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*Research Article*

# Development and Application of Urban Landslide Vulnerability Assessment Methodology Reflecting Social and Economic Variables

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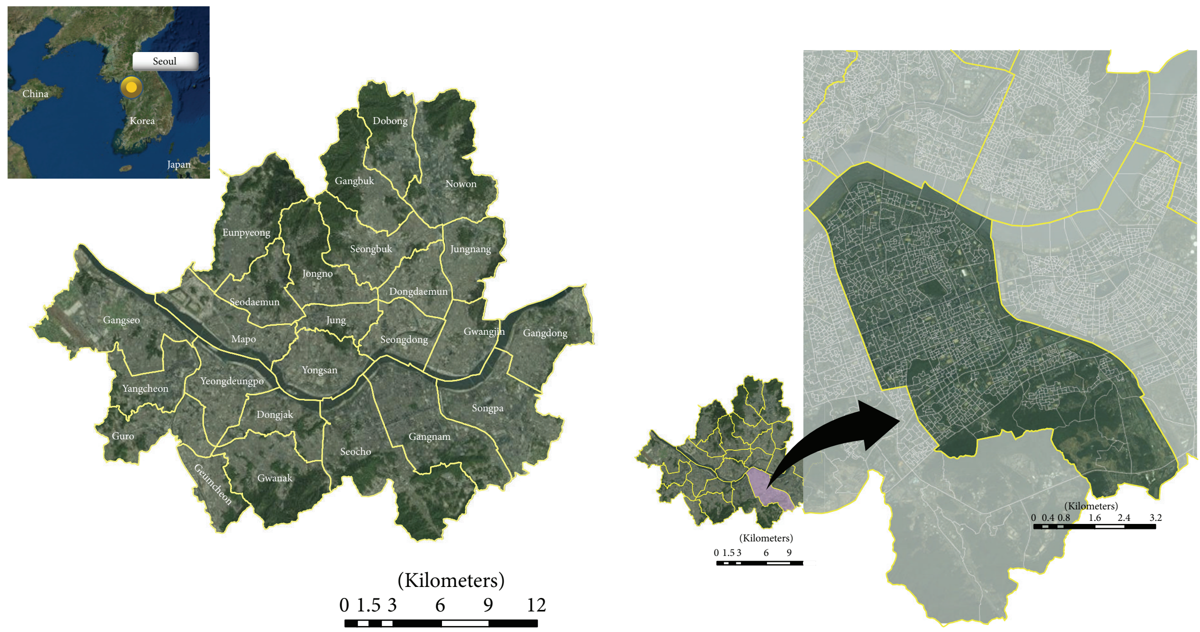
An urban landslide vulnerability assessment methodology is proposed with major focus on considering urban social and economic aspects. The proposed methodology was developed based on the landslide susceptibility maps that Korean Forest Service utilizes to identify landslide source areas. Frist, debris flows are propagated to urban areas from such source areas by Flow-R (flow path assessment of gravitational hazards at a regional scale), and then urban vulnerability is assessed by two categories: physical and socioeconomic aspect. The physical vulnerability is related to buildings that can be impacted by a landslide event. This study considered two popular building structure types, reinforced-concrete frame and nonreinforced-concrete frame, to assess the physical vulnerability. The socioeconomic vulnerability is considered a function of the resistant levels of the vulnerable people, trigger factor of secondary damage, and preparedness level of the local government. An index-based model is developed to evaluate the life and indirect damage under landslide as well as the resilience ability against disasters. To illustrate the validity of the proposed methodology, physical and socioeconomic vulnerability levels are analyzed for Seoul, Korea, using the suggested approach. The general trend found in this study indicates that the higher population density areas under a weaker fiscal condition that are located at the downstream of mountainous areas are more vulnerable than the areas in opposite conditions.

## 1. Introduction

In South Korea, there has been continuous interest in reducing landslide or debris flow damage because about 70% of the Korean territory is covered with mountainous areas. Many researchers have analyzed the factors causing landslides [1, 2]. Landslide susceptibility maps have been built on the mainland across South Korea by Korea Forest Service (KFS) and have been used as the basis for the studies to predict landslides or reduce the damage. The resolution of KFS landslide susceptibility maps is 10 m by 10 m, and the maps are classified into 5 grades according to the probability of landslides. Since the maps were developed to limit the mountain areas, the impacts of landslides on the downstream side are not reflected or evaluated. The Mt. Umyeon landslide that occurred in Seoul, South Korea, in July 2011 suggested that the impact of mountain landslides on the downstream city should be considered in the landslide and debris flow information system. From the lessons of Mt. Umyeon landslide, this study was planned to evaluate the landslide vulnerability to reflect the impact on the urban areas under the mountains.




(a) Boroughs in Seoul

(b) Census output area of Gangnam in Seoul

Figure 1: Study area, Seoul, South Korea, with Census Output Area.

In view of this, the damage type classification proposed by Smith and Ward [3] provides important insights in the vulnerability assessment framework configuration. They classified the types of damage from natural disasters into direct and indirect damage. Representative examples of the direct damage is the damage of life and property. On the other hand, examples of the indirect damage can be the intangible damage caused by traffic disruptions. In order to evaluate properly the urban vulnerability to natural disasters, various types of damage should be reflected in the vulnerability assessment framework [4].

Although many studies have evaluated the damage of buildings due to a landslide [5–7], studies evaluating the damage of life or secondary damage are not sufficient to provide a guideline. In recent years, however, some studies on the socioeconomic vulnerability assessment considering the damage of life or secondary damage have been attempted [8–11]. Those studies mainly focused on evaluating the vulnerability in terms of sensitivity to natural disasters and ability to respond to them.

In this study, a combined methodology for evaluating the urban physical and socioeconomic vulnerability to landslides is proposed. Urban landslide vulnerability is assessed by two categories; physical and socioeconomic aspect. The damage of buildings by landslides is considered to be a proxy variable representing the physical vulnerability. On the other hand, the socioeconomic vulnerability is evaluated using a number of proxy variables that can explain the exposure degree of vulnerable people in landslide disasters, factors causing a variety of secondary damage, and disaster preparedness of local governments.

## 2. Study Area and Scale

The study area is Seoul, the capital of South Korea, which has a complicated socioeconomic infrastructure and a high population density. In countries most of the critical national infrastructure is highly concentrated in one single city (such as South Korea), and the vulnerability evaluation methods applied to many cities by previous studies are not suitable to the current study area. In order to properly evaluate the vulnerability of a large metropolitan area, it should be evaluated in much higher spatial resolution.

Korea National Statistical Office (KNSO) has set up "Census Output Area (COA)" as a minimal spatial scale to publish national standard statistical data in South Korea [12]. The size is determined by the amount of people and the social homogeneity resulting in an average population size of about 500 people per COA. Therefore the COA level was considered the basic mapping unit for the vulnerability assessment in this study. Seoul is composed of 16,230 COAs. The area of COAs ranges from $0.00012\,\text{km}^2$ to $10.10\,\text{km}^2$ (average $0.037\,\text{km}^2$). Figure 1 shows the locations of Seoul with 25 boroughs and COAs constituting the Gangnam region in the boroughs. Other boroughs also show similar COA distribution to Gangnam.

## 3. Urban Landslide Vulnerability Assessment

The proposed urban landslide vulnerability assessment process consists of three steps. The first step is to identify potential landslide hazard areas, which can be carried out by combining landslide susceptibility maps and Flow-R model [13]. The second step is to assess separately physical and

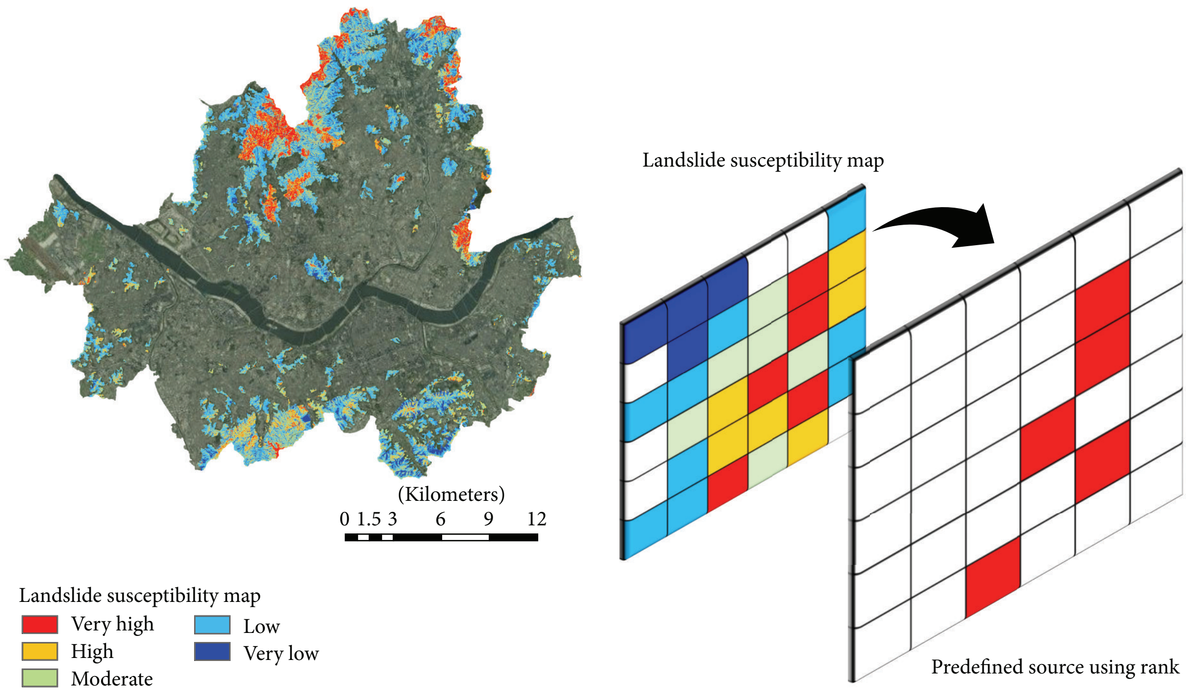



FIGURE 2: Identification of predefined source areas using landslide susceptibility map.

socioeconomic vulnerability based on identified potential landslide susceptibility areas. As a final step, the urban landslide vulnerability is generated by combining physical and socioeconomic vulnerability.

*3.1. Potential Landslide Areas Identification.* Vulnerability assessment under landslide disaster requires information on the propagation extent and intensity by debris flows. Such information on debris flow susceptibility mapping can be obtained by regional scale runout simulation. Since landslides are caused by various natural factors, landslide analysis in regional scale is difficult. Horton et al. [13] developed a distributed empirical model, Flow-R, for flow path assessment of gravitational hazards at a regional scale. The model is available free of charge at http://www.flow-r.org/. One advantage of this model is that the amount of data required for the simulation is small. A Digital Elevation Model (DEM) may be sufficient to identify potential landslide source areas and to process the propagation. Data such as slope, curvature, and flow accumulation are required for more accurate analysis.

This study applies Flow-R to obtain two landslide characteristics: spreading probability and impact pressure. DEM and predefined sources are used for Flow-R simulation. Predefined source is potential grids where landslide may occur. The predefined source used in this study is obtained by using landslide susceptibility maps. The maps developed by KFS are displayed by classifying the landslide probability to five ranks. Rank 1 areas in the maps have the highest probability of landslide occurrence.

In other words, landslide event is the most frequent in the area. This study is the first step in South Korea about urban landslide vulnerability. It is necessary to study the extreme cases. "Predefined source" is defined by rank 1 area in the map to apply extreme case (red grids in Figure 2). The resolution of DEM and predefined source areas is 10 m by 10 m.

TABLE 1: Selected landslide disaster algorithms of Flow-R.

| Propagation routine | Applied method |
|---|---|
| Spreading algorithm | |
| Flow direction algorithm | Holmgren [14] modified |
| Persistence function | Inertial parameter |
| Friction law | Simplified friction-limited model |

Flow-R provides a variety of algorithms to analyze debris flow. Table 1 shows the algorithms applied to analyze landslide disaster in this study. Spreading algorithms control the path and the spreading of debris flow. Friction law determines the runout distance. All algorithms in Flow-R are described in detail by Horton et al. [13]. The parameters for simulating Flow-R have to be calibrated and verified using actual data. But such data set is not provided in Seoul. So this study has no choice but to use the reference values from Horton et al. [13].

The result of Flow-R simulation is the total area that can be potentially propagated by debris flows with an associated susceptibility value and kinetic energy. The resolution of the output is the same as that of the input data. The susceptibility value is used to extract COAs which are influenced by landslide runout. Equation (1) is used to estimate the impact pressure ($p$, kPa) in each grid [15]:

$$\text{impact pressure } (p) = \frac{\sqrt{2E_{\text{kin}}\rho_b}}{1000}, \tag{1}$$

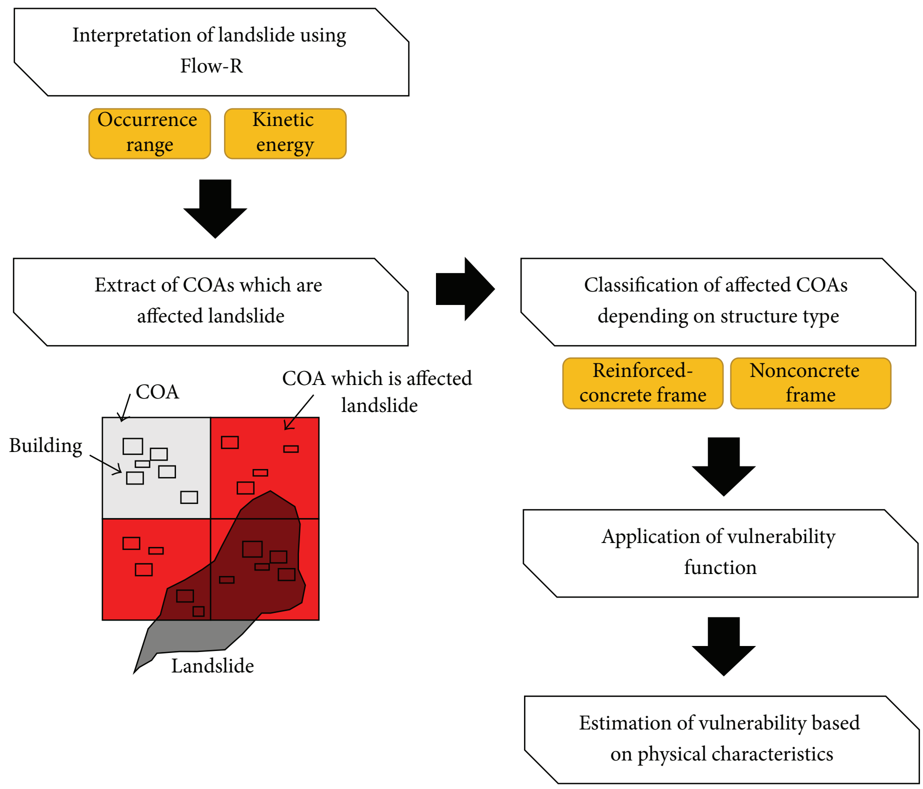



Figure 3: Procedure of physical vulnerability assessment.

where $E_{\mathrm{kin}}$ is the kinetic energy calculated by Flow-R internally and $\rho_b$ is the bulk density of debris flow (2,239.17 kg/m$^3$ was used in this study). If the impact pressure of landslide exceeds about 34 kPa, houses built with bricks or woods would be destroyed completely [6].

*3.2. Physical Landslide Vulnerability Assessment.* When a landslide occurs, the physical characteristics such as velocity, depth, and impact pressure are determining the level of damage of buildings. Many studies have been conducted to find the relationship between physical characteristics and the damage of various structures [16–18]. These previous studies mainly focused on creating a vulnerability curve by correlating the relationship between landslide characteristics and the damage of buildings. Based on those findings, this study developed vulnerability curves for two different structure types in the study area, and then the curves were used to assess physical vulnerability. Figure 3 shows the procedure of the physical vulnerability assessment.

The first stage of the physical vulnerability assessment is to identify COAs affected by landslides using Flow-R simulations and to calculate the spatially averaged impact pressure in identified COAs. The second stage is to classify the buildings in an identified COA into two categories: non-reinforced concrete (non-RC) frame and reinforced-concrete (RC) frame. Finally, the physical vulnerability assessment is to calculate the physical vulnerability by linking the spatially averaged impact pressure in the identified COA and vulnerability curves.

Table 2: Vulnerability functions [6].

| Frame type | Vulnerability function |
|---|---|
| Non-RC frame | $V = 1 - e^{-0.0010p^{2.227}}$ |
| RC frame | $V = 1 - e^{-0.0005p^{1.690}}$ |

*Note. V*: physical vulnerability; *p*: impact pressure (kPa).

Two kinds of vulnerability curves, which have been developed by Kang and Kim [6], are applied in accordance with each of the two building structure types (Figure 4). The physical vulnerability therefore ranges from 0 (the lowest vulnerability) to 1 (the highest vulnerability) as shown in Table 2. The highest vulnerability (value equals 1) means buildings are broken down completely when landslide event happens.

*3.3. Socioeconomic Vulnerability Assessment.* Socioeconomic vulnerability aims to evaluate the social and economic factors that may be affected by landslides. Socioeconomic vulnerability should be evaluated by a variety of factors with various perspective. This can be carried out using an index-based model [8]. In this study, the modified version to match the conditions in Korea based on the socioeconomic vulnerability assessment framework of landslides developed

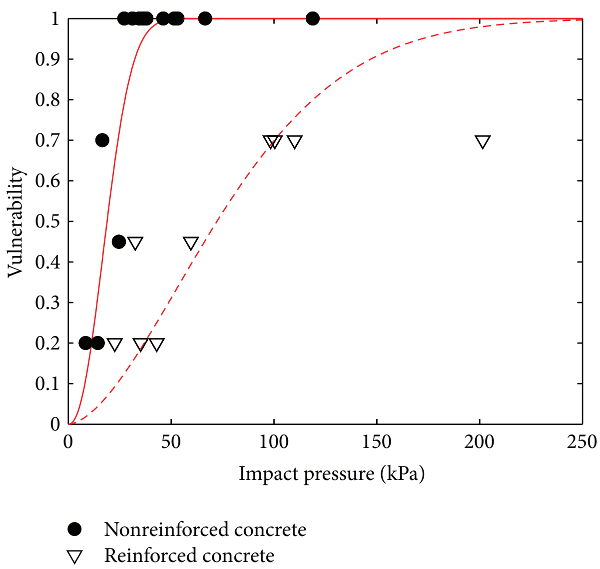



FIGURE 4: Vulnerability curves depending on impact pressure [6].

by Safeland [19] is proposed. The proposed model can evaluate demographic factors, economic factors, and landslide disaster preparedness and response capabilities. The potential proxy variables are identified as age distribution, population density, housing type, personal assets, risk perception, the presence of disaster warning system, and so on. Those variables are mainly selected by a literature review and expert interviews. The procedure of socioeconomic vulnerability assessment is shown in Figure 5.

The model is composed of a total of three subindexes: Demographic and Social Index (DSI), Secondary-Damage-Triggering Index (STI), and Preparation and Response Index (PRI). DSI is evaluated by six population-related and social variables that may be affected by natural disasters. For example, “age distribution” is classified into vulnerable people group. The children or elderly people are more vulnerable than young people. It is the reason to select “age distribution” as proxy variable in DSI (Table 4). “Population density” influences vulnerability. If landslide event happens in high population density area, it will caused heavy casualties. Therefore, “population density” can be used as proxy variable to assess socioeconomic vulnerability.

STI is an index to evaluate the indirect damage caused by natural disasters. For instance, when roads are malfunctioning, damage such as traffic jam and destruction of many life lines is caused [20]. Public office becomes control tower in emergency situation. Damage in public office causes secondary damage due to absence of control systems in emergency situation such as landslide event. For this reason, “the number of public offices” is selected as proxy variable of STI (Table 5).

PRI assesses the ability to prevent and respond to natural disasters. All used proxy variables and subindexes are listed in Table 3. Statistical data that used in this study are obtained from KOSIS (Korea Statistical Information Service). Statistics used in this study were compiled in 2010 as a base year,

TABLE 3: Proxy variables and their weights in socioeconomic vulnerability assessment model.

| Social-economic vulnerability index | Weights |
|---|---|
| *DSI (demographic and social index): 31%* | |
| Age distribution | 13.8% |
| Number of workers who may be exposed to disasters | 26.4% |
| Population density | 24.4% |
| Foreigner ratio | 6.8% |
| Education level | 9.4% |
| Housing type | 19.2% |
| *STI (secondary-damage-triggering index): 34%* | |
| Number of public offices | 14.7% |
| Road area ratio | 25.8% |
| Number of electronic supply facilities | 28.2% |
| School area ratio | 11.4% |
| Commercial and industrial area ratio | 19.9% |
| *PRI (preparation and response index): 35%* | |
| Disasters frequency | 12.4% |
| Internet penetration rate | 8.6% |
| Number of disaster prevention facilities | 25.8% |
| Perceived safety | 27.8% |
| Number of medical doctors | 13.2% |
| Financial independence of the borough | 12.2% |

and the spatial resolution of the data is COA. However, the resolution of the proxy variables for PRI is a borough (Table 6). Application of PRI is suitable in borough scale because disaster response system of South Korea is the local government.

The structure of the socioeconomic vulnerability is modified to be suitable in South Korea using the result of them [21].

Tables 4, 5, and 6 show the suggested socioeconomic vulnerability assessment model with proposed proxy variables and criteria for ranking of the variables. These variables have been used in many previous researches (see citations in Tables 4, 5, and 6).

Finally, the socioeconomic vulnerability index is calculated by weighted average of quantified proxy variables ranks (using (2)). The weights are determined after extensive expert survey based on the analytic hierarchy process developed by Saaty [22, 23]. The weights can be found in Table 3. Consider

$$\text{Total vulnerability score value} = \frac{\sum \text{Weighted vulnerability score}}{\sum \text{Weight}}. \quad (2)$$

To assess the socioeconomic vulnerability to landslide disasters, exposure information of landslide should be combined. By applying the proposed methodology to the COAs identified from previous Flow-R simulation, the vulnerability is evaluated for each COA. The vulnerability of the COAs identified as nonaffected areas is assigned to be 0.

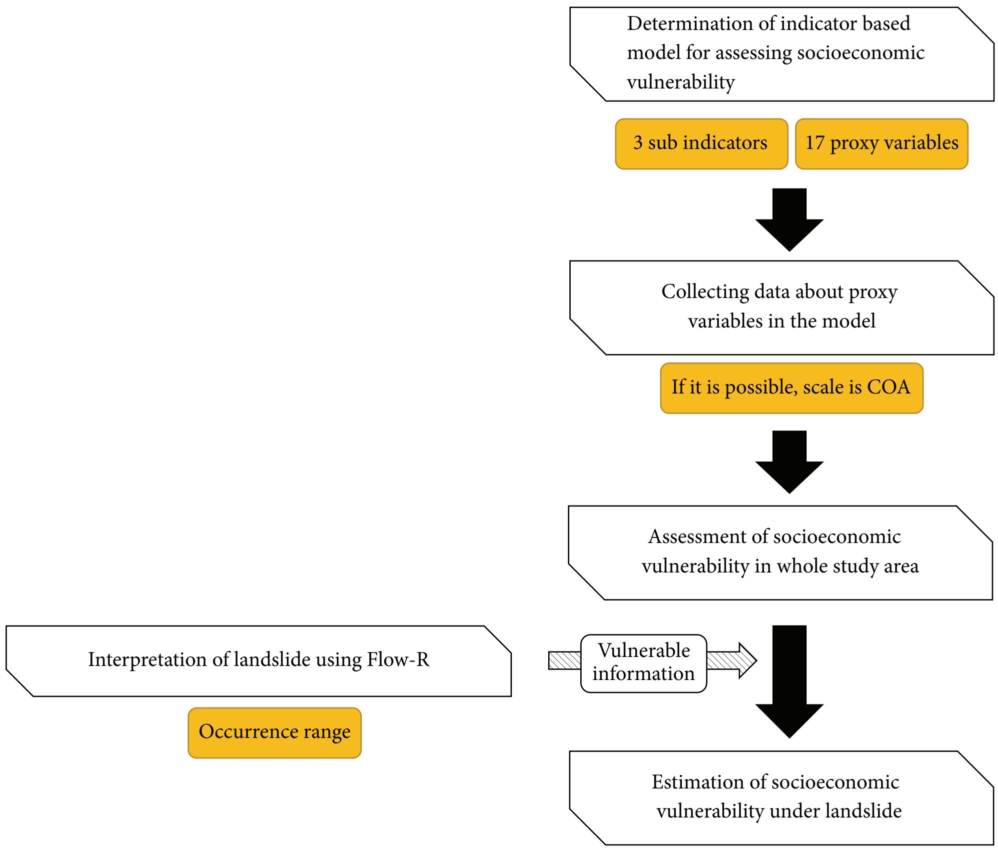



Figure 5: Procedure of socioeconomic vulnerability assessment.

## 4. Results and Discussion

*4.1. Physical Vulnerability Assessment.* Landslide affected COAs were identified by Flow-R simulation, and the corresponding impact pressure for each identified COA was estimated. Figure 6 shows the spatial distribution of identified landslide affected regions and the corresponding impact pressure. The impact pressure was not calculated for the COAs that are not affected by landslide disasters. The number of identified COAs is 2,249 and the maximum average impact pressure is estimated to be 37 kPa.

The physical vulnerability index is calculated by combining the impact pressure presented in Figure 6(b) and vulnerability functions (Table 2) developed by Kang and Kim [6]. In this study, two patterns of vulnerability functions were applied to two building structure types, non-RC and RC. It is noted that the average physical vulnerability is estimated to be 0.96 in the case that the impact pressure 37 kPa is applied to non-RC, while it is 0.20 for the RC case. Figure 7 shows the landslide physical vulnerability assessment map calculated by the proposed methodology.

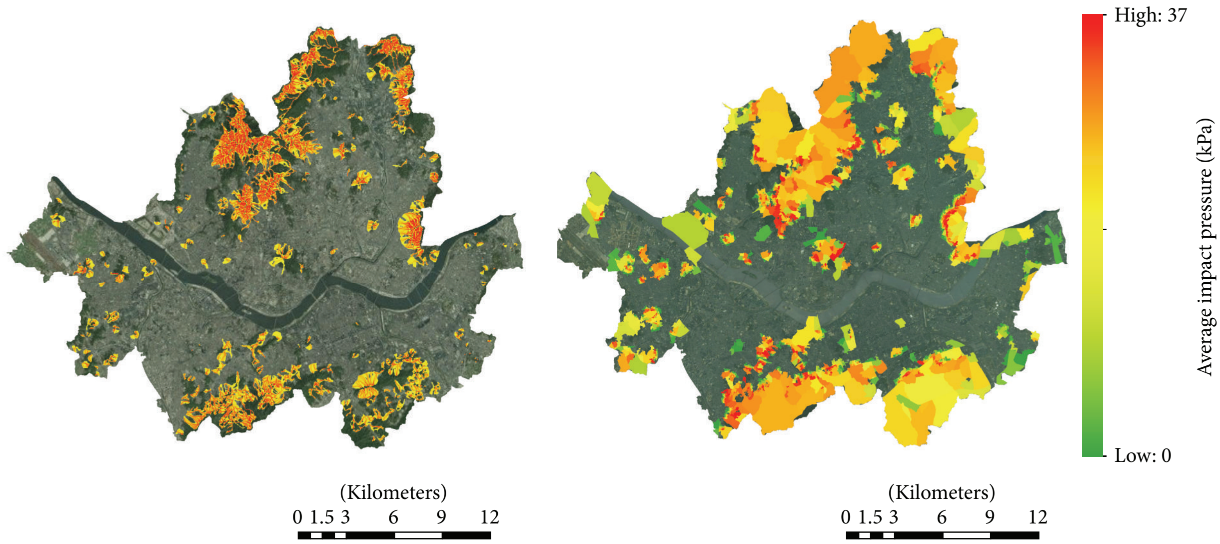
If physical vulnerability in a certain COA is estimated to be 1, it means that the buildings in the area are completely destroyed when landslide event happens. Therefore, a high physical vulnerability range (e.g., from 0.841 to 0.960 in Figure 8) means that the buildings in the area are damaged severely by landslide event.

It can be observed that the COAs located below the mountainous areas with denser residential areas are more vulnerable to landslide disasters in physical aspect than the nonmountainous or less dense.

However, there are clear limitations to the use of the regional scale Flow-R model for obtaining quantitative output that can be used in combination with physical vulnerability curves. The Flow-R is an empirical model, which does not take into account source volume, entrainment, or rheology. In further research, a regional scale model that can calculate the volume of landslide should be applied [27, 28].

*4.2. Socioeconomic Vulnerability Assessment.* Socioeconomic vulnerability is evaluated by three detailed subindexes (Table 3) and the results of each vulnerability assessment are presented in Figure 8.

DSI is a vulnerability assessment subindex related to the population. In general, it can be seen that COAs where the population density is high are more vulnerable (Figure 8(a)). STI is a vulnerability assessment subindex related to the impact on other areas of the occurrence of a disaster event at a COA. In general, it can be seen that COAs including major urban areas are more vulnerable (Figure 8(b)). PRI is a vulnerable assessment subindex related to preparedness and ability to respond to disasters in a borough (Figure 8(c)). This vulnerability index is inversely proportional to the fiscal




(a) Identified regions

(b) Impact pressure (kPa)

FIGURE 6: Results of Flow-R simulation.

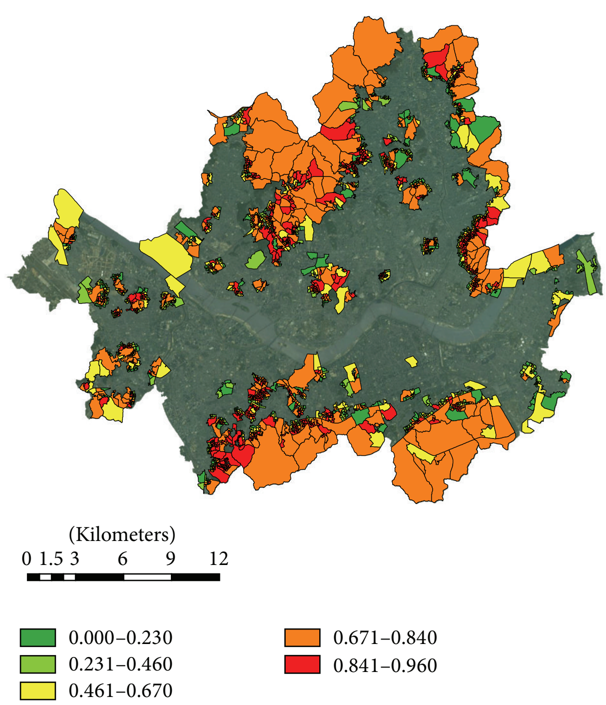



FIGURE 7: Physical vulnerability to landslide disaster.

health of local governments. Therefore, the boroughs in a weak fiscal condition (northwestern and southeastern regions of the study area, Seoul) are classified as a lack of preparedness and ability to respond to disasters. Socioeconomic vulnerability assessment calculated by the weighted average of three detailed subindexes is shown in Figure 8(d). Overall, the southern region in Seoul is more vulnerable against the disaster in a socioeconomic perspective. The results shown in Figure 8(d) assume that natural disasters have occurred uniformly throughout the whole study area, Seoul.

To evaluate the vulnerability to landslides specifically for COAs, Figures 8(d) and 6(a) should be combined. The combined landslide vulnerability assessment in a socioeconomic aspect is shown in Figure 9 as a result. It is suitable

Table 4: Criteria for ranking of proxy variables of DSI.

| Proxy variable | Ranking criteria | |
|---|---|---|
| | Rank | Description |
| Age distribution [4, 11, 19, 20, 24] | 1 | Less than 20% of population is either between 0 and 4 years or over 65 years |
| | 2 | 20–30% of population is either between 0 and 4 years or over 65 years |
| | 3 | 30–40% of population is either between 0 and 4 years or over 65 years |
| | 4 | 40–50% of population is either between 0 and 4 years or over 65 years |
| | 5 | Over 50% of population is either between 0 and 4 years or over 65 years |
| Number of workers who may be exposed to disasters [4, 19, 20, 24] | 1 | Less than 10 workers work in either agriculture, forestry, mining, transportation, or construction |
| | 2 | 10–20% of workers work in either agriculture, forestry, mining, transportation, or construction |
| | 3 | 20–30% of workers work in either agriculture, forestry, mining, transportation, or construction |
| | 4 | 30–40% of workers work in either agriculture, forestry, mining, transportation, or construction |
| | 5 | Over 40% of workers work in either agriculture, forestry, mining, transportation, or construction |
| Population density [19, 20] | 1 | Population density is less than 100 people/km$^2$ |
| | 2 | Population density is between 100 and 150 people/km$^2$ |
| | 3 | Population density is between 150 and 300 people/km$^2$ |
| | 4 | Population density is between 300 and 600 people/km$^2$ |
| | 5 | Population density is over 600 people/km$^2$ |
| Foreigner ratio [4, 19, 20] | 1 | Foreigner ratio is less than 1% |
| | 2 | Foreigner ratio is between 1 and 3% |
| | 3 | Foreigner ratio is between 3 and 4% |
| | 4 | Foreigner ratio is between 4 and 5% |
| | 5 | Foreigner ratio is over 5% |
| Education level [4, 19–21] | 1 | Over 30% of population have attended or are attending a postsecondary education |
| | 2 | 20–30% of population have attended or are attending a postsecondary education |
| | 3 | 10–20% of population have attended or are attending a postsecondary education |
| | 4 | 5–10% of population have attended or are attending a postsecondary education |
| | 5 | Less than 5% of population have attended or are attending a postsecondary education |
| Housing type [19–21] | 1 | Over 45% of housing type is apartment |
| | 2 | 40–45% of housing type is apartment |
| | 3 | 35–40% of housing type is apartment |
| | 4 | 30–35% of housing type is apartment |
| | 5 | Less than 30% of housing type is apartment |

to apply quantitative characteristics of landslide events. But this study overlaid susceptibility map from Flow-R due to lack of quantitative data about landslide event. If the quantitative assessment is able to analyze landslide in regional scales [27, 28], more accurate socioeconomic vulnerability about landslide can be obtained.

The biggest difference between Figures 8(d) and 9 is observed in southwestern Seoul. In fact, the southwest area of Seoul is a very high likelihood of a flood disaster area. Therefore, although this region has higher vulnerability to common natural disasters, the region may not have high vulnerability to landslide.

*4.3. Urban Landslide Vulnerability.* Urban characteristics were reflected in vulnerability assessment under landslide disaster by combining physical and socioeconomic vulnerabilities. For the combination of the two vulnerability assessments, the physical vulnerability region (Figure 7) was multiplied by the socioeconomic vulnerability region (Figure 9) and the region values were normalized between 0 and 1 as one urban vulnerability to landslide. The urban vulnerability index can be classified into five categories as very low, low, moderate, high, and very high. The result of the integrated urban landslide vulnerability assessment is shown in Figure 10.

Table 5: Criteria for ranking of proxy variables of STI.

| Proxy variable | Ranking criteria | |
|---|---|---|
| | Rank | Description |
| Number of public offices [4, 20, 25] | 1 | There are less than 5 public offices |
| | 2 | There are 5–10 public offices |
| | 3 | There are 10–15 public offices |
| | 4 | There are 15–20 public offices |
| | 5 | There are over 20 public offices |
| Road area ratio [20, 25] | 1 | Road area is less than 5% |
| | 2 | Road area is between 5 and 10% |
| | 3 | Road area is between 10 and 15% |
| | 4 | Road area is between 15 and 20% |
| | 5 | Road area is over 20% |
| Number of electronic supply facilities [11, 20, 25] | 1 | Less than 2 electronic supply facilities |
| | 2 | There are 2–4 electronic supply facilities |
| | 3 | There are 4–6 electronic supply facilities |
| | 4 | There are 6–8 electronic supply facilities |
| | 5 | There are over 8 electronic supply facilities |
| School area ratio [20] | 1 | School area is less than 5% |
| | 2 | School area is between 5 and 10% |
| | 3 | School area is between 10 and 15% |
| | 4 | School area is between 15 and 20% |
| | 5 | School area is over 20% |
| Commercial and industrial area ratio [4, 20] | 1 | Commercial and industrial area is less than 0.5% |
| | 2 | Commercial and industrial area is between 0.5–1% |
| | 3 | Commercial and industrial area is between 1 and 2% |
| | 4 | Commercial and industrial area is between 2 and 3% |
| | 5 | Commercial and industrial area is over 3% |

Figure 10 indicates that 50% or more of COAs affected by landslides (Figure 7) have an urban vulnerability of less than 0.3 (urban vulnerability is very low or low). This means that these COAs are likely to be in a landslide damage but relatively less vulnerable. The size of these COAs varies ($0.00046\,\text{km}^2$–$7.52\,\text{km}^2$, average $0.11\,\text{km}^2$). On the other hand, the size of very vulnerable COAs where the urban vulnerability is at least 0.6 is small ($0.0047\,\text{km}^2$–$2.24\,\text{km}^2$, average $0.046\,\text{km}^2$). The size of a COA is mainly determined by the population and their socioeconomic homogeneity. When the size of a COA is very small, the COA has a very high population density and is highly urbanized. If landslides occurred in these COAs, the damage caused by the landslides would be amplified. Therefore, these COAs are extremely vulnerable to the landslide disaster, and disaster mitigation measures must be taken first in these priority areas.

## 5. Summary and Conclusion

For suitable vulnerability assessment of natural disasters including landslides, this study showed that both direct damage and indirect damage should be considered in the vulnerability assessment processes. In this study, vulnerability assessment for landslides among various natural disasters was conducted. In particular, the proposed methodology properly reflects the urban characteristics in terms of vulnerability to natural disasters. Therefore, the results of this study can be directly utilized for setting the priority of various landslide damage reduction projects in urban areas.

In the proposed methodology, the possible landslide source areas were first identified using existing landslide susceptibility maps. Flow-R simulation provided the extents and impact pressure of debris flow routed from the identified sources areas of landslide. The outcomes were served as landslide exposure information for physical and socioeconomic vulnerability assessment.

Direct damage due to landslide disasters was considered by physical vulnerability. Vulnerability functions quantifying the degree of damage of buildings were applied to evaluate the physical vulnerability. By applying vulnerability functions to building information and impact pressure of each affected COA, the physical vulnerability index was estimated.

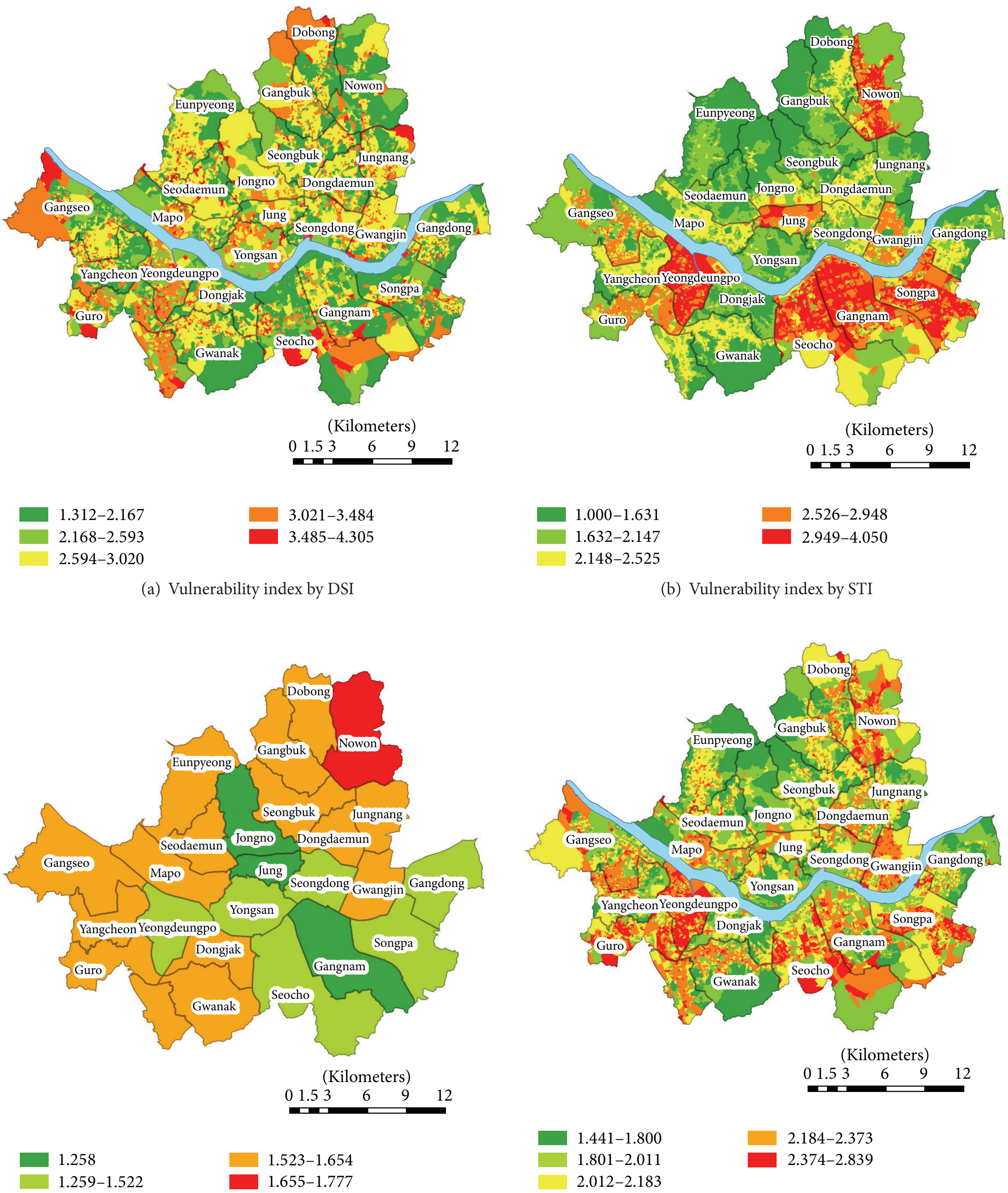
Table 6: Criteria for ranking of proxy variables of PRI.

| Proxy variable | Ranking criteria | |
|---|---|---|
| | Rank | Description |
| Disasters frequency [20, 24, 26] | 1 | Over 1000 cases are disasters |
| | 2 | 800–1000 cases are disasters |
| | 3 | 600–800 cases are disasters |
| | 4 | 400–600 cases are disasters |
| | 5 | Less than 400 are cases disasters |
| Internet penetration rate [20, 24] | 1 | Internet penetration rate is over 80% |
| | 2 | Internet penetration rate is 76–80% |
| | 3 | Internet penetration rate is 73–76% |
| | 4 | Internet penetration rate is 70–73% |
| | 5 | Internet penetration rate is less than 70% |
| Number of disaster prevention facilities [20] | 1 | There are over 200 disaster prevention facilities |
| | 2 | There are 150–200 disaster prevention facilities |
| | 3 | There are 100–150 disaster prevention facilities |
| | 4 | There are 50–100 disaster prevention facilities |
| | 5 | There are less than 50 disaster prevention facilities |
| Perceived safety [20, 24] | 1 | Over 20% of people feel very safe or safe regarding natural disaster |
| | 2 | 18–20% of people feel very safe or safe regarding natural disaster |
| | 3 | 16–18% of people feel very safe or safe regarding natural disaster |
| | 4 | 14–16% of people feel very safe or safe regarding natural disaster |
| | 5 | Less than 14% of people feel very safe or safe regarding natural disaster |
| Number of medical doctors [19, 20] | 1 | There are over 8 medical doctors per 1,000 people |
| | 2 | There are 6–8 medical doctors per 1,000 people |
| | 3 | There are 4–6 medical doctors per 1,000 people |
| | 4 | There are 2–4 medical doctors per 1,000 people |
| | 5 | There are less than 2 medical doctors per 1,000 people |
| Financial independence of the borough [4, 20] | 1 | Financial independence is over 30% |
| | 2 | Financial independence is between 25 and 30% |
| | 3 | Financial independence is between 20 and 25% |
| | 4 | Financial independence is between 15 and 20% |
| | 5 | Financial independence is less than 15% |

Socioeconomic vulnerability was applied to assess indirect damage caused by landslides. An index-based model was used to assess the socioeconomic vulnerability. The model was comprised of three subindexes and 17 proxy variables. Three subindexes were the demographic-social index, the secondary-damage-triggering index, and the preparation-response index. The socioeconomic vulnerability index calculated by the index-based model is applicable to common natural disasters. Although this study only demonstrated an example that the landslide exposure information obtained by Flow-R simulation is combined to assess the socioeconomic vulnerability of landslide disasters, the socioeconomic vulnerability of flood disasters can be assessed by combining with flood exposure information.

Finally, the urban landslide vulnerability was assessed by combining the physical vulnerability and socioeconomic vulnerability. The combined vulnerability therefore reflects both direct and indirect aspects of damage caused by landslides. The general trend of the findings in this study reveals that the higher population density areas under a weaker fiscal condition that are located at the downstream of mountainous areas are more vulnerable than the areas in opposite conditions. The framework and results of this study are expected to be used directly to prioritize the landslide damage reduction plans for the Seoul metropolitan area in South Korea.

The previous studies about landslide in South Korea were focused on mountainous areas. On the other hand, the influence of landslide in urban areas has not been analyzed. This study is prototype about assessing vulnerability in urban areas. The study area is Seoul, in South Korea. Therefore, this study has some limitations. One of limitations is that this study did not use quantitative output about landslide process. It is not the accurate landslide vulnerability assessment. However it is good enough as the first step for high quality landslide disaster vulnerability assessment in urban area including mountainous area.




(a) Vulnerability index by DSI

(b) Vulnerability index by STI

(c) Vulnerability index by PRI

(d) Vulnerability by combining subindexes

Figure 8: Result of socioeconomic vulnerability assessments.

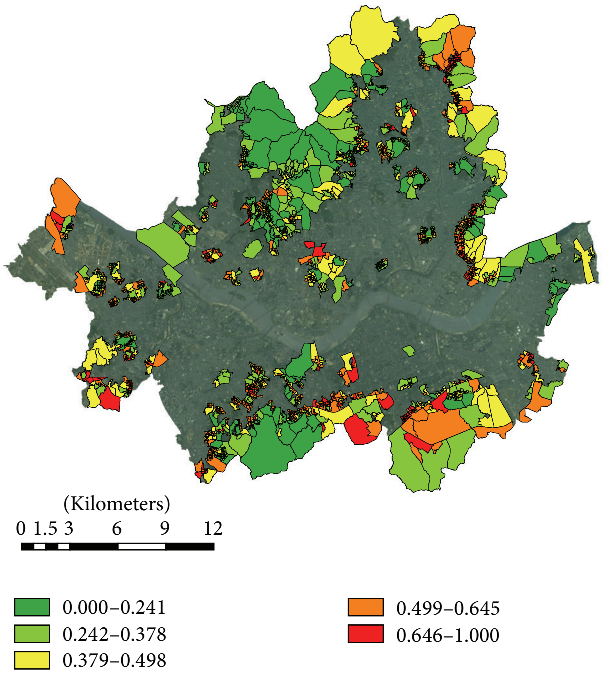



Figure 9: Socioeconomic vulnerability to landslide disaster.

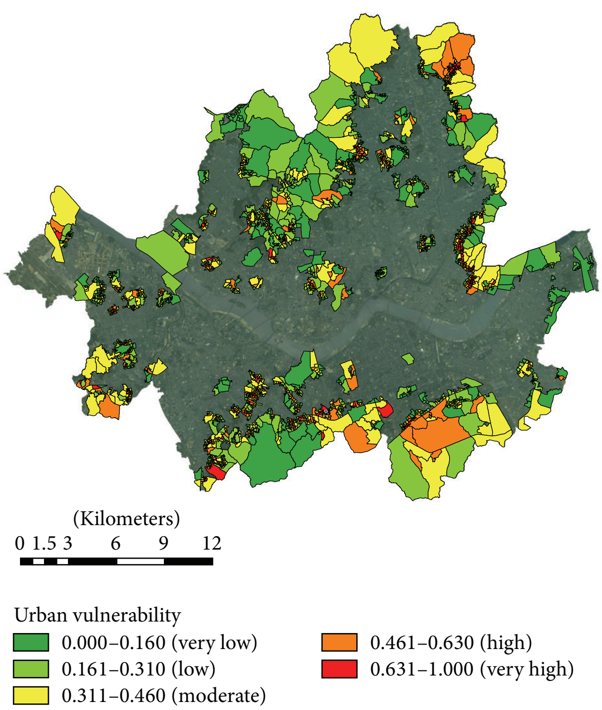



Figure 10: Urban vulnerability to landslide disaster.

## Competing Interests

The authors declare that they have no competing interests.

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