Towards Socioeconomic Centered Resilience Modeling and Assessment of Critical Infrastructure Systems

Joseph Jonathan Magoua, Nan Li
Department of Construction Management, Tsinghua University, Beijing, China
nanli@tsinghua.edu.cn (Lead author email address)

Abstract. The resilience of critical infrastructure systems (CISs), which provide essential services such as energy, water, transportation, and communication, is crucial to the smooth functioning of modern societies. However, literature shows that the impact of disasters and recovery efforts of CISs are not evenly distributed among communities, leading to disparities in their resilience levels. This study uses data from a case study of a middle-sized county in China, which suffered a severe earthquake disaster, to measure the resilience disparities across different communities and analyze the correlation between socioeconomic and infrastructure resilience variables. The study also introduces a model to estimate the vulnerability of different communities served by the same large-scale CISs. The findings contribute to understanding the hidden influence mechanisms between socioeconomic factors and CISs resilience, and are expected to inform the development of advanced CISs resilience modeling and enhancement methods from a socio-technical perspective.

1. Introduction

Critical infrastructure systems (CISs) are the backbone of modern societies and ensure the provision of essential services such as energy, water, transportation, and communication. The resilience of CISs has become a major concern for decision-makers and policy makers due to the increasing frequency and severity of natural and human-made disasters. The ability of CISs to absorb and recover from disruptive events is critical to maintaining the smooth functioning of society and avoiding catastrophic consequences (Davis Craig, 2021).

CISs resilience depends on a multitude of factors, such as management and planning, operational procedures, and community preparedness (Magoua and Li, 2023). These factors are crucial in strengthening CISs ahead of disasters and in ensuring a speedy recovery process after a disruptive event. However, literature reveals that disaster impact and recovery efforts of CISs are usually not balanced across different communities, leading to disparities in the level of CISs resilience of the communities (Masozera et al., 2007, Emrich et al., 2020). In particular, communities with weaker socioeconomic status tend to suffer more infrastructure damages and recover slower. These may include communities with lower infrastructure investments, lower rates of urbanization and industrialization, and so on.

Socioeconomic inequity, therefore, has a considerable impact on the resilience of CISs, and understanding the hidden influence mechanisms is crucial to improving CISs resilience management. Prior studies adopt a holistic perspective when modeling and assessing the resilience of CISs that span multiple service areas or communities (Ouyang and Wang, 2015, Mottahedi et al., 2021). However, a holistic measure of the CISs resilience does not reflect the considerable imbalance of CISs resilience of individual service areas.

This study introduces a method to quantitatively analyze the relationship between the infrastructural resilience and socioeconomic status of communities. It employs data on infrastructure resilience and socioeconomic variables from a case study of a middle-sized county in China, which experienced a severe earthquake disaster. The research investigates the variation in the resilience of infrastructure across different communities and analyzes the association between socioeconomic variables and infrastructure resilience variables. Furthermore, it introduces a model that estimates the resilience poverty of different communities that rely on the same large-scale CISs.

The findings and discussion of this study will contribute to informing researchers and professionals in the area of CISs resilience management about the hidden influence mechanisms existing between socioeconomic factors and CISs resilience. At the same time, this study will lay the foundation for developing more advanced CISs resilience modeling and resilience enhancement methods from a socio-technical perspective.

2. Literature Review

Several studies have highlighted the critical role of socioeconomic factors in shaping the vulnerability of communities served by CISs (Cutter et al., 2008, Karakoc et al., 2020, Norris et al., 2008). These studies emphasize that socioeconomically disadvantaged communities are more vulnerable to disasters and less likely to recover afterward. Socioeconomic vulnerability refers to a range of factors that affect an individual or group's ability to anticipate, cope with, resist, and recover from the impact of a hazard (St. Cyr, 2005).

A number of studies take a social approach to model socioeconomic vulnerability, utilizing individual and group characteristics to represent the inherent vulnerabilities of specific communities. For instance, Cutter et al. (2003) Social Vulnerability Index (SoVI) identifies socially vulnerable groups based on ethnicity, race, education, and gender and aggregates individual social characteristics to create a final index. Such studies emphasized on the importance of addressing the unique needs of vulnerable communities and laid the foundation for studies that integrate socioeconomic factors in CISs resilience assessment. For instance, Karakoc et al. (2020) proposed a method to determine system component importance based on the social vulnerability of the served communities, while Dhakal and Zhang (2023) developed a method to measure the resilience of CISs that serve multiple service areas, accounting for disparities in disaster impacts.

While an increasing number of studies attempt to model the role of communities in CISs' disaster resilience, few provide a clear understanding of the relationship between community socioeconomic status and resilience. This is because the social factors typically examined in these studies, such as race, gender, and age groups, only partially explain the interactions between communities and CISs. Therefore, there is a need to identify a more comprehensive set of socioeconomic factors that can better explain CISs resilience disparities across different communities. For instance, factors such as employment rates, percentage of the population involved in various industry sectors, and per capita income can provide a better understanding of how infrastructure services are utilized in specific service areas. By gaining a deeper insight into the complex relationship between communities and infrastructure systems, more effective pre-disruption preparedness plans and post-disruption restoration schedules can be developed to achieve equitable CISs' resilience across different communities.

3. Proposed Methodology

To quantitatively analyze the relationship between socioeconomic factors and the resilience of Critical Infrastructure Systems (CISs), this study will follow a series of steps. First, the study will identify a set of socioeconomic variables that characterize the level and quality of interactions between communities and CISs in the context of Chinese societies. Then, the study will identify a set of variables that characterize the resilience of CISs within different communities. Subsequently, the infrastructure resilience variables will be utilized to verify and measure the disparities in CISs resilience among different service areas. Following this, a correlation analysis will be conducted to analyze the relationship between the socioeconomic variables and infrastructure resilience variables. Finally, the study will propose a model to measure the vulnerability of CISs within each community based on the identified socioeconomic variables. The details of each of these steps are provided below. It is important to mention that in the proposed methodology communities refer to the various towns or geographical areas served by the same large-scale CISs.

3.1 Socioeconomic Data

Unlike previous studies that focus on analyzing the social profiles of individuals within communities, such as their ethnicity, occupation, and age groups, this study aims to analyze the socioeconomic factors that determine the interaction between communities and CISs. To achieve this, a set of eight socioeconomic variables were selected based on three criteria: they characterize the level and type of interaction that communities have with CISs, they are consistent with the context of Chinese societies, and the data is publicly available with sufficient granularity. These variables are listed and briefly explained in Table 1.

Table 1: List of Socioeconomic Variables and their Explanations.

Variable	Name	Explanation
S1	Percentage population living in urban area	Reflects the level of occupancy of the urban area in a service area and the use of urban infrastructure services.
S2	Percentage population working in secondary and tertiary sectors	Provides insight into the industrial focus of a service area and the main use cases of infrastructure services.
S3	Percentage unemployed population	Provides insight into the level of infrastructure services usage by individuals and families
S4	Urbanization level	Reflects the level of development of urban infrastructure services.
S5	Gross domestic product	Reflects the economic potential of communities and their ability to support infrastructure investments.
S6	Number of industrial enterprises	Provides insight into the level of infrastructure services usage by enterprises.
S7	Number of township committees	Reflects the ability of communities to organize themselves and influence major infrastructure investment decisions.
S8	Per capita income	Provides insight into the level of infrastructure services usage by individuals and families.

Data for each community can be collected from the statistical yearbooks published by the local government, which provide high-quality, reliable, and granular data. To identify and address any multicollinearity issues between the socioeconomic variables, the study will calculate the Variance Inflation Factor (VIF) for each variable. A strict VIF range from 1 to 4 indicates no significant issue of multicollinearity, while a moderate range from 1 to 10 can be adopted in studies with limited data. If the VIF values exceed the upper limits, the most common solution is to eliminate the variable causing the multicollinearity issue from the dataset (Chan et al., 2022).

3.2 Infrastructure Resilience Data

Infrastructure resilience refers to the ability of infrastructure systems to withstand and recover from natural disasters or other disruptions. It can be measured by several characteristics such as robustness, rapidity, resourcefulness, and redundancy (Bruneau and Reinhorn, 2006). These characteristics can be further represented by specific dimensions, such as functional loss, recovery time, economic resources, and alternate plans. In previous studies, functional loss, recovery time and recovery cost are the most used variables to represent the resilience of CISs. As such, in this study, functional loss, recovery time, and reconstruction cost of infrastructure were selected as three indicators of infrastructure resilience. Functional loss refers to the loss of infrastructure services due to disaster damage, while recovery time and reconstruction cost refer to the time and resources required to restore the infrastructure to its pre-disaster state.

Table 2: List of Infrastructure Resilience Variables and their Explanations.

Variable	Name	Explanation
R1	Percentage of infrastructure service outage	Loss of infrastructure services to a specific community due to disaster damage.
R2	Recovery time of infrastructure service	Time required for the infrastructure services to be recovered to its full functional level in a specific community.
R3	Recovery and reconstruction costs of infrastructures	Amount invested in repairing and rehabilitating the infrastructures serving a specific community.

Data for each indicator can be collected from various public or private sources, including utility companies, urban development planning departments, and disaster risk management departments. In cases where data is limited, for example, if data about the damaged infrastructure system components is known but the resultant functionality loss in each community is unknown, simulation models based on High Level Architecture (HLA) co-simulation of physics-based infrastructure models can be used to estimate missing data (Magoua et al., 2022). The layout of the simulation model is presented in Figure 1 below, consisting of multiple CIS federates and a runtime infrastructure (RTI) middleware. CIS federates simulate the states and flow of services within CISs based on domain-specific knowledge, while the RTI manages data exchange, synchronization, and coordination services during federation execution (IEEE, 2010). Using this model, functional loss and recovery time of CISs can be reasonably estimated while considering the interdependencies between systems. For further technical details refer to (Magoua et al., 2022, Yang et al., 2023).

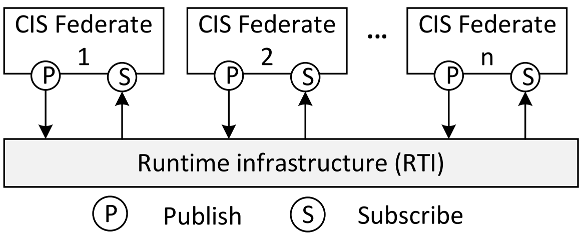

Figure 1: HLA Federation Architecture for Modeling CISs

3.3 Measuring Resilience Inequality

In an ideal society, all communities would be affected equally by disasters and would recover in similar timeframes if they face the same level of threat. However, in reality, communities are impacted differently, even under the same threat level. This unequal distribution of infrastructure loss and recovery time is similar to the welfare inequality in society. To measure this inequality, the Gini coefficient, which is commonly used to measure social welfare inequality, can be used (Atkinson and Brandolini, 2010). In this study, the Gini coefficient is used to measure the unequal distribution of functional loss, recovery time, and reconstruction costs among different communities. The coefficient ranges from 0 to 1, with 0 indicating complete equality and 1 indicating complete inequality in disaster resilience.

3.4 Correlation Analysis

To investigate the relationship between the socioeconomic status of communities and infrastructure resilience, a correlation analysis was conducted. The Pearson's product-moment correlation coefficient was used to examine the relationship between two continuous variables. The strength of a linear association between two variables was measured by Pearson's correlation, and the results were interpreted based on both the correlation coefficients and the p-value. The magnitude of the correlation coefficient determines the strength of the association, with a high, medium, or small association based on the absolute value of the correlation coefficient. When conducting hypothesis tests, commonly used significance levels for p-values are 0.1, 0.05, or 0.01. To account for small sample size, this study selects a p-value significance level of 0.1.

3.5 Measuring CISs Resilience Poverty

This study uses the term "resilience poverty" to describe the likelihood of a community having lower infrastructure resilience compared to neighboring communities. To calculate the resilience poverty of a community's infrastructure, the proposed method adapts the Social Vulnerability Index (SoVI) developed by Cutter et al. (2003). The approach identifies the socioeconomic factors that affect infrastructure resilience and formulates them into a final aggregated index, which describes the cumulative effect of individual socioeconomic characteristics.

Using the set of socioeconomic variables presented in Table 1 above, the resilience poverty (Res_P) can be formulated as follows:

$$Res\_P = 1 - \delta \tag{1}$$

$$\delta = \sum ZS_i \tag{2}$$

Here, δ is an additive model that generates a composite infrastructure resilience score for each community. An additive model with equal weights for all variables is selected to avoid any a priori assumption of the importance of each factor in the overall sum. ZS_i represents the Z-score calculation of socioeconomic variable S_i. Z-scores, also known as standard scores, provide a statistical method for normalizing different variables onto a similar numeric scale. A Z-score is calculated as follows:

$$Zscore = (q - \mu)/\sigma \tag{3}$$

where q is the normalized value of a variable in a given community, μ is the mean for that same variable across all communities, and σ is the standard deviation of that same variable across all communities.

4. Case Study

This section presents a case study of Mianzhu County's interdependent power and water systems. Mianzhu is a county in China's Sichuan Province, covering an area of 1,245 square kilometers and inhabited by around 500,000 people in 21 towns. In 2008, the county was struck by a devastating 8.0 magnitude earthquake, known as the "5-12" Wenchuan Earthquake, which caused significant damage to Mianzhu's infrastructure systems. The power and water distribution systems were particularly affected, with 11 major power substations, 14 water pumping stations, and 341 kilometers of water supply pipes destroyed, leading to extensive economic and humanitarian impacts. The direct economic losses to the power and water utilities were estimated to be over 3.4 billion yuan (approximately 480 million USD) (MLG, 2020). Table 3 summarizes the socioeconomic data of the 21 towns of Mianzhu County.

Table 3: Summary of the socioeconomic data of the 21 towns of Mianzhu County.

Towns	Socioeconomic variables							
	S1 (%)	**S2 (%)**	**S3 (%)**	**S4 (%)**	**S5 (￥)**	**S6**	**S7**	**S8 (￥)**
Jiannan	100.00	67.68	32.32	100.00	1,539,880,024	7	3	12,500
Dongbei	17.08	54.39	34.22	21.00	430,396,488	64	9	8,430
Xinan	57.81	29.29	58.29	33.32	360,005,136	19	6	5,250
Xinglong	4.80	30.75	41.22	5.29	383,745,716	13	5	4,500
Jiulong	8.39	35.32	38.33	3.78	235,766,316	15	4	3,850
Zundao	9.20	34.12	40.96	21.59	413,597,100	15	10	7,840
Hanwang	47.05	52.50	34.10	45.51	689,264,624	41	11	8,125
Gongxing	30.10	31.98	40.92	16.03	378,401,424	15	6	4,795
Tumen	8.01	46.34	32.74	39.72	516,863,300	27	9	4,500
Guangji	7.93	29.19	36.49	4.30	456,159,808	20	6	5,284
Jinhua	17.55	31.30	52.10	9.84	121,428,276	8	7	6,884
Yuquan	7.43	39.53	28.16	4.71	385,278,740	15	7	4,753
Banqiao	13.67	29.44	34.33	17.86	343,929,676	18	7	4,567
Xinshi	30.03	24.92	31.59	30.00	736,767,076	37	13	9,680
Lide	32.46	36.59	35.80	16.28	982,114,792	58	16	5,610
Fuxin	7.31	32.21	38.53	22.80	718,477,248	52	11	4,450
Qitian	7.08	23.73	30.89	10.21	308,073,948	10	5	4,723
Shendi	6.17	42.64	28.14	20.20	477,025,968	26	7	3,900
Mianyuan	5.24	25.34	56.93	4.08	308,542,372	10	4	4,743
Qingping	46.79	36.49	41.66	4.92	117,404,088	6	5	4,430
Tianchi	3.52	50.85	39.36	4.47	60,426,696	22	5	3,973

Data about the damages suffered by Mianzhu's power and water systems following the "5-12" Wenchuan Earthquake were collected from the county's power and water utility companies. Information about the post-disaster reconstruction plans and cost was also collected. Missing data about power/water outage levels and restoration time in the towns were estimated using HLA-based co-simulation. A pressure-driven hydraulic model was used to analyze the water system, which was simulated using the EPANET software. On the other hand, a power flow analysis model was used to analyze the power system, which was simulated using the OpenDss software. Both EPANET and OpenDss are well-tested engineering tools highly adopted among professionals and researchers for analyzing water and power supply systems. Table 4 summarizes the infrastructure resilience data of Mianzhu County's power and water systems following the "5-12" Wenchuan Earthquake.

Table 4: Summary of the infrastructure resilience data of Mianzhu county's power and water CISs.

<table>
<tr><th rowspan="2">Towns</th><th colspan="3">Water System</th><th colspan="3">Power System</th></tr>
<tr><th>R1 (%)</th><th>R2 (days)</th><th>R3 (x10000 ¥)</th><th>R1 (%)</th><th>R2 (days)</th><th>R3 (x10000 ¥)</th></tr>
<tr><td>Jiannan</td><td>57.12</td><td>7</td><td>4,200</td><td rowspan="21">100.00</td><td>13</td><td>7,800</td></tr>
<tr><td>Dongbei</td><td>37.12</td><td>14</td><td>1,084</td><td>20</td><td>2,200</td></tr>
<tr><td>Xinan</td><td>20.97</td><td>28</td><td>1,230</td><td>3</td><td>1,020</td></tr>
<tr><td>Xinglong</td><td>83.02</td><td>31</td><td>257</td><td>20</td><td>93</td></tr>
<tr><td>Jiulong</td><td>63.96</td><td>49</td><td>1,961</td><td>105</td><td>200</td></tr>
<tr><td>Zundao</td><td>82.36</td><td>48</td><td>1,026</td><td>20</td><td>938</td></tr>
<tr><td>Hanwang</td><td>55.58</td><td>28</td><td>1,048</td><td>48</td><td>12,000</td></tr>
<tr><td>Gongxing</td><td>0.00</td><td>0</td><td>0</td><td>30</td><td>675</td></tr>
<tr><td>Tumen</td><td>0.00</td><td>0</td><td>0</td><td>20</td><td>1,350</td></tr>
<tr><td>Guangji</td><td>98.79</td><td>35</td><td>413</td><td>3</td><td>257</td></tr>
<tr><td>Jinhua</td><td>100.00</td><td>87</td><td>300</td><td>27</td><td>310</td></tr>
<tr><td>Yuquan</td><td>100.00</td><td>28</td><td>400</td><td>3</td><td>81</td></tr>
<tr><td>Banqiao</td><td>100.00</td><td>28</td><td>400</td><td>3</td><td>100</td></tr>
<tr><td>Xinshi</td><td>100.00</td><td>48</td><td>1318</td><td>10</td><td>3,960</td></tr>
<tr><td>Lide</td><td>44.90</td><td>35</td><td>3740</td><td>10</td><td>760</td></tr>
<tr><td>Fuxin</td><td>100.00</td><td>48</td><td>196</td><td>27</td><td>90</td></tr>
<tr><td>Qitian</td><td>0.00</td><td>0</td><td>0</td><td>35</td><td>200</td></tr>
<tr><td>Shendi</td><td>93.92</td><td>31</td><td>349</td><td>35</td><td>320</td></tr>
<tr><td>Mianyuan</td><td>89.97</td><td>63</td><td>162</td><td>30</td><td>350</td></tr>
<tr><td>Qingping</td><td>98.15</td><td>87</td><td>952</td><td>65</td><td>100</td></tr>
<tr><td>Tianchi</td><td>0.00</td><td>0</td><td>0</td><td>105</td><td>100</td></tr>
</table>

Analysis of the Gini coefficient for each infrastructure resilience variable in each system (Table 5) reveals that there were significant inequalities in the resilience levels of the CISs across the different towns. For reference, $G < 0.2$ represents perfect equality, 0.2 – 0.3 represents relative equality, 0.3 – 0.4 represents adequate equality, 0.4 – 0.5 represents a big gap, and $G > 0.5$ represents a severe gap (Atkinson and Brandolini, 2010). The Gini coefficient for variables R2 and R3 ranked above 0.4 in both systems, demonstrating major infrastructure resilience gaps across Mianzhu's towns. The Gini coefficient of 0.33 for variable R1 in the water system shows adequate infrastructure resilience equality across the towns for this variable. The Gini coefficient of 0 was obtained for variable R1 in the power system since all the towns experienced 100% loss of power supply following the earthquake disaster. The above results may indicate that the robustness of the infrastructures across the county was comparable; however, the recovery and reconstruction efforts were not evenly distributed.

Table 5: Analysis results of the Gini coefficient for the infrastructure resilience variables.

	Water System			**Power System**		
	R1	**R2**	**R3**	**R1**	**R2**	**R3**
G	0.33	0.42	0.59	0.00	0.47	0.73

After testing the socioeconomic variables for multicollinearity issues using VIF, variable S1 was eliminated from the dataset to solve a moderate issue of multicollinearity that was identified. The remaining dataset was used to conduct a correlation analysis with infrastructure resilience variables. Considering the p-value significance at 0.1, we observe from Table 6 that several investigated relationships showed a significant correlation.

In the water system, R3 demonstrated a significant and strong correlation with S4 ($r = 0.590$; $p = 0.005$), S5 ($r = 0.750$; $p = 0.000$), and S8 ($r = 0.596$; $p = 0.004$), and a medium correlation with S2 ($r = 0.437$; $p = 0.048$). The variable R2 demonstrated significant and medium correlation with S2 ($r = -0.400$; $p = 0.072$) and S3 ($r = 0.457$; $p = 0.037$). The variable R1 did not show any significant correlation with any of the socioeconomic variables.

In the power system, R3 demonstrated a significant and strong correlation with S2 ($r = 0.580$; $p = 0.006$), S4 ($r = 0.731$; $p = 0.000$), S5 ($r = 0.594$; $p = 0.005$), and S8 ($r = 0.714$; $p = 0.000$). The variable R2 demonstrated a significant and medium correlation with S5 ($r = -0.416$; $p = 0.060$). The correlation with variable R1 was not analyzed in the power system since the entire county experienced complete power failure following the earthquake disaster.

Table 6: Correlation analysis results between socioeconomic variables and infrastructure resilience variables for the water and power systems (Blue: strong correlation; Orange: medium correlation).

	Water System		**Power System**			**Water System**		**Power System**	
Relationship	**r**	**p**	**r**	**p**	**Relationship**	**r**	**p**	**r**	**p**
R1 versus S2	-0.267	0.242	-	-	R2 versus S6	-0.162	0.482	-0.148	0.523
R1 versus S3	0.010	0.967	-	-	R2 versus S7	0.070	0.762	-0.324	0.152
R1 versus S4	-0.170	0.461	-	-	R2 versus S8	-0.047	0.839	-0.318	0.160
R1 versus S5	0.022	0.926	-	-	R3 versus S2	0.437	0.048	0.580	0.006
R1 versus S6	-0.091	0.696	-	-	R3 versus S3	-0.135	0.559	-0.232	0.311
R1 versus S7	0.081	0.728	-	-	R3 versus S4	0.590	0.005	0.731	0.000
R1 versus S8	0.078	0.738	-	-	R3 versus S5	0.750	0.000	0.594	0.005
R2 versus S2	-0.400	0.072	0.191	0.406	R3 versus S6	0.199	0.388	0.210	0.361
R2 versus S3	0.457	0.037	0.043	0.855	R3 versus S7	0.217	0.345	0.199	0.388
R2 versus S4	-0.336	0.136	-0.272	0.234	R3 versus S8	0.596	0.004	0.714	0.000
R2 versus S5	-0.264	0.247	-0.416	0.060					

Collectively, the results above may imply that R3 has the strongest correlation with socioeconomic variables compared to other infrastructure resilience variables. Towns with higher urbanization level, GDP and per capita income were likely to be allocated more resources for the recovery and reconstruction of their infrastructures. For R2, results showed a negative correlation between levels of urbanization and industrialization and recovery time, which could be explained by more complex recovery processes and higher demand for infrastructure services in more developed regions. Finally, the study results did not show any strong relationship between the socioeconomic variables and the loss of infrastructure services in different towns (R1) in this particular case study.

Lastly, following the correlation analysis presented above, the infrastructure resilience poverty of each town in Mianzhu county was calculated. The sign of each variable in the additive model δ was determined based on the variable's coefficient in a linear regression model. The resilience poverty scores were rated high (> 0.70), medium (0.30 – 0.70) and low (< 0.30). The results are presented in Table 7 below.

Table 7: Infrastructure resilience poverty scores of Mianzhu County's towns.

Community	Res_P	Rating	Community	Res_P	Rating
Jiannan	0.00	Low	Yuquan	0.65	Medium
Dongbei	0.28	Low	Banqiao	0.71	High
Xinan	0.83	High	Xinshi	0.32	Low
Xinglong	0.83	High	Lide	0.27	Low
Jiulong	0.84	High	Fuxin	0.47	Medium
Zundao	0.59	Medium	Qitian	0.80	High
Hanwang	0.23	Low	Shendi	0.57	Medium
Gongxing	0.76	High	Mianyuan	1.00	High
Tumen	0.47	Medium	Qingping	0.88	High
Guangji	0.74	High	Tianchi	0.76	High
Jinhua	0.86	High			

5. Conclusion

This study has presented a method for quantitatively analyzing the relationship between infrastructure resilience and the socioeconomic status of various towns in a middle-sized county in China following the "5-12" Wenchuan Earthquake. Our findings indicate significant inequalities in the resilience levels of the CISs across different towns, with more developed towns more likely to receive more resources for infrastructure recovery. The study highlights the need for a more nuanced approach to CISs resilience modeling that considers the varying resilience levels of individual service areas. Furthermore, the study provides a foundation for developing more advanced resilience enhancement methods from a socio-technical perspective, which can help decision-makers and policy-makers better allocate resources and improve the overall resilience of CISs.

Future research should expand the scope of this study by examining other case studies and investigating the factors that contribute to disparities in resilience across communities, and explore community-based approaches to resilience management. Overall, this study adds to the literature on CISs resilience and provides valuable insights for improving resilience in the face of disasters.

6. Acknowledgments

This material is based on work supported by the National Natural Science Foundation of China (NSFC) under Grant No. 72242107, and the Beijing Natural Science Foundation (BJNSF) under Grant No. 8202027. The authors are grateful for the support of NSFC and BJNSF. Any opinions, findings, and conclusions, or recommendations expressed in this paper are those of the authors and do not necessarily reflect the views of the funding agencies.

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