

Some experts have also tried comparing AHP with other popular techniques in decision making such as multiple regression approach in landslide hazard zonation of Langan Watershed in Ardabil, Iran (Ouri & Amirian, n.d.). Likewise, Yalcin *et al.* (2011) compared AHP with bivariate and logistics regression methods in landslide susceptibility mapping in Trabzon, NE Turkey. Marjanovic *et al.* (2009) compared AHP with machine learning algorithms used in landslide susceptibility assessment in Serbia.

In the Philippines, AHP technique is still seldom used as an approach in developing landslide susceptibility models. This study aims to bridge that gap by generating a landslide susceptibility model of the Pagsanjan–Lumban Watershed using AHP and GIS.

Study Area

The Pagsanjan–Lumban Watershed is located in the Southern Tagalog Region, mainly at the southeastern part of Laguna de Bay with geographic coordinates of 14°37′ to 14°21′ north latitude and 121°24′ to 121°37′ east longitude (Figure 1). It is bounded by the Laguna Lake in the north; Paete, Pakil and Pangil watersheds in the east; Sta. Cruz watershed in the west; and Mt. Banahaw in the south. The watershed has a total land area of 45,444 ha covering a total of 13 municipalities namely Cavinti, Kalayaan, Liliw, Luisiana, Lumban, Magdalena, Majayjay, Mauban, Paete, and Pagsanjan in the province of Laguna, and Lucban, Sampaloc, and Tayabas in the province of Quezon.

The topography of the area is relatively flat to rolling from the shore going up to the mountains. The elevation ranges from 20 to 2,080 meters above sea level (masl) and the highest point of the mountain is located in Mt. Banahaw de Tayabas.

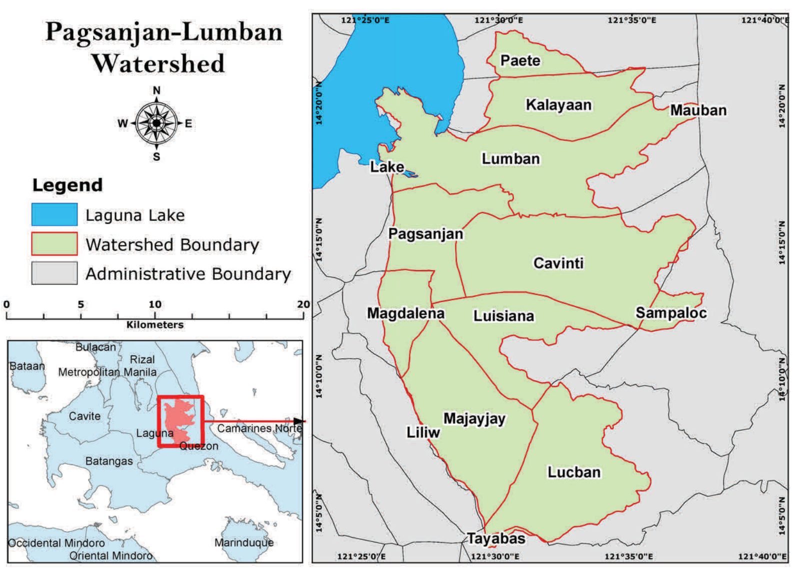


Figure 1. Location map of the study area.

MATERIALS AND METHODS

Factors for Landslide Susceptibility

The stability of slopes is dependent on numerous factors including the biophysical characteristics of the area and anthropogenic influences. In this study, only seven biophysical factors were considered namely, elevation, slope, rainfall, soil type, land cover, proximity to roads, and proximity to fault lines (Figures 2a to 2g). The number of parameters used in this modelling is in accordance with the results of Ozdemir (2005) who limited the number of elements used in pair–wise comparison to about seven to have a consistent and valid result in AHP.

All thematic maps were converted into raster with a 30m x 30m cell size resolution using appropriate tools in ArcGIS^{TM}. A scale of 1 to 5 was utilized to indicate the levels of susceptibility for each factor, 1 being the least susceptible and 5 being the most susceptible. Each thematic map was then reclassified and divided into five classes to conform to the developed scales.

The elevations were categorized using a 500–m interval while the slope was reclassified into five classes and these are 0–8% (flat), 8–18% (rolling), 18–30% (moderate), 30–50% (steep), and >50% (very steep). Rainfall was categorized into five classes with 1000 mm interval. The soil map of the area was grouped depending on soil textural classes. The land cover map was classified into closed forest, open forest/plantation, shrub lands/natural grasslands, cultivated/built–up areas, and barren lands. For fault lines and road networks, the proximity analysis function was used. A buffer of 100–m interval was applied for the road network to generate the classes while a 500–m interval distance was used for fault lines and collapsed structures.

Analytical Hierarchy Process

AHP is a semi–quantitative approach which involves pair–wise comparison of identified factors to a particular phenomenon or event. In this case, it is employed in modelling landslide susceptibility of a watershed. In the model, AHP assigns values to the different factors based on their level of influence to landslide occurrence. This assigning of values is usually done by various experts.

AHP also utilizes a pair–wise comparison matrix that involves comparison of an individual factor to the other factors. This was designed to remove biases in decision–making. Factors in this matrix are being compared based on their relative importance or influence to landslide. As an input value in this matrix, the Saaty Rating Scale (Table 1) was used as a guide in comparing the different factors. This means that factors given higher value have higher level of importance or influence to the occurrence of landslide.

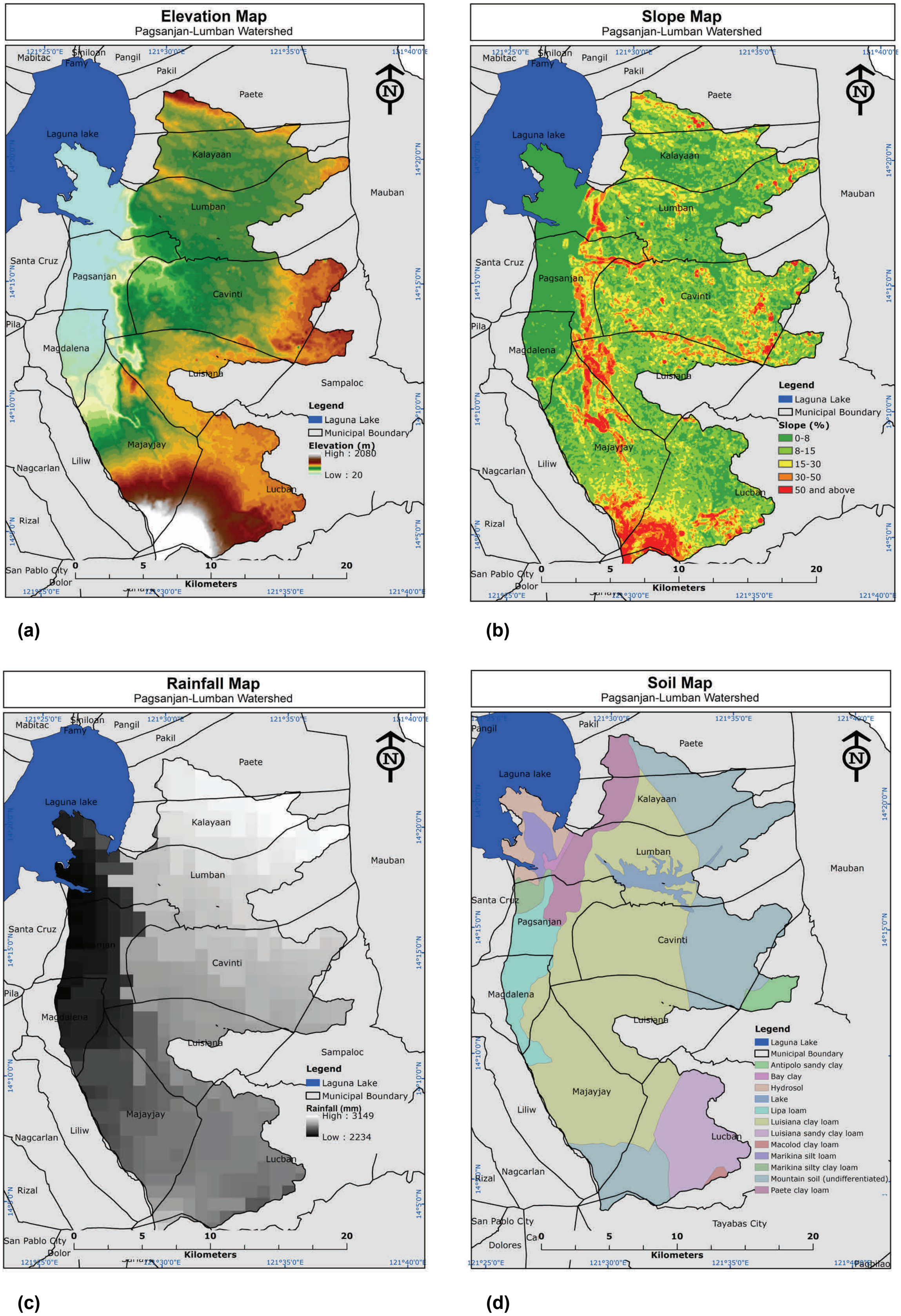
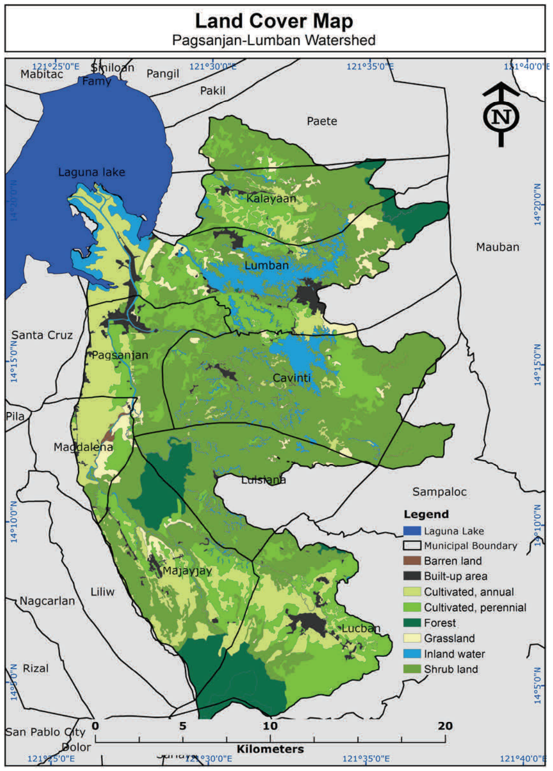


Figure 2. Biophysical factors of Pagsanjan-Lumban Watershed.



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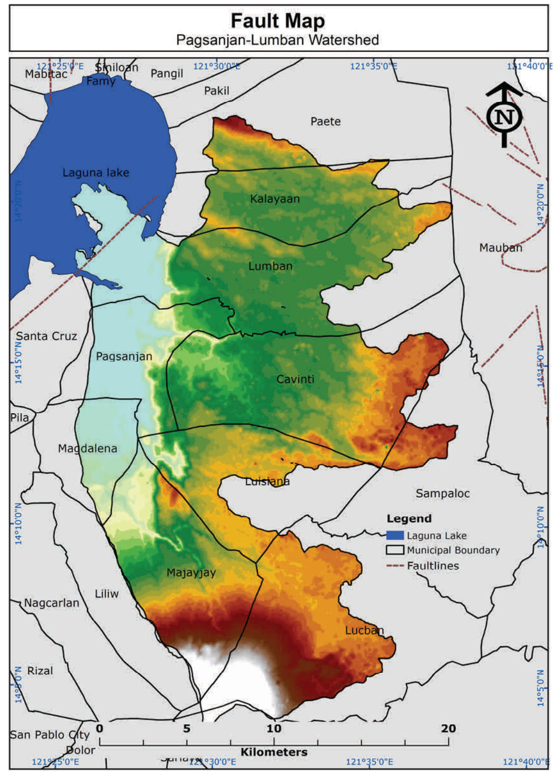

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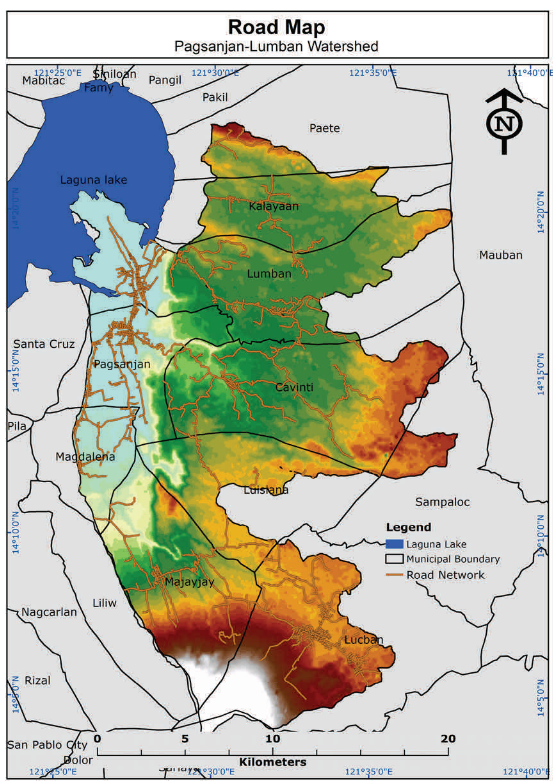


(g)

Figure 2. Biophysical factors of Pagsanjan-Lumban Watershed. *(Cont.)*

Table 1. The Saaty rating scale adapted from Saaty (1980).

Intensity of Importance	Definition	Explanation
1	Equal importance	Two factors contribute equally to the objective
3	Somewhat more important	Experience and judgment slightly favor one over the other
5	Much more important	Experience and judgment strongly favor one over the other
7	Very much more important	Experience and judgment very strongly favor one over the other. Its importance is demonstrated in practice.
9	Absolutely more important	The evidence favoring one over the other is of the highest possible validity.
2,4,6,8	Intermediate values	When compromise is needed

In this study, the pair–wise comparison matrix was accomplished through experts′ interview. Six experts were interviewed for this study. However, only four of them were finally selected since the matrix of the other two exceeded the maximum consistency ratio value of 0.1. The four remaining experts interviewed for this study include two geologists, a forester and an environmental scientist. These experts were purposely selected based on their knowledge and experience in the field of hazard mapping specifically on landslides. It is important to interview experts from different fields to acquire a variety of perceptions as well. Upon completion of the matrix, the data were then processed and the important parameters such as Eigenvectors and Consistency Ratio were computed. Eigenvector, as defined by Saaty (1980), corresponds to the relative weight, importance or value of the factors whereas Consistency Ratio measures the consistency of the judgments done.

The matrix in AHP is in the form: $m \times m$ matrix, where m is the number of factors considered. Each value, a_{jk} in the matrix represents the importance of the j^{th} criterion relative to k^{th} criterion, where j is the factor in rows and k is factor in columns. The first step in the manual computation of Eigenvector (E) and Consistency Ratio (CR) is the calculation of the n^{th} root (X) of the product values by multiplying together the entries in each row of the matrix (Equation 1).

Equation 1:

$$X\ of\ A = \sqrt[n]{ajk1 * ajk2 * \ldots * ajkn}$$

where: X = nth root of the product value
A = factor A
ajk = values in the row of the factor A

To normalize the eigenvector of elements, the sum of the X of A: X of n was computed and then used as the divisor for all the X computed. The result here is the eigenvector factor for each row. The higher the eigenvector value means higher relative importance or value.

In order to compute the Consistency Index (CI), the maximum vector (λmax) must be computed first using Equation 2 with the assumption that vector $A\omega = \lambda\omega$ (ω is the eigenvector of order n and λ is the eigenvalue).

Equation 2:

$$\lambda\omega\ of\ A = (a_{jk1} * E_A) + (a_{jk2} + E_B) \ldots + (a_{jkn} * E_n)$$

The equation only says that the value entry a_{jk} is multiplied to the eigenvector of the Factor A and so on and so forth. For Factor B and the remaining factors, there is a difference such that the first entry value jk for all remaining factors was multiplied to the eigenvector of Factor A and the rest was the same, such that b_{jk1} was multiplied to eigenvector of Factor A and c_{jk1} was multiplied to E of A. According to the AHP theory, $A\omega = \lambda max\omega$. This means that to get the estimate of λmax, divide each component of λω by the corresponding eeigenvector. Then the mean of these values is computed to derive the estimate of λmaxω. Estimate of λmaxω should not be less than n, otherwise there is an error in the computation. The next step would be the computation of Consistency Index (Equation 3).

Equation 3:

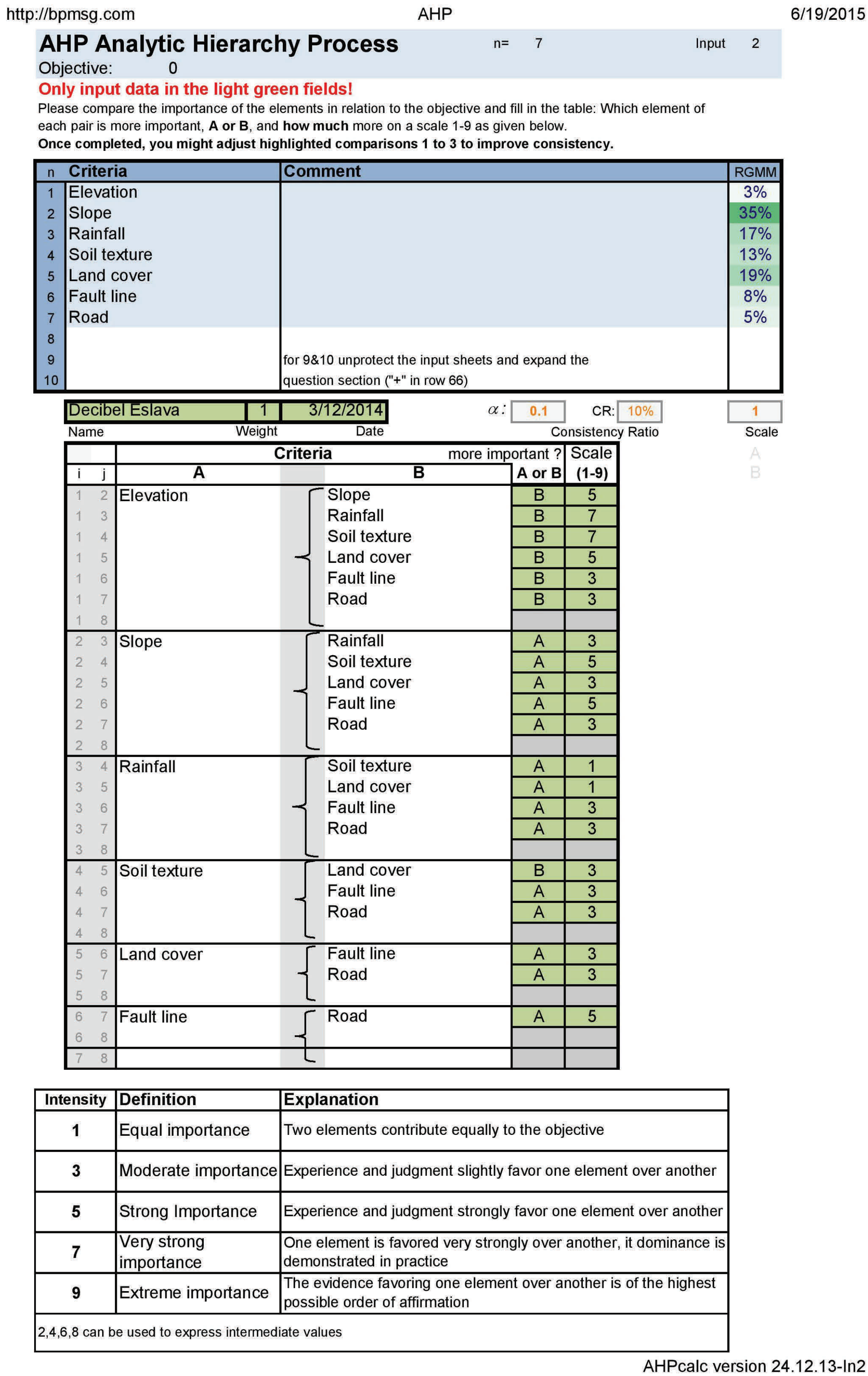
$$CI = (\lambda max\omega - n)/(n - 1)$$

The final step is the computation of CR which will determine the consistency of the judgment done by the experts. CR > 0.1 would usually be rejected because this means that there are some inconsistencies in judgments. However, in some cases, judgments with CR > 0.1 are accepted − this means that the judgment has slight inconsistencies − for as long as it does not reach CR > 0.9. It means that the judgment has reached randomness. The CR was computed by dividing the CI computed by the value of Random Index (RI) in the table of inconsistency for random judgments (Equation 4).

Equation 4:

$$CR = \frac{CI}{RI}$$

In the study, the eigenvector and CR were computed using an excel template developed by Goepel (2013) instead of manual computation that may cause some errors (Figure 3). In the template, weight of factors in column A was compared to the factors in column B by selecting which factor has more weight over the other; then input the relation of the weights being compared to the Saaty Rating Scale (1–9) column (refer to Table 1).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AHP Analytic Hierarchy Process n= 7 Input 2

Objective: 0

Only input data in the light green fields!

Please compare the importance of the elements in relation to the objective and fill in the table: Which element of each pair is more important, **A or B**, and **how much** more on a scale 1-9 as given below.

Once completed, you might adjust highlighted comparisons 1 to 3 to improve consistency.

n	Criteria	Comment	RGMM
1	Elevation		3%
2	Slope		35%
3	Rainfall		17%
4	Soil texture		13%
5	Land cover		19%
6	Fault line		8%
7	Road		5%
8			
9		for 9&10 unprotect the input sheets and expand the	
10		question section ("+" in row 66)	

Name	Weight	Date	α:	CR: Consistency Ratio	Scale
Decibel Eslava	1	3/12/2014	0.1	10%	1

i	j	Criteria A	B	more important ? A or B	Scale (1-9)
1	2	Elevation	Slope	B	5
1	3		Rainfall	B	7
1	4		Soil texture	B	7
1	5		Land cover	B	5
1	6		Fault line	B	3
1	7		Road	B	3
1	8				
2	3	Slope	Rainfall	A	3
2	4		Soil texture	A	5
2	5		Land cover	A	3
2	6		Fault line	A	5
2	7		Road	A	3
2	8				
3	4	Rainfall	Soil texture	A	1
3	5		Land cover	A	1
3	6		Fault line	A	3
3	7		Road	A	3
3	8				
4	5	Soil texture	Land cover	B	3
4	6		Fault line	A	3
4	7		Road	A	3
4	8				
5	6	Land cover	Fault line	A	3
5	7		Road	A	3
5	8				
6	7	Fault line	Road	A	5
6	8				
7	8				

Intensity	Definition	Explanation
1	Equal importance	Two elements contribute equally to the objective
3	Moderate importance	Experience and judgment slightly favor one element over another
5	Strong Importance	Experience and judgment strongly favor one element over another
7	Very strong importance	One element is favored very strongly over another, it dominance is demonstrated in practice
9	Extreme importance	The evidence favoring one element over another is of the highest possible order of affirmation
2,4,6,8 can be used to express intermediate values		

AHPcalc version 24.12.13-In2

Figure 3. Sample of an AHP Template.

Landslide Susceptibility Mapping Using GIS

This study employed AHP to develop a landslide susceptibility map of the Pagsanjan–Lumban Watershed. Seven biophysical factors were considered, namely elevation, slope, rainfall, soil texture, land cover, distance to roads, and distance to fault lines. These factors were given relative weights through the use of AHP. The relative weights are based on expert judgment to determine the levels of influence of each factor through the computation of its eigenvector. This then corresponds to the relative weight of influence of each factor and finally applied in the computation of the landslide susceptibility index (LSI). Each factor in the process was translated into a map and a weighted overlay process was applied using GIS to generate the LSI of the entire watershed. The LSI of each pixel was computed by taking the summation of the product of the class weights (R) and factors weights (W) as shown in Equation 5.

Equation 5:

$$LSI = \sum_{i=1}^{n} (Wi \times Ri)$$

After the LSI was computed, the range was divided into five classes using the Natural Breaks (Jenks) classification method. This classification technique was used since it relies on inherent data and set boundaries based on big jumps in data values (Ayalew *et al.* 2004).

RESULTS AND DISCUSSION

Eigenvector and Consistency Ratio

In order to achieve reasonable and acceptable results, it is necessary to check for the consistency of the eigenvectors provided by the experts consulted. The computed consistency ratio of the consolidated experts' judgments is 0.023, lower than the threshold set by Saaty. According to Saaty (1980), a consistent judgment should not exceed a CR of 0.1. However, although the CR is acceptable, it can be noticed that the value of the percentage consensus is quite low with only 62.3%. The consensus percentage is the uniformity of judgment wherein low consensus value corresponds to variation in judgments of the consulted experts. The consolidated expert judgment can be considered with relatively low uniformity because it has low percentage consensus.

In the application of AHP, the relative weights given to a particular landslide factor depend solely on expert judgment. Based on experts' judgment, Table 2 showed that the highest eigenvector obtained was 23.18% for the slope, followed by rainfall (21.50%), land cover (14.01%), soil texture (13.16%), and distance to fault line (8.70%) while the lowest was found in the elevation factor (6.61%). All the experts consulted gave high values to slope and rainfall compared to other factors which was the reason why these two factors got the highest eigenvector. Slope and rainfall were given more importance than the other factors because of their proven influence in the occurrence of landslide. Related studies conducted give emphasis on slope and the occurrence of landslide on steep slopes. For instance, Komac (2005) found that slope got the highest relative weight while Mondal & Maiti (2012) gave slope the second highest weight next to drainage factor. Ayalew & Yamagishi's (2005) study in Central Japan found that slope gradient and slope aspect have more significant contribution in landslide occurrence than elevation.

The lowest relative weight was given to elevation. This means that this factor has the least influence to landslide occurrence. However, this should still be considered as important as the other factors especially in AHP because it uses a pair–wise comparison matrix that does not treat factors independently but as related to each other.

For other factors, experts gave different scores wherein some favored soil texture over land cover and distance to road over distance to fault line. The differences in scores of the four other factors – soil texture, land cover, distance to road, and distance to fault line – explains why their scores were close to each other. All the experts gave different rankings for other factors except for rainfall and slope which may be influenced by their experiences and training in their own field of discipline.

Landslide Susceptibility Map

The results from the computation of CR were then applied in generating the LSI of the watershed using GIS. Since AHP does not have a standard scale for classification, the study employed the Natural Breaks (Jenks) classification scheme. According to experts, this classification depends on natural jumps or big changes in values. Ayalew *et al.* (2004) applied this classification scheme in their landslide study in Agano River, Japan. They asserted that this classification scheme divides values that best maximize the difference between classes.

The results of the processed pair–wise comparison matrix and the computed eigenvector generated a range of LSI values from 1.43 to 3.65. These values were then divided into five categories, as summarized in Table 3, representing various susceptibility levels to landslide.

After generating the landslide susceptibility map (Figure 4) of the entire watershed, the area in each susceptibility class per municipality was also determined through intersect analysis (Table 4). The municipalities of Lucban (2,648.57 ha or 40.55%) and Lumban (1,959.96 ha or 23.21%) were revealed to have the largest areas with high and very high susceptibility to landslide. On the other hand, the municipalities of Cavinti (5,697.60 ha or 72.61%) and Majayjay (4,592.09 ha or 67.86%) were observed to have the largest areas in terms of low and very low susceptibility levels.

Table 3. Area in ha per susceptibility class.

Range	Susceptibility	Area (ha)	Percentage (%)
1.430–2.214	Very low	11,576	25.48
2.214–2.483	Low	14,070	30.97
2.483–2.703	Moderate	11,010	24.23
2.703–2.935	High	6,280	13.82
2.935–3.646	Very high	2,502	5.51

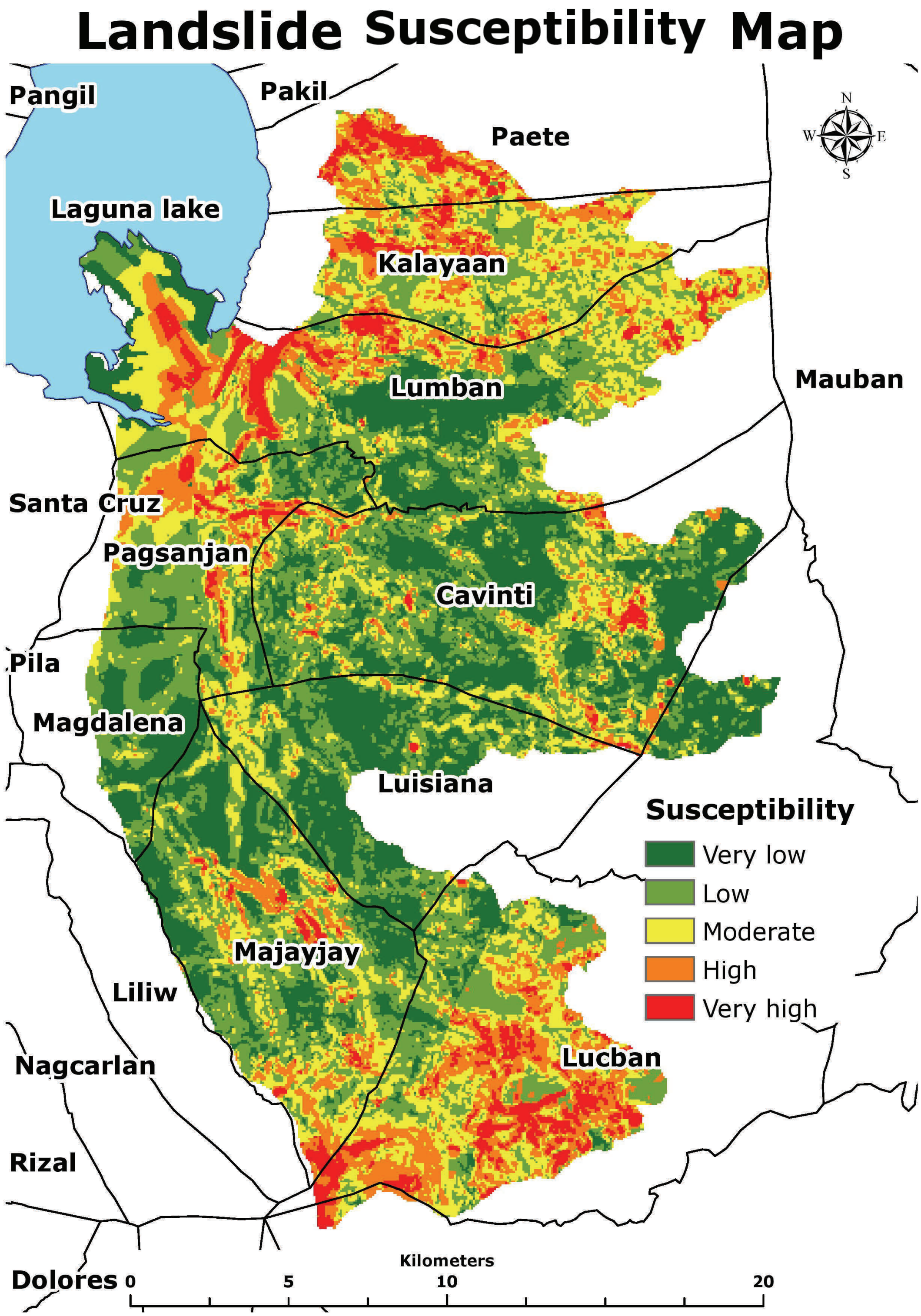

Figure 4. Landslide susceptibility map of Pagsanjan–Lumban Watershed.

Table 2. Consolidated results of experts judgements and normalized eigenvector.

FACTORS	A	B	C	D	E	F	G	Normalized
(a) Elevation	1	2/5	1/3	1/3	2/5	1/2	6/7	6.61%
(b) Slope		1	1	3	1 3/4	1 1/2	2 3/5	23.18%
(c) Rainfall			1	1 1/4	2 5/7	1 3/4	1 2/3	21.50%
(d) Soil texture				1	5/6	7/8	1 2/3	13.16%
(e) Land Cover					1	1 1/6	2	14.01%
(f) Fault						1	1 1/3	12.84%
(g) Road							1	8.70%
TOTAL								**100%**

Table 4. Area per susceptibility class of municipalities within Pagsanjan–Lumban Watershed.

Municipality	Area per susceptibility class (ha)					Total (ha)
	Very low	Low	Moderate	High	Very high	
Cavinti	2,750.48	2,947.12	1,553.35	532.4	63.64	7,847.01
Kalayaan	40.41	986.14	145.16	821.1	211.16	2,203.93
Liliw	288.43	5.76	1.43	1.2		296.79
Lucban	529.45	1,675.06	1,678.46	1,754.6	893.97	6,531.58
Luisiana	1,928.65	1,328.78	1,351.82	62.5	9.02	4,680.78
Lumban	1,824.52	2,252.17	2,397.33	1,297.1	659.86	8,430.97
Magdalena	724.54	836.50	269.57	28.9	0.0005	1,859.50
Majayjay	2,253.71	2,338.38	1,365.19	653.9	155.93	6,767.08
Mauban				1.04	0.16	1.20
Paete	7.37	94.91	499.37	456.6	324.08	1,382.31
Pagsanjan	689.09	1,647.60	1,788.63	613.2	168.10	4,906.61
Sampaloc	518.13	173.10	50.56	10.3	3.19	755.32
Tayabas	3.60	10.03	34.48	53.9	35.01	137.02
Laguna Lake	180.52	37.57	17.46	1.62		237.18

The results of this study can be utilized by local government units (LGUs) in improving their comprehensive management plan to address issues related to hazards in their areas. Also, this may aid in formulating policies that would further improve their capacity in addressing disaster risk related issues and concerns.

CONCLUSION AND RECOMMENDATION

The results of the study showed that slope had the largest contribution to the occurrence of landslide based on the computed relative weights through AHP. This suggests that areas characterized with steep slopes are generally more prone to landslide. On the other hand, elevation had the lowest computed eigenvector which corresponds to low influence to landslide occurrence. It also showed that the consistency of the results is very much affected by the number of elements used in the pair–wise comparison.

Having experts from different fields of interest resulted also in the variability of judgments which eventually led to the low consensus percentage. However, the consolidated judgment was still within the acceptable threshold of consistency ratio set by Saaty.

One of the requisites in generating accurate results from modelling is the availability of good data sets of the study area. Hence proper characterization of the watershed especially its biophysical profile must be undertaken and thoroughly conducted. The use of updated thematic maps alongside with updated geographic data sets should be greatly considered to come up with more reliable results.

The use of AHP in assessing landslide susceptibility captured the potential of this tool in integrating the knowledge and experiences of the experts into the model. However, the number of experts should be increased in future studies so that there will be more choices if ever some of the judgments appeared to be inconsistent.

Moreover, it is highly recommended that monitoring of landslide occurrences in the area must be established so that future studies will have a means to validate the results of the model. Likewise, it is recommended that the profile of the watershed, both in the biophysical and socio–economic aspects, are being updated. Some of the thematic layers seem to be outdated such as the land cover map which was produced using satellite images taken in 2010.

Aside from the development of a landslide susceptibility map, it is also recommended that other susceptibility maps such as flood, soil erosion, and fire should be modeled as well to generate a multi–hazard map of the watershed. This is important to minimize the danger and damages these climate hazards can bring to the watershed.

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