A Clustering Approach to Supporting GIS-based Urban Disaster Resilience Assessment

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Abstract
It has been recognized that the local features of a region perform a considerable impact during and after a disaster. For an assessment at city level, qualitative approaches to disaster resilience have been applied. Some quantitative approaches made an attempt to assess city level resilience using socio-economic census data. This paper introduces the first phase of the combinatorial research process on socio-economic recoverability using GIS (Geographic Information System) and open source data clustering. The primary goal of this research is to employ clustering methods for effective assessment of disaster resilience of the region with multiple features including structural, social, political, and economical aspects. A case study was performed with regional data of a district of Seoul, Korea for validation purpose. As a result, 5 regions in Gwanak-gu district were evaluated as low recoverability areas that needs careful attention as to disasters. An in-depth study was conducted to investigate specific conditions of each factor to support strategic decision-making process for disaster management.

Keywords: Resilience, urban disaster, disaster management, GIS, clustering, recovery

1 Introduction

For the past decades, the prediction of future disaster events and the analysis of their impact have played a major role in the field of disaster management. However, as avoiding the occurrence of natural disaster is tough, building a resilient city is becoming a common objective that an urban community should seek with a priority. Under the same disastrous event, the ultimate outcome may differ largely depending on the resilience of urban disaster.

The concept of 'disaster resilience' has recently emerged as an important factor to evaluate the local performance of natural disaster in many research fields including structural engineering, social science, and economics (Cutter et al. 2008). It has been used to minimize direct and indirect losses from hazards through the enhancement of resistance and robustness to extreme events, as well as more effective recovery strategies (Bocchini et al. 2014). Thus, the quantification of urban disaster resilience assessment is critical to support a decision-making process for strategic disaster management.

The quantitative assessment of disaster resilience can be made at a wide range, from a single component to community. At component and network levels, 'resilience triangle' has been widely adopted to quantify resilience (Bruneau et al. 2003). The resilience triangle can be derived by performance level through the time period. However, unlike a single component or network system level, a city is comprised of various elements and is difficult to measure the performance of the city itself before and after a disastrous event; reliable recovery models of such elements are not available.

For an assessment at city level, qualitative approaches have been mainly applied. Some quantitative approaches made an attempt to assess the city level resilience using socio-economic census data. It has been recognized that the local characteristics, such as structural, social, political, and economical, of a region also perform a significant impact on the performances of disaster management during and after the disaster: the regional disaster resilience can determine the vulnerability and recoverability of the disaster (Choi et al. 2016).

The primary goal of our research is to employ a clustering method for an effective assessment of disaster resilience of the region with multiple features, such as structural, social, political, and economical aspects. More specifically, the research aims to define specified meanings of resilience for urban disaster, suggest a quantitative model for measurement of resilience on physical vulnerability and socio-economic recoverability, and support decision makers with strategic management processes by developing possible management scenarios. This paper introduces the first phase of the combinatorial research process on socio-economic recoverability using GIS (Geographic Information System) and open source data clustering. Factors related to socio-economic recoverability were integrated without introducing weights on multiple resilience measures. A case study is performed with regional data of a district of Seoul, Korea for validation purpose.

2 Sorting and Selecting Resilience Factors

The characteristics of an urban disaster resilience can be represented by the ability to reduce initial damage, socio-economic impact of physical damage, recovery time, etc. (Choi et al. 2016). Although the first definition of resilience is more than 40 years old, introduced in the 1970s, the concept of resilience is still considered novel and under being developed due to the complexity of resilience. General methods to measure and combine resilience factors in multi aspects have not been studied extensively. It is necessary to study beyond qualitative conceptualizations of disaster resistance and resilience to more quantitative measures, focusing on better understanding of factors related to resilience and more systematic assessment of potential contributions and benefits of various research activities. Thus, a clear definition of resilience, identification of resilience dimensions, and development of measurement and quantification of the dimensions are needed.

The resilience factors were selected to describe various perspectives of the resilience. To describe the urban disaster resilience, the authors divided factors into two groups: physical vulnerability and socio-economical recoverability. After the division of resilience groups, factors related to each category were selected to measure vulnerability and recoverability. Through in-depth literature review, a number of indicators were considered appropriate to quantify vulnerability and recoverability. This study mainly focused on the resilience recoverability, so for more information on resilience vulnerability can be found from Choi et al. (2016).

The socio-economic recoverability can be quantified in four major categories: educational, social, economic, and political aspects. Considering the data attainability, parameters were preliminarily selected based on the previous research findings that investigated the relationship of the factor to resilience. For the feasibility analysis of the proposed model, the rate of college graduate was selected as a parameter in the ‘educational’ category: people who are more educated tend to better understand and act against accidental events. Thus, educational information can describe the resilience of the community effectively (Park et al. 2016). For the ‘social status’, the number of people over 65 and the number of volunteers were selected. These parameters represent the workability of the community during and after disaster (Cutter et al. 2008). For the ‘economic’, the distribution of household income level was selected. It has been widely noticed that poverty is highly related to recovery status (Freeman 2004). For the ‘political’, the level of turnout rate was selected. Political interest can be a parameter that presents the activeness of a local resilience (Cutter et al. 2008).

3 Quantification of Resilience Assessment

The factors of the socio-economic recoverability are composed with different units. To arrogate the units to combine the factors into resilience recoverability, each value of factor was preprocessed into ordinal data type in five scales. Weak recoverability is located at division 1, in other words, rank 1. Strong recoverability is located at division 5, which is rank 5. Each level equally contains 20% of each factor. The total resilience recoverability was calculated using Equation (1). The average rank of factors represents the regional resilience recoverability.

$$\text{Recoverability (rank)} = \frac{\sum_{k=1}^{n} R_k}{N} \quad \text{(Eq. 1)}$$

For clustering, the vulnerability and recoverability values of each region were displayed in the data space. The coordinates of each point in the data space represented the quantified damage measure and recovery resource of a single region. By using the *k*-means clustering method, the values were grouped into a selected number of clusters. The number of cluster can vary based on the plans for improving disaster resilience what decision-makers layout. In this study, three cluster groups were selected for the *k*-means analysis using the optimal cluster number assessing method (Figure 1).

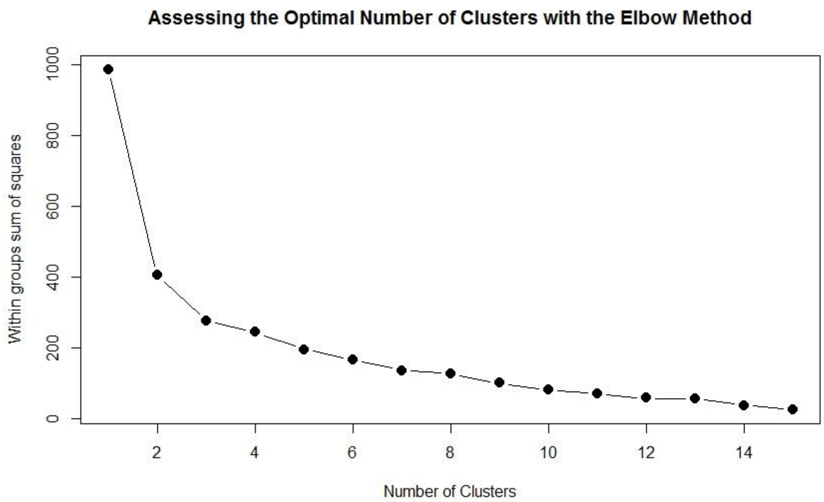

Figure 1 Defining optimal number of clusters by Elbow Method

The clustered resilience classes or patterns can be analyzed to support decision-making process. For many hazard-prone regions, the ability to financing reconstruction after a natural disaster is a key component to maintaining long-term economic growth (Freeman 2004). Thus, regional manager must analyze regional disaster resilience to execute fair distribution of financial support to the demanding regions.

4 Case Study

For the purpose of validation, a case study was conducted to quantify and cluster regional resilience in terms of recoverability. Gwanak-gu, a district located in Seoul, South Korea, was selected for the methodology application. The district was recorded one that had biggest amount of flood damage, about 2.7 million US dollars, from 2009 to 2013 (Choi et al. 2014). There are 21 regions (dongs) in Gwanak-gu district (Table 1, Figure 2).

Table 1 Regions in Gwanak-gu district

No.	Region (dong)	No.	Region (dong)
1	Boramae-dong	**12**	Sillim-dong
2	Cheongnim-dong	**13**	Nanhyang-dong
3	Haengun-dong	**14**	Jowon-dong
4	Nagseongdae-dong	**15**	Daehak-dong
5	Jungang-dong	**16**	Euncheon-dong
6	Inheon-dong	**17**	Seonghyeon-dong
7	Namhyeon-dong	**18**	Cheongnyong-dong
8	Sewon-dong	**19**	Nangok-dong
9	Sinwon-dong	**20**	Samseong-dong
10	Serim-dong	**21**	Miseong-dong
11	Sinsa-dong		

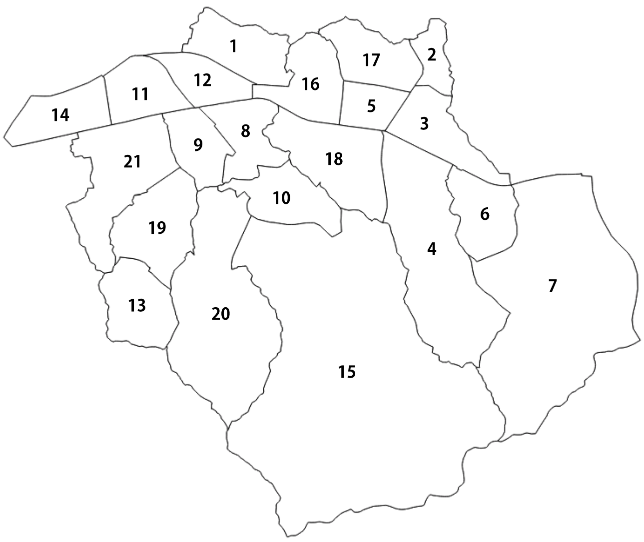

Figure 2 Spatial distribution of regions (dong) in Gwanak-gu district

Generally, if a flood disaster occurs the borough office becomes the control tower of the region at the early stage. The disaster managers are in charge of regional assessment for disaster management. Through intensive interview with the managers, they confirmed that they have willingness to understand the current resilience status of the region through resilience assessment. To support this, the research assessed the recoverability of Gwanak-gu. The factors used in the case study were age distribution, financial status, educational level, emergency volunteering, and political power (Table 2). All data were collected from public statistics (Seoul Open Data Plaza 2016, Seoul Census Data 2016).

Table 2 Description and rank about factors of resilience recoverability

Factor	Description		Rank
Age distribution	Population ratio about age over 65	Over 4000	1
		3153 – 4000	2
		2627 – 3152	3
		2104 – 2626	4
		0 – 2103	5
Financial status	Personal local tax	0 – 548	1
		549 – 1105	2
		1106 – 1509	3
		1510 – 1710	4
		Over 1710	5

Educational level	Ratio about population who have attended a 4-years-college	0 – 532	1
		533 – 739	2
		740 – 1125	3
		1126 – 1451	4
		Over 1452	5
Emergency Volunteers	Number of volunteers in the region	0 – 76	1
		77 – 100	2
		101 – 125	3
		126 – 157	4
		Over 157	5
Political power	Ratio of regional turnout rate	44.01% – 51.99%	1
		51.00% – 52.29%	2
		52.30% – 54.86%	3
		54.87% – 56.33%	4
		56.34% – 62.24%	5

The analysis result of the regional recoverability measures in Gwanak-gu district is plotted in Figure 3. The darker area demonstrates the weaker regions that have lower recoverability than other regions. Region 2, 3, 9, 13 and 14 were identified as relatively low recoverability regions. These five regions are the main areas that should be carefully considered during and after disaster since they are evaluated to have low socio-economic recovery resources than other regions in the district.

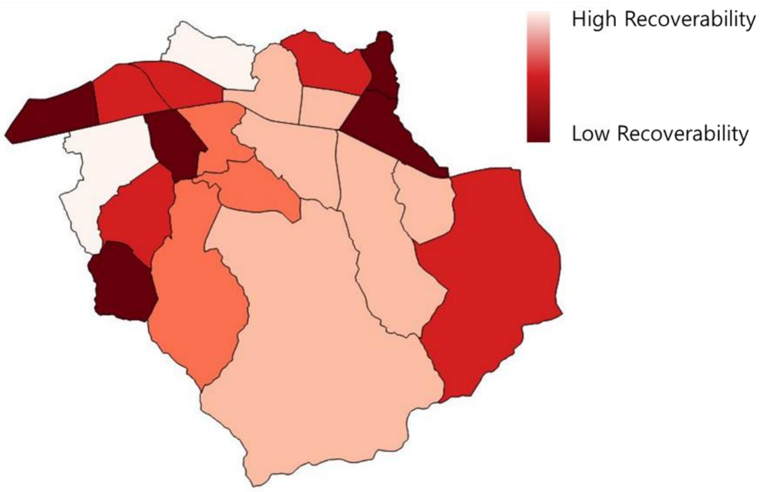

Figure 3 Spatial distribution of the recoverability measures in Gwanak-gu district by regions

To get specific information about the result that would support strategic decision-making, a clustering analysis was adapted. By this process, regions were categorized by similar characteristics and made it easier to understand the regional resilience recoverability in a lower level. The set of observations in this study was 21 and each observation contains five-dimensional vectors. The authors parted the observations into three sets by using the *k*-means clustering method. The sets were named Cluster A, Cluster B, and Cluster C. Cluster A, B, and C contained nine, seven, and five regions, respectively (Figure 4 and Figure 5).

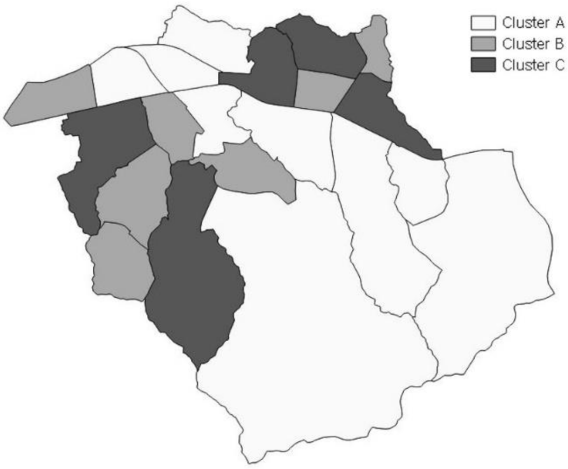

Figure 4 Spatial distribution of clustered group A, B, C in Gwanak-gu district by regions

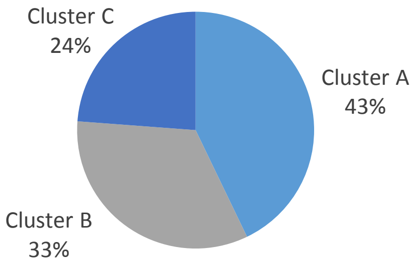

Figure 5 Cluster size by regions

In Figure 6, specific information of recoverability factors can be observed. The regions were grouped into 3 categories: Cluster A, Cluster B, and Cluster C. The factors were Age distribution(R_O), financial status(R_I), educational level(R_E), emergency volunteers(R_V), and political power(R_T). Each factor is colored according to the level of recoverability.

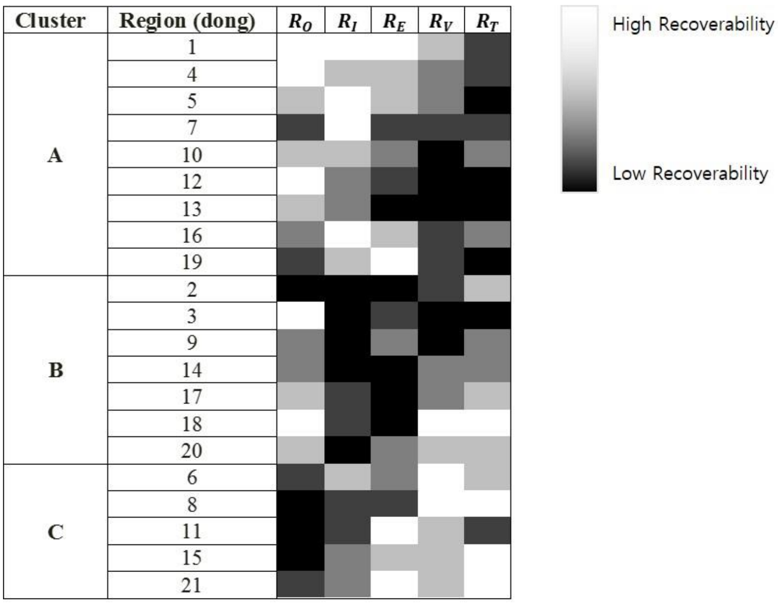

Figure 6 Distribution of recoverability variable levels by each cluster and region

The recoverability assessment identified five regions (region 2, 3, 9, 13, and 14) as the areas that required high considerations to natural disaster. From the result in Figure 6, it was clear that four out of five regions were categorized into Cluster B except region 13 in Cluster A.

Each cluster also had unique patterns. Most of the regions in Cluster A had high recoverability at age distribution but low recoverability at political power, emergency volunteers, and educational level. Cluster B mostly had low recoverability at financial status and educational level. Cluster C mostly had high recoverability at political power and low recoverability at age distribution.

The result also showed that each cluster group had different combination of factor levels. For Cluster A, the area had low emergency volunteers and educational levels so allocating volunteers in advance could be effective. Providing more educational service in the region could be another solution to improve the recoverability before disastrous event. For Cluster B, financial support was crucial compared to the other regions. During the recovery stage, the residents in Cluster B could have delay in the repairmen of their residence after disaster. For Cluster C, the political power was a compelling factor that must be focused on. For these regions, making a prompt action plan could be necessary since the region could have active claims. Also, the high population of elderly residents needs additional help during and after disaster so the providing plans primarily focusing on elder people could be effective for the Cluster C regions.

5 Conclusion

This research aims use a clustering-based method to assess disaster resilience of communities using two measures of resilience: physical vulnerability and socio-economic recoverability. Especially, the paper focused on the recoverability factors to support a decision-making process at the recovery stage. A GIS platform visualized information that provided additional insight into the urban resilience assessment.

The sorting and selecting resilience factors step was performed with consideration to previous studies and data availability of the case study region. After the factor selection, a GIS-based resilience assessment was done. Finally, clustering method was used to figure out the types of socio-economic recoverability for the development of disaster management scenarios which will assist the decision-making process. From the case study, five regions in Gwanak-gu district in Seoul were evaluated as the low recoverability areas that needed careful attention as to disasters. The in-depth study revealed that each cluster group had unique patterns, thus considering each factor information could be effective to support strategic decision-making process for disaster management. Furthermore, recovery stage decision-making on construction plans must reference the assessed resilience recoverability to get efficient progress.

The proposed method can be used to assess physical vulnerability and socio-economic recoverability. By developing appropriate disaster resilience scenarios, it can be applied to resilience improvement plans. Although this paper focuses on socio-economic recoverability, further research to develop the assessment method on physical vulnerability is currently in progress. The future work includes developing model in two dimensions, including physical vulnerability and socio-economic recoverability, and providing appropriate disaster management scenarios based on community resilience.

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