【原著論文】

How does community disaster resilience affect individual resilience?
An empirical analysis of Japanese prefectures

地域の災害レジリエンスは個人のそれにどう影響するか：都道府県データによる実証分析

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SUMMARY

This study empirically analyzed the impact of community disaster resilience on individual resilience. It employed quantitative empirical analysis using cross-sectional data from 47 Japanese prefectures to examine the extent to which the level of community resilience in Japanese prefectures affects the Disaster Resilience Scale for Individuals (DRSi), based on individual surveys across Japan. The analysis used a multilevel resilience model in which community-level resilience and personal attributes at the individual level determine DRSi. The primary conclusion was that community resilience decreased individual resilience to some extent. This is the first study to identify trade-offs between community and individual resilience and recommend strategic decisions to build resilience at the community and individual levels.

Key words

Sustainable recovery, individual disaster resilience, community disaster resilience, disaster risk reduction, multilevel analysis

要約

本研究では，地域社会の災害レジリエンスが個人のレジリエンスに与える影響について実証分析を行う．日本の47都道府県の横断データを用いた定量的実証分析により，日本の都道府県の地域社会のレジリエンスレベルが，松川ら（2024）が日本全国の個人調査に基づいて開発したDisaster Resilience Scale for Individuals（DRSi）にどの程度影響を与えるかを調査する．この分析では，コミュニティ（都道府県）レベルのレジリエンスと個人レベルの個人属性がDRSiを決定する，マルチレベル・レジリエンス・モデルを用いている．我々の第一の結論は，コミュニティのレジリエンスが個人のレジリエンスを低下させるということである．これは，コミュニティと個人のレジリエンスの間のトレードオフを発見し，コミュニティと個人のレベルという異なるレイヤーでレジリエンスを構築するための戦略的決定を推奨する初めての研究である．

1. Introduction

The increasing frequency and intensity of disasters and climate extremes over the past 50 years has highlighted the importance of building disaster resilience. As the global cost of disasters continues to increase, it is essential to enhance community resilience to effectively mitigate its adverse effects, ensure swift recovery, and address future global challenges.

This concern has driven numerous studies[1],[2] to develop metrics for measuring disaster resilience, most of which focus on community resilience[3],[4] for two main reasons. First, communities play a pivotal role in managing disaster response and recovery efforts, including evacuation, rescue operations, shelter provision, and the formulation of recovery strategies. Second, the contrasting outcomes observed post-disaster — where some communities face decline and loss of residents and economic activities, whereas others experience unprecedented growth — have led scholars to recognize communities' resilience.

However, some studies also focused on individual resilience[5],[6]. Even within the same community, there is a notable disparity between individuals who can cope and recover from disasters and those who cannot, suggesting that individuals have different levels of resilience. Thus, our research question explores the relationship between community and individual resilience. Community resilience is more than the sum of individual resilience[7]; it is regarded as the result of complex synergy among social networks, support systems, and communal resources. Individual resilience is essential to community resilience; it plays a crucial role in a community because the bonds among community members and the altruistic behavior of individuals are regarded as the source of community resilience.

Therefore, assuming that community and individual resilience interact is reasonable. However, few studies have attempted to demonstrate this relationship empirically, and this knowledge gap hinders the development of effective strategies to bolster resilience at both levels.

Thus, this study empirically analyzes the relationship between community and individual resilience using a multilevel analysis. This approach aims to provide a comprehensive understanding of the interplay between these two levels of resilience, particularly the effect of community resilience on individual resilience.

This study employs a quantitative empirical analysis using cross-sectional data from 47 Japanese prefectures to examine the extent to which the level of community resilience affects the Disaster Resilience Scale for Individuals (DRSi) developed by Matsukawa et al. (2024)[5], based on responses from 10,000 individuals nationwide. We also incorporated socioeconomic statistics at the prefectural level as an indicator of community resilience. We used Japanese data owing to their availability.

It was primarily concluded that geographical communities affect individual resilience. Contrary to our intuitive expectations, community and individual resilience are substitutive in some areas. To the best of our knowledge, this is the first study to identify the trade-offs between community and individual resilience.

The remainder of this paper is structured as follows: Section 2 reviews the existing literature review to elucidate the relationship between individual and community resilience through an empirical assessment. Section 3 explains the methodology used to examine this relationship in Japanese prefectures. Section 4 presents the data. Sections 5 and 6 present the results and discussions, respectively. Finally, Section 7 concludes the paper and provides recommendations for further research.

2. Literature review

2. 1. Multi-Layers of Resilience

The concept of multilayered resilience, as emphasized by Paton and Johnston (2001)[8], is crucial in disaster management and involves preparedness and response at the individual, community, and national levels. They argued that integrating these layers creates a comprehensive defense against disasters, ensuring both individual and community resilience. This approach, exemplified by flood risk reduction measures such as dikes, resilient spatial planning, and crisis management[9], is vital for minimizing damage and enhancing overall resilience.

Individual disaster resilience is defined as a person's ability to withstand, adapt, and recover from disasters through self-reliance and adaptability. Meanwhile, community disaster resilience is the collective capacity of a community to prepare for, adapt to, withstand, and recover from disasters, emphasizing social cohesion, shared resources, and coordinated efforts. Eachus (2014)[7], Aldrich et al. (2024)[9], and Paton and Johnston (2001)[8] argued that community resilience involves broader social, economic, and infrastructural dynamics rather than merely being the sum of individual resilience.

Despite the interconnected nature of individual and community disaster resilience, empirical investigations into their relationships are limited. One perspective suggests that individual resilience fosters community resilience because healthy individuals contribute to a healthier community. Matsukawa et al. (2024)[5] highlighted the benefits of focusing on individual resilience in disaster risk reduction. Another study posits that community resilience fosters individual resilience by providing a supportive environment with access to resources, social networks, and community programs (Shelton et al., 2023)[10]. Boon et al. (2012)[11] identified factors contributing to individual resilience, including personal attributes such as self-efficacy and autonomy and contextual and environmental factors such as peers, family, and work support. Kimhi (2014)[12] emphasized the dynamic interplay between personal attributes and coping strategies, underscoring the need for a nuanced understanding of resilience at both the individual and community levels.

2. 2. Is resilience a public or private good?

Discussions on whether social capital is a public or private good have been emerging recently[12],[13]; this is also applicable for resilience. Those who believe that resilience is an ability that belongs to a community view it as a public good that benefits all members of the community. This includes shared resources, collective action, and social networks that enhance a community's ability to respond to and recover from disasters. However, individual disaster resilience can be considered a private good that benefits individuals through personal preparedness, skills, and resources. Boon et al. (2012)[11] advocated using Bronfenbrenner's bioecological theory to model community resilience. Tierney (2019)[13] critiqued the concept of disaster resilience and emphasized the social dimensions of disasters. Song et al. (2017, 2022)[14],[15] provided evidence of the role of social networks and community cohesion in disaster recovery, supporting the idea that community resilience acts as a public good that benefits individual resilience.

If we assume that community resilience is a public good, it can influence individual disaster resilience. A resilient community provides a supportive environment that enhances individual resilience. Strong social networks, community cohesion, and access to resources help individuals more effectively cope with and recover from disasters. Paton and Johnston (2001)[8] discussed how community resilience can enhance individual preparedness and resilience by providing a supportive environment and resources. Shelton et al. (2023)[10] highlighted the importance of community-level protective action guidance to improve individual resilience during floods. Research on social capital emphasizes its role in disaster resilience, highlighting how community resources and networks can enhance individual resilience. Crisis Lab (Aldrich et al., July 2024)[9] discusses the interplay between individual and community resilience, providing insights into how community-level factors influence individual resilience.

A similar interaction between the community and individual resilience may occur if individual disaster resilience is considered a private good with positive externalities. Although individuals benefit privately from their own resilience through personal resources such as savings and insurance, their preparedness can reduce the strain on community resources and emergency services, creating positive spillover effects. This externality enhances the overall community resilience by contributing to social stability and recovery; however, it remains distinct from a public good, which is non-excludable and non-rivalrous. Thus, individual resilience, while beneficial to society, primarily serves the individual and differs from the collective nature of public good.

2. 3. Is community resilience complementary, substitutional, or independent of individual resilience?

As discussed in subsection 2.2, community and individual disaster resilience can complement and reinforce each other. A positive relationship in which strengthening one reinforces the other creates a feedback loop that enhances overall disaster resilience. Resilient communities can offer resources, social support, and infrastructure to enhance individual resilience. Conversely, resilient individuals can contribute to the overall resilience of a community by participating in preparedness activities and supporting others. Eachus (2014)[7] explored the concept of resilience from a psychological perspective and suggested that this mutual reinforcement creates a synergistic effect in which community resilience is greater than the sum of individual resilience. Paton and Johnston (2001)[8] emphasized the importance of community-level interventions in enhancing individual preparedness and resilience. Hikichi et al. (2020)[16] discussed how community-level interventions can mitigate the impact of disasters on individuals, emphasizing the complementary relationship between community and individual resilience.

However, community and individual resilience can also work substitutionally. They can negatively relate to each other; strengthening one may compensate for another's weaknesses or gaps another or decrease them in worse cases. Strong community resilience may compensate for weak individual resilience. Community-level interventions such as emergency shelters and public health services can provide support to individuals who lack personal resources or coping mechanisms. Thus, even if individuals are not personally resilient, they can benefit from the community resilience (Aldrich et al., - Crisis Lab, July 5th, 2024[9], Shelton et al., 2023[10], Gero et al., 2020[17]).

Finally, community and individual resilience may operate independently with no significant interactions between them. This scenario could occur in situations where individual resilience is primarily determined by personal factors such as psychological traits and financial resources, rather than community-level factors. Aldrich et al. (2024)[9] stated that community resilience does not significantly impact individual resilience. To confirm this statement, Kimhi (2014)[12] examined the associations among individuals, communities, and national resilience and stated that while there are positive correlations, they are relatively low.

These insights underscore the complex and multifaceted relationship between community and individual disaster resilience. They highlighted the importance of considering both levels of resilience, the necessity of multi-layered resilience, and the role of social capital in enhancing overall disaster resilience while being mindful of its potential downsides.

Based on our review of the existing literature, the relationship between community and individual resilience has not been established. This is a significant gap between our knowledge and disaster risk reduction policy practices; the strategy of building disaster resilience depends on this relationship. Thus, this study significantly contributes to both academia and policymaking.

3. Methodology

According to Shiozaki et al. (2024)[18], resilience research focusing on significance analysis uses regression-based and random forest methods to assess the importance of indicators or indices in determining outcomes. These methods validate the relationships among indicators, indices, and outcomes based on existing findings and theories.

However, regression-based approaches test their ability to predict outcomes, particularly in studies focusing on predictive validation, by examining the values related to the explanatory power of the regression models.[18]

At the prefectural level, community resilience variables were selected from Japanese prefectural statistics equivalent to the Baseline Resilience Indicators for Communities (BRIC) developed by Cutter et al. (2010)[3].

A multilevel linear regression model was used to analyze the data. The model included fixed effects based on individual characteristics (age, gender, and marital status) and random effects based on community resilience. The multilevel linear regression model is expressed as follows:

Hypothesis 1: *The level of individual resilience is affected by the place where they live (geographical community).*

Estimate the following model:

$$Y_{ij} = \alpha_j + \Sigma_k \beta_{1k} X_{ijk} + e_{ij}. \qquad (1)$$

where,

- Y_{ij} : level of disaster resilience of individual i in community j.
- α_j : the intercept for community j,
- X_{ijk} : the individual level variables (e.g., age, gender, and marriage status).
- β_{1k} : the slope for the kth individual variables.
- e_{ij} : the error term.

The null hypothesis (H0) is $\alpha_j = \alpha$, which means the effect of geographical community α_j is constant for different communities, whereas the alternative hypothesis (H1) is not H0. If Hypothesis 1 is true, H0 is rejected. This indicates that geographical communities significantly influence individual resilience levels.

Hypothesis 2: *If Hypothesis 1 is true, community resilience influences the level of individual resilience.*

We assume the second level is modeled as follows:

$$\alpha_j = \beta_0 + \Sigma_l \beta_2 Z_{jl} + u_j. \qquad (2)$$

where,

- β_0 : the intercept,

- β_{2l} : the slope for lth community-level variables,
- Z_{jl} : the fixed effects of community-level variables (e.g., social capital and infrastructure),
- u_j : the error term (random effects).

Substituting (2) into (1) yields the following equation:

$$Y_{ij}=\beta_0+\Sigma_k\beta_{1k}X_{ijk}+\Sigma_l\beta_{2l}Z_{jl}+u_j+e_{ij}. \quad (3)$$

This model indicated that DRSi is determined by both individual- and community-level factors. This equation was used in the analytical model.

4. The Data

4. 1. Disaster Resilience Scale for Individuals (DRSi)

The dependent variable and data for the individual components in this study were obtained from the DRSi. The DRSi was created by collecting survey data from 10,000 individuals across Japan and extracting 3 subcomponents and 8 factors from 24 items. The first subcomponent is (A) knowledge, which includes 1) knowledge of the hazards and their effects, and 2) knowledge to overcome disasters. The second subcomponent is (B) readiness, which comprises 3) discussing disaster preparedness with family and neighbors, 4) providing daily necessities, and 5) having the financial ability to address disasters. The third subcomponent is (C) action, which comprises 6) the ability to make decisions independently during an evacuation, 7) the ability to adapt to changes after a disaster, and 8) proactive involvement in local recovery.

According to Matsukawa et al. (2024)[5], DRSi, as a component of both communal (meso-level) and national (macro-level) resilience, is based on the idea that individual resilience is promoted or constrained by social relationships, and vice versa. It goes beyond the psychological state or function of individuals by integrating behavioral, economic, and social aspects. DRSi is not simply a person's ability to maintain their current state or function, but also their capacity to improve or transform. This conceptual framework is based on Béné et al.[19] and is widely known as it was adopted by the United Nations Office for Disaster Risk Reduction, UNDRR[20].

Finally, DRSi is a function of all the stages that an individual encounters in the disaster management process: mitigation, preparedness, response, and recovery[8], as illustrated in Figure 1.

The box plot shown in Figure 2 presents the distribution of DRSi and its median value grouped by the 47 prefectures. The prefectures are in descendent order of the mean value of DRSi, which ranges from 62.8 of Kumamoto at the highest to 53.4 of Okinawa at the lowest. This figure indicates that there might be significant differences in DRSi between prefectures. However, this may be due to a sample bias in each prefecture. For example, prefectures with high DRSi scores included individuals whose attributes were advantageous for high DRSi scores. To identify the effect of community resilience, we should distinguish individual- from community-level variables. As our dataset has a hierarchical

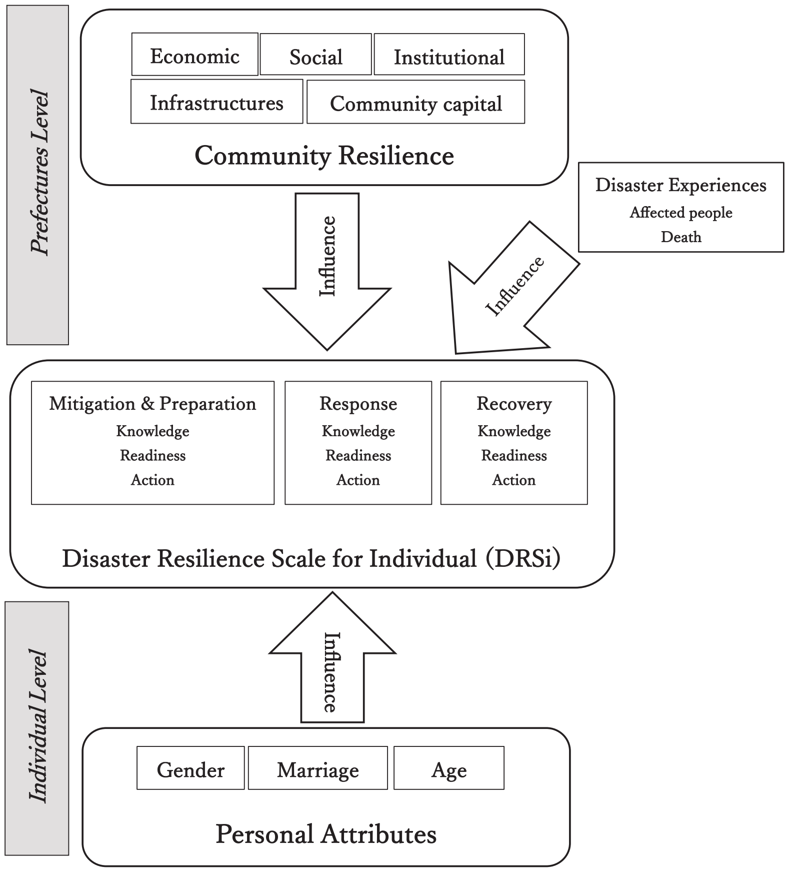

Figure 1: Analytical Framework: Communal disaster resilience and Personal Attributes affect Individual Resilience
Sources: Authors

structure, we attempted to identify the community-level effect on DRSi using multi-level analysis.

4. 2. Community Resilience variables

Numerous studies have attempted to measure community resilience using existing statistics. As most of these studies were conducted in the U.S., some of the variables are not available in the Japanese prefectural data. However, we identified 27 variables equivalent to those used in the existing literature. Table 1 summarizes the variables according to the categories defined by the Baseline Resilience Indicators for Communities (BRIC) developed by Cutter et al. (2010)[3] and Burton (2015)[4]: social, economic, institutional, community engagement and capital, and housing and infrastructure. The BRIC is recognized as the baseline indicator of resilience, which means that better scores support the resilience process, such as adaptation and recovery. As the data source column indicates, all the variables were derived from official statistics provided by the Japanese government.

Social resilience variables examine whether the social capacity of a community, such as social capital, influences the DRSi of individuals in the community. Economic resilience variables determine the impact of community

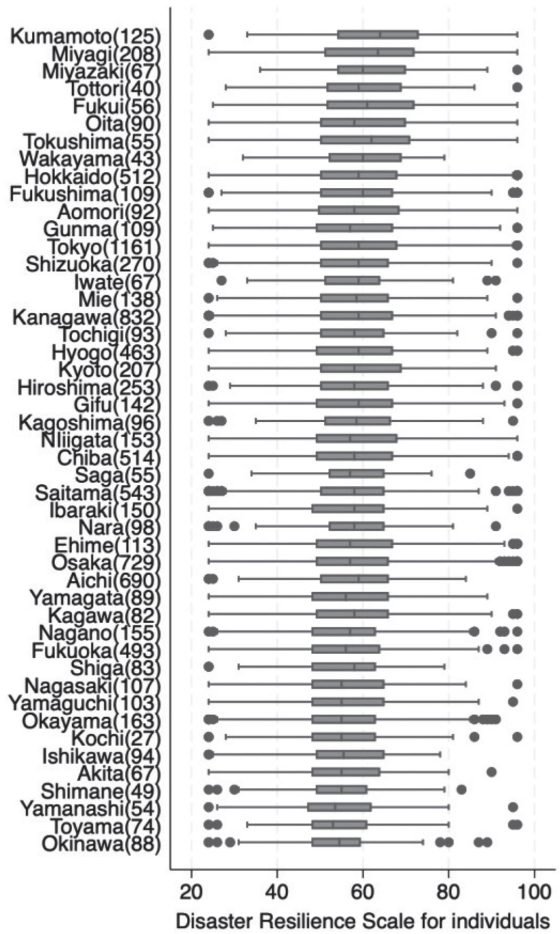

Figure 2: Box Plot of the DRSi values grouped by 47 prefectures.

Note: Number of observations are shown in parenthesis.
Sources: Authors

economic vitality. Institutional resilience includes characteristics related to mitigation, planning, and prior disaster experience[3]. Institutional resilience variables evaluate whether community mitigation and planning abilities influence DRSi. Infrastructure resilience refers to the relationship between individuals and their larger neighborhoods and communities. The selected community capital variables illustrate whether the following three social capital dimensions — sense of community, place attachment, and citizen participation — affect DRSi.

As our dataset only comprised 47 prefectures, we could not include all community resilience variables in the analysis because of the limited degrees of freedom and multicollinearity. Therefore, we included a composite community resilience variable in our analysis in two ways.

First, we created composite variables for the subcomponents of community resilience as proposed by Cutter et al. (2010)[3]. We conducted min-max rescaling, a method in which each variable is decomposed into an identical range between zero and one. After normalization, our final community resilience score employed an aggregation of equally weighted average sub-index scores. The subcomponents were based on the BRIC categories presented in Table 1: social, economic, institutional, infrastructure resilience, and community capital.

Second, we included some of the variables listed in Table 1. We selected the following seven variables from the 27 whose correlation with DRSi was statistically significant at the 10% level: number of libraries (2018), Gini index (2014), number of houses built before 1970, GDI per capita (2018), number of houses built between 2016 and 2019 (2018), number of Non-Profit Organizations (NPOs), and number of religious groups. We included these variables without any transformation.

We standardized most community-level variables into per capita terms. The exception is the length of the principal roads, which are transformed per 1000 square meters of the prefectural area. We used the Gini index and voting rate because they were originally normalized.

Table 1: Community resilience variables

Category	Variable	Effect on Resilience	Justification	Data source
Social resilience				
Age	Number of people over 65 years.	+	Cutter, Burton, and Emrich (2010)[3]	National Census, Ministry of Internal Affairs and Communications
Transportation access	Number of owned passenger cars	+	Tierney (2009)[21]	Ministry of Land, Infrastructure, Transport and Tourism
Communication capacity	Number of contracts of mobile phone	+	Colten et al. (2008)[22]	Ministry of Internal Affairs and Communications
Special needs	Number of issued disability certificates	+	Heinz Center (2002)[23]	Ministry of Health, Labour and Welfare
Educational equity	Number of people who graduated from university or college	–	Norris et al. (2008) Morrow (2008)[24],[25]	National Census, Ministry of Internal Affairs and Communications
Equity	Number of foreigners	+	Tobin (1999)[26]	Basic Resident Register, Ministry of Internal Affairs and Communications
Community health/well being	Community services (recreational facilities, parks, historic sites, libraries, museums) per 1,000 population		Burton (2015)[4]/ Lochner et al. (1999)[27]	
	▶Number of libraries (2018)	+		Ministry of Education, Science, and Technology
	▶Number of city parks (2020)	+		Ministry of Land, Infrastructure, Transport and Tourism
Economic resilience				
Employment	▶Number of employees (2020)	+	Tierney et al. (2001)[28]	Ministry of Health, Labour and Welfare
	▶Number of female employee (2005)	+	Cutter et al. (2010)[3]	Ministry of Health, Labour and Welfare
Income and equality	▶GINI coefficient	+	Norris et al. (2008)[24]	Ministry of Internal Affairs and Communications
	▶GDI per capita (2018) (1000 yen)	+	Norris et al. (2008)[24]	Economic and Social Research Institute, Cabinet Office
Housing capital	▶Number of owned house (2018)	+	Cutter et al. (2008a)[29]	Ministry of Land, Infrastructure, Transport and Tourism
Institutional resilience				
Municipal services	Public expenditure for police	+	Sylves (2007)[30]	Ministry of Internal Affairs and Communications
Preparedness	Percentage of workforce employed in emergency services (firefighting, law enforcement, protection) ▶Number of fire brigade members (Voluntary Firefighters) (2023)	+	Burton (2015)[4]/ Cutter et al. (2008b)[31]	Fire and Disaster Management Agency
Mitigation and social connectivity	Participation rate in volunteer activities (2016)	+	Murphy (2007)[32]	Statistics Bureau, Ministry of Internal Affairs and Communications

Category	Variable	Effect on Resilience	Justification	Data source
Infrastructure resilience				
Shelter capacity	Number of rent (2018)	+	Tierney (2009)[21]	Ministry of Land, Infrastructure, Transport and Tourism
	Number of shelters (2018)	+	Tierney (2009)[21]	Cabinet Office
Access/evacuation/potential	Length of principle roads	+	NRC (2006)[33]	Ministry of Land, Infrastructure, Transport and Tourism B1101 Total area (ha) (source: Geospatial Information Authority of Japan)
Housing age	Number of houses built before 1970	+	Mileti (1999)[34]	Ministry of Land, Infrastructure, Transport and Tourism
	Number of houses built between 2016 to 2019	+	Mileti (1999)[35]	Ministry of Land, Infrastructure, Transport and Tourism
Medical capacity	Number of hospitals (2020)	+	Birkmann et al. (2013)[36]	Ministry of Land, Infrastructure, Transport and Tourism
Housing type	Number of houses (2018)	+	Cutter et al. (2003)[37]	Ministry of Land, Infrastructure, Transport and Tourism
Community capital				
Social capital-advocacy	Number of acknowledged Non-Profit Organizations, NPOs (2021)	+	Morrow (2008)[25]/ Murphy (2007)[32]	Cabinet Office
Social capital-religion	Number of religious believers (2020)	+	Morrow (2008)[25]/ Murphy (2007)[32]	Agency for Cultural Affairs
	Number of religious groups (2020)	+	Norris et al. (2008)[24]	Agency for Cultural Affairs
Political engagement	Voting rate in the election of the member of House of Representatives	+	Morrow (2008)[25]	Ministry of Internal Affairs and Communications

4. 3. Disaster experiences as control variable

Disaster experience may impact the level of individual resilience. Matsukawa et al. (2024)[5] indicated that the Tohoku region exhibited a higher DRSi score, probably because of the 2011 earthquake and tsunami. Therefore, to explore its potential influence on DRSi, we included the number of affected people and the number of disaster deaths. Both numbers were transformed into per-capita values over a 15-year period in each prefecture from 2008 to 2022.

The descriptive statistics of all variables are presented in Table 2.

5. Result and interpretations

Before the analysis, we checked whether we should use a multilevel model. We built an empty model and calculated the Intraclass Correlation Coefficient (ICC) and Design Effect (DEFF), as suggested by Sommet and Morselli (2021)[19]. ICC measures how similar or related individuals are within the same group. Our ICC of 0.0085245 indicates that only an extremely small portion of the differences (variance) in scores was due to differences between prefectures. Therefore, individuals from the same prefecture did not

Table 2: Descriptive statistics of the variables

Variable description	N	mean	s.d.	Min.	Max.
Disaster Resilience Scale for Individuals	10000	57.84	13.87	24	96
Personal Attribute variables					
Age	10000	50.92	16.59	18.00	99.00
Gender	10000	0.48	0.50	0.00	1.00
Marital status (1 if married)	10000	0.67	0.47	0.00	1.00
Social Resilience	47	0.42	0.10	0.27	0.68
Number of people over 65 years (2021)†	47	3.1E-01	3.2E-02	2.3E-01	3.8E-01
Number of employees (2020)†	47	4.7E-01	2.8E-02	3.9E-01	5.2E-01
Number of passenger cars owned (2015)†	47	5.7E-01	1.1E-01	2.3E-01	7.1E-01
Number of contracts of mobile phone (2020)†	47	9.7E-01	3.0E-01	5.1E-02	1.6E+00
Number of issued disability certificates (2020)†	47	4.4E-02	8.4E-03	2.8E-02	5.9E-02
Number of people who graduated from university or college (2020)†	47	1.5E-01	3.4E-02	9.9E-02	2.5E-01
Number of city parks (2020)†	47	9.0E-04	3.8E-04	2.6E-04	2.1E-03
Economic Resilience	47	0.41	0.14	0.12	0.77
Number of libraries (2018)†	47	3.4E-05	1.3E-05	9.2E-06	6.6E-05
Number of female employees (2005)†	47	1.8E-01	1.4E-02	1.4E-01	2.0E-01
Gini index of annual income for the household with more than two s (2014)	47	3.1E-01	1.4E-02	2.8E-01	3.4E-01
Gross Domestic Income per capita (2018) (thousand yen)	47	3003.83	467.9124	2391.00	5415.00
Number of owned houses (2018)†	47	2.7E-01	2.5E-02	1.7E-01	3.1E-01
Institutional Resilience	47	0.26	0.13	0.09	0.75
Public expenditure for police (2019) (thousand yen)†	47	2.6E+01	4.6E+00	2.0E+01	4.6E+01
Number of voluntary firefighters (2023)†	47	7.9E-04	7.0E-04	1.1E-05	2.7E-03
Participation rate in volunteer activities (2016)	47	2.8E-01	3.5E-02	2.1E-01	3.4E-01
Infrastructure Resilience	47	0.42	0.10	0.21	0.66
Number of rented houses (2018)†	47	1.3E-01	3.3E-02	8.2E-02	2.4E-01
Number of shelters†	47	9.1E-04	4.9E-04	1.2E-04	2.6E-03
Ratio length of principle roads (2020) area (ha) (2021)	47	6.3E-01	2.2E-01	2.4E-01	1.3E+00
Number of houses built before 1970 (2018)†	47	1.7E-02	2.7E-03	1.2E-02	2.3E-02
Number of houses built between 2016 to 2019 (2018)†	47	4.5E-02	1.2E-02	2.1E-02	7.3E-02
Number of hospitals (2020)†	47	8.1E-05	3.3E-05	3.6E-05	1.8E-04
Number of houses (2018)†	47	4.9E-01	3.6E-02	4.3E-01	5.7E-01
Community Capital	47	0.38	0.15	0.18	0.73
Number of residents (foreigners) (2021)†	47	1.6E-02	8.9E-03	4.3E-03	3.7E-02
Number of acknowledged NPOs (2021)†	47	4.0E-04	8.3E-05	2.7E-04	6.5E-04
Number of religious groups (2020)†	47	2.1E-03	1.1E-03	1.4E-04	4.7E-03
Number of religious believers (2020)†	47	1.5E+00	6.1E-01	5.8E-01	3.2E+00
Voting rate in the election of the member of House of Representatives (2017)	47	5.5E+01	4.0E+00	4.6E+01	6.4E+01
Disaster experience variables					
Number of affected people (2008-2022)†	47	5.7E-03	9.2E-03	1.1E-04	4.1E-02
Number of deaths (2008-2022)†	47	2.3E-04	8.6E-04	1.3E-06	4.5E-03

†: per capita

have similar scores. Moreover, the DEFF in our dataset was 2.8054831, above 1.5, indicating that multilevel modeling is warranted[19].

Table 3 summarizes the results of the different mixed-effects models of the multilevel regressions. Please note that the prefecture-level and individual-level variances in the table show the variance of u_j and e_{ij} in Eq. (3), respectively. Model (1) uses Level 1 variables, with no prefectural-level variables except the constant term. All variables in this analysis were cluster-mean-centered (CMC).

Although none of the Level 1 variables are significant, the log-likelihood ratio indicates that the model is significant compared with the one-level ordinary regression model. Based on these results, we rejected the following hypotheses:

Hypothesis 1 stated that part of the DRSi value is determined at the second (prefectural) level.

Hypothesis 2 proposed that community resilience determines DRSi at the prefectural level. Therefore, we estimated Models (2)-(5), including the prefectural level and control variables. The control variables were all positive and significant at the 5% level for the affected population and at the 1% level for death. Disaster prefectures experience variables (Prefecture Level) suggest that experiences related to higher mortality rates in the community after a disaster could lead to an increase in individual resilience, possibly due to increased awareness and preparedness. This aligns with the analysis by Matsukawa et al.(2024)[5].

Model (2) included the composite variables of BRIC at the prefectural level. However, none of these variables were significant. As Shiozaki et al.(2024)[18] suggested, most existing resilience indicators are created by theoretical induction and lack empirical evidence. Our results revealed that community resilience based on the BRIC was not effective in the DRSi. However, we cannot comfirm that this is because of the underdevelopment of community resilience metrics or because community resilience is naturally independent of individual resilience.

Model (3) included some of the elemental variables listed in Table 3 for community resilience instead of the composite variables. The inclusion criterion for the variables was a correlation coefficient with DRSi that is statistically significant at the 10% level. Model (4) eliminated insignificant variables to demonstrate the robustness of the results. Both results revealed that the numbers of libraries per capita and NPOs per capita were significant.

The number of libraries per capita is an element of social resilience, community health, and well-being (Table 2). Interestingly, this had a significant negative effect on individual disaster resilience. This implies that greater community health and well-being, in terms of more resources and information, may paradoxically lower individual resilience scores.

The number of NPOs per capita is an element of community capital advocacy (Table 2). The outcomes indicated a significantly positive effect on individual disaster resilience. This finding indicates that the greater presence of NPOs in a community enhances individual

Table 3: Summary of the results for Mixed effects of Multilevel Regression

	(1)	(2)	(3)	(4)	(5)
Dep. Var.	DRSi	DRSi	DRSi	DRSi	DRSi
Individual level variables	CMC	CMC	CMC	CMC	ABS
Prefecture level variables	None	BRIC	CR variables	CR variables	CR variables
Age	6.8 E-4 (0.0098)	6.8 E-4 (0. 0098)	10.78E-4 (0.098)	9.24E-4 (0.01)	−6.05E-4 (0.008)
Male	0.280 (0.279)	0.293 (0.279)	0.293 (0.279)	0.291 (0.28)	0.570^{**} (0.27)
Married	−0.0798 (0.346)	−0.0726 (0.346)	−0.066 (0.346)	−0.065 (0.35)	5.636^{***} (0.29)
Social		−1.108 (4.210)			
Economic		1.051 (3.298)			
Institutional		−3.091 (2.912)			
Infrastructures		1.328 (2.423)			
Community Capital		1.707 (2.590)			
Libraries			-63415.7^{***} (25168.58)	-54932.9^{***} (17205.4)	-54251.6^{***} (16511.06)
Gini index			−1.617 (19.202)		
Houses before 1970			31.51 (126.43)		
Houses 2016 to 2019			−19.201 (24.54)		
NPOs			6415.20^{**} (2783.51)	5650.58^{***} (2167.32)	6356.949^{***} (2051.676)
Religious groups			396.38 (326.32)		
Number of affected		50.18^{**} (25.234)	49.296^{**} (22.477)	49.48^{**} (22.46)	50.116^{**} (21.69)
Number of deaths		749.08^{***} (257.14)	751.436^{***} (257.04)	711.91^{***} (233.03)	732.45^{***} (224.38)
Constant	57.73^{***} (0.258)	57.06^{***} (1.548)	56.73^{***} (5.21)	56.74^{***} (0.862)	52.42^{***} (0.858)
Prefecture level variance	1.649 (0.703)	0.777 (0. 507)	0.386 (0.355)	0.457 (0.354)	0.383 (0.321)
Individual level variance	191.20 (2.711)	191.278 (2.714)	191.25 (2.712)	191.24 (2.711)	184.3717 (2.614)
N	10000	10000	10000	10000	10000
Number of clusters	47	47	47	47	47
Chi-square for LR test	20.86^{***}	5.73^{***}	1.99^{*}	3.61^{**}	2.89^{**}

Note: Standard error in parentheses $^{*}p<0.1$, $^{**}p<0.05$, $^{***}p<0.01$
CMC: Cluster Mean Centered　　ABS: Absolute value.

resilience, possibly by providing better support and resources.

We used the absolute value of the 1st layer variables in Model (5). The outcomes in Models (1) to (4) show that the 1st layer variables are not significant. However, Model (5) shows that gender and marital status are positively significant for DRSi. This implies that, in general, men and married individuals are more resilient than women and unmarried individuals.

6. Discussion

The analytical results suggest differences in individual resilience levels among prefectures. No significant variables among the subcomponents of community resilience composite variables were found. However, some second-level variables, which are elements of community resilience, also demonstrated a significant effect. First, the positive effect of per-capita NPOs as an element of community capital advocacy on individual resilience suggests that community resources complement individual efforts. When communities have various NPOs, individuals feel more supported and resilient, demonstrating the complementary nature of public and private goods in disaster resilience.

Therefore, based on this discussion, NPOs should be supported to enhance resilience at both the community and individual levels. The positive impact of NPOs per capita on individual resilience suggests that policies should encourage the establishment and support of NPOs. This could involve providing funding, resources, and training to NPOs to enhance their capacity to effectively support community members[6].

Second, the negative effect of libraries per capita on social resilience, community health, and well-being may indicate a substitutional relationship. Existing research expected libraries to increase the knowledge level of community members, foster community culture, and therefore contribute to increased community health and well-being. Therefore, we also expected the number of libraries to have a positive correlation with DRSi. This finding contradicts the theoretical induction.

One possible explanation for this negative relationship is that DRSi includes knowledge as a key element (Matsukawa et al., 2024)[5]. Thus, it is plausible that more libraries increase community health and well-being, including knowledge about disasters and recovery. Hence, libraries increase the resilience of individuals within the community. However, there may be opposite causal relations: in cases where more public libraries are constructed to improve community health in communities with more low-DRSi people, such as poor and illiterate people, it is natural to find a negative relationship between the number of libraries and DRSi.

This finding suggests that investing in community resources does not necessarily increase resilience. Our policy recommendation encourages policymakers to balance resource allocation to support both social community resilience and individual capacity building by integrating personal development programs with community resources[20] such as libraries.

7. Conclusion

This study reviewed the empirical understanding of the impact of community resilience on individual resilience. It used a quantitative empirical analysis of communal resilience data from 47 Japanese prefectures to examine how community resilience affects DRSi scores. A multilevel regression model with a mixed-effects approach was applied. The main finding suggests that, contrary to common assumptions, community resilience can at times decrease individual resilience and that personal characteristics alone do not determine individual resilience. This research is groundbreaking in its identification of the trade-offs between community and individual resilience and offers recommendations for making strategic decisions to enhance resilience at various levels.

However, this study has some limitations. Some individual attributes that could potentially influence DRSi were excluded, such as income, educational level, employment status, health condition, and personal experiences of past disasters. Including these variables could provide a more comprehensive understanding of the factors influencing individual disaster resilience. By considering a broader range of attributes, we could better identify the needs of different population groups and tailor interventions to enhance resilience.

Despite these challenges, this study presents evidence contradicting our intuitive understanding of the complementary relationship between community and individual resilience. This highlights that personal attributes alone do not determine individual resilience. Further studies are necessary to explore this resilience structure.

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References

[1] Zuzak, C., et al., The national risk index: establishing a nationwide baseline for natural hazard risk in the US. *Natural Hazards*, 2022. 114(2): p.2331-2355.

[2] Parsons, M. and P.Morley, The Australian natural disaster resilience index. *The Australian Journal of Emergency Management*, 2017. 32(2): p.20-22.

[3] Cutter, S.L., Burton, C.G., and C.T. Emrich, Disaster resilience indicators for benchmarking baseline conditions. *Journal of homeland security and emergency management*, 2010. 7(1).

[4] Burton, C.G., A Validation of Metrics for Community Resilience to Natural Hazards and Disasters Using the Recovery from Hurricane Katrina as a Case Study. *Annals of the Association of American Geographers*, 2015. 105(1): p.67-86.

[5] Matsukawa, A., et al., Disaster Resilience Scale for individuals: A fundamental requirement for a disaster-resilient society. *International Journal of Disaster Risk Reduction*, 2024. 107: p.104405.

[6] Carmen, E., et al., Building community

resilience in a context of climate change: The role of social capital. *Ambio*, 2022. 51(6): p.1371-1387.

[7] Eachus, P., Community Resilience: Is it Greater than the Sum of the Parts of Individual Resilience? *Procedia Economics and Finance*, 2014. 18.

[8] Paton, D. and D. Johnston, Disasters and communities: vulnerability, resilience and preparedness. *Disaster Prevention and Management: An International Journal,* 2001. 10(4): p.270-277.

[9] Aldrich D.P., Katz, C., and Levanon, T., *The Interplay between Individual and Community Resilience*, in Crisis Lab. 2024: Online

[10] Shelton, S.R., et al., *Community and Individual Disaster Resilience for Floods: Options for Improving Protective Action Guidance*. 2023.

[11] Boon, H.J., et al., Bronfenbrenner's bioecological theory for modelling community resilience to natural disasters. *Natural Hazards*, 2012. 60(2): p.381-408.

[12] Kimhi, S., Levels of resilience: Associations among individual, community, and national resilience. *Journal of Health Psychology*, 2014. 21(2): p.164-170.

[13] Tierney, K., *Disasters: A sociological approach*. 2019: John Wiley & Sons.

[14] Song, J., B. Huang, and R. Li, Measuring Recovery to Build up Metrics of Flood Resilience Based on Pollutant Discharge Data: A Case Study in East China. *Water*, 2017. 9(8): p.619.

[15] Song, J., et al., Urban-rural disparity in community resilience: A multilevel analysis of the relief progress after the 2015 Nepal Earthquake. *Sustainable Cities and Society*, 2022. 79: p.103698.

[16] Hikichi, H., et al., Community-level social capital and cognitive decline after a natural disaster: A natural experiment from the 2011 Great East Japan Earthquake and Tsunami. *Social Science & Medicine*, 2020. 257: p.111981.

[17] Gero, K., et al., Associations between community social capital and preservation of functional capacity in the aftermath of a major disaster. *American Journal of Epidemiology*, 2020. 189(11): p.1369-1378.

[18] Shiozaki, Y., Nagamatsu, S., Sato, K., and Bhattacharya, Y., A Systematic Literature Review of Empirical Validation of Disaster Resilience Indicators. *International Journal of Disaster Risk Reduction*, 111.

[19] Béné, C., et al., Resilience, poverty and development. *Journal of International Development*, 2014. 26(5): p.598-623.

[20] UNDRR, Resilience, *Sendai framework terminology on disaster risk reduction* https://www.undrr.org/terminology/resilience.

[21] Tierney, K., Disaster Response: Research Findings and Their Implications for Resilience Measures. *CARRI Research Report 6. Oak Ridge: Community and Regional Resilience Institute*, 2009.

[22] Colten, C.E., R.W. Kates, and S.B. Laska, Community resilience: Lessons from new orleans and hurricane katrina. *CARRI Report*, 2008. 3(1): p.2-4.

[23] H. John Heinz III Center for Science Economics, and the Environment. 2002. *Human Links to Coastal Disasters*. Washington, D.C.: H. John Heinz Center.

[24] Norris, F.H., et al., Community resilience as a metaphor, theory, set of capacities, and strategy for disaster readiness. *American Journal of Community Psychology*, 2008. 41: p.127-150.

[25] Morrow, B.H., Community resilience: A social justice perspective. 2008, *CARRI Research Report*, Oak Ridge, TN.

[26] Tobin, G.A., Sustainability and community resilience: the holy grail of hazards planning? *Global Environmental Change Part B: Environmental Hazards*, 1999. 1(1): p.13-25.

[27] Lochner, K., I. Kawachi, and B.P. Kennedy, Social capital: a guide to its measurement. *Health & Place*, 1999. 5(4): p.259-270.

[28] Tierney, K.J., M.K. Lindell and R.W. Perry.

Facing the Unexpected: Disaster Preparedness and Response in the United States, Natural Hazards and Disasters. Washington, D.C.: Joseph Henry Press, 2001.

[29] Cutter, S.L., L. Barnes, M. Berry, C.G. Burton, E. Evans, E.C. Tate and J. Webb. Community and Regional Resilience: Perspectives from Hazards, Disasters, and Emergency Management. *CARRI Research Report 1*. Oak Ridge: Community and Regional Resilience Institute, 2008a. http://www.resilientus.org/library/FINAL_CUTTER_9-25-08_1223482309.pdf

[30] Sylves, R., Budgeting for Local Emergency Management and Homeland Security. *Emergency Management: Principles and Practice for Local Government*, edited by W.L. Waugh and K. Tierney. Washington, D.C.: International City Managers Association, 2007. pp.183-206.

[31] Cutter, S.L., L. Barnes, M. Berry, C.G. Burton, E. Evans, E.C. Tate and J. Webb., A Place-Based Model for Understanding Community Resilience to Natural Disasters. *Global Environmental Change,* 2008b. 18: 598-606.

[32] Murphy, B.L., Locating social capital in resilient community-level emergency management. *Natural Hazards*, 2007. 41: p.297-315.

[33] National Research Council (NRC)., *Facing Hazards and Disasters: Understanding Human Dimensions*. Washington, DC: National Academy Press, 2006.

[34] Mileti, D., *Disasters by design: A reassessment of natural hazards in the United States*. 1999: Joseph Henry Press.

[35] Birkmann, J., Cardona, O.D., Carreño, M.L., Barbat, A.H., Pelling, M., Schneiderbauer, S., ... & Welle, T., Framing vulnerability, risk and societal responses: the MOVE framework. *Natural Hazards*, 2013; *67*, 193-211.

[36] Cutter, S.L., B.J Boruff and W.L. Shirley., Social Vulnerability to Environmental Hazards. *Social Science Quarterly, 2003*. 84 (1): 242-61.

[37] Sommet, N. and D. Morselli, Keep calm and learn multilevel linear modeling: A three-step procedure using SPSS, Stata, R, and MPlus. *International Review of Social Psychology*, 2021. 35(1).

[38] Nguyen, H.L. and R. Akerkar, Modelling, Measuring, and Visualising Community Resilience: A Systematic Review. *Sustainability,* 2020. 12(19): p.7896

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