Preparation of a landslide susceptibility map of Summit County, Ohio, USA, using numerical models

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Abstract: Summit County in Ohio, USA, is well known for the occurrence of frequent landslides along the Cuyahoga River valley. This study investigates the factors that affect the frequency and distribution of landslides in Summit County using different numerical models in Geographic Information Systems (GIS) database. The landslide locations in the county were identified from aerial photographs, field checks, and the existing literature, and a landslide inventory map was prepared for the region at a scale of 1:24,000. The occurrence of landslides in a given area generally depends upon the complex interaction of different dependent and independent factors like slope angle, slope aspect, soil type, erodible soil, depth to groundwater, land cover pattern, distance from the river, etc. These factors were imported as raster data layers in ArcGIS for the landslide susceptibility analysis in Summit County. Each of the above-listed factors was classified and coded using a numerical scale corresponding to the physical conditions of the region. In order to investigate the role of each factor in controlling the spatial distribution of landslides, susceptibility priority number model, landslide susceptibility index model, and logistic regression model were generated using the Summit County digital dataset. Each model was superimposed on the landslide inventory map and was evaluated for its suitability. The logistic regression model was found to be the best model for predicting the landslide susceptibility for Summit County, Ohio. The results indicate that the factors such as slope angle, soil type, distance from the river, and the erodible soil are statistically significant in controlling the slope movement, whereas liquidity index, precipitation, land cover, and depth to water table are not very significant and, thus, were excluded from the model. The data from this model were used in ArcGIS to produce a landslide susceptibility map of Summit County. The landslide susceptibility was classified into three categories: low, moderate, and high. The results of the study demonstrate that landslide susceptibility of a region can be effectively modeled using GIS technology and logistic regression analysis.

Résumé: Cette étude compare l'utilisation de trois modèles numériques différents pour la préparation d'une carte de susceptibilité du glissement de terrain de comté de Summit, en Ohio, aux Etats-Unis). Des endroits de glissement dans le comté ont été identifiés à partir des photographes aériennes, des vérifications sur terrain, et de la littérature existante. Aussi, une carte d'inventaire des glissements a été préparée pour la région à une échelle de 1:24,000. Des facteurs influençant l'occurrence des éboulements dans le comté ont été apportés en tant que couches données de trame dans ArcGIS pour l'analyse de susceptibilité d'éboulement. Chaque facteur a été classifié et codé avec une échelle numérique correspondant aux conditions physiques de la région. Pour étudier le rôle de chaque facteur en contrôlant la distribution spatiale des éboulements et pour préparer une carte de susceptibilité d'éboulement, on a employé le nombre prioritaire de susceptibilité, l'index de susceptibilité, et les modèles de régression logarithmique. Chaque modèle a été superposé sur la carte d'inventaire des éboulements et a été évalué pour sa convenance. Le modèle logarithmique de régression s'est avéré le meilleur modèle pour la susceptibilité d'évaluation d'éboulement pour le comté de Summit. Les résultats de ce modèle indiquent que seulement l'angle de pente, la distance à partir du ruisseau le plus proche, le type de sol, et la vulnérabilité du sol à l'érosion sont statistiquement significatifs dans le contrôle des glissements de terrain.

Keywords: data analysis, engineering properties, geographic information systems, mapping, models, slope stability

INTRODUCTION

Landslides cause continuous road obstructions, infrastructure damage, loss of agricultural land, loss of buildings, and loss of human lives. The cumulative damage caused by landslides is far more wide spread, and poses greater total financial loss than any other geological calamity (Schuster and Fleming, 1986). Careful assessment of landslides and a coordinated hazard reduction programs can reduce the socio-economic losses around the world (Aleotti and Chowdhury, 1999). The first step of any landslide hazard reduction program is to prepare a landslide inventory map. A systematic mapping through various techniques (field survey, air photo interpretation, extraction of historical landslide records, etc.) of past and recent landslides in a region is called landslide inventory mapping (Wieczorek, 1984). The next major step in a hazard reduction program is to prepare a landslide susceptibility map. Susceptibility is the likelihood that a phenomenon will occur in an area on the basis of the local terrain conditions (Soeters and Western, 1996). The landslide susceptibility map is generated using data about the distribution of past landslides, steepness of the slopes, type of bedrock, structure, hydrology, and other input data depending upon availability. The susceptibility to landsliding is categorized as low, moderate, and, high (Brabb et al., 1998; Lee and Min, 2001).

A Landslide susceptibility assessment can be performed using GIS technology qualitatively as well as quantitatively (Figure 1). The qualitative approach of landslide susceptibility mapping using GIS is widespread (Bertocci et al., 1992; Van Western, 1993). The quantitative approach of landslide susceptibility analysis is comparatively recent. However, Carrara (1988) used quantitative multivariate statistical analysis in landslide studies in Italy more than two decades ago. At present both qualitative and quantitative methods are used in landslide susceptibility studies. The qualitative approach includes geomorphological and heuristic models. The geomorphological model uses expert's opinion and field data to prepare landslide susceptibility maps. In the heuristic method the hazard is determined directly either in the field or by air photo or satellite image interpretation by the earth scientist. This approach is based on the previous knowledge of the causes of landslides in an area. A weighting scheme is used in this type of analysis; however, this weighting scheme is quite subjective and "blind weighting" is suggested by Gee (1992). The reliability of the heuristic approach is directly dependent on the experience of the researcher and his/her geomorphology related knowledge of the factors affecting the study area. Some examples of geomorphological analysis/heuristic approach can be found in Barredo et al. (2000), and Esmali and Ahmadi (2003).

The quantitative approach of landslide susceptibility evaluation uses either the deterministic model or the statistical model (Guzzetti et al., 1999). Deterministic modelling is often used in smaller areas and the hazard is expressed as safety factor values (Refice and Capolongo, 2002). Deterministic methods are applicable only when the geomorphic and geologic conditions are fairly homogeneous over the entire study area and the landslide type is not so complex (Hammond et al. 1992). In a statistical model the factors that have led to landslides in the past are determined using bivariate or multivariate statistical analysis and the results are used to predict future landslide activity (Dai and Lee, 2002; Donati and Turrini, 2002). The statistical approach is based on the observed relationship between each factor and the past and present landslide distribution (Carrara et al., 1991). In GIS different factor map layers (slope map, landuse map, vegetation map, soil/rock map, etc.) are overlaid and the landslide data are extracted from each layer.

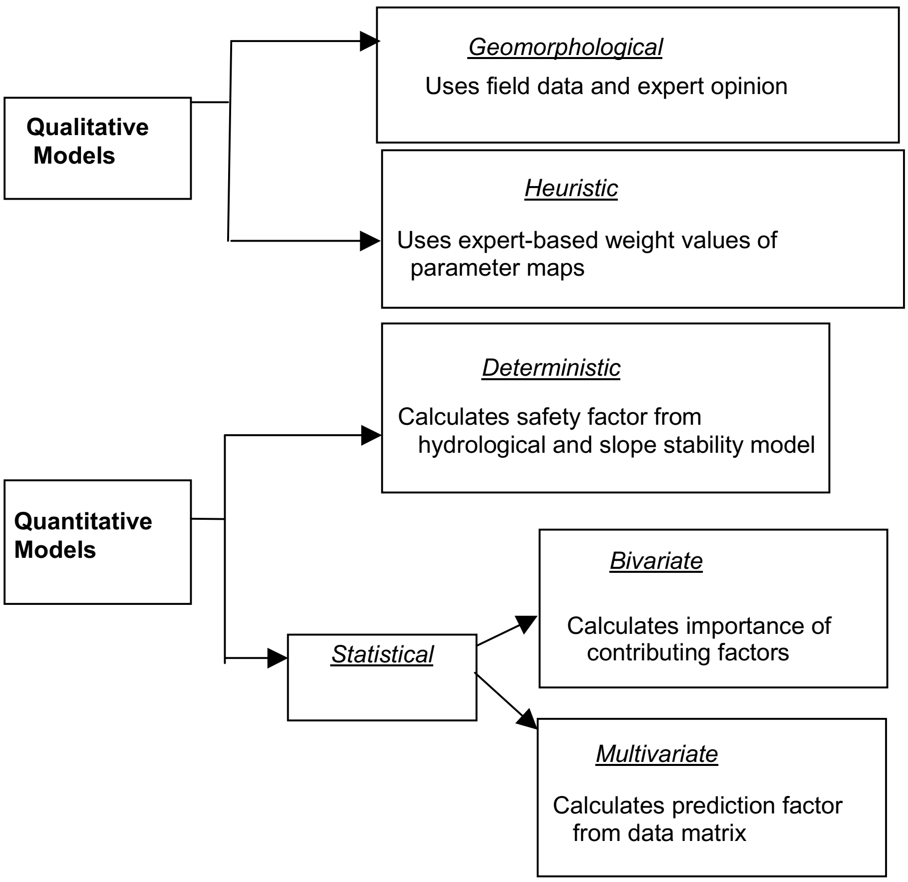

Figure 1. Schematic diagram showing different models used in landslide susceptibility studies.

The landslide susceptibility evaluation is performed by estimating the contributory factors on a statistical basis (bivariate and multivariate). Multivariate statistical analysis models for landslide hazard zonation were developed in Italy, mainly by Carrara (1988) and his colleagues (Carrara et al., 1990, 1992). This type of analysis gives the relative contribution of each of the factors responsible for the slope movement. Several multivariate techniques are used in the literature such as discriminant analysis, multiple regression, and logistic regression. Although multiple regression and discriminant analyses are often found in the literature, a main drawback of these analyses is that the data used have to be distributed normally, which is frequently not the case when dealing with natural data (Süzen and Doyuran, 2004). Several normality conversions are used in order to transfer the data into normal distribution such as log-log or log-normal conversions, adding bias to the natural distribution of data. The use of logistic regression, which is free of data distribution issues, is not so well exploited in the literature. Only a few examples of logistic regression approach are observed in recent literature such as Lee and Min (2001), and Süzen and Doyuran (2004).

The main objective of the study presented here is to prepare a landslide susceptibility map of Summit County, Ohio, using both heuristic and statistical models. A secondary objective of the study is to evaluate the effectiveness of different models used in the study.

THE STUDY AREA

Summit County is located in the northeastern part of the state of Ohio, USA (Figure 2). The area is a part of the Allegheny Plateau section of the Appalachian Plateaus Province that consists of Devonian, Mississippian, and Pennsylvanian age siliciclastic rocks (Szabo, 1987). During Pleistocene, the area was extensively glaciated. The evidence of glaciation is present in the region in the form of a thick heterogeneous blanket of clay, silt, sand, gravel, and boulders.

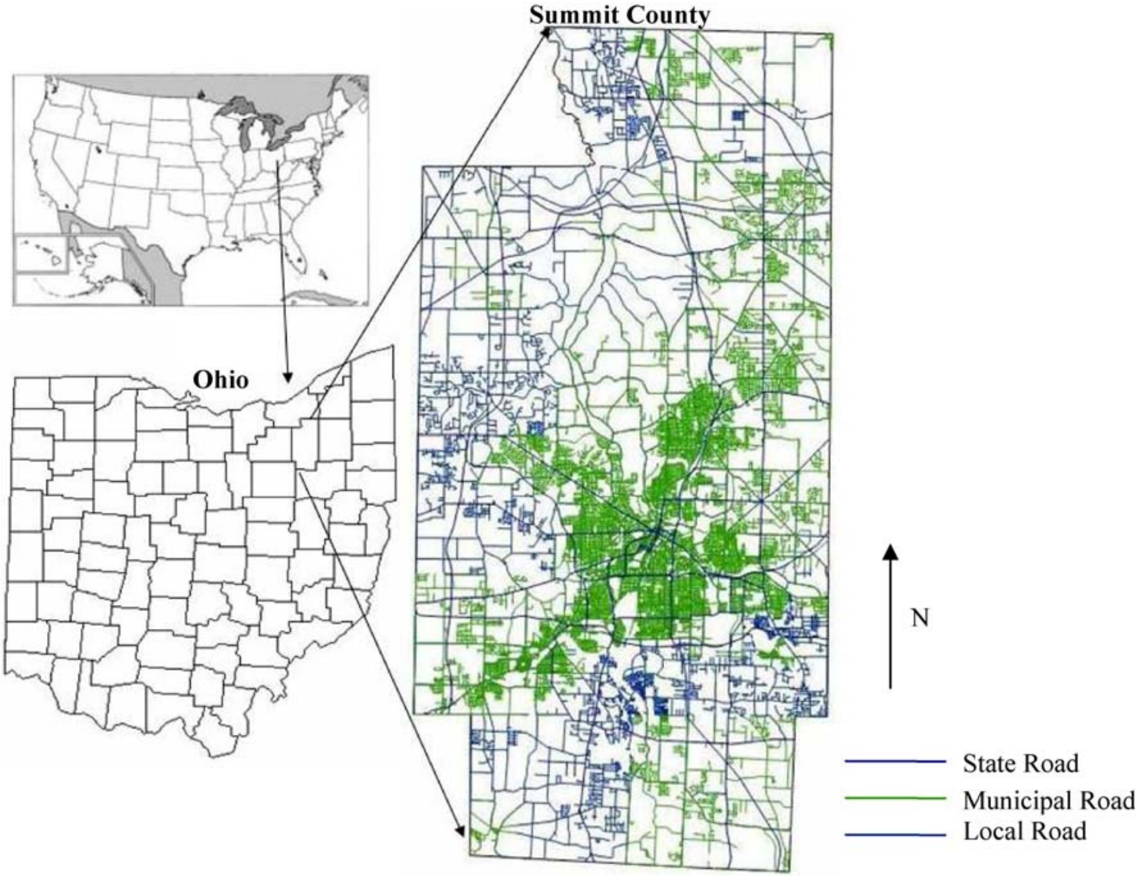

Figure 2. Location of the study area.

Summit County is drained by the Cuyahoga River and its tributaries. Rapid downcutting of the glacial deposits by the Cuyahoga River and its tributaries has resulted in numerous steep sided valleys with unstable slopes. Undercutting of the toes of the valley slopes by stream water further contributes to slope instability (Jones and Shakoor, 1989). The various types of slope movement in the study area are soil creep, rotational slides, translational slides, earthflows, and combinations of these (Figure 3). These landslides damage roadways and properties situated near top of the valley slopes.

METHODOLOGY

The methodology for this study consisted of two parts: (1) preparation of a landslide inventory map of Summit County and (2) preparation of a landslide susceptibility map, using different numerical models and GIS software. Landslide inventory map was prepared by using remote sensing techniques (Figure 4), field work, and available records. This map served as the base map for further analyses with respect to landslide susceptibility. The important input data for landslide susceptibility analysis included Digital Elevation Model and data regarding soil type, erodible soil, engineering properties of soil, precipitation, proximity to the stream, groundwater table, and land cover.

The input datasets were converted in grid format (rastarization) and different factor map layers controlling the landslides were prepared in ArcGIS. Landslide susceptibility models were developed using both heuristic and statistical approaches. The reliability of these models was evaluated by comparing the model output maps with the already prepared inventory map.

Figure 3. Examples of various types of slope movement in the study area: (a) rotational slide, (b) translational slide, and (c) earthflow.

DATA SOURCE AND DATA LAYER PROCESSING

For the landslide inventory map, 1:1200 colored digital aerial photographs, taken in April 2000, were used. The digital orthophoto tiles in TIFF format, with a 0.6 m pixel resolution, were merged into a single image and compressed to Mr. SID format. The landslides identified from the aerial photographs were cross checked by field investigation. Apart from using the aerial photos, landslide locations were also obtained from previous studies (Jones, 1986; Andrews, 2004). The final landslide inventory map of Summit County was prepared at a scale of 1:24,000.

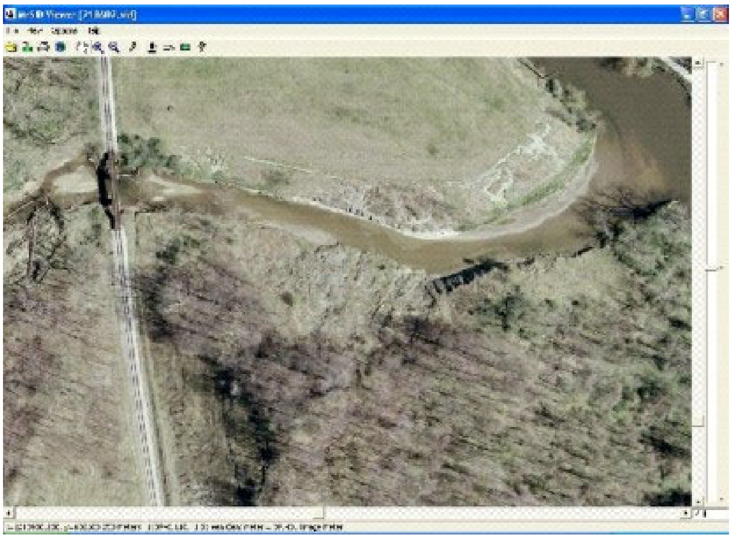

Figure 4. Example of a landslide in aerial photograph used for preparation of inventory map.

The USGS 7.5 minute Digital Elevation Model (DEM) data were used as a data layer for preparation of the landslide susceptibility map. The 7.5 minute DEMs correspond to the USGS 1:24,000 scale topographic quadrangle maps. The horizontal spacing for each pixel or grid on DEM is 30 m. The DEMs were imported in ArcMap of ESRI ArcGIS, and slope angle and slope aspect maps of Summit County were prepared directly from a DEM using surface analysis (a menu choice in spatial analyst in ArcMap). The soil mapping units of the county were obtained from the soil survey geographic (SSURGO) database prepared by U.S. Department of Agriculture, Natural Resource Conservation Service. A soil mapping unit designates a specific type of soil which has unique characteristics including texture, slope and erosion class. The erodible soil classes of Summit County have been determined by Ohio Division of Natural Resources (ODNR) using the universal soil loss equation to estimate soil loss in tons/acre/year. The land cover map of Summit County was extracted from the 1994 state-wide land cover inventory of Ohio produced by ODNR. The land cover inventory is the digital image processed by Landsat Thematic Mapper Data with the resolution of a 30 m by 30 m cell. The data is classified into the general land cover categories of urban, agriculture/open urban, shrub/scrub, wooded, open water, non-forested wetlands, and barren areas. The precipitation dataset, published by Water and Climate Center of the Natural Resources Conservation Service for the climatological period of 1961-1990, was interpolated using Kriging method in the ArcMap (spatial analyst interpolation menu). The groundwater table dataset, taken from the well log data of ODNR, was also interpolated in ArcMap. The proximity to the stream system map was created using a 500 m buffer zone around the Cuyahoga River and its tributaries. A buffer zone is an area that is within a given distance from a map feature like streams, roads etc. The layer concerning the engineering properties of soil was generated from the laboratory test results of 38 soil samples taken from the existing landslide locations in Summit County as well as engineering property data of other parts of the county complied by the US Department of Agriculture. The engineering property data included natural water content, Atterberg limits, and liquidity index (which compares natural water content with Atterberg limits). Since liquidity index uses the Atterberg limits as well as the natural water content, liquidity index was used to prepare the engineering property layer. The liquidity index values for the Summit County were plotted in ArcMap.

All datalayers were georeferenced to the Universal Transverse Mercator (UTM) projection system and were oriented to the North American Datum (NAD) of 1927 (NAD27). The scale of each data layer was chosen to be 1:24,000 scale, in line with the USGS topographic quadrangle maps. The vector layers were converted to the raster (grid based) layers for further calculations.

EVALUATION OF FACTORS CONTRIBUTING TO LANDSLIDES

In order to evaluate the physical factors (slope angle, soil type, erodible soils, engineering properties of soil, precipitation, land cover, proximity to the stream, groundwater table) contributing to the occurrence of landslides in Summit County, the landslide frequency was correlated with the factor maps described in the previous section. The landslide inventory map was overlaid on the raster data layers of the factor maps in ArcGIS and the landslide frequency was calculated with respect to each factor (Figure 5). Correlation of the landslide frequency with the slope angle showed that the landslide frequency increases with increasing slope angle, reaching a maximum at the 31 - 40 degree category and then decreasing beyond that range. The landslide frequency distribution analysis also indicated that silty and clayey soils were most susceptible to landslide occurrence. Similarly, the highly to very highly rated erodible soils and the proximity to the streams showed good correlation with the occurrence of landslides. Based on the frequency distribution of landslides with respect to the individual factors affecting the landslides in Summit County, a numerical ranking was implemented and the factor maps were reclassified. The categories in which the landslides were found to be most dominant were assigned the highest number in the numerical scale (Table 1).

LANDSLIDE SUSCEPTIBILITY MODELS

In this study, both heuristic and statistical models were used for landslide susceptibility analysis. A brief description of these models is given below:

Susceptibility Priority Number (SPN)

This model, developed by Temesgen et al. (2001), primarily uses the heuristic approach where the landslide susceptibility is indicated by a susceptibility priority number (SPN). In order to apply this model to the present study, all of the reclassified factor layers were superimposed in a common geographic reference grid (raster layer) using spatial analyst menu in ArcGIS by using Raster Calculator as follows:

$$SPN = \frac{\left[\left(\frac{X_{1p}}{X_{1\max}}\right) + \left(\frac{X_{2p}}{X_{2\max}}\right) + \ldots\ldots\ldots\ldots\right]}{n}$$

where, $X_{ip\ (i=1\ to\ n)}$ are the priority values of each class (1 to 5), $X_{imax(i=1\ to\ n)}$ are the maximum priority value of the respective classes (5), and n is the number of factors used in the study. In this study n is 8, and the SPN value ranges from 0 to 1. A value close to 0 implies a more stable region and a value close to 1 implies a more unstable zone.

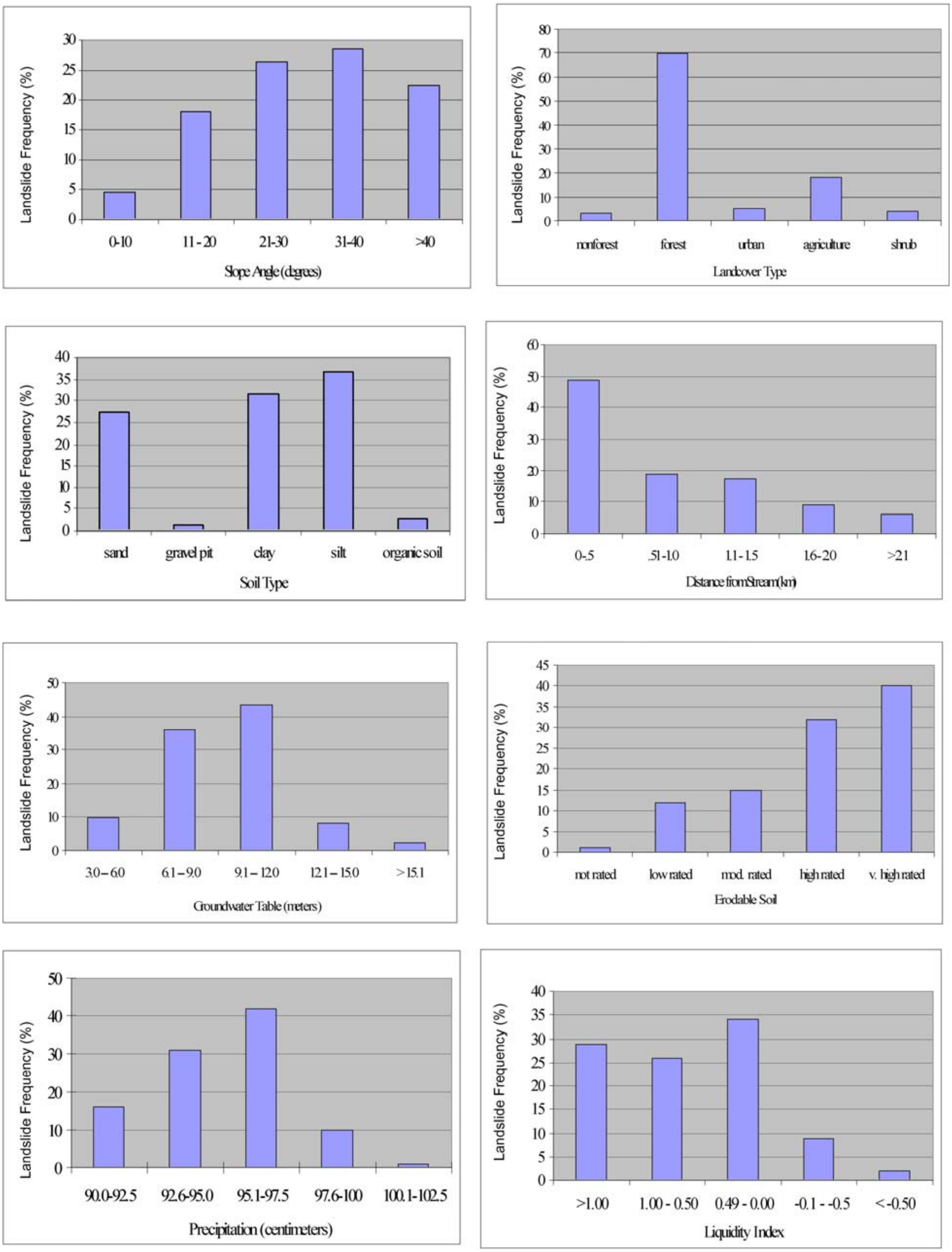

Figure 5. Histogram analysis of different factors contributing to the landslide frequency distribution.

Table 1. Numerical ranking of the factor map categories.

Factors	Categories	Ranking	Factors	Categories	Ranking
Slope Angle	0 – 10° 11° – 20° 21° – 30° 31° – 40° > 40°	1 2 4 5 3	Soil Type	Silt Clay Sand Organic Soil Gravel Pit	5 4 3 2 1
Landuse	Non-forest Forest Urban Agricultural Shrub	1 5 3 4 2	Groundwater Table	10-20 ft 21 -30 ft 31 -40 ft 41 -50 ft >50 ft	3 4 5 2 1
Erodible Soil	Not rated Low rated Moderately rated Highly rated Very Highly rated	1 2 3 4 5	Precipitation	36.0 – 37.0 ° C 37.1 - 38.0 ° C 38.1 – 39.0 ° C 39.1 – 40.0 ° C 40.1 – 42.0 ° C	3 4 5 2 1
Proximity to the Stream	0 -500 m 501 -1000 m 1001 -1500 m 1501 – 2000 m > 2000 m	5 4 3 2 1	Liquidity Index	>1.00 1.00 – 0.50 0.49 – 0.00 -0.10 – -0.50 < -.50	4 3 5 2 1

In the case of this model, evaluating landslide susceptibility is time efficient so it can be used for a quick investigation. The main limitation is all factors contributing to slope movement are given equal importance.

Landslide Susceptibility Index (LSI)

This model, proposed by Wachal and Hudak (2001), also uses the heuristic approach where susceptibility of landsliding is expressed as landslide susceptibility index (LSI). The reclassified factor maps were overlaid and weights ranging from 0% to 100% were assigned to each factor. For this study, the weight values were assigned based on the percentage of landslides in the highest ranked category of individual factors. This information was transferred in GIS database and Raster Calculator of the spatial analyst tool was used to calculate LSI as shown in the equation.

$$LSI = \frac{[(W_1 X_1) + (W_2 X_2) + ...]}{n}$$

where, $W_{i(i=1\ to\ n)}$ are the weights of the classes (factors), $X_{i\ (i\ =\ 1\ to\ n)}$ are the categories of the factors, and *n* is the number of factors. As stated earlier, *n* for this study was set equal to 8. The LSI value ranged from 1 to 8 in this study. Finally, LSI was classified into susceptibility categories (low, medium, and high). The reliability of LSI model approach is directly dependent on the experience of the researcher, field scenario, and his/her adequate geomorphology-related knowledge of the interrelationship of environmental factors acting upon the study area. This type of model should be modified carefully depending on the local variability in geology, hydrology, landuse pattern, etc. Numerous combinations are possible in deciding the weight values of the causal factors, so no specific model used by this method is absolutely perfect. Like SPN model this model does not exclude the factors which have less or no contribution in landslide activities.

Logistic Regression

This model, previously used by Bernknof et al. (1988), Dikau et al. (1996), and Jager and Wieczorek, (1994), represents a statistical approach based on the observed relationship between each factor and the landslide distribution (Carrara et al., 1991). This approach uses multivariate statistics to analyze the factors responsible for landslide activities. The approach is more robust than the multivariate linear regression model as it can handle a variety of datasets. For example, the model accepts dichotomous data (yes/no data), categorical data (land cover, soil type, etc.), and continuous data (slope angle, groundwater table, etc.) as the dependent and independent factors (variables). The advantage of the logistic regression approach is that the dependent variable can have only two values (an event occurring or not occurring) and the predicted value is calculated as probability which falls within the interval of 0 to 1 (Dai and Lee, 2002). In the landslide susceptibility studies, the binary, dichotomous dependent variable represents presence of landslide (1) or absence of landslide (0). The probability (*P*) of the landslide occurrence can be calculated from the following equation:

$$P = \frac{1}{(1 + e^{-z})}$$

where, P is the probability of landslide occurrence which varies from 0 to 1 as z varies from $-\infty$ to $+\infty$ and z is the linear combination of all the independent variables.

$$z = B_0 + B_1X_1 + B_2X_2 + \dots\dots\dots + B_nX_n$$

where $B_{i\,(i=1\ to\ n)}$ is the coefficient estimated from the sample data, n is the number of independent variables (slope angle, soil type, erodible soil, etc.), and $X_{i\ (i=1\ to\ n)}$ is the independent variables (Dai and Lee, 2002). By using backward stepwise process in SPSS (a statistical software package), the less significant factors are eliminated from the algorithm. The results are then transferred in GIS to develop the probabilistic landslide susceptibility map of the area with probability P ranging from 0 to 1. For Summit County, the independent variables used were slope angle, distance from the stream, soil type, erodible soil, precipitation, groundwater table, liquidity index, and land cover. For the purpose of unbiased sample representation, both presence (1) and absence of landslide (0) were used to fit the logistic regression analysis by choosing similar number of points from non-landslide areas as the sample representing the absence of landslides. Therefore, each sample point had its representative binary value on the presence/ absence of landslide as well as the information on the independent variables. These data were then used as input in the logistic regression algorithm within the SPSS statistical software package to obtain the coefficients (B_i) and intercept (B_0) of the logistic regression. A logistic regression model of the study area was then constructed based on the eight independent variables by using backward stepwise method. At each step, a variable that did not contribute sufficiently to the strength of the regression analysis was eliminated. The final regression analysis retained only those variables which significantly contributed to slope movement. The B_0 and B_i values (Table 2) from the final step of the logistic regression analysis model were then transferred into Arc Map and a landslide susceptibility map of the study area was created using Raster Calculator. The logistic regression model is based on the observed relationship between each factor and the past and present landslide distribution. Landslide susceptibility evaluation is performed by estimating the contributory factors on a statistical basis. This method strongly depends upon the collected data and much less on the experience of the analyst. The strength of this method is directly dependent on the quality and quantity of dataset. Trivial error in mapping the boundaries of landslides does not have a significant influence on the model. The limitation of this model is that, being data-driven, it cannot be readily extrapolated to another region.

Table 2. Calculation of the probability of landslide occurrence by logistic regression model.

Factors	**B**	
Slope Angle	29	$z = -193 + 29X_{slo.ang} + 14X_{prox.riv} + 6X_{soiltyp} + 44X_{erod}$
Proximity to Stream	14	
Soil Type	6	$P = \frac{1}{(1+e^{-z})}$ *P varies from 0 to 1*
Erodible Soil	44	
Constant (B_0)	-193	

RESULTS

Figures 6, 7, and 8 show the landslide susceptibility maps for a portion of Summit County as produced by the three models. The landslide susceptibility map produced by the SPN model (Figure 6) has a susceptibility range of 0 to 1, with 0.0 – 0.3, 0.31 – 0.60, and 0.61 – 1.00 categories representing low, medium, and high landslide susceptibility regions, respectively. In the LSI model, the susceptibility zones are 0.0 – 2.5, 2.6 –5.2, and 5.3 – 8, which corresponds to low, medium, and high landslide susceptibility respectively (Figure 7). The range of the landslide susceptibility produced by the logistic regression model is also classified in three categories: low (0.00 - 0.30), medium (0.31 – 0.60), and high (0.61 – 1.00) (Figure 8). In the logistic regression model all eight factors were used initially. In four successive steps, the precipitation, groundwater table, liquidity index, and land cover data were eliminated from the algorithm, as these variables were not found to be significant. The final logistic regression model utilized only four variables: slope angle, distance from the stream, soil type, and erodible soil.

In order to evaluate efficiency of each model landslide inventory map was overlaid on the three landslide susceptibility maps produced by three different models. The three models in the study yield different results (Table 3). The SPN model yields unreliable results where 61% of the landslides are plotted in the low susceptibility zones and only 10% of the landslides fall in the high susceptibility zones. In the LSI model, the known landslides are distributed in the moderate and high landslide susceptibility zone (45% and 38% respectively). In the case of logistic regression model, 91% of the landslides plot in the high landslide susceptibility zone. The places where the landslides are already present are designated as the high susceptibility area with respect to slope failure. The Logistic regression model results appear to be the most reliable as they match with the actual physical conditions in Summit County to the maximum extent.

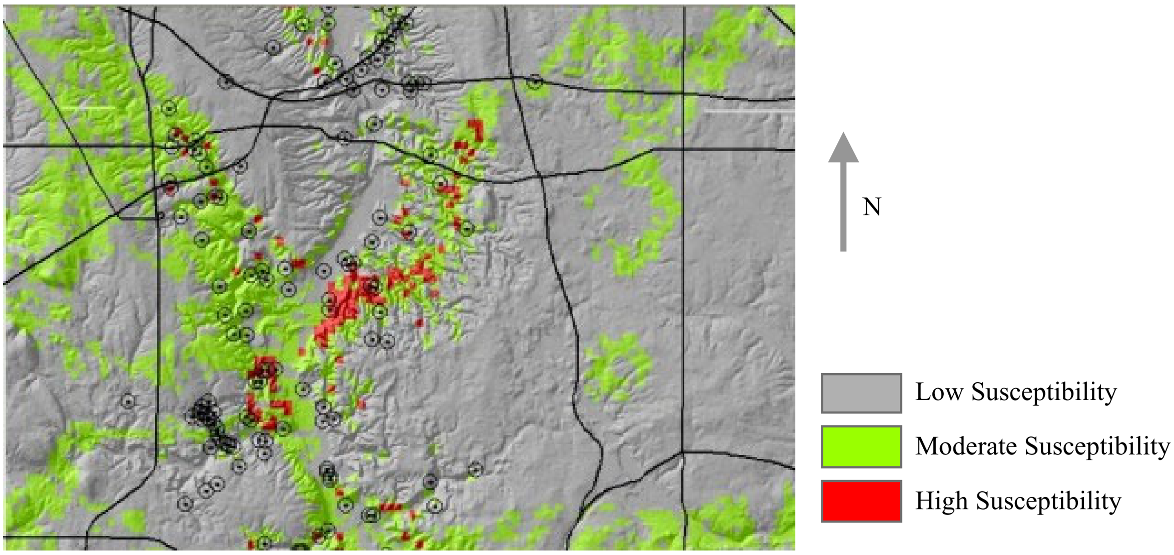

Figure 6. Landslide susceptibility map of a portion of Summit County using SPN model.

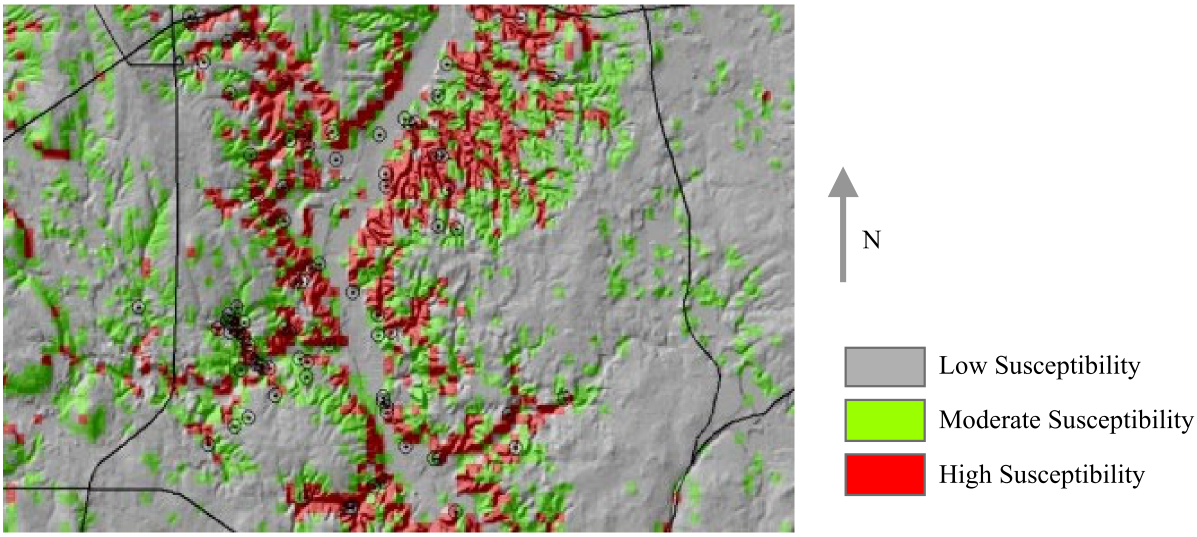

Figure 7. Landslide susceptibility map of a portion of Summit County using LSI model.

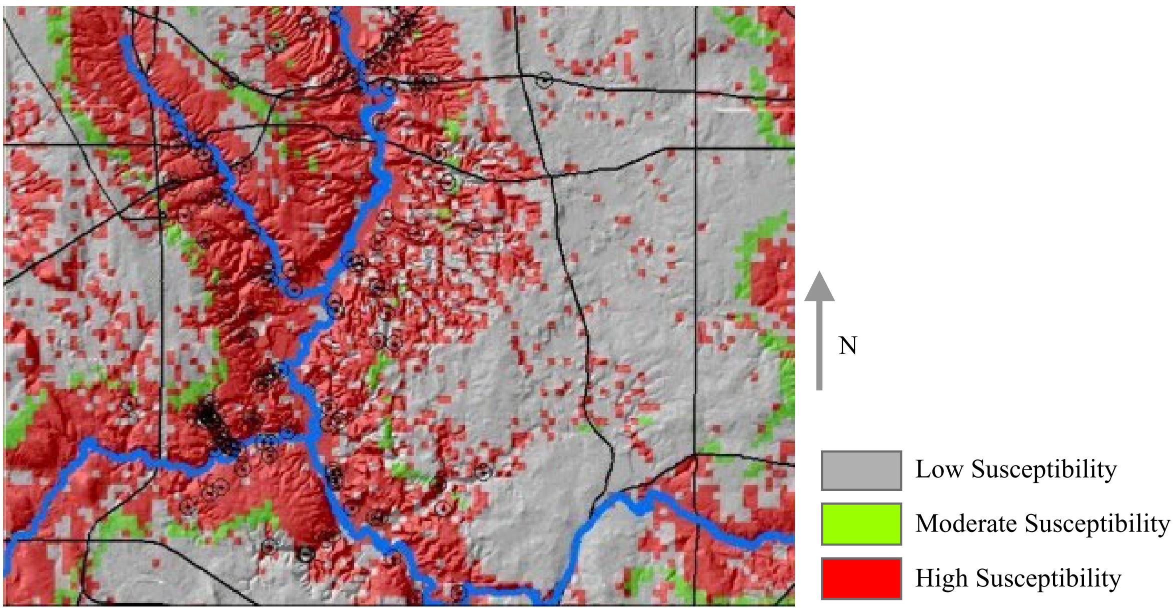

Figure 8. Landslide susceptibility map of a portion of Summit County using logistic regression model.

Table 3. Comparison of results by three different models.

Landslide % in Susceptibility Zones	**SPN Model**	**LSI Model**	**Logistic Regression Model**
Low Susceptibility	*61%*	*17%*	*7%*
Medium Susceptibility	*29%*	*45%*	*2%*
High Susceptibility	*10%*	*38%*	*91%*

CONCLUSION

The logistic regression model is found to be the best model to use in the study area among the three models. It is also found that all the factors used in the landslide susceptibility studies are not equally responsible for the occurrence of landslides. Logistic regression model results show that slope angle, proximity to the stream, soil type, and erodible soil group are the most important factors contributing to the landslides in Summit County, Ohio.

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