Geosciences Journal
Vol. 9, No. 1, p. 63 − 71, March 2005

Application and cross-validation of spatial logistic multiple regression for landslide susceptibility analysis

Saro Lee* *Geoscience Information Center, Korea Institute of Geoscience and Mineral Resources (KIGAM), 30, Gajeong-Dong, Yuseong-gu, Daejeon, 305-350, Korea*

ABSTRACT: The aim of this study is to apply and cross-validate a spatial logistic multiple-regression model at Boeun, Korea using a Geographic Information System (GIS). For this landslide locations in the Boeun area were identified by interpretation of aerial photographs and field surveys. Maps of the topography, soil type, forest cover, geology and land cover were constructed from a spatial database. The 13 factors that influence landslide occurrence were calculated and extracted from the spatial database. Using the 13 factors, landslide susceptibility was analyzed by logistic multiple-regression methods. For validation and cross-validation, the result of the landslide susceptibility analysis obtained from Boeun area was applied to Yongin area in Korea. The validation and cross-validation results showed 75.0% and 85.3% prediction accuracy between the susceptibility map and the existing landslide locations. The GIS was used to analyze the vast amount of data efficiently and statistical programs were used to maintain specificity and accuracy.

Key words: landslide, susceptibility, GIS, logistic regression, validation

1. INTRODUCTION

There are frequent landslides in Korea, which often result in significant damage to people and property. The most recent occurred in 1996, 1998, 1999 and 2002 in Korea. In the study area, Boeun, much damage was caused on these occasions. The landslides were triggerd by heavy rainfall and the damage was extensive. Through scientific analysis of landslides, we can assess and predict landslide-susceptible areas and so landslide damage can be reduced by proper preparation. In order to achieve this, landslide assessment and prediction techniques were developed, applied and validated in the study area using spatial logistic multiple-regression.

There have been many studies of landslide susceptibility evaluation using GIS. Guzzetti et al. (1999) summarized many landslide susceptibility evaluation studies. Recently, there are studies for landslide susceptibility evaluation using GIS. Saha et al. (2002) have used expert opiniton to overlay of factors. Many researchers (Gokceoglu et al., 2000; Luzi et al., 2000; Parise et al., 2000; Randall et al., 2000; Rautelal and Lakheraza, 2000; Baeza and Corominas, 2001; Lee and Min, 2001; Temesgen et al., 2001; Donati and Turrini, 2002; Lee et al., 2002a, 2002b; Lee and Choi, 2003; Rece and Capolongo, 2002) have applied probabilistic and statistical method to landslide susceptibility mapping. Especially, Clerici et al. (2002) have applied conditional analysis method and Dai and Lee (2002) and Atkinson and Massari (1998) applied logistic multiple regression model. Ercanoglu and Gokceoglu (2002) and Pistocchi et al. (2002) have used the fuzzy logic approach to produce a landslide susceptibility map.

A flow chart of the landslide-susceptibility analysis study is shown in Figure 2. A key assumption in this approach is that the potential (occurrence possibility) of landslides will be comparable to the actual frequency of landslides. The places where landslides had occurred in the Boeun area were identified by aerial photographs and field surveys. A map of recent landslides was produced from 1:20,000 scale aerial photographs, in combination with the GIS and this was used to evaluate the frequency and distribution of shallow landslides in the area. Topography, soil, forest, geology and land cover databases were constructed as part of the analysis. Topographic factors such as altitude, slope, aspect and curvature were calculated from the topographic database. Soil texture, material, drainage, effective thickness and topographic type were extracted from the soil database. Forest type, forest diameter and forest density were extracted from the forest database. Lithology was extracted from the geological database and land cover data was classified from Landsat TM images. Using the detected landslide locations and the constructed spatial database, a landslide susceptibility analysis method, spatial logistic multiple regression, was applied and validated. For this, the calculated and extracted factors were converted to a 5 m×5 m grid (ARC/INFO GRID type). The grid data was converted into ASCII file and then imported to the statistical program used. Then, using a logistic multiple-regression model, the spatial relationships between the landslide location and each landslide-related factor, such as topography, soil, forest, geology and land cover, were analyzed and a formula of landslide occurrence possibility was extracted using the relationships in the statistical program. This formula was used to calculate the landslide susceptibility index and was mapped using the grid. The susceptibility map was validated using existing landslide locations. For cross-validation, the formula was

*Corresponding author: leesaro@kigam.re.kr

also applied to another study area, Yongin in Korea, to calculate and map the landslide susceptibility index there. The same spatial database and factors for the Yongin area as for Boeun were available to us. Finally, the susceptibility map was again validated using the existing landslide location.

In this study, GIS software, ArcView 3.2 and ARC/INFO 8.1 NT software and the statistical software SPSS 12.0 were used as the basic analysis tools for spatial management and data manipulation.

2. STUDY AREA

The Boeun area had much landslide damage by heavy rain in 1998 and was selected as a suitable case to evaluate the frequency and distribution of landslides (Fig. 1). The site lies between the latitudes 36°25'21"N and 36°30'00"N and longitudes 127°39'36"E and 127°45'00"E and covers an area of 68.43 km^2. The bedrock geology of the study area consists mainly of biotite granite. In the study area, the landslides occurred in soil soil layer and the landslides occurred when the maximum daily rainfall is 407 mm. For cross-validation, another study area, Yongin, Korea was used (Fig. 1). The Yongin area had high landslide damage after heavy rain in 1991 and was selected as a suitable case to evaluate the frequency and distribution of landslides. The site lies between the latitudes 37.14°N and 37.19°N and longitudes 127.11°E and 127.23°E, and covers an area of 66 km^2. In the study area, the landslides were mainly debris flows and shallow soil slips that occurred when the maximum daily rainfall exceeded 114 mm, with a maximum hourly rainfall of 40 mm. The bedrock geology of the study area consists mainly of granite and gneiss.

3. SPATIAL DATABASE

Identification and mapping of a suitable set of instability factors bearing a relationship to slope failures requires a priori knowledge of the main causes of landslides (Guzzetti et al., 1999). These instability factors include surface and bedrock lithology and structure, bedding altitude, seismicity, slope steepness and morphology, stream evolution, groundwater conditions, climate, vegetation cover, land-use and human activity. The availability of such thematic data varies greatly, depending on the type, scale and method of data acquisition. Geomorphologic, lithological, structural geologic, soil, forest and land cover data should be available for the entire area. To apply the logistic multiple-regression method, maps relevant to landslide occurrence were constructed to a vector-type spatial database using the GIS software ARC/INFO. These included 1:5,000 scale topographic maps, 1:25,000 scale soil maps, 1:25,000 scale forest maps and 1:50,000 scale geological maps. These data are available in Korea either as a paper map or as a digital map. The land cover was classified from satellite images such as those from Landsat TM. The spatial databases are shown in Table 1.

There are 13 factors considered in calculating the landslide probability. These factors were extracted from the constructed spatial database. Contour and survey base points had their elevation value read from the topographic map and were used to build a Digital Elevation Model (DEM). The DEM has 5 m resolution. Using the DEM, the slope angle, slope aspect and slope curvature were calculated. The topography, texture, drainage, material and thickness of soil were acquired from the soil map and the type, diameter and density of forest were obtained from the forest maps. The lithology map was obtained from the geologic map. Finally, land cover data were classified from a LANDSAT TM image using the unsupervised classification method. The five classes (urban, water, forest, agricultural area and barren area) were extracted for land cover mapping.

4. THEORY OF LOGISTIC MULTIPLE REGRESSION

Logistic regression allows one to form a multivariate regression relation between a dependent variable and several independent variables. Logistic regression, which is one of the multivariate analysis methods, is useful for predicting the presence or absence of a characteristic or outcome based on values of a set of predictor variables. The advantage of logistic regression is that, through the addition of an appropriate link function to the usual linear regression model, the variables may be either continuous or discrete, or any combination of both types and they do not necessarily have normal distributions. In the case of multi-regression analysis, the factors must be numerical and in the case of a similar statistical method, determinant analysis, the variables must have a normal distribution. In the present situation, the dependent variable is a binary variable representing presence or absence of landslide. Where the dependent variable is binary, the logistic link function is applicable (Atkinson and Massari, 1998). For this study, the dependent variable must be input as either 0 or 1, so the method applies well to landslide occurrence possibility analysis. Logistic regression coefficients can be used to estimate odds ratios for each of the independent variables in the model.

In the present situation, the dependent variable is a binary variable representing the presence or absence of landslides. Quantitatively, the relationship between the occurrence and its dependency on several variables can be expressed as:

$$p = \exp(z)/(1+\exp(z)) \tag{1}$$

where p is the probability of an event occurring. In the present situation, the value p is the estimated probability of landslide occurrence. The probability varies from 0 to 1 on an S-shaped curve and z is the linear combination. It follows that logistic regression involves fitting an equation of the

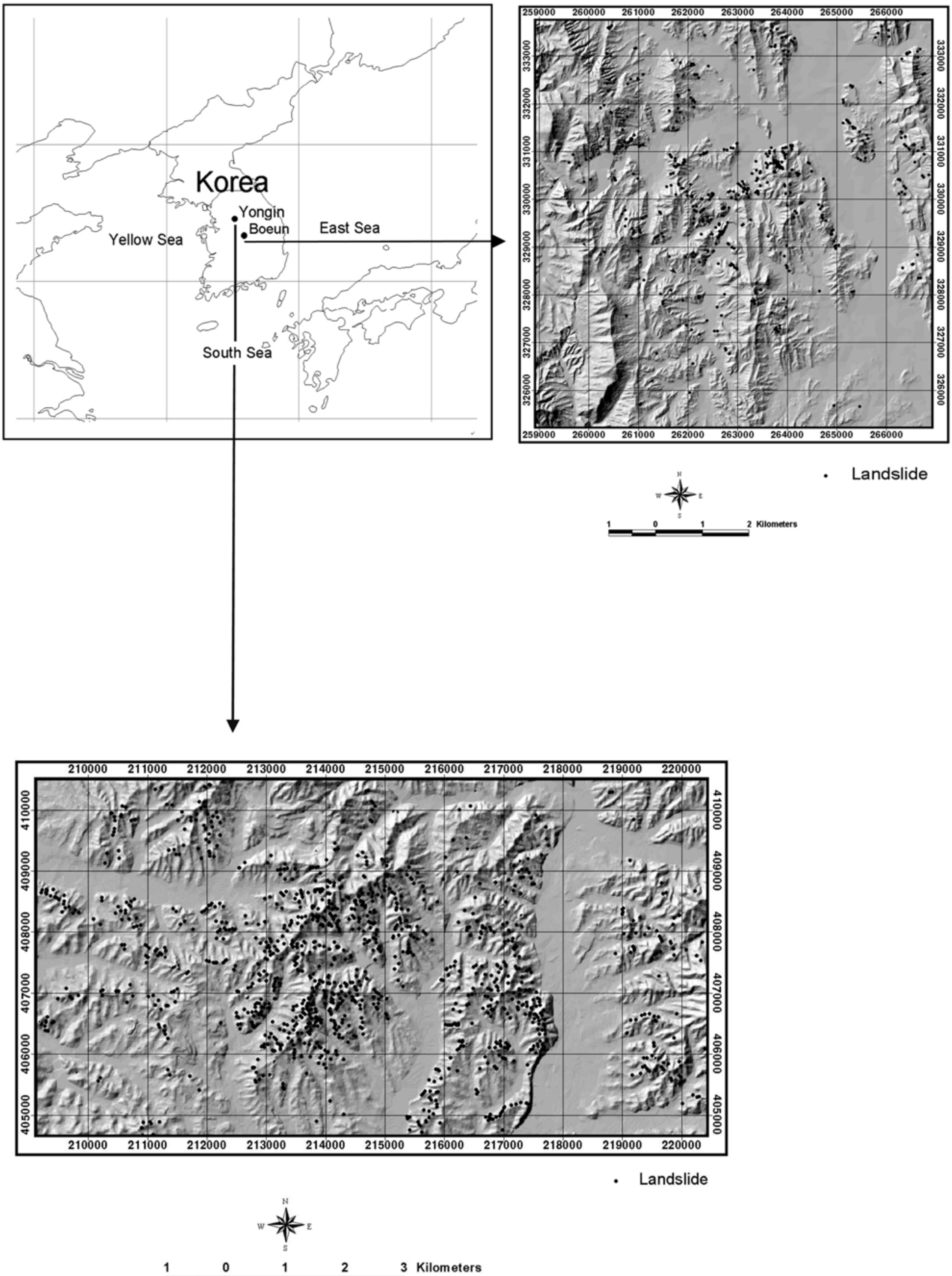

Fig. 1. Landslide location with hillshaded map.

Table 1. Data layer of study area.

Classification	Sub-Classification	GIS Data Type	Scale
Geological Hazard	Landslide	Polygon coverage	1:5,000
	Topographic Map	Line and Point coverage	1:5,000
	Geological Map	Polygon coverage	1:50,000
Basic Map	Soil Map	Polygon coverage	1:25,000
	Forest Map	Polygon coverage	1:25,000
	Land cover	GRID	30 m × 30 m

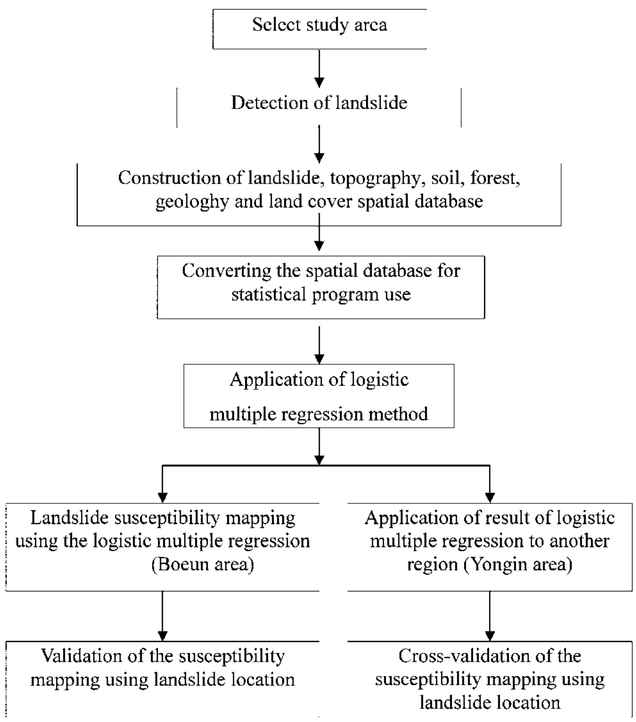

Fig. 2. Flow chart of the study.

following form to the data:

$$z=b_0+b_1x_1+b_2x_2+\ldots+b_nx_n \quad (2)$$

where z is parameter, b_0 is the intercept of the model, the b_i (i=0, 1, 2,..., n) are the slope coefficients of the logistic regression model and the x_i (i=0, 1, 2,..., n) are the independent variables. The linear model formed is then a logistic regression of presence or absence of landslides (present conditions) on the independent variables (pre-failure conditions).

5. APPLYING AND INTERPRETING LOGISTIC MULTIPLE-REGRESSION FOR LANDSLIDE SUSCEPTIBILITY MAPPING

A key concept for understanding the tests used in logistic multiple-regression is that of log likelihood. Usually, however, the overall significance is tested using the chi-squared test, which is derived from the likelihood of observing the actual data under the assumption that the model that has been fitted is accurate. It is convenient to use –2 times the log (base e) of this likelihood (–2LL). Table 2 contains the base model results for the logistic multiple-regression analysis. The log likelihood value (–2LL) here is 8418.480. Several criteria can be used to guide entry: these include the greatest reduction in the –2LL values, or the greatest Wald coefficient.

There are Wald statistics for each regressor in each model, together with a corresponding significance level. The Wald statistic has a chi-squared distribution, but apart from that, it is used in just the same way as the t values for individual regressors in linear regression.

In assessing model fit, several measures are available. Smaller values of the –2LL measure indicate better model fit. The goodness-of-fit measure compares the predicted probabilities to the observed probabilities, with higher values indicating better fit. The value for the single variable model is 8418.480. Next, three measures comparable to the R^2 measure in multiple regression are available.

A statistical program was used to calculate the correlation of a landslide event to each factor. Firstly, all factors were constructed in the database and then logistic multiple-regression coefficients of the factors were calculated (such as those in Table 2). The coefficients of the logistic multiple-regression model were estimated using the maximum-likelihood method. In other words, coefficients that make the observed results most likely are selected. Since the relationship between the independent variables and the probability is nonlinear in the logistic multiple-regression model, an iterative algorithm is necessary for parameter estimation (Dai and Lee, 2002). In Table 2, there are positive associations, such as slope and negative associations, such as curvature. After interpretation, formulas (1) and (3), which predict the landslide-occurrence possibility, were created.

$$\begin{aligned} z=&(0.049\times SLOPE)+(-0.029\times CURVA)+TOPOw \\ &+TEXTUREw+MATERIALw+DRAINw+THICKw \\ &+TYPEw+DIAMETERw+DENSITYw+GEOLw \\ &+LANDUSEw-33.173 \end{aligned} \quad (3)$$

where Slope is slope value; Curva is Curvature value; TOPOw, TEXTUREw, MATERIALw, DRAINw, THICKw, TYPEw,

Table 2. Logistic multiple regression coefeicnets (Boeun area).

Factors	B[1]	S.E.[2]	Wald[3]	Sig.[4]	Exp(B)[5]
SLOPE	.049	.005	81.845	.000	1.050
CURVATURE	-.029	.005	33.080	.000	.971
ASPECT			27.746	.001	
Flat	−.578	.392	2.174	.140	.561
N	−.344	.196	3.088	.079	.709
NE	−.015	.164	.008	.927	.985
E	−.515	.170	9.180	.002	.598
SE	−.173	.174	.983	.322	.841
S	−.720	.227	10.069	.002	.487
SW	−.663	.204	10.561	.001	.515
W	−.317	.173	3.364	.067	.728
SOIL TEXTURE			8.789	.641	
No data	4.401	13.679	.104	.748	81.522
Sandy loam	−.340	.408	.695	.404	.712
Fine sandy loam	−3.451	4.466	.597	.440	.032
Gravelly sandy loam	−1.084	.546	3.949	.047	.338
Gravelly silt loam	−3.215	2.218	2.101	.147	.040
Loam	−.243	.700	.120	.729	.784
Silt loam	−1.068	1.157	.853	.356	.344
Gravelly loam	−6.819	9.309	.537	.464	.001
Loamy fine sand	−4.826	7.614	.402	.526	.008
Overflow	8.792	11.232	.613	.434	6580.113
Rocky silt loam	−8.254	8.183	1.017	.313	.000
SOIL MATERIAL			4.821	.777	
Fluvial alluvium	.665	4.586	.021	.885	1.945
Alluvial-Colluvium	−1.475	2.542	.337	.562	.229
Okcheon System residuum formation	1.512	1.187	1.624	.203	4.537
Colluvium	−4.439	15.771	.079	.778	.012
Diluvium	1.478	4.751	.097	.756	4.386
Valley alluvium	1.482	4.615	.103	.748	4.402
Granite residuum	−.776	2.431	.102	.750	.460
Alluvium	−1.041	66.847	.000	.988	.353
SOIL DRAINAGE			5.841	.211	
Somewhat poorly drained	2.752	1.546	3.168	.075	15.669
Moderately well drained	2.657	1.577	2.837	.092	14.256
Well drained	6.406	4.613	1.928	.165	605.369
Excessively drained	5.259	4.781	1.210	.271	192.247
SOIL EFFECTIVE THICKNESS			4.448	.217	
50–100 cm	4.542	8.237	.304	.581	93.848
100–150 cm	4.218	8.234	.262	.609	67.883
20–50 cm	5.933	8.257	.516	.472	377.236
TOPOGRAPHIC TYPE			17.022	.009	
Lower illy area	−3.131	1.177	7.077	.008	.044
Hilly area	−1.644	.511	10.339	.001	.193
Piedmont slope area	3.143	15.732	.040	.842	23.177
Mountain and hilly area	−5.454	10.526	.268	.604	.004
Mountainous area	−.217	.209	1.075	.300	.805
Hilly and mountain area	−.400	.946	.179	.672	.670

Table 2. continued

Factors	B[1]	S.E.[2]	Wald[3]	Sig.[4]	Exp(B)[5]
FOREST TYPE			51.752	.000	
Non-forest	5.567	28.991	.037	.848	261.597
Rigida pine	7.273	29.009	.063	.802	1441.100
Pine	6.849	29.010	.056	.813	943.125
Needle and broad	6.738	29.009	.054	.816	843.927
Artificial broad leaf tree	6.780	29.027	.055	.815	880.293
Korea nut pine	7.449	29.011	.066	.797	1718.877
Larch	6.953	29.010	.057	.811	1046.758
Broad leaf tree	5.845	29.009	.041	.840	345.506
Field	5.386	28.999	.034	.853	218.263
Rock	1.654	36.238	.002	.964	5.229
Chestnut tree	6.946	29.018	.057	.811	1038.712
Poplat	2.350	50.167	.002	.963	10.482
FOREST DIAMETER			46.378	.000	
Very small diameter (timber diameter is below 6 cm)	−1.183	1.066	1.232	.267	.306
Small diameter (timber diameter is 6~16 cm)	−1.477	.217	46.310	.000	.228
FOREST DENSITY			16.757	.000	
Loose (Less than 50% forest area)	.832	1.006	.684	.408	2.298
Moderate (51~70% forest area)	−.273	1.039	.069	.793	.761
GEOLOGY			33.318	.000	
Pebble bearing argillaceous and calcareous schist limestone and dolomite	3.379	11.424	.087	.767	29.327
Biotite granite, biotite granodiorite	4.677	11.433	.167	.682	107.492
Jukjeonri two mica adamellite	5.376	11.434	.221	.638	216.232
Acidic dyke	4.590	11.439	.161	.688	98.512
Alluvium	4.544	11.436	.158	.691	94.024
LANDUSE			3.142	.791	
No data	−.522	17.821	.001	.977	.593
Water	.836	17.452	.002	.962	2.307
Urban	1.258	13.030	.009	.923	3.519
Forest	5.041	11.384	.196	.658	154.592
Grass	4.950	11.384	.189	.664	141.243
Agriculture	4.669	11.386	.168	.682	106.623
CONSTANT	−33.173	35.016	.898	.343	.000

B[1]=logistic coefficient
S.E.[2]=standard error
Wald[3]=Wald statistics
Sig.[4]=Significance
Exp(B)[5]=exponentiated coefficient
[*]Other types are 0

DIAMETERw, DENSITYw, GEOLw and LANDUSEw are logistic multiple-regression coefficients in Table 2; z is a parameter; and p is the landslide-occurrence possibility.

Using these formulae, a landslide susceptibility map was made. Logistic multiple-regression analysis was performed by dividing the study area into a 5 m×5 m sized grid and the factors were divided into a 5 m×5 m array and converted to an ASCII file to use in the statistical package. In the study area, the total cell number was 2,729,160 and the cell number where landslides occurred was 483. The distribution of the calculated possibility is shown in Figure 3. The value was classified by equal areas and grouped into five classes for easy interpretation: very low (0.00000), low (0.00000–0.00003), medium (0.00003–0.00010), high (0.00010–0.00030) and very high (>0.00030). Using Table 2 and formulas (1) and (3), the other study area, Yongin, was analyzed for cross-validation of landslide susceptibility. Logistical multiple regression analysis is performed for the Yongin area. In this study area, the total cell number is 2,633,346 and the cell number where landslides occurred is 1,149. The distribution of the calculated possibility is shown in Figure 4. The value is classified by equal areas and grouped into five

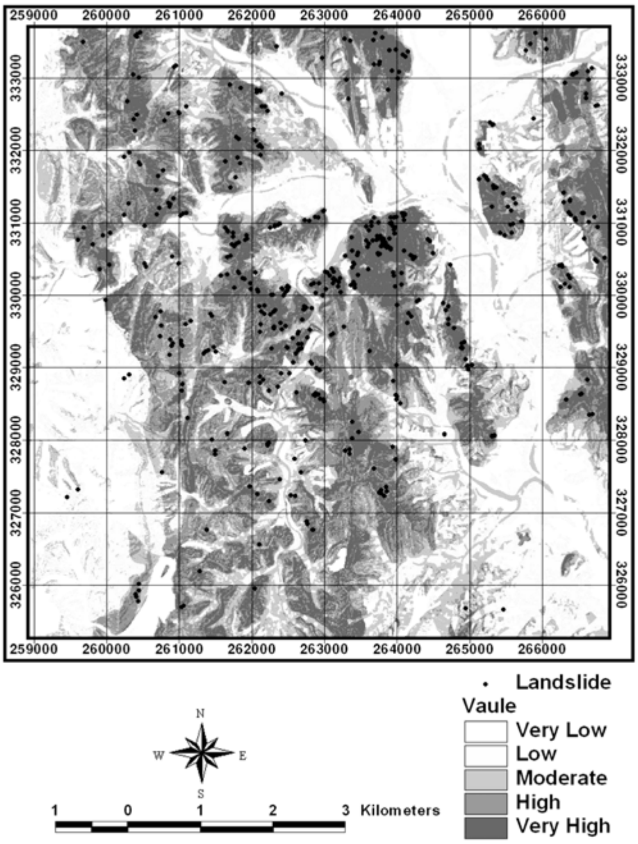

Fig. 3. Landslide susceptibility map of Boeun based on logistic multiple regression.

classes: very low (0.0000), low (0.0000–0.0009), medium (0.0009–0.0033), high (0.0033–0.0083), very high (0.0083<).

6. CROSS-VALIDATION OF LANDSLIDE SUSCEPTIBILITY

For validation of these landslide susceptibility calculation methods, two basic assumptions are needed. One is that landslides are related to spatial information such as topography, soil, forest, geology and land cover and the other is that future landslides will be precipitated by a specific impact factor, such as rainfall or an earthquake. In this study, the two assumptions are satisfied because the landslides are related to the spatial information and the landslides were precipitated by one cause, heavy rainfall in the Boeun and Yongin areas.

The landslide susceptibility analysis result was validated using the landslide locations for the Boeun study area and cross-validated using the landslide locations for the Yongin study area. The validation method was performed by comparison of existing landslide data and landslide susceptibility analysis results for the Boeun study area. The comparisons are shown in Figure 5 as a line graph, using the logistic multiple-regression method at the cases of success rate and prediction rate. The success rates in Figure 5 illustrate how well the estimators perform with respect to the left-side landslides used in constructing those estimators. The prediction rates in Figure 5, on the other hand, are used as measurements of how well the probability model and its estimators predict the distribution of future landslides (Chung and Fabbri, 1999). To obtain the relative ranks for sucess pattern, the calculated index values of all cells in the study area were sorted in descending order. The success rate validation results were divided into classes of accumulated area ratio percentage, according to the landslide suscepti-

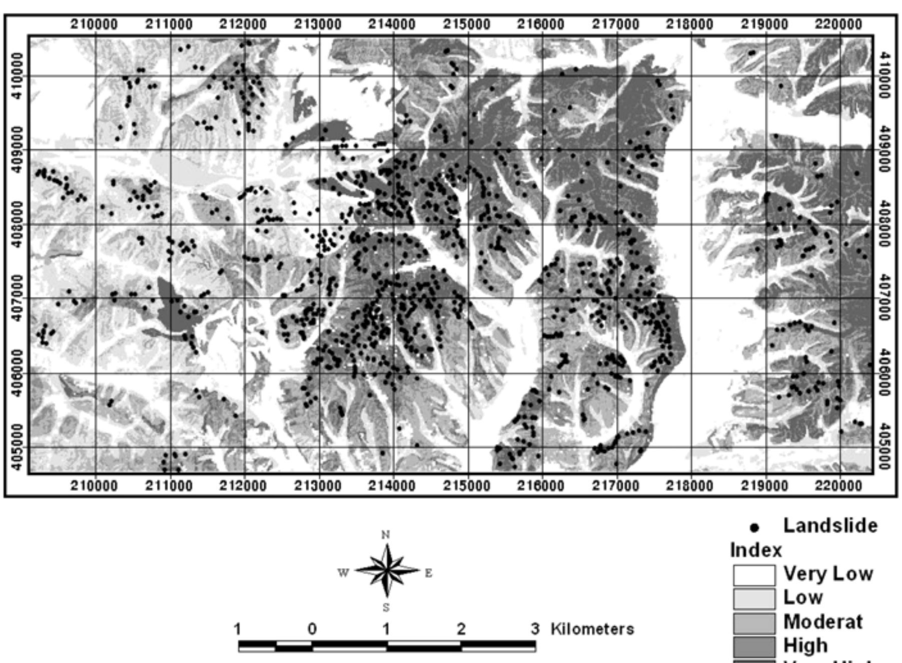

Fig. 4. Landslide susceptibility map of Yongin based on logistic multiple regression.

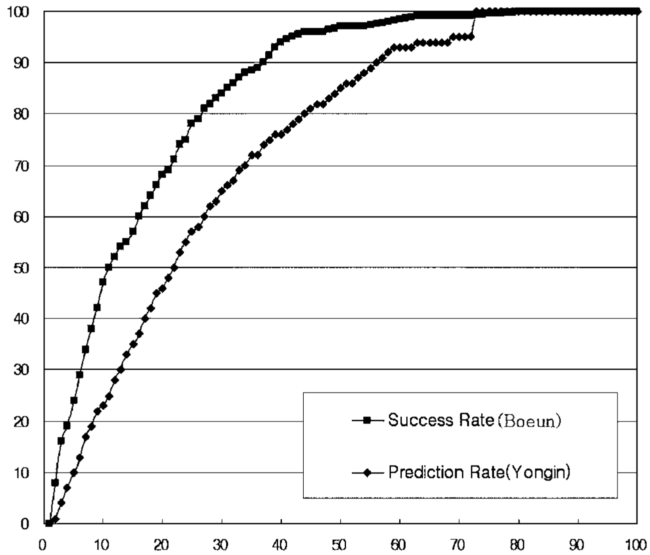

Fig. 5. Illustration of cumulative frequency diagram showing landslide susceptibility index rank (x-axis) occurring in cumulative percent of landslide occurrence (y-axis).

bility index value. The above procedure also was adapted for the Yongin area by comparing the classes obtained with the distribution in Yongin to obtain the prediction rate. The success rate validation results, obtained by comparing the susceptibility calculation results and landslide occurrence location using the logistic multiple-regression method, are shown in Figure 5. In Figure 5, the success rate validation results are divided into classes of accumulated area ratio percentage according to the landslide susceptibility index value. For example, the 90–100% (10%) class that has highest possibility of landslide in Figure 5 contains 50% of the Boeun area in its success rate using the logistic multiple-regression method. A 0–20% class (20%) contain 69% and the 0–30% class (30%) contains 85% of the study area. The values of 50%, 69% and 85% are higher value comparing with the existing result (Lee et al., 2002a; Pistocchi et al., 2002).

The prediction rate validation results, found by comparing the susceptibility calculation results and landslide occurrence locations using the logistic multiple-regression method, are shown in Figure 5. In Figure 5, the prediction rate validation results are divided into classes with accumulated area percentage according to landslide susceptibility index value. For example, the 90–100% (10%) class, with the highest possibility of landslide in Figure 5, contains 25% of the Yongin area in its success rate using the logistic multiple-regression method. The 0–20% class (20%) contains 48% and the 0–30% class (30%) contains 66% of the Yongin area.

To compare the result quantitative, the areas under the curve were re-calculated as the total area is 1 which means perfect prediction accuracy. So, the area under a curve can be used to assess the prediction accuracy qualitatively. In the case of success rate, the area ratio was 0.8532 and we could say the prediction accuracy is 85.3%. In the case of prediction rate, the area ratio was 0.7500 and we could say the prediction accuracy is 75.0%.

The success rate validation is from the landslide susceptibility analysis result validated in the Boeun area using the landslide occurrence locations and logistic multiple-regression methods. Therefore, strictly speaking, the success rate is not a perfect validation method. However, the success rate validation method needs to get information about the properties of the analysis method and checks the landslide susceptibility analysis calculation for major errors. It also needs to be tested against the prediction rate validation method.

7. CONCLUSION AND DISCUSSION

Landslide is one of the most hazardous natural disasters. Government and research institutions worldwide have attempted for years to assess the susceptibility of landslides, estimate their risk and show their spatial distribution. In this study, a statistical approach to estimating the susceptibility of an area to landslides using aerial photography and the GIS is presented. For the landslide susceptibility analysis, landslide location was detected using aerial photographs and a landslide-related database was constructed for the study area of Boeun and Yongin, Korea. For the landslide susceptibility analysis, logistic multiple-regression methods were applied and validated for the study area of Yongin, Korea, using the spatial database.

The validation and cross-validation results showed 75.0% and 85.3% prediction accuracy between the susceptibility map and the existing data on landslide locations. With respect to the Boeun study area, the success rates of the logistic multiple-regression method showed more accurate result than prediction rates of the Yongin study area. Generally, the success rate is higher than the prediction rate for all classes.

The statistical program can allow analysis of landslide susceptibility but it is inconvenient for the management of spatial data and modification of its input data is difficult. A GIS has none or few functions for statistical and artificial neural network analyses but has many functions for database construction, display, printing, management and analysis. Therefore, it is necessary to integrate the GIS and statistics to reduce the restrictions of using the three applications separately. The benefits of integrating GIS and statistical programs are efficiency and ease of management, input, display and analysis of spatial data for landslide susceptibility.

Landslide susceptibility maps are of great help to planners and engineers for choosing suitable locations to implement developments. These results can be used as basic data to assist slope management and land-use planning.

REFERRENCES

Atkinson, P.M. and Massari, R., 1998, Generalized linear modeling of susceptibility to landsliding in the central Apennines, Italy. Computer & Geosciences, 24, 373–385.

Baeza, C. and Corominas, J., 2001, Assessment of shallow landslide susceptibility by means of multivariate statistical techniques. Earth surface processes and landforms, 26, 1251–1263.

Chung, C.F. and Fabbri, A.G., 1999, Probabilistic prediction models for landslide hazard mapping. Photogrammetric Engineering & Remote Sensing, 65, 1389–1399.

Clerici, A., Perego, S., Tellini, C. and Vescovi, P., 2002, A procedure for landslide susceptibility zonation by the conditional analysis method. Geomorphology, 48, 349–364.

Dai, F.C. and Lee, C.F., 2002, Landslide characteristics and slope instability modeling using GIS, Lantau Island, Hong Kong. Geomorphology, 42, 213–228.

Donati, L. and Turrini, M.C., 2002, An objective method to rank the importance of the factors predisposing to landslides with the GIS methodology: application to an area of the Apennines (Valnerina; Perugia, Italy). Engineering Geology, 63, 277–289.

Ercanoglu, M. and Gokceoglu, C., 2002, Assessment of landslide susceptibility for a landslide-prone area (north of Yenice, NW Turkey) by fuzzy approach. Environmental Geology, 41, 720–30.

Gokceoglu, C., Sonmez, H. and Ercanoglu, M., 2000, Discontinuity controlled probabilistic slope failure risk maps of the Altindag (settlement) region in Turkey. Engineering Geology, 55, 277–296.

Guzzetti, F., Carrarra, A., Cardinali, M. and Reichenbach, P., 1999, Landslide hazard evaluation: a review of current techniques and their application in a multi-scale study, Central Italy. Geomorphology, 31, 181–216.

Lee, S. and Choi, U.C., 2003, Development of GIS-based geological hazard information system and its application for landslide analysis in Korea. Geosciences Journal, 7, 243–252.

Lee, S ., Choi, J. and Min, K., 2002a, Landslide susceptibility analysis and verification using the Bayesian probability model. Environmental Geology, 46, 149–162.

Lee, S., Chwae, U. and Min, K., 2002b, Landslide susceptibility mapping by correlation between topography and geological structure: the Janghung area, Korea. Geomorphology, 46, 149–162.

Lee, S. and Min, K. 2001, Statistical analysis of landslide susceptibility at Yongin, Korea. Environmental Geology, 40, 1095–1113.

Luzi, L., Pergalani, F. and Terlien, M.T.J., 2000, Slope vulnerability to earthquakes at subregional scale, using probabilistic techniques and geographic information systems. Engineering Geology, 58, 313–336.

Parise, M. and Randall, W. J., 2000, A seismic landslide susceptibility rating of geologic units based on analysis of characteristics of landslides triggered by the 17 January, 1994 Northridge, California earthquake. Engineering Geology, 58, 251–270.

Pistocchi, A., Luzi, L. and Napolitano, P., 2002, The use of predictive modeling techniques for optimal exploitation of spatial databases: a case study in landslide hazard mapping with expert system-like methods. Environmental Geology, 41, 765–775.

Randall, W.J., Edwin, L.H. and John, A.M., 2000, A method for producing digital probabilistic seismic landslide hazard maps. Engineering Geology, 58, 271–289.

Rautelal, P. and Lakheraza, R.C., 2000, Landslide risk analysis between Giri and Tons Rivers in Himachal Himalaya (India). International Journal of Applied Earth Observation and Geoinformation, 2, 153–160.

Rece, A. and Capolongo, D., 2002, Probabilistic modeling of uncertainties in earthquake-induced landslide hazard assessment. Computers & Geosciences, 28, 735–749.

Saha, A.K., Gupta, R.P. and Arora, M.K., 2002, GIS-based Landslide Hazard Zonation in the Bhagirathi (Ganga) Valley, Himalayas. International Jounal of Remote Sensing, 23, 357–369.

Temesgen, B., Mohammed, M.U. and Korme, T., 2001, Natural Hazard Assessment Using GIS and Remote Sensing Methods, with Particular Reference to the Landslides in the Wondogenet Area, Ethiopia. Physics and Chemistry of the Earth, 26, 665–615.

Manuscript received July 23, 2004
Manuscript accepted February 21, 2005