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Socioeconomic Impact on Urban Resilience against Flood Damage

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Abstract: While urban populations are rapidly increasing around the world, floods have been frequently and seriously occurring due to the climate crisis. As existing disaster prevention facilities have specific limitations in completely protecting against flood damages, the concept of resilience, which emphasizes the ability to recover after becoming injured and harmed by a flood, is necessary to mitigate such damages. However, there is still a scarcity of studies that quantitatively show the relationship between the resilience and the socioeconomic costs, even though a variety of evaluation methods exist in the literature. This study aims to quantitively analyze the socioeconomic impact of flooding on the urban environment based on the concept of resilience. A method of evaluating four properties of resilience (redundancy, rapidity, resourcefulness, and robustness) through damage function and network analysis was used to measure changes in resilience against flood damages. In addition, to determine the socioeconomic impact of flooding, the costs incurred due to transportation delays and the lack of labor participation were evaluated. Differences in structural and social systems have led to variations in resilience and socioeconomic costs. As a future study, if the circumstances after flood events based on risk-based recovery can be evaluated, more effective urban flooding defense decisions would be expected.

Keywords: urban flood; resilience; socioeconomic impact; inundation; disaster

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1. Introduction

As the urban population increases rapidly worldwide, disasters caused by the climate crisis are becoming more intense and frequent. Floods, especially in densely populated cities, cause significant harm to many people, and the direct and indirect damages resulting from them are severe [1–3]. The impact of flood damage can be observed across numerous fields [4–6]. Numerous structural measures have been implemented to prevent such damage, but the disaster prevention effectiveness of structures with a design frequency is facing limitations as the intensity and frequency of floods increase. In this context, the concept of resilience, emphasizing damage mitigation and recovery capacity, has been receiving attention in the disaster field for a long time [7]. Manyena [8] analyzed the concept of resilience, examining the differences in resilience and risk from social and structural perspectives. Nelson, D.R. et al. [9] argued that a resilience framework offered a dynamic perspective on adaptation processes, emphasizing the importance of maintaining adaptive capacity to cope with future uncertainties. Mensah, H. et al. [10] argued that resilience is crucial for sustainable urban development and mitigating the adverse impacts of climate change. Bulti, D.T. et al. [11] conducted a comprehensive review and analysis of the development and application of various resilience assessment frameworks. Jeon et al. [12] identified six dimensions (social, economic, institutional, infrastructure, community capacity, and environmental) for resilience assessment through domestic and international research and applied these to Korea to identify vulnerabilities.

Although research on evaluating resilience is extensive, there is a lack of analysis on the socioeconomic impact of resilience on cities. Jeong et al. [13] assessed the risk of flooding through flood depth and economic losses. However, they did not consider the concept of resilience in assessing the risk. Bruneau et al. [14] presented a resilience assessment model that incorporates failure, damage, and negative economic and social consequences, but they also did not provide a specific evaluation method. Vugrin et al. [15] introduced the concept of resilience and its evaluation methods, suggesting a way to assess the system's capacity and recovery efforts by economic cost. Although they included socioeconomic concepts in the resilience evaluation through monetary value, they did not provide a detailed valuation method for evaluating the methods. Yu et al. [16] evaluated resilience by applying recovery efforts as recovery costs, but it is challenging to view recovery efforts solely in terms of recovery costs. Langkulsen et al. [17] presented the socio-economic vulnerability of a region through the "socioeconomic vulnerability index" within resilience. Cutter et al. [18] introduced a resilience evaluation model that included social and economic indicators, thus incorporating the socioeconomic impact into the resilience evaluation. However, neither study reflected the actual physical damage from floods. Bertilsson [19] evaluated resilience by considering physical flood damage and annual income, but this was only incorporated into the evaluation formula, without presenting the socioeconomic impact in quantitative terms. Therefore, this study analyzed the impact of floods on cities in terms of socioeconomic costs and changes in resilience caused by flooding. To this end, a methodology to evaluate resilience and socioeconomic impact was presented, and socioeconomic changes resulting from changes in resilience were analyzed.

The sections of our work are structured as follows. Section 2 provides a methodology for evaluating resilience and socioeconomic cost. Section 3 applies the study to a pilot area to analyze the relationship between resilience and socioeconomic cost. Section 4 is the conclusion and discussion section, which describes future research plans that need to be undertaken.

2. Methodology

The definition of resilience in the field of urban flood and a methodology for evaluating resilience were introduced, followed by the presentation of a methodology for assessing socioeconomic damage. The methodology was then applied to a pilot area. Finally, the resilience of the city and its socio-economic impact were analyzed (Figure 1).

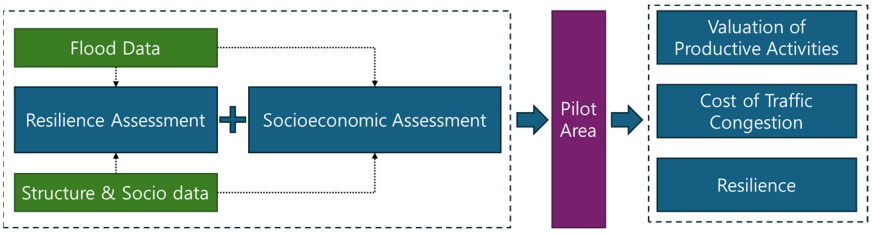


Figure 1. Methodology of this study: After assessing resilience, a socioeconomic evaluation is performed. The socioeconomic assessment consists of productive activities and the cost of traffic congestion.

2.1. Evaluation of Resilience

The concept of resilience is broadly consistent, yet there are some differences depending on the field of application and the researcher. Timmerman [20] defined it as the "Ability to absorb and recover from disasters", and Cutter et al. [18] described it as "The process by which the social system adapts while responding to the threat of disasters and risk-free architecture". Park et al. [21] conducted a text frequency analysis based on the definitions from various researchers and institutions, and on this basis, defined urban resilience as "The social and structural response ability of the city to maintain the system during urban flooding"(Figure 2). This study adopted the definition of resilience presented by

Park et al. [21], which was based on a synthesized concept derived from various definitions of resilience.

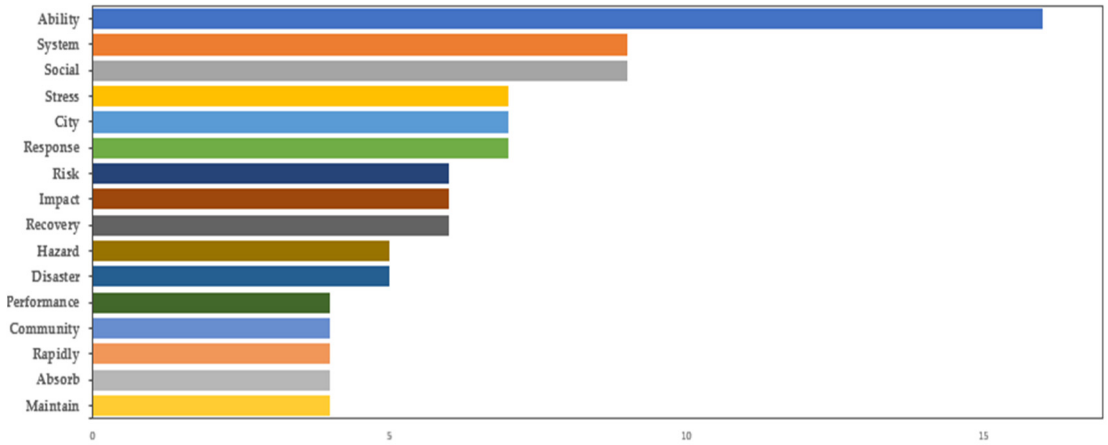


Figure 2. Results of text frequency analysis of resilience definition [21]. The word "ability" was the most prominently used, indicating that most researchers define resilience in terms of ability.

2.1.1. Urban Resilience

The measurement of resilience reflecting the physical damage or impact of floods is primarily evaluated through quantified formulae. Evaluating resilience by reflecting physical factors such as inundation depth, unlike indicator-based measurement methods, has the advantage of assessing resilience at different points in time during a flood. This approach allows for a detailed analysis of resilience and its related impacts. In this study, urban resilience was evaluated using the concept of "Dynamic Resilience" proposed by Park et al. [21]. It refers to the ability to evaluate a city's social, structural, and systemic capabilities by reflecting the depth of flood at specific points in time.

2.1.2. Evaluation of Each Attribute

Resilience is generally composed of four attributes, a concept utilized by various researchers [14,22,23]. Among these, the definition of resilience proposed by Park et al. [21] is particularly suitable for comparing resilience and socioeconomic impacts, as it allows for evaluation across different flood stages. Therefore, this study adopts Park et al.'s [21] definitions of the four attributes, which are as follows. Robustness refers to the "Ability to withstand disaster damage", while resourcefulness means the "Ability to access urban recovery resources". Redundancy means the "Ability to substitute when urban systems are not functioning". Lastly, rapidity refers to the "Ability for rapid urban recovery". Through the four attributes of resilience, 'Urban Resilience' was determined. The following describes the evaluation methods used in this study for each of the four attributes to determine 'Urban Resilience'.

- Robustness

Among the attributes of resilience, robustness allows for the assessment of the structural damage to urban facilities. Robustness is evaluated based on the flood damage to buildings and roads at different inundation depths, and is expressed as follows:

$$SI_t^{ci} = \left(SI_{b_t}^{ci} + SI_{r_t}^{ci}\right)/2 \quad (1)$$

$$SI_{b_t}^{ci} = \frac{\sum D_{max}^{id_b} - \sum D_t^{id_b}}{\sum D_{max}^{id_b}} \quad (2)$$

$$D^{id_b} = D^{id_b}(h) \times C^{id_b} \quad (3)$$

$$SI_{r_t^{ci}} = \frac{\sum D_{max}^{id_r} - \sum D_t^{id_r}}{\sum D_{max}^{id_r}} \quad (4)$$

$$D^{id_r} = D^{id_r}(h) \times A^{id_r} \quad (5)$$

where SI is systemic impact, ci is city, t is time, SI_b is system impact of building, h is inundation depth (m), SI_r is system impact of road, $D(h)$ is depth-damage function of each h, D_{max} is max damage, C^{idb} is cost of building (USD), and A is area of road (m^2).

- Resourcefulness

Resourcefulness enables the assessment of the capability to mobilize the resources needed for recovery when a city incurs damage. The city's resourcefulness is evaluated based on the expected damage from a flood and is expressed as follows:

$$DP_t^{ci} = \frac{RF_t^{ci}}{RF^{co}} \quad (6)$$

$$\frac{RF_t^{ci}}{RF^{co}} = \frac{\sum_{ci} D_{max}^{id_b}}{\sum_{co} D_{max}^{id_b}} \quad (7)$$

where DP is disaster preparedness, RF^{co} is reserve fund of county level, RF^{ci} is reserve fund of city level, $\sum_{\mathrm{ci}} D_{max}^{id_b}$ is maximum damage cost of city level and $\sum_{\mathrm{co}} D_{max}^{id_b}$ is maximum damage cost of county level.

- Redundancy

Redundancy is used to assess a city's evacuation capabilities. It assesses the number of alternative routes available for evacuation from flooded to unflooded roads at specific points in time during a flood, using network analysis in Python 3.8, and is expressed as follows:

$$SR_t^{ci} = \frac{\sum AR_t^{n,n_0}}{\sum AR_{max}^{n,n_0}} \quad (8)$$

where SR is system redundancy, $\sum AR_{max}^{n,n_0}$ is max route numbers from flooded (n) to unflooded roads (n_0) and $\sum AR_t^{n,n_0}$ is route numbers from flooded to unflooded roads at specific time t.

- Rapidity

Rapidity evaluates the city's ability for recovery and rescue operations. Rapidity is evaluated by the number of routes that allow access within 10 min from main facilities (police stations, fire stations, hospitals) to flooded locations. Similar to redundancy, rapidity is also based on network analysis and is expressed as follows:

$$RA_t^{ci} = \frac{\sum AT_t^{m,n_t}}{\sum AT_{max}^{m,n}} \quad (9)$$

where RA is rapid access, $\sum AT_{max}^{m,n}$ is the maximum number of paths within an access time of 10 min from main node (m) to flooded road (n) and $\sum AT_t^{m,n_t}$ is number of paths within an access time of 10 min from main node (m) to flooded road (n_t) at specific time.

- Urban Resilience

Due to the characteristics of resilience, objective weights were deemed unsuitable, and subjective weights, which vary depending on the respondent, were also not proper, so the weights were set equally at 1.0. Subsequently, the final resilience of the city was assessed through the ratio to the theoretical maximum resilience value of 4.0, and is expressed as follows:

$$R_t^{ci} = \left(\alpha_{SI} SI_t^{ci} + \alpha_{dp} DP_t^{ci} + \alpha_{sr} SR_t^{ci} + \alpha_{ra} RA_t^{ci}\right)/4 \quad (10)$$

where R_t is urban resilience and α_i is weight of each resilience's attribute (α_i = 1)

2.2. Evaluation of Socioeconomic Cost

To calculate the socioeconomic cost to the city, the valuation of productive activities and the traffic congestion costs were evaluated. The valuation of productive activities allows for the prediction of economic damage to households, while the traffic congestion costs enable the assessment of social damage caused by flooding through indirect costs.

2.2.1. Valuation of Productive Activities

The valuation of productive activities (VPA) refers to the economic value generated when labor activities are carried out [24]. It is evaluated based on the average wage and labor hours. The economic loss is calculated through the difference in the VPA at various flood stages, representing the loss incurred due to the inability to participate in labor because of flood damage.

$$PL_t^d = \sum VPA_{max}^{id_b} - \sum VPA_t^{id_b} \tag{11}$$

$$VPA_{max}^{id_b} = P^{id_b} \times W^{ci} \times T_{max}^{id_b} \tag{12}$$

$$VPA_t^{id_b} = P^{id_b} \times W^{ci} \times T_t^{id_b} \tag{13}$$

where PL is loss in production activities, VPA is valuation of productive activities, W^{ci} is average hourly wage of city (USD/h), T is working hours (h) and P^{id_b} is population capable of production per building.

The average hourly wage by region is not publicly available, so it was estimated using the available data. Based on the land value by public announcement by the Seoul Open Data Plaza [25], which is operated by the Seoul Metropolitan Government, each city was categorized into deciles. Subsequently, to estimate the average wage by decile, salary income data by percentile from the National Tax Service [26] was used to classify labor income by decile. Based on the classified labor income, the hourly wage by decile was estimated, and this was mapped to each city in Seoul to estimate the average hourly wage by city. The annual average salary income and the estimated hourly wage in the Table 1 below are based on the 2023 standards in South Korea.

Table 1. Estimated hourly wages.

Decile	Annual Average Salary Income (USD)	Ratio	Estimated Hourly Wage (USD)
1	2375	1.00	7
2	7695	3.24	24
3	13,205	5.56	41
4	17,480	7.36	54
5	20,853	8.78	65
6	25,270	10.64	79
7	31,018	13.06	97
8	39,401	16.59	123
9	52,963	22.30	165
10	88,944	37.45	277

2.2.2. Traffic Congestion Costs

Traffic congestion cost (TCC) refers to the social loss incurred due to traffic congestion. In the context of TCC, the cost of fixed value consists of labor costs, depreciation costs, insurance costs, and taxes and duties, while the cost of variable value refers to fuel expenses. Finally, the cost of time value represents the loss of economic activity that is not visibly apparent and is calculated through the value of travel time [27]. The data for the above content have been organized in Table 2 and calculation of traffic congestion costs is expressed as:

$$TCC = \sum_{i=1}^{n}\sum_{k=1}^{3}\sum_{j=1}^{24} V_{i,j,k} \times \left[\begin{array}{l}\left(Variable\ Costs_{i,k} \times Distance_i \times \left(Fuel\ Cosumption_{afteri,k} - Fuel\ Comsumption_{beforei,k}\right)\right.\\ \left.+\left(\left(Fixed\ Cost_{i,k} + Time\ Value\ Cost_{i,k}\right) \times \left(Driving\ Time_{afteri} - Driving\ Time_{beforei}\right)\right.\right.\end{array}\right] \quad (14)$$

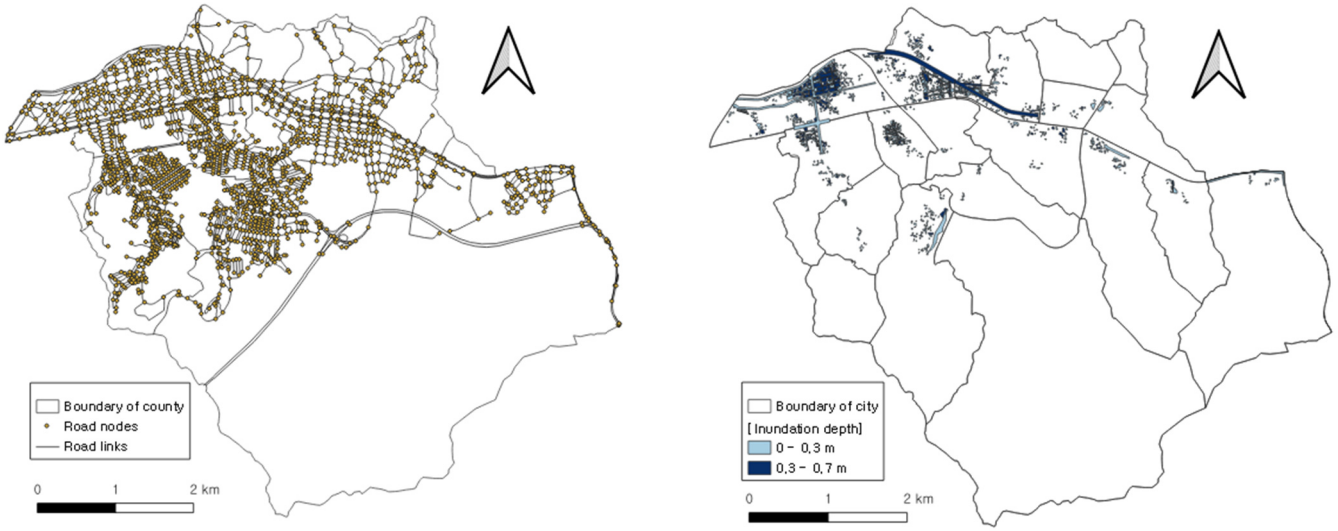
where i is road, j is hour and k is vehicle type (1: car, 2: bus and 3: truck).

Table 2. Value of each type of vehicle (v is speed (km/h)) [28,29].

Cost	Car	Bus	Truck
Fixed value (USD)	0	19.705	22.222
Variable value (USD)	17.915	81.288	0
Time value (USD)	0.310	0.332	0.332
Fuel consumption model (L/km)	$Car = 0.02882 + 0.910/V + 0.000003828 \times V^2$	$Bus = 0.02906 + 2.3225/V + 0.00000854 \times V^2$	$Truck = 0.08334 + 2.725/V + 0.00002086 \times V^2$

3. Results

The proposed evaluation methodology was applied to pilot cities located in Seoul, South Korea, areas that suffered significant damage from floods in 2022. For calculating urban resilience, building data and building damage functions provided by the Korea Institute of Civil Engineering and Building Technology were used [30], and for the road network, the road network from Open Street Map (OSM) and road damage functions from the Joint Research Centre were utilized [31]. The road network data from Open Street Map and the OSMnx library in Python 3.8 were used for network analysis. For the labor hours in VPA, the legal working hours of 8 h were assumed (40 h a week), and vehicle traffic by type for 2023 was calculated using the proportion of vehicles registered (car: 83%, bus: 3%, truck: 14%) according to the Ministry of Land, Infrastructure and Transport's vehicle registration data. Additionally, inundation depth data were utilized from the inundation trace maps of August 2022(Figure 3).



(**a**) Road Network (**b**) Inundation depth

Figure 3. Primary data for this study: (**a**) road network from Open Street Map; (**b**) inundation depth data based on inundation trace maps of August 2022.

3.1. Urban Resilience on the Pilot Area

In the urban resilience under normal conditions, excluding the DP that is pre-calculated through anticipated damage, all other factors are uniformly set to 1, resulting in similar values for the city's resilience under normal conditions (Table 3). However, the difference in

urban resilience after a flood was analyzed to be up to about 59% (Table 4; Figure 4). In particular, for Q and M City, while the values of SI, which indicate the extent of facility damage, are similar, there was a significant difference in the RA values, which represent restore and rescue capacity (approximately 62%, gray color in Table 4). Additionally, for cities L and C, while the SI values were similar, there was a difference in the SR values, which indicate evacuation capacity (approximately 30%, green color in Table 4). This means that even though the damage appears similar on the surface, the impact on the systemic ability of the city can differ significantly.

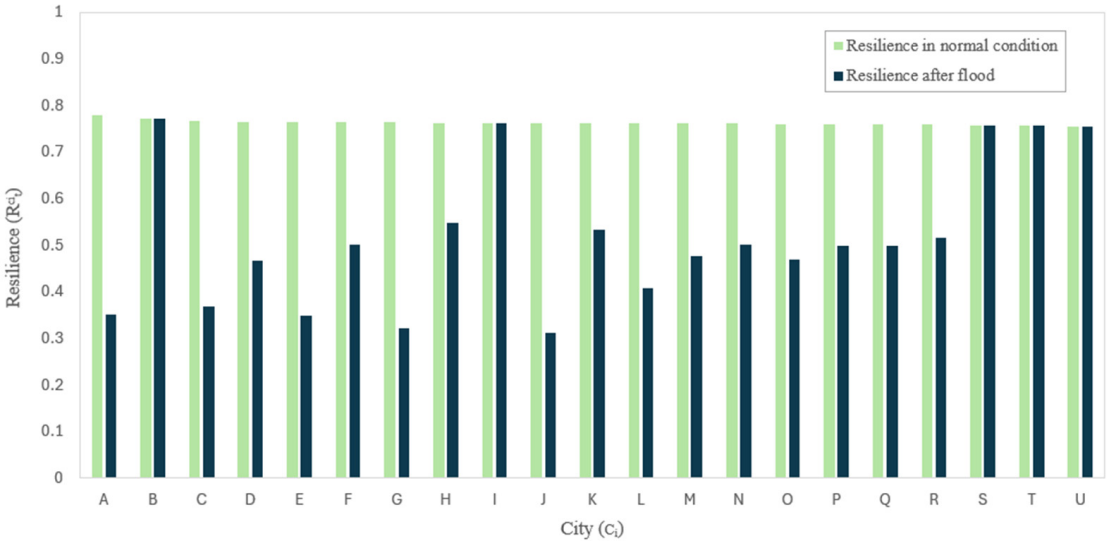


Figure 4. Resilience in normal conditions and after flood. Most cities experienced a decrease in resilience. Areas where resilience did not decrease indicate that flooding did not occur.

Table 3. Resilience of each city in normal condition.

City	SI		RA	SR	DP	R
	SI_b	SI_r				
A	1.000	1.000	1.000	1.000	0.119	0.780
B	1.000	1.000	1.000	1.000	0.084	0.771
C	1.000	1.000	1.000	1.000	0.071	0.768
D	1.000	1.000	1.000	1.000	0.058	0.765
E	1.000	1.000	1.000	1.000	0.058	0.764
F	1.000	1.000	1.000	1.000	0.057	0.764
G	1.000	1.000	1.000	1.000	0.056	0.764
H	1.000	1.000	1.000	1.000	0.051	0.763
I	1.000	1.000	1.000	1.000	0.048	0.762
J	1.000	1.000	1.000	1.000	0.047	0.762
K	1.000	1.000	1.000	1.000	0.046	0.761
L	1.000	1.000	1.000	1.000	0.045	0.761
M	1.000	1.000	1.000	1.000	0.045	0.761
N	1.000	1.000	1.000	1.000	0.044	0.761
O	1.000	1.000	1.000	1.000	0.039	0.760
P	1.000	1.000	1.000	1.000	0.039	0.760
Q	1.000	1.000	1.000	1.000	0.038	0.760
R	1.000	1.000	1.000	1.000	0.034	0.759
S	1.000	1.000	1.000	1.000	0.032	0.758
T	1.000	1.000	1.000	1.000	0.030	0.758
U	1.000	1.000	1.000	1.000	0.020	0.755

Table 4. Change in resilience of each city after 2022 flood event.

City	SI		RA	SR	DP	R	Change in City Resilience (%)
	SI_b	SI_r					
B	1.000	1.000	1.000	1.000	0.084	0.771	0.000
I	0.995	1.000	1.000	1.000	0.048	0.761	0.075
S	1.000	1.000	1.000	1.000	0.032	0.758	0.000
T	1.000	1.000	1.000	1.000	0.030	0.758	0.000
U	1.000	1.000	1.000	1.000	0.020	0.755	0.000
H	0.986	0.994	0.192	0.961	0.051	0.548	−28.122
K	0.995	0.997	0.120	0.972	0.046	0.533	−29.954
R	0.992	0.992	0.118	0.915	0.034	0.515	−32.122
N	0.990	0.986	0.038	0.938	0.044	0.502	−34.051
F	0.985	0.990	0.041	0.918	0.057	0.501	−34.466
P	0.995	0.990	0.039	0.924	0.039	0.499	−34.374
Q	0.985	0.975	0.121	0.855	0.038	0.498	−34.387
M	0.987	0.975	0.046	0.834	0.045	0.476	−37.408
O	0.857	0.979	0.085	0.834	0.039	0.469	−38.287
D	0.942	0.972	0.064	0.789	0.058	0.467	−38.921
L	0.958	0.952	0.010	0.627	0.045	0.409	−46.267
C	0.973	0.942	0.004	0.442	0.071	0.369	−51.990
A	0.766	0.924	0.019	0.423	0.119	0.352	−54.925
E	0.941	0.878	0.029	0.402	0.058	0.349	−54.312
G	0.925	0.912	0.006	0.303	0.056	0.321	−57.985
J	0.974	0.824	0.046	0.260	0.047	0.313	−58.925

3.2. Socioeconomic Cost

The inundation depth affecting the flooded area was assumed to be 0.3 m, which corresponds to the critical depth of human action defined by the Ministry of the Interior and Safety of South Korea [32]. It was assumed that if the flood depth exceeded the critical depth, labor activities would be halted (VPA; valuation of productive activities) and vehicle traffic would be prohibited, resulting in traffic congestion (TCC; traffic congestion cost).

3.2.1. Valuation of Productive Activities (VPA)

For VPA, which is calculated based on the number of people expected to be in buildings, average wages, and labor hours, E city was found to have incurred the greatest damage, as shown Figure 5. In particular, there was approximately a 53% difference between E city and A city, the second largest one. Each proportion of the inundation area to total urban area for both E city and A city was approximately 26%, but the average income was one level higher in A city, at the 10th decile. This indicates that the population exposed to inundation in E city is significantly larger, leading to a substantial difference in the PL values due to this disparity. Additionally, this means that E city is economically more vulnerable to urban flooding compared to A city. For cities O and D, although there was a difference in the flood area ratio, the VPA values were similar. In particular, city D had an average income that was one decile lower, at the 3rd decile. City D, with flood-affected areas concentrated around facilities, suggests a relatively higher probability of human casualties compared to city O.

3.2.2. Traffic Congestion Cost

TCC is calculated based on the social damage caused by traffic congestion resulting from the detouring of flooded roads (Figure 6). The city with the highest occurrence of TCC was L city, and there was approximately a 23% difference compared to the second highest city, F. For the cities with the second (F city) and third highest (D city) TCC, F city, with only a 0.5% flood area ratio, had a higher TCC than D city, which had a 4.8% flood area ratio. This indicates that even with a smaller flooded area in a city, the cost of traffic congestion is affected by how many different routes the flooded roads are part of. This

explanation also applies to cities where road damage occurred, but no TCC was assessed. For example, city H, with an SI_r of 0.994, had less structural damage compared to city F, which had an SI_r of 0.990. However, due to the flooding of detour routes with minimal before-and-after differences and other roads that have a minor impact on route changes, TCC did not occur.

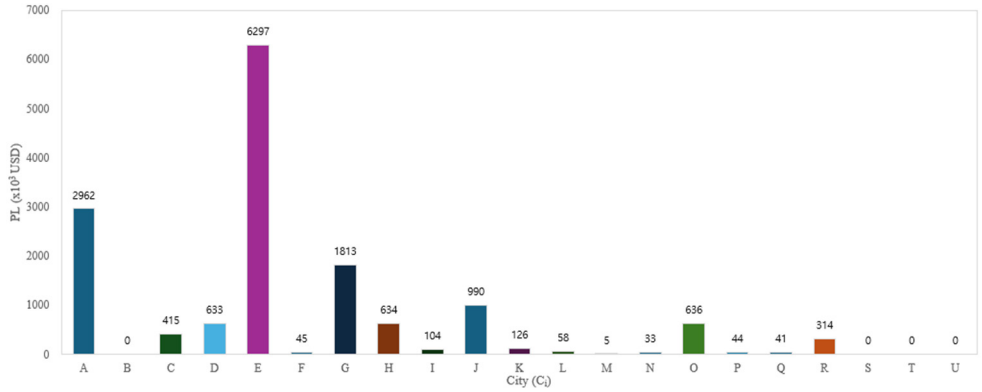


Figure 5. PL of each city. City E experienced the highest PL, followed by Cities A and G in terms of the severity of damage.

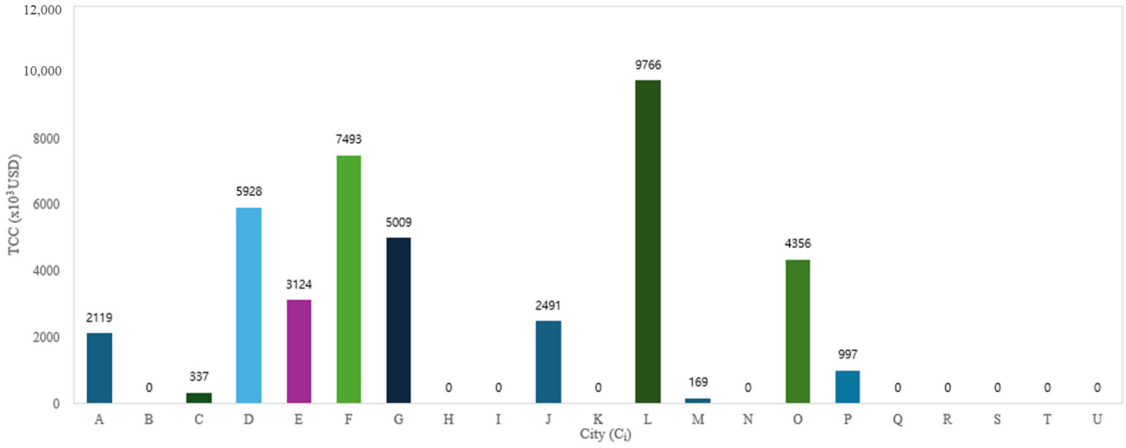


Figure 6. TCC of each city. In the case of City L, the most significant damage occurred, while City E, which experienced the highest PL, suffered damage six times.

3.3. Relationship between Urban Resilience and Socioeconomic Cost

The urban resilience and socioeconomic costs are summarized in Table 5, and the correlation analysis based on the summarized data is presented in Table 6. All variables exhibited negative relationships. Specifically, the correlation between resilience and PL was −0.498, showing a stronger negative correlation than the −0.355 between resilience and TCC. This analysis indicates that higher resilience tends to reduce social costs due to flood damage. It implies that as resilience increases, the loss increase rate of PL is greater than that of TCC. This can be interpreted as a result of the nature of TCC, which is more affected by the network structure and the location of the occurrence, even when the same flood depth occurs, compared to PL.

Urban resilience and socioeconomic cost had a roughly inverse relationship due to the characteristics of direct and indirect damages occurring from flooding (Figure 7). However, by breaking down into the attributes of resilience rather than overall resilience, it was possible to identify specific factors that socioeconomically impact the city. For instance, while the resilience of cities A and E was similar at approximately 0.35, there was a 35% difference in socio-economic costs (light gray color in Table 5). In the case of city A, it was identified that the S_{ib} is lower compared to city E, which leads to higher VPA. Similarly, cities F, P,

and Q, despite having similar resilience levels of 0.5, showed significant differences in TCC, ranging from USD 0 to USD 7493 (dark gray color in Table 5). This is due to the characteristics of TCC, which are determined by which roads are flooded among the numerous flood scenarios. These cases imply that even if a rainfall of similar intensity occurs, interpreting urban damage from the perspective of social capabilities, such as RA or SR, can result in varying degrees of damage. Indeed, cities F, P, and Q had similar flood areas and VPA, but there was a significant difference in TCC. Additionally, while the resilience of cities G and J was similar (about 0.31~0.32), the socioeconomic damage in G is approximately 1.8 million dollars, which was 1.8 times greater than that in J (light blue color in Table 5). The RA (resilience ability) of G city was about eight times lower than that of J, suggesting that G city was expected to face greater challenges in evacuation despite having higher resilience compared to J.

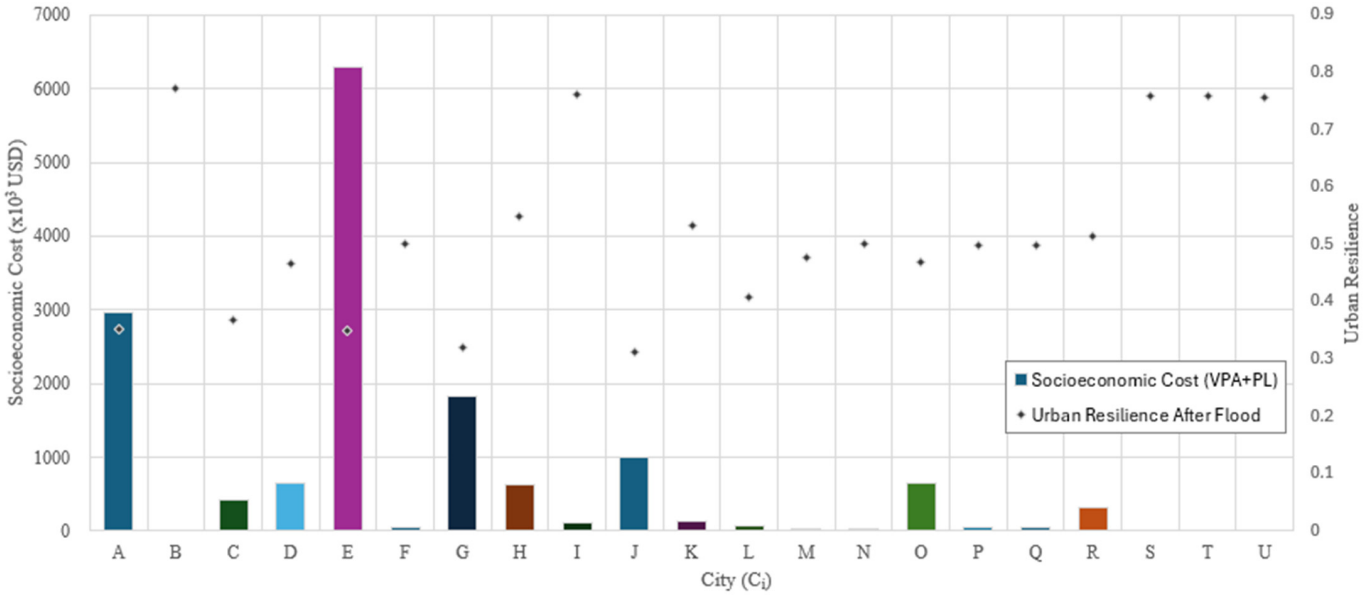


Figure 7. Urban resilience and socioeconomic cost; in the case of City E, it was found that although it does not have the lowest resilience, it experienced the highest level of damage.

Table 5. Urban resilience and socioeconomic factors of each city.

City	R			Socioeconomic		Flood Area Ratio (%)
	Flood Before	Flood After	Difference (%)	PL (USD)	TCC (USD)	
I	0.762	0.761	0.131	104,104	0	0.883
H	0.763	0.548	28.178	633,955	0	1.342
K	0.761	0.533	29.961	126,357	0	0.496
R	0.759	0.515	32.148	314,373	0	2.527
N	0.761	0.502	34.034	33,417	0	0.825
F	0.764	0.501	34.424	45,292	7493	0.479
P	0.760	0.499	34.342	43,540	997	0.364
Q	0.760	0.498	34.474	41,174	0	1.145
M	0.761	0.476	37.451	4533	169	0.647
O	0.760	0.469	38.289	636,302	4356	7.342
D	0.765	0.467	38.954	632,710	5928	4.759
L	0.761	0.409	46.255	57,805	9765	1.658
C	0.768	0.369	51.953	414,758	337	6.478
A	0.780	0.352	54.871	2,961,942	2119	25.537
E	0.764	0.349	54.319	6,297,107	3125	25.869
G	0.764	0.321	57.984	1,812,906	5009	20.268
J	0.762	0.313	58.924	989,560	2491	12.105

Table 6. Correlation matrix of resilience, socioeconomic costs, and flood area ratio.

Classification	Resilience	PL	TCC	Flood Area Ratio
Resilience	1.000	−0.498	−0.355	−0.681
PL	−0.498	1.000	0.101	0.878
TCC	−0.355	0.101	1.000	0.166
Flood area ratio	−0.681	0.878	0.166	1.000

4. Discussion and Conclusions

This study assessed urban resilience, considering socioeconomic cost due to urban flood damage. For this purpose, a comprehensive dataset including flood depth, building information, road condition, population, and vehicle data was built and used to verify the assessment. The evaluation formulas for resilience attributes and a socioeconomic evaluation methodology are presented to calculate the resilience of each city, respectively, and the socioeconomic damage due to flooding quantitatively, and the following characteristics were identified:

1. In the event of a flood, the resilience of each city varies, which is primarily due to the structural characteristics of the cities and their evacuation and response capabilities. For example, despite having similar levels of facility damage (SI), there was a significant difference in evacuation capability (RA or SR), which was expected to indicate critical disparities in the damage and recovery process due to flooding.
2. Each attribute value of resilience against flooding and socioeconomic damage is greatly influenced by the structural characteristics and social capabilities. In particular, it was analyzed that even if similar resilience outcomes are derived, socioeconomic damage can vary depending on the specific attribute values. For instance, the capacity to evacuate, such as RA, and regional population sizes influenced the scale of socioeconomic cost differently on the final value of urban resilience.
3. With the economic analysis, the expected benefits and costs of PSHP were estimated including the operation and maintenance. Urban resilience would indicate a foundational measure for establishing response strategies for the rapid recovery of cities after floods. The analysis method for each attribute value of resilience and socioeconomic cost in this study can provide useful information to decision-makers and stakeholders, contributing to minimizing and mitigating damage caused by floods and enhancing resilience.

In conclusion, this study has provided a comprehensive understanding of urban flood resilience and socioeconomic cost assessment. The correlation analysis further supports these findings, revealing that all variables exhibited negative relationships. Notably, a stronger negative correlation was observed between resilience (R) and labor loss (PL) at −0.498, compared to the −0.355 correlation between resilience and traffic congestion costs (TCC). This indicates that higher resilience tends to reduce social costs due to flood damage, with PL being more sensitive to changes in resilience than TCC. This observation can be attributed to the network structure's impact on TCC, where the location of the flood significantly affects traffic congestion differently than labor loss.

The analysis highlights the importance of not only structural protection measures but also enhancing social response capabilities and devising strategies to minimize and mitigate impact when developing flood preparedness and response strategies. However, this study did not consider the weight of each attribute during the resilience assessment and did not quantitatively analyze the impact on resilience changes after recovery due to the inability to set priorities for restoration and rehabilitation. Therefore, it is essential to establish a detailed resilience assessment that considers the weight of each attribute and risk assessment techniques for future recovery prioritization. Analyzing resilience changes under various scenarios with risk-based recovery will aid in developing efficient flood mitigation and effective response strategies.

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