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Risk-based resilience concentration assessment of community to seismic hazards

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Abstract

Risk and resilience assessments have been both widely, but separately, used as tools for guiding policymakers to formulate disaster-risk reduction policies. On one hand, risk assessment is utilized to estimate the risk associated with disasters in terms of operational metrics such as monetary or casualties' loss; on the other, most resilience analysis assesses and represent community resilience as an index, without a specific unit metric, to gauge levels of disparity in community's post-disaster recovery capability among the areas of interest. Although disaster-risk reduction policies should be best informed by both risk and resilience assessments, an informative integrated assessment approach accounting for both seems to be lacked in current research, insofar as the difficulty in properly integrating their distinct measurement metrics. This paper commences with a literature review of risk assessment and community resilience. It then proposes an integrated framework that can comprehensively assess both seismic risk and resilience, by taking into account the casualties and economic losses associated with earthquakes resulted from a risk assessment, and the infrastructure-system resilience and community socioeconomic-demographic resilience resulted from a resilience assessment. More specifically, an integrated tool, risk-based resilience-concentration curve, is proposed for assessing the inequality of given types of risk in the community's infrastructure-system resilience, and socioeconomic-demographic resilience, respectively. A case study is presented using the data from a city in Israel: the first phase of the case study focused on the concentration of casualties' risk in community's infrastructure-system resilience, and the second on the concentration of economic risk in community's socioeconomic-demographic resilience. The results show that unevenly distributed risk and community resilience can cause inequality of risk in resilience capacity in certain administrative tracts of the city. Based on these findings, the paper recommends a range of risk-reduction strategies for different administrative tracts based on their risk-based resilience concentration curves.

Keywords: Community resilience; Natural hazards; Resilience index; Seismic risk

1 Introduction

Reduction of natural-disaster risks is a major concern worldwide, and effective risk-reduction strategies for communities must be underpinned by both accurate risk assessment and comprehensive resilience assessment. On one hand, risk assessment is focused on the estimation of a system's potential losses under disaster events with taking into consideration the uncertainties of such events. Resilience assessment, on the other, generally research on the ability of the system to recover its functionality following events. Taking seismic risk as example, risk assessment has generally focused on estimating casualties or economic losses due to building damage in earthquakes, based on advanced understandings of the physical vulnerability of buildings and their seismic failure mechanisms. Yet, despite such assessment's usefulness when it comes to direct building-damage-related losses, it is not sufficient in itself to risk-reduction planning at a community level. This is because the risks associated with building damage, such as casualties or economic loss, resulting from earthquakes can be exacerbated by insufficient public infrastructure services; and widespread socioeconomic and demographic impoverishment. Studies on community resilience, on the other hand, have investigated how the community resilience, such as infrastructure-system and socioeconomic-demographic resilience, influences the community's capability to recover from disasters for the reduction of the risks planning at a community level. Though research on the natural-hazard risk reduction has gradually shifted from risk assessment to resilience assessment since the concept of resilience was emerged, interdisciplinary studies of natural disasters that integrate both risk and resilience assessment have recently been encouraged as a result that it is recognized that a community's natural-hazard risk is a far more complex concept than that either purely risk-assessment- or purely resilience-assessment based research can comprehensively assess ([Aven 2017](#); [Aven 2019](#); [Linkov and Trump 2019](#); [Park et al. 2013](#)).

Thus, the present study aimed to develop an operational tool for risk-reduction decision-making support, based on 1) an integrated framework that can comprehensively assess both seismic risk and resilience, by taking into account the casualties and economic losses associated with earthquakes resulted from a risk assessment, and the infrastructure-system resilience and socioeconomic-demographic resilience of community resulted from a resilience assessment; and 2) an integrated tool, called risk-based resilience concentration curve, for assessing the inequality

of given types of risk in community's infrastructure-system resilience, and socioeconomic-demographic resilience, respectively.

2 Review of risk assessment and community resilience research

Risk assessment has served as the dominant approach for risk-reduction decision-making purpose since such approach is able to provide quantitative information of the losses associated with disaster events for evaluating the effectiveness of risk-reduction planning, such as pre-event mitigation or post-event emergency plans. Generally, a risk assessment begins with hazard identification- an exercise for determining the characteristics of potential disaster events that would affect the system of interest, such as their magnitudes and frequencies, and thus such exercise involves consideration of the uncertainties of the events. Vulnerability is another crucial part in a risk assessment which captures the system's susceptibility to the events related to the functionality of the system. For example, in the specific case of seismic risk assessment for buildings, vulnerability means the physical susceptibility of buildings at particular levels of seismic intensity. On the other hand, without necessarily identifying the type of hazards and expressing their uncertainties ([Aven 2019](#)), resilience is the concept that the inherent ability of the system to recover its functionality after events and such concept has been widely applied to gauge community's recovery capacity to disasters ([Cutter et al. 2014](#)). However, though a resilience assessment of a system could be conducted without considering its risk, such assessment could benefit from risk assessment if properly conducted ([Aven 2017](#)).

Following the aforementioned idea, in the case of assessments of seismic risk and resilience of a community, vulnerabilities can be generally distinguished into two categories: a physical vulnerability of buildings for risk assessments; and socioeconomic-demographic vulnerability of community for community-resilience assessment. In [Schneiderbauer and Ehrlich \(2004\)](#)'s study, the former vulnerability is defined as "hazard-dependent," and the latter as "hazard-independent" vulnerability. Accordingly, this section firstly reviews the applications of physical vulnerability of buildings, as hazard-dependent vulnerability, for seismic risk assessment; and then the socioeconomic-demographic vulnerability, as hazard-independent vulnerability, for community-resilience assessment are reviewed. Finally, studies on the integrated approaches for risk and resilience assessment are reviewed.

2.1 Seismic risk assessment

In the case of seismic risk assessment, building damage needs to be firstly assessed so as to serve as a prerequisite for further assessment of seismic risk such as casualties and economic losses. The building damage is calculated by the building's response during ground shaking based on the building's physical vulnerability. Amid advancements in both earthquake engineering and computer science, computational structural modeling has emerged as a powerful tool for assessing buildings' responses during ground-shaking. The capacity-spectrum method, for example, provides a practical means of evaluating structure-displacement responses to a given earthquake, while taking account of the geological characteristics of the site. Since the failure mechanisms of structure systems can be closely investigated, such methods have been widely used for the estimation of damage in performance-based seismic design, including casualties, economic losses, and environmental performance (Ainuddin & Routray 2012; Wei et al. 2015; Aguirre et al. 2015). For instance, through statistical analysis of casualty data from past earthquakes, estimates of physical building damage can be used to further predict the number and severity of casualties within a building, with different levels of estimated building damage being translated into specific casualty severity: e.g., 10% occupancy is expected to subject to fatality in case of complete damage state; 0.0012% is expected to suffer from a fatality in case of severe damage state; and so on (Wei et al. 2015). It is worth noting that the risks estimated by such risk-assessment approaches are quantifiable in terms of money or numbers of casualties, and thus can serve as operational metrics for assessing the effectiveness of building-related risk-reduction actions, such as building seismic retrofit. Yet, despite such approach's usefulness when it comes to direct building-damage-related losses, it is not sufficient in itself to risk-mitigation planning at a community level. This is because the risks associated with building damage, such as casualties or economic loss, resulting from earthquakes can be exacerbated by insufficient public infrastructure services; and widespread socioeconomic and demographic impoverishment.

2.2 Community resilience assessment

Socioeconomic-demographic vulnerability is widely interpreted by social scientists as controlling individual and group actions in response to disasters (Lin et al. 2015) and in this view, different individuals and groups are differentially exposed to disaster risk, and also possess differential capacities for coping with and recover from it (Kasperson and Kasperson 2005). For instance,

through an investigation of the relationship between poverty and natural disasters in the United States, [Fothergill and Peek \(2004\)](#) argued that “the poor are more likely to perceive hazards as risky” but “less likely to prepare for hazards or buy insurance; less likely to respond to warnings; more likely to die, suffer injuries, and have proportionately higher material losses; have more psychological trauma; and face more obstacles during the phases of response, recovery, and reconstruction” (p.103). Conversely, from a rational-choice perspective, the elite has a greater economic ability to engage in disaster mitigation to protect their valued property as well as their lives ([Kahn 2005](#)). Other widely studied factors in socioeconomic-demographic vulnerability to natural disasters have included gender, age, race, and disability ([Fordham 2003](#); [Lin et al. 2015](#)). In one well-known study, geographer Cutter and her colleagues constructed a county-level social vulnerability index for gauging the community resilience by compositing established factors including demographic characteristics, poverty and income inequality, inappropriate urban development, and the mechanisms involved in building social networks and social support systems ([Cutter et al. 2003](#)). Other studies have also developed a variety of indexing systems for the assessment of socioeconomic-demographic vulnerability for the community resilience, based on some combination of the aforementioned socioeconomic-demographic factors at the national ([Yang et al. 2015](#)) or community level ([NOAA 2003](#); [Martins et al. 2012](#); [Noriega and Ludwig 2012](#); [Lenjani et al. 2020](#)).

Over the past decade, in addition to socioeconomic-demographic factors, environmental factors have been integrated into indexing systems for the comprehensive community-resilience assessment. Accordingly, to distinguish between the assessments of vulnerability that only take socioeconomic-demographic factors into account from those that investigate human-environment interplay, the Intergovernmental Panel on Climate Change defined the former as measuring *contextual vulnerability*, and the latter as measuring *outcome vulnerability* of the community ([Field 2014](#)). More specifically, *contextual vulnerability* is defined as a pre-existing inherent characteristic of a social system, generated by multiple factors and processes, that would amplify the losses suffered by that system’s population due to environmental changes or extreme events ([Field 2014](#); [Füssel 2007](#)). For instance, [Fekete \(2009\)](#) used 41 socioeconomic-demographic variables including age, gender, income, unemployment, rent subsidies, education, physical disability status, and housing conditions to create a vulnerability index of communities to river flood in Germany. Similarly, [Cutter et al. \(2013\)](#) used 32 SED factors including ethnicity, age,

gender, and membership of a rural farming population to assess the vulnerability of communities to flood in the southeastern U.S. *Outcome-vulnerability* assessment, on the other hand, is scenario-driven: i.e., built around the impact of specific environmental changes or other physical events on specific places (Lin et al. 2015). To assess earthquake disaster risk, for instance, Davidson (1997) developed a framework comprising five dimensions – hazard, exposure, vulnerability, external context, and response-and-recovery capability – each of which is further disaggregated into more specific factors. Although it is difficult to apply the same measurements to different disasters due to their uniqueness, similar logic has been widely adopted in numerous studies aimed at measuring *outcome vulnerability* to them (Eakin and Luers 2006; Koks et al. 2015; Lin and Polsky 2016).

However, despite studies in *contextual-* and *outcome* vulnerability having both shown that their proposed vulnerability factors could influence the degree of resilience to communities in natural hazards, questions still remain regarding how to assign proper weights to different factors to represent their separate influence on such resilience, due to their great variety and multifaceted nature (Asadzadeh et al. 2017). Also, most composite index systems proposed by such studies have not been empirically validated to test the efficacy of their proposed methods in risk-reduction policymaking (Bakkensen et al. 2017; Kontokosta and Malik 2018). Moreover, the community resilience estimated by such vulnerability-assessment approaches are not quantifiable in monetary term – and thus cannot properly serve as operational metrics for assessing the effectiveness of risk-reduction programs.

2.3 Integrated models of seismic risk and community resilience assessment

As previously noted, the community resilience estimated by socioeconomic-demographic vulnerability cannot readily be used for loss quantification; yet, despite conceding that most casualties caused by earthquakes are the immediate result of building damage, some researchers have argued that certain socioeconomic-demographic factors also influence people's chances of death or injury in earthquakes (Shapira et al. 2015; Sutley et al. 2017). Based on a comprehensive review of the epidemiological literature on major earthquakes worldwide, Shapira et al. (2015) argued that some socioeconomic-demographic factors, including gender, age, socioeconomic status and physical disability, could influence the chance of a given building occupant becoming a casualty during an earthquake. For example, based on the casualty data in Peek-Asa et al. (1998)'s study, which was originally collected by the Los Angeles Department of the Coroner

from a total 171 injuries caused by the 1994 Northridge earthquake in the U.S., [Shapira et al. \(2015\)](#) found that women face a higher risk of casualty, their odds ratio of the death being 2.4 compared to men. Similarly, [Lin et al. \(2015\)](#)'s investigation of the 1999 Chi-Chi earthquake in Taiwan tested whether casualties, as the dependent variable, were positively correlated with independent variables comprising several socioeconomic-demographic characteristics of damaged buildings' occupants. The results found statistically significant correlations between becoming a casualty and socioeconomic-demographic vulnerabilities, including gender, socioeconomic status, and being under age 14. More recently, [Sutley Elaina et al. \(2017\)](#) developed an integrated vulnerability framework for the prediction of earthquake casualties, arguing that despite building damage being the main contributory factor, the chance of a person becoming a casualty is affected to some extent by socioeconomic-demographic factors including age, ethnicity, family structure, gender, age and socioeconomic status. The same study calculated odds ratios for the impact of six socioeconomic-demographic factors on a person's casualty status, based on the same data used by [Peek-Asa et al. \(1998\)](#): females were approximately 1.2 times more likely than males to become casualties of the 1994 Northridge earthquake. Nonetheless, conversely, several other studies have found no statistically significant relation between some particular socioeconomic-demographic factors and seismic casualty rates ([Doocy et al. 2013](#); [Ellidokuz et al. 2005](#); [Liang et al. 2001](#)).

Much like the epidemiological research discussed above, some studies in geography and civil engineering have argued that the direct risk arising from building damage can be aggravated by community resilience to cause indirect (or, second-order) risk. Most such studies either developed a composite index by a linear combination of risk arising from building damage and socioeconomic-demographic vulnerability or investigated spatial relationships between them. To be more specific, several studies' proposed index linearly combined physical risk as direct risk (e.g., casualties, economic losses, etc.) derived from risk-assessment approach, and socioeconomic-demographic aggravating coefficient, which was calculated via a linear combination of several socioeconomic-demographic vulnerability factors such as delinquency rates, social disparity, numbers of hospital beds, and emergency-services manpower, which are believed to aggravate risk by enlarging indirect risk ([Carreño et al. 2007](#); [Salgado-Gálvez et al. 2016](#)). Yet, such composite indices could be criticized on the grounds that quantifiable units of physical risk, such as economic losses or numbers of casualties, must be normalized/unitless to facilitate their combination with socioeconomic-demographic vulnerability factors, which possess

no natural scale, resulting in missing operational metrics for assessing the effectiveness of risk-reduction planning.

Several scholars, recognizing the drawbacks of composite index systems as well as the need to integrate physical risk and socioeconomic-demographic vulnerability into a holistic risk-reduction method, have investigated the spatial relationships between physical risk and socioeconomic-demographic vulnerability of communities. For example, [Rashed and Weeks \(2003\)](#) conducted a qualitative comparison of the spatial patterns of socioeconomic-demographic vulnerability with those of building damage to highlight the importance of socioeconomic-demographic vulnerability; and [Schmidtlein et al. \(2011\)](#) examined the spatial linkage between socioeconomic-demographic vulnerability and seismic losses by using a spatial regression model, and found that higher levels of socioeconomic-demographic vulnerability made communities more susceptible to the losses of earthquakes, which in turn rendered such areas' post-event recovery more difficult. Similarly, [Brink and Davidson \(2015\)](#) investigated the spatial relationship between communities' seismic physical risk and their socioeconomic-demographic vulnerability by overlapping them in maps. Despite the advantages that such studies have in terms of making physical risk commensurate with a community's socioeconomic-demographic vulnerability, however, their mapping efforts have not resulted in any operational tools that would be useful in risk-reduction planning.

2.4 Summary

The context of risk assessment and community assessment in natural-risk studies can be summarized as follows:

- Although disaster-risk reduction policies should be best informed by both risk and resilience assessments, only purely risk assessment approaches have thus far resulted in quantitative risk measures, such as the number of casualties or monetary losses. On the other hand, with regard to community resilience assessment, there is no consensus on how resilience can serve as operational metrics for assessing the effectiveness of risk-reduction planning.
- Recognizing that direct risk in earthquakes can be estimated from risk-assessment approaches, while the indirect risk is closely related to community resilience considering its socioeconomic-demographic vulnerability, some studies have highlighted the need for approaches that integrate these two types of assessments. Accordingly, risk assessment is

firstly utilized to estimate direct risk, and then such risk can provide informative input to community resilience analysis for determining the degree of indirect risk.

- Due to the drawbacks of a composite index created via a linear combination of risk and community resilience, spatial mapping of them has seen a recent surge in popularity. However, such mapping cannot provide quantitative, operational tools for evaluating quantitative effectiveness of risk-reduction strategies, and further innovative work in that direction will be required.

3 Methodology

This study proposes an integrated framework that can comprehensively assess both seismic risk and resilience, by taking into account the casualties and economic losses associated with earthquakes resulted from a risk assessment, and the infrastructure-system resilience index and community socioeconomic-demographic resilience index resulted from resilience assessment. Also, an integrated operational tool, called risk-based resilience concentration curve, is proposed for assessing the inequality of given types of risk in the community's infrastructure-system resilience, and socioeconomic and demographic resilience, respectively.

3.1 Seismic risk assessment

The United Nations Disaster Relief Organization has defined natural-disaster risk as the impacts of a hazardous event that exploits the vulnerability of a system of interest on that system's exposure to the event (Brown 2013). The creation of equations for modeling such risks is known as catastrophe risk modeling (CRM). CRM has emerged as a widely accepted approach for assessing disaster risk (Grossi et al. 2004). The modelling comprises four modules: hazard, exposure, vulnerability and loss. As shown in Fig. 1, taking a seismic-risk assessment as an example, the hazard module determines the characteristics of potential seismic events, such as their locations, intensities and frequencies. The exposure module collects data on geological characteristics, such as site effects and soil attenuations (for calculating seismic intensities at particular sites), and data about the built environment, such as buildings' structural types and design codes. The vulnerability module calculates buildings' fragility curves, which represent their physical vulnerability at various levels of seismic intensity. And finally, the loss module transfers building damage to losses such as the economic loss due to the repair of damaged buildings, or numbers of casualties.

In the present study, the expected building damage and associated losses are estimated using *HAZUS* (FEMA 2013), a GIS-based risk-assessment software for CRM. *HAZUS* sets forth four seismic-damage states for reinforced concrete (RC) buildings: slight, moderate, extensive, and complete. In the present study, *HAZUS*-estimated physical building damage will be translated into two types of losses: 1) casualty losses, where the estimated building damage is used to estimate numbers of casualties by taking into account the building population and the four casualty rates proposed by (Wei et al. 2016): casualty rates for slight, moderate, extensive, and complete structural damage to a RC building are 0%, 0%, 0.0012%, and 10% of its population, respectively; and 2) economic losses, through the building-repair cost ratios presented in the same study: the repair costs for slight, moderate, extensive, and complete structural damage to a RC building will be 0.5%, 2.3%, 11.7%, and 23.4% of its replacement cost, respectively.

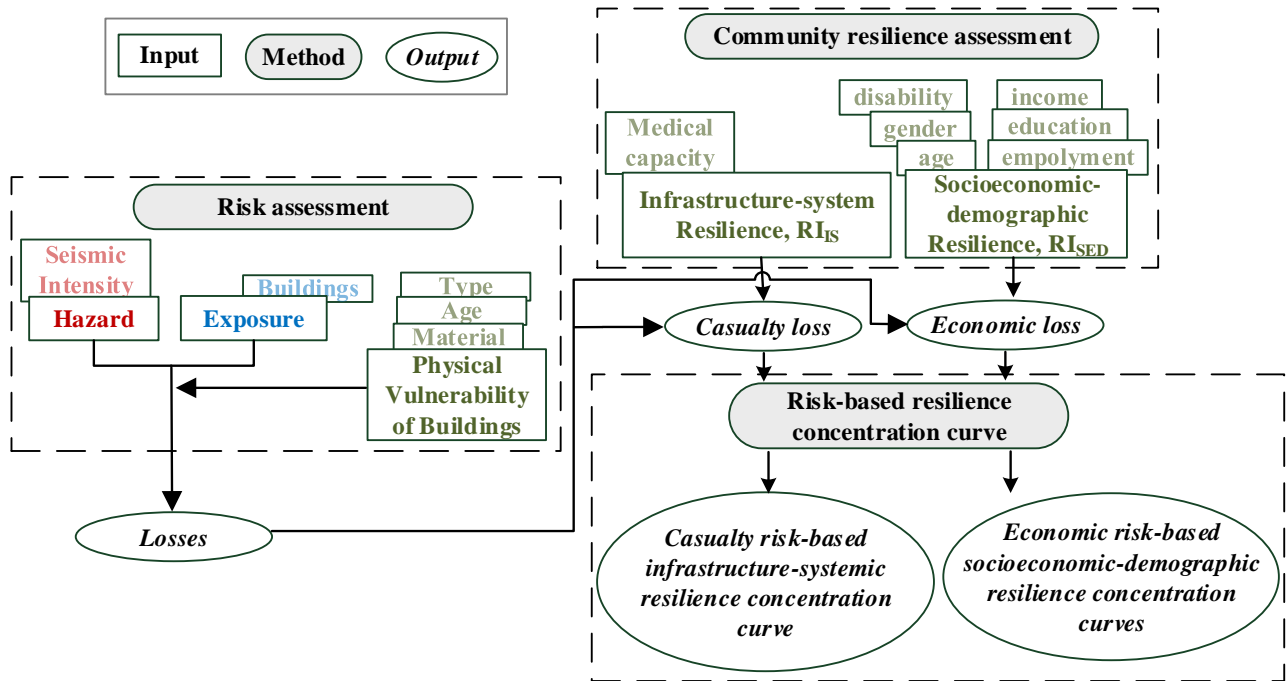


Fig. 1 Methodology of risk-based resilience concentration curve

3.2 Community resilience assessment

In the present study, as shown in Fig. 1, community resilience comprises two components: infrastructure-system resilience and socioeconomic-demographic resilience. The present study proposes the *infrastructure-system resilience index* (RI_{IS}) of the community as the post-event

recovery capacity of the community depending on its public infrastructure and facilities systems; and the socioeconomic-demographic resilience of the community as the post-event recovery capacity of community mainly governed by socioeconomic-demographic factors. It is noted that, though a great number and variety of factors have been used for the measurement of infrastructure-system resilience, the present study simply used the density of medical institutions' emergency-recovery capacity to represent the infrastructure-system resilience since there is not yet any clear consensus about which or how many factors should be included in measures of such resilience.

With regard to our proposed *socioeconomic-demographic resilience index* (RI_{SED}), some of the socioeconomic-demographic vulnerability factors purposed in the study of [Cutter et al. \(2010\)](#) for the measurement of social resilience of a community to the natural hazard are adopted in the presented study based on the data availability of our proposed case study, including age (percentage of population under 65), gender (ratio of male to female), disability (percentage of the population without disability), education (percentage of the population with tertiary education), income (average household income), and employment (percentage of employed population). The min-max method was used to normalize these factors' value into the same scale ranging from zero to one.

Finally, despite there is still no theoretical justification for the differential allocation of the importance across socioeconomic-demographic vulnerability factors, in the present study, such factors are linearly aggregated by an equal-weighting method. It is noted that weighting of factors is usually referenced as a challenge in disaster resilience measurement ([Cutter et al. 2014](#)) and, as such, equal weighting across different factors could be performed in case that investigators have no significant knowledge about the interactions among them and the tradeoffs is not fully perceived ([Asadzadeh et al. 2017](#)). Meanwhile, such a method of aggregation is transparent and easy for communication ([Cutter et al. 2010](#)), which is a criterion that we deemed critical for potential users.

3.3 Risk-based resilience concentration curve

Having avoided the drawbacks of previous studies that relied on either spatial mapping or a linear combination of risk due to building damage with community resilience, the present research proposes the *risk-based resilience concentration curve* to investigate the inequality of the risk

resulted from risk assessment in the community resilience. Following a concept originally proposed by [Suits \(1977\)](#) for the measurement of tax progressivity, concentration curves have been widely applied to support decision-making on public-policy issues, particularly in the sphere of human health. For instance, [van Doorslaer et al. \(1997\)](#) used them to assess whether inequalities in adult health were more pronounced in poor countries than in wealthy ones; [Wagstaff \(2000\)](#), to investigate unequal distributions of child mortality; and [O'donnell et al. \(2007\)](#), to examine differences in health inequality over time in multiple countries.

The application of concentration curves to seismic-risk research was originally proposed by [Bernknopf and Amos \(2014\)](#), who proposed the “risk concentration curve” as a tool for indicating the inequalities of seismic risk across different levels of household wealth in Los Angeles County in the U.S., by plotting the cumulative percentage of seismic risk in terms of seismic damage to buildings against the cumulative percentage of the incomes of the region’s households, ranked from lowest to highest. As such, if seismic risks are equally distributed across all income groups, the concentration curve would be a 45-degree straight line (known as a “line of equality”). When the risk variable on the y-axis has higher values among the lower-income groups on the x-axis, the curve will lie above the line of equality, indicating that inequity of seismic risk exists among lower-income households; and the farther the curve is above the line of equality, the greater the level of this increased risk is. Conversely, the curve will lie below the line of equality if the risk variable has higher values among higher income groups, meaning that higher-income households are disproportionately exposed to seismic risk.

[Bernknopf and Amos \(2014\)](#)’ study presents that seismic risk in terms of building damages showed a statistically significant risk concentration in census tracts with large numbers of residents of lower household income. However, despite the advantage of [Bernknopf and Amos \(2014\)](#)’ study in providing a new insight for investigating the risk inequalities of seismic risk across different levels of household wealth, their study can still be extended in several perspectives. Firstly, the distinction between risk assessment and resilience that were used in their study was not explicitly explained and made. Accordingly, their proposed risk concentration curve was too simplified when they investigated the inequality of their given types of risk – which only examined inequality of building damage by household income.

As such, we firstly make clear definitions and roles of risk assessment and community resilience in the estimation of risk: risk assessment is firstly used to estimate the risk associated with building damage, including casualty and economic losses; and, to generate the risk-based resilience concentration curve, infrastructure-system index (RI_{IS}) and socioeconomic-demographic resilience index (RI_{SED}) are calculated and integrated with the estimated risk due to building damage. **Fig. 1** is a flowchart of the proposed methodology. First, expected building damage is estimated using *HAZUS* and such estimation is translated into associated casualty and economic losses, respectively. Accordingly, two different curves are purposed and obtained in the present study: *casualty-based infrastructure-system resilience concentration curve* generated by coupling casualty losses with RI_{IS} ; and *economic-loss-based socioeconomic-demographic resilience concentration curve* generated by coupling economic losses with RI_{SED} . It is noted again that, though a great number and variety of factors have been used for the measurement of infrastructure-system and socioeconomic-demographic resilience, the present study simply used the density of medical institutions' emergency-recovery capacity to represent infrastructure-system resilience since (as already discussed) there is not yet clear consensus about which or how many factors should be included in measures of such resilience; and used the six factors for calculating socioeconomic-demographic resilience, including age, gender, disability, education, income and employment, based on the data availability of our proposed case study.

As compared to previous studies, the purposed model can provide more practical and comprehensive information about risk and resilience assessment, so as to provide more specific and operational guidance for risk-reduction planning. For instance, the purposed casualty-based infrastructure-system resilience concentration curve can be utilized to help investigate the inequality of causality risk in infrastructure-system resilience as the community's recovery capability during short-term recovery phase. Meanwhile, the purposed economic-loss-based socioeconomic-demographic resilience concentration curve can be utilized to help investigate the inequality of economic loss risk in socioeconomic-demographic resilience as the community's recovery ability during the long-term recovery phase.

4 Illustrative case study

This section illustrates the proposed methodology via a case study in the city of Tiberias, Israel. First, the process of *HAZUS* for assessing seismic risk is explained. Then, the calculations for RI_{IS}

and RI_{ISED} of community are presented; and finally, the risk-based resilience concentration curves are developed and discussed.

4.1 Risk assessment for casualties and economic losses

As shown in **Fig. 2**, Tiberias City comprises 13,235 households and 42,079 residents and is divided into 12 census tracts. Building-stock data from the city were classified by type and year built: 72% of all its buildings as pre-1980 RC, 16% as post-1980 RC, 10% as pre-1980 masonry, and 8% as post-1980 masonry (Wei et al. 2015). The fragility curves for all types of buildings were obtained from pushover analysis by (Shohet et al. 2014). HAZUS was conducted to assess risk in terms of building damage in a synthetic Jordan Mw 6.0 earthquake with a return period of 500 years, details of which – and of the building’s characteristics – can be found in Wei et al. (2014a, 2014b, 2015). Accordingly, this HAZUS-estimated building damage of all buildings was translated into casualties by multiplying the buildings’ population and the casualty rates of severe and fatal levels corresponding to building damage at the extensive and complete levels proposed by (Wei et al. 2016); and into economic losses by multiplying the buildings’ replacement cost and its repair cost ratios also proposed by (Wei et al. 2016).

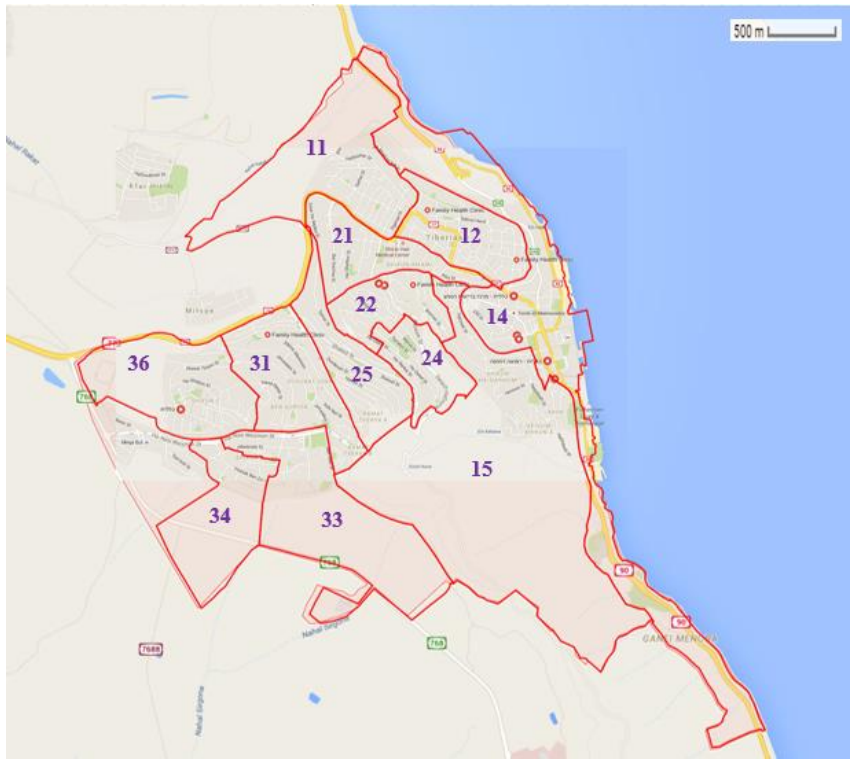


Fig. 2 Census tracts of Tiberias

Table 1 shows the resulting casualties and economic losses due to building damage at the extensive and complete levels. Based on these results, census tract 22 can be expected to suffer the highest casualties: 32 casualties, or 21.9% of the total expected casualties suffered by the city as a whole; and tract 15 to suffer the highest economic impact: NIS37,308,600, or 14.7% of the city's total economic losses.

Table 1 Casualties and economic loss

Tract	No. casualties	% total casualties	Economic Loss (NIS)	% total economic loss
11	14	9.6	25,633,800	10.1
12	4	2.7	27,410,400	10.8
14	3	2.1	32,994,000	13.0
15	5	3.4	37,308,600	14.7
21	25	17.1	22,588,200	8.9
22	32	21.9	18,527,400	7.3
24	12	8.2	22,842,000	9.0
25	3	2.1	28,425,600	11.2
31	18	12.3	15,481,800	6.1
33	6	4.1	126,900	0.5
34	8	5.5	1,522,800	0.6
36	16	11.0	20,050,200	7.9

4.2 Casualty risk-based infrastructure-system resilience concentration curve

Infrastructure-system resilience index

As previously mentioned, the emergency recovery capability of the community such as available medical resources can contribute to the infrastructure-system resilience of the community. There are 12 medical institutions unevenly distributed across the city, of which nine are clinics, two are regional hospitals and one a national medical center. The ratio of the medical capacities of clinics, regional hospitals and the national hospital in the city were set as 1:10:50 (Shohet et al. 2014). As shown in **Table 2**, we firstly calculated number of people that per medical capacity can serve in the tract and which can be obtained by dividing the tract's population by its medical capacity taking into account all medical institutions within the tract. Since the higher the number of people that per medical capacity can serve, the lower the medical-recovery capacity of the tract, we then defined 'medical-recovery capacity' as [1 minus 'the normalized number of people that per medical capacity can serve']. Accordingly, in the present study, we defined the proposed infrastructure-system resilience index (RI_{IS}) as the medical-recovery capacity, which represent

each tract's medical-recovery capacity provided by medical institutions within it. As such, the higher the RI_{IS} , the higher the infrastructure-system resilience of the tract. As shown in **Table 2**, tract 11 with RI_{IS} of zero was found to have the lowest medical-recovery capacity due to only one clinic locating in that tract and which is designated to serve a population of 5,926. On the other hand, the eight clinics located within tracts 14 for serving only 1,205 people gave it the best RI_{IS} in the city.

Table 2 Infrastructure-system resilience index, RI_{IS}

Tract	Medical capacity	Population	Number of people per medical capacity	Normalized Number of people per medical capacity	RI_{IS}	% RI_{IS}
11	1.0	5,926	5,926	1.00	0.000	0.0
31	1.6	5,467	3,417	0.566	0.434	5.0
24	1.0	2,152	2,152	0.347	0.653	12.5
34	1.0	1,974	1,974	0.316	0.684	20.3
12	4.0	7,023	1,756	0.278	0.722	28.6
25	1.8	3,038	1,688	0.266	0.734	37.0
36	2.0	2,584	1,292	0.198	0.802	46.2
33	2.0	1,752	876	0.126	0.874	56.2
22	6.0	4,638	773	0.108	0.892	66.4
21	10.0	5,122	512	0.063	0.937	77.1
15	7.0	1,198	171	0.004	0.996	88.5
14	8.0	1,205	151	0.000	1.000	100.0

Casualty risk-based infrastructure-system resilience concentration curve

The present study investigated inequality of risk in terms of casualties' loss using proposed infrastructure-system resilience concentration curve. As shown in **Table 3**, RI_{IS} is divided into quintiles in the first column, with the lowest being 0% – 20.3% and the highest, 77.1% – 100%; and the corresponding accumulated percentage of casualties to these quintiles are presented in the second column. **Fig. 3** shows the corresponding casualty-risk-based infrastructure-system resilience concentration curve, which plots the cumulative percentage of casualties' loss along its y-axis and the cumulative percentage of RI_{IS} along its x-axis. In the first RI_{IS} quintile in **Fig. 3** (i.e., 0% – 20.3%), the curve is above the line of equality, indicating greater casualties' risk among those households with lower infrastructure-system resilience, especially in tracts 11, 24, 31 and 34, which together account for 35.6% of total casualties but only 20.3% of total RI_{IS} (**Table 3**). On the other hand, shown in **Fig. 3**, the curve in the third RI_{IS} quintile (i.e., 37% – 56.2%) is slightly below the equality line, revealing that tracts 33 and 36 – which share 19.2% (i.e., 56.2% minuses

37%) of total RI_{IS} – can be expected to experience relatively fewer casualties (i.e., 11.7% of the city’s total). It can also be seen that the concentration curve in **Fig. 3** sharpens between cumulative RI_{IS} of 56.2% and 77.1%, meaning that those tracts with higher RI_{IS} would be subject to relatively greater proportions of casualties. Finally, in the same figure, the curve between cumulative RI_{IS} of 77.1% and 100% flattens out, indicating that the tracts with the highest RI_{IS} (tracks 14 and 15) would be subject to relatively low numbers of casualties. **Fig. 4** shows the spatial distributions of casualties and levels of RI_{IS} for all tracts.

Taken as a whole, the case study’s findings suggest that the group of households in tracts 11, 24, 31, and 34 are especially risky to casualties and less infrastructure-system resilient: with an estimated 35.6% of the total casualties in the city (**Table 1**), but 20.3% of total infrastructure-system resilience. As such, an effective risk-reduction plan would involve these tracts retrofitting their buildings to reduce the casualty risk and/or increasing their infrastructure-system resilience by enhancing medical-emergency recovery capacity. However, as shown in **Fig. 3**, the finding that the tracts belonging to fourth RI_{IS} quintile (tracks 21 and 22) would be subject to severe casualties (39% of the city’s total) implies that the more effective of these two risk-reduction actions would be the building retrofit since the fourth-quintile tracts already possess relatively high infrastructure-system resilience.

Table 3 Accumulated infrastructure-system resilience index, RI_{IS} and accumulated casualties’ loss

Accumulated RI _{IS} (%)	Accumulated % of casualty	Census tract
Lowest (0% – 20.3%)	35.6	11, 24, 31, 34
2 nd (20.3% – 37%)	40.4	12, 25
3 rd (37% – 56.2%)	55.5	33, 36
4 th (56.2% – 77.1%)	94.5	21, 22
Highest (77.1% – 100%)	100	14, 15

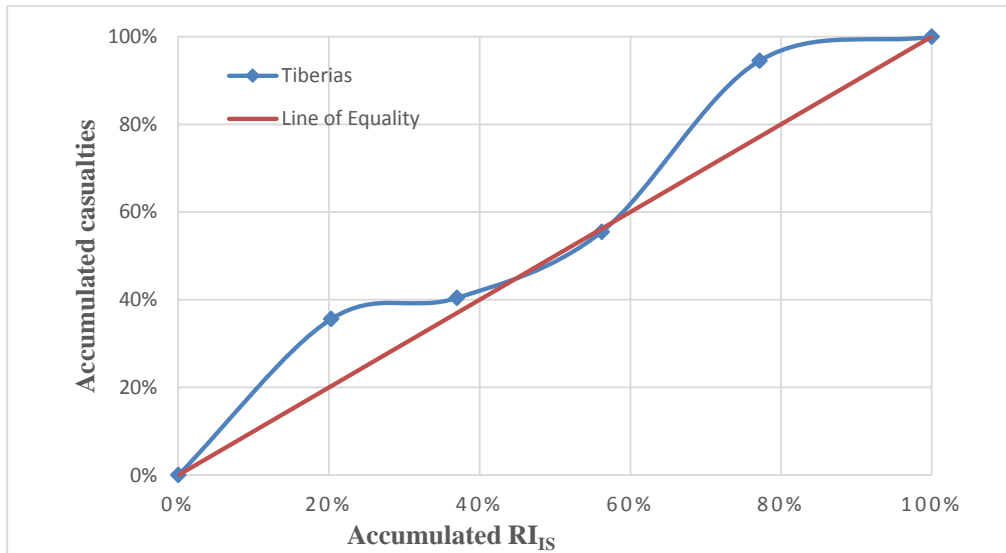


Fig. 3 Casualty-risk-based infrastructure-system resilience concentration curve

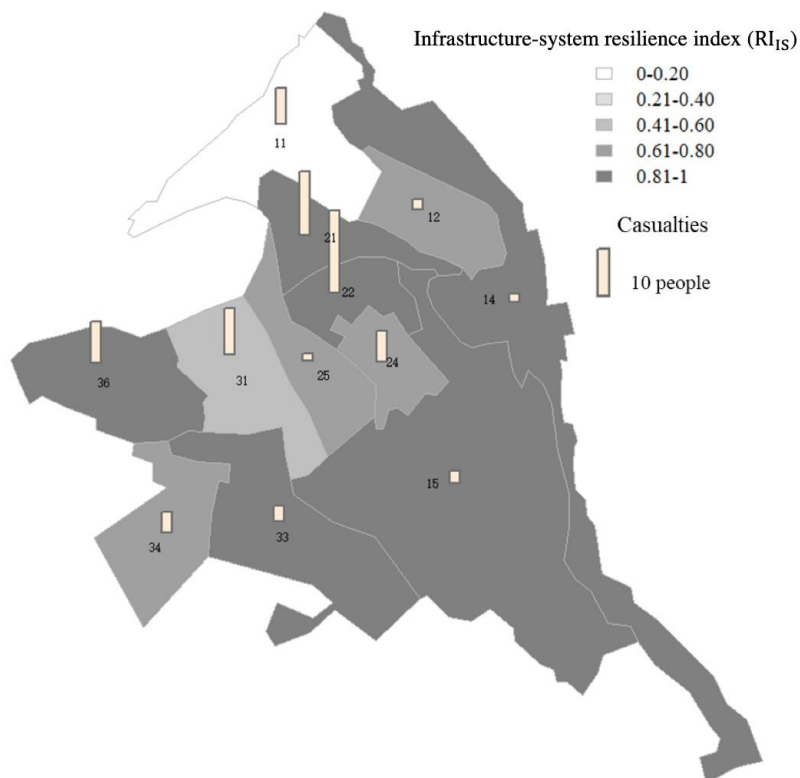


Fig. 4 Spatial distribution of casualties and infrastructure-system resilience index, RI_{IS}

4.3 Economic risk-based socioeconomic-demographic resilience concentration curve

Socioeconomic-demographic resilience index

As previously mentioned, socioeconomic-demographic resilience of community determines its long-term recovery capability. The present study used the purposed socioeconomic-demographic resilience concentration curve to investigate inequality of risk in terms of economic loss. We proposed the socioeconomic-demographic resilience index (RI_{SED}) in the present study, defined as an equal-weight composite index, ranging from zero to one, consisting of part of the community's socioeconomic-demographic vulnerability factors, including age (percentage of population under 65), gender (ratio of male to female), disability (percentage of the population without disability), education (percentage of the population with tertiary education), income (average household annual income), and employment (percentage of employed population). The min-max method was used to normalize these factors' value into the same scale ranging from zero to one. As shown in **Table 4**, RI_{SED} in the city are unevenly distributed, with RI_{SED} in tracts 11 (0.845) and 24 (0.967), while those in tracts 14, 33 and 34 are below 0.204, i.e., less than approximately one out of five that of tract 24, the city's highest.

Table 4 Socioeconomic-demographic resilience index, RI_{SED}

Tract	Age (%)	Gender (%)	Disability (%)	Education (%)	Income (NIS)	Employment (%)	RI_{SED}	% RI_{SED}
33	85	51	90	23	90,626	85	0.000	0.0
14	85	52	92	24	92,724	85	0.095	1.6
34	87	52	92	25	95,610	87	0.204	5.1
36	88	52	93	26	127,555	86	0.296	10.1
15	89	53	95	28	134,354	88	0.475	18.2
22	88	54	94	28	139,426	89	0.483	26.4
12	89	54	96	29	146,776	90	0.596	36.5
21	88	55	96	31	153,004	90	0.643	47.4
25	87	53	97	30	158,128	92	0.593	57.5
31	90	54	96	29	158,767	93	0.690	69.2
11	89	55	97	33	179,447	95	0.845	83.6
24	91	56	98	32	213,051	94	0.967	100.0

Economic risk-based socioeconomic-demographic resilience concentration curve

Table 5 divides RI_{SED} into quintiles, with the lowest ranging from 0% to 18.2% and the highest from 69.2% to 100%; and the corresponding accumulated percentage of economic loss to these

quintiles are presented in the second column. **Fig. 5** is the corresponding economic-risk-based socioeconomic-demographic resilience concentration curve, which plots the cumulative percentage of economic loss along its y-axis, and the cumulative percentage of RI_{SED} along its x-axis. For the lowest RI_{SED} quintile in this figure (i.e., 0% – 18.2%), the concentration curve is far above the line of equality, which indicates that the economic loss is much greater in census tracts 14, 15, 33, 34, and 36, which together account for 36.7% of total economic loss but only 18.2% of total RI_{SED} (**Table 5**). The slopes of the second and third quintiles are approximately parallel to the line of equity, which means that the tracts (12, 22, 21 and 25) in those two quintiles would be subject to “average” economic losses relative to their RI_{SED} resilience. For example, in the third quintile, which has 21% (i.e., 57.5% minuses 36.5%) of the city’s total RI_{SED} , tracts 21 and 25 are expected to suffer 20.1% (i.e., 74.8% minuses 54.7%) of the city’s total economic loss (**Table 5**). Finally, the curve flattens in the fourth and highest quintiles, indicating that those tracts with relatively high RI_{SED} (11, 24 and 31) would be subject to relatively lower economic losses than all other quintiles. For instance, with 30.8% (i.e., 100% minuses 69.2%) of the city’s total RI_{SED} , tracts 11 and 24 are expected to be subject to only 19.1% (i.e., 100% minuses 80.9%) of the city’s total economic loss (**Table 5**). **Fig. 6** shows the spatial distribution of economic loss and levels of RI_{SED} for all tracts.

Overall, the findings suggest that city’ economic risk is concentrated in areas with lower RI_{SED} , including tracts 14, 15, 33, 34, and 36. As such, building retrofitting or earthquake insurance aimed at reducing economic loss could be effective risk-reduction actions. Conversely, shown in **Table 5** and **Fig. 5**, the finding that the tracts in the fourth and highest RI_{SED} quintiles – with 42.5% (i.e., 100% minuses 57.5%) of the city’s total RI_{SED} between them – would be subject to only 25.2% (i.e., 100% minuses 74.8%) of its total economic loss implies that risk-reduction actions for the tracts in this quintile (tracts 11, 24 and 31) are not an urgent priority. It is therefore recommended that these tracts be given the lowest priority for risk-reduction actions, if budgets for such actions are limited.

Table 5 Accumulated socioeconomic-demographic resilience index, RI_{SED} and accumulated economic loss

Accumulated RI_{SED} (%)	Accumulated % of economic loss	Census tract
Lowest (0% – 18.2%)	36.7	14, 15, 33, 34, 36
2 nd (18.2% – 36.5%)	54.7	12, 22
3 rd (36.5% – 57.5%)	74.8	21, 25
4 th (57.5% – 69.2%)	80.9	31
Highest (69.2% – 100%)	100	11, 24

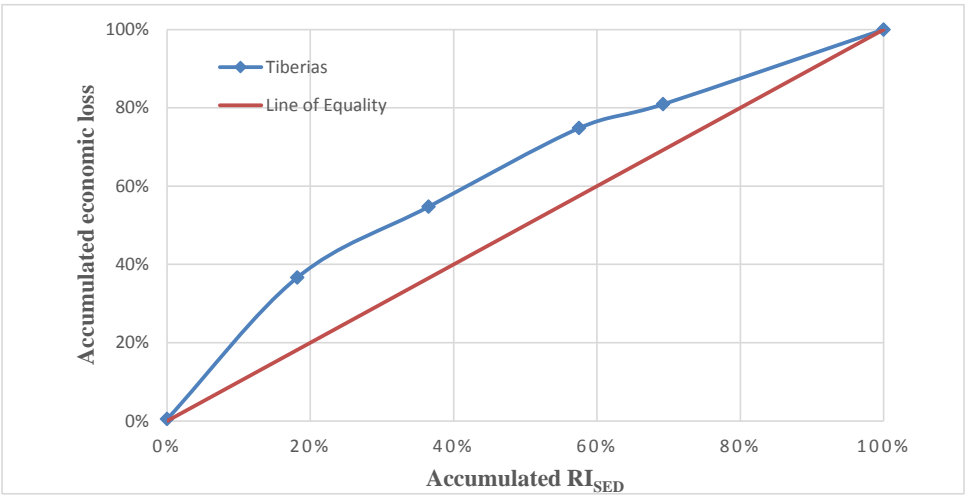


Fig. 5 Economic-risk-based socioeconomic-demographic resilience concentration curve

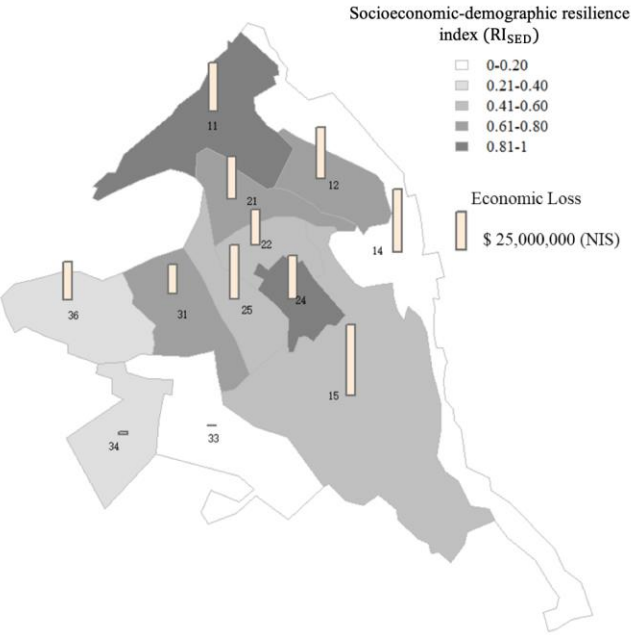


Fig. 6 Spatial distribution of economic loss and socioeconomic-demographic resilience index, RI_{SED}

5 Conclusion

Effective risk-reduction planning can be best informed by the integration of risk and resilience assessment. On one hand, risk assessment can estimate the risk associated with disasters in terms of monetary or casualties' losses; on the other, community resilience assessment can appraise the community's recovery capability from the disasters. This study developed an integrated seismic risk and resilience assessment framework by accounting the seismic risk in terms of casualties and economic losses; and the community's infrastructure-system resilience and the socioeconomic-demographic resilience. More specifically, to investigate inequality of given types of risk in the resilience of a community, and to provide operational information that can support decision-making in risk-reduction planning, two different curves are purposed in the present study: casualty-based infrastructure-system resilience concentration curve generated by coupling casualty losses with infrastructure-system resilience; and economic-loss-based socioeconomic-demographic resilience concentration curve generated by coupling economic losses with socioeconomic-demographic resilience.

The proposed methodology was illustrated by a case study of an Israeli city's 11 census tracts' varying responses to a modeled Mw 6.0 earthquake. Compared to purely seismic risk assessment or purely community resilience assessment in previous studies, our case study shows the advantage of our purposed methodology in providing more informative support for specific risk-reduction planning tailored to different tracts based on their risk-based resilience concentration curves. For instance, the first phase of the case study found that some tracts were disproportionately risky to casualties due to their relatively high casualty loss and low infrastructure-system resilience. As such, an effective risk-reduction plan would involve these tracts retrofitting their buildings to reduce the casualty loss and/or increasing their infrastructure-system resilience by enhancing medical-recovery capacity. On the other hand, the finding that the tracts with relatively high infrastructure-system resilience would be subject to severe casualties implies that the more effective risk-reduction actions would be the building retrofit since these tracts already possess relatively high infrastructure-system resilience. Similar conclusion can be made by the result of the second phase of the case study, which found that those tracts with lower socioeconomic-demographic resilience could be expected to experience disproportionately high economic loss risk. Also, the finding that the tracts with relatively high socioeconomic-demographic resilience

would be subject to relatively low economic loss and it is therefore recommended that these tracts be given the lower priority for risk-reduction actions if budgets for such actions are limited.

Despite the advantage, the proposed methodology is subject to some limitations. First, in our case study, medical-emergency recovery capability was used as the sole metric for infrastructure-system resilience of the community, and some of the socioeconomic-demographic factors as the metric for socioeconomic-demographic resilience, but the proposed methodology can readily be extended to include a much broader variety of factors, like the number of ambulances as a metric for infrastructure-system resilience and/or insured rate of population, population with first-aid training experience, and networks of social relationships as a metric for socioeconomic-demographic resilience. Second, it is admitted that the present work is limited to only a fraction of the ultra-complex social problem generated by a natural disaster scenario. Since community resilience is much more complex from the social point of view, a more detailed analysis of the hazard risk, such as displaced households, business interruption, debris, etc., can be conducted in future study so that a variety of risk can be integrated with community infrastructure-system and/or socioeconomic-demographic resilience for a more comprehensive disaster risk-reduction planning. Third, although our proposed risk-based resilience concentration curves can provide decision-makers valuable information on local communities' risk-resilience inequality, it is noteworthy that the practical application of the proposed concentration curves may need to be justified by measurement of statistical inference. For instance, in Bernknopf and Amos' study (2014), a numerical index named "concentration index" was used for a t-statistic test (equations see O'donnell et al. (2007)) for testing their proposed concentration index' and curves' statistical significance. However, being limited to available time and resources for the collection of required building data in our risk analysis and socioeconomic factors in calculation of the proposed socioeconomic-demographic resilience index, the present study is subject to a limited number of census tracts of 12 in terms of sample size in a t-statistic test, and such small sample size may make it the results of t-statistic tests not robust. Future studies may conduct a statistical test with a greater number of geographic units (e.g., census tracts) for supporting the proposed concentration curves' practical applications in disaster risk reduction. Nonetheless, it is hoped that this preliminary study will inspire future work focused on the integration of risk and resilience assessment, and thus ultimately facilitate better decision-making about risk reduction in the face of natural hazards.

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