Qualitative and Quantitative Landslide Susceptibility Assessments in Hulu Kelang area, Malaysia

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ABSTRACT
Hulu Kelang is an area in Malaysia that is very susceptible to landslides. From 1990 to 2011, a total of 28 major landslide events had been reported in this area. This paper compares and evaluates the analytical hierarchy process (AHP), probability-frequency ratio (FR), statistical index (Wi), and weighting factor (Wf), used for assessing landslide susceptibility in the Hulu Kelang area. Eleven landslide influencing factors were considered in the analyses. These factors included two indices (the stream power index (SPI) and the topographic wetness index (TWI)) and several other factors including lithology, land cover, curvature, slope inclination, slope aspect, drainage density, elevation, distance to lake and stream, distance to road and trenches found in the area. The accuracy of the maps produced from the four models were verified using a receiver operating characteristics (ROC), and relative distributions of susceptibility level and active landslide zone. All the verification results indicated that the probability-frequency ratio (FR) model which was developed quantitatively based on probabilistic analysis of spatial distribution of historical landslide events was capable of producing a more reliable landslide susceptibility map in this study area compared to its other counterparts. About 89% of the landslide locations have been predicted accurately by using the FR map. On the contrary, the analytical hierarchy process (AHP) model that relies mainly on qualitative judgment yielded the least accuracy in landslide prediction.

KEYWORDS: Landslide susceptibility, landslide mapping, probability-frequency ratio, bivariate approach, analytical hierarchy process
INTRODUCTION

Landslides are one of the most common geohazards in many parts of the world. The frequency of landslide occurrences increases with growing human populations. The needs to protect natural and agricultural areas have further pressed human developments ever closer to unstable slopes. To minimize losses incurred by landslides, it is essential to develop a good understanding of the causative factors responsible for landslide susceptibility in an area.

State of the art research pertaining to landslide susceptibility analyzing has witnessed the development of sophisticated assessment techniques that have included inventory, bivariate, multivariate, probabilistic frequency ratio, logistics regression, fuzzy logic, such as AHP, probabilistic frequency and artificial neural network analysis (van Westen, 1997; Dai et al., 2001; Lee and Min, 2001; Ercanoglu and Gokceoglu, 2004; Lee, 2005; Pradhan et al., 2006; Dahal et al. 2008; Sarkar et al., 2008a,2008b; Dwikorita et al., 2011).

The techniques used to map a region’s landslide hazard can typically be labeled as being either a qualitative or quantitative approach (Guzzetti et al., 1999). Qualitative methods are a relatively subjective approach that represents the prone levels of a landslide in descriptive expressions based on decisions of experts (Sarkar et al., 2008a; 2008b; Wang et al., 2010; Pradhan et al. 2010; Dwikorita et al., 2011; Pradhan et al. 2012).

Quantitative models use a numerical assessment of the relationship between slope instability and other controlling factors. Two examples of a quantitative method are deterministic and statistical methods, which were frequently used in previous landslide susceptibility studies (Ercanoglu and Gokceoglu, 2002; Suzen and Doyuran, 2004; Ercanoglu and Gokceoglu, 2004; Yesilnacar and Topal, 2005; Kanungo et al., 2006; Garcia-Rodriguez et al., 2008; Nefeslioglu et al., 2008; Nandi and Shakoor, 2009; Dongyeob Kim et al., 2010; Pradhan, B., 2012 etc.). Deterministic approaches are mainly based on factor of safety (FOS) computation (Refice and Capolongo, 2002; Zhou et al., 2003), while statistic methods focus on historical correlations between landslide-controlling parameters and the distribution of landslide events.

The goal of this study was to compare and evaluate both qualitative and quantitative methods including AHP approaches, a probabilistic frequency ration model, a statistical index (Wi) and weighting factor (Wf) techniques for their ability to assess the probabilistic frequency landslide susceptibility of a case study. The first step was to set parameter weights and combined the decision alternatives with AHP, probabilistic frequency ratio technique and bivariate methods, to create a landslide susceptibility map. Then, the landslide susceptibility maps created as a result of this process are subjected to a comprehensive validation process. The models are validated using either data for landslides that was used to create the map or independent landslide information can be uses (Chung and Fabbri, 2003; Guzzetti et al., 2005; 2006).

GEOGRAPHICAL LOCATION OF THE STUDY AREA

Hulu Kelang region in Malaysia is very susceptible to landslides (Mukhlisin et al., 2010). Hulu Kelang is located in Kuala Lumpur, the capital city of Malaysia between 3º 09′ 25" and 3º 13′ 45" East latitude and 101º 44′ 13" and 101º 47′ 51" North longitudes (Fig. 1). Urban development has caused many problems to this region including numerous landslide and mudflow events. The Hulu kelang area has suffered several fatal Landslide caused by rainfall events. There were 28 major landslide events were identified as rainfall-induced landslides since 1984. The block of Highland
Towers as one of the important tragedies involving 48 deaths collapsed after several days’ rainfall in 1993.

**SPATIAL EFFECTIVE FACTORS**

**Historical Slope Failures**

This study began with data from past landslides found in previous reports, it is essential to document the distribution of landslides in an area, to investigate the extent, sample and types of landslide, and to determine landslide susceptibility, hazard, and vulnerability. According to the data sources from the Ampang Jaya Municipal Council (MPAJ) and the Slope Engineering Branch of Public Works Department Malaysia (PWD), a total of 28 major historical landslide events have been reported in the Hulu Kelang area from 1990 to 2011 (Lee et al., 2013)(Fig. 1).

![Inventory map of Hulu Kelang area, Serdang, Malaysia](image)

*Figure 1:* Inventory map of Hulu Kelang area, Serdang, Malaysia
Terrain

The most important terrain factors influencing slope stability is the elevation, slope inclination, slope aspect, slope curvature (Wilson and Gallant 2000; Gruber and Peckham 2008). The elevation factor influences the surface of the terrain and other topographical characteristics such as profile curvatures, the angle and aspect of a slope, and the determination of catchment areas and planning concerns in the study area. The area investigated in this study ranged in elevation from 0 to 425m above sea level. The Digital Elevation Model (DEM) was created by digitalizing 1/10.000 scaled standard topographic Ampang and Kampung Kelang Gates Baharu maps. The contours were drawn at 25m intervals. A DEM of the study area was prepared using ArcGIS 10 software. The pixel dimensions used was 30×30m pixel for the landslide and factor maps. Most of the landslide distribution densities occurred at 0–100m (57.6%) and 100-200m (42.4%).

Slope inclination as one of the factors used controls areal hydraulic continuity, and consequently factor of safety of slopes. In this study, six categories of slopes were used (0-10°, 10-20°, 20-30°, 20-40°, 40-50° and 50-90°). Based on the distributions of the historical landslide events, it was found that 98.8% of the landslides occurred on slopes between 0 and 40°.

Slope aspect as other factors used influences intensity of rainfalls received on a sloping surface and weathering process in a soil slope (Cevik and Topal 2003; Lee 2005; Galli et al. 2008). Nine different regions were investigated in the present study: flat area (−1°), north (337.5°–22.5°), northeast (22.5°–67.5°), east (67.5°–112.5°), southeast (112.5°–157.5°), south (157.5°–202.5°), southwest (202.5°–247.5°), west (247.5°–292.5°), and northwest (292.5°–337.5°). Slopes facing the in the same direction as the monsoons (northeast and southwest) are more prone to landslides. Observations from the landslide inventory map revealed that about 48.5% of the landslides occurred on the slopes inclined to these directions.

The term curvature as one of the terrain factors used in the study area defines the morphology of topography. Curved land normally increases the moisture content of soil, keeps the soil saturated, and consequently increases the susceptibility of slopes to erosion and landslides. In this study, three zones were identified based on their plan curvatures: positive curvature (convex), negative curvature (concave), and zero curvature representing flat surface. The analysis of landslide distribution density showed that 40% of the landslides located in the concave zone, while 31% of the landslides occurred in the convex zone (Table 1).

Residual Soil

Most shallow landslides in tropical areas happen to extremely weathered or residual soils (Rahardjo et al., 1996; Au, 1998; Zhu and Anderson, 1998). They are made set up from bedrock, by physical, chemical, and biological weathering processes. The bedrock lithological settings in the study area can generally be classified into three main types, namely granite, phyllite and schist, and limestone. The analysis of landslide distribution and residual soil units performed in this area revealed that 72.73% of the historical landslide events in Hulu Kelang occurred on highly or completely weathered granitic rock formation, while the remaining 27.27% of the landslides were located on phyllite and schist rock (Table 1).
### Table 1: AHP, FR, Wi and Wf values of the data layers

<table>
<thead>
<tr>
<th>Factor</th>
<th>Class</th>
<th>% of total area</th>
<th>% of landslide area</th>
<th>AHP</th>
<th>FR</th>
<th>Wi</th>
<th>Wf</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Residual soil</strong></td>
<td>Granite</td>
<td>54.08</td>
<td>44.08</td>
<td>0.571</td>
<td>0.216</td>
<td>1.345</td>
<td>0.296</td>
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<td></td>
<td>Phyllite-schist</td>
<td>42.51</td>
<td>16.53</td>
<td>0.286</td>
<td>0.642</td>
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<tr>
<td></td>
<td>Limestone</td>
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<td>0.00</td>
<td>0.143</td>
<td>0.000</td>
<td></td>
<td></td>
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<tr>
<td><strong>Land cover</strong></td>
<td>Primary forest</td>
<td>31.61</td>
<td>7.35</td>
<td>0.04</td>
<td>0.383</td>
<td>-0.958</td>
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<tr>
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<td>Secondary forest</td>
<td>1.88</td>
<td>2.20</td>
<td>0.158</td>
<td>1.934</td>
<td>0.661</td>
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<tr>
<td></td>
<td>Rubber</td>
<td>14.29</td>
<td>21.67</td>
<td>0.285</td>
<td>2.502</td>
<td>0.917</td>
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<td>Sundry tree cultivation</td>
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<td>0.04</td>
<td>0.000</td>
<td></td>
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<tr>
<td></td>
<td>Grassland</td>
<td>2.87</td>
<td>3.67</td>
<td>0.315</td>
<td>2.112</td>
<td>0.748</td>
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<td>Cleared land</td>
<td>4.64</td>
<td>2.57</td>
<td>0.082</td>
<td>0.914</td>
<td>-0.089</td>
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<tr>
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<td>Developed area</td>
<td>43.25</td>
<td>23.14</td>
<td>0.04</td>
<td>0.883</td>
<td>-0.125</td>
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<tr>
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<td>Lake</td>
<td>0.47</td>
<td>0.00</td>
<td>0.04</td>
<td>0.000</td>
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<td><strong>Terrain</strong></td>
<td>0-10</td>
<td>56.69</td>
<td>3.23</td>
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<td>10-20</td>
<td>15.16</td>
<td>15.43</td>
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<td>20-30</td>
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<td>9.92</td>
<td>0.148</td>
<td>0.743</td>
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<td>30-40</td>
<td>5.54</td>
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<td>0.193</td>
<td>0.656</td>
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<td>40-50</td>
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<td>0.73</td>
<td>0.259</td>
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<td>0.11</td>
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<td>North</td>
<td>5.77</td>
<td>6.61</td>
<td>0.024</td>
<td>1.891</td>
<td>0</td>
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<td>Northeast</td>
<td>5.08</td>
<td>2.57</td>
<td>0.113</td>
<td>0.835</td>
<td>-0.181</td>
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<td>East</td>
<td>7.5</td>
<td>7.35</td>
<td>0.215</td>
<td>1.616</td>
<td>0.480</td>
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<td>Southeast</td>
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<td>0.37</td>
<td>0.093</td>
<td>0.069</td>
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<td></td>
<td>South</td>
<td>8.08</td>
<td>7.71</td>
<td>0.024</td>
<td>1.575</td>
<td>0.455</td>
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<td>Southwest</td>
<td>8.75</td>
<td>3.67</td>
<td>0.134</td>
<td>0.693</td>
<td>-0.367</td>
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<td>West</td>
<td>10.77</td>
<td>1.47</td>
<td>0.215</td>
<td>0.225</td>
<td>0</td>
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<td>Northwest</td>
<td>7.93</td>
<td>8.45</td>
<td>0.134</td>
<td>1.758</td>
<td>0.564</td>
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<td>Flat</td>
<td>37.37</td>
<td>22.41</td>
<td>0.049</td>
<td>0.989</td>
<td>-0.011</td>
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<tr>
<td></td>
<td>Concave</td>
<td>34.87</td>
<td>23.88</td>
<td>0.588</td>
<td>1.130</td>
<td>0.122</td>
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<td>Flat</td>
<td>30.89</td>
<td>17.63</td>
<td>0.089</td>
<td>0.942</td>
<td>-0.060</td>
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<tr>
<td></td>
<td>Convex</td>
<td>34.24</td>
<td>19.10</td>
<td>0.323</td>
<td>0.920</td>
<td>-0.083</td>
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<td><strong>Elevation</strong></td>
<td>0-100</td>
<td>48.24</td>
<td>34.89</td>
<td>0.467</td>
<td>1.194</td>
<td>0.177</td>
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<td></td>
<td>100-200</td>
<td>31.92</td>
<td>25.71</td>
<td>0.277</td>
<td>1.329</td>
<td>0.284</td>
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<tr>
<td></td>
<td>200-300</td>
<td>17.99</td>
<td>0.00</td>
<td>0.16</td>
<td>0.000</td>
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<td></td>
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<tr>
<td></td>
<td>300-425</td>
<td>1.85</td>
<td>0.00</td>
<td>0.095</td>
<td>0.000</td>
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<td><strong>Distance to the road construction</strong></td>
<td>0-25</td>
<td>10.13</td>
<td>11.75</td>
<td>0.442</td>
<td>1.915</td>
<td>0.650</td>
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<td>25-50</td>
<td>13.22</td>
<td>19.83</td>
<td>0.228</td>
<td>2.476</td>
<td>0.907</td>
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<td></td>
<td>50-75</td>
<td>7.22</td>
<td>1.47</td>
<td>0.112</td>
<td>0.336</td>
<td>-1.091</td>
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<td></td>
<td>75-100</td>
<td>5.82</td>
<td>2.94</td>
<td>0.091</td>
<td>0.833</td>
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<td>100-125</td>
<td>5.04</td>
<td>6.61</td>
<td>0.07</td>
<td>2.165</td>
<td>0.772</td>
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<td>125-250</td>
<td>58.57</td>
<td>18.00</td>
<td>0.056</td>
<td>0.507</td>
<td>-0.679</td>
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<tr>
<td><strong>Distance to flows</strong></td>
<td>0-0.0025</td>
<td>12.29</td>
<td>6.61</td>
<td>0.391</td>
<td>0.888</td>
<td>-0.119</td>
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<td></td>
<td>0.0025-0.005</td>
<td>22.11</td>
<td>9.92</td>
<td>0.175</td>
<td>0.740</td>
<td>-0.301</td>
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<td>0.005-0.0075</td>
<td>12.51</td>
<td>8.45</td>
<td>0.14</td>
<td>1.114</td>
<td>0</td>
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<td>0.0075-0.01</td>
<td>8.74</td>
<td>3.31</td>
<td>0.078</td>
<td>0.624</td>
<td>-0.471</td>
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<td>0.01-0.15</td>
<td>10.96</td>
<td>2.20</td>
<td>0.059</td>
<td>0.332</td>
<td>-1.103</td>
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<td>0.15-0.25</td>
<td>5.86</td>
<td>2.57</td>
<td>0.059</td>
<td>0.724</td>
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<tr>
<td></td>
<td>0.25-0.250</td>
<td>5.26</td>
<td>7.35</td>
<td>0.049</td>
<td>2.304</td>
<td>0.836</td>
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<td></td>
<td>0.250-0.500</td>
<td>22.26</td>
<td>16.53</td>
<td>0.049</td>
<td>1.225</td>
<td>0.203</td>
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</tr>
<tr>
<td><strong>Drainage Density</strong></td>
<td>0-0.0025</td>
<td>44.22</td>
<td>11.75</td>
<td>0.102</td>
<td>0.439</td>
<td>-0.824</td>
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</tr>
<tr>
<td></td>
<td>0.0025-0.005</td>
<td>8.69</td>
<td>0.00</td>
<td>0.046</td>
<td>0.000</td>
<td></td>
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</tr>
<tr>
<td></td>
<td>0.005-0.0075</td>
<td>8.88</td>
<td>2.94</td>
<td>0.09</td>
<td>0.546</td>
<td>-0.605</td>
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<tr>
<td></td>
<td>0.0075-0.01</td>
<td>14.17</td>
<td>19.10</td>
<td>0.127</td>
<td>2.224</td>
<td>0.799</td>
<td></td>
</tr>
</tbody>
</table>
Land Cover

Land covers could act as a buffer to limit rainwater infiltration into soil slopes by evapotranspiration from the canopies (interception loss) and, to a lesser extent, absorbed by plants (Rutter et al. 1971, 1975). Under the classification system, eight types of land covers were identified, i.e. primary forest, secondary jungle, rubber, sundry tree cultivation, grassland, cleared land, developed area, and lake. Historical slope failures were mainly scattered on the rubber and grassland areas. These land covers with no canopy allow for more rainfall infiltration, which increases soil pore-water pressure and increases the potential for landslides (Table 1).

Distance to Road Constructions

Distance to road construction activities such as soil excavation, imposing of surcharge load, cut slope, embankment construction, and removal of vegetation cover may cause failures to the slopes which are otherwise stable. Six regions were identified in this study based on their distances from roadways (0-25m, 25-50m, 50-75m, 75-100m, 100-125m, and less than 125m). About 86% of past landslides occurred 0–50m from a roadway (Table 1).

Distance to Flows

Several studies have shown that susceptibility to landslides could be affected by preferential flows in soil (Tsukamoto et al. 1982; Sidle et al. 2000, 2006; Uchida et al. 2002) and rock masses (Montgomery et al. 1997; Uchida et al. 2002; Sidle and Chigira 2004). In this area, distance to stream as one of factors used represented at eight buffer zones (0–25m, 25–50m, 50–75m, 75–100m, 100-150m, 150-200m, 200-250m, and less than 250m) based on their proximity to were identified as shown in Table 1. Most of the historical landslides were located between 0 and 75m from a stream.
Drainage Density

Drainage density is defined as the proportion of the total length of the water flow to the total area of the drainage basin. Drainage networks also as one of factor used in this study were extracted directly from the digital elevation map (DEM). Eight drainage buffer zones were produced to define the extent of slope instability caused by streams. These drainage buffer zones were: Zone A (0-0.0025m⁻¹), Zone B (0.0025-0.005m⁻¹), Zone C (0.005-0.0075m⁻¹), Zone D (0.0075-0.01m⁻¹), Zone E (0.01-0.0125m⁻¹), Zone F (0.0125-0.015m⁻¹), Zone G (0.015-0.03m⁻¹), and Zone H (0.03-0.135m⁻¹). The drainage density analyses showed that all the historical landslides occurred within the density range of 0–0.015 m⁻¹ (Table 1).

Saturation Condition

The Compound Saturation Condition is also known as the Topographic Moisture Index or the Topographic Wetness Index (TWI) that used in this study. The saturation condition is a ratio of contributing catchment area to slope inclination (Wilson and Gallant, 2000). The study area was divided into eight different classes of saturation condition ranging from 0 to 19.3. Table 1 shows that 35.76% of the historical landslides occurred within the TWI range of 11.04-17.9.

Stream Power Index (SPI)

The Stream Power Index (SPI) is a way of measuring the power of surface water to erode surfaces based on the hypotheses that discharge ($q$) is proportional to the specific catchment area ($A_s$). The SPI value is governed by two parameters: viscosity of the land slope and steepness of the terrain. Seven SPI classes were used in this study and they ranged from 0 to 16.6. The SPI analysis showed that 57% of the historical landslides occurred within the SPI range of 10.44–15.56 (Table 1).

ANALYSIS OF LANDSLIDE SUSCEPTIBILITY

In this study, an analysis of the susceptibility to landslides was carried out using the analytical hierarchy process (AHP), probabilistic frequency ratio, and bivariate (Wi and Wf) models. Prior to the analyses, the factors affecting landslides in Hulu Kelang area were identified.

Analytical Hierarchy Process (AHP)

One method of analyzing complex decisions based on quantifiable and tangible criteria is the Analytical Hierarchy Process (AHP) (Vargas, 1990). This qualitative method creates a hierarchy for the decision parameters and then compares possible pairs in a matrix so that a weight and consistency ratio can be assigned to each element and also a consistency ratio (Malczewski, 2004). This technique has been used successfully to map landslide susceptibility (Ayalew et al. 2004, 2005; Komac 2006; Yoshimatsu and Abe 2006; Castellanos EA and Van-Westen CJ 2008; Akgün and Bulut 2007; Akgün et al. 2008).

AHP involves structuring a problem into primary and secondary objectives. Upon establishment of the hierarchy, a pairwise comparison matrix for each factor in each level is constructed. Each factor is weighed against other factors within the same level, and correlate to the levels above and below its position. The entire scheme is mathematically joined, resulting in a priority statement for each individual or group.

The consistency of a matrix can be checked by calculating the principal Eigen value, $\lambda_{max}$. 
The upper bound of the eigen value is the same size as the matrix. In this study, \( n = 11 \). \( \lambda_{\text{max}} = n \), where \( n \) is the order of the matrix. In other words, a perfectly consistent matrix should yield an Eigen value of \( n \). To define the deviation or degree of consistency, a consistency index or \( CI \) can be computed as follows:

\[
CI = \frac{\lambda_{\text{max}} - n}{n - 1}
\]  

(2)

A high \( CI \) value indicates a matrix of low consistency. The most consistent matrix should yield a \( CI = 0 \). To determine the satisfactory consistency level of a matrix, consistency ratio (\( CR \)) is normally computed as shown below.

\[
CR = \frac{CI}{RI}
\]  

(3)

where \( RI \) is the average value of the consistency index created using a random matrix that depends on the matrix order. A matrix with a satisfactory consistency level should yield a \( CR \) of less than 0.10. The consistency index (\( CI \)) and average \( RI \) obtained from the matrices 11*11 in the present study were 0.453 and 1.51, respectively yielding an consistency ratio (\( CR \)) of 0.03. The low consistency ratio (<0.10) implied that the computed weight for each factor was acceptable.

### Probabilistic Frequency Ratio Model

When evaluating the probabilistic landslide susceptibility of an area, it is critical that the effective factors and the process that could trigger movement are identified. The probabilistic frequency ratio method is based on the distribution of landslides and the parameters related to landslides so that the correlation between the location of the landslide and the parameters for the area can be represented (Pradhan et al. 2010). The first step was to calculate the frequency ratio for each parameter based on its relationship to landslides. Next, the frequency ratio for the sub-criteria of each parameter was calculated. These ratios were used to find the landslide susceptibility index (LSI) (refer to Eq. 1) (Lee and Pradhan, 2007).

\[
LSI = Fr_1 + Fr_2 + Fr_3 + \ldots + Fr_n
\]  

(4)

Where, \( Fr \) is the rating for each parameter. According to the probabilistic frequency ratio method, an average LSI has a value of unity. A value of > 1 indicates that there is a strong relationship between the landslide and the parameter being investigated.

### Bivariate Statistics Method

This study used a statistical bivariate model based on Wi (van Westen, 1997) and Wf approaches, which are widely considered to be a simple and quantitative method of susceptibility mapping (Cevik and Topal, 2003; Lan et al., 2004; Wang and Sassa, 2005; Thiery et al., 2007; Dahal et al. 2008), were used to compute the distribution of landslides for each factor class. These density values can be standardized by correlating them to the overall density in an area (Oztekin and Topal,
In this study, the \( W_i \) for each class was computed using the formula proposed by vanWesten (1997):

\[
W_i = \ln \left( \frac{N_{pix}(Si)}{N_{pix}(Ni)} \right) = \ln \left( \frac{SN_{pix}(Si)}{SN_{pix}(Ni)} \right)
\]  

(5)

where \( W_i \) is the weight given to a determined class of parameter. \( Dens_{class} \) refers to the landslide density within the class of parameter and the \( Dens_{map} \) is the landslide density for the whole map. \( N_{pix}(Si) \) is the number of pixels that contain a determined parameter class of landslide, \( N_{pix}(Ni) \) is the total number of pixels for a determined parameter class, \( SN_{pix}(Si) \) is the total number of pixels in all the landslides, and \( SN_{pix}(Ni) \) is the total number of all pixels.

Table 1 shows the \( W_i \) value of each computed attribute. All the layers were laid on top of one and other to create a susceptibility map. The \( W_i \) susceptibility map was separated into equal classes labeled very low, low, moderate, high, very high, and critical susceptibility. However, these maps indicate that each factor map had an equal effect on landslides, which is not an accurate reflection of what really happens (Oztekin and Topal, 2005). To resolve this issue, a \( W_f \) was produced for each factor shown on a map. The first step in this process is to define the \( W_i \) value of each pixel using the \( W_i \) method. In the next step, the values for all the pixels within the landslide zones for each layer were added together. The results were stretched using the maximum and minimum for all layers (Cevik and Topal, 2003). The weighting factors that ranged from 1 to 100 for each layer were defined using the formula shown below.

\[
W_f = \frac{(TW_{i\text{value}}) - (MinTW_{i\text{value}})}{(MaxTW_{i\text{value}}) - (MinTW_{i\text{value}})} \times 100
\]  

(6)

where \( W_f \) is the calculated weighting factor for each layer and \( TW_{i\text{value}} \) is the total weighting index value of the cells in the landslide bodies for each layer. The minimum total weighting index value in selected layers is represented using \( MinTW_{i\text{value}} \) and the Maximum total weighting index value within selected layers is calculated using \( MaxTW_{i\text{value}} \). In this analysis, the \( W_f \) value was multiplied by the \( W_i \) value. All the factors shown on the map were added together to determine final landslide susceptibility.

RESULTS AND DISCUSSIONS

The landslide susceptibility maps produced from the four prescribed approaches, i.e. analytical hierarchy process (AHP), probabilistic frequency ratio, statistical index (\( W_i \)), and weighting factor (\( W_f \)) models yielded six susceptibility classes, namely very low (the lowest susceptibility), low, moderate, high, very high, and critical (the highest class) susceptibility.
Landslide Susceptibility Maps

In general, the obtained weight factor / ratio / index of using AHP, Wi, Wf, and FR showed good agreement with the historical landslide data and fundamental theories of slope stability. For instances, the highest weight was assigned to granite, followed by phyllite and schist and limestone in view of most historical landslides occurred on granitic formation. In the case of land cover, grasslands and rubber plantations were given higher weights than other land covers planted by humans. The slope weight inclination factor generally increased with the increase in slope inclination classes. This is consistent with the force equilibrium of slopes whereby steep slopes would yield a higher mobilized force, and thus are more prone to failure than gentle slopes. In the case of slope aspect, as mentioned earlier, northeast and southwest facing slopes that are influenced by the two monsoon seasons in this area are more susceptible to landslide. In terms of plan curvature, concave region has the highest weight as the terrain promotes accumulation of soil moisture at the toe of slope and weakens the shear strength of soil. In the case of altitude, the 0–100m class and 100–200m class were given the higher weights than the classes of higher elevations because in the past, most landslides in this area occurred at an elevation of 200m. The weight factors decreased with increasing distances to road and drainage and this is compatible with what is expected. With respect to the drainage density, the weight factor increased with the increased drainage density, particularly for classes between 0 and 0.015 m\(^{-1}\). The correlation between topographic wetness index (TWI) and landslide probability showed that the 12.76-14.48 class has the highest value of weight factor. Similarly, the stream power index (SPI) class of 10.44-12.15 yielded the highest weight. Based on the weight factor / ratio / index assigned for each landslide influencing factors, the landslide susceptibility maps produced using AHP, probabilistic frequency ratio, Wi, and Wf models are presented in Figure 2.

Figure 2a: Landslide susceptibility map produced from FR and AHP models.
Comparison of the Susceptibility Maps using Receiver Operating Characteristics

Four landslide susceptibility maps were produced in this study and their spatial effectiveness was evaluated by comparing the maps with the data used to analyze the landslides to determine what areas might be affected by future landslides based on receiver operating characteristics (ROC). The final landslide susceptibility maps were evaluated in regards to unknown future landslides (Chung and Fabbri, 2003). A ROC curve is an effective way to indicate the quality of probabilistic and deterministic findings and forecast systems. In this study a ROC curve test was used as a cross-validation method. First, the historical landslide events were divided into two groups. The modeling group, which represented approximately 70% of the total landslides, was used as a training set to construct the susceptibility maps. The remaining 30% of landslides were used for prediction testing. The regions that were not affected by landslides were used as prediction group during the training phase. The regions affected by landslides were used in the training set labeled “areas prone to landslides.” The ROC curve was used to evaluate the prediction database and the region under the curve (AUC) was computed (Pradhan et al., 2010; Pourghasemi et al., 2012). The AUC indicates how well a forecast system performed by determining how accurate the model was and if it was threshold independent (Yesilnacar and Topal, 2005). The true positive rate of the Y-axis and the false positive rate of the X-axis were plotted using the ROC curve. This revealed the relationship between the true positive and false positive rates (Biggerstaff, 2000). This value ranged from 0.5, which indicated a random prediction, represented by the diagonal straight line, to 1, which indicated an excellent prediction that could be used to collect the relative ranks for each prediction type (Cervi et al., 2010). The result of the ROC curve test was used to evaluate how sensitive the model was. In
this study, the percentage of unstable pixels was correctly predicted by the model as was the specificity validation or the percentage of predicted unstable pixels. The result of sensitivity analysis indicated that the probabilistic frequency ratio model (Fig. 3) was more efficient in terms of its predictions when compared to the other models used in this study.

The AUC for the landslide susceptibility map produced using the probabilistic frequency ratio model was 0.8154 (prediction accuracy = 81.5%) as determined by the ROC plot assessment. The AUC for the other 3 models ranged from 0.7130 to 0.7475 as shown in Figure 3. With respect to predicted unstable pixels (Fig. 4), the AUC for the probabilistic frequency ratio was also the highest (0.7904), followed by the Wi model (0.7441), the Wf model (0.7246), and the ASP model (0.6787) (Fig. 4). From the ROC curve test, it can be concluded that the probabilistic frequency ratio model was the best modeling technique used in this study.

<table>
<thead>
<tr>
<th>Model</th>
<th>AUC</th>
<th>Prediction</th>
</tr>
</thead>
<tbody>
<tr>
<td>Probability-Frequency ratio</td>
<td>0.8154</td>
<td>Very GOOD</td>
</tr>
<tr>
<td>Statistical index (Wi)</td>
<td>0.7475</td>
<td>GOOD</td>
</tr>
<tr>
<td>weighting factor (Wf)</td>
<td>0.7305</td>
<td>GOOD</td>
</tr>
<tr>
<td>Analytical hierarchy process (AHP)</td>
<td>0.7130</td>
<td>GOOD</td>
</tr>
</tbody>
</table>

**Figure 3.** Success rate curves for the four landslide susceptibility maps

<table>
<thead>
<tr>
<th>Model</th>
<th>AUC</th>
<th>Prediction</th>
</tr>
</thead>
<tbody>
<tr>
<td>Probability-Frequency ratio</td>
<td>0.7904</td>
<td>GOOD</td>
</tr>
<tr>
<td>Statistical index (Wi)</td>
<td>0.7441</td>
<td>GOOD</td>
</tr>
<tr>
<td>weighting factor (Wf)</td>
<td>0.7246</td>
<td>GOOD</td>
</tr>
<tr>
<td>Analytical hierarchy process (AHP)</td>
<td>0.6787</td>
<td>MEDIUM</td>
</tr>
</tbody>
</table>

**Figure 4.** Prediction rate curves for the four landslide susceptibility maps
Relative Distributions of Susceptibility Levels

The distribution of the landslide prone areas was identified from the four landslide inventory maps represented by a GIS-based tool. An equal distribution classifier was used because the data values for all landslide inventory maps exhibited normal distribution (Fig. 5). Apparently, the relative distributions of susceptibility levels for the four models exhibited a similar normal distribution trend, whereby the class of low susceptibility has the highest distribution. The distributions for high, very high, and critical susceptibility were significantly lower than the classes of lower susceptibilities. Nevertheless, the absolute percentage of area for each susceptibility class varied with the model adopted. The relative distribution obtained from the probabilistic frequency ratio model has a more widely spread normal distribution. Comparatively, the area of low susceptibility for the probabilistic frequency ratio model was significantly lower than other models, while higher distributions were observed for classes of high, very high, and critical susceptibility.

![Histogram showing the relative distributions of landslide areas for various classes of susceptibility](image)

**Figure 5:** Histogram showing the relative distributions of landslide areas for various classes of susceptibility

The landslide inventory map containing twenty eight major active landslide zones was laid on top of the landslide susceptibility maps. A histogram that summarizes the percent of active landslide zones in various classes is shown in Figure 6. None of the landslides occurred in the very low susceptibility zone. Landslides that fell into the low susceptibility zone were significantly lower in the landslide susceptibility map created using the frequency ratio model (2%) than those of AHP, Wi, and Wf models (16, 13, 13%, respectively). The high, very high, and critical susceptibility zones defined using AHP, FR, Wi, and Wf methods contained 1%, 49%, 33%, and 21% of the active landslide zones, respectively. These results indicated that the frequency ratio model was the landslide susceptibility mapping method preferred for use in this study as the resultant map contained a relatively low percentage of active landslide zones in the very low and low susceptibility
classes, and a high percentage of active landslide zones in the high, very high and critical susceptibility zones.

![Figure 6: Histogram showing the percentages of active landslide zones for various classes of susceptibility](image)

From the foregoing verification analyses (ROC and relative distribution of susceptibility level), it can be concluded that the probabilistic frequency model is capable of producing a more reliable landslide susceptibility map than the other 3 models adopted in the present study. This is because the weight factors of FR model were determined quantitatively from probabilistic analysis of spatial distribution of historical landslide events obtained from the landslide inventory map. On the contrary, the AHP model yielded the most unfavorable verification results. A plausible explanation to this result is that the AHP model determines the priority weight of factors based on qualitative judgment that could be very subjective to the decision of experts.

**CONCLUSIONS**

This paper compared and evaluated four different models used to assess landslide susceptibility in the Hulu Kelang area of Kuala Lumpur, Malaysia. The susceptibility level was classified into five categories, namely equal, moderate, high, very high, and extreme. Four landslide susceptibility maps were produced and their reliabilities were verified by the receiver operating characteristics (ROC), frequency ratio, and relative distributions of the susceptibility levels and active landslide zones.

The prediction rate of ROC curves for the susceptibility maps indicated that the probabilistic frequency ratio model had the highest prediction accuracy (>81%), while the AHP model showed the least prediction accuracy (71.3%). Active landslide zone locations (89%) were predicted more accurately with the FR map than its counterparts, the AHP, Wi and Wf maps (34%, 54%, and 66%, respectively). The spatial distributions of the landslide susceptibility zones showed that most of the
landslide prone areas located near the toe of hillsides with intensive new developments. The relatively flat and well developed areas at the east of Hulu Kelang are less susceptible to landslide.

A landslide susceptibility map for Hulu Kelang area was successfully developed. And the field observation verification results showed that 96.37% of the historical landslide events occurred in the zones of high - very high landslide susceptibility based on FR model. The results proved that the developed landslide susceptibility map is reliable and capable of providing good predictions on the spatial distributions of landslide occurrence in the study area.

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REFERENCES


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