

Spatial Dynamic Model of Index-Based Disaster Resilience

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Abstract. *Measurement and development of resilience are essential in disaster risk reduction programs. Furthermore, efforts are needed to measure resilience baselines to track changes over time and compare areas for monitoring and evaluating resilience development. Therefore, this study identified dimensions and indicators for measuring resilience using a statistical approach and developed an index-based spatial resilience model in a web-GIS environment. This paper presents the spatial distribution of urban resilience to disasters in Semarang City at the sub-district level. Factor analysis showed that 21 selected indicators could represent five dimensions of resilience: social, economic, infrastructure, environmental, and institutional. Furthermore, the model results showed that 88% of the sub-districts were in the moderate resilience class. The spatial distribution of each dimension showed considerable heterogeneity in its coastal and plain areas (city center) as well as better resilience in the social and infrastructure dimensions than in its hilly areas. The hilly areas in the west have relatively better resilience than those in the east. These results can be used as a reference in managing resilience to disasters. The model presents a spatial distribution of resilience based on an index that quickly provides an overview of the conditions and determines priorities for increasing resilience in supporting disaster risk reduction programs.*

Keywords. *Disasters, spatial distribution, resilience indicators*

Abstrak. *Pengukuran dan pembangunan ketahanan menjadi kunci dalam program pengurangan risiko bencana. Diperlukan upaya pengukuran baseline ketahanan agar bisa melacak perubahan dari waktu ke waktu dan perbandingan antar lokasi untuk monitoring dan evaluasi pembangunan ketahanan. Penelitian ini bertujuan untuk mengidentifikasi dimensi dan indikator untuk mengukur ketahanan menggunakan pendekatan statistik, menyusun model spasial ketahanan berbasis indeks dalam lingkungan web-GIS dan menyajikan distribusi spasial ketahanan perkotaan terhadap bencana di Kota Semarang pada level kecamatan. Hasil analisis faktor menunjukkan 21 indikator terpilih yang mewakili lima dimensi ketahanan:*

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sosial, ekonomi, infrastruktur, lingkungan dan kelembagaan. Hasil model menunjukkan bahwa 88% kecamatan berada pada kelas ketahanan moderat. Distribusi spasial ketahanan per dimensi menunjukkan heterogenitas spasial yang cukup besar pada wilayah pantai dan dataran (pusat kota) dan ketahanan yang lebih baik pada dimensi sosial dan infrastruktur dibandingkan wilayah perbukitan. Wilayah perbukitan di bagian barat mempunyai ketahanan per dimensi yang relatif lebih baik dibandingkan di bagian timur. Temuan studi ini dapat digunakan sebagai referensi dalam pengelolaan ketahanan terhadap bencana di mana model menyajikan distribusi spasial ketahanan berbasis indeks yang secara cepat memberikan gambaran kondisi ketahanan dan menentukan prioritas peningkatan ketahanan dalam mendukung program pengurangan risiko bencana.

Kata kunci. *bencana, distribusi spasial, indikator ketahanan.*

Introduction

Over the last decade, the trend of natural disasters occurring in Indonesia has increased (BNPB, 2021; Puteri et al., 2018). Hydrometeorological disasters such as floods, landslides, and tornadoes have high incidence. In the 2010-2020 period, the highest number of disaster events (4,941) occurred in 2020 (BNPB, 2021). As one of the most disaster-prone countries globally, Indonesia, through the National Disaster Management Authority (BNPB), has adopted different methods to reduce disaster risk and strengthen resilience (Stanton-Geddes & Vun, 2019). Resilience measurement is needed to determine the resilience of a particular system. Moreover, it is also an important step to reduce the impact of disasters and prepare a system to deal with disturbances and to apply adaptation patterns (Cutter et al., 2010, 2014).

Resilience is not a result-oriented but a process-oriented phenomenon (Cai et al., 2018; Gonçalves & Marques da Costa, 2013; Saja et al., 2018). Therefore, apart from statistical measurement as a result-oriented characterization, dynamic analysis as a process-oriented characterization is needed to describe the dynamic nature of resilience. In addition, resilience measurement is needed to evaluate the baseline conditions of a site and the factors that hinder an adequate response (Kabir et al., 2018). Limited human resources, budget, and time are challenges in realizing regional resilience. This means quick and precise efforts are needed to determine which areas should be prioritized and what dimensions of resilience should be increased. The question is how to build an appropriate model of urban resilience to disasters, since efforts to realize regional resilience will be more effective in view of these limitations. Therefore, it is crucial to develop a spatially-based inclusive resilience measurement framework.

This study aimed to determine indicators for measuring urban resilience to disasters and developed an index-based spatial dynamic model of disaster resilience. This paper also presents the urban resilience's spatial distribution to disasters in Semarang City, Indonesia. The novelty of this research is to contribute to solving problems on the topic of urban resilience, namely the development of an index-based dynamic spatial model of urban resilience to disasters that can measure urban resilience at the sub-district level. The dynamic spatial model of urban resilience was built in a web-based GIS environment. This makes it possible to dynamically conduct spatial simulations of resilience indices and makes it easier for stakeholders who do not have access to GIS applications to carry out assessment of urban resilience. The model results and the spatial distribution of overall and dimensional resilience as well as the indicator values will tell which areas and dimensions should be prioritized to overcome the increasingly destructive impacts of environmental change. Furthermore, the model's ability to dynamically perform

simulations is useful in guiding practitioners’ and stakeholders’ decision-making to increase resilience in sustainable urban development efforts.

Study area

Semarang is the capital of Central Java and has very high mobility and population density. It had a growth rate of 1.57% in 2019 and a population of 1.653 million people in 2020 (BPS, 2021). Physically and topographically, the city is unique because it consists of hilly, lowland as well as coastal areas. The disaster hazards, identified in relatively complex urban risks, are floods (river and tidal floods), land subsidence, sea-level rise, landslides, fires, strong winds, and droughts (100RCSemarang, 2018; BNPB, 2020; Gunawan et al., 2015; Setiadi & Wulandari, 2016). The trend of disaster incidence has consistently increased from 2011 to 2020. Disasters with the highest probability of occurrence were landslides, with as many as 104 events. At the same time, floods were the disaster type with the most significant impact; they submerged 1,221 houses and heavily damaged 186 (BNPB, 2021).

The city has a geostrategic position, located on the main economic traffic artery of Java Island and is an important development corridor for Central Java. Semarang plays a significant role in the development and growth of Central Java as a main regional transportation node and transit city, specifically due to the presence of ports, land transportation networks (railway and road), and air transportation (BPBD, 2021). The location of Semarang City is presented in Figure 1.

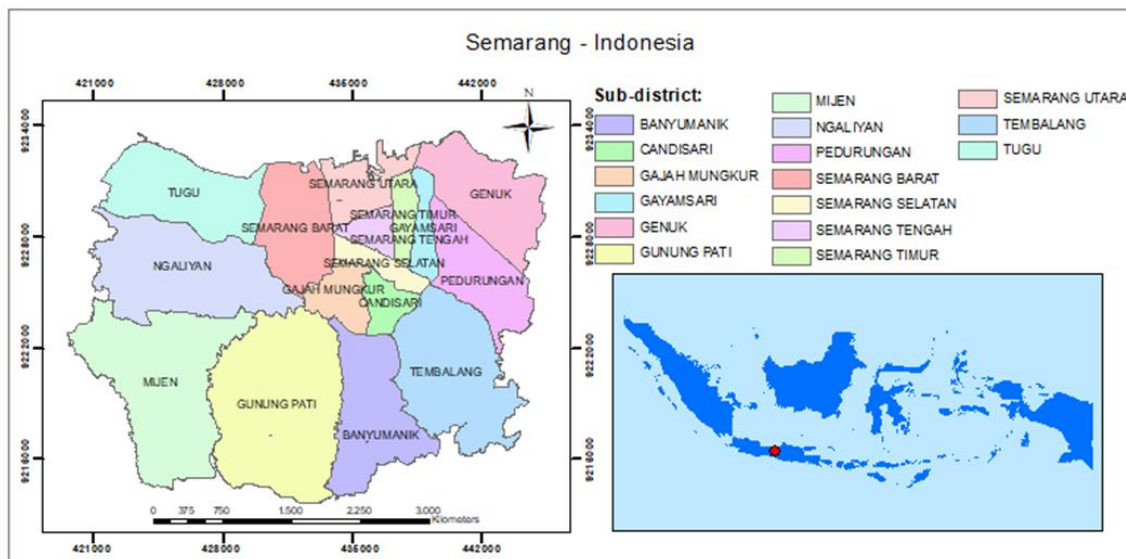


Figure 1. Map of Semarang city.

Research Methods

The data used were collected from various sources in the form of tabular (2018-2021) and spatial data (topographic, disaster, infrastructure, and spatial planning map). The sub-district indicator data were obtained through an online questionnaire among 37 respondents representing 16 sub-districts. Furthermore, data from various related agencies was transformed by converting raw data of various sizes into percentages, ratios, and per capita (Cutter et al., 2010; Narieswari et al., 2019). The spatial analysis was performed using GIS techniques such as overlays, intersections, queries, and spatial joints.

The proposed index-based urban resilience spatial dynamic model is structured in three stages (Figure 2). The first stage consists of the selection of indicators using factor and principal component analysis (PCA) (Mavhura et al., 2021). The output consists of indicators used in calculating the index-based urban resilience. Based on this output, the second stage categorizes and determines the indicators' scores for each sub-district. Finally, the output of the third stage is the index-based city resilience spatial dynamic model.

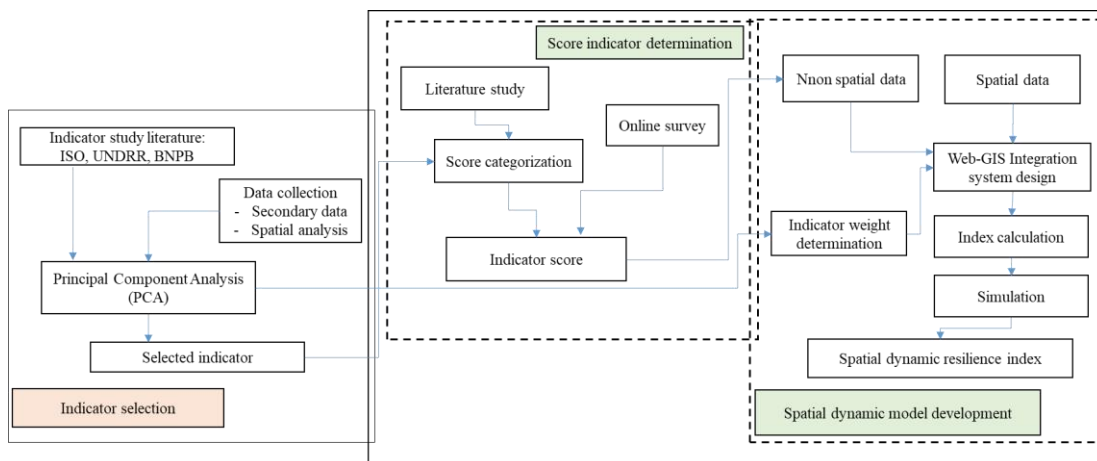


Figure 2. Stages of building a spatial dynamic model of index-based resilience.

Indicator selection

Factor analysis was used to determine the indicators used to prepare the model. It was performed using the Statistical Package for Social Sciences (SPSS) software with the PCA algorithm to reduce the data and group the indicators. The correlation matrix was examined before the analysis by performing Bartlett's Test of Sphericity (BTS), Kaiser-Meyer-Olkin (KMO), and the Measure of Sampling Adequacy (MSA) with p -value <0.05 , >0.5 , and >0.5 (Fekete, 2010; Hair et al., 2014; Mavhura et al., 2021), respectively. The factor analysis was conducted separately for each dimension by considering the number of samples in each of the sub-districts in Semarang City. To produce an optimum model, based on the factor analysis, 21 indicators from the 51 original ones were selected to measure urban resilience. Table 1 contains descriptions of the 21 indicators, dimensions, data sources, and justifications for using these indicators.

Determination of indicator score

For calculation of the index, each indicator was classified by giving a score range of 0 to 5 based on the questionnaire survey data. A score of 0 represents little or no awareness related to disaster risk reduction or conditions that do not fulfill the city's minimum service standards. A score of 5 represents the ideal city conditions expected or implementing full integration towards disaster reduction (UNDRR, 2017). Category classification for indicators that have a negative effect on resilience (e.g., vulnerable population, people with a disability, unemployed people) was adjusted by reversing the order of the indicators' data values. The highest data value of the indicators, which represents lower resilience, was classified as the lowest score. The lowest data value of the indicators, which represents high resilience, was classified as the highest score.

Table 1. Indicators used

Resilience dimensions	Indicator descriptions	Justification/references	Sources
Social	% vulnerable population (PCTVUL)	(Cutter et al., 2014; ISO, 2019; Shi et al., 2021)	Semarang City Government
Demography	% pop with disability (PCTDIS)	(Beccari, 2016; ISO, 2019)	
Special needs	% female school-aged pop enrolled in school (PCTFEMSCH)	(Normandin et al., 2009; UNISDR, 2013)	
Educational equity	number of physicians per 10,000 population (NOPHY)	(Al Rifat & Liu, 2020; Bappenas, 2015; BSN, 2018)	
Health access	% pop enrolled in social assistance programs (PCTSOCAS)	(Beccari, 2016; ISO, 2019; Shi et al., 2021)	Village Potential-BPS
Economic	% pop living in poverty (PCTPOOR)	(Cai et al., 2016; Kusumastuti et al., 2014)	Semarang City Government
Subsidy	% homeownership (PCTHOME)	(Cai et al., 2018; Cutter et al., 2014; Ji et al., 2021)	
Livelihood/welfare	% unemployed (PCTUNEMP)	(Cutter et al., 2008; Kamh et al., 2016; Shi et al., 2021)	2018-2021
Housing capital/asset			
Employment			
Infrastructure			
Building structure	% building structurally vulnerable to high-risk hazards (PCTBUILDRISK)	(ISO, 2019; Shi et al., 2021)	RBI-BIG, Disaster Risk Map-BPBD Semarang
Electricity accessibility	% households with access to electricity (PCTELECTRIC)	(DasGupta & Shaw, 2015; Shi et al., 2021)	Village Potential-BPS
Recovery	Number of public schools per sq. km (NOPUBSCH)	(Cai et al., 2016; Gonçalves & Marques da Costa, 2013)	Semarang in Figures-BPS Semarang
Medical capacity	health care facility per 1000 population (NOHEALTH)	(Al Rifat & Liu, 2020; Cai et al., 2016; Kamh et al., 2016)	Semarang City Government
Water accessibility	% pop with accessed to improved water sources/ (PCTWATER)	(Beccari, 2016; BSN, 2018; Mavhura et al., 2021)	
Environment	Green open space (NOGREEN)	(BSN, 2018; Li et al., 2021; Sajjad et al., 2021)	RBI-BIG, RTRW-Distaru
Urban planning	% area covered by tree canopy (PCTTREE)	(ISO, 2019; Li et al., 2021)	
	% informal settlement area (PCTSLUM)	(BSN, 2018; Shi et al., 2021)	Semarang City Government
	%, population living in slums (PCTPOPSLUM)	(BSN, 2018; DasGupta & Shaw, 2015; UNISDR, 2013)	Village Potential, (BPS)
Institutional	% pop covered by early warning systems (PCTEWS)	(Gonçalves & Marques da Costa, 2013; ISO, 2019)	Semarang City Government
Mitigation	% trained population (PCTTRAIN)	(ISO, 2019; Shi et al., 2021)	
Disaster awareness	% disaster prepared village (PCTKSB)	(Kusumastuti et al., 2014; Shi et al., 2021)	Regional General Election Commission - KPUD Semarang
Political engagement	% voter participation (PCTVOTER)	(Al Rifat & Liu, 2020; Cai et al., 2018; Cutter et al., 2014; Huang et al., 2019)	

Development of an index based spatial dynamic model of resilience

The spatial dynamic model of resilience was built in a Web-GIS environment. The data process in the developed model is shown in Figure 3.

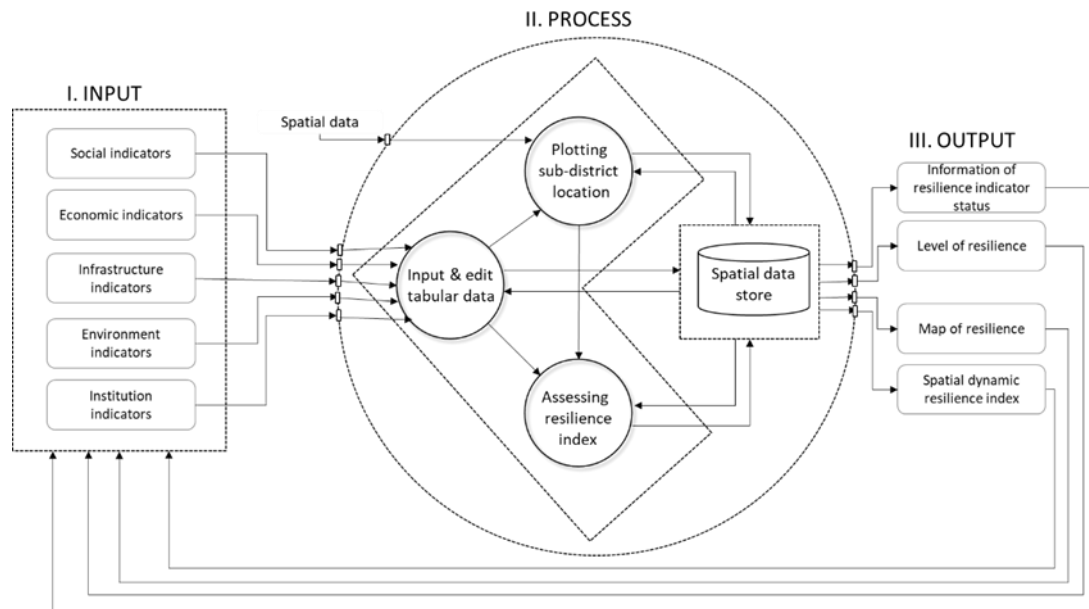


Figure 3. Data flow model

The model consists of data input, process, and output. The data flow begins with the input process for non-spatial indicator class data. Then, it is plotted with spatial data according to area, calculated, and stored in the data store. The output generated from the model is in the form of information on the status of each indicator in five dimensions, the level of sub-district resilience, resilience maps, and spatial dynamic resilience indexes.

The weight of each indicator is calculated based on the optimal arrangement of factors forming urban resilience in the index calculation process (Figure 4) using PCA (weighted by factor scores) (Beccari, 2016). It is calculated based on the value of the loading factor and the value of the rotation sums of squared loading (% of variance) through two stages. The first is the calculation of the weight of each indicator in the factor using the following formula (Bappenas & BPS, 2015):

$$B = \frac{LF}{RLF} \times RSSL$$

where B is the weighted value, LF is the loading factor, RLF is the average loading factor in one factor, and RSSL is the value of the rotation sums of squared loading (% of variance).

Furthermore, the calculation of the contribution of each indicator in urban resilience is conducted using the following formula (Bappenas & BPS, 2015):

$$b = \frac{B}{JB}$$

where b is the contribution value of each indicator, B is the weighted value, and JB is the sum of all weights. The contribution value of each indicator is used as a weight to produce the index.

The index resilience value is obtained from the sum of each indicator score multiplied by the weight of each indicator. In addition, the total index value is the current state of resilience and can be used as a benchmark for urban disaster resilience. The index value ranges from 0 to 100, with a high and low score indicating higher and lower resilience. Furthermore, the index scores are categorized into five classes for visualization and ease of interpretation (Figure 4).

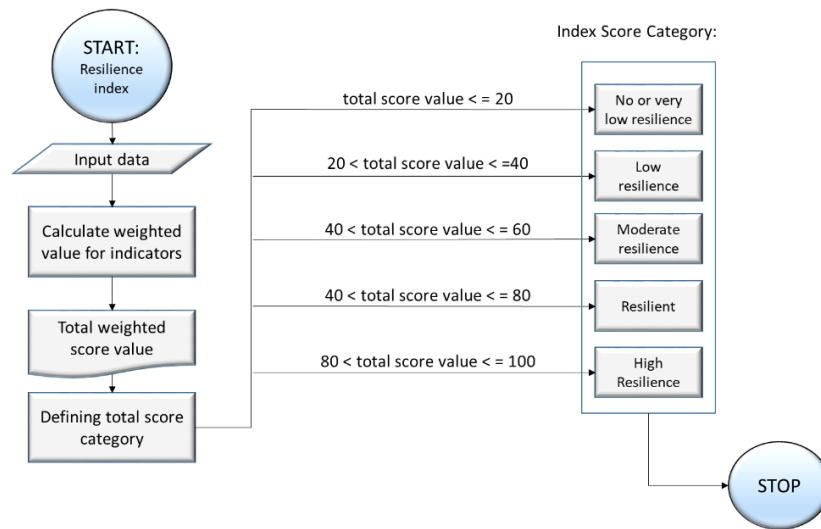


Figure 4. Index calculation and classification rules.

Results and Discussions

Indicator Analysis

The statistical analysis of each dimension resulted in a KMO value greater than 0.5, therefore, the indicators used in the analysis are suitable for PCA. In addition, the PCA model provides >60% variance in each dimension, hence, each indicator is expected to have a contribution to the index. The amount of contribution describes the magnitude influence of the indicator on the dimensions and index. Furthermore, the contribution of each indicator is not determined with the same value or based on a subjective assessment; rather, it is calculated based on the distribution of the statistical analysis data. Table 2 shows the factors, factor loading, variance, and weight of each indicator.

Table 3 shows the scores for each indicator. Analysis of the indicator values showed a substantial variation/heterogeneity among the sub-districts from 0 to 5 in approximately 60%. These include vulnerable population, disability, number of physicians, social assistance program, homeownership, unemployment, building structure, access to improved water, tree cover, slum areas, early warning system, and trained population. Some indicators (7 out of 21) had values below the average of more than 50%, including the female school-age population, unemployment, number of hospitals/residents, green space area, tree canopy, disaster training, and disaster prepared village (Kelurahan Siaga Bencana-KSB). Tree canopy (D2) was the indicator with the most significant variance, showing very diverse conditions between sub-districts.

Table 2. Summary of indicator analysis in each dimension

Dimensions	Code	Indicator	KMO	Bartlett	loading factor	% variance	Weight
Social	A1	PCTVUL	0.655	0.002	0.729	64.039	0.0404
	A2	PCTDIS			0.781		0.0432
	A3	PCTFEMSCH			0.869		0.0481
	A4	NOPHY			0.816		0.0452
Economic	B1	PCTSOCAS	0.709	0.000	0.947	70.457	0.0404
	B2	PCTPOOR			0.849		0.0432
	B3	PCTHOME			0.581		0.0481
	B4	PCTUNEMP			0.929		0.0452
Infrastructure	C1	PCTBUILDRIK	0.769	0.000	0.849	61.619	0.0480
	C2	PCTELECTRIC			0.581		0.0413
	C3	NOPUBSCH			0.929		0.0442
	C4	NOHEALTH			0.913		0.0490
	C5	PCTWATER			0.778		0.0417
Environment	D1	NOGREEN	0.563	0.000	0.982	66.337	0.0646
	D2	PCTTREE			0.959		0.0631
	D3	PCTSLUM			0.947		0.0442
	D4	PCTPOPSLUM			0.973		0.0454
Institution	E1	PCTEWS	0.708	0.000	0.956	67.727	0.0563
	E2	PCTTRAIN			0.832		0.0490
	E3	PCTVOTER			0.96		0.0566
	E4	PCTKSB			0.426		0.0251

Table 3. Indicator score for each sub-district (the indicator codes are s

Sub-district	Social				Economic				Infrastructure					Environment				Institution			
	A1	A2	A3	A4	B1	B2	B3	B4	C1	C2	C3	C4	C5	D1	D2	D3	D4	E1	E2	E3	E4
Mijen	5	4	2	1	4	3	4	4	4	5	5	1	0	5	5	4	4	4	2	1	2
Gunung Pati	4	3	2	1	2	0	3	4	5	5	5	0	3	5	5	0	0	3	3	1	2
Banyumanik	1	1	2	4	3	1	2	2	1	5	5	1	3	4	3	1	0	1	1	1	2
Gajah Mungkur	5	2	2	4	5	2	2	2	1	5	5	3	2	3	0	5	5	3	0	1	2
Semarang Selatan	5	4	3	5	4	2	1	4	3	5	5	3	1	2	0	0	1	0	3	1	2
Candisari	1	5	2	1	5	0	0	2	3	5	5	1	0	2	0	3	3	5	1	1	2
Tembalang	1	2	1	3	5	1	1	3	1	5	5	1	2	4	0	4	1	0	2	1	2
Pedurungan	5	3	2	4	5	2	3	2	3	5	5	1	2	2	0	4	2	0	1	1	2
Genuk	1	1	2	2	3	3	3	1	3	5	5	1	3	3	0	4	4	4	5	1	2
Gayamsari	1	1	3	3	1	1	1	0	1	5	5	1	1	2	0	1	2	0	1	1	2
Semarang Timur	3	2	3	4	4	3	1	3	5	5	5	3	4	2	0	2	2	1	1	1	1
Semarang Utara	4	3	1	1	3	1	2	1	5	5	5	0	5	3	0	5	4	5	5	1	2
Semarang Tengah	1	1	3	5	3	2	3	2	3	5	5	2	3	2	0	1	4	4	5	1	1
Semarang Barat	5	4	2	4	4	0	1	2	2	5	5	1	4	3	0	3	3	1	3	1	2
Tugu	3	4	2	1	4	3	3	2	3	5	5	0	1	5	0	2	2	3	3	2	2
Ngaliyan	4	2	2	2	3	1	3	2	3	5	5	1	3	5	4	4	4	2	1	2	2

Indicators of access to electricity (C2) and public school (C3) (Table 3) had the smallest variance and the most significant average value, which indicates very good and homogeneous conditions in all sub-districts. Meanwhile, indicators for female population enrolled in school and population in poverty, health care facilities, KSB, and voter involvement showed a poor condition, having a maximum indicator value of 3 and an even distribution in all sub-districts. The KSB indicator had the lowest average, at 1.1 out of 5, and a high variance value, indicating improvement priorities.

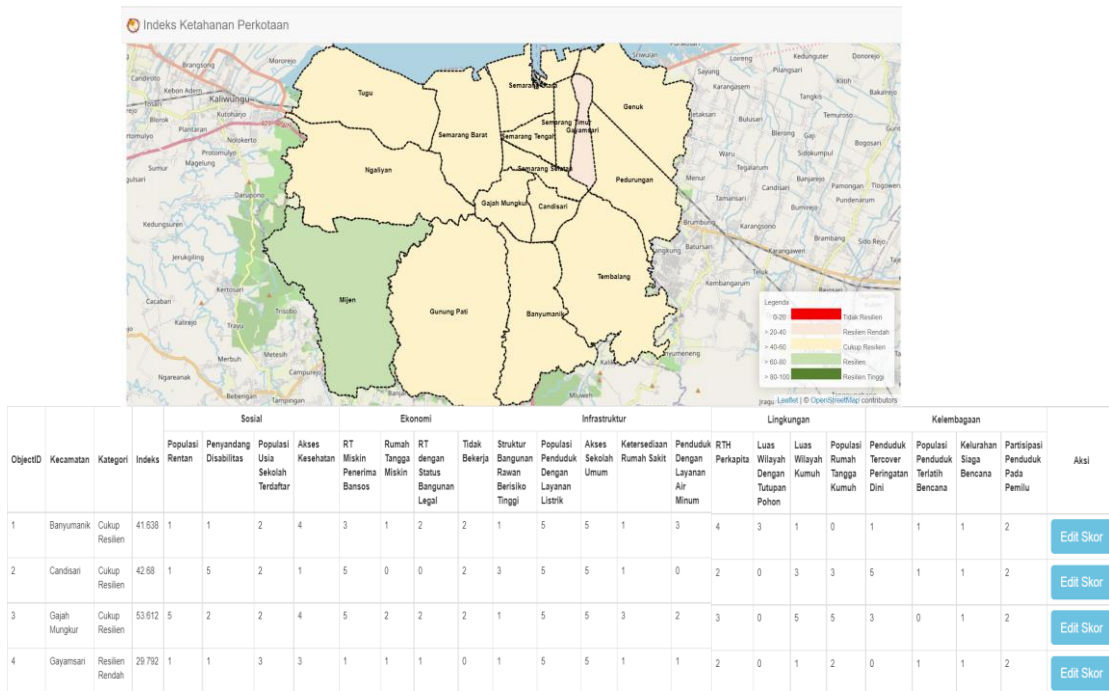
Spatial dynamic models and spatial distribution of disaster resilience

The modeling results provide an overview of the disaster resilience conditions, which were relatively homogeneous in the moderate resilience class, as shown in Figure 5. From the distribution, 88% of sub-districts had moderate resilience, with a score of 40-60 (Table 4). Mijen had the highest score of 66.69, classified as resilient. Meanwhile, Gayamsari, with a score of 27.79, was classified as low resilience (Figure 5). The total score results showed that approximately 40% of the total sub-districts had a score below the average of less than 49.79.

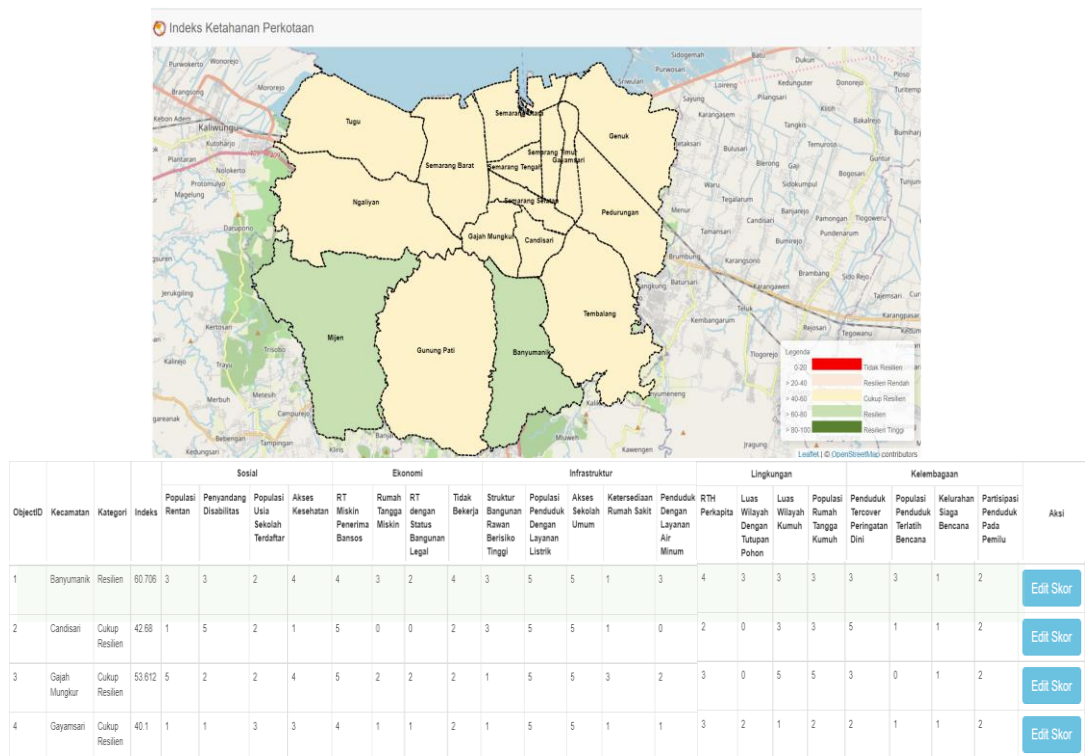
The model was built to measure the urban resilience of disasters. Referring to the whole process, several outputs are produced from the compiled model. These include information related to the condition of the resilience indicators, the level in each sub-district, and the dynamic resilience index. The urban resilience is monitored and evaluated using these outputs. The developed model is web-based, allowing stakeholders without access to GIS applications to assess urban resilience (Lathrop et al., 2014). The developed model also allows simulating the indicators, therefore, changes made to the score will automatically change the total resilience index and the visualization of the map.

Table 4. Value of total resilience to disasters and value of resilience each dimension

Sub-district	Resilience Score						Index category
	Social	Economic	Infrastructure	Environment	Institutional	Total	
Mijen	58.35	74.28	59.63	91.75	45.96	66.69	Resilient
Ngaliyan	49.10	42.93	66.51	85.95	34.74	57.13	Moderate
Semarang Utara	43.44	32.17	78.14	34.55	67.70	56.06	Moderate
Gunung Pati	48.88	44.93	70.70	58.77	45.18	54.47	Moderate
Gajah Mungkur	63.87	50.54	62.97	59.07	29.47	53.61	Moderate
Semarang Tengah	65.61	44.82	74.60	28.61	26.01	52.58	Moderate
Genuk	30.53	48.76	66.51	42.69	61.68	52.39	Moderate
Tugu	49.20	57.89	54.70	46.22	51.23	51.87	Moderate
Semarang Timur	60.18	53.24	87.54	28.38	19.99	50.55	Moderate
Semarang Barat	73.64	30.44	65.95	42.58	33.15	49.20	Moderate
Semarang Selatan	84.18	53.13	67.81	16.07	27.13	49.01	Moderate
Pedurungan	68.76	55.68	62.79	36.52	16.65	48.14	Moderate
Candisari	44.96	28.82	55.35	36.63	46.75	42.68	Moderate
Banyumanik	40.74	37.79	57.95	45.27	22.67	41.64	Moderate
Tembalang	35.08	45.30	54.23	44.23	21.89	40.89	Moderate
Gayamsari	41.07	14.38	50.51	24.32	16.65	29.79	Low
Average	52.70	44.93	64.51	47.13	37.49		
Variance	211.20	197.47	91.34	410.10	280.07		



(a)



(b)

Figure 5. Spatial distribution of total urban resilience: (a) spatial distribution of the baseline index, (b) example of the simulation and spatial distribution of the resilience index after simulation by changing the score of several indicators.

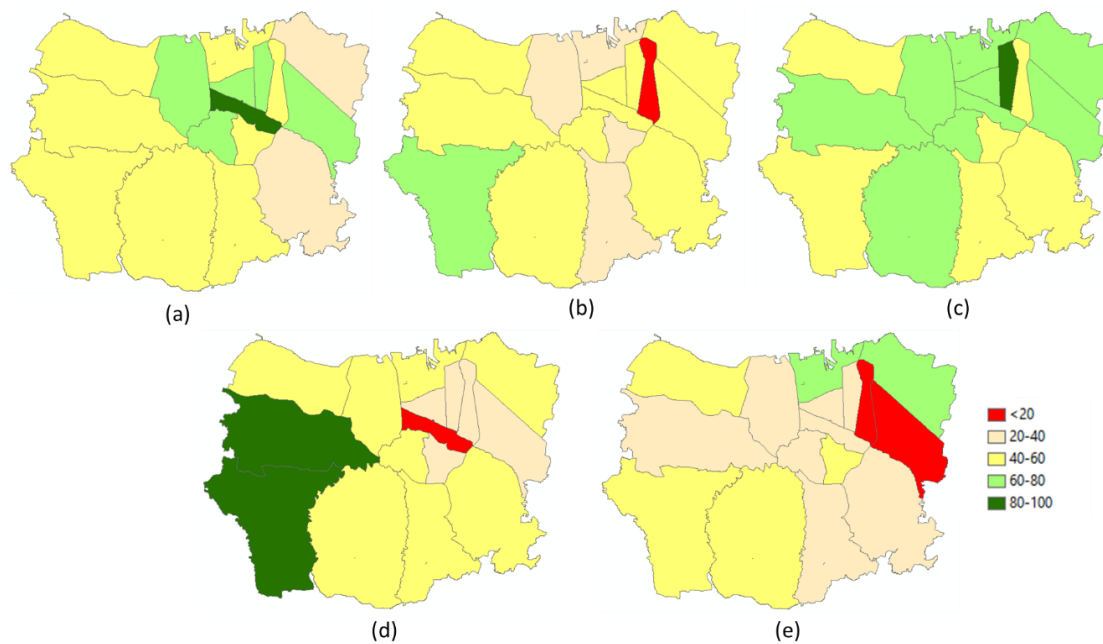


Figure 6. Resilience scores in five classes for each dimension: a) social; b) economics; c) infrastructure; d) environment; e) institutional.

The main display of the spatial model is a resilience map equipped with information related to the total resilience index of each sub-district and the value of each indicator. Users can zoom in and out on the map and obtain information regarding the name of the sub-district, the total index, the category, and the status according to each indicator using the information tool. Users can also simulate the resilience index by changing the values using the Score Edit menu. The model will automatically calculate and change the total index value, category, and visualization on the map. This will be very helpful for related parties, specifically the Semarang City government, in increasing resilience to disasters. Furthermore, the spatial dynamic simulation will automatically prioritize the indicators to be improved.

Describing the resilience index based on five dimensions allows further exploration of the geographic trends of data, as shown in Figure 6. The map shows what dimensions affected the index resilience in each sub-district. For dimension scores, approximately 50% of sub-districts had scores below the average scores for the social, infrastructure, environmental, and institutional dimensions. Moreover, approximately 40% of sub-districts had scores below the average for the social dimension (Table 4). The analysis results showed that none of the sub-districts achieved the highest possible score, both for the dimension and the total score (100).

The environmental dimension had the most significant variation in its scores, indicating great inequality or heterogeneity among sub-districts. The infrastructure dimension had the highest average and minimum score. It had the lowest score variation value, which indicates that the condition is very good and evenly distributed in each sub-district. Finally, the institutional dimension had the lowest average and maximum value (67 out of 100), indicating conditions that require special attention.

The spatial distribution of resilience on each dimension showed considerable spatial heterogeneity in the north-middle area, as can be seen in Figure 6. Concerning the social and

infrastructure dimensions, the area in the city center (north-middle area) had better resilience than the hilly areas in the south (Figures 6a and 6c). On the other hand, these areas had poor economic, environmental, and institutional resilience. The north-middle area is the downtown area, where economic growth occurs and the population is concentrated, so it has good infrastructure services. The attractiveness of being a city center causes economic, industrial activities, and high population concentration. This means it has a large number of workers as well as high unemployment. Concerning the environmental dimension, the high environmental burden causes environmental conditions to decline due to the loss of green area, the emergence of slums, and high-density and irregular buildings. Pressures on the environment cause land subsidence due to groundwater exploitation, waste problems, and an increasing frequency of disasters such as rob (tidal floods), floods, and fires. The red color in Figures 6b, 6d and 6e, indicates the condition of the sub-districts with low resilience. The conditions of infrastructure resilience in the north-central part (sub-districts of Ngaliyan, West Semarang, central-east-south Semarang, Gayamsari, and Pedurungan) are opposite to institutional resilience. Infrastructure resilience was better than institutional resilience, colored green in Figures 6c and 6e. The opposite condition in the area shows that social resilience was higher than institutional resilience, as shown in Figures 6a and 6d. Despite the significant heterogeneity in the city center, all dimensions of resilience showed relatively high and homogeneous conditions in the south-west region (Ngaliyan, Mijen, and Gunungpati sub-districts). Meanwhile, the resilience conditions were relatively low and homogeneous on every dimension for the south-east area.

The institutional dimension had the lowest average value. Generally, areas with a low to moderate total resilience index had low institutional resilience, therefore, immediate action is needed according to all indicators.

Promoting resilience-based risk management

The spatial distribution of resilience (of indicators, dimensions as well as overall) and the identification of hotspots facilitate the prioritization process to manage resilience overall and across all dimensions and indicators. For example, the average value of resilience in the institutional dimension, which was the lowest among all dimensions (average value of 37.49 out of 100), indicates a condition that should be addressed immediately. This is because the dimension is crucial in realizing resilience (Jha et al., 2013). Institutions as a priority for building resilience is in line with the study conducted by Narieswari et al., (2021). Institutional strengthening is one of the main processes targeted in developing urban resilience (BPBD, 2021; Sitadevi, 2016).

Furthermore, the Gayamsari Sub-district, had the lowest resilience score (Figure 5). A study by Narieswari et al., (2019) also stated that Gayamsari is one of the sub-districts in Semarang City that have low resilience conditions. This sub-district may be at risk of worse resilience conditions when appropriate steps are not given priority. The spatial distribution presented in Figures 5 and 6 supports this.

This index-based spatial model of disaster resilience benefits government stakeholders to support the strategic interests of the city at a broader level in natural disaster management. The index can be used as a benchmark for urban disaster resilience and measurable changes in the future. In addition, this index-based model can be a tool to quickly identify areas with high and low resilience in Semarang City. Furthermore, it can identify coping and adaptive capacity (Sajjad, 2021).

Action focus and policy implementation

Identifying areas with low resilience to natural disasters is important for policymakers (Frigerio et al., 2018; Sajjad et al., 2021). Spatial distribution capability in identifying resilience hot spots facilitates disaster risk reduction actions at the desired level. The urban resilience index highlights sub-districts with low resilience that require special attention. These results can be integrated with existing disaster risk reduction activities at the sub-district level.

Increased resilience can also be conducted in a focused manner by analyzing the indicators (Table 3). For example, the results show low resilience scores for indicators A3 and B2 in the economic dimension, C4 in the infrastructure dimension, D2 in the environmental dimension, and E1, E3, and E4 in the institutional dimension. Therefore, increasing resilience on these indicators will effectively increase the total resilience.

Specifically, the spatial distribution of indicators and dimensions can be used as a reference in simulations to increase indicator values. This will effectively increase overall resilience in each sub-district by considering the weight of the indicators. For example, indicators D2, E1, and E4 had reasonably high weights, at 0.0631, 0.0563, and 0.0566, respectively (Table 2). Therefore, program efforts to increase the scores on these indicators will effectively increase the total resilience.

The main advantage is to propose a comprehensive selection of indicators and models to dynamically visualize urban resilience's spatial distribution. Resilience is dynamic, in harmony with social, economic, and environmental dynamics (Rus et al., 2018; Sajjad, 2021). The proposed model can visualize the dynamic conditions of resilience through simulation. Thus, it allows the formulation of strategies and the evaluation of policies to implement resilience enhancement with reasonable efforts to improve city conditions.

The application of this urban resilience measurement model has several challenges, such as the availability and consistent quality of data to represent indicators at the sub-district level. Generally, sectoral thematic data are available regularly and uniformly at the city and provincial scales but not at the sub-district scale. In addition, the number of samples for the sub-districts is smaller than indicators analyzed, therefore, the analysis is carried out on each dimension. For future studies, similar indicators should be used based on the availability of existing data. The study and field measurements should include simulation scenarios and policy suggestions to improve the application of future study models (Zhang, 2020). Combining resilience results with hazard data/maps for a more comprehensive risk measurement of single or multiple hazards is also a consideration for future research.

Conclusion

This study developed a replicable and robust baseline indicator model to measure and visualize the spatial distribution of resilience in Semarang City. An index system and a web-GIS (index-based spatial dynamic model) were used to determine the urban resilience and spatial distribution. Furthermore, the developed model allows dynamic spatial simulation of the urban resilience index at a sub-district level and can be used by stakeholders who do not have access to GIS applications to carry out assessments of urban resilience.

The factor analysis resulted in the selection of 21 indicators to measure resilience to disasters, grouped in social, economic, infrastructure, environmental, and institutional dimensions. The results of index-based spatial modeling showed that 88% of sub-districts had a score in the

moderate class. Mijen had the highest resilience index value (66.69), categorized in the resilient class. On the other hand, Gayamsari had the lowest resilience index value (29.79), classified in the low-class category. Therefore, it is a priority to increase urban resilience to disasters in Gayamsari. The spatial distribution of resilience in each dimension showed considerable spatial heterogeneity in the coastal and land areas (city center), which had better resilience in the social and infrastructure dimensions than the hilly areas. In the west, the hilly areas had relatively high resilience, while in the east, they had relatively low resilience on each dimension. The spatial distribution of resilience and the model's ability to dynamically perform simulations are useful in providing a quick overview of the condition and determining priorities for increasing resilience in supporting disaster risk reduction programs.

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