Research on Urban Seismic Resilience Assessment System Based on Improved PSR Model

A Case Study of Harbin

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Abstract. This article analyzes the PSR model's features and limitations in assessing urban stability and presents an urban earthquake resistance evaluation system adopting the PSIR model, adding the "impact" factor to assess the robustness of cities. By evaluating the seismic resilience of Harbin from 2021 to 2021, this article analyzes the changes in resilience levels and looks forward to the future application scope and professional improvement of the model.

Keywords: Urban Seismic Resilience, PSR Model, Interdisciplinary Research

1 Introduction

Facing constant earthquake threats, China prioritizes seismic resilience, a concept originating from engineering and now applied in psychology, ecology, and sociology [1-2]. In seismology, it emphasizes prevention, response, recovery, and learning [3]. Studying seismic resilience, crucial for enhancing mitigation and sustainable development, bears theoretical and practical importance [4].

The "Pressure-State-Response" (PSR) model, used in urban seismic resilience assessment, lacks the ability to capture post-earthquake urban disorder. To remedy this, an "Impact" indicator is introduced, forming the "PSIR" framework for assessing Harbin's urban seismic resilience.

2 Current Research Status of Urban Seismic Resilience

Urban seismic resilience, an evolution of Performance-Based Seismic Design (PBSD), broadens the focus from individual buildings to the entire urban system, including infrastructure and services, aiming not just at functionality during earthquakes, but also rapid post-quake recovery. This concept introduces innovative methods like system analysis and risk assessment [5].

Q. Gao et al. (eds.), *Proceedings of the 2024 7th International Conference on Structural Engineering and Industrial Architecture (ICSEIA 2024)*, Atlantis Highlights in Engineering 30,
https://doi.org/10.2991/978-94-6463-429-7_29

Since the 1970s, "resilience" has been defined by C.S. Holling as the capacity to absorb disturbance and maintain stability [2]. The Resilience Alliance introduced the adaptive cycle theory, foundational to seismic resilience research [6]. In 2003, Bruneau extended this to "seismic resilience", emphasizing its Robustness, Redundancy, Resourcefulness, and Rapidity [7]. A formula for community resilience is:

$$R = \int_{t_0}^{t_1} [100 - Q(t)] dt \tag{1}$$

R measures resilience, *Q(t)* reflects community function, and t_0 and t_1 represent earthquake occurrence and restoration. Concurrently, Lili Xie suggested an urban earthquake prevention index considering mortality, economic loss, and recovery speed [8]. Peacock's 2010 resilience framework emphasized economic, social, physical, and human capital [9]. The 2011 Resilience Capacity Index prioritized economy, demographics, and connectivity [10]. In 2016, Cimellaro identified seven factors influencing urban resilience [11]. China's urban resilience research has progressed. Cong Yang created a seismic resilience assessment for urban areas using repair time and recovery paths [12]. Li Xiaoping devised an evaluation system with 24 indicators, assessing 31 shelters' capacities [13].

3 Urban Earthquake Resilience Based on the PSR Model

3.1 The "Pressure-State-Response" (PSR) Model

The PSR model, proposed in the early 1970s, has found applications in various fields like ecology, urban planning, and natural resource management [14]. In PSR model: Pressure refers to external environmental impacts like natural disasters; State represents resilience and vulnerability [16]; Response involving measures. This model reveals the causal relationship between these three elements, emphasizing the dynamic and evolving nature of environmental issues, as shown in Fig 1. The ongoing interaction among them forms an endless process of evolution.

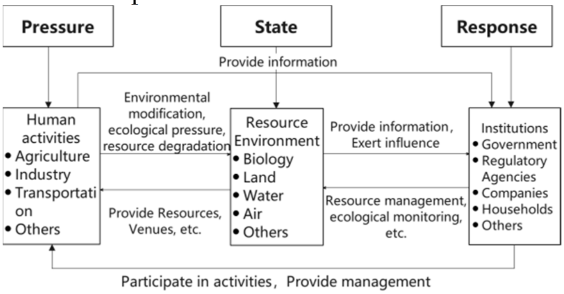

Fig. 1. PSR Model Logical Framework

3.2 Urban Seismic Resilience Process from the PSR Model Perspective

Urban resilience, a cycle of stabilization, recovery, and adaptability, is divided by the PSR model into Pressure (seismic hazard), State (resistance and post-quake status), and

Response (recovery, adaptation, enhancement). Seismic resilience assessment aims for safer, stronger, adaptable cities. The current PSR model misses urban system's anti-interference abilities during quakes. To rectify this, the article suggests an "Impact" factor to evaluate if urban disorder surpasses its threshold. [16].

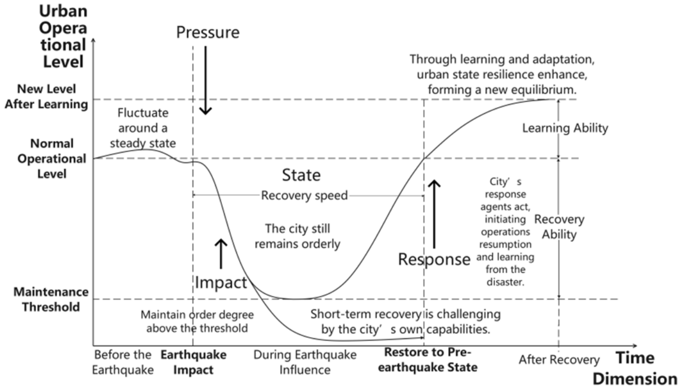

Fig. 2. Schematic Diagram of Urban Resilience Process

Comparing the urban system to a human body, 'Pressure' is akin to pathogens, 'State' symbolizes immunity capacity and speed, 'Impact' denotes endurance, and 'Response' is the post-immune activation reaction. The article categorizes urban seismic resilience into four processes, as shown in Fig 2, and chooses indicators.

4 Resilience Evaluation System Based on PSIR Model

4.1 Principles of indicator selection

Indicators should be chosen based on specific risks and resilience processes, reflecting the system's hierarchy and systematicness. The selection should consider China's current conditions, statistical standards, and existing resilience research[3,17].

4.2 Resilience evaluation indicator system

From the analysis and data from 2012 to 2021, we derived an evaluation indicator system with 4 dimensions, 12 domains, and 47 indicators, as shown in Table 1.

Table 1. Resilience evaluation index

Dimension	Domain	Indicator	Effect	Weight
Pressure	Earthquake Risk	Seismic Fortification Intensity[1]	Negative	6.78%
	Statistical Data	Frequency Above M3.0	Negative	0.91%
		Average Magnitude Above M3.0	Negative	0.96%
State	Resource	Forest Coverage Rate	Positive	0.87%

	Status	Average Green Space	Positive	1.56%
		Average Water Resources	Positive	2.64%
		Average Water Consumption	Negative	2.33%
		Average Electricity Consumption	Negative	1.71%
		Average Carbon Emissions	Negative	1.31%
		Energy Consumption	Negative	1.85%
	Social Status	Aging Index[2]	Negative	1.97%
		New Employment	Positive	3.01%
		Net Migration Rate[3]	Positive	1.45%
		Unemployment Rate	Negative	1.50%
		Natural Population Growth Rate	Positive	0.90%
	Economic Status	Average GDP	Positive	1.67%
		Per Capita Disposable Income of Urban Residents[1]	Positive	1.70%
		Per Capita Deposits	Positive	1.97%
		Engel's Coefficient of Urban Households1	Negative	1.67%
		Industrial Advancement Index[4]	Positive	2.20%
Impact	Early Warning	Television Coverage Rate	Positive	0.81%
		Internet Coverage Rate	Positive	0.95%
	Personal Safety	Population Density[1]	Negative	5.73%
		Average Evacuation Drills Time	Positive	1.47%
		Average Shelter Area	Positive	1.96%
	Secondary fire	Number Of Deaths from Fires	Negative	2.03%
		Amount Of Losses from Fires	Negative	1.26%
	Building Resistance	Rate Of Buildings Constructed After 1990	Positive	1.45%
		Structural Vulnerability[5]	Negative	2.16%
	Infrastructure Status	Per Capita Power Generation	Positive	2.19%
		Daily Water Supply Capacity	Positive	1.71%
		Per Capita Heating Area	Positive	2.16%
		Daily Public Transportation Traffic Volume	Positive	1.36%
		Number Of Public Transportation Vehicles[6]	Positive	1.35%
		Per Capita Paved Road Area	Positive	2.87%
		Per Length of Drainage Pipes	Positive	2.12%
Response	Recovery Capability	Fiscal Revenue	Positive	1.68%
		Fiscal Self-Sufficiency Rate	Positive	1.92%
		Coverage Rate of Basic Medical Insurance[1]	Positive	4.54%
		Hospital Beds Per[6]	Positive	1.91%
		Number Of Health Technicians[6]	Positive	1.96%
		Coverage Rate of Basic Pension Insurance	Positive	2.32%
		Construction Industry Workers[6]	Positive	2.64%
	Adaptability and Learning Ability	University Students [6]	Positive	2.32%
		Number Of Teachers[6]	Positive	3.48%
		Rate Of R&D Expenditure In GDP	Positive	3.03%
		Actual Utilization of Foreign Capital	Positive	3.63%

1. Only data from built-up areas with dense concentrations of population and high building densities are included in the statistics.
2. Ratio of population aged 65+ to labor force aged 15-64.
3. Yearly proportion of net migration to total population in an area.
4. Contribution of each industry: First Industry * 1 + Second Industry * 2 + Third Industry * 3.
5. Maximum vulnerability index for different structural types from Zhiqian Yin's *Basic Content and Disaster Reduction Decision-Making Process of Urban Earthquake Prediction*.
6. These statistics is the average for every 10,000 people.

4.3 Constructing a Model for Urban Seismic Resilience Assessment

4.3.1. Determination of Indicator Weights.

In this study, we use a hybrid approach that combines subjective and objective weighting methods, integrating the Analytic Hierarchy Process (AHP) to evaluate domain-level indicators and employing the Entropy Method for indicators.

Weight of Domain-level Indicators

a. Construction of Hierarchical Structure

A hierarchical chart compares same-level elements using a 1-9 importance scale, resulting in a comparison matrix.

b. Calculation of Weights:

$$\partial w = \frac{w_i}{\sum_i^n w_i} \tag{2}$$

$$w_i = \sqrt[n]{\prod_{j=1}^{n} u_{ij}} \tag{3}$$

Weights of elements at each level are calculated through consistency checks and normalization of comparison matrix's eigenvectors.

c. Consistency Check:

$$CI = \frac{\lambda_{\max} - n}{n-1} \tag{4}$$

$$\lambda_{\max} = \frac{\sum_{i=1}^{n} \lambda_i}{n} \tag{5}$$

$$\lambda_i = \frac{\sum_{j=1}^{n} u_{ij} \partial w_j}{\partial w_j} \tag{6}$$

The consistency ratio evaluates the comparison matrix's rationality. If CI/RI is less than 0.1, the judgment matrix is considered consistent. See Table 2 for results.

Table 2. Domain-Level Weights

Dimension	Domain	AHP Weight	λ	CI	RI	CR
Pressure	Earthquake Risk	0.667				
	Statistical Data	0.333				
State	Resource Status	0.080	3.033	0.016	0.520	0.031

	Social Status	0.265				
	Economic Status	0.656				
Impact	Early Warning	0.080	5.095	0.024	1.120	0.021
	Personal Safety	0.093				
	Secondary fire	0.047				
	Building Resistance	0.497				
	Infrastructure Status	0.283				
Response	Recovery Capability	0.800				
	Adaptability and Learning Ability	0.200				

Weight of Indicator-level Indicator

a. Original Matrix

Construct a matrix, with xij representing the value of the jth indicator in the ith year.

$$A=\begin{pmatrix} x_{11} & \cdots & x_{1m} \\ \vdots & \ddots & \vdots \\ x_{n1} & \cdots & x_{nm} \end{pmatrix}=\left(x_{ij}\right)_{nxm} \tag{7}$$

$$(i=1,2,3,\ldots,n;\ j=1,2,3,\ldots m)$$

b. Data Standardization

For positive indicators, the formula is:

$$x'_{ij}=\frac{x_{ij}-\min\{x_{1j},\ldots x_{nj}\}}{\max\{x_{1j},\ldots x_{nj}\}-\min\{x_{1j},\ldots x_{nj}\}} \tag{8}$$

For negative indicators, the formula is:

$$x'_{ij}=\frac{\max\{x_{1j},\ldots x_{nj}\}-x_{ij}}{\max\{x_{1j},\ldots x_{nj}\}-\min\{x_{1j},\ldots x_{nj}\}} \tag{9}$$

c. Calculation of Information Entropy Value of Indicators:

$$p_{ij}=\frac{x'_{ij}}{\sum_{i=1}^{n}x'_{ij}} \tag{10}$$

$$Y_j=-\frac{1}{\ln n}\sum_{i=1}^{n}p_{ij}\ln p_{ij} \tag{11}$$

d. Calculation of Indicator Weights:

$$Z_j=\frac{1-Y_j}{m-\sum_{j=1}^{m}Y_j} \tag{12}$$

The indicators weights are shown in Table 1.

Determination of Combined Weights:

The combined weights are determined as follows:

$$W_j=\partial w_j\times Z_j \tag{13}$$

4.3.2. Calculation of Resilience Levels

Let "Pressure Resilience" be denoted as Q_P, "State Resilience" as Q_S, "Impact Resilience" as Q_I, and "Response Resilience" as Q_R. Then, we have:

$$Q = Q_P + Q_S + Q_I + Q_P = \sum W_j P_{ij} \tag{14}$$

The earthquake resilience of Harbin from 2021 to 2021 is shown in Table 3.

Table 3. Top 10 Indicators Ranked by Weight

Year	Pressure Resilience	State Resilience	Impact Resilience	Response Resilience	Urban Seismic Resilience
2012	0.01186	0.00517	0.00255	0.00980	0.02871
2013	0.01144	0.00661	0.00312	0.01406	0.03391
2014	0.01183	0.00763	0.00552	0.01359	0.03614
2015	0.01184	0.00847	0.00763	0.01568	0.04022
2016	0.00039	0.00931	0.01041	0.01264	0.02831
2017	0.00052	0.01078	0.01293	0.01911	0.03729
2018	0.00044	0.01223	0.01757	0.01867	0.04123
2019	0.00054	0.01111	0.01868	0.01790	0.04041
2020	0.00063	0.01012	0.01772	0.01790	0.04001
2021	0.00067	0.01211	0.02161	0.02134	0.04644

4.3.3. Correlation Analysis

The Pearson correlation coefficient, which measures the correlation between two variable sets, can be used. Its formula is:

$$\rho = \frac{N\sum x_i y_i - \sum x_i \sum y_i}{\sqrt{N\sum x_i^2 - (\sum x_i)^2} - \sqrt{N\sum y_i^2 - (\sum y_i)^2}} \tag{15}$$

If data doesn't meet Pearson's criteria, we use Spearman's coefficient, where $R(x_i)$ and $R(y_i)$ denote x_i's and y_i's ranks:

$$d = \sum_{i=1}^{N} \left| R(x_i) - R(y_i) \right|^2 \tag{16}$$

$$\rho = 1 - \frac{6d}{N \times (N^2 - 1)} \tag{17}$$

When both correlation coefficient indicate no correlation, it is concluded that there is no correlation between the two sets of data. The conclusion is shown in Table 4.

Table 4. Correlation Coefficient to Urban Seismic Resilience

		Pressure	State	Impact	Response
Pearson	Correlation Co-efficient	-0.372	0.734^{*}	0.749^{*}	0.898^{**}
	ρ	0.29	0.016	0.013	0
	Conclusion	Non-Correlation	Positive Correlation	Positive Correlation	Significant Positive Correlation
Spear-man	Correlation Co-efficient	-0.127	0.794^{**}	0.770^{**}	0.818^{**}
	ρ	0.726	0.006	0.009	0.004

Conclusion	Non-Correlation	Positive Correlation	Significant Positive Correlation	Significant Positive Correlation

4.3.4. Investigating Indicator Correlations

This study uses the Grey Relational Analysis (GRA) method, which uses resilience levels as the parent series and each indicator as a subsequence to compute their correlation coefficient, to examine system uncertainty.

$$\zeta_i(j)=\frac{\underset{i}{\min}\,\underset{j}{\min}\left|Q_i-x_i'(j)\right|+\rho*\underset{i}{\max}\,\underset{j}{\max}\left|Q_i-x_i'(j)\right|}{\left|Q_i-x_i'(j)\right|+\rho*\underset{i}{\max}\,\underset{j}{\max}\left|Q_i-x_i'(j)\right|} \tag{18}$$

$$r_j=\frac{W_j*\sum_{i=1}^{n}\zeta_i(j)}{n} \tag{19}$$

The average correlation coefficients over time show the relationship between resilience and indicators. Higher correlation means greater contribution to resilience levels. Table 5 shows the top 10 indicators by correlation.

Table 5. Top 10 Indicators Ranked by Correlation Coefficients

Indicator	**Average Correlation Coefficients**	**Ranking**
Seismic Fortification Intensity	0.7297	1
Population Density[1]	0.7192	2
Average Water Resources	0.6777	3
Number Of Teachers	0.6772	4
Proportion Of R&D Expenditure In GDP	0.6599	5
Coverage Rate of Basic Medical Insurance	0.6535	6
Actual Utilization of Foreign Capital	0.6522	7
Construction Industry Workers	0.6414	8
New Employment	0.6363	9
Average Water Consumption	0.6243	10

5 Conclusions

This article uses the PSIR model to create a seismic resilience evaluation system for Harbin City, with four levels, 12 areas, and 47 indicators. From 2012 to 2021, Harbin's resilience improved despite fluctuations due to China's seismic intensity zoning in 2016 and the 2020 pandemic. Analysis shows a positive correlation between urban resilience and the levels of "status", "impact", and "response", but not "pressure resilience". This model helps decision-makers and urban planners understand urban seismic resilience and its key factors. It guides the enhancement of seismic capacity through urban planning, building renovation, structural design, and emergency response mechanisms.

The system's limitations stem from its disregard for urban subsystems' interactions and reliance on abstract, large-scale data. This leads to abstract results, subjective indicator selection, and calculation errors, complicating its use in urban planning and disaster prevention. Its flexible indicator selection and weight assessment limit city comparability, restricting its widespread use. [18-20]. Future research can include:

a. Apply the evaluation to other provincial capital cities like Shenyang and Changchun, compare resilience levels, and analyze differences.
b. Integrates professional models to assess urban subsystems' seismic resilience, such as identify earthquake risks through surveys, and calculate seismic resistance by examining infrastructure distribution.

Acknowledgments

This paper is financially supported by the Key R&D Program of Heilongjiang Province (Grant No. GA22C001) and the Scientific Research Fund of the Institute of Engineering Mechanics, the China Earthquake Administration (Grant No. 2021EEEVL0203).

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