

Article

Probabilistic Seismic Resilience Assessment for Circular Shield Tunnels in Soft Soils Considering Vulnerability Model Uncertainty

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Abstract

As critical infrastructure supporting sustainable urban development globally, the seismic resilience evaluation of tunnels is paramount to metropolitan safety. This paper proposes a probabilistic seismic resilience analysis framework for tunnel structures in soft soils. By integrating vulnerability models and functionality functions, resilience metrics for shallow, medium-depth, and deep tunnels are obtained, revealing how these metrics evolve with seismic intensity. The research further investigates the impact of different vulnerability models on tunnel resilience, treating occurrence probabilities of different damage states as random variables. Resilience metrics incorporating multiple vulnerability models are derived based on the Dirichlet distribution. The results of the study show that tunnel resilience metrics increase progressively with greater burial depth. At $PGA = 0.8$ g, for example, the resilience metrics calculated using a single model are 0.907, 0.962, and 0.985 for shallow, medium-depth, and deep tunnels, respectively. When accounting for multiple vulnerability models, the composite resilience metric tends to align with results from models carrying higher weights. This work establishes a scientific decision-making basis for optimizing seismic tunnel design, post-disaster functional recovery, and urban infrastructure resilience management.

Keywords: underground structures; model uncertainty; resilience metric; Dirichlet distribution



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1. Introduction

Rapid urbanization has spurred extensive utilization of underground space, positioning tunnels as essential elements of urban transportation and lifeline systems. Earthquakes, as natural disasters with randomness, suddenness, and high risks [1], not only affect structural safety and functionality but also may induce secondary disasters, causing chain destruction to cities. The 1995 Kobe earthquake inflicted widespread damage on Japan's subterranean networks, affecting subway stations and utility pipelines [2]. Similarly, the 1999 Taiwan Chi-Chi earthquake resulted in serious damage to multiple highway tunnels, including annular spalling of tunnel linings, oblique cracks, and even portal collapses [3].

The 2008 China Wenchuan earthquake led to severe damage to numerous mountain tunnels [4]. These disasters caused not only direct structural damage but also urban system paralysis due to transportation artery interruptions and underground pipeline ruptures. Facing increasingly frequent extreme seismic events, enhancing the seismic resilience of soft-soil tunnels has become a crucial development direction for safeguarding urban operational safety.

Resilience was first introduced into ecosystem research by Holling [5]. Timmerman [6] applied the concept of resilience to social systems, defining resilience as the level at which social systems or their components restore original functionality after external disasters. Bruneau et al. [7] introduced resilience theory into civil engineering, indicating that resilience includes four characteristics: robustness, redundancy, resourcefulness, and rapidity. Currently, resilience analysis has been widely applied in infrastructure systems [8–11], building engineering [12–14], bridge engineering [15–17], and underground structures [18–21]. Rinaudo et al. [18] first proposed relevant definitions for tunnel fire resilience. Huang et al. [20] established a resilience analysis model for shield tunnels based on intelligent monitoring systems. Saadat et al. [21] conducted resilience analysis of the Washington Metro system under extreme events using graph theory and network topology methods, considering two extreme scenarios: station failure and tunnel section failure.

Existing studies have shown that, even for the same or similar tunnel structures, different vulnerability models may yield markedly different damage state probabilities because of variations in data sources, damage state definitions, model assumptions, site conditions, soil-structure interaction, and parameter calibration methods [22]. Such inter-model variability can further propagate into post-earthquake functionality recovery and resilience estimates, thereby affecting the evaluation of tunnel seismic performance. Chen [23] compared alternative ordinal regression formulations for seismic fragility assessment and demonstrated that different statistical model structures can produce appreciably different damage state probabilities. Nardin et al. [24] developed a state-dependent seismic fragility framework incorporating surrogate modeling, polynomial chaos expansion, and bootstrap resampling, highlighting the effects of limited data, model simplification, and parameter uncertainty on fragility estimates. Although various models are reasonable, using only one model for seismic resilience analysis may likely overestimate or underestimate structural resilience. However, existing studies have mainly focused on uncertainty within an individual fragility model, whereas the uncertainty arising from the selection of multiple plausible vulnerability models has rarely been propagated into the damage state probabilities, post-earthquake functionality recovery, and seismic resilience indices of circular shield tunnels in soft soils.

To address this unresolved problem, this study develops a probabilistic seismic resilience assessment framework for circular shield tunnels in soft soils by integrating vulnerability models, post-earthquake functionality recovery functions, and a Dirichlet-based model combination approach. The specific objectives are to (1) establish a fragility- functionality-resilience calculation procedure for tunnels at different burial depths; (2) investigate the influence of seismic intensity and vulnerability model selection on tunnel resilience; (3) represent the probabilities of different damage states as random variables and combine alternative vulnerability models using credibility-based weighting coefficients; and (4) quantify the composite resilience index and its uncertainty bounds. The principal contribution of the proposed approach lies not in the Dirichlet distribution itself, but in its use to explicitly propagate inter-model uncertainty and unequal model credibility into tunnel seismic resilience estimates. Compared with single model analysis or simple arithmetic averaging, the framework provides a more transparent basis for vulnerability model selection, seismic design evaluation, and post-earthquake recovery planning. Although the

numerical application focuses on circular shield tunnels in soft soils, the general framework may be extended to other tunnel types after appropriate calibration of the vulnerability and recovery models.

2. Methodology

2.1. Deterministic Seismic Resilience Assessment Framework

Tunnel vulnerability curves are calculated based on the relationship between different levels of seismic intensity measures (*IM*) and corresponding damage measures (*DM*). The calculation formula primarily adopts the two-parameter logarithmic distribution model [25]:

$$P_f(d_s \geq d_{si}|S) = \phi\left[\frac{1}{\beta_{tot}} \cdot \ln\left(\frac{S}{S_{mi}}\right)\right] \quad (1)$$

In this equation, d_s is the damage state; d_{si} is a specific damage state i ; $P_f(d_s \geq d_{si}|S)$ is the probability that the damage state exceeds a specific damage state i ; ϕ is the cumulative distribution function of the standard normal distribution, used to calculate the probability value; β_{tot} is the total logarithmic standard deviation, characterizing the comprehensive impact of uncertainties, including uncertainty in damage state definition, uncertainty in tunnel seismic response and bearing capacity, and uncertainty in ground motion; S is the seismic intensity measure; S_{mi} is the seismic intensity measure corresponding to a specific damage state i .

By combining vulnerability models and functionality functions, the tunnel seismic restoration curve $Q(t)$ under different seismic intensities can be established. The tunnel restoration curve $Q(t)$ can be obtained according to the following formula [26]:

$$Q(t) = \sum_{i=1}^4 Q_d(d_{si}|t) P_f(d_s \geq d_{si}|IM) \quad (2)$$

In this equation, $Q_d(d_{si}|t)$ is the performance percentage of the tunnel under damage state d_{si} at time point t after the commencement of post-earthquake repair work, obtained from the tunnel functionality recovery function; for undamaged conditions, $Q_d(d_{si}|t)$ takes the value 1. $P_f(d_s \geq d_{si}|S)$ is the probability that the damage state exceeds a specific damage state i , that is, the vulnerability model. In the analysis of this paper, the tunnel functionality recovery function is selected according to that provided in reference [27]. The tunnel functionality recovery function is a mathematical model used to quantify the post-earthquake recovery process of tunnel operational capacity and to evaluate and optimize seismic resilience. By determining the mean and standard deviation of the repair time for each damage state, the recovery function is expressed in the form of a normal distribution. The structural performance of the tunnel is then represented by the probability that the tunnel can complete the required repairs within time t after an earthquake, as shown in Figure 1.

The seismic resilience metric Re of tunnel structures can be calculated from the tunnel restoration curve $Q(t)$ corresponding to different damage states. It can usually be calculated using the following formula [28]:

$$Re = \frac{\int_{t_0}^{t_h} Q(t) dt}{t_h - t_0} \quad (3)$$

In this equation, t_0 is the occurrence time of seismic action. This paper starts the study from the time when seismic action occurs, with the reference initial value taken as 0; t_h is the time for full recovery of tunnel structural performance. Synthesizing the preceding

analysis, the basic flow of tunnel seismic resilience analysis in this paper can be represented by Figure 2 below:

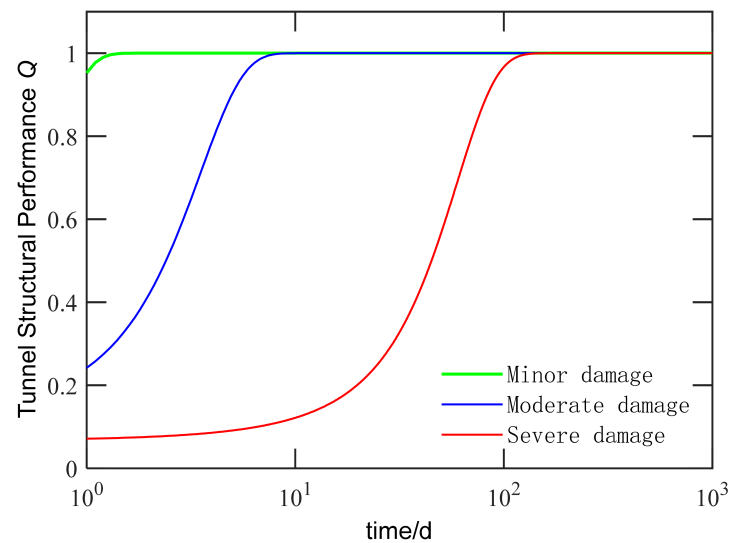


Figure 1. Post-repair functionality for tunnel structures.

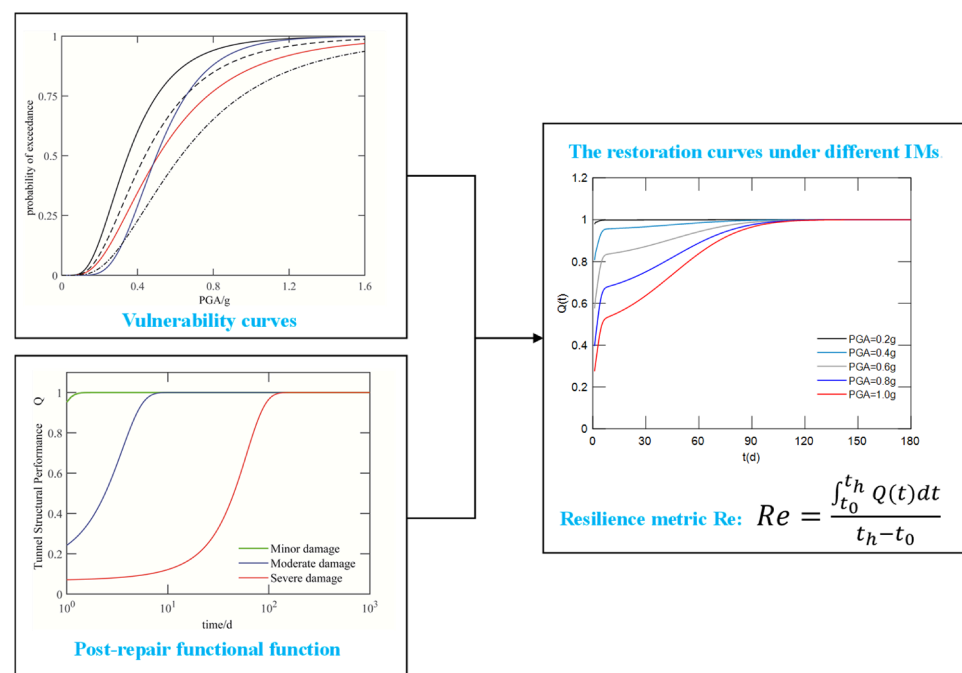


Figure 2. Fundamental procedure for seismic resilience analysis of tunnels.

Taking the tunnel resilience metric Re as the evaluation indicator for tunnel seismic resilience, the seismic resilience of tunnels is divided into four classes based on the magnitude of the resilience metric [29]: Class I represents the best seismic resilience, where the tunnel possesses excellent self-recovery capability after an earthquake, restoring structural functionality within a very short time without human intervention; Class II corresponds to strong resilience, where main functionality can be restored under moderate human intervention; Class III indicates moderate resilience, requiring significant resources for restoration; Class IV reflects limited recoverability and poor resilience, with potential for irreparable damage. The classification of tunnel resilience classes is shown in Table 1.

Table 1. Classification of tunnel resilience classes and corresponding thresholds.

Tunnel Resilience Class	Range of Resilience Metric Re
Class I	$0.875 < Re \leq 1.00$
Class II	$0.585 < Re \leq 0.875$
Class III	$0.500 < Re \leq 0.585$
Class IV	$Re \leq 0.500$

2.2. Probabilistic Seismic Resilience Analysis Framework for Tunnels Accounting for Vulnerability Model Uncertainties

In the analysis of soft-soil tunnels, numerous researchers have proposed various seismic vulnerability models based on different analytical methods, comprehensively considering distinct soil-structure interactions or local site characteristics. In Section 3.1, the seismic resilience of soft-soil tunnels was analyzed using one vulnerability model as an example. Section 3.2 addresses different vulnerability models by treating them as random variables, investigating an integrated approach for tunnel seismic resilience analysis that incorporates multiple vulnerability models.

Based on the vulnerability curves, the discrete probabilities P_0 , P_1 , P_2 , and P_3 for tunnel damage states of no damage, minor damage, moderate damage, and severe damage can be obtained. The calculation formula is as follows, and the sum of P_0 , P_1 , P_2 , and P_3 is 1:

$$P_0 = 1 - P(\geq \text{minor damage}) \quad (4)$$

$$P_1 = P(\geq \text{minor damage}) - P(\geq \text{moderate damage}) \quad (5)$$

$$P_2 = P(\geq \text{moderate damage}) - P(\geq \text{severe damage}) \quad (6)$$

$$P_3 = P(\geq \text{severe damage}) \quad (7)$$

For different vulnerability models, the values of P_0 , P_1 , P_2 , and P_3 under different seismic intensity measures (PGA) differ. For shallow-buried tunnels in soft soils under $PGA = 0.5$ g, the discrete probabilities P_0 , P_1 , P_2 , and P_3 for no damage, minor damage, moderate damage, and severe damage of the FC_1 vulnerability model are 0.251, 0.387, 0.254, and 0.108, respectively; for the FC_2 vulnerability model, they are 0.513, 0.315, 0.100, and 0.072, respectively. A fundamental premise underlying the proposed multi-model approach is that the various candidate vulnerability models represent alternative plausible realizations of a unique underlying vulnerability function for the specific site conditions considered. For different seismic intensity levels, P_0 , P_1 , P_2 , and P_3 of vulnerability models are treated as random variables, each having certain probability density functions and satisfying the condition that the sum of P_0 , P_1 , P_2 , and P_3 is 1. To characterize the joint distribution of these probabilities, a Dirichlet distribution $f(P, a)$ is adopted, which naturally accommodates the constraint that $\sum_{i=0}^3 P_i = 1$ [25], as expressed in Formula (8).

$$f(P_0, P_1, P_2, P_3, a_0, a_1, a_2, a_3) = \frac{1}{B(a)} \prod_{i=0}^3 P_i^{a_i-1} \quad (8)$$

In this equation, the random variable $P = (P_0, P_1, P_2, P_3)$, the Dirichlet distribution hyperparameters are $a = (a_0, a_1, a_2, a_3)$; these parameters satisfy $P_i > 0$, and the sum of P_i is 1, $B(a)$ is the multivariate beta function, which can be expressed using the Gamma function as follows:

$$B(a) = \frac{\prod_{i=0}^3 \Gamma(a_i)}{\Gamma(\sum_{i=0}^3 a_i)} \quad (9)$$

In the above formula, $\Gamma(a_i)$ is the Gamma function, and its expression is shown in the following formula:

$$\Gamma(a) = \int_0^{+\infty} t^{a-1} e^{-t} dt (a > 0) \quad (10)$$

The mean E and variance V_{ar} of the above Dirichlet distribution are given by

$$b = \sum_{i=0}^3 a_i, E(P_i) = \frac{a_i}{b}, Var(P_i) = \frac{a_i(b - a_i)}{b^2(b + 1)} \quad (11)$$

to determine the joint probability density function f of P_0, P_1, P_2 , and P_3 , that is, to determine the corresponding hyperparameters a_0, a_1, a_2 , and a_3 . Within the Bayesian framework, the vulnerability models FC_1 and FC_2 are treated as independent observations drawn from the underlying distribution. The hyperparameters are then estimated by maximizing the weighted likelihood function expressed in Equation (12), where the weights reflect the relative credibility of each candidate model.

$$L(a^*) = \text{Max}(\prod_{i=1}^k f(P(FC_i), a)^{m_i}) \quad (12)$$

In the above formula, a^* is a set of maximum likelihood estimates for the hyperparameters a . The fundamental principle is to find a set of hyperparameters a_0, a_1, a_2 , and a_3 that maximizes the function $L(a^*)$, thereby maximizing the influence of the two vulnerability model samples. Here, FC_i represents each considered vulnerability model, m_i denotes the confidence weight of each vulnerability model, and the sum of m_i is 1.

After determining the hyperparameters a_0, a_1, a_2 , and a_3 according to the above method, seismic resilience analysis can be conducted using the newly obtained vulnerability model FC_0 . Simultaneously, values corresponding to different confidence intervals (5% and 95% percentiles) can be acquired, which also reflects the transmission of uncertainty in tunnel seismic resilience calculations. The calculation process for the Dirichlet distribution-based tunnel resilience metric Re under different PGA magnitudes is shown in Figure 3.

2.3. Methods for Determining Weighting Coefficients

When two candidate vulnerability models are considered, the confidence weight m_i assigned to each model is determined according to the similarity between the site conditions represented by the model and those of the target tunnel site. The average shear wave velocity in the upper 30 m, $V_{s,30}$, is adopted as the primary site condition indicator because it reflects the overall stiffness of the near-surface soil profile and is widely used for site classification. Let V_0 denote the $V_{s,30}$ value of the target site, and let V_i denote the representative $V_{s,30}$ value corresponding to vulnerability model FC_i . The determination of the weighting coefficients involves three steps. First, the absolute difference between the target site and the site represented by each candidate model is calculated. A smaller difference indicates that the site conditions represented by FC_i are more similar to those of the target site and that the model should therefore be assigned a higher confidence weight. Second, the similarity of each model is converted into a non-negative preliminary weight. Finally, the preliminary weights are normalized according to Equation (13).

$$m_1 = \frac{|V_2 - V_0|}{|V_1 - V_0| + |V_2 - V_0|}, m_2 = \frac{|V_1 - V_0|}{|V_1 - V_0| + |V_2 - V_0|} \quad (13)$$

For example, among the two vulnerability models FC_1 and FC_2 considered here, V_1 is 160 m/s, and V_2 is 149 m/s. Depending on the value of the study site's V_0 , different weight coefficients can be obtained. If V_0 is 155 m/s, then m_1 is 0.45 and m_2 is 0.55.

Accordingly, a vulnerability model whose representative V_{s_30} is closer to V_0 contributes more strongly to the combined resilience assessment, whereas a model associated with less similar site conditions receives a lower weight. It should also be noted that for specific project applications, additional compatibility criteria, such as tunnel geometry, burial depth, lining condition, groundwater level, damage state definition, and intensity measure consistency, should be considered before the final weights are assigned. Below, a parametric analysis will be conducted by taking different values for m_1 and m_2 .

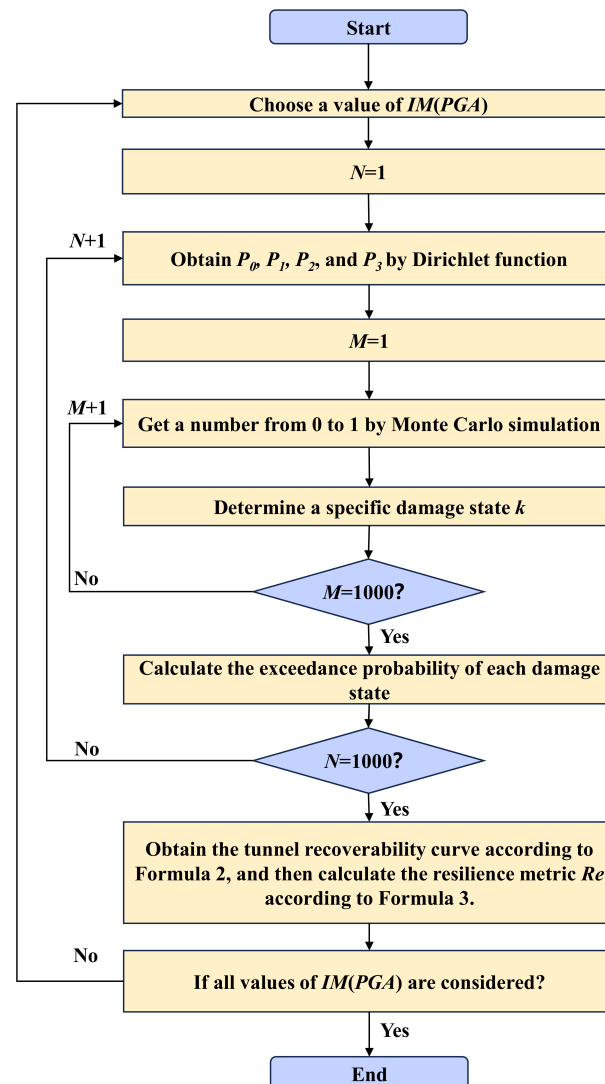


Figure 3. Flowchart for computing seismic resilience metric Re of tunnels.

2.4. Practical Implications

The proposed framework can support engineering decision-making in several ways. First, it can be used to compare alternative vulnerability models and identify whether seismic resilience estimates are sensitive to model selection. This information may assist engineers in screening fragility models, evaluating the expected effectiveness of seismic isolation or strengthening measures, and prioritizing retrofit schemes. Second, by linking damage state probabilities with functionality recovery, the framework can support post-earthquake inspection planning, repair resource allocation, and service restoration scheduling under different seismic scenarios. The confidence bounds also provide a quantitative basis for risk-informed decisions when model credibility is uncertain.

The proposed framework is not restricted to soft soils or a specific region and can, in principle, be applied to tunnels under different soil conditions and regional settings. However, vulnerability models are generally site-dependent because they reflect local geological conditions, seismic characteristics, structural configurations, and damage definitions. Therefore, when applying the framework to a new region, candidate vulnerability models consistent with the local soil conditions, tunnel characteristics, and seismic environment should first be identified or developed. The proposed probabilistic method can then be used to quantify the uncertainty among these candidate models, assign appropriate credibility weights, and establish a composite vulnerability model that is most suitable for the target region.

3. Numerical Implementation and Results

3.1. Seismic Resilience Analysis of Tunnels During In-Service Period

3.1.1. Vulnerability Models for Tunnels at Varying Burial Depths

This paper aims to investigate the influence of different vulnerability models on tunnel seismic resilience, employing three distinct models for study: the vulnerability model for tunnels at various burial depths [30], the seismic vulnerability model for shallow tunnels in Class D sites [25], and the empirical vulnerability model for general tunnels with good construction quality based on statistical survey methods (including all burial depths and site classes) [31]. Parameters of these vulnerability models are shown in Table 2, while a comparative diagram of the established vulnerability curves is presented in Figure 4. FC_1 , FC_3 , and FC_5 are numerical vulnerability models for circular tunnels in soft soil deposits and explicitly distinguish burial depth; they reflect soil–lining interaction under the assumptions and parameter ranges. FC_2 is a shallow circular tunnel model for Class D sites that includes soil–structure interaction and lining condition effects. FC_4 is an empirical lifeline guideline based on heterogeneous tunnel observations and is less specific to shield tunnel geometry, burial depth, and local soft-soil stratigraphy. Thus, differences among the curves arise from data source, tunnel typology, damage definitions, site class, numerical idealization, and uncertainty treatment. FC_4 is retained as a deliberately broad reference model to test epistemic uncertainty, not as a claim that it is equally representative of every shield tunnel. The project application should screen candidate models for geometry, construction method, lining condition, site class, intensity measure definition, and damage state compatibility before weighting. In this chapter, the vulnerability model for tunnels at different burial depths is first adopted as a case to introduce seismic resilience analysis of tunnels [30], analyzing the variation patterns of resilience metrics with seismic intensity across various burial depths.

Table 2. Summary of vulnerability curve parameters adopted in this study.

Reference	Symbol	Tunnel Typology	Minor IM_1 (g)	Moderate IM_2 (g)	Severe IM_3 (g)	β_{tot}
Huang et al. [30]	FC_1	Shallow tunnel	0.35	0.60	0.97	0.53
Argyroudis et al. [25]	FC_2	Shallow tunnel	0.51	0.89	1.22	0.61
Huang et al. [30]	FC_3	Moderately deep tunnel	0.44	0.84	1.49	0.58
ALA [31]	FC_4	Moderately deep tunnel and Deep tunnel	0.50	0.70	–	0.40
Huang et al. [30]	FC_5	Deep tunnel	0.63	1.23	2.18	0.61

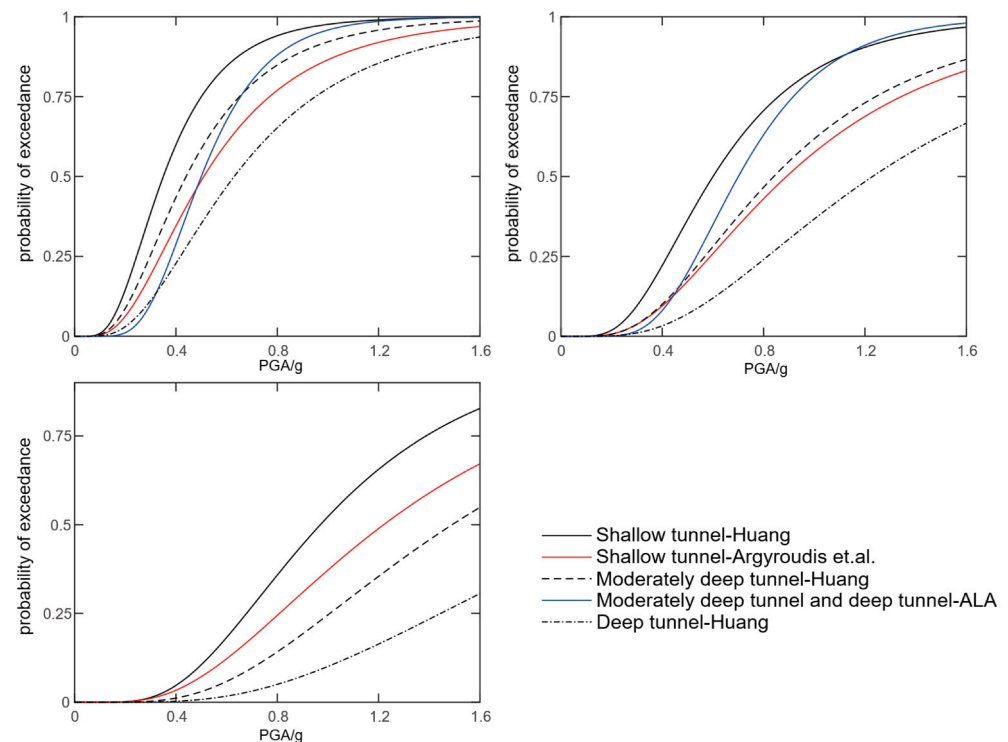


Figure 4. Comparison of seismic vulnerability curves for tunnels [25,30,31].

3.1.2. Using Peak Ground Acceleration (PGA) as Seismic Intensity Measure

According to Formula (2) and the functionality function in Figure 1, combined with the adopted vulnerability model for tunnels at different burial depths, the tunnel restoration curves under different PGAs, considering the influence of various damage states, can be obtained, as shown in Figures 5–7. For tunnels at the same burial depth, a larger PGA results in a smaller enclosed area of the restoration curve, indicating a smaller resilience metric; for tunnels at different burial depths under the same PGA, deeper burial depth corresponds to a larger enclosed area of the tunnel restoration curve, that is, representing a larger resilience metric.

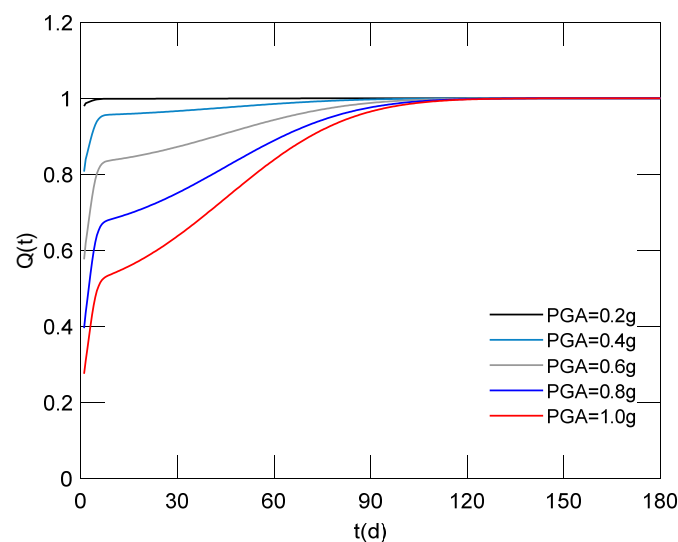


Figure 5. The restoration curves of shallow-buried tunnels under different PGAs.

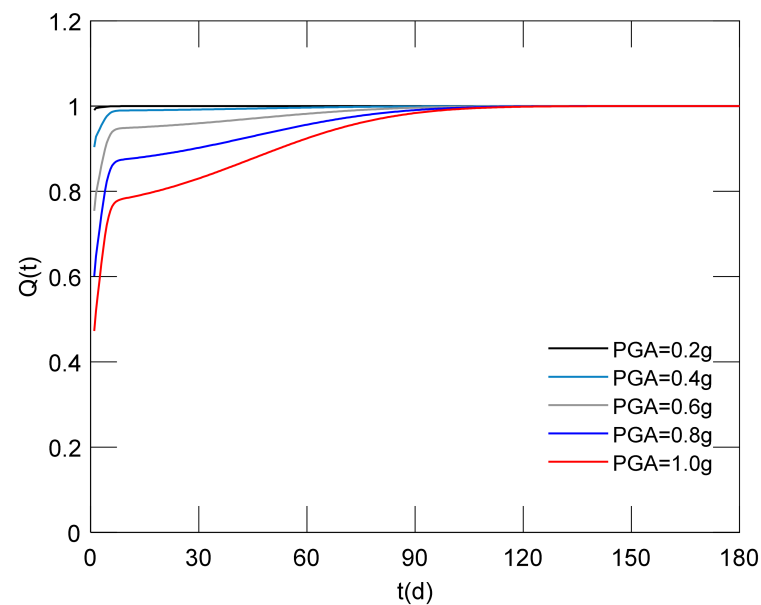


Figure 6. The restoration curves of medium-buried tunnels under different PGAs.

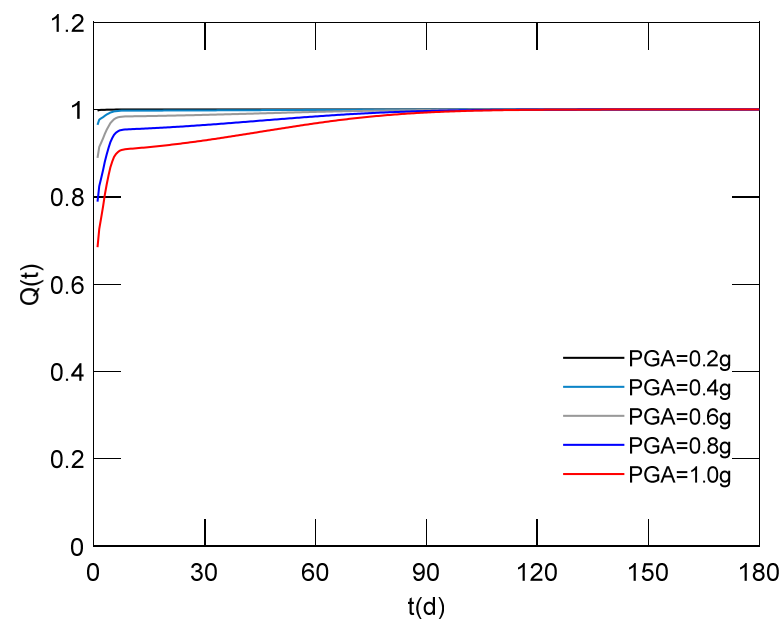


Figure 7. The restoration curves of deep-buried tunnels under different PGAs.

According to Formula (3) and the tunnel restoration curves under different $PGAs$, the seismic resilience metric Re for tunnels at different burial depths under various $PGAs$ can be calculated, as shown in Figure 8. As the PGA increases, the tunnel seismic resilience metric gradually decreases, and the shallower the relative burial depth, the smaller the resilience metric. For example, when PGA is 0.8 g, the resilience metric of deep-buried tunnels is 0.985, that of medium-buried tunnels is 0.962, and that of shallow-buried tunnels is 0.907, which is 8.5% and 6.1% smaller than deep-buried and medium-buried tunnels, respectively. Differences of only 1–9% in Re should not be dismissed automatically. Because Re is an area-based normalized metric, a small change may represent several additional days of reduced service or a shift in the probability of costly moderate damage.

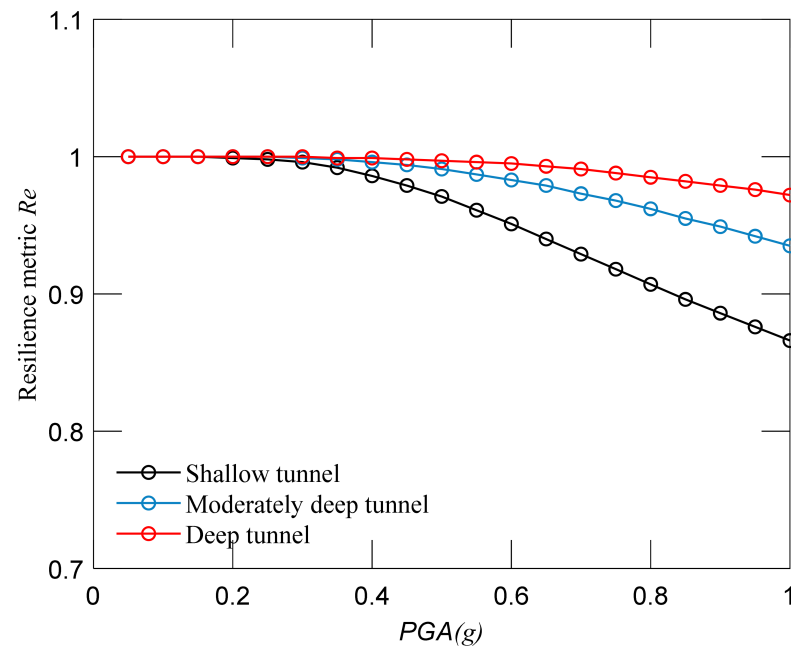


Figure 8. Resilience metric Re for tunnels under varying PGAs.

3.1.3. Using Peak Ground Velocity (PGV) as Seismic Intensity Measure

Similarly to the seismic resilience analysis method using PGA as the seismic intensity measure in the previous section, according to Formula (2) and the functionality function in Figure 1, combined with the adopted vulnerability model for tunnels at different burial depths, the tunnel restoration curves under different PGV , considering the influence of various damage states, can be obtained, as shown in Figures 9–11. For tunnels at the same burial depth, a larger PGV results in a smaller enclosed area of the restoration curve, indicating a smaller resilience metric; for tunnels at different burial depths under the same PGV , deeper burial depth corresponds to a larger enclosed area of the tunnel restoration curve, that is, representing a larger resilience metric.

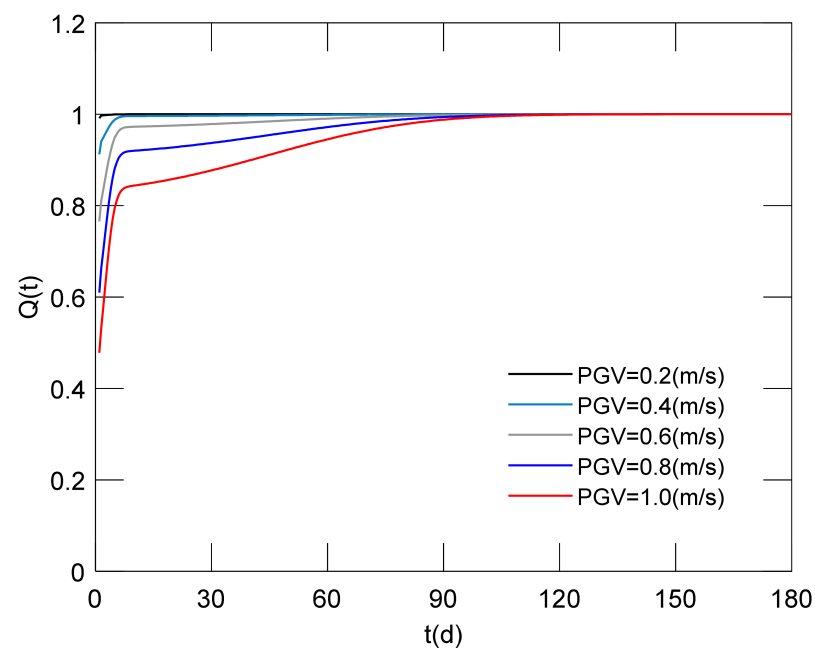


Figure 9. The restoration curves of shallow-buried tunnels under different PGVs.

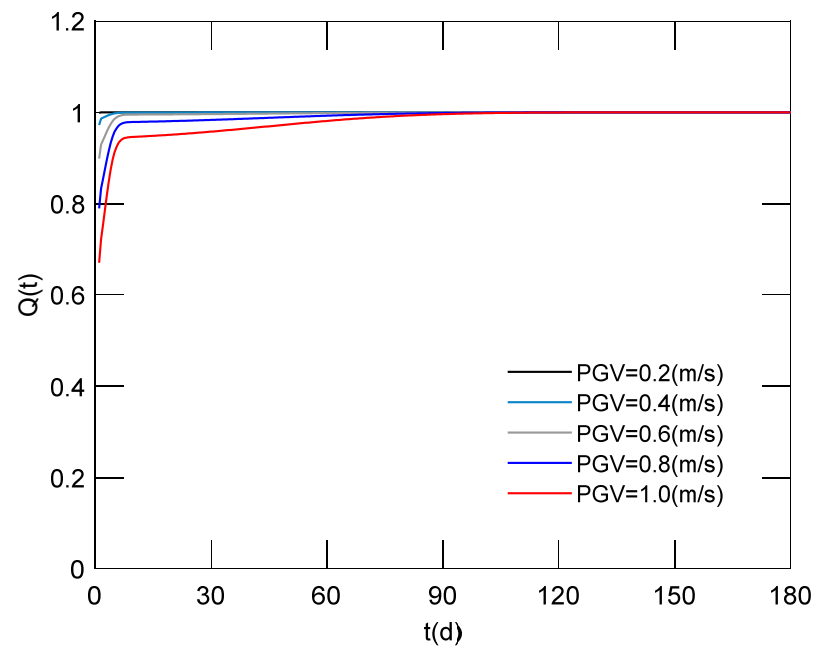


Figure 10. The restoration curves of medium-buried tunnels under different PGVs.

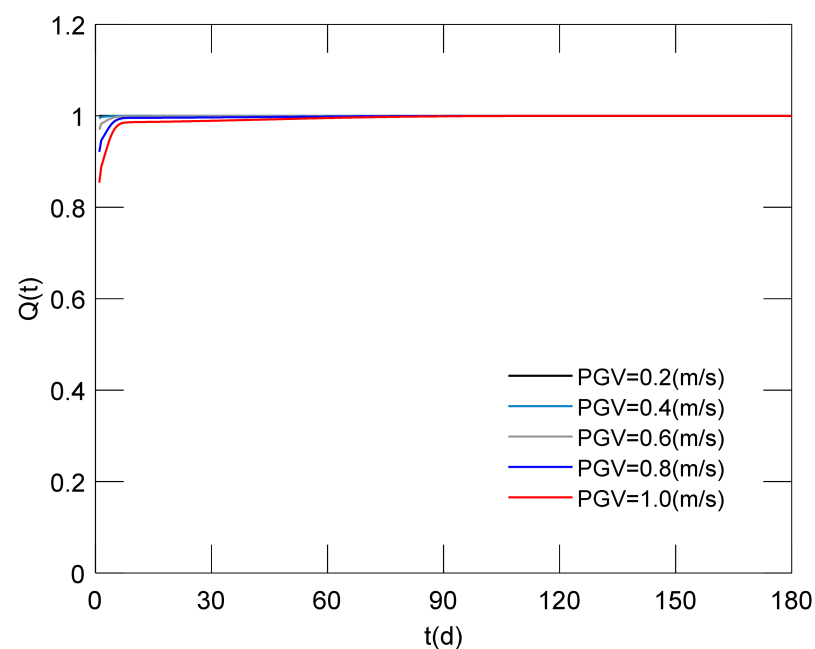


Figure 11. The restoration curves of deep-buried tunnels under different PGVs.

According to Formula (3) and the tunnel restoration curves under different PGV , the seismic resilience metric Re for tunnels at different burial depths under various PGV can be calculated, as shown in Figure 12. As PGV increases, the tunnel seismic resilience metric gradually decreases, and the shallower the relative burial depth, the smaller the resilience metric. For example, when PGV is 0.8 m/s, the resilience metric of deep-buried tunnels is 0.998, that of medium-buried tunnels is 0.992, and that of shallow-buried tunnels is 0.974, which is 2.5% and 1.8% smaller than deep-buried and medium-buried tunnels, respectively.

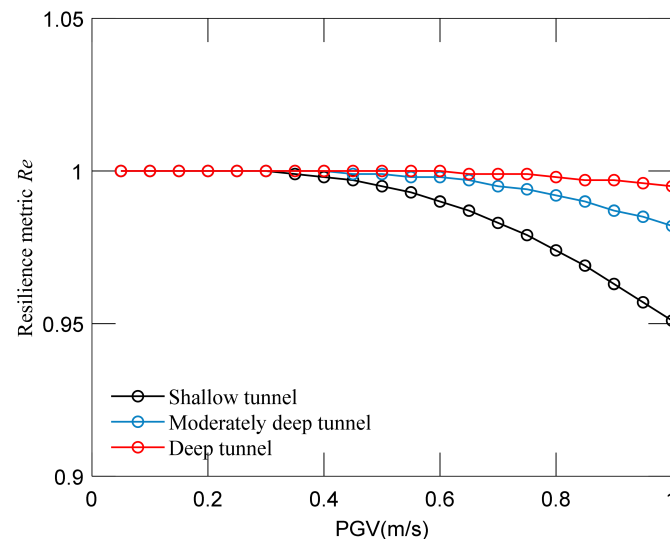


Figure 12. Resilience metric Re for tunnels under varying PGVs.

3.2. Case Study on Seismic Resilience of Tunnels Accounting for Vulnerability Model Uncertainties

3.2.1. Shallow-Buried Tunnel

For shallow-buried tunnels, considering the FC_1 and FC_2 vulnerability models from Section 3.1.1 of this paper, the vulnerability curve model based on the Dirichlet distribution is denoted as FC_0 . When the weight coefficients of the two seismic vulnerability models are $m_1 = 0.5$ and $m_2 = 0.5$, the comparison diagram of the seismic resilience metric Re for shallow-buried tunnels and the 5% to 95% confidence interval of FC_0 are shown in Figure 13. The results of both FC_1 and FC_2 models fall within the 5% to 95% confidence interval of FC_0 , which considers model uncertainty, demonstrating that this method effectively accounts for model uncertainty. On the other hand, the resilience metric Re for all three models decreases with increasing PGA . Among them, the FC_2 model is the largest and the FC_1 model is the smallest, and the FC_0 probability model results lie between the two. When PGA is 0.8 g, the Re for FC_2 is 0.937, for FC_1 is 0.907, and for FC_0 , the probability model is 0.925. Relative to the FC_0 probability model, which comprehensively considers the influence of both vulnerability models, the FC_2 model overestimates by 1.3%, while the FC_1 model underestimates by 1.9%.

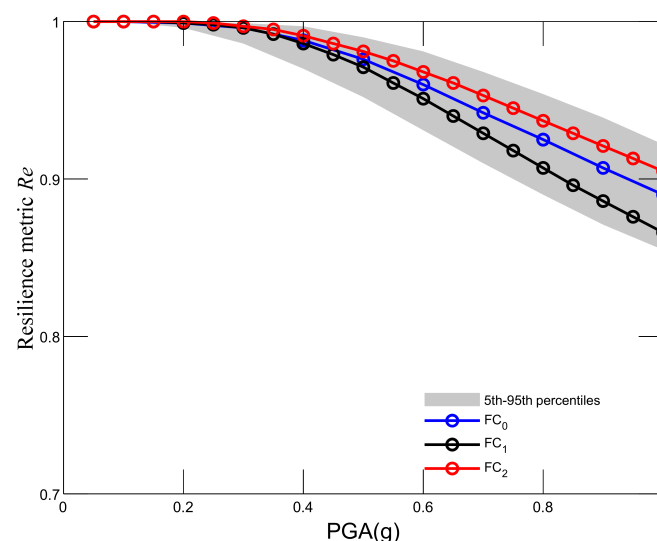


Figure 13. Resilience metric Re for shallow-buried tunnels ($m_1 = 0.5$, $m_2 = 0.5$).

Similarly, when the weight coefficients of the two seismic vulnerability models are $m_1 = 0.3, m_2 = 0.7$; $m_1 = 0.7, m_2 = 0.3$; $m_1 = 0.1, m_2 = 0.9$; and $m_1 = 0.1, m_2 = 0.9$ (four scenarios), the comparison diagrams of the seismic resilience metric Re for shallow-buried tunnels are shown in Figures 14–17, respectively. Overall, the fundamental conclusions are essentially identical to the previous case with $m_1 = 0.5, m_2 = 0.5$: the computational results of the FC_0 probability model lie between those of the FC_1 and FC_2 models and are closer to the seismic vulnerability model with larger weight coefficients. On the other hand, the FC_0 probability model results also reflect the influence of the seismic vulnerability model with smaller weight coefficients. It can be seen that considering the combined effects of multiple vulnerability models is crucial in seismic resilience analysis.

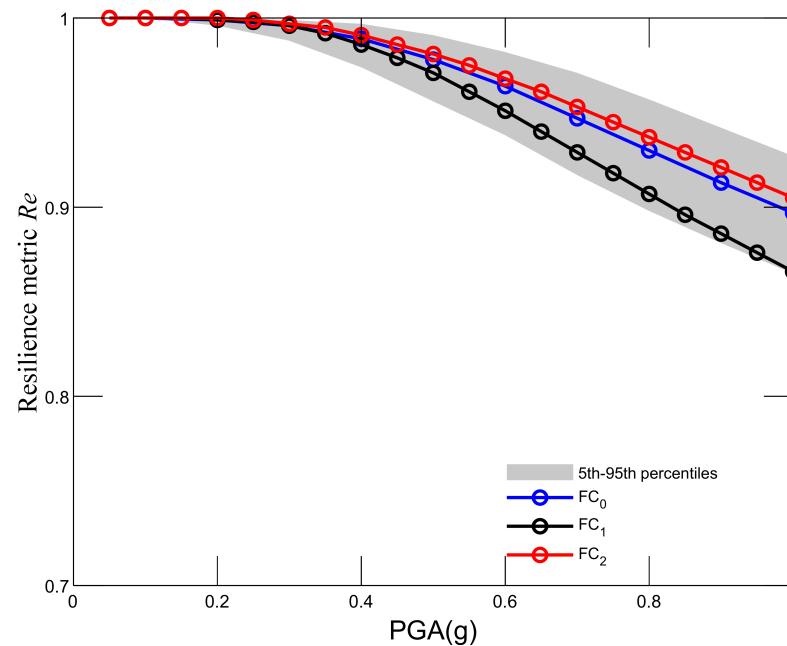


Figure 14. Resilience metric Re for shallow-buried tunnels ($m_1 = 0.3, m_2 = 0.7$).

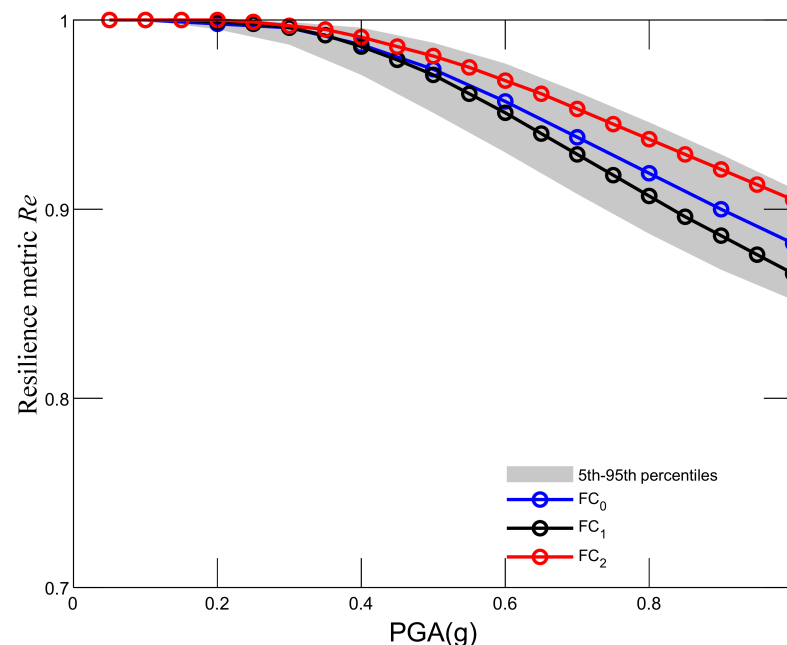


Figure 15. Resilience metric Re for shallow-buried tunnels ($m_1 = 0.7, m_2 = 0.3$).

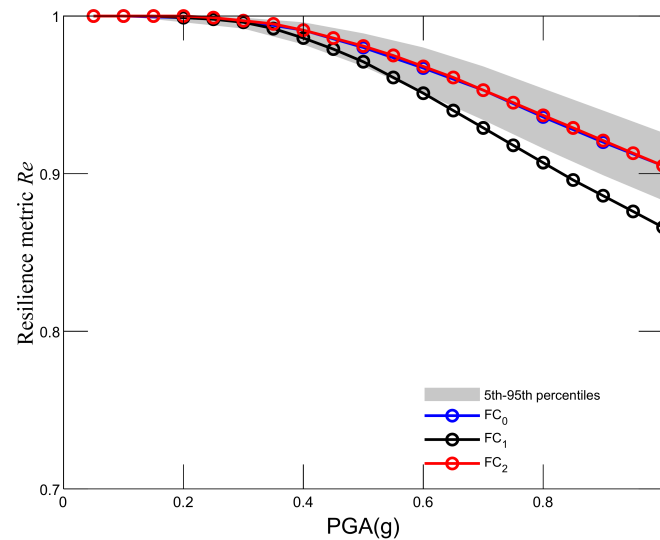


Figure 16. Resilience metric Re for shallow-buried tunnels ($m_1 = 0.1$, $m_2 = 0.9$).

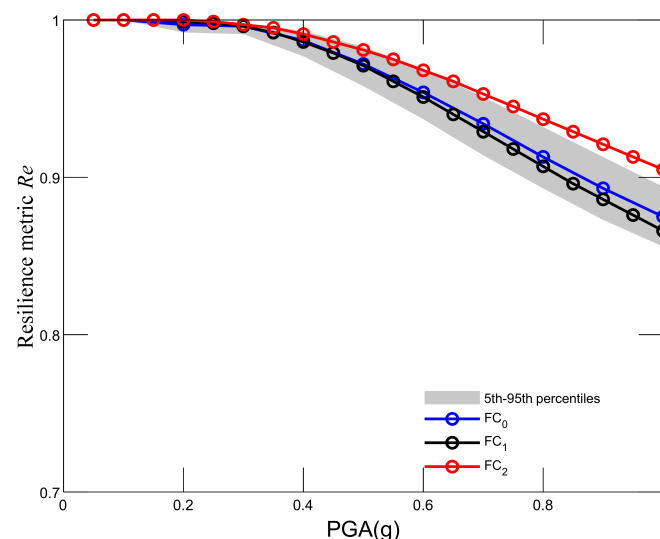


Figure 17. Resilience metric Re for shallow-buried tunnels ($m_1 = 0.9$, $m_2 = 0.1$).

3.2.2. Medium-Buried Tunnel

For medium-depth tunnels, considering the FC_3 and FC_4 vulnerability models from Section 3.1.1 of this paper, the vulnerability curve model based on the Dirichlet distribution is denoted as FC_0 . When the weight coefficients of the two seismic vulnerability models are $m_3 = 0.95$ and $m_4 = 0.05$, the comparison diagram of the seismic resilience metric Re for medium-depth tunnels and the 5% to 95% confidence interval of FC_0 are shown in Figure 18. The results of both FC_3 and FC_4 models are generally near the 5% to 95% confidence interval of FC_0 , which considers model uncertainty. The resilience metric Re for all three models decreases with increasing PGA ; the FC_4 model is the largest, the FC_3 model is the smallest, and the FC_0 probability model results lie between the two. When PGA is 0.8 g, the Re for FC_4 is 0.994, for FC_3 is 0.962, and for the FC_0 probability model is 0.974. Relative to the FC_0 probability model, which comprehensively considers the influence of both vulnerability models, the FC_4 model overestimates by 2.1%, while the FC_3 model underestimates by 1.2%. The results of the FC_0 probability model are closer to those of the FC_3 model with larger weight coefficients.

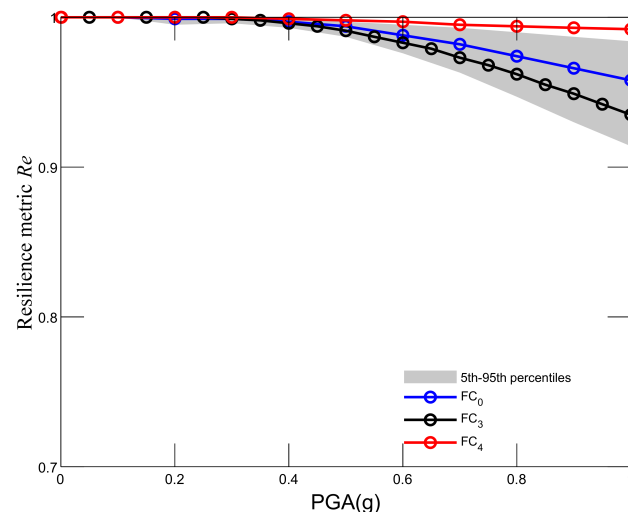


Figure 18. Resilience metric Re for medium-buried tunnels ($m_3 = 0.95$, $m_4 = 0.05$).

3.2.3. Deep-Buried Tunnel

For deep-buried tunnels, considering the FC_5 and FC_4 vulnerability models from Section 3.1.1 of this paper, the vulnerability curve model based on the Dirichlet distribution is denoted as FC_0 . When the weight coefficients of the two seismic vulnerability models are $m_5 = 0.95$ and $m_4 = 0.05$, the comparison diagram of the seismic resilience metric Re for medium-depth tunnels and the 5% to 95% confidence interval of FC_0 are shown in Figure 19. The results of both FC_5 and FC_4 models are generally near the 5% to 95% confidence interval of FC_0 , which considers model uncertainty. The resilience metric Re for all three models decreases with increasing PGA ; the FC_4 model is the largest, the FC_5 model is the smallest, and the FC_0 probability model results lie between the two. When PGA is 0.8 g, the Re for FC_4 is 0.994, for FC_5 is 0.985, and for the FC_0 probability model is 0.987. Relative to the FC_0 probability model, which comprehensively considers the influence of both vulnerability models, the FC_4 model overestimates by 0.2%, while the FC_5 model underestimates by 0.2%. The results of the FC_0 probability model are closer to those of the FC_5 model with larger weight coefficients. However, overall, the resilience metrics of the three models are relatively close when PGA is small (<0.65 g), but when PGA continuously increases (>0.65 g), the results of the FC_4 model are relatively larger. The calculated resilience metrics and assigned weights for different tunnel burial depths are summarized in Table 3.

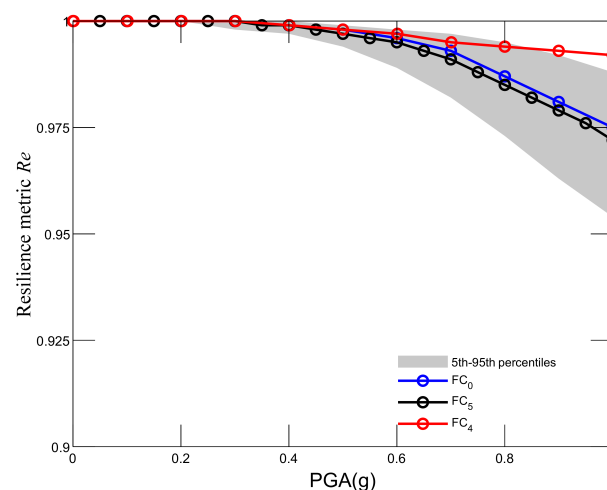


Figure 19. Resilience metric Re for deep-buried tunnels ($m_5 = 0.95$, $m_4 = 0.05$).

Table 3. Seismic resilience metric and model weights for tunnels at different burial depths.

Burial Depth	Model 1 <i>Re</i>	Model 2 <i>Re</i>	Composite <i>Re</i>	<i>m</i> ₁	<i>m</i> ₂
Shallow	<i>FC</i> ₁ : 0.907	<i>FC</i> ₂ : 0.937	0.925	0.50	0.50
Medium	<i>FC</i> ₃ : 0.962	<i>FC</i> ₄ : 0.994	0.974	0.95	0.05
Deep	<i>FC</i> ₅ : 0.985	<i>FC</i> ₄ : 0.994	0.987	0.95	0.05

4. Conclusions

Seismic resilience of soft-soil tunnels constitutes a crucial research focus in tunnel seismic performance analysis. This paper establishes a seismic analysis methodology for tunnel structures, conducting seismic resilience assessments for shallow-buried, medium-buried, and deep-buried tunnels under normal service conditions. It reveals the variation patterns of resilience under different seismic intensities (*PGA* or *PGV*). Compared to analysis methods considering a single vulnerability model, this study further develops a tunnel seismic resilience analysis approach that accounts for uncertainties in multiple vulnerability models. Corresponding analyses were conducted for shallow-buried, medium-buried, and deep-buried tunnels during normal service periods, with main conclusions as follows:

- (1) The definition and concept of tunnel seismic resilience metrics are proposed, and a seismic resilience analysis framework for tunnel structures is established.
- (2) Seismic resilience analyses were conducted for tunnels at different burial depths in soft-soil sites under normal service conditions. Respectively, tunnel restoration curves considering different damage states under varying seismic intensities (*PGA* or *PGV*) were obtained, revealing the variation patterns of tunnel seismic resilience metrics with seismic intensity (*PGA* or *PGV*) across different burial depths. Under identical seismic intensity, shallower burial depth corresponds to smaller resilience metrics. For example, when *PGA* is 0.8 g, the resilience metric for deep-buried tunnels is 0.985, for medium-depth tunnels is 0.962, and for shallow-buried tunnels is 0.907—8.5% and 6.1% smaller than deep-buried and medium-depth tunnels, respectively.
- (3) By accounting for uncertainty in tunnel seismic vulnerability models and assigning determining weighting coefficients to alternative models, this study establishes a probabilistic framework for seismic resilience assessment of tunnels at different burial depths. The results demonstrate that resilience estimates are sensitive to both burial depth and vulnerability model selection. Although the composite estimate is influenced by the assigned model weights, the more important finding is that its confidence bounds generally encompass the predictions of the individual models, thereby explicitly representing model selection uncertainty. Therefore, vulnerability models should be carefully screened according to tunnel type, burial depth, site conditions, lining characteristics, and damage state definitions before being combined.

The method proposed in this paper can more precisely quantify and analyze tunnel resilience metrics under different seismic intensities, scientifically revealing the seismic resistance and post-earthquake recovery capabilities of soft-soil tunnels. In engineering applications, candidate models should first be screened according to tunnel geometry, construction method, burial depth, lining condition, site class, intensity measure definition, and damage state compatibility. Appropriate credibility weights can then be assigned based on the similarity between the conditions represented by each model and those of the target site, allowing model selection uncertainty to be explicitly propagated into the composite resilience metric and its confidence bounds. The resulting assessment can provide a quantitative basis for vulnerability model selection, seismic design evaluation, retrofit or isolation prioritization, post-earthquake inspection planning, repair resource allocation, and service restoration scheduling. However, the functionality recovery function

adopted in this study does not account for the repair difficulties encountered by deep-buried tunnels under high earth and groundwater pressures. In addition, the potential influence of the spatial variability of the surrounding soil properties on damage probabilities has not been considered. Future studies should further incorporate repair cost and resource allocation analyses, together with fragility models based on random field representations of soil properties, to improve the reliability and engineering applicability of tunnel seismic resilience assessment.

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References

- Guo, L.; Huang, Z.; Zhang, D.; Pitilakis, K.; Lu, D.; Yao, Z. Seismic response of soil-shield tunnel system considering spatial variability of multivariate soil properties via random field theory. *Tunn. Undergr. Space Technol.* **2026**, *174*, 107726. [\[CrossRef\]](#)
- Iida, H.; Hiroto, T.; Yoshida, N.; Iwafuji, M. Damage to Daikai subway station. *Soils Found* **1996**, *36*, 283–300. [\[CrossRef\]](#)
- Wang, W.L.; Wang, T.T.; Su, J.J.; Lin, C.H.; Seng, C.R.; Huang, T.H. Assessment of damage in mountain tunnels due to the Taiwan Chi-Chi earthquake. *Tunn. Undergr. Space Technol.* **2001**, *16*, 133–150. [\[CrossRef\]](#)
- Wang, Z.Z.; Zhang, Z.J.S.D. Seismic damage classification and risk assessment of mountain tunnels with a validation for the 2008 Wenchuan earthquake. *Soil Dyn. Earthq. Eng.* **2013**, *45*, 45–55. [\[CrossRef\]](#)
- Holling, C.S. Resilience and stability of ecological systems. *Annu. Rev. Ecol. Syst.* **1973**, *4*, 1–23. [\[CrossRef\]](#)
- Timmerman, P. *Vulnerability, Resilience and the Collapse of Society: A Review of Models and Possible Climatic Applications*; Institute for Environmental Studies, University of Toronto: Toronto, ON, Canada, 1981.
- Bruneau, M.; Chang, S.E.; Eguchi, R.T.; Lee, G.C.; O'Rourke, T.D.; Reinhorn, A.M.; Shinozuka, M.; Tierney, K.; Wallace, W.A.; Von Winterfeldt, D. A framework to quantitatively assess and enhance the seismic resilience of communities. *Earthq. Spectra* **2003**, *19*, 733–752. [\[CrossRef\]](#)
- Miles, S.B.; Chang, S.E.L. *A Simulation Model of Urban Disaster Recovery and Resilience: Implementation for the 1994 Northridge Earthquake*; MCEER-07-0014 Technical Report; Multidisciplinary Center for Earthquake Engineering Research: Buffalo, NY, USA, 2006.
- Cimellaro, G.P.; Reinhorn, A.M.; Bruneau, M. Seismic resilience of a hospital system. *Struct. Infrastruct. Eng.* **2010**, *6*, 127–144. [\[CrossRef\]](#)
- Francis, R.; Bekera, B. A metric and frameworks for resilience analysis of engineered and infrastructure systems. *Reliab. Eng. Syst. Saf.* **2014**, *121*, 90–103. [\[CrossRef\]](#)
- Burton, H.V.; Deierlein, G.; Lallemand, D.; Lin, T. Framework for incorporating probabilistic building performance in the assessment of community seismic resilience. *J. Struct. Eng.* **2015**, *142*, C4015007.
- Titi, A.; Biondini, F. Resilience of concrete frame structures under corrosion. In Proceedings of the 11th International Conference on Structural, Safety & Reliability, New York, NY, USA, 16–20 June 2013; pp. 16–20.
- Tirca, L.; Serban, O.; Lin, L.; Wang, M.; Lin, N. Improving the seismic resilience of existing braced-frame office buildings. *J. Struct. Eng.* **2015**, *142*, C4015003.
- Ranjbar, P.R.; Naderpour, H. Probabilistic evaluation of seismic resilience for typical vital buildings in terms of vulnerability curves. *Structures* **2020**, *23*, 314–323. [\[CrossRef\]](#)
- Dong, Y.; Frangopol, D.M. Risk and resilience assessment of bridges under mainshock and aftershocks incorporating uncertainties. *Eng. Struct.* **2015**, *83*, 198–208. [\[CrossRef\]](#)

16. Andrić, J.M.; Lu, D.G. Fuzzy methods for prediction of seismic resilience of bridges. *Int. J. Disaster Risk Reduct.* **2017**, *22*, 458–468. [[CrossRef](#)]
17. Vishwanath, B.S.; Banerjee, S. Life-Cycle Resilience of Aging Bridges under Earthquakes. *J. Bridge Eng.* **2019**, *24*, 04019106. [[CrossRef](#)]
18. Rinaudo, P.; Paya-Zaforteza, I.; Calderón, P.A. Improving tunnel resilience against fires: A new methodology based on temperature monitoring. *Tunn. Undergr. Space Technol.* **2016**, *52*, 71–84. [[CrossRef](#)]
19. Huang, H.-W.; Zhang, D.-M. Resilience analysis of shield tunnel lining under extreme surcharge: Characterization and field application. *Tunn. Undergr. Space Technol.* **2016**, *51*, 301–312. [[CrossRef](#)]
20. Huang, H.; Zhang, D.; Ayyub, B. An integrated risk sensing system for geo-structural safety. *J. Rock Mech. Geotech. Eng.* **2017**, *9*, 226–238. [[CrossRef](#)]
21. Saadat, Y.; Ayyub, B.M.; Zhang, Y.; Zhang, D.; Huang, H. Resilience of Metrorail Networks: Quantification With Washington, DC as a Case Study. *ASCE-ASME J. Risk Uncertain. Eng. Syst. Part B Mech. Eng.* **2019**, *5*, 041011. [[CrossRef](#)]
22. Selva, J.; Argyroudis, S.; Pitilakis, K. Impact on loss/risk assessments of inter-model variability in vulnerability analysis. *Nat. Hazards* **2013**, *67*, 723–746. [[CrossRef](#)]
23. Chen, L. Seismic fragility curves fitting revisited: Ordinal regression models and their generalization. *arXiv* **2024**, arXiv:2405.15513.
24. Nardin, C.; Marelli, S.; Bursi, O.S.; Sudret, B.; Broccardo, M. UQ state-dependent framework for seismic fragility assessment of industrial components. *Reliab. Eng. Syst. Saf.* **2025**, *261*, 111067. [[CrossRef](#)]
25. Argyroudis, S.; Tsinidis, G.; Gatti, F.; Pitilakis, K. Effects of SSI and lining corrosion on the seismic vulnerability of shallow circular tunnels. *Soil Dyn. Earthq. Eng.* **2017**, *98*, 244–256. [[CrossRef](#)]
26. Liu, Y.; Lu, D.; Paolacci, F. Probabilistic seismic resilience analysis for bridges shocked by near-fault pulse-like ground motions. In Proceedings of the Eighth International Conference on Bridge Maintenance, Safety and Management, Foz Do Iguacu, Brazil, 26–30 June 2016.
27. Fema, H. *Multi-Hazard Loss Estimation Methodology, Earthquake Model*; Federal Emergency Management Agency: Washington, DC, USA, 2003.
28. Ayyub, B.M. Systems resilience for multihazard environments: Definition, metrics, and valuation for decision making. *Risk Anal.* **2014**, *34*, 340–355. [[PubMed](#)]
29. Chen, Y. Seismic Fragility and Resilience Analysis of Long-Span Cable-Stayed Bridge. Master's Thesis, Chang'an University, Xi'an, China, 2018.
30. Huang, Z.-K.; Pitilakis, K.; Tsinidis, G.; Argyroudis, S.; Zhang, D.-M. Seismic vulnerability of circular tunnels in soft soil deposits: The case of Shanghai metropolitan system. *Tunn. Undergr. Space Technol.* **2020**, *98*, 103341. [[CrossRef](#)]
31. American Lifelines Alliance. *Seismic Fragility Formulations for Water Systems: Guideline*; American Lifelines Alliance: Washington, WA, USA, 2001.

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