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Original article

# A Comparative Analysis of Landslide Susceptibility Assessment by Using Global and Spatial Regression Methods in Inje Area, Korea

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**Abstract**

Landslides are major natural geological hazards that result in a large amount of property damage each year, with both direct and indirect costs. Many researchers have produced landslide susceptibility maps using various techniques over the last few decades. This paper presents the landslide susceptibility results from the geographically weighted regression model using remote sensing and geographic information system data for landslide susceptibility in the Inje area of South Korea. Landslide locations were identified from aerial photographs. The eleven landslide-related factors were calculated and extracted from the spatial database and used to analyze landslide susceptibility. Compared with the global logistic regression model, the Akaike Information Criteria was improved by 109.12, the adjusted R-squared was improved from 0.165 to 0.304, and the Moran's I index of this analysis was improved from 0.4258 to 0.0553. The comparisons of susceptibility obtained from the models show that geographically weighted regression has higher predictive performance.

Keywords : Landslide, Landslide Susceptibility Map, Geographically Weighted Regression, Logistic Regression Model

## 1. Introduction

Over the last decade, natural disasters such as hurricanes, earthquakes, extreme erosion, tsunamis, and landslides have increased sharply. Because of increasing threats from these phenomena, national and local government agencies have expressed concern for human injuries and economic loss (Yilmaz, 2009). Landslides, which account for 4.4% of natural disasters around the world, have increased rapidly in frequency and cause significant damage (1990-2009) (Akgun *et al*., 2008; Vos *et al*., 2010; Park *et al*., 2013). This trend will continue in the coming decades, as regional precipitation, deforestation, urbanization, and development increase (Schuster, 1996).

Under these circumstances, interest in landslide assessment has grown significantly among experts in various fields, such as engineers, geologists, planners, local administrators, and decision makers (Ercanoglu and Gokceoglu, 2004). Assessment and management of landslide damage can be aided by thematic mapping, with the following steps: 1. Landslide inventory maps; 2. Landslide susceptibility maps; 3. Landslide hazard maps; and 4. Landslide risk maps (Kamp *et al*., 2008). Among these maps, the production of a landslide susceptibility map in the early stage of the assessment process is of crucial importance.

Landslide susceptibility maps have been drawn using various methods across numerous research studies. The methods are divided into qualitative and quantitative. Currently, quantitative techniques are widely used, aided by the technological development of GIS (Geographical

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Information Systems), which provide a powerful tool for managing and manipulating spatial data. Quantitative techniques are based on numerical expressions of the relationships between controlling factors and landslides (Aleotti and Chowdhury, 1999). Quantitative techniques are divided into deterministic and statistical methods (either bivariate or multivariate), and the majority of researchers prefer the GLR (Global Logistic Regression) model, a statistical method (Ayalew and Yamagishi, 2005; Bai *et al*., 2010; Bui *et al*., 2011; Chauhan *et al*., 2010; Chen and Wang, 2007; Falaschi *et al*., 2009; Xu *et al*., 2013).

However, the GLR model cannot take into account the spatial dependence or autocorrelation characteristics of observational data (Erener and Düzgün, 2010). This reduces the efficiency of estimated parameters when evaluating landslide susceptibility. Therefore, the GWR (Geographically Weighted Regression) has been introduced as a method that incorporates spatial variation (Feuillet *et al*., 2014). Because the GWR model uses a regression model, the advantages of existing models can be applied, and different factors can be estimated for respective regions. This makes it possible to confirm a spatially heterogeneous pattern that is difficult to grasp with existing models. Additionally, it enables the visualization of spatial interactions among data by mapping the results of the GWR analysis using GIS (Ercanoglu and Gokceoglu, 2004).

The goal of our study is to analyze and quantify improvements in the accuracy and explanatory power of landslide susceptibility compared with a previously used the GLR model when analyzing landslide susceptibility using the GWR. To accomplish this, the Inje region was selected as the research area, as it was subjected to severe landslide damage in 2006. A spatial database of landslide-related factors was compiled using the DEM (Digital Elevation Model) and various thematic maps. The GWR model was analyzed and compared with the GLR model analysis results using conformity-measured values and various diagnostic indices.

## 2. Study Area

Approximately 81% of the total area of Gangwon-do in the central eastern region of Korea is composed of mountains. Most of these mountains have steep and rough terrain with 2 m or less of effective soil depth: suitable conditions for landslides (Im, 2009).Three instances of localized heavy rainfalls occurred in the Gangwon-do area in 2006 (July 11–13, July 14–20, July 25–29), including Ewiniar, a category 3 typhoon. These rains were regionally concentrated in the Inje, Yangyang, and Pyeongchang areas, with the heaviest rainfall in about 500 years lasting for about 1–6 hours (Lee and Talib, 2005). This caused approximately 160 billion won in property damage and resulted in 40 or more human deaths. According to Kim et al. (2012), landslides occurred in about 400 locations around Inje-eup, Girin-myun, and Nam-myun, Inje-gun. Among these, a survey revealed that Inje-eup experienced the most landslides and the most damage. Therefore, the entire area of Inje-eup was selected as the study area for this analysis of landslide susceptibility (Fig. 1).

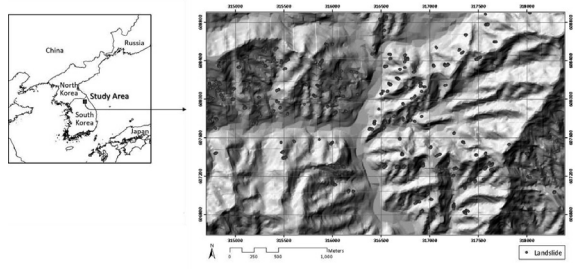


**Fig. 1. Study area**

## 3. Data set and methodology

### 3.1. Landslide identification

Accurate identification of landslide locations is critical to analyses of landslide hazards. Field surveys are the most accurate way to identify landslide locations, but terrain and environmental conditions may make it difficult and costly to access these areas as an initial landslide identification method. Remote sensing methods using data such as aerial photos and satellite imagery are more effective due to their lower cost, and are widely used to identify landslide locations (Liangjie *et al*., 2012).

Landslide locations for this study were identified using aerial photos taken soon after landslide occurrences. Aerial photos taken on 2 August 2006 using the PKNU (Pukyong

**Table 1. Data type and scale of data used in the study**

| Main data sets | Produced map | GIS data type | Scale | Source |
|---|---|---|---|---|
| Topographic map | Slope | GRID | 1:5,000 | National Geographic Institute |
| | Aspect cosine | GRID | 1:5,000 | |
| | Aspect sine | GRID | 1:5,000 | |
| | Slope degree | GRID | 1:5,000 | |
| | Slope length | GRID | 1:5,000 | |
| | Curvature | GRID | 1:5,000 | |
| | Topographic wetness index | GRID | 1:5,000 | |
| Soil map | Drainage | Polygon | 1:25,000 | Science and Technology |
| | Effective thickness | Polygon | 1:25,000 | |
| Forest map | Diameter | Polygon | 1:25,000 | National forest Research Institute |
| | Density | Polygon | 1:25,000 | |

National University) IV system were used to identify the locations of landslides that had occurred in the Inje area in July 2006. The collected aerial photos were geometrically corrected using a 1:5,000 digital topographic map and then used to produce orthophotos by creating a mosaic using a DTM (Digital Terrain Model). Landslide locations were digitized by visual interpretation using orthorectified aerial photos.

### 3.2 Spatial dataset

Because landslides result from a combination of various factors such as topology, soil, and forest, these landslide-related factors need to be built into a spatial database for landslide susceptibility analysis. The relevant thematic maps acquired from government were used to construct a spatial database (Table 1). A total of eleven landslide-related factors were compiled into a spatial database with 10×10-m cells relative to the research area using ArcGIS 10.2 software.

The dataset consisted of 232 rows×370 columns, for a total of 85,840 cells, with landslides represented in 446 of the cells. A total of 446 cells were divided randomly into two groups, training and validation set. 624 cells, accounting for 70% of the total positive events (landslide affected areas), were randomly selected as the training set. In addition, cells of the negative events (landslide non-affected areas) were collected with same number of the positive events. The remaining portion of the training set was used as validation set.

### 3.3. GLR

Regression approaches including linear regression, log-linear regression and logistic regression can be considered a process to extract the coefficients of empirical relationships from observations (Ozdemir and Altural, 2013). The goal of GLR is to find the best-fitting model to describe the relationship between a dichotomous depend variable (the presence or absence of landslides) and several explanatory variables.The explanatory variables may be continuous or discrete (with dummy variables) and do not need a normal frequency distribution (Ayalew and Yamagishi, 2005; Van Den Eeckhaut *et al*., 2006). Quantitatively, the relationship between depend variable and explanatory variables can be expressed in Eq. (1).

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

where, $P$ is the probability of landslide occurrence, ranging between 0 and 1 on an s-shaped curve, and $z$ represents a linear combination of the variables through Eq. (2).

$$z = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_n x_n \quad (2)$$

where, $\beta_0$ is the intercept of the model, $\beta_i$ $(i = 1, 2, 3 \cdots \mathrm{n})$ are the regression coefficients, and $x_i$ $(i = 1, 2, 3 \cdots \mathrm{n})$ are the explanatory variables (Youssef *et al*., 2015). The value *z* varies from $-\infty$ to $+\infty$.

A positive sign of the probability represents that the explanatory variables has increased the probability of change, and a negative sign indicates the opposite effect. In addition, maximizing likelihood function is used to obtain the regression coefficients. A coefficient is significant if the tested null hypothesis that the estimated coefficient was zero could be rejected at a 0.05 significance level(Hosmer and Lemeshow, 2000; Kleinbaum and Klein, 2002; Van Den Eeckhaut *et al*., 2006).

In addition, multicollinearity among the independent variables is tested using the TOL (tolerance) and the VIF (Variance Inflation Factor) to improve the model fitting. The variables with VIF > 10 and TOL < 0.1 are represented serious multicollinearity between explanatory variables and excluded from the logistic analysis (Hosmer and Lemeshow, 2000; Menard, 2002; Zhu and Huang, 2006).

### 3.4. GWR

GWR, which is a local modeling technique, aims to capture spatial non-stationarity in the influence of factors on the occurrence of a landslide (Feuillet *et al*., 2014). The spatial non-stationarity is identified by generating a set of local-specific coefficients, including local R square, local model residuals, local parameter estimates as well as the corresponding *t*-test values (Fotheringham *et al*., 2002). The GWR model extends the OLS (Ordinary Regression Squares) regression by allowing regression coefficients to be estimated locally (Feuillet *et al*., 2014).

The GWR model can be expressed as:

$$y_j = \beta_0 (u_j, v_j) + \sum_{i=1}^{k} \beta_i (u_j, v_j)\, x_{ij} + \varepsilon_j \quad (3)$$

where $u_j$ and $v_j$ are the spatial position of location j, $\beta_0 (u_j, v_j)$ acts as intercept, and $\beta_i (u_j, v_j)$ is the local estimated coefficient for explanatory variables (Su *et al*., 2012).

The GWR uses kernel bandwidth to determine the spatial scope of spatialdependence, and then employs distance decay function to weight all the observations within the spatial scope. Because it is assumed that observations near point *i* have more influence on the estimation of $\beta_i (u_j, v_j)$ than observations located farther from *i* (Feuillet *et al*., 2014; Tu and Xia, 2008). The distance decay functions can be calculated by Gaussian and bi-square (Brunsdon *et al*., 1998; Fotheringham *et al*., 2002). In this research, the Gaussian distance decay is used to express the weight function:

$$w_{ij} = \exp(-d_{ij}^2 \,/\, h^2) \quad (4)$$

where $w_{ij}$ is the weight for observation $j$ within the neighborhood of observation $i$, $d_{ij}$ represents the distance between observations $i$ and $j$, and *h* denotes the kernel bandwidth (Su *et al*., 2012). The CV (Cross-Validation) and AICc (Akaike Information Criterion) are used to select optimum bandwidth. The AICc is generally more applicable and can be applied in non-Gaussian GWR than CV (Fotheringham *et al*., 2002; Lloyd, 2010).

Three goodness-of-fit criteria such as deviance, AICc, and the BIC (Bayesian Information Criterion (BIC, also known as the Schwartz criterion) are used to consider both fit and complexity of the model. Lower values of these criteria indicate a more efficient model (Feuillet *et al*., 2014).

## 4. Results and Discussion

### 4.1. Logistic regression

The results of logistic regression model are represented in Table 2.All explanatory variables had the value of VIF < 10 and TOL > 0.1 respectively. This result indicated that there was no serious multicollinearity between explanatory variables. In addition, the significance probability value was less than 0.01 against all variables except for aspect sine, topographic wetness index, and soil thickness. This indicates that the other variables with exception of the above three variables had statistically significant effects on landslide at the 5% significance level. From the analysis results, Aspect sine, slope degree, slope length, soil drainage, soil thickness, timber diameter, and timber density had positive effects on landslide occurrence and showed a higher possibility of

**Table 2. Result of logistic regression**

| Variable | Coefficient | Std. Error | t-statistic | Sig. | Tolerance | VIF |
|---|---|---|---|---|---|---|
| Intercept | 0.1870 | 0.1853 | 1.0089 | 0.3133 | - | - |
| Elevation | -0.0015 | 0.0002 | -6.3425 | 0.0000* | 0.6686 | 1.4956 |
| Aspect cosine | -0.0875 | 0.0223 | -3.9188 | 0.0000* | 0.9548 | 1.0474 |
| Aspect sin | 0.01489 | 0.0222 | 0.6717 | 0.5019 | 0.9584 | 1.0434 |
| Slope degree | 0.0055 | 0.0021 | 2.6573 | 0.0080* | 0.6719 | 1.4883 |
| Slope length | 0.0041 | 0.0014 | 2.8707 | 0.0042* | 0.3910 | 2.5576 |
| Curvature | -0.0139 | 0.0058 | -2.4156 | 0.0159* | 0.5775 | 1.7316 |
| Topographic wetness index | -0.0044 | 0.0069 | -0.6387 | 0.5232 | 0.3915 | 2.5540 |
| Soil drain | 0.0930 | 0.0421 | 2.2077 | 0.0275* | 0.5922 | 1.6887 |
| Soil thickness | 0.0261 | 0.0321 | 0.8135 | 0.4161 | 0.7452 | 1.3420 |
| Timber diameter | 0.0974 | 0.0220 | 4.4224 | 0.0000* | 0.7757 | 1.2891 |
| Timber density | 0.0842 | 0.0220 | 3.8260 | 0.0002* | 0.7518 | 1.3302 |

landslide. On the other hand, the other variables except for the above variables had less effect on landslide occurrence. Timber diameter was the most influential of the landslide-related factors, whereas aspect cosine contributed least to landslide occurrence.

### 4.2. GWR

Table 3 summarizes the spatially varying coefficients for 714 sample points. All of the eleven explanatory variables have both positive and negative coefficient values although with differences in the portions of both values. This represented that the constant coefficient estimates in the logistic regression tent to make the spatially non-stationary process of landslide occurrence. The values of slope degree, slope length, and timber density represented over 80% of positive coefficients and the values of elevation and aspect cosine had over 80% of negative coefficients. Also, the values of aspect sin, curvature, topographic wetness index, soil drainage, soil thickness, and timber diameter had apparent divisions of positive and negative results. Such spatially varying coefficients are mostly ignored in the orthodox logistic models.

**Table 3. Summary of spatially varying coefficients**

| Variable | Mean | SD | Min | Max | % positive | % negative |
|---|---|---|---|---|---|---|
| Intercept | -0.0617 | 0.7054 | -2.5460 | 1.8137 | 55.83 | 44.17 |
| Elevation | -0.0010 | 0.0010 | -0.0038 | 0.0021 | 9.19 | 90.81 |
| Aspect cosine | -0.0646 | 0.0726 | -0.2291 | 0.2268 | 17.15 | 82.85 |
| Aspect sin | 0.0225 | 0.0916 | -0.1005 | 0.3063 | 51.01 | 48.99 |
| Slope degree | 0.0049 | 0.0041 | -0.0043 | 0.0183 | 87.89 | 12.11 |
| Slope length | 0.0042 | 0.0049 | -0.0040 | 0.0210 | 90.13 | 9.87 |
| Curvature | -0.0126 | 0.0152 | -0.0379 | 0.0241 | 24.33 | 75.67 |
| Topographic wetness index | -0.0033 | 0.0158 | -0.0327 | 0.0291 | 36.77 | 63.23 |
| Soil drain | 0.1264 | 0.2027 | -0.5917 | 0.5371 | 76.35 | 23.65 |
| Soil thickness | 0.0379 | 0.1251 | -0.2506 | 0.3952 | 57.85 | 42.15 |
| Timber diameter | 0.0491 | 0.0675 | -0.1813 | 0.2424 | 77.80 | 22.20 |
| Timber density | 0.0670 | 0.0643 | -0.1346 | 0.2318 | 86.43 | 13.57 |

### 4.3. Comparison of model performances

The model performance between the GLR and the GWR models was compared using statistical parameters (Table 4). The GWR model showed significant improvement over the GLR. First, the GWR model had a much better goodness-of-fit than the GLR though the significant decrease of -2 Log likelihood. Second, the AICc index was 1148.2641 in the GLR model and 1049.1441 in the GWR model. If the difference in the AICc index between two models is greater than 4, the model is considered to be improved (Charlton and Fotheringham, 2009). The difference between two models in this study was 109.12, indicating that the conformity of the GWR model was significantly improved. Third, the adjusted R-squared value was 0.165 in the GLR model and 0.304 in the GWR model. Examination of model conformity reveals whether the general explanation power of the model has improved. Fourth, spatial autocorrelation can be examined more quantitatively using Moran's I index. Moran's I index in the GLR model was 0.3018 ($p<0.01$), indicating the existence of a spatial autocorrelation. However, Moran's I index in the GWR model was 0.1765 ($p<0.01$), indicating that the spatial dependence evident in the standardized residual in the GWR model was removed through geographical weighting.

### 4.4. Spatial varying relationships

The GWR model generates a set of coefficient estimates of explanatory variables for each landslide sample point. A set of coefficient surfaces based on the sample points with coefficient estimates were generated to reveal the spatially non-stationary relationship between landslide

**Table 4. Comparison of GLR and GWR results**

| | GLR | GWR |
|---|---|---|
| Residual sum of squares | 183.6933 | 134.6205 |
| -2 Log likelihood | 1121.8495 | 1019.8201 |
| Corrected AICc | 1148.2641 | 1039.1441 |
| Adjusted R-square | 0.1650 | 0.3040 |
| Moran's I of standardized residuals | 0.3018 | 0.1765 |

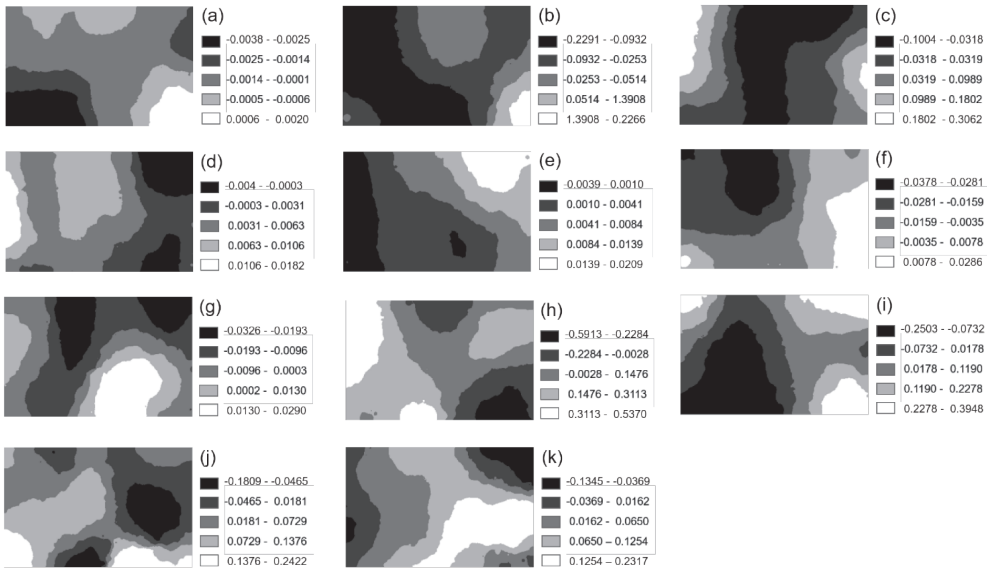


**Fig. 2. GWR coefficient surfaces of elevation (a), aspect cosine (b), aspect sin (c), slope degree (d), slope length (e), curvature (f), topographic wetness index (g), soil drainage (h), soil thickness (i), timber diameter (j), and timber density (k)**

occurrence and explanatory variables. An IDW (Inverse Distance Weighted) interpolation was employed to generate coefficient surfaces. Fig.2 represents the coefficient surface of each explanatory variables. As an example, the coefficient of aspect cosine had a negative effect from the result of the GLR model and were mostly negative across the entire study area (Fig.2-b). However, although the coefficient of slope degree obtained from the GLR model had a positive effect on landslide occurrence, this did not hold true for the entire study area. From the result of the GWR model, slope degree had a stronger negative influence in the east of the study area than the west (Fig.2-d).

## 5. Summary and Conclusions

This study analyzed landslide susceptibility in the Inje region. A spatial database was compiled using landslide-related factors derived from aerial photographs and various thematic maps produced by the government. This study analyzed landslide susceptibility using a GWR model, compared it with the results of the GLR model analysis, and analyzed how much the model has improved. The adjusted R-squared value improved from 0.165 to 0.304 and the AICc, a conformity-measured value of a model, was 1148.2641 in the GLR model and 1039.1441 in the GWR model, for a difference of 109.12. In addition, Moran's I index for the GWR model was 0.1765 compared to 0.3018 for the GLR model for spatial dependence. From these result, the GWR model has significantly improved the GLR model with better goodness-of-fit. It also reduced the spatial dependence of residuals.

Therefore, the GWR model was more powerful and effective in interpreting relationships between landslide-related factors and landslide occurrence. Especially, character and strength of the relationships identified by the GWR model showed great spatial non-stationarity and scale-dependence. However, the GWR model still presents some disadvantages. The lack of independence among local estimates may led to the failure in valid inferences for the local estimates. In addition, when the number of sample is quite small, the estimated local coefficients can be ineffective or invalid (Su *et al*., 2012).

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