A comparative study on the landslide susceptibility mapping using evidential belief function and weights of evidence models

QIQING WANG, WENPING LI*, YANLI WU, YABING PEI, MAOLIN XING and DONGDONG YANG

School of Resources and Geosciences, China University of Mining and Technology, Xuzhou 221116, China.

**Corresponding author. e-mail: wpligroup@126.com*

The purpose of this study is to produce landslide susceptibility map of a landslide-prone area (Daguan County, China) by evidential belief function (EBF) model and weights of evidence (WoE) model to compare the results obtained. For this purpose, a landslide inventory map was constructed mainly based on earlier reports and aerial photographs, as well as, by carrying out field surveys. A total of 194 landslides were mapped. Then, the landslide inventory was randomly split into a training dataset; 70% (136 landslides) for training the models and the remaining 30% (58 landslides) was used for validation purpose. Then, a total number of 14 conditioning factors, such as slope angle, slope aspect, general curvature, plan curvature, profile curvature, altitude, distance from rivers, distance from roads, distance from faults, lithology, normalized difference vegetation index (NDVI), sediment transport index (STI), stream power index (SPI), and topographic wetness index (TWI) were used in the analysis. Subsequently, landslide susceptibility maps were produced using the EBF and WoE models. Finally, the validation of landslide susceptibility map was accomplished with the area under the curve (AUC) method. The success rate curve showed that the area under the curve for EBF and WoE models were of 80.19% and 80.75% accuracy, respectively. Similarly, the validation result showed that the susceptibility map using EBF model has the prediction accuracy of 80.09%, while for WoE model, it was 79.79%. The results of this study showed that both landslide susceptibility maps obtained were successful and would be useful for regional spatial planning as well as for land cover planning.

1. Introduction

Landslides, often causing property damage and economic losses and creating high maintenance costs, are dangerous natural hazards in many parts of the world (Lee and Oh 2012). Every year, hundreds of people all over the world lose their lives in landslides; furthermore, there are large impacts on the local and global economy from these events (Yalcin *et al.* 2011). In China, during the last 60 years, natural hazards associated with landslides caused more than 25,000 human deaths. The

average annual death number caused by landslides was more than 400 people, and the annual economic losses emanating from landslides are about US \$50 million (Sang 2013). In addition, currently tens of millions of people still live under the high-risk threat of landslides (Liu *et al.* 2013). It is therefore necessary to assess and manage areas that are susceptible to landslides in order to mitigate any damage associated with them (Lee 2004).

Landslide susceptibility maps can be produced by common assessment methods such as probabilistic approach (Lee and Pradhan 2006; Akgun *et al.*

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2008; Vijith and Madhu 2008; Yilmaz and Keskin 2009; Youssef *et al.* 2009, 2012; Pradhan and Youssef 2010; Demir *et al.* 2013; Saponaro *et al.* 2014; Sujatha *et al.* 2014), statistical models including logistic regression, bivariate and multivariate models, etc. (Ayalew *et al.* 2005; Lee and Pradhan 2007; Bai *et al.* 2010; Bednarik *et al.* 2010; Choi *et al.* 2012; Raman and Punia 2012; Grozavu *et al.* 2013; Ozdemir and Altural 2013; Regmi *et al.* 2014; Solaimani *et al.* 2013). In addition, other different methods such as analytic hierarchy process (AHP) (Komac 2006; Yoshimatsu and Abe 2006; Yalcin 2008; Ma *et al.* 2013; Daneshvar 2014), certainty factor (CF) model (Kanungo *et al.* 2008, 2011; Sujatha *et al.* 2012; Devkota *et al.* 2013; Pradhan and Kim 2014; Wang *et al.* 2015), artificial neural network model (Prabu and Ramakrishnan 2009; Chauhan *et al.* 2010; Pradhan and Buchroithner 2010; Park *et al.* 2013; Tsangaratos and Benardos 2014), index of entropy (IoE) model (Mihaela *et al.* 2011; Davis and Sims 2013; Devkota *et al.* 2013; Jaafari *et al.* 2014; Sharma *et al.* 2015), fuzzy approach (Kanungo *et al.* 2008; Ercanoglu and Temiz 2011; Suh *et al.* 2011; Guettouche 2013; Sharma *et al.* 2013), etc., have also been applied to prepare landslide susceptibility maps. Every assessment model for landslide susceptibility has its advantages and drawbacks; hence, there is no agreement on either the models or the scope of susceptibility map production (Duman *et al.* 2006; Ma *et al.* 2013). Therefore, assessment methods for higher precision evaluation need to be developed (Ma *et al.* 2013). In this paper, two models, including evidential belief function (EBF) and weights of evidence (WoE) were used to assess landslide susceptibility in a landslide-prone area located in the southwest of China. In order to find the better model that is more accurate in landslide susceptibility mapping in the study area, both models were developed, applied, and verified.

2. The study area

The selected study area, shown in figure 1, extends to about 1692 km² and belongs to Daguang County of Yunnan, China. This site lies between latitudes 27°36'–28°15'N and longitudes 103°43'–104°07'E and is located in the northern edge of the Yungui plateau buffer area. The altitude of the area ranges from 523 to 2773 m asl. The terrain disparity of the area is notable, which takes appearance of higher in the north and south area and lower in the middle. The climate in the study area belongs to the semi-tropical monsoon, with high temperature climate summers and a rainy season normally lasting from June to September. The temperature varies between –6° and 40°, and the mean

annual rainfall is around 1140 mm based on the records from the China Meteorological Administration. Main streams in the study area include five main rivers. These rivers and their tributaries form dendritic drainage system due to topographical and geological features of the area. In this area, the traffic is convenient. Up to now, the County road mileage is about 1547 km. The population of the County was about 281,900 in the year 2011. This site is one of the frequent landslide occurrence areas in China due to the coupling effects of special geological and climatic conditions and the influences of human engineering activities. In total, 194 landslides were identified and mapped in the study area. Of these, 156 landslides are rotational earth slides, while 38 landslides are earth flow (Sun 2007). The largest landslide encompasses about 1.82 km², and the smallest one covers approximately 2450 m². In addition, most of the landslides occurred after heavy rainfall in the region.

3. Data used

3.1 Landslide inventory map

Historic information on landslide occurrences is considered as the fundamental part of the landslide hazard studies, which give shrewdness into the frequency, volumes, damage, and types of the landslide phenomena (Van Westen *et al.* 2006; Regmi *et al.* 2014; Youssef *et al.* 2014). Therefore, landslide occurrences in the past and present are keys to future spatial prediction; a landslide inventory map, providing the basic information for evaluating landslide hazards or risk, is a pre-requisite for such a study (Guzzetti *et al.* 1999; Regmi *et al.* 2014). Accurate collection of the data related to landslides is very important for landslide susceptibility analysis. In this study, the landslide inventory map of the region was prepared by using 1:50,000 scale aerial-photo interpretation and extensive field surveys. Besides, the historical landslide records obtained from the internet and published literature were also used (Sun 2007; Yang 2014). A total of 194 landslides were identified and mapped (figure 1). From these, 136 (70%) landslides were randomly selected as training data and the remaining 58 (30%) landslides were kept for validation purposes (Lee and Oh 2012; Pourghasemi *et al.* 2012a, b; Zare *et al.* 2013; Youssef 2015). In this study, all data layers were transformed in raster format with pixel size of 30 m × 30 m, hence the area grid was 2515 rows by 1503 columns with a total of 1,880,85 pixels.

3.2 Conditioning factors

Identification of suitable conditioning factors in a certain area requires prior knowledge of the

Figure 1. The study area with landslide locations.

landslides (Guzzetti *et al.* 1999; Ma *et al.* 2013). In this study, 14 landslide conditioning factors (slope angle, slope aspect, general curvature, plan curvature, profile curvature, altitude, distance to rivers, distance to roads, distance to faults, lithology, NDVI, STI, SPI, and TWI) were chosen to assess the landslide susceptibility of the study area. These factors fall under the category of preparatory factors, responsible for the occurrence of landslides in the region for which pertinent data can be collected from available resources, as well as, from the field surveys.

Slope angle, frequently used in preparing landslide susceptibility maps, is a major parameter in the assessment of slope stability since land sliding is directly related to slope angle (Lee and Min 2001; Saha *et al.* 2005; Yalcin *et al.* 2011). The slope map

of the study area was prepared from the $30\text{ m} \times 30\text{ m}$ digital elevation model (DEM) collected from the Advanced Space-borne Thermal Emission and Reflection Radiometer (ASTER) using ArcGIS 10.0 (ESRI Inc., Redlands, CA, USA) and was classified into seven categories (figure 2a), considering the steepness of the terrain (Kayastha *et al.* 2013a).

The slope aspect is also considered as an important factor in landslide susceptibility studies since slope aspect is related to the physiographic trends and the main precipitation direction (Ercanoglu and Gokceoglu 2002; Regmi *et al.* 2014). The aspect of the study area was divided into nine directional classes as flat (-1), north ($337.5^\circ\text{--}360^\circ$, $0^\circ\text{--}22.5^\circ$), northeast ($22.5^\circ\text{--}67.5^\circ$), east ($67.5^\circ\text{--}112.5^\circ$), southeast ($112.5^\circ\text{--}157.5^\circ$), south ($157.5^\circ\text{--}202.5^\circ$), southwest

Figure 2. Landslide conditioning factors of the study area: (a) slope angle, (b) slope aspect, (c) general curvature, (d) plan curvature, (e) profile curvature, (f) altitude, (g) distance to rivers, (h) distance to roads, (i) distance to faults, (j) lithology, (k) NDVI, (l) STI, (m) SPI, and (n) TWI.

(202.5°–247.5°), west (247.5°–292.5°), and northwest (292.5°–337.5°) (figure 2b).

The curvature values represent the morphology of the topography (Devkota *et al.* 2013). General curvature, defined as the rate of change of slope degree or aspect, has been argued to affect slope stability. The characterization of slope morphology and flow can be analyzed with the help of the general curvature map (Nefeslioglu *et al.* 2008). Plan curvature influences the convergence and divergence of flow across a surface and profile curvature affects the acceleration and deceleration of

downslope flows and, as a result, influences erosion and deposition (Kannan *et al.* 2013; Pourghasemi *et al.* 2013; Kritikos and Davies 2014). In this study, the general curvature, plan curvature and profile curvature were derived from the DEM in ArcGIS 10.0 and were divided into three classes, respectively (figure 2c, d, e).

Altitude or elevation is another frequent conditioning factor for landslide susceptibility analysis. Generally, the landslides have more tendency to occur at higher elevations (Ercanoglu *et al.* 2004; Devkota *et al.* 2013). In the study area, the

Figure 2. (Continued.)

elevation values were divided into seven categories using an interval of 300 m (figure 2f).

Runoff plays an important role as a conditioning factor for landslide occurrences (Devkota *et al.* 2013). The closeness of the slope to drainage structures is another important factor for landslide susceptibility analysis. In the present study, the distance to rivers map was divided into five categories (figure 2g).

The distance to roads has been considered as one of the most important anthropogenic factor influencing landslide occurrence that can be the cause of cut slope creations through construction of roads that disturbs the natural topology and affects the

stability of the slope (Pourghasemi *et al.* 2012a; Devkota *et al.* 2013; Demir *et al.* 2013). In the present study, five different buffer zones were created within the study area to determine the degree to which the roads affected the slopes (figure 2h).

The distance to faults was also a necessary parameter in the susceptibility analysis. Commonly, geological fault is responsible for triggering a large number of landslides because of the tectonic breaks that usually decrease the rock strength (Qiao *et al.* 2014). In this study, five different buffer zones of the distance to faults were prepared from geological maps using the Euclidean distance interpolation method (figure 2i).

Figure 2. (Continued.)

In general, different lithological units have different landslide susceptibility values, which can provide important information regarding landslide susceptibility of a region (Yalcin and Bulut 2007; Pourghasemi *et al.* 2012b). Therefore, lithology is also one of the most common determinant factors in landslide susceptibility analysis. Based on the geology database, types of lithology were extracted and all rock masses were divided into three categories, viz., hard rocks, medium-hard rocks, and weak rocks (figure 2j). Among them, hard rocks include limestone, dolomite, sandy dolomite, sandstone and basalt; the medium-hard rocks consist of argillaceous dolomite and silty

sandstone, and limestone and dolomite interbedding; the weak rocks include argillaceous dolomite with intercalation of shale, mudstone, siltstone mixed mudstone and shale, shale with intercalation of coal, coal, strong weathering rocks and soil.

The NDVI is often considered as a conditioning factor in landslide susceptibility mapping. Its value denotes areas of vegetation in an image (Youssef 2015). In this study, NDVI map was obtained from Landsat satellite image and five classes of the NDVI were extracted as shown in figure 2(k).

The sediment transport index (STI) is often used to reflect the erosive power of the overland

Figure 2. (Continued.)

flow (Pourghasemi *et al.* 2012a). STI is defined in equation (1) as:

$$STI = \left(\frac{A_S}{22.13} \right)^{0.6} \left(\frac{\sin \beta}{0.0896} \right)^{1.3} \quad (1)$$

where A_S is the specific catchment area (m^2/m), and β the slope gradient. In the present study, the STI was calculated as shown in figure 2(1).

The stream power index (SPI), a compound topographic attribute, is often considered as a conditioning factor in landslide susceptibility analysis (Pourghasemi *et al.* 2012a, b; Devkota *et al.* 2013; Park *et al.* 2013; Pradhan and Kim 2014; Saadatkhah *et al.* 2014). It is a way of measuring the erosive power of water flow based on the assumption that discharge is proportional to the specific catchment area (Conforti *et al.* 2011). The SPI is expressed as $SPI = A_S \times \tan(\beta)$, where A_S is the specific catchment area and β is the local slope gradient measured in degrees (Moore *et al.* 1988; Park *et al.* 2013). In this study, the SPI map was classified into four classes (figure 2m).

The topographic wetness index (TWI) is another important topographic factor within the runoff model. It describes the effect of topography on the location and size of saturated source areas of runoff generation (Pourghasemi *et al.* 2012a; Regmi *et al.* 2014). TWI is calculated as: $\ln[A_S/\tan(\beta)]$, where A_S is the specific catchment area of each cell and β represents the slope gradient (in degrees) of the topographic heights (Moore *et al.* 1988; Regmi *et al.* 2014). In this study, the TWI was calculated as shown in figure 2(n).

4. Methodology

4.1 Evidential belief function (EBF) model

The Dempster–Shafer theory of evidence, proposed by Dempster (1967) and developed by Shafer (1976), is a generalization of the Bayesian theory of subjective probability. The main advantage of the Dempster–Shafer theory is that it has the ability to combine the beliefs from several sources of evidence and the relative flexibility to accept uncertainty (Thiam 2005; Bui *et al.* 2012). The Dempster–Shafer theory of evidence provides a framework for the estimation of EBFs according to Dempster’s rule of combination (Liu *et al.* 2015). The EBFs are compound of *Bel* (degree of belief), *Dis* (degree of disbelief), *Unc* (degree of uncertainty) and *Pls* (degree of plausibility), each in the range of 0 and 1 (Althuwaynee *et al.* 2012; Amiri *et al.* 2014). *Bel* and *Pls* represent the upper and lower bounds of the probability, respectively, for the suggestion (Awasthi and Chauhan 2011; Althuwaynee *et al.* 2012). *Unc*, representing the ignorance, is the difference between the belief and the plausibility. *Dis* is the belief of the suggestion being untrue based on given evidence (Bui *et al.* 2012; Awasthi and Chauhan 2011; Althuwaynee *et al.* 2012). $Dis = 1 - Pls$ (or $1 - Unc - Bel$). Therefore, the sum $Bel + Dis + Unc = 1$. For cases of C_{ij} with no landslide occurrence demonstrating that $Bel = 0$, Dis is reset to 0, even if Dis is not (Carranza *et al.* 2008; Al-sharif and Pradhan 2015).

By overlaying the landslide inventory map on every thematic map of landslides conditioning

factors, we determined the number of pixels with landslides and pixels with no-landslides for each factor class. Suppose an exploration area (C) consists of $N(C)$ total number of unit cells or pixels and landslides (L) occur in $N(L)$ number of pixels. Suppose, further that C_{ij} ($i=1, 2, \dots, n; j=1, 2, \dots, m$) is the j th class of the i th landslide conditioning factor and $N(C_{ij})$ is the total number of pixels in the class C_{ij} . Also, $N(L \cap C_{ij})$ represents the number of landslide pixels in C_{ij} (Bui et al. 2012; Liu et al. 2015). The data driven estimation of EBF could be obtained by (Bui et al. 2012; Liu et al. 2015):

$$Bel_{C_{ij}} = \frac{W_{C_{ij}L}}{\sum_{j=1}^m W_{C_{ij}L}} \quad (2)$$

where

$$W_{C_{ij}L} = \frac{N(L \cap C_{ij})/N(L)}{[N(C_{ij}) - N(L \cap C_{ij})]/[N(C) - N(L)]} \quad (3)$$

$$Dis_{C_{ij}} = \frac{W_{C_{ij}\bar{L}}}{\sum_{j=1}^m W_{C_{ij}\bar{L}}} \quad (4)$$

where

$$W_{C_{ij}\bar{L}} = \frac{[N(C_{ij}) - N(L \cap C_{ij})]/N(L)}{\left\{ \frac{[N(C) - N(L) - N(C_{ij}) + N(L \cap C_{ij})]}{[N(C) - N(L)]} \right\}} \quad (5)$$

The $W_{C_{ij}L}$ in equation (3) is the ratio of the conditional probability that landslide (L) exists given the presence of C_{ij} to the conditional probability that landslide (L) exists given the absence of C_{ij} . The $W_{C_{ij}\bar{L}}$ in equation (5) is the ratio of the conditional probability that landslide (L) does not exist given the presence of C_{ij} to the conditional probability that landslide (L) does not exist given the absence of C_{ij} . The $W_{C_{ij}L}$ is the weight of C_{ij} that supports the belief that landslides are more present than absent, while the $W_{C_{ij}\bar{L}}$ is the weight of C_{ij} that supports the belief that landslides are more absent than present. The formulas for combining EBFs of two landslide conditioning factors (C_1, C_2), according to an OR operation, are as follows (Carranza et al. 2005; Bui et al. 2012):

$$Bel_{C_1C_2} = \frac{Bel_{C_1}Bel_{C_2} + Bel_{C_1}Unc_{C_2} + Bel_{C_2}Unc_{C_1}}{1 - Bel_{C_1}Dis_{C_2} - Dis_{C_1}Bel_{C_2}} \quad (6)$$

$$Dis_{C_1C_2} = \frac{Dis_{C_1}Dis_{C_2} + Dis_{C_1}Unc_{C_2} + Dis_{C_2}Unc_{C_1}}{1 - Bel_{C_1}Dis_{C_2} - Dis_{C_1}Bel_{C_2}} \quad (7)$$

$$Unc_{C_1C_2} = \frac{Unc_{C_1}Unc_{C_2}}{1 - Bel_{C_1}Dis_{C_2} - Dis_{C_1}Bel_{C_2}} \quad (8)$$

Integrated EBF of the remaining landslide conditioning factors are implemented one after another by using equations (5, 6, and 7). The calculation of Bel , Dis , Unc , and Pls for each class of conditioning factor are shown table 1. Finally, the landslide susceptibility index (LSI_{Bel}) is calculated by the summation of all values of Bel for each factor contributing to landslide occurrence and this formula is as follows (Pradhan et al. 2014):

$$LSI_{Bel} = \sum_{i=1}^n Bel_i, \quad (9)$$

where n is the number of conditioning factors.

4.2 Weights of evidence (WoE) model

In this study, weights-of-evidence (WoE) model was used for the landslide susceptibility mapping. The method is based on Bayesian probability framework, which was originally developed for mineral potential assessment (Bonham-Carter et al. 1988; Agterberg et al. 1993; Dahal et al. 2008). Currently, several authors have applied the weights-of-evidence method to landslide susceptibility mapping using the GIS (Dahal et al. 2008; Sharma and Kumar 2008; Ghosh et al. 2009; Ozdemir and Altural 2013). Detailed description of the mathematical formulation of the method was given in several research papers (Bonham-Carter et al. 1988; Van Westen 2000; Lee et al. 2002; Dahal et al. 2008; Regmi et al. 2010). Weights for each landslide predictive factor (B) are calculated based on the presence or absence of landslides (D) within the different classes of a conditioning factor (Kayastha et al. 2012):

$$W_i^+ = \ln \frac{P\{B|D\}}{P\{B|\bar{D}\}} \quad (10)$$

$$W_i^- = \ln \frac{P\{\bar{B}|D\}}{P\{\bar{B}|\bar{D}\}} \quad (11)$$

where W^+ and W^- are the weights for the presence or absence of landslides within a certain class of a conditioning factor map, $P(B|D)$ is the conditional probability of B occurring given the presence of D , B is a class of the particular predictive variable and the $\bar{B}$ represents the absence of the class and/or of the event (landslide). D is the presence of landslide, and $\bar{D}$ is the absence of a landslide (Dahal et al. 2008; Kayastha et al. 2012). W_i^+ was used to indicate the importance of the presence of parameter for the occurrence of landslides. If it has a positive value, presence of the factor is favourable for the occurrence of landslides and if W_i^+ is negative, it is not favourable. Similarly,

W_i^- was used to evaluate the importance of the absence of a parameter for the occurrence of landslides (Sharma and Kumar 2008). The difference between the two weights is known as the weight contrast, C ($C = W_i^+ - W_i^-$), which provides a measure of the strength of correlation between the predictable variable and landslides (Armaş 2012). The standard deviation of contrast, $S(C)$, is calculated from the variances of the weights, viz., (Ghosh *et al.* 2009): $S(C) = \sqrt{S^2(W^+) + S^2(W^-)}$. The Studentised contrast, $C/S(C)$, gives a measure of confidence (Kayastha *et al.* 2012).

5. Results and discussion

5.1 Evidential belief function (EBF) model

The range of correlation between conditioning factors and incidences of landslide depends on the *Bel* value. Higher the *Bel* value, stronger the relationship between the factors and the incidence occurrence probability and *vice versa* (Pradhan *et al.* 2014). It can be observed from table 1 that slope angles in the range of 50°–60° have the high *Bel* and low *Dis* values, indicating the highest probability of landslides. In the case of slope aspect, high *Bel* and low *Dis* values for southwest and west facing slopes indicate that these categories have positive spatial associations with landslides. They are followed by the northwest, southeast and north categories. In the case of relationship between landslide occurrence and general curvature, plan curvature and profile curvature, the results show that as their values increase, the landslide probability decreases. For altitude, there are high *Bel* and low *Dis* values for the classes 800–1100 m and 1100–1400 m, indicating high probability of landslide occurrence. In case of distance from rivers, the highest probability for landslide occurrence is within distances less than 500 m. There is very low probability of landslide occurrence at distances of 1500–2000 m. In case of distance from roads, the closer the road, the greater is the landslide probability. At a distance of <500 m, the *Bel* value is 0.41, showing a high probability of a landslide. The *Bel* value is lowest at a distance >2000 m and this indicates a low probability. For distance to faults, the *Bel* and *Dis* values show that the classes 2000–3000 m, and 3000–4000 m have high *Bel* and low *Dis* values, indicating high probability of landslide occurrence. Values of *Bel* for the remaining categories are relatively low and indicate low probability of landslides. The main reason for this result is that other conditioning factors, such as slope, altitude, distance to rivers, distance to roads, and lithology, play a more important role in landslide occurrence compared to the distance to faults in this study

area. For the lithology, it can be seen that the weak rock groups has high *Bel* and low *Dis* values. This indicates a higher probability of landslide occurrence than in other lithologies. The *Bel* value for NDVI showed that classes of 0.02–0.04, >0.04 have the most effect on the occurrence of landslides with high value of 0.61. The relation between STI and landslide probabilities showed that >60 class has the highest value of *Bel* (0.3), and for SPI, the class of 30–60 shows a high *Bel* value (0.29). Similarly, for TWI, the highest *Bel* value (0.28) was obtained for the class of <4.5.

In this study, the final calculated landslide susceptibility index (LSI) values of the area for EBF model, range from about 1.950 to 4.806. Using the natural breaks method in ArcGIS 10.0, the landslide susceptibility map generated was reclassified into five classes: very low, low, moderate, high, and very high (figure 3). According to this model, the very low and low susceptibility areas are 17.65% and 26.60%, respectively. Meanwhile, the percentages of moderate, high, and very high susceptibility areas are 23.47%, 21.26%, and 11.03%, respectively. In addition, 40.21% and 38.66% of the total landslides fall in the very high and high susceptibility zones, respectively. Moderate, low, and very low susceptible zones represent 15.98%, 4.1%, and 1.03% of the landslides, respectively (figure 5a).

5.2 Weights of evidence (WoE) model

Using the weights of evidence model, the spatial relationship between landslide-occurrence and factors influencing landslides was assessed (table 1). The relationship between landslide occurrence and slope angle shows how gentle slopes have a low probability of landslide occurrence because of the generally lower shear stresses. The slope of 50°–60° is shown to have the highest Studentized contrast, indicating that this category is most susceptible to landslides. In the case of slope aspect, slope class –16° shows a good positive relationship with the occurrence of landslides. The slope aspects of west are more susceptible to landslides. This is likely due to the orientation of the main valley, which makes the slopes with west aspect drier while resulting in less natural vegetative cover and making the slopes unstable. The results show that general curvature >0.6, plan curvature >0.3 and profile curvature < –0.5 have high influence in triggering landslides. In the case of relationship between landslide occurrence and altitude, class of 1100–1400 m has the highest Studentized contrast, indicating a high probability of landslide occurrence. In the case of distance from rivers, the weight value is higher in the class 0–500 m, indicating a higher probability of landslides occurrence. The distance from roads

Table 1. Spatial relationship between each landslide conditioning factor and landslide for each model.

Factors	Classes	Percentage of landslide (%)	Percentage of domain (%)	Bel	Dis	Uncer	Plau	W ⁺	W ⁻	C	S(W ⁺)	S(W ⁻)	S(C)	C/S(C)
Slope angle (°)	0-10	7.35	15.40	0.08	0.16	0.77	0.84	-0.74	0.09	-0.83	0.10	0.01	0.33	-2.53
	10-20	25.74	29.52	0.14	0.15	0.71	0.85	-0.14	0.05	-0.19	0.03	0.01	0.20	-0.97
	20-30	36.77	28.53	0.21	0.13	0.67	0.87	0.25	-0.12	0.38	0.02	0.01	0.18	2.11
	30-40	20.59	18.05	0.18	0.14	0.68	0.86	0.13	-0.03	0.16	0.04	0.01	0.21	0.77
	40-50	7.35	6.71	0.18	0.14	0.68	0.86	0.09	-0.01	0.10	0.10	0.01	0.33	0.30
	50-60	2.21	1.59	0.22	0.14	0.64	0.86	0.33	-0.01	0.34	0.33	0.01	0.58	0.58
	>60	0.00	0.21	0.00	0.00	1.00	1.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00
	Flat	0.00	3.54	0.00	1.00	0.00	0.00	0.00	0.04	0.00	0.00	0.01	0.00	0.00
	North	8.82	10.22	0.11	0.11	0.78	0.89	-0.15	0.02	-0.16	0.08	0.01	0.30	-0.54
	Northeast	9.56	11.61	0.10	0.11	0.79	0.89	-0.19	0.02	-0.22	0.08	0.01	0.29	-0.75
Slope aspect	East	11.77	13.93	0.10	0.11	0.78	0.89	-0.17	0.03	-0.19	0.06	0.01	0.27	-0.73
	Southeast	14.71	13.46	0.13	0.11	0.76	0.89	0.09	-0.01	0.10	0.05	0.01	0.24	0.42
	South	8.09	10.38	0.10	0.11	0.79	0.89	-0.25	0.03	-0.27	0.09	0.01	0.31	-0.87
	Southwest	15.44	11.96	0.16	0.11	0.74	0.89	0.26	-0.04	0.30	0.05	0.01	0.24	1.25
	West	16.91	12.58	0.16	0.11	0.73	0.89	0.30	-0.05	0.35	0.04	0.01	0.23	1.51
	Northwest	14.71	12.32	0.15	0.11	0.75	0.89	0.18	-0.03	0.20	0.05	0.01	0.24	0.85
	General curvature	19.85	21.52	0.31	0.34	0.35	0.66	-0.08	0.02	-0.10	0.04	0.01	0.22	-0.47
	<-0.6	56.62	57.02	0.33	0.34	0.33	0.66	-0.01	0.01	-0.02	0.01	0.02	0.17	-0.10
	>0.6	23.53	21.46	0.36	0.32	0.31	0.68	0.09	-0.03	0.12	0.03	0.01	0.20	0.59
	<-0.3	14.71	22.21	0.23	0.37	0.40	0.63	-0.41	0.09	-0.50	0.05	0.01	0.24	-2.08
Plan curvature	-0.3 to 0.3	58.09	54.63	0.37	0.31	0.32	0.69	0.06	-0.08	0.14	0.01	0.02	0.17	0.81
	>0.3	27.21	23.16	0.41	0.32	0.28	0.68	0.16	-0.05	0.22	0.03	0.01	0.19	1.12
	<-0.5	19.12	15.64	0.39	0.31	0.30	0.69	0.20	-0.04	0.24	0.04	0.01	0.22	1.12
	-0.5 to 0.5	64.71	68.27	0.30	0.36	0.34	0.64	-0.05	0.11	-0.16	0.01	0.02	0.18	-0.89
	>0.5	16.18	16.09	0.32	0.33	0.36	0.68	0.01	0.00	0.01	0.05	0.01	0.23	0.03
	<800	5.88	2.82	0.26	0.14	0.61	0.86	0.74	-0.03	0.77	0.13	0.01	0.36	2.11
	800-1100	23.53	9.58	0.30	0.12	0.58	0.88	0.90	-0.17	1.07	0.03	0.01	0.20	5.28
	1100-1400	43.38	17.02	0.31	0.10	0.59	0.90	0.94	-0.38	1.32	0.02	0.01	0.17	7.62
	1400-1700	20.59	26.96	0.09	0.15	0.75	0.85	-0.27	0.08	-0.35	0.04	0.01	0.21	-1.67
	1700-2000	5.88	24.10	0.03	0.18	0.79	0.82	-1.41	0.22	-1.63	0.13	0.01	0.36	-4.46
Altitude (m)	2000-2300	0.74	15.51	0.01	0.17	0.83	0.83	-3.05	0.16	-3.21	1.00	0.01	1.00	-3.20
	>2300	0.00	4.02	0.00	0.00	1.00	1.00	0.00	0.04	0.00	0.01	0.01	0.00	0.00

Figure 3. Landslide susceptibility map derived from the EBF model.

also has a clear influence on landslides, because at a distance of <500 m the contrast is much higher than for the other classes, indicating a lower probability of landslides further away from the roads. In the case of the relationship between landslide occurrence and distance from faults, the weight value is higher in the class 3000–4000 m. The influence of lithology is also very evident as the contrast is highest for the lithological unit of weak rocks. In the case of NDVI, the class >0.04 have higher values, indicating that the probability of occurrence of landslide in this normalized difference vegetation index is high. Most of the landslides are located at >60 class for STI as the value is highest here. Relation between SPI, and TWI and landslide probability showed that 30–60 and <4.5 classes have highest weight value, respectively.

In this study, the final calculated LSI values of the area for WoE model range from about –38.454 to 42.046. The LSI on the produced maps was grouped into five classes (very low, low, moderate,

high, and very high) (figure 4) using the natural break method. From the output of analysis carried out using the ArcGIS 10.0 (figure 5b), it was found that 19.23% of the study area was placed in the group with very low susceptibility. Low, moderate and high susceptibility landslide classes comprised of 27.81%, 22.63%, and 17.97% of the area, respectively. In all, 12.36% of the region was placed in the class with very high landslide susceptibility. It can be observed from figure 5(b) that 1.03% and 6.19% of the total landslides fall in the very low and low susceptibility zones respectively. Moderate, high, and very high susceptible zones represent 14.95%, 29.90%, and 47.94% of the landslides, respectively.

5.3 Validation of the landslide susceptibility maps

A proper validation is necessary to make a certain landslide susceptibility map for any area (Youssef 2015). To do this validation, the area under curve (AUC) method was used in this research

Figure 4. Landslide susceptibility map derived from the WoE model.

Figure 5. Histograms representing the distribution of observed landslides falling into various susceptibility classes of different landslide susceptibility zonation maps: (a) EBF model and (b) WoE model.

(Chung and Fabbri 2003; Van Westen *et al.* 2003; Yesilnacar and Topal 2005; Intarawichian and Dasananda 2011; Kayastha *et al.* 2013b). This method works by creating specific rate curve which explains percentage of known landslides that fall into each defined level of susceptibility rank

and displays as the cumulative frequency diagram (Intarawichian and Dasananda 2011). The specific rate curves can be divided into success rate curve and prediction rate curve (Chung and Fabbri 2003). The success rate curve is based on a comparison of the susceptibility map with the landslides used

Figure 6. AUC representing quality model. (a) Success rate curve and (b) prediction rate curve.

in modelling. The prediction rate curve can be created by the validation landslide inventory (Pradhan and Kim 2014). In rate curve, the y axis is considered as the cumulative percentage of observed landslide occurrences in different susceptibility classes and the x axis corresponds to the cumulative percentage of the area of the susceptibility classes (Chung and Fabbri 2003; Intarawichian and Dasananda 2011). The area under the curve (AUC) represents prediction accuracy of the susceptibility map qualitatively, in which larger area means higher accuracy achieved (Intarawichian and Dasananda 2011).

In this study, both success rate and prediction rate curves have been used for validation is shown in figure 6. The success rate curves of EBF and WoE models shown in figure 6(a), indicate that the first 10% of the area of the susceptibility classes can explain about 38%, 44% of all used landslides (out of 136 events), respectively. The first about 80% for EBF and WoE models can accommodate all known landslides. Similarly, the prediction rate curves (figure 6b) indicate that the first 10% of the area of the susceptibility classes can explain about 35%, 34% of all used landslides (out of 58 events), respectively. The first about 95% for EBF and WoE models can accommodate all known landslides. In the success rate method, the AUC values for the EBF and WoE models are 0.8019 and 0.8075, respectively. In the prediction rate method, the AUC values for EBF and WoE models are 0.8008 and 0.7979, respectively. It can be concluded that both the success rate and prediction rate curves show values above 0.8 which represent reasonable models for landslide susceptibility mapping of the study area.

6. Conclusions

In this study, both evidential belief function (EBF) and weights of evidence (WoE) models to estimate areas susceptible to landslides for the Daguan

County of Zhaotong city, China, using GIS has been presented. The relationship between a landslide occurrence and the identified 14 conditioning factors such as slope angle, slope aspect, general curvature, plan curvature, profile curvature, altitude, distance to rivers, distance to roads, distance to faults, lithology, normalized difference vegetation index (NDVI), sediment transport index (STI), stream power index (SPI), and topographic wetness index (TWI) is discussed. The selection of the 14 conditioning landslide factors, based on consideration of relevance, availability, and scale of data that was available for the study area, is relative and subjective, and can be improved in future research. Before susceptibility analysis, of the total 194 identified landslide locations in the study area, 136 (70%) were used as training data and the remaining 58 (30%) were used for validation goals. The area under the rate curve quantitatively indicates the performance of the susceptibility maps. The results show that the EBF model has a success rate of 80.19% and predictive accuracy of 80.08% and WoE model has success rate of 80.75% and predictive accuracy of 79.79%. The results showed that both landslide susceptibility maps obtained were successful. However, in comparison with WoE model or other spatial data integration models, the EBF model can support a series of mass functions including belief, disbelief, uncertainty and plausibility. Hence, the results can adequately represent quantitative relationships between landslide occurrences and multiple spatial data layers by modelling the degree of uncertainty (Park 2011; Lee *et al.* 2013). The WoE model is restricted by the assumption on conditional independence. Nevertheless, the WoE model can provide results easy to interpret, and spatial patterns with complex geometries can be modelled with the same computational effort as simple patterns with simple geometry (Neuhäuser and Terhorst 2007). The two models employed in this study area showed reasonably good accuracy in predicting the landslide susceptibility. Meanwhile, it can be observed that

the landslide occurrence potential map produced by the WoE method is a little bit highly believable, because the method's very high landslide occurrence potential classes correctly predicted more landslides. The landslide susceptibility map presented in this study can be a good source for the decision makers, managers, urban planners, engineers, and land-use developers. Also, it is worth mentioning that a similar method can be used elsewhere where the same geological and topographical feature prevails.

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