



Seismic risk and vulnerability models considering typical urban building portfolios

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Received: 30 October 2023 / Accepted: 21 February 2024 / Published online: 22 March 2024
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Abstract

The seismic risk and vulnerability of urban building clusters are fundamental indicators for quantifying urban seismic resilience. The empirical vulnerability and risk models developed using various risk probability assessment theories and real seismic loss observation data from typical building clusters can provide positive references for predicting and evaluating urban earthquake resilience. However, the data used to validate and optimize the vulnerability and resilience models of building portfolios are mostly discrete points within a city. The coupling effect of multiple intensity measures is rarely considered, resulting in a relatively low evaluation accuracy of the established seismic hazard model. This study considers the comprehensive impact of macroseismic and instrumental intensity on the vulnerability of typical urban building portfolios. A multidimensional parameter seismic risk and vulnerability model considering updated damage states is proposed. Based on field inspection data from the 2008 Wenchuan earthquake in China, an optimized hazard and vulnerability model considering all the buildings (8669 buildings) in Dujiangyan city was developed. An innovative structural vulnerability membership index was proposed to estimate the correlation between typical damage states, and vulnerability correlation parameter models were developed. An improved nonlinear vulnerability regression model considering hybrid intensity measures was proposed, and vulnerability comparison curves and matrices were generated considering the empirical damage data of buildings in Dujiangyan city. An optimized seismic damage index calculation model was developed considering five typical building portfolios in Dujiangyan city.

Keywords Seismic risk model for urban building clusters · Empirical seismic vulnerability · Vulnerability membership parameter · Optimized vulnerability model · Updated damage index model

Abbreviations

RC Reinforced concrete

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DS	Damage state
MMS	Multistory masonry structure
BFM	Bottom frame seismic wall masonry
WS	Workshop building
OB	Other building
PBEE	Performance-based earthquake engineering
EDP	Engineering demand parameter
SD	Seismic epicentral distance
M	Magnitude
CSIS	Chinese seismic intensity
OHIM	Optimized hybrid intensity measures
SC	Sichuan
UDR	Updated damage ratio
OEP	Optimized exceedance probability
VMP	Vulnerability membership parameter
LDFM	Logarithmic distribution function model
EDFM	Exponential distribution function model
UGFM	Updated Gaussian distribution function model
HIM	Hybrid intensity measure
UADI	Updated average damage index
HSI	Hybrid seismic intensity

1 Introduction

Earthquake disasters have brought severe challenges and impacts to cities' economic losses and social development. Most economic losses caused by earthquakes in cities are due to the destruction and failure of building clusters (Hu 2006). An earthquake event directly or indirectly affects the sustainable development of cities. To improve the seismic resilience and functional resilience of typical urban and rural building clusters, conducting research on seismic risk and structural vulnerability based on regional buildings has significant scientific significance and value. This approach can contribute positively to evaluating and predicting urban seismic resilience (Chen et al. 2022). Seismic intensity is a pivotal indicator for quantifying regional buildings' seismic hazard and vulnerability (Iervolino 2022). Probability model theory, reliability algorithms, seismic risk models, soft computing technology (machine learning, artificial intelligence, and digital imaging technology), Bayesian models, empirical seismic fragility, and analytical seismic vulnerability are ubiquitously used to assess and predict the features of seismic hazards, vulnerability, and economic loss of urban building portfolios (Gardoni et al. 2016; Tabandeh and Gardoni 2014; Boakye et al. 2022).

Seismic hazard theory, nonlinear dynamics, probabilistic risk theory, and Bayesian models are implemented to evaluate and predict the vulnerability of typical urban buildings and the sustainability and seismic resilience of cities. A probability risk function was proposed by Rezael et al. (2023), and a multivariate vulnerability analysis was conducted on nonreinforced masonry walls, generating vulnerability curve bundles based on different structural characteristic parameters. Manfredi et al. (2023) considered the impact of the construction period of typical regional building clusters in Italy on structural vulnerability. They used the European Intensity Standard (EMS-98) to develop design spectra

and vulnerability curves for regional building portfolios based on different return periods. Du et al. (2023) selected and developed the regional seismic risk and resilience assessment method to analyse the potential physical processes and uncertainties of typical urban structures under the influence of an earthquake disaster. They compared the structural vulnerability curve model developed based on the incremental dynamic method and cloud computing. Tekeste et al. (2023) and Yoshida et al. (2023) proposed a quantitative program for vulnerability assessment of typical urban buildings using Bayesian model updating algorithms. They developed a structural hazard prediction model based on Bayesian update models by combining vibration test data and Gaussian processing models. Gioiella et al. (2023) conducted an earthquake damage and economic loss analysis of school buildings in the Italian region. Using a probabilistic earthquake risk model, a vulnerability function was developed considering five structural failure states and the seismic risk distribution of urban building clusters.

Shrestha et al. (2022) compared the structural damage modes of two cities, Christchurch, New Zealand, and L'Aquila, Italy, under similar earthquakes. Using collapse probability risk and seismic hazard models (Sharma et al. 2023), the seismic risk distribution of building clusters based on two cities was developed. Bigdeli et al. (2023) established a suitable probability demand model to evaluate the seismic hazard of building structures. Using the base finite element model, they developed an earthquake demand hazard curve considering 36 scalar strengths. A seismic vulnerability matrix considering large-scale probabilistic structural safety assessment was proposed by Sandoli et al. (2023). They proposed a method for estimating seismic vulnerability in large-scale urbanized areas and developed a vulnerability matrix model based on hypothetical vector seismic intensity measures, taking typical urban building clusters in Italy as an example.

With the development of artificial intelligence, digital detection technology, and modern means of earthquake economic loss assessment, many soft computing technologies and algorithms have been broadly used in predicting the earthquake risk and vulnerability of urban buildings. Kazemi et al. (2023) developed a risk model for evaluating the seismic vulnerability of reinforced concrete (RC) structures using machine learning algorithms. They compared and analysed the sample information of 165 data points using artificial neural networks, additional tree regressors, random regressors, and limit gradient enhancement algorithms. They also derived the seismic risk curve of regional RC buildings. Zhang et al. (2023) used random forest, extreme gradient enhancement, and active machine learning algorithms to develop a model for the rapid assessment of earthquake damage in China; trained and tested 9,900 data points; and established a model capable of assessing structural damage status. Meyers-Angulo et al. (2023) studied the seismic vulnerability of urban building portfolios and combined machine learning bipartite clustering analysis and neural network algorithms to predict the vulnerability of typical urban building portfolios. Kazemi et al. (2023) and Luo and Paal (2019) incorporated quantified uncertainty into the seismic risk assessment of typical building portfolios. They obtained damage datasets for RC buildings using incremental dynamic analysis methods. They utilized machine learning and intelligent algorithms for model training and testing and developed an earthquake risk prediction model based on urban building clusters. Ruggieri et al. (2021, 2022) and Blagojević et al. (2023) utilized machine learning, regional risk analysis, and remote sensing image automation technologies to conduct vulnerability analysis on existing building clusters in typical urban areas and generated vulnerability curves based on modern intelligent technology.

Assessing the seismic damage and economic losses of typical urban buildings is the core work for quantifying urban seismic resilience and vulnerability. Kalantari et al. (2023)

used probabilistic seismic risk assessment methods to assess the seismic risk and predict the economic losses of urban buildings in Tehran (the Iranian capital). They evaluated the vulnerability of different building categories in this city and generated seismic risk distributions for urban structures. Ruggieri et al. (2020) considered the influence of building components on seismic vulnerability and developed a numerical application program that considers the influence of structural floor deformation; this program was used for structural response and seismic vulnerability estimations. Xi (2022) and Xu et al. (2019) studied the housing reconstruction plan of Dujiangyan city after the Wenchuan earthquake in China. They developed an economic cost prediction and evaluation model considering the reconstruction of typical urban buildings using the nonlinear regression method.

The seismic vulnerability index is critical for evaluating the seismic resilience and risk assessment of typical urban building portfolios. Kassem et al. (Kassem et al. 2023) and El-Maissi et al. (2023) proposed an evaluation method for the seismic vulnerability of regional building clusters based on an improved seismic vulnerability index and used it to monitor and evaluate the seismic vulnerability of typical urban building portfolios in Malaysia. The traditional probabilistic seismic risk analysis method was considered by Eudave et al. (2022), Fontenele et al. (2023), Zhong et al. (2023c), Li et al. (2024a, b), Yang et al. (2023), Jiménez et al. (2021) and Chieffo et al. (2022, 2023), and a seismic vulnerability index-based method was established to evaluate the seismic risk of typical historical cities in Mexico, Brazil, Chile, and Italy. The model was validated against actual seismic damage observation data.

Using probabilistic seismic hazard theory, actual seismic hazard inspection data, and physical-based methods, scholars in earthquake engineering from different regions worldwide have developed multidimensional regional empirical structural vulnerability models. Mouloud et al. (2023) conducted an actual structural damage survey on Mira in northeastern Algeria during the 2022 earthquake, collecting damage data on masonry, concrete, and colonial-era buildings. They developed an earthquake risk distribution based on evaluating a typical urban seismic zone. Surana et al. (2022) processed historical earthquake damage data from northern India and analysed various traditional buildings' actual earthquake damage mechanisms. Orntharmarath et al. (2023) reported the actual seismic damage characteristics of Thailand's 2014 Mae Lao earthquake. They developed a quantitative relationship model for the seismic vulnerability of typical urban building clusters.

In Italy, research on the empirical seismic vulnerability of regional structures has rapidly developed. Many experts have established multidimensional empirical vulnerability models, contributing significantly to this field. Di Ludovico et al. (2023) conducted actual seismic damage observations in Abruzzo city, which was affected by the L'Aquila earthquake in 2009, and obtained actual loss data for school clusters. A vulnerability curve based on empirical structural loss was generated by combining probability models and nonlinear regression methods. Rosti et al. (2023) proposed a physical-based numerical simulation method to conduct damage analysis on an empirical earthquake database and establish a seismic risk distribution considering multiple building structures. Cardinali et al. (2022) proposed a hybrid-based seismic vulnerability assessment method and established a seismic risk and vulnerability model for typical urban buildings. Lagomarsino and Giovanazzi (2006) proposed a seismic vulnerability assessment function for regional structures based on macroscopic intensity scales. They established various quantitative curve models for the seismic risk and vulnerability of building portfolios. Formisano and Chieffo (2023), Formisano et al. (2023), Longobardi and Formisano (2022) and Chieffo et al. (2019, 2021a) collected and processed actual seismic damage data for historical urban buildings in Italy, taking into account the effects of age, material characteristics, and geometric forms

on the seismic vulnerability of urban buildings. A regression model for the seismic risk distribution and vulnerability of urban buildings considering multiple damage levels was developed. Del Gaudio et al. (2021), Scala et al. (2022), Gaudio et al. (2019), Gaudio et al. (2017) investigated the damage mechanism of masonry and RC structures affected by the L'Aquila earthquake and proposed a regression model to evaluate the seismic risk and vulnerability of regional structures. Follador et al. (2023), Sandoli et al. (2022) and Acito et al. (2023) reported the seismic damage features of building structures in typical urban zones of historical earthquakes in Italy. They developed vulnerability curves of multiple modes using the theory of probabilistic models.

China is one of the countries with the highest frequency of earthquakes (Hu 2006). Many catastrophic earthquakes have caused serious damage to lifeline engineering structures and buildings in different cities. Acquiring actual seismic loss data for buildings has contributed significantly to developing multidimensional empirical vulnerability models. Sun and Zhang (2018) conducted an authentic seismic damage assessment of the 2008 Panzhihua earthquake in China, proposed a seismic loss index calculation function based on multiple damage levels (Zhong et al. 2023a, b), and modified the model using earthquake data. Gong et al. (2015) analysed the actual failure mechanisms of various building structures during the 2011 Yushu earthquake, collected empirical earthquake loss data from 63 cities and villages, and developed a vulnerability hazard matrix. Li et al. (2023), Li (2024a), Li and Zhong (2024) studied the seismic damage features of various buildings and bridge clusters in more than ten cities after the Wenchuan earthquake and developed an empirical vulnerability database and probability model based on macroseismic intensity measures. Using the macroseismic intensity standards of different periods in China GB/T 17742 (1999, 2008, 2020), Li (2024b) evaluated the vulnerability and economic losses of more than 200 destructive earthquakes in China and developed a vulnerability matrix and financial loss prediction model for various building clusters considering actual earthquake damage databases. Li and Gardoni (2024) investigated and analysed the actual earthquake loss of three typical catastrophic earthquakes (Li 2024c) (Li and Formisano 2023), considered various factors affecting the vulnerability of buildings and developed a quantitative model based on an empirical vulnerability database. Chieffo et al. (2021b), (Chieffo and Formisano 2019), Biglari and Formisano (2020), Kohns et al. (2022), Yazdananah (2021), and Mai et al. (2017) considered the seismic risk and vulnerability characteristics of buildings in typical historical central regions and used probabilistic risk assessment methods, damage probability matrices, vulnerability functions, and curves to demonstrate the risk and resilience of building clusters under different intensity measures.

The above research evaluated and predicted earthquake damage and economic losses in typical areas and urban building clusters through different methods. Multiple vulnerability and hazard quantification models considering actual earthquake loss have been developed, contributing positively to the study of earthquake risk and vulnerability (China Earthquake Administration and National Bureau of Statistics 2001, 1996, 2005). However, most studies have focused on discrete seismic damage sample points in a specific zone for earthquake risk research and have neglected the dynamic disaster and vulnerability features of entire urban building portfolios. Reference Li (2024b) used sample data from the Dujiangyan earthquake zone to establish a vulnerability model based on a statistical algorithm. However, this study ignored the impact of nondamaged buildings on the vulnerability and seismic risk of the overall buildings. Some earthquake damage samples were omitted, resulting in relatively low accuracy of the established urban building vulnerability statistical model. This study improved upon the actual earthquake damage observation sample from Dujiangyan city affected by the 2008 Wenchuan earthquake in China and updated

the traditional disaster database of urban buildings. A comprehensive evaluation function considering instrument and macroseismic intensity (hybrid intensity) is proposed using reliability and seismic risk probability analysis methods. The assessment level of building damage in the Chinese macrointensity standard has been expanded, and the classification of the nondamaged state (DS0) has been added, making the damage assessment more detailed. The vulnerability membership parameter is innovatively proposed to measure the degree of membership of the DS0 level to other damage states. An updated seismic risk and vulnerability parameter model based on five typical building clusters (multistory masonry structure (MMS), RC, bottom frame seismic wall masonry (BFM), workshop buildings (WS), and other buildings (OBs)) in Dujiangyan city is developed. An optimized nonlinear regression function is proposed, and a vulnerability and risk regression model for urban building clusters based on a typical earthquake is developed. The traditional seismic damage index calculation matrix has been updated. An optimized average seismic damage index matrix, point cloud, and curve for five building portfolio types in typical cities were established. The structural seismic vulnerability and risk model and index proposed in this paper have been validated by actual structural seismic failure data. We processed and statistically analysed 8,669 buildings surveyed on site, and a structural disaster database was established according to different structural categories. The developed sample database was subjected to structural damage estimation and calibration using the proposed updated vulnerability model and index. Figure 1 shows the flowchart of this paper.

2 Vulnerability model of urban buildings considering seismic hazard theory

The core task of seismic design and risk assessment for urban buildings is to estimate the probability of casualties caused by structural failure. Earthquake hazards assess the probability of exceeding a given ground motion (Hu 2006). A probability seismic hazard function based on urban buildings is proposed by combining seismic hazard theory, probability model analysis

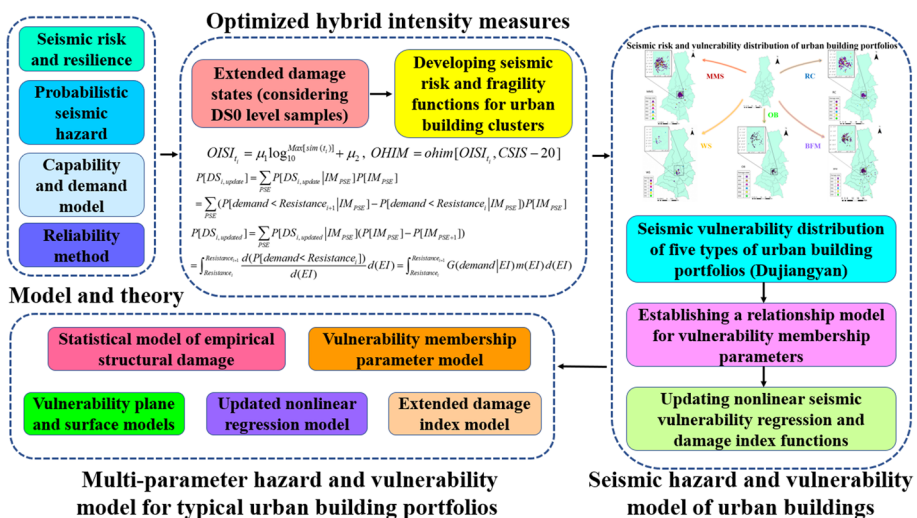


Fig. 1 Flowchart of this paper

methods, seismic intensity measures, and exceedance probability algorithms, as expressed in Eq. 1 (Hu 2006) (Gardoni et al. 2016) (Tabandeh and Gardoni 2014).

$$\kappa_{I_s} = A \left[\left(\frac{M_C}{\exp(\beta_1)} \right)^{\frac{1}{\beta_2}} \right] \times \exp \left[0.5 \times k^2 \left(\frac{\beta_{D|IM}^2 + \beta_C^2}{\beta_2^2} \right) \right] \tag{1}$$

where κ_{I_s} is the seismic hazard function for different damage levels. $A[\cdot]$ is a function that assumes a power exponential relationship between earthquake demand and earthquake intensity. β_1 and β_2 are power exponential relationship parameters between seismic demand and seismic intensity, respectively. M_C and β_C represent the median and standard deviation of the seismic resistance of the structure, respectively. $\beta_{D|IM}$ denotes the logarithmic standard deviation of seismic demand D under the action of the seismic intensity measure IM . k is the risk uncertainty coefficient.

Performance-based earthquake engineering (PBEE) and performance-based seismic design have become development trends in the international seismic engineering field. The *Pacific Earthquake Engineering Research Center* has developed a risk model considering the mathematical basis of PBEE probability decision-making. By combining this algorithm, seismic hazard, vulnerability, and loss model, a full probability seismic risk function was proposed by Li and Gardoni (2024), Gardoni et al. (2016), and Tabandeh and Gardoni (2014), as expressed in Eq. 2.

$$\kappa_{I_s} = \iiint_{D, EDP, IM} G(I_s|D) |dG(D|EDP)| |dG(DEP|IM)| d\kappa(IM) \tag{2}$$

where EDP is an engineering demand parameter. $G(\cdot)$ represents the seismic risk probability damage quantification function.

The risk probability model, seismic intensity measures, magnitude, and time-varying damage parameters of urban building clusters were adopted by Iervolino (2022) for the development of seismic hazard models, and a probability function was proposed to evaluate urban seismic risk, as expressed in Eq. 3.

$$\begin{aligned} P[IM(\Delta t + t, t) > x] &= 1 - P[EM_{IM>x}(\Delta t + t, t) = 0] \\ &= 1 - \sum_{m=0}^{+\infty} P[IM \leq x|ES]^m \cdot \frac{(\epsilon \times \Delta t)^m}{m!} \cdot e^{-\epsilon \times \Delta t} \\ &= 1 - e^{-\kappa_{IM>x} \cdot \Delta t} \end{aligned} \tag{3}$$

$EM_{IM>x}(\Delta t + t, t)$ denotes the function of IM exceeding x under the influence of earthquake magnitudes, Δt , and t . $P[IM \leq x|ES]$ is the conditional probability of $IM \leq x$ under the influence of a random earthquake ES . ϵ is the magnitude uncertainty coefficient. $P[IM(\Delta t + t, t) > x]$ is the probability of the IM reaching the limited threshold x based on the influence of the time parameter t and interval Δt .

The principles of probabilistic seismic risk and data statistics are considered. A Bayesian update model for evaluating the seismic vulnerability of urban building portfolios was proposed (Tekeste et al. 2023), (Yoshida et al. 2023), as expressed in Eq. 4.

$$p(\vartheta|UB) = \frac{p(\vartheta, UB)}{p(UB)} = \frac{p(UB|\vartheta) \cdot p(\vartheta)}{\int p(UB|\vartheta) \cdot p(\vartheta) d\vartheta} \tag{4}$$

$p(\vartheta|UB)$ is the posterior probability distribution of vulnerability ϑ of the seismic damage sample data UB of a given urban building. $p(UB|\vartheta)$ and $p(UB)$ are the probabilities and evidence of the vulnerability ϑ of building clusters under the influence of a given sample of urban earthquake damage data. $p(\vartheta)$ is a prior probability.

The seismic vulnerability $V(x)$ of urban building portfolios is the probability that the building cluster reaches or exceeds a specific limit state at a given seismic intensity level $IM = x$ (Eq. 5):

$$V(x) = P[\text{Demand} \geq \text{Capacity} | IM = x] \tag{5}$$

Li and Gardoni (2024) analysed multiple influencing factors (seismic epicentral distance (SD), fault mode (l), and magnitude (M)) of potential source areas in typical cities and developed an urban building seismic risk assessment model considering the coupling effects of multiple factors, as expressed in Eq. 6.

$$P[IM \geq x | PSE] = \iiint_{M \ SD \ l} P[IM \geq x | SD, M, l] \times w(M) \times w(l|M) \times w(SD|M, l) dM \cdot dSD \cdot dl \tag{6}$$

$P[IM \geq x | PSE]$ is the seismic hazard probability of urban buildings within the potential seismic source area (PSE) of the city, where the intensity measures exceed a given threshold $IM \geq x$.

The traditional seismic vulnerability function (Eq. 7) is a correlation model that establishes a structure’s dynamic characteristics, failure state, and seismic intensity parameters. This study combines Eq. 7 with the convolutional seismic risk model (Eq. 8) to propose a risk model for evaluating the seismic risk resilience and vulnerability of typical urban building clusters, as expressed in Eqs. 9–10.

$$V(x) = \Theta \left[\frac{\ln \lambda_{D|IM} - \ln \lambda_c}{\sqrt{\alpha_{D|IM}^2 + \alpha_c^2}} \right] \tag{7}$$

$$P_{DS} = \int_x V_R(x) |d\kappa(x)| \tag{8}$$

$\Theta [\cdot]$ is the traditional logarithmic normal distribution function. $\lambda_{D|IM}$ and $\alpha_{D|IM}$ are the median and logarithmic standard deviation, respectively, of seismic demand D under the influence of the IM . In λ_c and α_c are the median and logarithmic standard deviation, respectively, of the capacity of urban building portfolios. P_{DS} is a convolutional model of seismic risk and vulnerability $\kappa(x)$ based on multiple damage states DS_i .

$$P[DS_{i,updated}] = \sum_{PSE} P[DS_{i,updated} | IM_{PSE}] P[IM_{PSE}] \\ = \sum_{PSE} (P[\text{demand} < \text{Resistance}_{i+1} | IM_{PSE}] - P[\text{demand} < \text{Resistance}_i | IM_{PSE}]) P[IM_{PSE}] \tag{9}$$

$$\begin{aligned}
 P[DS_{i, updated}] &= \sum_{PSE} P[DS_{i, updated} | IM_{PSE}] (P[IM_{PSE}] - P[IM_{PSE+1}]) \\
 &= \int_{Resistance_i}^{Resistance_{i+1}} \frac{d(P[demand < Resistance_i])}{d(EI)} d(EI) = \int_{Resistance_i}^{Resistance_{i+1}} G(demand | EI) m(EI) d(EI)
 \end{aligned}
 \tag{10}$$

$P[DS_{i, updated}]$ shows the failure probability of optimized urban buildings in different extended (updated) damage states. $P[DS_{i, updated} | IM_{PSE}]$ represents the conditional probability of the i -th extended (updated) damage state of the urban structures under the influence of IM in the potential source area (PSE) in a typical city. The damage state is expanded to six levels, and the value of i is an integer between 0 and 5, namely, DS0 (no damage), DS1 (minor damage), DS2 (mild damage), DS3 (general damage), DS4 (severe damage), and DS5 (local failure or collapse). $m(\cdot)$ and $G(\cdot)$ are continuous density functions and seismic hazard probability models used to evaluate the seismic risk of urban building portfolios, respectively.

Based on Eqs. 5–10, this study innovatively considers the impact of instrument intensity, the latest version of the Chinese seismic intensity measure (CSIS-20), the time-varying damage effects of urban building portfolios, and the directionality of ground motion on urban seismic risk and building vulnerability. A hazard model considering optimized hybrid intensity measures (OHIM) is proposed to evaluate typical urban buildings’ seismic risk and vulnerability, as expressed in Eqs. 11–12.

$$OISI_{t_i} = \mu_1 \log_{10}^{Max[sim(t_i)]} + \mu_2
 \tag{11}$$

$$OHIM = ohim [OISI_{t_i}, CSIS - 20]
 \tag{12}$$

where $OISI_{t_i}$ is the optimized instrument seismic intensity of the urban building portfolio at time t_i . $sim(t_i)$ represents the seismic intensity measured considering the coupling effects of multiple directions of seismic motion at time t_i . μ_1 and μ_2 are the logarithmic regression and undetermined parameters, respectively.

The seismic risk and vulnerability assessment model for urban buildings proposed in this study can provide a more refined estimation of building cluster vulnerability and seismic resistance based on traditional macroscopic intensity assessments of large-scale regional building damage. The expanded damage (vulnerability) state comprehensively measures and refines the traditional vulnerability level, contributing positively to membership studies and impacting the ability to build samples with nondamage states at other damage levels.

3 Seismic risk model of typical urban building portfolios

3.1 Seismic risk assessment model of buildings in Dujiangyan city

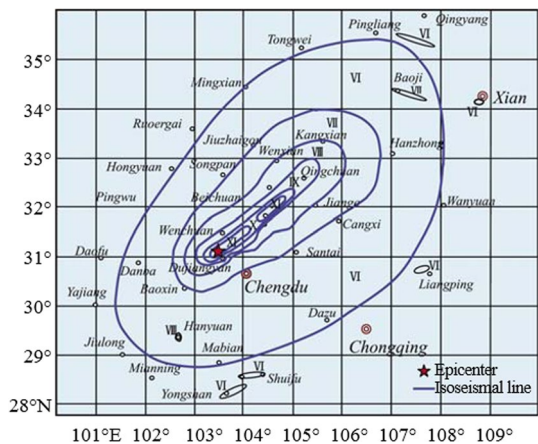
Earthquakes have caused significant economic losses and casualties in urban buildings. The seismic risk and vulnerability assessment of urban building portfolios is one of the core issues in the study of urban seismic resilience and functional resilience. Improving the seismic resistance of urban building clusters is a hot topic in sustainable development research on cities in different regions worldwide. However, most of the research on

earthquake risk and fragility has focused more on estimating the actual earthquake losses of discrete building clusters and less on conducting earthquake hazard and vulnerability analyses for all the buildings in a typical city. Considering the actual damage of typical urban overall building clusters has significant research value for exploring the seismic risk and vulnerability of urban building portfolios.

On May 12, 2008, a strong earthquake with a magnitude of Mw7.9 occurred in Wenchuan, China, affecting more than half of China and multiple regions in Asia (Li et al. 2023). According to data reported by the *Japan Meteorological Agency*, the seismic waves of this earthquake circled the Earth six times (Li and Zhong 2024). The Wenchuan earthquake severely damaged an area of approximately 500,000 square meters, including ten severely affected areas (cities) and 41 more severely affected counties. This resulted in 69,227 deaths, 17,923 missing persons, and 374,643 injured persons to varying degrees, resulting in economic losses of 845.14 billion (Li and Zhong 2024). After the earthquake, the *China Earthquake Administration* immediately sent hundreds of earthquake engineering experts, scholars, and projects from different regions worldwide to the disaster area for field disaster research and assessment. The macroseismic intensity distribution was released, as depicted in Fig. 2 (Li and Zhong 2024). Dujiangyan city is 21 km from the epicenter, the overall damage to the city is relatively heavy, and all types of buildings have been damaged to varying degrees. Based on the preliminary investigation conducted by the *China Earthquake Administration*, the city spans multiple macroseismic intensity zones with various structural types and significant damage features, which can provide favourable basic data for studying seismic resilience and dynamic urban disasters in typical cities. From May to August 2008, the *Institute of Engineering Mechanics of the China Earthquake Administration* organized more than 30 researchers in the field of seismic engineering, including the author, to form a field inspection team. Detailed field observations were conducted on all buildings in Dujiangyan city, and 8,669 actual earthquake damage samples were collected from various building portfolios.

A damage state assessment was conducted on the urban building cluster sample dataset using the optimized seismic hazard and vulnerability quantification model proposed in this paper. Figure 3 shows the administrative division distribution of a typical city (Dujiangyan). The overall building samples of Dujiangyan city were divided into MMS, RC, BFM, WS, and OB samples. We assessed the damage states of all the urban building clusters,

Fig. 2 The seismic intensity distribution of the Wenchuan earthquake in China



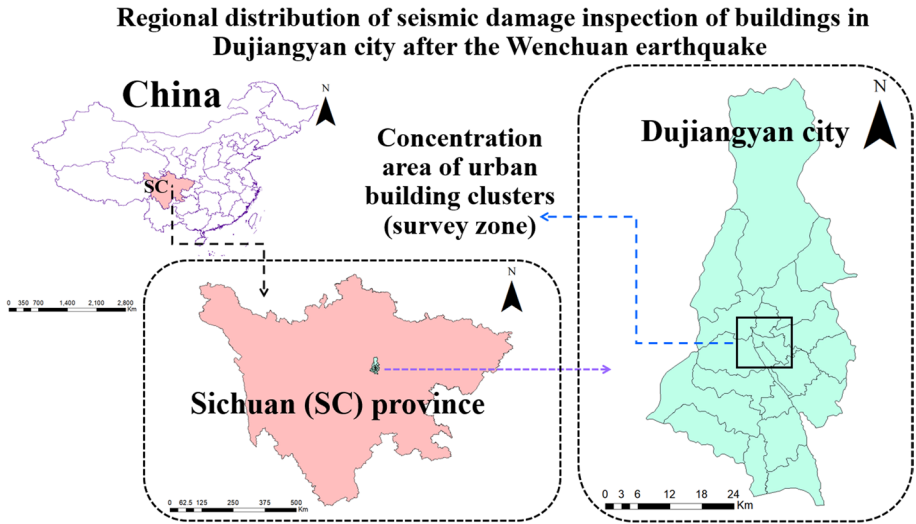


Fig. 3 Location and administrative division of Dujiangyan City, China

Seismic risk and vulnerability distribution of urban building portfolios

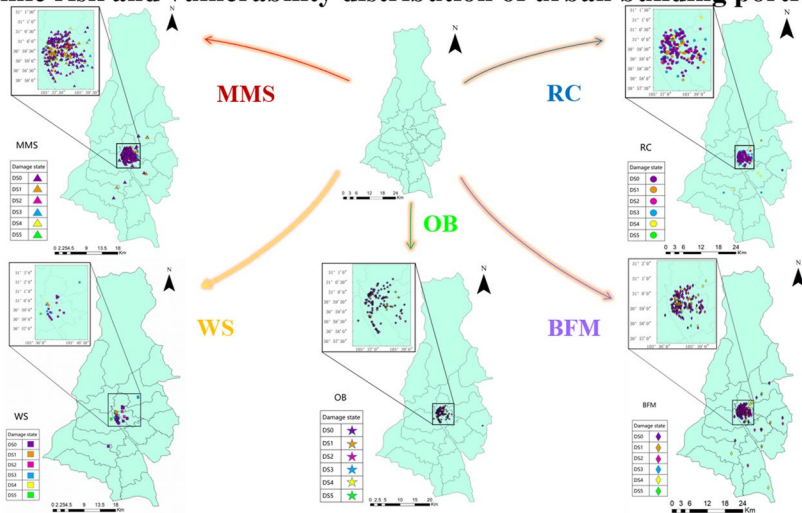


Fig. 4 Seismic risk and vulnerability distribution of typical urban building portfolios (Dujiangyan City)

generating the distributions of seismic risk and vulnerability for five typical building portfolios based on the expanded damage state (with the added nondamaged state), as shown in Fig. 4.

Utilizing the updated seismic risk and vulnerability assessment model proposed in this paper, the impact of extended damage states on the seismic risk assessment of urban building clusters was comprehensively considered. The instrumental intensity calculation model was used as an auxiliary indicator for assessing the vulnerability of urban buildings.

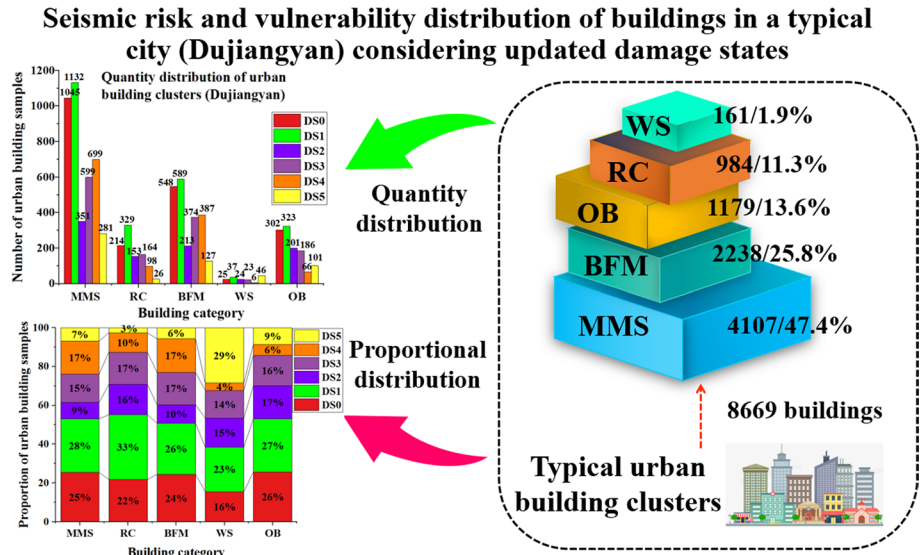


Fig. 5 Statistical distribution of seismic damage in urban building clusters (updated damage status)

Fragility judgement and statistical analysis were conducted on 8669 building clusters using the latest version of China’s macrointensity index (CSIS-20). The statistical vulnerability distribution of a typical building portfolio considering updating risk model algorithms was developed, as shown in Fig. 5. According to the distribution of seismic risk and vulnerability of buildings in a typical city (Dujiangyan), the area spans multiple intensity zones. Several buildings have suffered different degrees of damage under multiple seismic intensity measures. The stock of MMS and BFM was relatively large, and more than 50% of the samples were at the DS0 and DS1 levels. The number of RCs is relatively small, and the damage is relatively mild. It is worth noting that the construction quantity of such a structure (RC) is constrained by local economic development. Dujiangyan is a developing city. Therefore, this type of building is relatively less commonly used. The WS damage is more severe than the OB damage is, and the proportion is approximately 29% at the DS5 level.

3.2 Seismic vulnerability model of urban buildings in multiple intensity zones

An earthquake has caused varying degrees of impact and damage to multiple city zones. Significant differences exist in the damage caused by earthquakes of different intensities to urban building portfolios. A detailed study of the damage modes and dynamic disaster mechanisms of urban building clusters in multiple intensity zones significantly contributes to developing earthquake vulnerability and resilience models for urban building portfolios. Using the proposed seismic risk and vulnerability quantification scale and model, seismic intensity (Fig. 2), and urban seismic risk distribution (Figs. 3–4), we conducted vulnerability rating and classification for all building portfolios (8669 buildings) in different intensity zones of Dujiangyan city. To better demonstrate the vulnerability of various structures under the influence of different intensity measures, data from two typical earthquake events in China (the Yushu earthquake in 2010 and the Jiuzhaigou earthquake in

Table 1 Actual disaster matrix of urban building portfolios considering the updated damage state (the Wenchuan, Yushu and Jiuzhaigou earthquakes)

Earthquake events	Structural typologies	Intensity region	Number of buildings and damage ratio under multiple updated damage levels							Total
			DS0	DS1	DS2	DS3	DS4	DS5		
Wenchuan (Dujiangyan)	MMS	VI	489/0.48	405/0.4	79/0.08	41/0.04	1/0	0/0	1015/1	
		VII	352/0.36	440/0.45	92/0.09	75/0.08	25/0.02	0/0	984/1	
		VIII	136/0.16	171/0.21	78/0.1	217/0.26	216/0.26	9/0.01	827/1	
		IX	62/0.11	95/0.16	51/0.09	168/0.28	184/0.31	29/0.05	589/1	
		X	4/0.01	18/0.04	43/0.1	77/0.18	202/0.48	80/0.19	424/1	
		XI	2/0.01	3/0.01	8/0.03	21/0.08	71/0.26	163/0.61	268/1	
	RC	VI	118/0.36	182/0.57	18/0.06	2/0.01	0/0	0/0	320/1	
		VII	59/0.27	88/0.39	59/0.26	17/0.08	0/0	0/0	223/1	
		VIII	28/0.14	34/0.17	41/0.2	79/0.39	21/0.1	0/0	203/1	
		IX	7/0.05	20/0.13	26/0.17	53/0.35	42/0.28	3/0.02	151/1	
		X	1/0.02	3/0.05	7/0.13	10/0.18	28/0.5	7/0.12	56/1	
BFM	XI	1/0.03	2/0.06	2/0.06	3/0.1	7/0.23	16/0.52	31/1		
	VI	319/0.49	308/0.48	16/0.02	4/0.01	0/0	0/0	647/1		
	VII	182/0.32	213/0.37	79/0.14	65/0.11	33/0.06	0/0	572/1		
	VIII	38/0.08	46/0.1	73/0.16	174/0.37	121/0.26	14/0.03	466/1		
	IX	9/0.03	21/0.06	37/0.1	113/0.31	139/0.39	39/0.11	358/1		
WS	X	0/0	1/0.01	7/0.05	16/0.1	81/0.52	49/0.32	154/1		
	XI	0/0	0/0	1/0.02	2/0.05	13/0.32	25/0.61	41/1		
	VI	15/0.32	23/0.49	8/0.17	1/0.02	0/0	0/0	47/1		
	VII	6/0.29	7/0.33	6/0.29	2/0.09	0/0	0/0	21/1		
	VIII	3/0.13	5/0.22	5/0.22	6/0.26	0/0	4/0.17	23/1		
	IX	1/0.06	2/0.12	2/0.12	4/0.23	0/0	8/0.47	17/1		
OB	X	0/0	0/0	3/0.11	6/0.22	4/0.15	14/0.52	27/1		
	XI	0/0	0/0	0/0	4/0.15	2/0.08	20/0.77	26/1		
	VI	168/0.39	160/0.38	80/0.19	16/0.04	1/0	0/0	425/1		

Table 1 (continued)

Earthquake events	Structural typologies	Intensity region	Number of buildings and damage ratio under multiple updated damage levels							
			DS0	DS1	DS2	DS3	DS4	DS5	Total	
Yushu		VII	90/0.36	78/0.32	54/0.22	20/0.08	4/0.02	0/0	246/1	
		VIII	32/0.16	56/0.29	31/0.16	67/0.35	6/0.03	2/0.01	194/1	
		IX	8/0.06	23/0.18	26/0.21	55/0.43	8/0.06	7/0.06	127/1	
		X	4/0.04	6/0.06	7/0.07	24/0.24	28/0.28	32/0.31	101/1	
		XI	0/0	0/0	3/0.03	4/0.05	19/0.22	60/0.7	86/1	
	MMS	VI	60/0.34	67/0.38	42/0.24	6/0.03	1/0.01	0/0	176/1	
		VII	15/0.16	23/0.25	40/0.43	11/0.12	4/0.04	0/0	93/1	
		VIII	0/0	3/0.04	9/0.13	34/0.49	16/0.24	7/0.1	69/1	
		IX	93/0.04	170/0.07	279/0.11	613/0.23	805/0.31	631/0.24	2591/1	
		VI	1/1	0/0	0/0	0/0	0/0	0/0	1/1	
		VII	1/1	0/0	0/0	0/0	0/0	0/0	1/1	
Juzhaigou		IX	4/0.07	10/0.18	11/0.19	14/0.25	14/0.25	3/0.06	56/1	
		VI	15/0.09	14/0.08	63/0.38	57/0.34	17/0.11	0/0	166/1	
		VII	10/0.07	12/0.09	38/0.27	60/0.42	20/0.14	1/0.01	141/1	
		VIII	5/0.04	9/0.06	35/0.25	54/0.38	31/0.22	7/0.05	141/1	
		IX	2/0.03	5/0.07	17/0.22	30/0.39	12/0.16	10/0.13	76/1	
	RC	VI	21/0.17	15/0.12	51/0.41	38/0.3	0/0	0/0	125/1	
		VII	12/0.1	9/0.08	37/0.32	56/0.48	2/0.02	0/0	116/1	
		VIII	7/0.06	8/0.06	35/0.28	67/0.54	7/0.06	0/0	124/1	
		IX	2/0.03	4/0.06	22/0.34	26/0.41	10/0.16	0/0	64/1	
		VI	10/0.11	14/0.15	38/0.4	29/0.3	4/0.04	0/0	95/1	
		VII	5/0.06	8/0.09	22/0.26	36/0.42	15/0.17	0/0	86/1	
BFM		VIII	4/0.07	4/0.07	20/0.36	16/0.28	11/0.2	1/0.02	56/1	
		IX	2/0.04	4/0.08	15/0.3	18/0.36	8/0.16	3/0.06	50/1	

2017) were collected and supplemented. We established the actual disaster matrix of urban building portfolios based on the updated damage status of five typical building clusters, as summarized in Table 1. To derive the variation features of various building clusters at different damage states, a vulnerability plane model of typical urban buildings based on the updated damage ratio (the UDR is the number of samples of typical urban buildings in the updated damage state divided by the total number) was developed using two-dimensional numerical and modal analysis methods, as presented in Fig. 6. Admittedly, the cumulative response of regional building clusters to different intensity measures and damage states has apparent anomalies in terms of their effects. Using the cumulative damage probability calculation model (Eq. 13) and the three-dimensional modal numerical algorithm, numerical calculations and modal damage analysis were conducted on the disaster matrix of the established urban building portfolio. A vulnerability comparison surface based on the optimized exceedance probability (OEP) was developed, as shown in Fig. 7.

$$OEP_t = P[DS_i \leq ds_i | IM_j] \quad (13)$$

where OEP_t is the optimized exceeding probability of the actual earthquake loss of urban buildings in category t and $P[DS_i \leq ds_i | IM_j]$ represents the cumulative probability of UDR for typical urban building clusters under the influence of hybrid intensity measures at different updated damage states. i and j are integers ranging from 0 to 5 and 6 to 11, respectively.

According to the damage estimation and statistics of building samples in different intensity zones of Dujiangyan city, the number of five types of buildings shows a decreasing trend with increasing intensity. In zone VI, the damage to various structures is relatively mild, and the degree of difference is relatively small. In zone VII, MMS damage is slightly lighter than RC and BFM, while WS damage is heavier than OB. In zone VIII, the damage similarity between MMS and BFM is relatively high, the damage to WS is relatively severe, and the seismic loss to the RC structure is relatively mild. In zone IX, the damage of MMS was slightly greater than that of RC, and the damage of WS was the most severe. The OB damage was relatively mild. Notably, this type of building includes a portion of wooden frames and composite structures, which improves the seismic resistance of this type of building portfolio. Various urban buildings have suffered severe earthquake damage in zones X and XI. The RC structure indicates excellent seismic resistance. However, approximately 50% of the samples did not collapse in the isoseismal zone. WSs suffered the most severe damage, with approximately 77% experiencing collapse or local failure. It is worth emphasizing that the construction materials of MMS are brittle. A certain number of MMSs with seismic designs in Dujiangyan city still have not failed.

3.3 Vulnerability membership model considering extended damage states

The urban building portfolio suffered various damages during a strong earthquake attack. The damage state is widely recognized as a pivotal fuzzy quantitative indicator for evaluating building portfolios. The damage status and sample proportion distribution of urban building clusters directly affect the disaster matrix and vulnerability function of urban buildings. Nevertheless, the damage states defined by different macroscopic intensity scales have inconsistent features. In combination with the actual damage of typical buildings in Dujiangyan city, this study innovatively expanded the five-level

damage quantification scale in the traditional Chinese seismic intensity standard (CSIS), added an assessment level (DS0) of undamaged building samples, and expanded the assessment scale to a six-level damage state. According to the assessment of all the building seismic damage samples (8,669 buildings) in Dujiangyan city, the development of the DS0 level has different degrees of impact on the other damage states. To study the impact of DS0 level samples on the urban building disaster matrix and vulnerability curve, we innovatively proposed a vulnerability membership parameter based on DS0 (VMP, which is the UDR of each damage state divided by the UDR value of the DS0 level) using fuzzy membership theory to estimate the degree of impact between different damage levels. The established disaster matrix for typical urban building clusters was calculated, and a seismic damage state correlation coefficient matrix considering VMP was developed, as noted in Table 2. By combining spline interpolation and conformal regression model algorithms, VMP comparison curves and surface models were generated for five typical urban building clusters under the influence of the overall zone and different optimized intensity measures (zones), as shown in Figs. 8 and 9.

The analysis of matrix, curve, and surface models based on VMP for urban building clusters showed that in the overall urban seismic zone, the membership of DS1- and DS2- level VMP for various building clusters in DS0 is relatively high. The difference in membership parameters indicates an increasing trend with increasing damage state. It is worth emphasizing that the membership degree of the WS at the DS5 level significantly increased, indicating that the damage to this type of structure was relatively severe.

In zone VI, the DS1 level samples of RC and WS have a higher degree of membership in DS0, indicating that the proportion of these two types of urban buildings in DS1 is significantly greater than that in DS0. In zone VII, the VMP similarity between MMS and BFM was relatively high at the DS1 and DS2 levels. However, as the damage state increases, the membership of MMS slightly decreases, and the damage is less severe than that of BFM. In zone VIII, the VMP of BFM at the DS3 level is significantly greater than that at the DS0 level, indicating that many BFMs have undergone damage at the DS3 level.

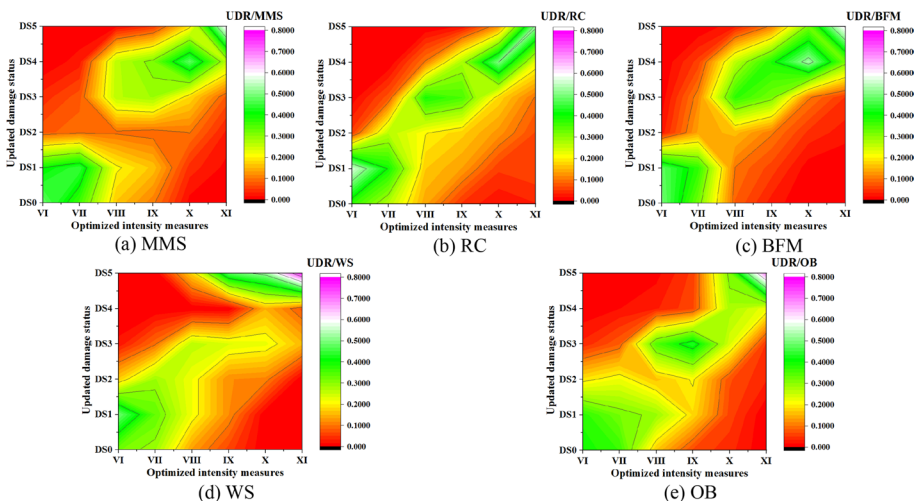


Fig. 6 Seismic hazard and vulnerability plan of typical urban buildings (UDR)

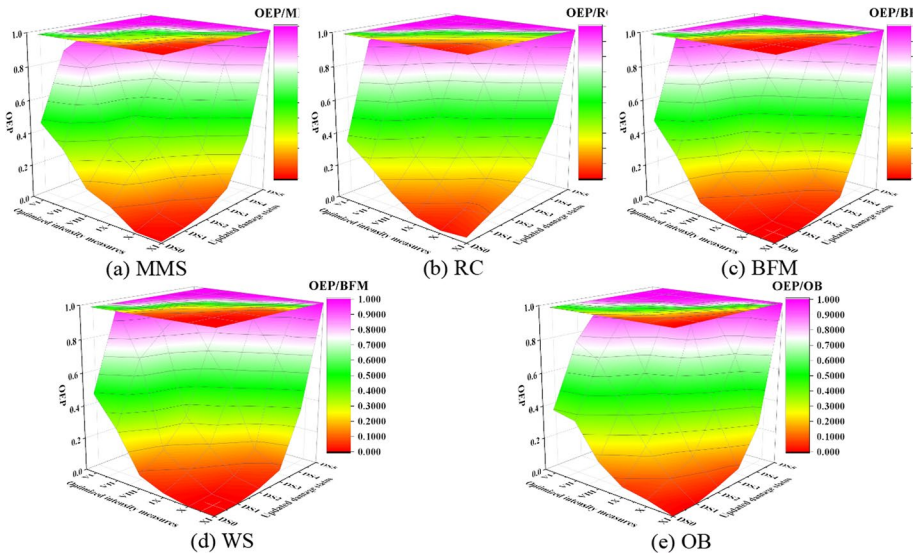


Fig. 7 Seismic hazard and vulnerability surface of typical urban buildings (OEP)

The VMP of the WS at the DS5 level is relatively high, indicating that the sample of collapses in this type of building is slightly greater than that of undamaged buildings. In zone IX, the VMP of BFM at the DS4 level is significantly greater than that at the other DS4 levels, reaching 15.44 times the UDR value of the nondamaged sample, and the damage is relatively severe. RC, OB, and MMS had relatively high membership at the DS3 level, while WS had a significant membership at the DS5 level, indicating that this type of structure was the most severely damaged. Notably, some urban buildings are in an extreme earthquake zone, resulting in the absence of DS0-level samples for BFM, WS, and OB. Therefore, the VPM with the DS0 level has no affiliation with other damage states in this zone. In zone X, the VPM of MMS and RC at the DS4 level was significantly greater. A large number of buildings have experienced DS4-level damage, while the VPM curve and surface of the OB show a slow-increasing trend. In zone XI, the VPM value of MMS at the DS5 level was significantly greater than that of RC, indicating that the MMS damage was significantly more severe than that of RC. The membership index of structural vulnerability is based on the vulnerability level evaluation scale. Therefore, the developed model can be used to estimate the damage caused by other natural disasters to structures, but the impact of different disaster intensity measures on structural damage should be considered.

4 Seismic vulnerability regression and optimized damage index model

4.1 Updated vulnerability regression model

Various nonlinear vulnerability regression models have been used to predict and evaluate regional building cluster seismic risk and damage using probability distribution functions, seismic hazard methods, and reliability theory. Formisano et al. (2023) and Chieffo et al.

Table 2 Correlation coefficient matrix of the seismic damage state of urban buildings based on the VMP (Dujiangyan)

Intensity region	Structural typologies	VMP					
		DS0	DS1	DS2	DS3	DS4	DS5
Overall zone	MMS	1	1.083	0.336	0.573	0.669	0.269
	RC	1	1.537	0.715	0.766	0.458	0.121
	BFM	1	1.075	0.389	0.682	0.706	0.232
	WS	1	1.48	0.96	0.92	0.24	1.84
	OB	1	1.07	0.666	0.616	0.219	0.334
VI	MMS	1	0.828	0.162	0.084	0.002	0
	RC	1	1.542	0.153	0.017	0	0
	BFM	1	0.966	0.05	0.013	0	0
	WS	1	1.533	0.533	0.067	0	0
	OB	1	0.952	0.476	0.095	0.006	0
VII	MMS	1	1.25	0.26	0.21	0.07	0
	RC	1	1.49	1	0.29	0	0
	BFM	1	1.17	0.43	0.36	0.18	0
	WS	1	1.17	1	0.33	0	0
	OB	1	0.87	0.6	0.22	0.04	0
VIII	MMS	1	1.257	0.574	1.596	1.588	0.066
	RC	1	1.214	1.464	2.821	0.750	0
	BFM	1	1.211	1.921	4.579	3.184	0.368
	WS	1	1.667	1.667	2	0	1.333
	OB	1	1.75	0.969	2.094	0.188	0.063
IX	MMS	1	1.532	0.823	2.71	2.968	0.468
	RC	1	2.857	3.714	7.571	6	0.429
	BFM	1	2.333	4.111	12.556	15.444	4.333
	WS	1	2	2	4	0	8
	OB	1	2.875	3.25	6.875	1	0.875
X	MMS	1	4.5	10.75	19.25	50.5	20
	RC	1	3	7	10	28	7
	OB	1	1.5	1.75	6	7	8
XI	MMS	1	1.5	4	10.5	35.5	81.5
	RC	1	2	2	3	7	16

(2019, 2021a) developed a logarithmic distribution function model (LDFM) considering continuous seismic intensity measures, as expressed in Eq. 14. They used the proposed model to perform regression analysis on the actual seismic damage data of MMS and RC in the historical center of Italy and generated building vulnerability curves based on typical cities and regions. An exponential distribution function model (EDFM) for predicting the seismic vulnerability of RC building clusters was proposed by Del Gaudio et al. (2021, 2019, 2017), as expressed in Eq. 15. They applied the proposed model to assess the seismic vulnerability of typical urban building clusters affected by the L'Aquila earthquake.

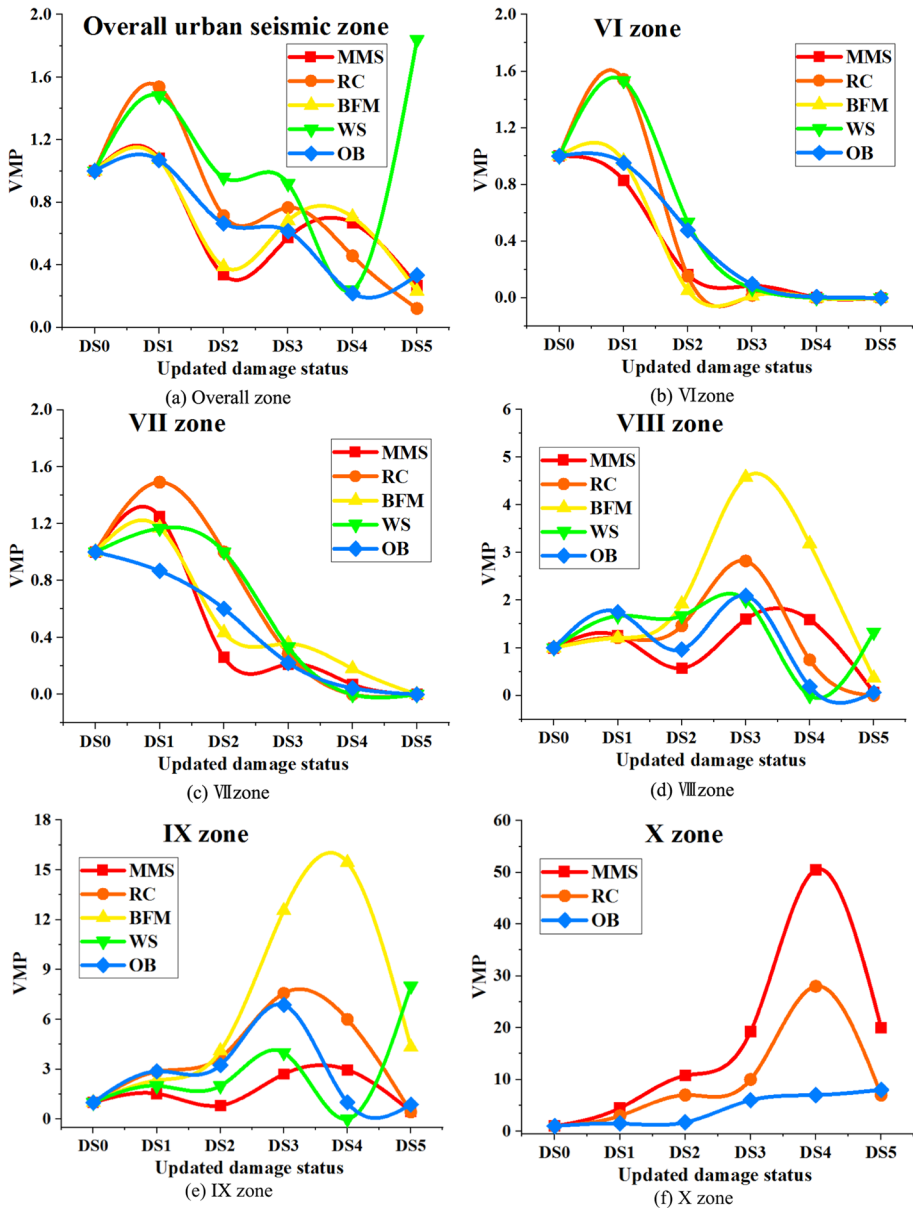


Fig. 8 Vulnerability curve of urban typical building portfolios considering VMP

$$P(VL_j \geq v_j | IM) = \Lambda \left[\frac{\ln(IM) - \mu}{\sigma} \right] = \Lambda [IM, \tau_1, \tau_2 \dots \tau_n] \tag{14}$$

$P(VL_j \geq v_j | IM)$ is the probability of urban building damage reaching or exceeding the given vulnerability level v_j under the specific continuous intensity measures, with j values ranging from 1 to 5. $\Lambda[\cdot]$ is the logarithmic normal distribution function, and μ and σ are

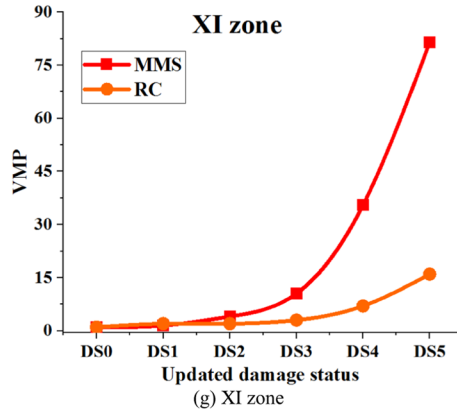


Fig. 8 (continued)

the mean value and variance, respectively. $\tau_1, \tau_2 \dots \tau_n$ represent characteristic coefficients considering n -dimensional influence factors.

$$P(VI_j \geq vI_j | IM) = 1 - e^{-\alpha \cdot IM^\beta} = B [IM, \delta_1, \delta_2, \dots \delta_n] \tag{15}$$

where $B[\cdot]$ is the exponential distribution function. α and β are evaluation parameters for urban building clusters. $\delta_1, \delta_2, \dots \delta_n$ are the uncertainty regression coefficients of the exponential distribution function.

Li et al. (2023) proposed a regression model based on the traditional Gaussian distribution function and applied it to evaluate the structural vulnerability of more than 200 typical earthquakes in China. However, the proposed model ignores the influence of DS0 level samples and does not consider the scale of regional seismic risk assessment, resulting in relatively low accuracy of the established model. This study comprehensively considers the model features of the above distribution functions, combines the Chinese macrointensity scale and the proposed urban building hazard and vulnerability model (Eqs. 7–12), and proposes an updated Gaussian distribution function model (UGFM) based on the damage state and optimizing intensity measures, as expressed in Eq. 16. The nonlinear vulnerability regression model proposed in this paper considers more of the impact of nondamaged building sample sets on the damage probability matrix than do existing models (risk and hazard models) and refines the estimation scale of vulnerability. The proposed model can effectively improve the accuracy of seismic vulnerability and hazard assessment for these five types of urban building clusters. Nonlinear vulnerability fitting of Dujiangyan’s building portfolio dataset was also conducted. The vulnerability regression curves and parameter matrices of five typical urban buildings considering UDR parameters were generated, as shown in Figs. 10, 11, 12, 13, 14, 15 and 16 and Table 3.

$$P[DS_i \geq ds_i | HIM] = \Phi [HIM, \omega_1, \omega_2, \dots \omega_n] \tag{16}$$

The HIM is a hybrid intensity measure. $\Phi[\cdot]$ denotes the updated Gaussian regression function model used to evaluate the seismic vulnerability of urban building clusters. $\omega_1, \omega_2, \dots \omega_n$ are the uncertainty coefficients. DS_i values are integers from 1 to 6.

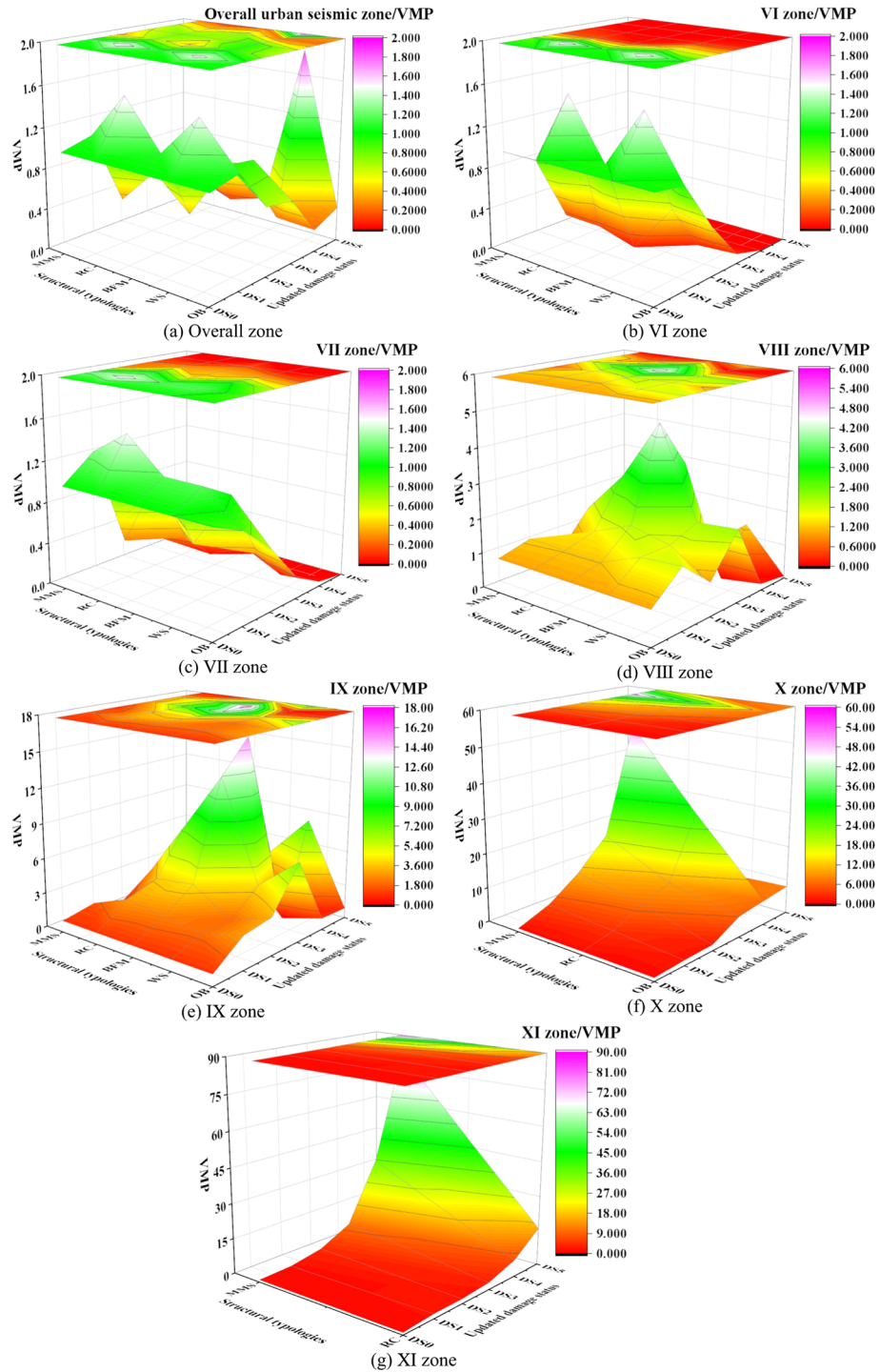


Fig. 9 Vulnerability surface of urban typical building portfolios considering VMP

The 8,669 buildings in Dujiangyan city are classified and counted according to the overall seismic zone and multiple macroseismic intensity zones. Vulnerability regression analysis was conducted on five typical urban building clusters based on the proposed nonlinear regression model. In the overall zone, the distributions of MMS, BFM, and OB were relatively balanced at the different damage levels, and the difference in the multidimensional fitting models was inconspicuous. The EDFM curve of the RC building cluster shows a peak between DS0 and DS1, while the WS curve has low value between DS4 and DS5, indicating that the overall damage to the RC structure is relatively mild, while the WS is relatively heavy. In zone VI, the LDFM of MMS, RC, and WS exhibited maximum values at the DS0 and DS1 levels, while the EDFM predicted slightly more at higher failure levels than did the UGFM. The three types of regression curves of BFM have high similarity, and those of LDFM and UGFM have excellent goodness of fit (greater than 0.9). In zone VII, the similarity of the vulnerability regression curves for the various urban building clusters is relatively high, showing a slow decreasing trend as the damage level increases. In zone VIII, the peak value of UGFM in the RC is between DS2 and DS3, while that of BFM is approximately at the DS3 level, indicating that the structural damage in the RC is less than that in the BFM. In zone IX, various types of urban building damage significantly increase. The peak values of the EDFM and UGFM curves for MMS, BFM, and WS are located at higher damage states. Notably, the damage prediction peaks of RC and OB are still at the DS3 level, indicating that these structures have excellent seismic resistance and toughness characteristics. In zone X, the EDFM peaks of MMS and RC are greater than those of EDFM and UGFM, and DS4 damage occurs. The BFM curve at the DS5 level was significantly greater than that of RC and MMS curves, indicating that this type of structure causes relatively severe damage. The regression curves of the WS show an increasing trend, indicating that this type of building is severely damaged. In zone XI, serious damage has occurred to various urban buildings, and the various curves show a strict increasing trend. MMS and BFM damage is similar, while WS is more severe than OB. Notably, in the extreme earthquake zone (XI), an increase in the vulnerability curve of the RC is not apparent, indicating that this type of structure has excellent seismic performance.

4.2 Vulnerability model considering the optimized damage index

The seismic damage (vulnerability) index is one of the core indicators for evaluating the seismic risk and vulnerability of urban building portfolios. Lagomarsino and Giovinazzi (2006) proposed a model for calculating the mean failure index based on the European macroscopic intensity standard, as expressed in Eq. 17. A calculation model for the seismic vulnerability index based on the probability mass and cumulative distribution function was developed by Kassem et al. (2023), (El-Maissi et al. 2023), as expressed in Eq. 18. Formisano et al. (2023), Longobardi and Formisano (2022) and Chieffo et al. (2019, 2021a) proposed an earthquake vulnerability model based on multiple influences on seismic damage in urban buildings (Eqs. 19–20) and validated the model using historical urban buildings in Italy.

$$AF_I = 2.5 \times \left[1 + \tanh \left(\frac{MSI_{EMS-98} + 6.25 \times Vi - 13.1}{W} \right) \right] \quad (17)$$

where AF_I is the average fragility index used to evaluate urban building clusters and MSI_{EMS-98} represents macroseismic intensity measures based on the European intensity

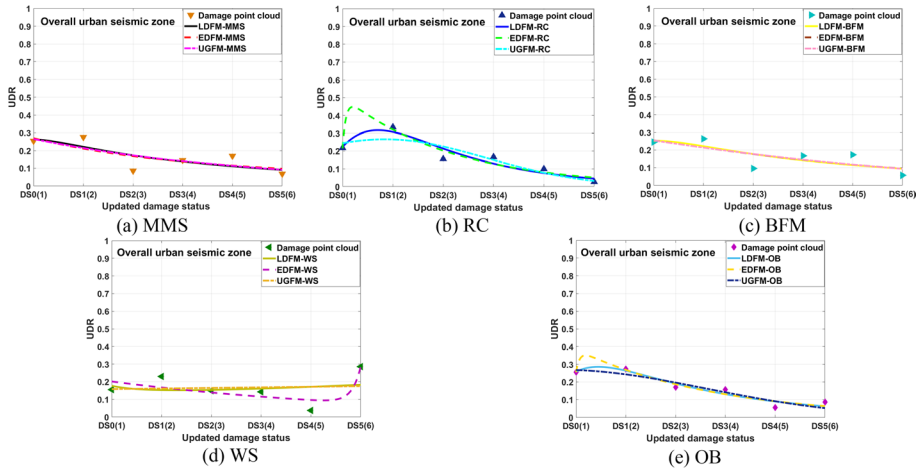


Fig. 10 Vulnerability regression curve of typical building clusters considering the overall seismic zone of the city (Dujiangyan)

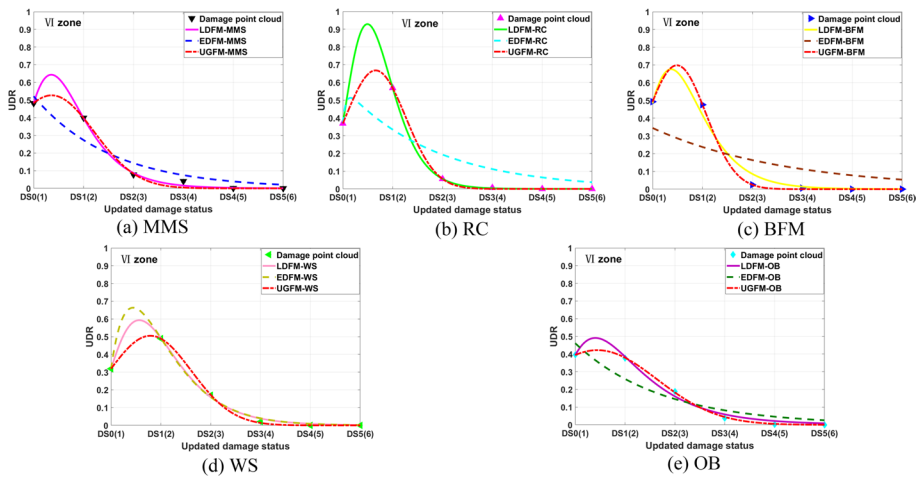


Fig. 11 Vulnerability regression curve of typical building clusters considering intensity zone VI

standard (EMS-98). W is the urban building resilience index, and V_i is the seismic vulnerability index of urban building clusters.

$$AF_I = \sum_{k=1}^5 p_k \times k \tag{18}$$

$$p_k = \frac{5!}{k!(5-k)!} \times (0.2AF_I)^k \times (1 - 0.2AF_I)^{5-k}$$

p_k is the failure probability of urban buildings considering damage factor k .

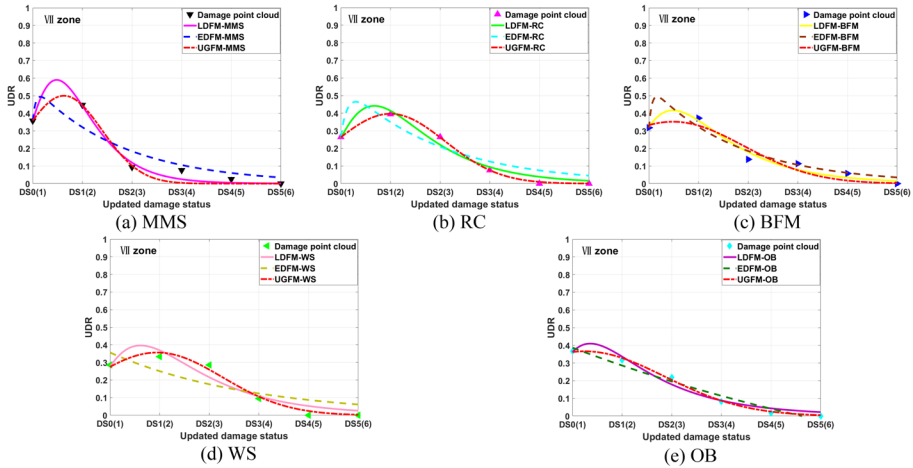


Fig. 12 Vulnerability regression curve of typical building clusters considering intensity zone VII

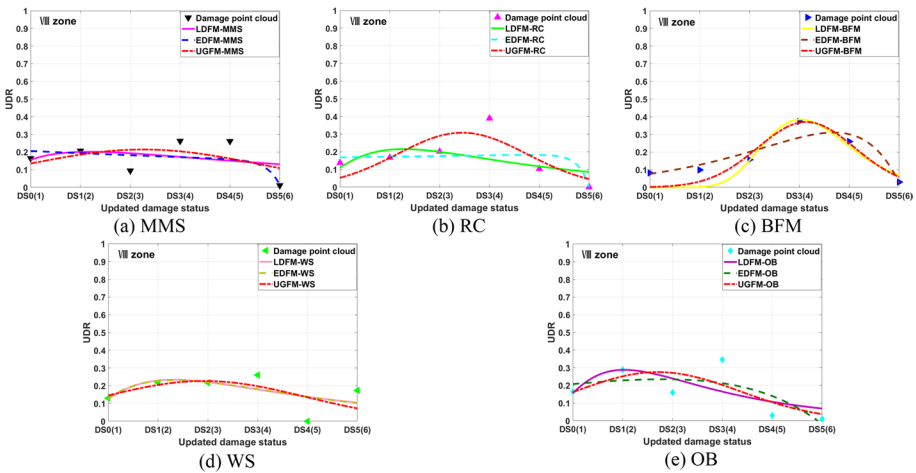


Fig. 13 Vulnerability regression curve of typical building clusters considering intensity zone VIII

$$Vi = \sum_{n=1}^w Q_n \cdot T_n \tag{19}$$

$$SHI = \left[\frac{VI - \left(\sum_{n=1}^s Q_n \cdot P_{\min} \right)}{\left\| \sum_{n=1}^s [(Q_n \cdot P_{\max}) - (Q_n \cdot P_{\min})] \right\|} \right] \tag{20}$$

Q_n and T_n are the weights and scores of the n -factors that affect seismic damage to urban buildings, with n values ranging from 1 to w . The SHI is the seismic risk index for urban

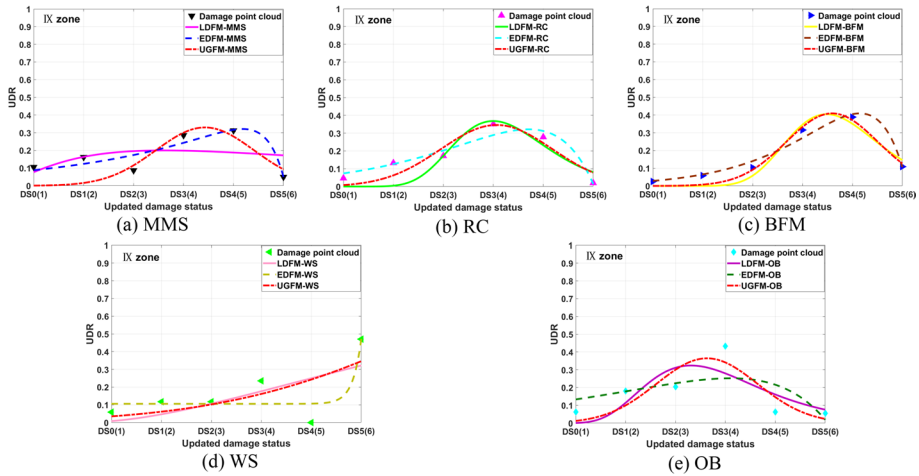


Fig. 14 Vulnerability regression curve of typical building clusters considering intensity zone IX

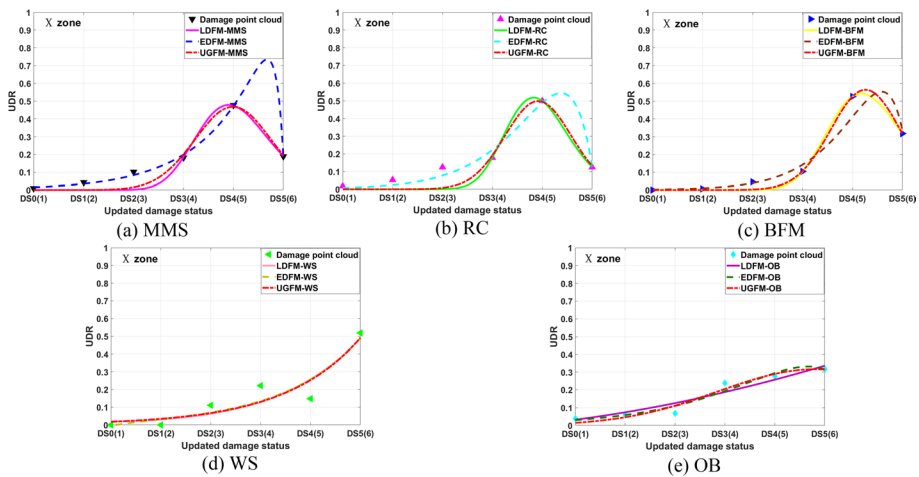


Fig. 15 Vulnerability regression curve of typical building clusters considering intensity zone X

building portfolios. P_{min} and P_{max} are the minimum and maximum scores, respectively, of the n -factors that affect urban building clusters.

Using the Chinese macrointensity standard and probability damage model theory, Li and Gardoni (2024) proposed a vulnerability index calculation model for evaluating the seismic risk of regional buildings and bridges. Typical earthquake damage survey data from China were selected to verify the proposed model. However, the structural seismic damage dataset used for model validation neglects the quantification of nondamaged building samples. The assessment of vulnerability levels of engineering structures does not consider the influence of mixed intensities, resulting in insufficient accuracy of established vulnerability index models. Optimizing outdated computational models using updated empirical structured datasets and hazard quantification models has become an urgent scientific issue to be addressed. This paper proposes an updated

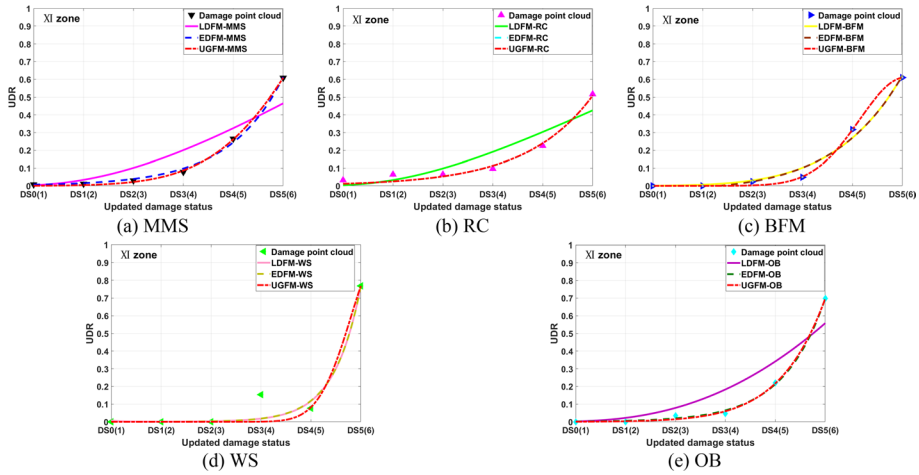


Fig. 16 Vulnerability regression curve of typical building clusters considering intensity zone XI

average damage index (UADI) model based on the extended damage state (level) and the urban building seismic risk model, as expressed in Eq. 21.

$$UADI = \sum_{i=0}^5 ELC_{t,i} \cdot \left[\frac{Q_i(DSi|HSI_j)}{\sum_{i=0}^5 Q_i(DSi|HSI_j)} \right] \tag{21}$$

$ELC_{t,i}$ is the seismic loss coefficient for the expansion damage state DSi ($i \in \{0, 1, 2, 3, 4, 5\}$) of t -type urban building clusters considering hybrid intensity indicators, as noted in Table 4 (tl , al , and ll are the upper, middle, and lower bounds of $ELC_{t,i}$, respectively). $Q_i(DSi|HSI_j)$ and $\sum_{i=0}^5 Q_i(DSi|HSI_j)$ are the number and total number of damaged areas that occur in the extended damage state DSi of the type t structure in potential seismic source area j of the city under the influence of hybrid seismic intensity measures ($HSIs$), respectively.

The vulnerability parameter matrix, point cloud, and curve considering UADI are developed considering the actual seismic damage sample data of five typical building portfolios in Dujiangyan, as shown in Table 5 and Figs. 17–18.

The proposed UADI function model is used for damage estimation and model calculations for buildings in Dujiangyan city. The developed matrix, point cloud, and curve indicate the seismic risk and vulnerability of the urban structures in zones with different intensities. The risk and vulnerability assessment results for typical buildings in five types of cities are consistent with actual field earthquake damage observations. The obtained UADI model can provide a positive reference for the development of earthquake risk and vulnerability models for a typical urban building portfolio.

Table 3 Vulnerability fitting coefficient matrix of typical urban building clusters (Duijiangyan city)

Inten-sity zone	Type	The nonlinear vulnerability regression model															Goodness of fit
		Formisano et al. (2023)					Del Gaudio et al. (2019)					This Study					
		LDFM/ τ_h	τ_1	τ_2	τ_3	Good-ness of fit	EDFM/ δ_h	δ_1	δ_2	δ_3	δ_4	Good-ness of fit	UGFM/ ω_h	ω_1	ω_2	ω_3	
VI	Overall	MMS	0.5544	1.538	3.179	0.5882	0.2326	-0.3626	0.117	-0.08429	0.5779	1.737 × 10 ⁹	1.737 × 10 ⁹	-0.214	45.23	0.5753	
	RC	0.6623	0.939	0.814	0.8824	0.8062	-0.4604	-8.122 × 10 ⁵	-14.84	0.9116	0.2662	0.2662	1.84	2.853	0.7971		
	BFM	0.5727	1.572	2.998	0.5725	10.82	-0.3012	10.52	-0.3057	0.5645	0.6656	0.6656	-10.69	11.91	0.565		
	WS	0.1102	-1.497	-4.705	0.0161	2.08 × 10 ⁻¹⁶	5.755	0.2426	-0.1855	0.7103	2.414	2.414	274.1	165.5	0.0017		
	OB	0.5762	1.032	1.327	0.9236	0.5532	-0.3609	-1.411 × 10 ⁵	-13.9	0.9279	0.2698	0.2698	0.6599	4.162	0.8859		
	MMS	0.9425	0.4611	0.3171	0.997	0.9976	-0.6474	-51.69	-10.86	0.8938	0.5266	0.5266	1.359	1.209	0.9943		
VII	RC	1.449	0.488	0.174	1	0.9997	-0.5478	-1.667 × 10 ⁶	-15.89	0.6944	0.6679	0.6679	1.658	0.8537	0.9998		
	BFM	0.998	0.464	0.2974	0.9762	0.5	-0.3719	-114.5	-19.04	0.6097	0.6981	0.6981	1.488	0.8274	0.9999		
	WS	1.006	0.609	0.3224	0.9975	2972	-1.763	-2985	-1.768	0.9972	0.505	0.505	1.789	1.166	0.9997		
	OB	0.7841	0.5972	0.5175	0.9898	0.8207	-0.5765	0	-0.5765	0.8546	0.422	0.422	1.443	1.703	0.9995		
	MMS	0.9456	0.5493	0.3113	0.9788	0.9743	-0.5551	-8.067 × 10 ⁵	-15.21	0.8442	0.4999	0.4999	1.628	1.09	0.9666		
	RC	0.8349	0.7602	0.4927	0.9673	0.9746	-0.5124	-457.5	-7.271	0.8874	0.3966	0.3966	1.997	1.56	0.9992		
VIII	BFM	0.7159	0.6893	0.5929	0.9636	0.9715	-0.5519	-2.856 × 10 ⁶	-16.29	0.9439	0.3521	0.3521	1.48	2.032	0.9164		
	WS	0.7494	0.7949	0.6321	0.9161	0.134	-0.3528	0.3729	-0.3524	0.6918	0.3564	0.3564	1.948	1.863	0.9824		
	OB	0.6723	0.6847	0.7577	0.973	0.975	-0.1168	-0.4754	0.0109	0.9651	0.3662	0.3662	1.241	2.302	0.9958		
	MMS	0.7962	1.966	2.364	0.0955	0.2188	-0.0613	-5.064 × 10 ⁻¹²	4.006	0.4217	0.2142	0.2142	3.265	3.325	0.2274		
	RC	0.632	1.332	1.017	0.2339	0.1646	0.02251	-1.897 × 10 ⁻¹³	4.605	0.3815	0.3079	0.3079	3.451	1.845	0.6282		
	BFM	1.585	1.439	0.09362	0.7751	0.1232	0.7015	-0.07933	0.7744	0.8426	0.3699	0.3699	4.136	1.378	0.8474		
IX	WS	0.7169	1.401	1.126	0.2882	0.9138	-0.3527	-1.183	-0.8331	0.2857	0.2269	0.2269	2.923	2.88	0.2357		
	OB	0.7184	1.12	0.8222	0.4615	49.54	0.3222	-49.36	0.3228	0.5384	0.2753	0.2753	2.703	2.335	0.5498		
	MMS	1.109	2.145	1.724	0.1424	0.06267	0.3402	-2.457 × 10 ⁻⁸	2.781	0.8122	0.3298	0.3298	4.428	1.394	0.3905		
	RC	1.512	1.44	0.1087	0.7052	-77.96	0.7592	78.01	0.7591	0.9197	0.3459	0.3459	4.067	1.583	0.8434		

Table 3 (continued)

Intensity zone	Type	The nonlinear vulnerability regression model														
		Formisano et al. (2023)						Del Gaudio et al. (2019)						This Study		
		LDFM/ τ_n			Goodness of fit			EDFM/ δ_n			Goodness of fit			UGFM/ ω_n	Goodness of fit	
τ_1	τ_2	τ_3	δ_1	δ_2	δ_3	δ_4	δ_5	δ_6	δ_7	δ_8	δ_9	δ_{10}	ω_1	ω_2	ω_3	
X	BFM	1.852	1.542	0.08312	0.9111	-4.692	1.048	4.704	1.047	0.9666	0.4093	4.593	1.301	0.9354		
	WS	52.37	4.643	2.464	0.3226	0.1059	-0.0007	2.201×10^{-16}	5.841	0.7829	0.987	12.36	6.218	0.407		
	OB	1.139	1.318	0.2437	0.4999	492.2	0.5119	-492.1	0.5119	0.4104	0.3645	3.631	1.433	0.6746		
	MMS	2.372	1.613	0.04407	0.9163	0.006176	0.8682	-1.651×10^{-17}	6.43	0.9949	0.4678	4.991	1.081	0.9309		
	RC	2.522	1.591	0.03348	0.8752	-0.218	1.446	0.22	1.444	0.9646	0.4984	4.916	0.94	0.8851		
XI	BFM	2.837	1.665	0.04057	0.9907	-0.007287	1.679	0.007786	1.668	0.9328	0.564	5.261	0.9783	0.9916		
	WS	0.01718	-0.3968	-0.932	0.8649	0.01044	0.6411	-0.09437	-1.363	0.8757	2.443×10^{95}	1367	64.1	0.8728		
	OB	2.756×10^{-7}	-10.95	-10.27	0.9116	-1.857	0.8608	1.872	0.8597	0.9468	0.3162	5.814	2.753	0.9509		
	MMS	283.7	4.992	2.216	0.8409	0.5694	-6.035	0.002493	0.9173	0.9968	1.611	8.731	2.768	0.9992		
	RC	95.67	4.421	1.908	0.8453	0.005535	0.7537	-1.929	-11.54	0.9846	3.96×10^{92}	1189	56.12	0.9845		
OB	BFM	1.406×10^{-7}	-4.265	-2.146	0.9831	0.7935	0.5159	-0.8118	0.506	0.9825	0.6118	6.073	1.322	0.9984		
	WS	0.002161	0.5337	-0.2066	0.9558	-0.2138	-8.069	1.074×10^{-5}	1.862	0.9558	0.987	6.465	0.9298	0.9485		
	MMS	1.052×10^6	8.742	3.816	0.8518	-6.6	-10.09	0.000562	1.188	0.9982	98.13	14.96	4.028	0.9983		

5 Conclusion

This paper studies the seismic risk and vulnerability of typical urban building portfolios. Taking all the buildings in Dujiangyan city affected by the Wenchuan earthquake as a case study, multidimensional structural damage assessment and vulnerability analysis were conducted in combination with the proposed optimized seismic hazard probability model. An innovative quantitative model has been proposed to evaluate the seismic risk and vulnerability of urban building clusters. A new probabilistic risk model for urban building clusters based on multidimensional seismic vulnerability indicators has been developed. The following conclusions were drawn:

1. Using reliability, probabilistic seismic risk, the Bayesian probability probabilistic model, and the traditional seismic fragility function model, a new probabilistic demand and capability model of seismic risk based on updated seismic intensity measures is developed. The traditional damage state and threshold have been expanded, and an earthquake risk and vulnerability assessment model for urban building clusters has been established based on optimized hybrid intensity measures. According to the analysis results of the model, the developed model has more detailed and precise features than historical hazard models.
2. Using the proposed quantitative model of seismic risk, a vulnerability assessment and statistical analysis of all the buildings (8,669 buildings) in Dujiangyan city were conducted. The distributions of urban earthquake risk and building vulnerability are generated based on various basic data from actual field inspection. Using seismic risk and multidimensional damage modal analysis methods, seismic risk and vulnerability models of five types of buildings (multistory masonry structures (MMSs), reinforced concrete structures (RCs), bottom frame seismic wall masonry structures (BFMs), workshop buildings (WSs), and other buildings (OBs)) in Dujiangyan city were developed considering updated damage rates, quantities, and optimized exceeding probability parameters. The analysis results indicate that the developed multidimensional quantitative model can reasonably display the damage modes of buildings in Dujiangyan city overall and in zones with different seismic intensities.
3. Using the developed extended damage state (level), an innovative vulnerability membership parameter (VMP) considering the nondamaged state (DS0) is proposed to estimate the degree of membership of different damage levels to DS0. The results indicate that the DS1 level of most building clusters in lower-intensity zones has a relatively high degree of membership in DS0. With increasing intensity, the VPM range for higher damage levels increases, and the membership in DS0 decreases accordingly.
4. The traditional nonlinear vulnerability regression model is updated, and a multidimensional vulnerability regression comparison curve and parameter matrix based on the overall building portfolio in Dujiangyan city are established. The goodness of fit of

Table 4 Earthquake loss (fragility) evaluation coefficient (Li 2024b), (Li and Gardoni 2024)

Threshold of structural damage index	Vulnerability evaluation coefficient ($ELC_{t,i}$)					
	DS0	DS1	DS2	DS3	DS4	DS5
<i>ll</i>	0	0.05	0.13	0.32	0.56	0.84
<i>al</i>	0.025	0.09	0.225	0.44	0.7	0.92
<i>tl</i>	0.05	0.13	0.32	0.56	0.84	1

Table 5 Seismic vulnerability parameter matrix of urban buildings considering the UADI

Structural typologies	Threshold	Seismic intensity measures/UADI					
		VI	VII	VIII	IX	X	XI
MMS	<i>ll</i>	0.0436	0.0731	0.262	0.3269	0.4987	0.6888
	<i>al</i>	0.0839	0.1215	0.3523	0.4261	0.6139	0.7874
	<i>tl</i>	0.1243	0.1699	0.4425	0.5253	0.729	0.886
RC	<i>ll</i>	0.0378	0.0785	0.2171	0.3138	0.4611	0.6026
	<i>al</i>	0.0759	0.1352	0.3076	0.4192	0.577	0.6966
	<i>tl</i>	0.1139	0.1919	0.3981	0.5247	0.6929	0.7906
BFM	<i>ll</i>	0.029	0.1052	0.3154	0.4263	0.6013	0.7086
	<i>al</i>	0.0635	0.1629	0.4199	0.54	0.7175	0.8099
	<i>tl</i>	0.0979	0.2206	0.5243	0.6538	0.8336	0.9113
WS	<i>ll</i>	0.0534	0.0843	0.2687	0.4918	0.604	0.7384
	<i>al</i>	0.0997	0.1433	0.3465	0.575	0.7035	0.8292
	<i>tl</i>	0.146	0.2024	0.4244	0.6582	0.8029	0.9199
OB	<i>ll</i>	0.0567	0.0795	0.1717	0.2558	0.5094	0.7292
	<i>al</i>	0.1043	0.1343	0.2491	0.3493	0.612	0.8248
	<i>tl</i>	0.152	0.189	0.3266	0.4428	0.7146	0.9205

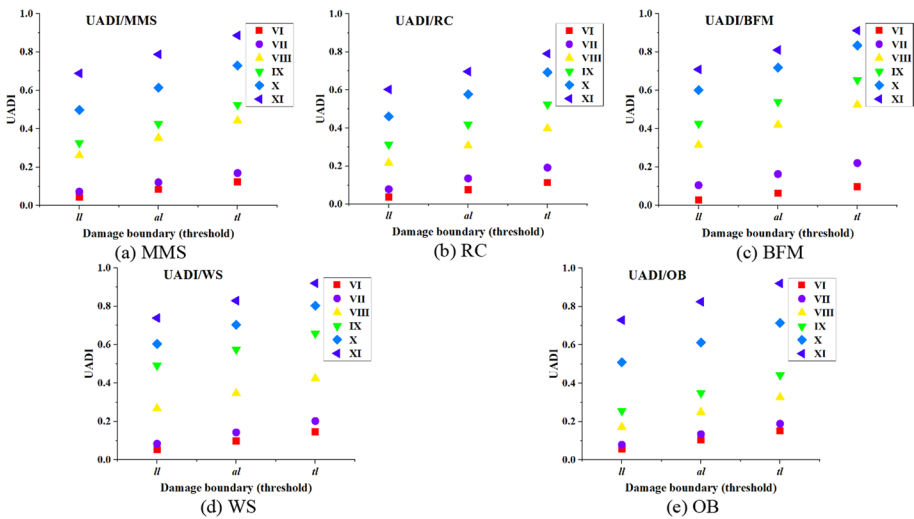


Fig. 17 Seismic vulnerability point cloud of urban buildings considering UADI

more than 68.5% of the UGFMs is more than 0.8%, which indicates that the proposed updating model has a good prediction effect.

- By combining traditional earthquake damage index models and theories, an updated average damage index (UADI) model has been proposed to evaluate the seismic risk and vulnerability of urban building clusters. Based on the proposed seismic risk and extended structural damage state model, the UADI point cloud and curve of five typical building clusters in Dujiangyan city are developed. According to the identification and

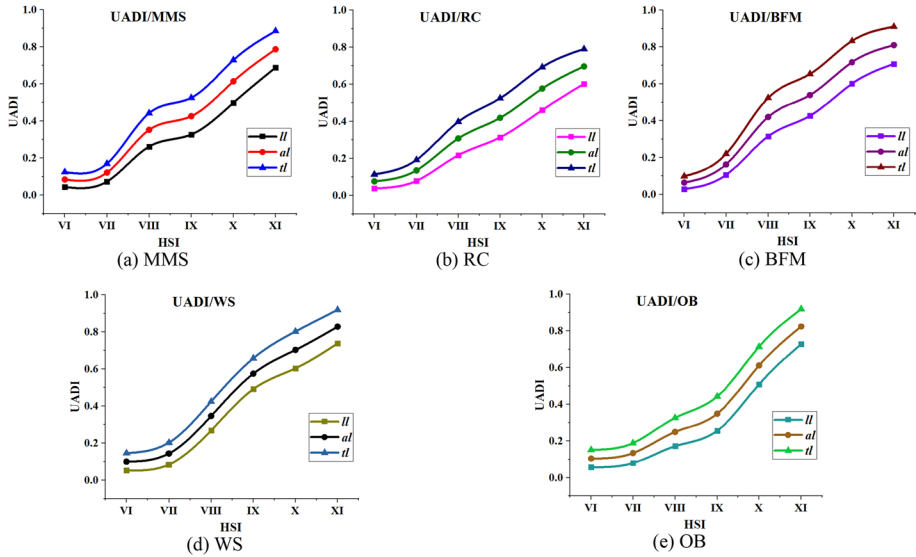


Fig. 18 Seismic vulnerability curve of urban buildings considering UADI

analysis of UADI parameters, the developed model can provide a more detailed assessment of the seismic risk and vulnerability of typical urban building portfolios.

This study involved seismic analysis and evaluation of urban building clusters and revealed the damage modes and disaster characteristics of various structures under the influence of different intensity measures. Another crucial finding is that the damage to RC buildings is relatively mild in zones with different seismic intensities. The seismic risk and vulnerability assessment model for urban building clusters established in this paper can provide favourable references for developing relatively reasonable quantitative models for evaluating the seismic resilience and sustainability of typical cities. It is worth emphasizing that the urban building seismic damage samples used for model validation in this paper were distributed at different sites. Additionally, different geological conditions potentially impact the vulnerability of urban buildings. Therefore, the model proposed in this paper can be extended to other cities and regions based on different sites and geological categories. The various structural seismic vulnerability and risk models and indices proposed in this paper provide positive references for seismic risk estimation and prevention of urban building clusters. The research results obtained can provide reasonable references for urban planners and disaster management authorities to revise earthquake risk zoning and structural seismic resistance levels. The structural seismic risk and vulnerability model in this paper was developed based on different intensity measures and updated vulnerability level scales. Therefore, the proposed model can be extrapolated to structural risk and vulnerability assessments of the same seismic intensity in other seismic events.

Acknowledgements This paper’s structural damage sample data were derived from the earthquake field inspection database of the Institute of Engineering Mechanics of the China Earthquake Administration (IEM). I would like to express my sincere gratitude to the IEM.

Funding The research described in this paper was financially supported by the Basic Scientific Research Business Expenses of Provincial Universities in Heilongjiang Province (2022-KYYWF-1056), the Scientific Research Fund of Institute of Engineering Mechanics, China Earthquake Administration (Grant No. 2023D39), and a project funded by Heilongjiang Postdoctoral Science Foundation (LBH-Z22294), China.

Declarations

Conflict of interest The authors declare no conflict of interest, ethics, or otherwise. Confirm informed consent.

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