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Regional seismic risk and resilience assessment: Methodological development, applicability, and future research needs – An earthquake engineering perspective

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A R T I C L E I N F O

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A B S T R A C T

Given the devastating losses incurred by past major earthquake events together with the ever-increasing global seismic exposures due to population growth and urbanization, strategic decision-support tools are required to help stakeholders make more contemplated decisions that promote seismic resilience of the built environment. Such decision-support is enabled by regional seismic risk and resilience assessment, which holistically incorporates the various underlying physics processes and uncertainties for quantitative and probabilistic assessment of regional seismic hazard impacts, and has thereby attracted increasing research focus over the past twenty years. As a significant departure from the traditional site-specific assessment, where only an individual structure and site-specific seismic hazard are of interest, such regional-level assessment introduces additional dimensions and complexity. To date, there is a lack of review studies summarizing the related research advancements in seismic risk and resilience assessment from a regional-level perspective in the context of earthquake engineering. This study fills this gap by conducting a systematic review covering: the methodological development of regional seismic risk assessment (RSRiA) across its key modules, including hazard analysis, exposure modeling, fragility assessment, and consequence evaluation, as well as the associated uncertainty quantification and propagation; the development of resilience metrics, restoration modeling and planning in regional seismic resilience assessment (RSReA); and the applicability of existing computational workflows. Insights into the features, applicability, compatibility, and limitations of existing models and tools are provided. This study also highlights the challenges and future directions toward further advancing the research frontiers of RSRiA and RSReA.

1. Introduction

As witnessed in the past major earthquake events, earthquake hazards can impose significant structural damages and economic losses to the regional built environment, and the resulting lengthy recovery process can severely hinder a region's economic prosperity and societal well-being. Earthquakes nowadays would incur more severe losses to regional-scale urban areas as the built environment is becoming more populated and densely covered with spatially distributed structural and infrastructure portfolios such as buildings, road and bridge networks, water and power supply systems, etc. With the rapid population growth and urbanization, the global seismic hazard exposure in terms of the affected population and built-up area nearly doubled over the past 40 years [1]. It is thus imperative to better help the built environment prepare and plan for, absorb, recover from, and more successfully adapt to earthquake events, which is in line with the notion of resilience as defined by the US National Academies [2]. To this aim, a rich body of research closely related to earthquake engineering has been conducted in regional seismic risk and resilience assessment to probabilistically quantify the seismic hazard impacts on the built environment, thereby informing risk mitigation and post-earthquake restoration planning.

Within the earthquake engineering community, the term ***seismic risk*** generally indicates the level of severity of seismic hazard impact on the built environment, and can be quantified in various forms (e.g., expected

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losses, probability or annual rate of exceeding a given level of consequences, or risk indexes). The widely adopted Pacific Earthquake Engineering Research (PEER) center seismic risk assessment framework [3, 4] offers a viable conceptual formulation to incorporate different stochastic processes into seismic risk quantification via the convolutional integral shown in Eq. (1):

$$\lambda(DV) = \int\int\int G(DV|DM)\cdot|dG(DM|EDP)|\cdot|dG(EDP|IM)|\cdot|d\lambda(IM)| \quad (1)$$

where $\lambda(\cdot)$ denotes the mean annual rate of exceedance, $G(\cdot)$ is the complementary cumulative distribution function, DV is the decision variable, DM stands for the structural damage measure, EDP denotes the engineering demand parameter, and IM denotes the ground motion intensity measure. Under the conditional independence assumption, the PEER formulation allows seismic risk assessment to be decomposed into multiple individual modules, which facilitates studies from different disciplines. Although the PEER framework was originally developed for performance-based seismic design or site-specific seismic risk assessment for individual buildings, it has experienced increasing applications in **R**egional **S**eismic **Ri**sk **A**ssessment (RSRiA) to evaluate the seismic hazard impacts on spatially distributed and functional structure and infrastructure systems. RSRiA consists of four major analysis modules, including (1) regional seismic hazard analysis, which estimates the earthquake occurrence, the resulting ground shaking, and the associated co-seismic hazards; (2) exposure modeling that characterizes the exposed civil structure and infrastructure assets in terms of structural characteristics, spatial location and connection, and occupancy, among others; (3) fragility assessment, which probabilistically evaluates structural seismic damage potential conditioned on the ground motion intensity and other structure-specific parameters; and (4) consequence assessment that estimates direct and indirect seismic losses in terms of quantitative indicators such as economic losses, casualties, debris, down time, etc., through a convolution of the above three modules.

While past research mainly focused on RSRiA to evaluate the instantaneous regional seismic hazard impact, RSRiA typically does not inform how the affected built environment would recover from the initial earthquake perturbation, as well as how to adapt to future sequential earthquakes or other hazard threats. Note that seismic damage to regional-scale structural and infrastructure portfolios may not only yield enormous direct losses but also trigger significant indirect losses over a prolonged time horizon due to the reduced functionality from sequential hazards, aging effects, complex interdependency of the distributed portfolios, and their tremendous impacts on economic, social and environmental aspects of communities [5]. In this regard, there have been emerging studies on **R**egional **S**eismic **Re**silience **A**ssessment (RSReA). As mentioned previously, the notion of resilience incorporates four major dimensions: preparation, absorption, recovery, and adaptation, thereby more holistically covering the different aspects that are of interest to the stakeholders. RSReA is rooted in RSRiA while focusing more on the temporal aspect to characterize the time-dependent functionality trajectories of the regional built environment, and is vital to evaluating the efficacy of different mitigation and restoration strategies over a prolonged planning time horizon [6,7].

Past research has made significant strides in developing related models, tools, and workflows to actually enable the RSRiA and RSReA pipelines. Several previous studies have conducted state-of-the-art reviews on seismic fragility modeling [8,9], application of machine learning in earthquake engineering [10], seismic loss estimation software [11], earthquake risk reduction for resilience [12], or more broadly on multi-hazard fragility and restoration modeling [13], natural hazard engineering computational simulation [14], and natural hazard community resilience [15]. Still, there is a lack of holistic review on regional-level seismic risk and resilience assessment to summarize the research advancements of the backbone analysis modules and their interconnections, as well as discussion on the issues and challenges yet to be addressed to further advance the research frontiers toward more reliable and confident decision-support. This study will fill these gaps by carrying out an integrated review on RSRiA and RSReA from an earthquake engineering perspective, offering new insights into the features, applicability, compatibility, and limitations of existing models and tools. Considering the multi-disciplinary nature and broad scope of the problem, such a systematic review provides timely guidance that can benefit practitioners and researchers in real-world implementations, and underscores the potential pitfalls and remaining research gaps to be addressed. A schematic overview of the general RSRiA and RSReA framework is shown in Fig. 1. Specifically, the first part of the present study is centered on summarizing the methodological development of the major analysis modules in RSRiA. Additional components for RSReA are then reviewed with an emphasis on regional-level post-earthquake restoration modeling and optimization. In addition, current computational workflows are summarized and commented regarding their respective features and applicability. Finally, critical questions and challenges are elaborated to highlight the needs for future research.

2. Methodological development of regional seismic risk assessment (RSRiA)

2.1. Regional probabilistic seismic hazard analysis (RPSHA)

As the very first step within the RSRiA workflow, RPSHA generally consists of the following two major components: (1) characterization of earthquake sources and occurrences; and (2) for any given earthquake source, simulation of the spatially correlated ground motion random field or co-seismic hazards, which offers quantitative seismic inputs to the subsequent fragility analysis module.

2.1.1. Earthquake source and occurrence characterization

Earthquake is a complex natural and physical phenomenon. The increasingly available data and scientific advancements in geological, geophysical, geodetic, and earthquake engineering have improved our understanding of the recurrence and magnitude-scaling relationships, and locations of potential earthquakes [16]. There have been global efforts in developing and updating seismic hazard models and products, for example, the U.S. Geological Survey (USGS) hazard maps [17], the Uniform California Earthquake Rupture Forecast (UCERF) [18], Canada's National Seismic Hazard Model (CSHM) [19], the Seismic Hazard Harmonization in Europe (SHARE) [20,21], and the National Seismic Hazard Model for New Zealand [22], among others. The outputs of these earthquake hazard models are typically the occurrence rates, locations, magnitudes, and fault mechanisms of potential earthquake ruptures, which are then coupled with ground motion simulation techniques to estimate the spatial ground motion intensity for any site of interest.

Many studies [23–29] in RSRiA focused on deterministic earthquake scenarios (i.e., ***scenario-specific***), based on either major historical events, mean deaggregated events (calculated from conventional PSHA) that dominate the regional seismic hazard for a given return period, or arbitrary fault ruptures. Considering an individual deterministic event is computationally efficient since the uncertainties in the potential seismic ruptures are significantly reduced, and it is also intuitive to visualize the spatial extension of seismic damages and consequences pertinent to particular scenarios. Although this single-event approach may be adequate for regions that are dominated by a specific seismic source, it fails to consider the multi-modal effect for regions that are controlled by several distributed major seismic sources (e.g., the San Francisco Bay Area and British Columbia in Canada). In this regard, it is of merit to comprehensively consider all the seismic sources with a magnitude large than a threshold value and within a specific source-to-site distance, and generate a stochastic earthquake catalog over a sufficiently long investigation time horizon. Such a ***fully probabilistic*** approach has been employed by many RSRiA studies [30–37] to provide more holistic seismic risk estimates for a wide spectrum of hazard levels.

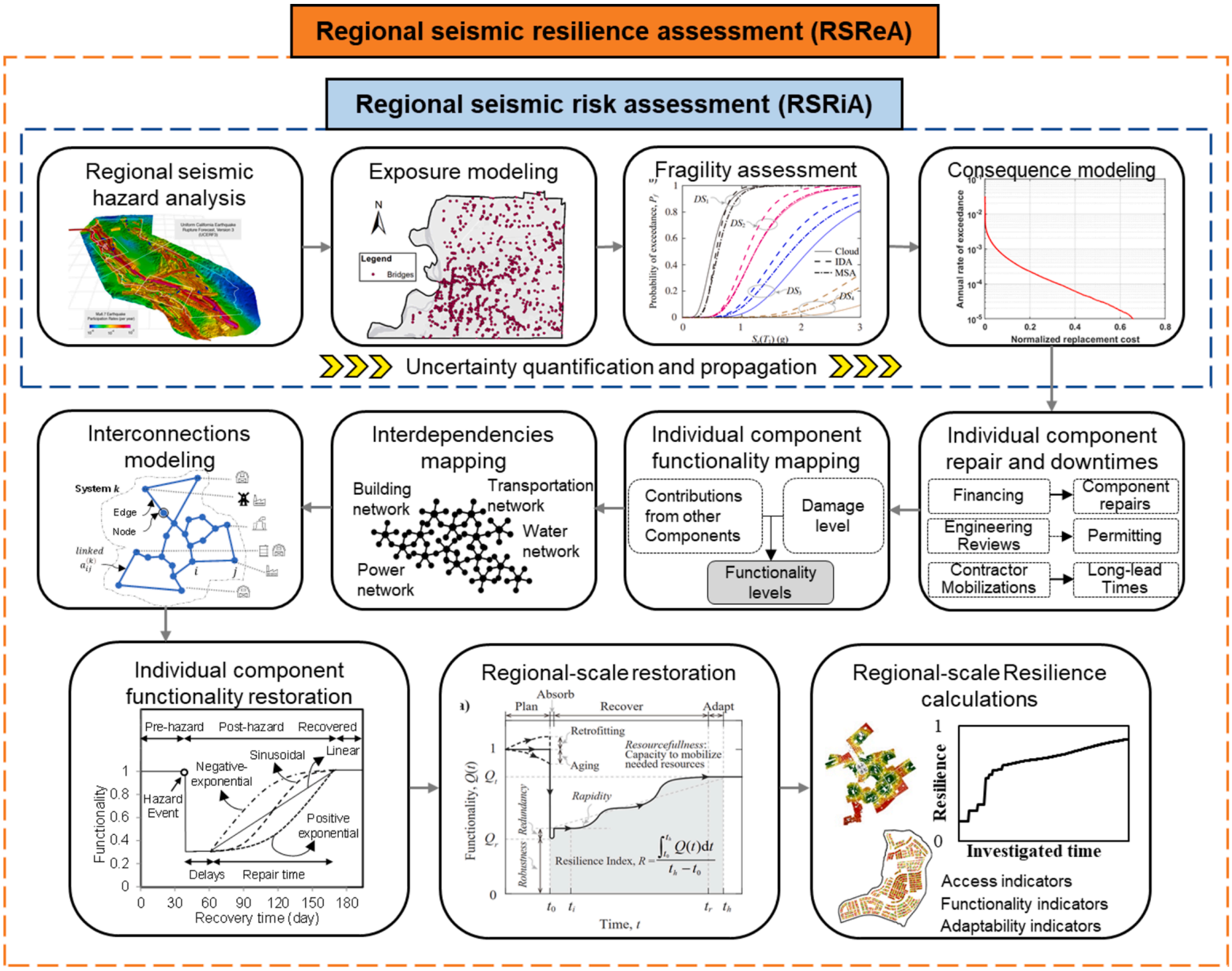

Fig. 1. Overview of the analysis modules and their interconnections within the general regional seismic risk and resilience assessment framework.

2.1.2. *Ground motion random field (GMRF) simulation*

Once the potential seismic source is specified, the following step is to simulate the ground motion intensities at multiple spatially distributed sites, i.e., the ground motion random field. Past studies [38,39] have reported that the GMRF is spatially correlated because of the common seismic source and wave propagation path effects. Unlike site-specific seismic risk assessment, accurately considering such IM spatial correlation is particularly important in RSRiA when considering the aggregated losses or loss of functionality of spatially distributed lifeline systems [33,40].

Simulation techniques to generate random realizations of the GMRF can be generally categorized into two approaches, namely the ***IM-based*** and the ***physics-based*** ground motion simulation (GMS). Specifically, the IM-based GMS has gained popularity for its simplicity and widely available empirical models. Based on the well-received multivariate normality assumption of IMs at spatially distributed sites [38], the multivariate normal distribution of the spatial IM random field can be conveniently constructed by leveraging the existing ground motion prediction equations (GMPEs) (e.g., [41–43]) and empirical IM correlation models (e.g., [44–49]). Aleatory uncertainties of the IMs are incorporated via the GMPE standard deviations, and the epistemic uncertainties in the GMPEs are typically incorporated through a logic-tree-based approach by assigning different weights to different candidate GMPEs. The IM-based GMS has been widely adopted by past RSRiA studies [28,31,32,34–37,50–53] as well as by the ShakeMap [54]. The influence of different considerations of spatial IM correlation was also studied by previous research [32,35,55–57].

Beyond the IM-based GMS, some recent efforts have been committed to developing three-dimensional (3D) physics-based broadband GMS to more realistically estimate the spatial GMRF. In particular, CyberShake [58], as part of the Southern California Earthquake Center's Community Modeling Environment, aims to incorporate deterministic source and wave propagation effects into regional seismic hazard analysis via physics-based 3D ground motion simulations. Uncertainties in seismic ruptures and the related rupture parameters (e.g., hypocenter and slip distributions) are explicitly incorporated. Considering detailed 3D velocity models that better incorporate the basin and other crustal effects, a physics-based anelastic wave propagation simulation is employed to calculate strain Green tensors for the site of interest. The calculated strain Green tensors are then processed by leveraging seismic reciprocity to derive synthetic seismograms [58]. Finally, site-specific ground motion IMs can be computed from the resulting synthetic seismograms. Such physics-based GMS is explicitly site-specific and free from the traditional ergodicity assumption, thereby offering more realistic seismic hazard estimation [58]. It can also effectively complement the limited recorded ground motion data and facilitate an improved understanding of the underlying earthquake mechanisms [58,59]. Moreover, spatial correlation in the ground motion field is readily incorporated in the 3D physics-based simulation. Based on the much richer ground motion data offered by Cybershake, a recent study by Chen and Baker [39] concluded that geological conditions, and source and path effects could significantly affect spatial correlations.

2.1.3. Other co-seismic hazards

Estimates of regional seismic hazards have also focused on co-seismic hazards, i.e., secondary effects of ground shaking, mainly categorized into ground failures, tsunamis, and fires [60,61]. While tsunamis and fires commonly occur upon or after the end of earthquake loading, ground failures usually take place during the ground shaking, thereby more closely related to earthquakes from a temporal viewpoint of hazard. Moreover, tsunamis and fires are relatively infrequent and primarily characterized by other non-seismic factors in occurrence mechanisms [62,63], which worth separate considerations. For this reason, this section focuses on the ground failures, in which liquefaction and landslide are the two major co-seismic hazards [60]. Liquefaction refers to a phenomenon as a consequence of the reduction in soil effective stress caused by the buildup of pore water pressure in saturated soil deposits under seismic loads [64], while landslide is defined as the incremental displacement of earth, rock, or debris down a slope triggered by inertial loading during earthquakes. Landslide can be further classified by different physical attributes, such as slope ranges, slide velocities, volumes, etc., into multiple failure modes, such as shallow disrupted soil slides, rock slides/falls, coherent rotational slides, and lateral spreads [65–67], in which the lateral spreads is usually observed in gently sloping ground with liquefied soil deposits. As liquefaction and landslide were the major causes of the extensive damage to massive ground areas and the associated regional infrastructure and structures in historical earthquakes [68], regional-scale seismic hazard assessment of these co-seismic hazards has drawn vast attractions [69,70]. Such regional-scale assessment is of vital importance in both pre-earthquake planning and post-earthquake relief efforts.

In analogy with ground motion simulation, methodologies for regional seismic liquefaction hazard assessment can be theoretically categorized into the ***IM-based*** empirical evaluation and ***physics-based*** numerical simulation [14]. Due to the noted challenges in developing and validating effective and efficient numerical simulation methods for regional liquefaction assessment, the state of the liquefaction studies is generally limited to empirical evaluation. The past four decades have witnessed the evolution of the empirical methods from geology-based deterministic liquefaction potential mapping for qualitative descriptions (e.g., [71–74]) to geostatistics-based probabilistic liquefaction hazard mapping towards quantitative inferences (e.g., [75–82]). Despite this evident evolution on the enhanced consideration of multi-source geospatial statistics (e.g., geologic, geotechnical, hydrologic, topographic), namely from in-situ testing only to the coupling with satellite remote-sensing [83], the development of IM-related liquefaction intensity parameter, a fundamental index for liquefaction hazard assessment, is relatively less. The liquefaction potential index (LPI) [84] and its modifications such as the Ishihara-inspired index (LPI_{ISH}) [85], liquefaction severity index (LSI) [86], and liquefaction severity number (LSN) [87] are often used in either deterministic or probabilistic methods. A common feature of these liquefaction intensity parameters is that they are mostly based on the assumption that peak ground acceleration (PGA) could well represent the potential or severity of liquefaction. This assumption, however, stands in contrast with some ad-hoc studies showing that PGA is not an appropriate IM for liquefaction hazard evaluation, as it often leads to significant dispersions in regression models between PGA and liquefaction indicators, such as the excess pore pressure ratio [88]. Such large dispersions could propagate throughout the RSRiA pipeline, resulting in unreliable risk and loss estimates. By contrast, velocity-related IMs such as peak ground velocity (PGV) and modified cumulative absolute velocity (CAV_5) are reported as being more appropriate (e.g., [76,88]). This finding stimulates a motivation to explore more advanced liquefaction intensity parameters toward high-confidence empirical evaluation methods.

Various analytical or numerical methods have been proposed and implemented for analyzing individual slopes or earth systems such as ports, dams, retaining walls, etc. These methods feature different levels of computational and user-skill demands, i.e., from empirical pseudo-static stability analyses (e.g., [89,90]) to semi-empirical sliding-block analyses (e.g., [91–93]), and to physics-based dynamic nonlinear effective stress analyses (e.g., [94–96]). By contrast, the state of the practice in analyzing regional co-seismic landslides (e.g., [97–99]) overwhelmingly uses the infinite slope sliding-block approach [100] due to the enormous computational challenge of implementing more sophisticated methods at the regional scale (e.g., the dynamic nonlinear effective stress analyses that capture fluid-solid interaction, grain-level dynamics, etc.). Moreover, due to the practical limitation in accessing region-wide massive ground characteristics, infinite slope sliding-block analyses have to ignore local geological and topographical details and the associated failure modes. To break this limitation, Grant et al. [67] developed a multimodal framework, which leverages regional topographical information to identify the specific landslide failure modes at individual geologic units, thereby leading to more accurate regional assessment. However, methods for the individual failure modes are still limited to empirical or semi-empirical approaches mentioned above. In other words, these methods are only applicable to scenarios that have similar characterizations to those for developing the empirical or semi-empirical approaches.

2.2. Exposure modeling

Exposure models encompass data describing the locations and characteristics of buildings, infrastructures, and other constructed facilities that are exposed to seismic hazards. Such data can be structural characteristics (e.g., floor area, column diameter, structural systems and materials, etc.) to form a topological class for fragility model development, and/or asset attribute metrics (e.g., occupancy, replacement cost, and functionality, etc.) for regional vulnerability and consequence assessment. Reliable and complete data on exposed assets in many cases are not readily available, calling for researchers to leverage viable acquisition techniques to collect, assemble, and harmonize datasets from different sources. As listed in Table 1, such datasets may come from publicly available property databases created by research institutions and governments, or proprietary databases maintained by government agencies or private organizations. Dictated by the scale of analysis, data availability, and the required model resolution, different data acquisition approaches have been explored in the literature. A top-down downscaling approach has been used in De Bono and Chatenoux [101] to disaggregate the socio-economic, building type, and capital stock data using geographic population and gross domestic product (GDP) distribution models. Conversely, a European building exposure model has been developed using a two-step bottom-up approach: (1) identify the predominant building classes in a given country; and (2) model the spatial distribution of the number of buildings, replacement cost, and the number of occupants within each building class [102]. This approach requires considerable time and effort to gather, clean, integrate, and harmonize a large inventory of data, yet it produces much more reliable data attributes on the exposed assets. To achieve a proper balance between data accuracy and analysis efforts, a hybrid top-down/bottom-up approach has been considered in Wieland et al. [103] to develop a multi-scale building exposure model for central Asia. In their study, building types and their relative frequency were defined by expert judgment and refined through medium-resolution satellite images, whereas per-building data was further integrated using visual screening and high-resolution satellite image analysis. Recently, research efforts have also focused on developing more advanced data acquisition techniques to improve the efficiency and accuracy of exposure modeling. Research outcomes include (1) an algorithm to automatically extract and recognize two-dimensional building shape information using integrated aerial imagery processing and GIS data [104]; (2) a deep learning technique to extract building information from street-view or satellite images [105]; and (3) a deep learning-based automated procedure to identify soft-story buildings from street-view images at a regional scale [106]. Although building information

Table 1
Example data sources for exposure modeling.

Data resource	Inventory type	Region	Website link
CoreLogic	Buildings	United States Australia New Zealand United Kingdom	https://www.corelogic.com/
Emporis	Buildings	Worldwide	https://www.emporis.com/
GEM Exposure Database	Buildings	Worldwide	https://storage.globalquakemodel.org/what/physical-integrated-risk/exposure-database/
Google OpenStreetMap	Geospatial map	Worldwide	https://www.openstreetmap.org/
HAZUS Inventory Data	Buildings Infrastructures Other facilities	United States	https://www.fema.gov/flood-maps/products-tools/hazus
Homeland Infrastructure Foundation-Level Data	Infrastructures	United States	https://hifld-geoplatform.opendata.arcgis.com/
Microsoft Building Footprints	Buildings	United States Canada Uganda Tanzania	https://www.microsoft.com/en-us/maps/building-footprints
National Bridge Inventory	Bridges	United States	https://www.fhwa.dot.gov/bridge/nbi.cfm
UrbanSim	Buildings	United States	https://urbansim.com/urbansim
World Housing Encyclopedia	Buildings	Worldwide	http://db.world-housing.net/
Energy Information Administration	Energy Infrastructure	United States	https://atlas.eia.gov/
Africa Infrastructure Country Diagnostic	Infrastructure	Africa	https://www.infrastructureafrica.org/
Omoya et al. (2022) [107]	Buildings	California	https://www.designsafe-ci.org/data/browser/public/designsafe.storage.published/PRJ-3025
SafeGraph	Buildings	Worldwide	https://www.safegraph.com/

modeling has been adopted widely by architecture, engineering, and construction professionals, the existing literature on exposure modeling in the context of RSRiA is still limited and mainly focuses on buildings. In general, high-resolution large-scale exposure modeling remains a laborious and expensive undertaking, which requires ongoing research that takes advantage of recent advances in data mining, image processing, and machine learning.

2.3. Regional seismic fragility assessment

The past two decades have witnessed remarkable developments in the field of seismic fragility assessment, which provides the exceedance probability of certain limit state conditioned on the ground motion intensities and other factors. A handful of state-of-the-art review works have been conducted to summarize the associated research advances, challenges, and future needs. The relevant review studies include (1) a synthesis of different fragility functions used in seismic risk assessment of buildings, lifelines, utility systems, transportation infrastructures and critical facilities in Europe [108]; (2) a review of the different methodologies developed for seismic fragility assessment of highway bridges along with their features, limitations and applications [9]; (3) a discussion of different statistical strategies (e.g., incremental dynamic analysis (IDA) versus multiple stripe analysis (MSA)) to estimate fragility function parameters using nonlinear dynamic structural analysis results [109]; (4) a summary of current seismic and multi-hazard fragility and restoration models for typical highway bridge classes in the United States [13]; (5) a reflection of European practice and research on the critical topics in analytical fragility and vulnerability assessment, including ground motion selection, structural modeling, uncertainty propagation, and validation of vulnerability results [8]; and (6) a review of the recent advances on fragility assessment of transport assets subjected to earthquake hazard and other geotechnical and climatic hazards [110]. Approaches for developing a seismic fragility function can be generally grouped into four categories – empirical, expert judgmental, analytical, and hybrid [9,13,108]. Among the four categories, analytical fragility models rely on numerical simulations of structural models to generate sample seismic damage data. Owing to the advances in computational power and finite element modeling, they become attractive due to the merit of high-fidelity numerical data to emulate earthquake damages to structures in a physics-based manner. Targeting at different structure portfolios (e.g., buildings, bridges, water systems, electric power stations, etc.), analytical fragility assessment involves a multi-step procedure to convolve the seismic demand models with structural capacity limit states to assess their probabilities of reaching different damage states. As shown in Fig. 2, this multi-step procedure consists of several crucial topics, each of which may entail a comprehensive review (e.g., the reviews on IM selection by Kostinakis et al. [111] and ground motion (GM) selection by Katsanos et al. [112]). However, given the enclosed broad range of research topics, the survey herein is selective, focusing on cutting-edge research advances towards ***regional*** seismic fragility assessment that have not been discussed extensively in the above-mentioned review publications.

2.3.1. Selection of intensity measure (IM)

Within the PEER risk integral (Eq. (1)), ground motion IMs serve as the point of contact between seismic hazard and seismic demand (i.e., structural response). The IM selection constitutes an essential step that identifies the ground motion characteristics to best correlate with seismic demand. Extensive efforts have been made previously to identify the optimal IM for structure-specific seismic demand and fragility models. Marginal IM selection criteria include practicality, effectiveness, efficiency, sufficiency, robustness, computability, etc. (e.g., [113]). Among various IMs, the PGA and spectral acceleration at a given vibrational period, $S_a(T)$, were commonly considered as viable IM candidates (e.g., [111,114]), mostly due to their widely available GMPEs that enable practical hazard analyses. Emerging studies have also shown performance improvement when using more advanced IMs, such as vector-valued IMs (e.g., [115]) and fractional order IMs (e.g., [116,117]). Unlike structure-specific seismic fragility assessment, RSRiA deals with spatially distributed structural portfolios with different characteristics, which call for more rigorous IM selection strategies to accommodate the heterogeneous structural portfolios for more confident risk outputs. As pointed out by Kazantzi and Vamvatsikos [118], the geometric mean of the spectral acceleration values at several periods, S_{avg}, could significantly improve efficiency and sufficiency when performing seismic vulnerability assessment across a building class. S_{avg} takes into account not only the period variability in each building but also the period elongation associated with the structural damage in an averaged sense. Besides, a subsequent study from Kohrangi et al. [119] showed that the use of S_{avg} can also substantially reduce site-to-site variability of the fragility function, being more reliable to represent the seismic vulnerability for a class of buildings everywhere within the region of interest. It should be noted that S_{avg} is still a scalar IM that incorporates different spectral content in an averaged sense. To fully exploit the hazard information and explanatory power, recent studies [28,37] have also shown that adopting vector IMs can even better preserve the high dimensional ground motion attributes, and is particularly favorable to accommodate the varying structural characteristics of

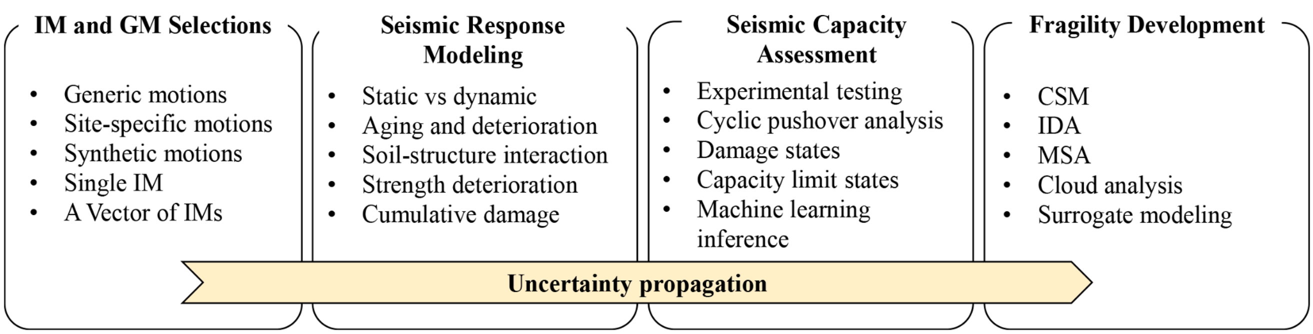

Fig. 2. Crucial topics involved in the multi-step procedure of regional seismic fragility assessment.

heterogeneous regional structural portfolios. Beyond the marginal IM selection criteria mentioned above, an information theoretic IM selection methodology was recently proposed by Du and Padgett [37,120] through minimizing the joint entropy of the unconditional seismic demands, which holistically integrates uncertainties in spatial IM random field, structural parameters, and demand models.

2.3.2. Selection of ground motions (GMs)

The selection of GMs provides ground motion inputs to nonlinear dynamic analyses for the generation of sample demand data to be used for demand and fragility modeling. Rigorous and consistent GM selection consists of two important steps: (1) the determination of a target (e.g., target response spectra) pertaining to the seismic hazard of interest, and (2) the development of an objective method for the selection and modification of GMs to match the target [121]. A uniform hazard spectrum (UHS) was commonly utilized for force-based seismic design as it implies that the spectral accelerations at different periods will have a uniform rate of exceedance. Because of its fundamental conservatism in representing individual earthquake scenarios, UHS has been shown to be unsuitable for GM selection and scaling (e.g., [121,122], among others). One viable alternative lies in using a conditional mean spectrum (CMS), which provides the expected response spectrum conditioned on the occurrence of a target spectral acceleration value at the period of interest [122]. Later on, efforts have been made to further advance the CMS based GM selection by generating the target conditional spectra (CS) that incorporate both the aleatory and epistemic uncertainties in PSHA [123], and a computationally efficient algorithm was developed for the selection and scaling of GMs to match target CS distribution [124]. Moreover, risk-based assessment has shown the insensitivity to the choice of the conditioning IM in CS when the ground motions are carefully selected to ensure hazard consistency [125]. Along the same direction, a generalized conditional intensity measure (GCIM) approach was proposed by Bradley [121], which accounts for the correlation with additional IMs (e.g., duration and energy based metrics) together with those reflected in a response spectrum. Based on the GCIM approach, the same researcher developed a GM selection algorithm using random realizations from the conditional multivariate distribution of various IMs [126]. Besides, Kohrangi et al. [127] proposed selecting GMs from a CS that is conditioned on S_{avg} over a period range, to improve predictability, hazard consistency, and efficiency. Beyond using a scalar conditioning IM, several recent studies have also developed GM selection methodologies that are consistent with a vector of IMs for more holistic seismic hazard characterization and conditional dispersion reduction [128].

2.3.3. Seismic response modeling

Analytical fragility assessment relies on numerical simulation to idealize a structural system and generate sample seismic demand data for model training. Related studies have discussed the state of research in seismic response modeling schemes for a variety of structural systems [8,14]. Without repeating such discussions, this paper focuses on surveying the most relevant modeling approaches for RSRiA. Such a review is necessitated given the added challenges to deal with spatially distributed structural portfolios that call for (1) rigorous efforts in synthesizing, indexing, and sampling data inputs, and (2) extensive computations to incorporate structure-to-structure variabilities across the region. To this end, Table 2 lists the commonly used modeling and analysis approaches for regional-level seismic response modeling, as well as the associated example studies and the applied structural types. Dictated by model fidelity, computational efficiency, and data availability, researchers adopted distinct modeling and analysis approaches for different fragility assessment tasks.

As listed in Table 2, idealized single-degree-of-freedom (SDOF) or multi-degree-of-freedom (MDOF) models have been coupled with either static analyses (e.g., the capacity spectrum method, CSM) or time history analyses (THAs) to estimate the seismic fragilities of large-scale structure portfolios or non-engineered structure systems (e.g., [129–131, 136]). The adoption of such modeling strategies results from (1) the complexity of structure inventory that prevents timely development of detailed models for each structure class (e.g., the 500 building topologies considered in Martins and Silva [130] to represent typical building classes at the global scale); (2) the lack of design information required for constructing more refined models; and (3) the unavailability of more accurate modeling schemes at present (e.g., as shown in Novelli et al. [136] for non-engineered masonry buildings). These model and data constraints are somewhat alleviated concerning specific classes of code-conforming building structures across a relatively small region, where beam-column frame models with lumped plasticity and/or nonlinear phenomenological springs have been typically utilized in RSRiA (e.g., [132–134,137]). The use of plastic hinges to connect elastic beam-column elements bears a proper balance between prediction accuracy and computational efficiency [132]. At the same time, ad-hoc uniaxial phenomenological springs can be added to simulate additional failure modes or connection details (e.g., to model column shear

Table 2
Response modeling and analysis approaches for regional seismic response modeling.

Modeling/Analysis approach		Example studies	Structural type
SDOF static		[129]	RC building stock Non-engineered masonry buildings
SDOF THA		[130]	Building portfolios
MDOF THA		[131]	Building portfolios
Frame model THA	Lumped plasticity	[132]	Non-Ductile RC Buildings Modular steel buildings
	Nonlinear springs	[133]	Wood-frame houses
	Lumped plasticity + nonlinear springs	[134]	RC buildings Industrial precast building classes
	Fiber-section + nonlinear springs	[135]	Bridge classes

and axial failures in Shokrabadi and Burton [134]). Unlike building frames where lumped plasticity models have been commonly used, the state of the art adopted a more fundamental fiber-section model to emulate the seismic behavior of bridge columns, whereas abutment components and bridge foundations were typically simulated as uniaxial phenomenological springs [135]. As shown in Fig. 3, a recent study has developed a physics-based nonlinear spring system to simulate the seismic responses of various abutment components, including bearing, shear key, pounding, abutment backwall, backfill, and foundation [138]. This effort is a part of a pilot project to develop a new generation of seismic fragility models for statewide bridges in California.

2.3.4. Seismic capacity modeling

After obtaining the seismic demand estimates, seismic capacities are required as limit state thresholds to determine the extent of damage states (DSs) (e.g., concrete cracking and spalling, reinforcement yielding, and diagonal bracing buckling) [139]. Seismic damage at different scales can be characterized through different EDPs, such as material strains and stresses (e.g., [140,141]), section curvatures (e.g., [142,143]), inter-story drifts (e.g., [144,145]), floor accelerations (e.g., [139]), and global displacements (e.g., [130]). The selection of an EDP largely depends on the adopted modeling and analysis schemes – idealized SDOF and MDOF models can provide macro-level EDPs such as inter-story drift ratios and global displacements. In contrast, more refined FEMs enable the incorporation of micro-scale EDPs such as material strains and section curvatures. Large-scale experimental testing provides a sound reference to determine the seismic capacity values for different DSs and structural components, such as reinforced concrete (RC) columns, walls, and column-beam joints [146,147], steel beams and columns, and RC beams [148], masonry-infilled frames [149], and wood frame shear walls [150], among others. These experimental tests offer a ground truth to describe structural damage, capture disruptive changes in response, and identify the associated capacity thresholds that are physically consistent with the observed damage states. To expand their applicability, test results have been utilized to develop regressive capacity models conditioned on geometric and material properties of the test specimens (e.g., [140,151]), allowing seismic capacity estimates for a wide variety of structural components. Furthermore, outcomes from cyclic pushover tests also provide a viable reference to develop and validate high-fidelity numerical models that can capture complex damage behaviors, including strength/stiffness degradation and hysteresis [152], steel buckling [153] and fatigue [154], flexure-shear interaction [155], strain penetration effect [156], etc. These multi-scale well-validated numerical models have been considered an alternative for seismic capacity modeling when the associated experimental results are limited. Recently, previous seismic damage records, simulated data, and test outcomes have been increasingly utilized to develop various machine learning algorithms that recognize, classify, and assess the seismic capacity/damage of civil engineering structures [10]. Other than these efforts, judgment-based empirical LS values have been commonly assigned for certain structural types where no reliable data is available (e.g., [130]).

2.3.5. Methods for developing fragility models

Different approaches have been proposed for analytical fragility modeling. These approaches essentially fit statistical models on the distributions of EDPs at each IM level and compare them with the associated capacity models for different damage states. In general, five distinct approaches have experienced prevalent usage in the literature: CSM, IDA, MSA, *cloud* analysis approach, and parameterized fragility approach. The fundamental assumptions, inherent advantages, potential limitations, and recent advances of these five approaches are briefly discussed subsequently.

CSM is associated with the SDOF static analysis approach and was developed by Freeman [157]. In its basic graphic form, CSM compares the equivalent capacity of a structure (in the form of a spectral acceleration-displacement pushover curve) with its demand (in the form of a highly damped elastic spectrum) [139]. In this respect, research efforts have been made to develop the inelastic response spectra as the demand curves for improved accuracy [158,159]. Despite such improvements, CSM fails to fully capture the dynamic behavior of a multi-component structural system when subjected to the time history excitation of a ground motion – features such as significant duration and cumulative energy cannot be incorporated through the CSM.

IDA arguably is the most frequently used approach for developing seismic fragility models using dynamic analysis data [160]. IDA relies on nonlinear THAs of a structural model when subjected to a suite of ground motions that are scaled to increasing levels of the IM until structural collapse [145,161]. For each incremented ground motion, the analysis stops until dynamic or numerical instability occurs, or the EDP

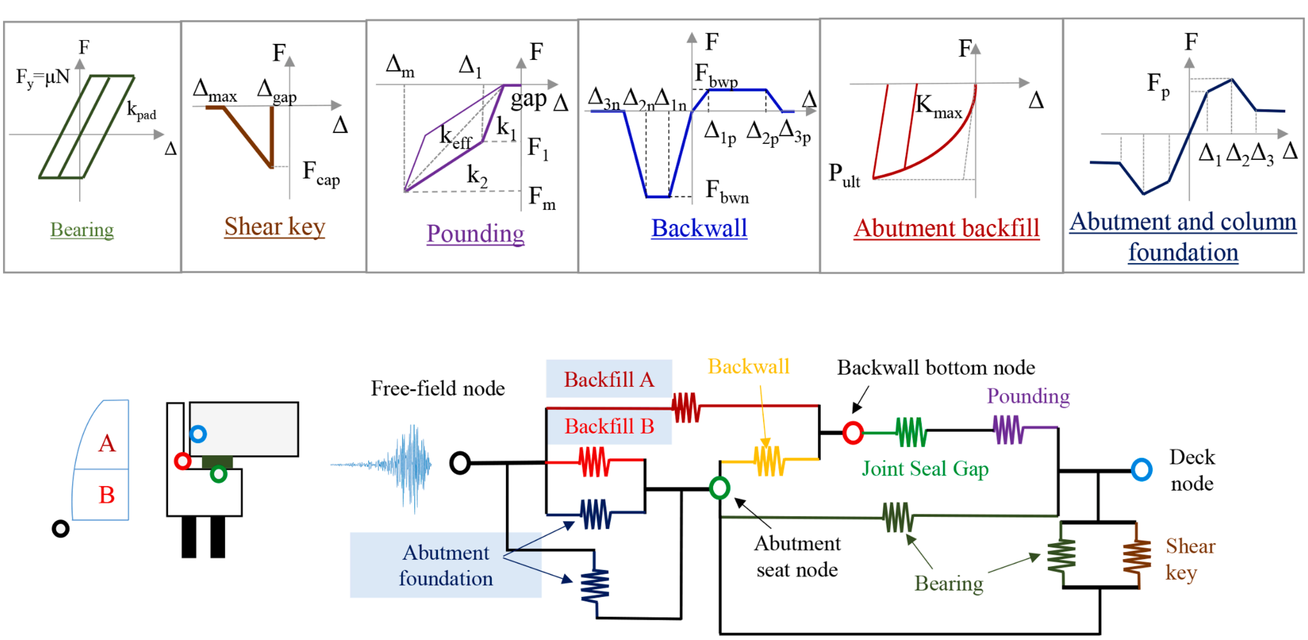

Fig. 3. A physics-based nonlinear spring system for simulating seismic responses of various abutment components in bridges [138].

exceeds a preassigned collapse limit. Other than the collapse state, the probability of exceeding a specific DS at a given IM level can be empirically estimated as the fraction of ground motions leading to DS exceedance. Given its robustness, IDA has been employed in several studies to assess the impact of modeling uncertainties on the resultant seismic demand and capacity of building frames [162,163]. Such sensitivity analyses are particularly relevant to RSRiA where regional structural portfolios call for non-deterministic input parameters to capture the embedded structure-to-structure variability. However, conducting IDA remains computationally intensive and often requires significant scaling of the original ground motion records to various IM levels. These challenges have been addressed through various attempts, including (1) the use of parallel computing to accelerate the computation [164]; (2) the development of more efficient IMs to reduce the dispersion and the needed number of records [165]; (3) the design of a precedence list to optimize and select the fewest number of required records [166]; and (4) the development of a *cloud* to IDA procedure towards the reduced amount of analyses and scaling [167].

Another related variant lies in the MSA that performs the structural analyses at a small and discrete set of IM levels, at each of which different ground motions can be used [109]. The MSA provides the fractions of ground motions at each IM level that reach different damage states, which can be fitted using the maximum likelihood technique to develop continuous fragility models [109]. A recent study has investigated the accuracy and effectiveness of MSA for seismic performance assessment [168]; their study concludes that with the proper settings (e.g., the number of IM-stripes and the number of ground motions per stripe), MSA can provide reliable risk estimates at a fraction of the computational cost.

Unlike IDA and MSA, the *cloud* analysis approach directly fits a regression model to the EDP-IM pairs for structures excited under a suite of un-scaled ground motions. Due to its relative simplicity and improved efficiency, the *cloud* approach has been widely adopted in the literature [169,170], particularly for developing seismic fragility models of bridges (e.g., [142,171]). In essence, the *cloud* approach relies on three fundamental assumptions to develop the EDP-IM regressive models (also termed as probabilistic seismic demand models, PSDMs) – EDP being a linear function of IM in the logarithmic scale; constant standard deviation across the entire IM range; and EDP conditioned on the IM follows a lognormal distribution [113]. The validity of these assumptions depends on the selected GMs and IM, as well as the embedded nonlinearity of the structural system. For instance, a previous study indicated that the logarithmically-linear model and the constant dispersion assumption could cause a substantial error for fragility, resilience, and life-cycle loss analyses of a steel girder bridge class [172]. To that respect, several researchers have proposed variations to the *cloud* approach by relaxing some of the abovementioned assumptions. Such efforts include (1) the use of a quadratic equation to replace the linear logarithmic function [173]; (2) the use of non-parametric approaches, namely the binned Monte Carlo simulation and kernel density estimation, for fragility development [174]; (3) the incorporation of two IMs for developing a fragility surface [175,176]; (4) coupling the linear logarithmic regression with logistic regression to take into account structural collapse [177]; and (5) the convertibility among the *cloud* approach, IDA, and MSA [178].

The IDA, MSA, and *cloud* approaches can often cause significant variabilities in the derived fragility models. For example, as illustrated in Fig. 4 for a steel moment-resisting frame (Fig. 4a) [179] and a reinforced-concrete (RC) bridge column (Fig. 4b) [178], more considerable fragility disparities can be observed at higher levels of damage states (i.e., DS_3 and DS_4). Such disparities would lead to noted differences in the subsequent risk and resilience assessment. In this regard, it remains crucial to examine the selected GMs and IM, the embedded dynamics and nonlinearity of the structural system, and the validity of each method's assumptions. Such examinations are essential for determining the most reliable fragility approach.

These methods consider ground motion IM as the only variable for fragility development. In RSRiA, such univariate fragility models are used to represent the damage probabilities of structure classes where the embedded structure-to-structure variability is not explicitly addressed. To alleviate this limitation, recent research efforts have focused on developing multi-dimensional parameterized fragility models. Namely, these fragility models can be tailored to individual structures across a region since they depend not only on the IMs but also on other predictors such as material, geometric, and aging parameters of the structure. To this aim, a multi-step procedure is needed to form a computational workflow that consists of experiment design, surrogate metamodeling, Monte Carlo simulation, and logistic regression (e.g., [180–182]). As a critical step, surrogate metamodeling is commonly realized through developing response surface models (e.g., [183–185]) or machine learning models (e.g., [186–188]). Due to limited space, methodological details for each analysis step are not provided herein, while relevant discussions can be found in Xie et al. [10].

2.4. Regional seismic consequence evaluation

With the knowledge of damage state probability estimates of the structures after convolving the regional seismic hazard with the fragility models, the next module of RSRiA is to link the damage estimates to the resulting regional direct and indirect losses (or consequences). Note that seismic consequences are not only limited to economic losses, but can also be any quantitative consequence metrics, such as casualties, debris,

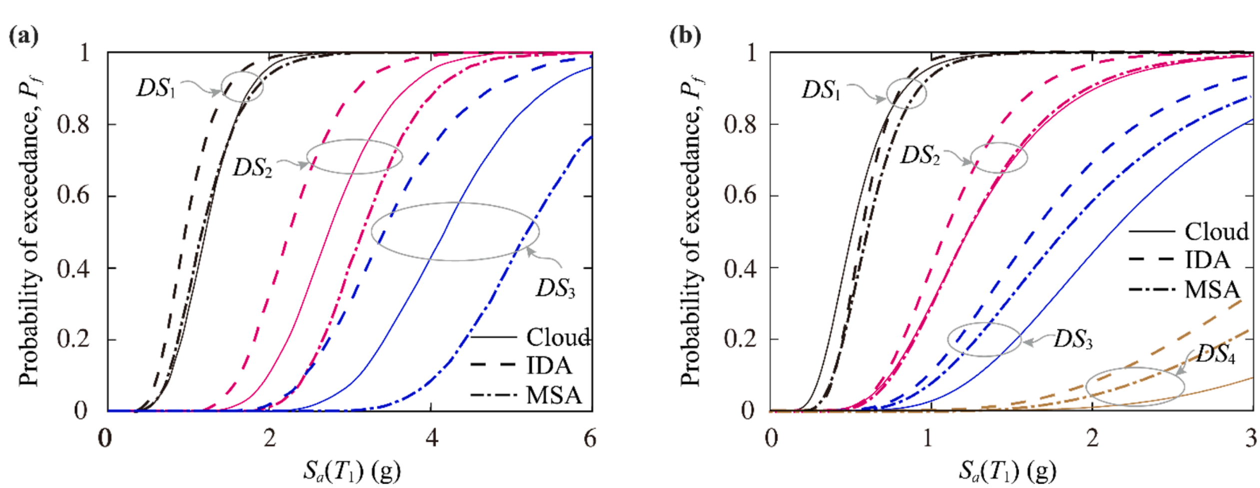

Fig. 4. *Cloud*-, IDA-, and MSA-based fragility curves for (a) a steel moment-resisting frame with viscous dampers [179], and (b) an RC highway bridge column [178].

downtime, displaced population, shelter needs, and functionality of lifeline systems. Confusions regarding the definition of direct and indirect losses exist in the engineering and economics fields. In fact, it is hard to strictly delineate the boundary between the two concepts as they are typically overlapped with each other. Here we adopt the definition from an economic point of view, which we believe makes a clearer distinction between the direct and indirect losses based on their relation to stocks and flows [189]. In economics, stocks refer to quantities at a specific point in time, while flows refer to the services or outputs offered by stocks over time [189]. In the context of RSRiA, direct losses occur instantly after the initial impact of the earthquakes, and are typically time-independent. Some typical types of direct losses include (1) repair and replacement costs related to structural systems, non-structural components, building contents, and business inventories, (2) construction and demolition debris, and (3) casualties. On the other hand, indirect losses are incurred by the prolonged interruptions (e.g., loss of occupancy of buildings, loss of functionality of lifeline infrastructure systems, and business interruptions), and are time-dependent and accumulate with the recovery process. Quantification of indirect losses is a complex problem and is still an open area of research that involves multi-disciplinary knowledge and data spanning the field of engineering, economics, and social science. From an analysis perspective, direct losses can be more straightforwardly computed as the product of damage state probabilities and the associated loss quantities, whereas indirect losses are compound outcomes of the initial earthquake disruption and the post-hazard recovery process, and often require more sophisticated interdependency modeling.

As for the ***direct losses***, traditionally, direct economic cost related to repair and replacement of damaged structural and non-structural components, and building contents, has been prevalently considered in RSRiA [24,28,35,190,191], where the cost estimates for different damage states can be reasonably estimated based on material and labor costs, and engineering practice. Other than the direct economic cost, several studies characterized the rates or spatial distribution of earthquake-induced casualties [192–196]. In addition, some research efforts have also been committed to modeling the amount and spatial extent of roadside debris and post-earthquake fire events, which may hinder the post-earthquake emergency response and recovery process [197–203]. As for the ***indirect losses***, the indirect economic cost is perhaps the most considered metric, which can be comparable to or even surpass the amount of direct economic cost [204]. Depending on the scope of analysis, the indirect cost can correspond to different infrastructure lifeline networks, economic sectors, or, more broadly, to the entire regional socio-economic environment. If the scope of analysis is on a given regional building stock or lifeline infrastructure system, the system-wide loss of revenue related to the reduction of product or demand can be generally estimated based on seismic damage assessment, recovery modeling, and indirect loss quantification. However, things get more complicated when estimating the more holistic regional indirect economic cost, as almost all the different sectors within the regional built environment are interdependent with each other. Some preliminary efforts strived to quantify the indirect economic cost due to the regional seismic disruptions to a specific lifeline infrastructure system, particularly the transportation infrastructure [6,205–208]. This approach typically involves explicit graph-theoretical network modeling and flow analysis of the lifeline system of interest, and calculates the pre- and post-earthquake differences in regional-level network performance or functionality measures, which can then be associated with certain empirical socio-economic unit cost. Yet, without also modeling the other interdependent systems, this approach may not be able to accurately capture the dynamic inter-network interactions. A more comprehensive review on network modeling and interdependencies of lifeline infrastructure networks can be found in Ouyang [209]. However, it is still a daunting task to model all the links within the interconnected economy system, due to data scarcity (or privacy) and the complicated network-interdependency modeling. In this regard, economic models such as input-output (I-O) models or the more sophisticated computable general equilibrium (CGE) analysis may be able to serve as higher-level alternatives to trace the interindustry chain reactions or ripple effects [210,211]. Note that the I-O and CGE approaches are most suitable for short- and mid-term analysis, while the longer-term indirect effects require more in-depth and complicated analysis [189]. In addition, risk indexes obtained from multi-criteria decision methods such as analytic hierarchy process (AHP) and multi-attribute utility theory (MAUT) also offer practical solutions to combine decision variables from different aspects [212–215].

2.5. *Uncertainty quantification and propagation*

Since various sources of uncertainties exist in each of the aforementioned RSRiA analysis modules, the resulting regional risk estimates can be regarded as sophisticated nonlinear functions convoluting all the involved input random variables. To yield accurate and unbiased risk estimation, it is vital to accurately quantify and propagate these uncertainties throughout the RSRiA pipeline. In this regard, uncertainty quantification (UQ) is typically performed at the individual analysis module or model level, to provide probabilistic descriptions of the key random input parameters or physical processes. For example, seismic source models employ logic trees to assign different occurrence rates to the seismic sources; and GMPEs offer not only the median intensity estimates but also the aleatory uncertainty terms. However, it should be noted that UQ is yet to be ubiquitously incorporated in all the models involved in RSRiA. For example, deterministic structural component limit state capacities (e.g., prescribed inter-story drift ratio thresholds) are still commonly adopted in building fragility modeling. In UQ, two types of uncertainties exist, namely aleatory uncertainty and epistemic uncertainty. Aleatory uncertainty refers to the intrinsic, and thereby irreducible, randomness of the stochastic processes involved in RSRiA [216], such as earthquake occurrence, ground motion intensities, and structural material properties. On the other hand, epistemic uncertainty emerges due to the lack of knowledge, data, or powerful techniques when developing numerical or mathematical models (e.g., GMPEs, finite element models, structural capacity models, and surrogate demand and fragility models) to characterize the natural and physical processes [216]. Over the past several decades, the advancements in seismic hazard characterization, GMPEs, structural finite element modeling, and the adoption of advanced statistical and machine learning techniques have contributed greatly to the reduction of epistemic uncertainties in different RSRiA analysis modules.

After quantifying the uncertainties, the final step of RSRiA is to integrate the different analysis modules and perform uncertainty propagation for risk estimation, where the resulting risk estimates can be expressed in terms of point estimates (e.g., annual mean values) or the full probability distribution (i.e., rate/probability of exceedance). Since the general RSRiA framework is a convolutional integral of several conditional probability statements, it is desirable for uncertainty propagation to be performed in an efficient and unbiased manner. To this end, Monte-Carlo simulation (MCS) techniques are widely adopted for uncertainty propagation in modern RSRiA for their powerful and explicit uncertainty propagation capability. However, due to the curse of dimensionality, crude or naive MCS requires a huge number of random realizations for the high-dimensional uncertainty propagation in RSRiA. Intractable computational expenses can be easily incurred if one or more analysis modules involve computationally demanding simulations (e.g., co-simulation of spatial ground motion random field; high-fidelity nonlinear time history analyses of structural seismic responses; and traffic flow simulation of regional transportation network systems). As such, many alternative approaches have been proposed and employed to alleviate the computational hurdle, including (1) identifying key input parameters for each analysis module via sensitivity analysis, thus reducing the number of random variables involved in the sampling process [37]; (2) more efficient sampling of the high-dimensional probability space via advanced variance reduction techniques such as Latin Hypercube Sampling and Importance Sampling [33,217]; (3) improving the scalability when dealing with large regional systems via dimensionality reduction techniques [33,218]; (4) reducing the computational burden of physics-based modeling by developing statistical or machine learning surrogate models [188,217,219,220]; and (5) developing surrogate models to combine multiple consecutive analysis modules or even the entire RSRiA pipeline [221].

3. Methodological development of regional seismic resilience assessment (RSReA)

Recall that ***resilience*** is defined as 'the ability to prepare and plan for, absorb, recover from, and more successfully adapt to adverse events' [222], which can be conceptually illustrated as a functionality recovery curve as shown in Fig. 5(a) including four phases: (1) the pre-event planning phase, where the functionality can be enhanced via retrofitting actions, or reduced by aging effects; (2) the absorbing phase right after an earthquake event with an instantaneous loss of functionality (to a residue, Q_r) together with a rapid rebound of functionality owing to prepared protective actions (e.g., using emerging techniques [223]); (3) the post-event recovery phase, which contains a response stage (t_0 to t_i) with an idle time and a restoration stage (t_i to t_r) that gradually recovers the system to a target functionality, Q_t, and (4) post-recovery adapting phase that accommodates the system to future threats. Following this generic definition, a bunch of seismic resilience assessment frameworks, from qualitative to quantitative manners, have been proposed for structures and infrastructure systems (e.g., [224–230]), where the majority conform to the 4R principles of resilience as per Bruneau et al. [231], i.e., ***robustness, redundancy, rapidity***, and ***resourcefulness***, as denoted in Fig. 5(a).

Since RSRiA typically quantifies the extent of the impact of earthquakes (i.e., the 'absorb' component in resilience), RSReA is further needed to more synergistically address the different resilience dimensions. Particularly, RSReA incorporates an additional time dimension to evaluate the time-evolving performance of the regional built environment before, during, and after earthquake events. As such, proper selection of resilience quantification metrics is important to accurately reflect the specific performance of the regional built environment of interest. The functionality and levels of services of spatially distributed and functional infrastructure systems evolve with the recovery of their individual components. Therefore, it is necessary to characterize the recovery trajectory of individual structure and infrastructure components. Regional infrastructure systems are highly interdependent with other structural and lifeline systems, making RSReA even more complicated. It should be noted that the affected

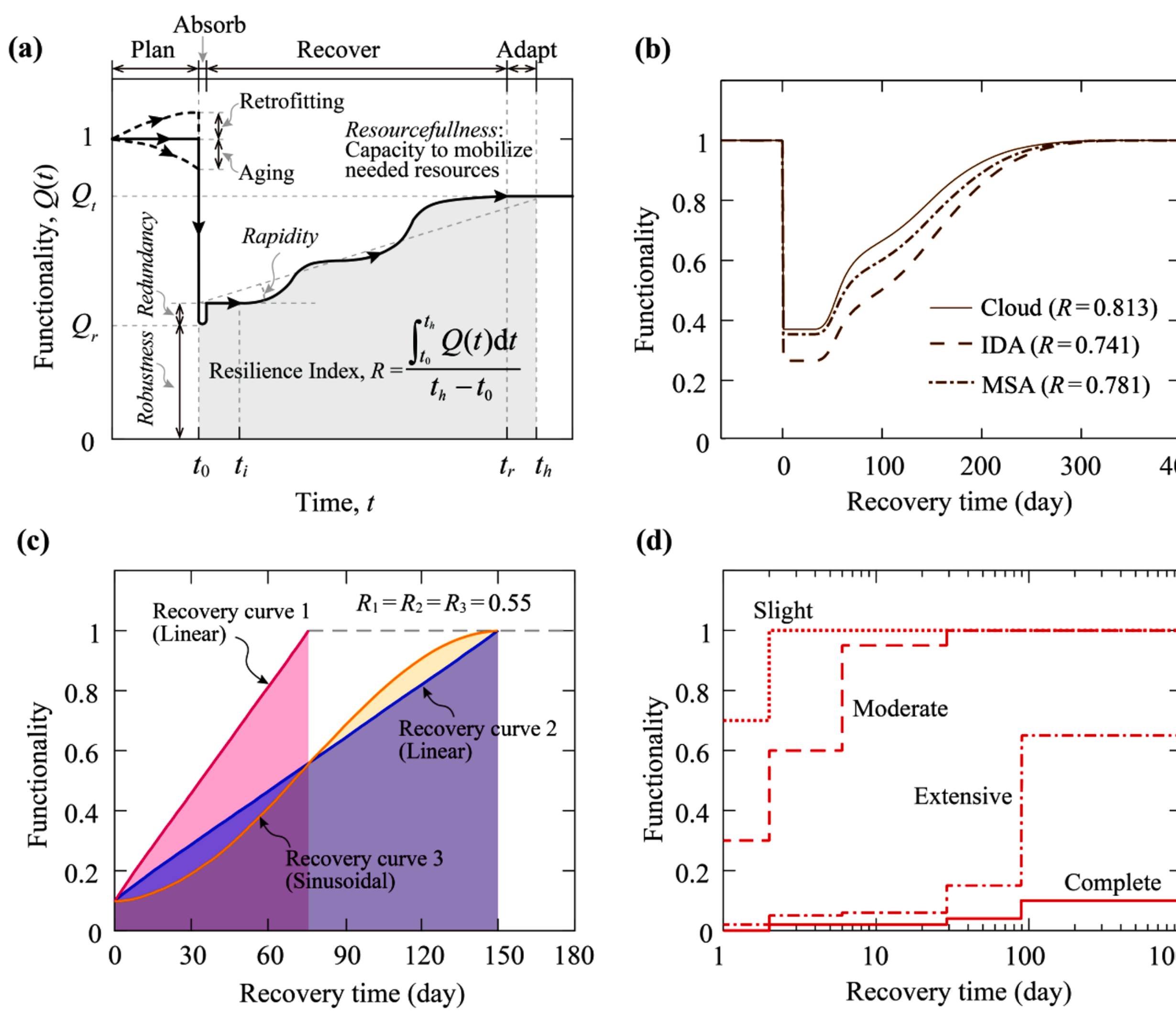

Fig. 5. (a) functionality loss and recovery process, (b) influence of fragility modeling methods (*cloud*, IDA, and MSA) on resilience processes of a highway bridge [178], (c) different recovery curves leading to the same value of Resilience Index, R, and (d) stepwise restoration model for highway bridges at different damage states from HAZUS [232].

structures and their functionality do not automatically heal by themselves. Rather, they require additional resources (e.g., funding, repair crews, or services provided by other lifeline systems), and their recovery trajectories are thus highly stochastic and are dictated by various factors and constraints. In fact, most of the indirect consequences stem from the post-earthquake recovery phase due to the interruptions to socioeconomic activities. This section aims to provide an overview of the major RSReA research components, including seismic resilience metrics, structural-scale restoration modeling, and regional-scale restoration planning and optimization.

3.1. Seismic resilience metrics

Seismic resilience metrics provide decision-makers with quantitative evidence to evaluate the potential influence of preparedness actions and recovery policies on the resilience of the built environment against earthquake events. Early attempts on community resilience assessment developed qualitative metrics (e.g., [233]) that are more or less subjective, thereby not able to achieve reliable conclusions on comparative studies across different communities, infrastructure systems, and resilience-driven mitigation and restoration plans. To address this issue, many quantitative metrics have been proposed in the past two decades (e.g., [234–236]). Existing quantitative resilience metrics are mostly based on functionality curves (e.g., Fig. 5(a)), while relatively few is based on socioeconomic factors (e.g., [237,238]). For this reason, from the perspective of earthquake engineering, the development of functionality curve-based resilience metrics is summarized below with extended descriptions of the milestone ones.

The functionality curve-based resilience metrics can be grouped into three types according to their definitions, i.e., (1) metrics dependent on the area above the functionality curve (e.g., [231,235,239]); (2) metrics measured by the area below the curve (e.g., [7,240,241]), and (3) other mathematical attributes of the curve that provide more information of the recovery process (e.g., [242–244]). Although these metrics have specific merits for their assessed systems, several limitations should be pointed out. For instance, the first resilience metric in earthquake engineering (termed ***resilience loss***) [231] is measured as the area of the triangle above the functionality curve by assuming a full functionality (100%) before an event and a full recovery afterward. This assumption, however, is often beyond engineering practices due to the pre-event aging effects and post-event resourcefulness. Moreover, ***resilience loss*** does not have an upper boundary, which cannot be compared across different types of systems. In this regard, a time normalized metric called ***resilience index***, R (varies between 0 and 1) was later developed [240] based on the area below the curve, as shown in Fig. 5(a). An R value approaching 1 indicates a more resilient system. Owing to the normalized feature, R has been broadly used for comparative studies on recovery processes [234]. Fig. 5(b) shows an application of R to quantify the influence of fragility modeling approaches (i.e., *cloud*, IDA, and MSA) for resilience modeling of a typical highway bridge [178]. Nevertheless, it should be noted that in current practices, the recovery period t_h - t_0 is hard to be determined a priori and is often roughly estimated by the users. Moreover, different restoration plans with different recovery periods may lead to the same R value (e.g., see Fig. 5 (c)).In that respect, Sharma et al. [242] explored other attributes of the functionality curve that can more comprehensively quantify the recovery process. They drew an analogy between the functionality curve and the cumulative distribution function from the probability theory, and proposed a series of resilience metrics, such as ***resilience density function*** that represents the instantaneous rate at any time of the recovery process, ***resilience disparity*** that quantifies the degree of disparity between any pair of functionality curves, ***resilience bandwidth*** that indicates the degree of the spread of the recovery process, ***resilience skewness*** that describes the skewness of the recovery process, etc.

3.2. Structural-scale restoration modeling of performance and functionality

As civil engineering structures are often comprised of various structural components with different seismic damage mechanisms and extents, the restoration time of each component depends on a multitude of interrelated factors. For instance, structural-level restoration may depend on not only structural damage and the availability of restoration resources, but also socioeconomic attributes such as stakeholders' requirements and policies. Due to such complexity, current methods for restoration modeling of structures are primarily based on empirical estimates or expert judgments, ranging from simple mathematical functions (e.g., linear [245], exponential [246], and trigonometric [247]), to relatively complex ones (e.g., two-parameter logistic function [248] and probabilistic six-parameter ones [249]), and to field surveys (e.g., [250, 251]) and expert questionnaires (e.g., [252]) that more or less characterize the physical behavior of recovery processes using stepwise [253, 254], normal [254], and lognormal [255] functions. To further characterize real-world practices toward realistic recovery processes, such as structural safety- and construction-induced traffic disruptions for bridges, Karamlou and Bocchini [256] developed a simulation-based probabilistic restoration modeling approach considering construction methods and steps, and resource availability at both component and system levels. Such a simulation-based probabilistic approach represents the current trend of studies on structural-scale restoration modeling. What remains challenging is the lack of country/region-specific restoration models, as the availability of restoration resources and socioeconomic attributes could be vastly different for different countries/regions. In particular, utilizing restoration models of structures and infrastructure in developed countries/regions for resilience assessment of those in developing countries/regions would significantly underestimate the recovery time, probably leading to mis-informed decision-making for stakeholders. Therefore, more studies are warranted on establishing country/region-specific restoration models for individual structures and infrastructure.

3.3. Regional-scale restoration planning and optimization

RSReA provides a quantitative means to compare the efficacy of different resilience-driven pre-event mitigation and post-event restoration strategies over short-term and long-term planning horizons. To this aim, one critical task of resilience assessment is regional-level restoration planning or optimization, which is needed for both ex-ante and ex-post analyses, and is a complicated problem as it involves a huge search space of structural damage states and intervention actions among a vast number of different structural systems. Restoration planning is essentially a time-dependent sequential optimization problem under the constraints of available resources. Moreover, as the regional built environment is becoming increasingly interdependent and interconnected, it is also desirable to develop coordinated restoration planning approaches that are able to holistically consider the impact of individual structures on the regional built environment resilience. Recently, a major breakthough on this topic is the development of mathematical models for classifying and quantifying infrastructure interdependencies (e.g., [257–259]). Furthermore, socioeconomic factors such as the census information of communities can be a useful supplement to enhance regional restoration modeling (e.g. [260]).

A large body of studies conducted RSReA without explicit restoration optimization, where the damaged structures are assumed to follow some prescribed restoration models based on engineering judgement and past experience [208,225,259,261–268]. Although these studies offer a general depiction of the regional recovery behavior and provide a venue to compare different mitigation alternatives, they did not explicitly consider the actual constraints such as budget, repair crews, or availability of the essential service from lifeline infrastructure systems. Several recent studies further incorporated an optimization module into

RSReA to optimally select and schedule the structures to be retrofitted or repaired with the consideration of practical constraints. Particularly, centralized optimization approaches have been the mainstream of restoration planning. Among the efforts, several studies employed traditional optimization approaches (e.g., mixed integer optimization and genetic algorithm) through the planning horizon [269–272]. Although such models offer rigorous mathematic formulations and are able to deliver coordinated restoration schemes that globally maximize regional resilience, they rely on the assumption that the built environment is fully observable with exact information, which is often not the case, especially in the aftermath of earthquakes [273]. Emerging studies on regional infrastructure recovery and resilience [274–279] have investigated the efficacy of stochastic dynamic programming, especially reinforcement learning and deep reinforcement learning, which can more robustly deal with the stochastic environment and uncertain observations and are thereby more suitable for sequential decision-support.

However, different stakeholders may have competing interests in the restoration phase [280], and thus may not necessarily comply with the centralized coordination. Moreover, centralized optimization also suffers from the lack of scalability due to the curse of dimensionality, where intractable computational expenses can be incurred if a large number of structure and infrastructure components are involved [281]. In this regard, decentralized or partially cooperative restoration optimization can be promising solutions to the scalability issues. Talebiyan and Duenas-Osorio [273] proposed algorithms for decentralized post-earthquake restoration by introducing the notion of Judgment Call to model human decision-making behaviors. Smith et al. [282] proposed an ad-hoc sequential game-theoretic model based on the discrete-time noncooperative game. Another promising alternative is multi-agent reinforcement learning [281,283,284], where different agents develop their own optimal policies instead of a fully coordinated policy for all the agents in a centralized fashion, while the goal is still on maximizing the collective regional resilience. Nevertheless, the balance between model complexity and information sharing (i.e., communication and cooperation) among different agents still needs further investigation.

4. Applicability of existing workflows for RSRiA and RSReA

Existing workflows formally integrates the above-mentioned analysis modules in a consistent manner to deliver probabilistic regional risk and resilience estimates. Developing such workflows and analysis software or platforms requires a lot of collective efforts. This section mainly focuses on those widely used, publicly accessible, and continuously updating workflows, which are typically supported by national or regional organizations. These workflows generally follow the PEER framework, although they may have different features and focus that make them suitable for different kinds of tasks in RSRiA and/or RSReA.

4.1. HAZUS

Developed by the federal emergency management agency (FEMA), the HAZUS earthquake loss estimation methodology [232] is the pioneer and perhaps so far the most widely employed RSRiA computational workflow by many past studies [285–289]. HAZUS adopts the classic PEER framework, and is comprised of a chain of interconnected analysis modules from seismic hazard modeling, exposure modeling, fragility and damage modeling, and consequence modeling. It also provides a wide spectrum of built-in data to enable different RSRiA tasks, including historical earthquake scenarios and ShakeMaps, GMPEs, census-tract level exposure information, an inventory of fragility models for different structural and non-structural components and systems, as well as default direct and indirect loss data. Moreover, HAZUS also integrates economic models such as I-O models and the more sophisticated computable general equilibrium (CGE) to allow the estimation of regional indirect losses. This method was intended to be used for RSRiA in the U.S. but has also been adopted or adapted for RSRiA of other countries or regions.

However, the HAZUS methodology also has several limitations. Particularly, the lack of aleatory variability in ground motion maps and the dearth of simulation-based uncertainty propagation capability are the main barriers that hinder HAZUS from offering fully probabilistic RSRiA and RSReA. As a result, the loss estimates typically only correspond to the expected losses from a single median ground motion map, or a particular ground motion map random realization, or a probabilistic seismic hazard map (e.g., the USGS National Seismic Hazard Maps [16]). It should be noted that even the USGS probabilistic hazard maps are derived based on site-specific PSHA, and directly importing them as the regional seismic inputs may lead to biased aggregated regional losses [290], and such losses are only limited to annualized mean estimates rather than the loss exceedance risk curves. Furthermore, the built-in fragility models are largely based on empirical expert judgment without scrutinized calibration and validation, and are typically defined using the conventional lognormal fragility functional forms conditioned on a scalar IM. As a result, a large amount of epistemic uncertainty may be propagated into the final risk estimates. Finally, the HAZUS loss module also lacks consideration of the indirect consequences for lifeline systems.

4.2. OpenQuake

OpenQuake [291] is an open-source platform for seismic hazard and risk assessment developed by the Global Earthquake Model (GEM) Foundation (http://www.globalquakemodel.org). Although it shares a common general architecture to the HAZUS methodology, it offers major advancements by incorporating more detailed regional seismic hazard modeling and simulation tools, including seismic source specification, stochastic earthquake catalog generation, logic trees for source models and GMPEs, and spatial ground motion random map simulation. Seismic hazard uncertainty is propagated via a Monte-Carlo simulation scheme, thus enabling more powerful uncertainty quantification/propagation and hence fully probabilistic risk estimates. OpenQuake currently supports seven types of analysis, including (1) scenario damage assessment; (2) scenario risk assessment; (3) classical probabilistic seismic damage analysis; (4) classical probabilistic seismic risk analysis; (5) stochastic event based probabilistic seismic damage analysis; (6) stochastic event based probabilistic seismic risk analysis; and (7) retrofit benefit-cost ratio analysis. Its open-source nature and the offered different analysis workflows enable users to conduct more tailored and customized RSRiA studies. Moreover, OpenQuake also archives a comprehensive database of worldwide state-of-the-art models such as seismic hazard models and exposure data for different countries and regions, and fragility models. Owing to its powerful and flexible modeling capability, OpenQuake has received emerging applications in RSRiA over the past years [37,292–294]. Despite its open-source nature and ongoing development and updating, as of now, OpenQuake did not directly integrate temporal analysis to model the post-earthquake recovery process, thereby lacking the full capability to support RSReA. Moreover, the current focus of OpenQuake is more toward traditional regional structural damage and direct loss modeling, while network-level analysis and broader indirect loss modeling are yet to be incorporated.

4.3. SimCenter

As part of the Natural Hazards Engineering Research Infrastructure (NHERI), SimCenter aims to provide both research and education communities with access to state-of-the-art software tools for computational modeling and simulation of the natural hazard impacts on buildings, infrastructure systems and other constructed facilities [295]. Same as other existing workflows, SimCenter's application framework adopts the classic PBEE methodology to characterize and simulate regional hazards and their damaging effects on the built environment, as well as quantify the resulting economic losses, disruption, and other societal consequences [14]. An expansible modular architecture has been developed by SimCenter that enables users to build, launch, monitor, and introduce different applications in a complete scientific workflow towards multi-fidelity and multi-resolution RSRiA. To date, the SimCenter workflow tools consist of (1) ***BE*** that defines the inventory of physical assets with artificial intelligence tools to facilitate data collection and enhancement [105,106]; (2) ***EVENT*** that supports both ***IM-based*** and ***physics-based*** GM simulations; (3) ***SAM*** that translates descriptive information in ***BE*** into data information for structural response simulation; (4) ***FEM*** that interacts with OpenSees [296] for seismic response modeling; (5) ***EDP*** that manages the demand models; (6) ***DL*** that uses a newly developed application, PELICUN [297], to evaluate earthquake damage and losses based on the FEMA P-58 methodology [298]; (7) ***UQ*** for uncertainty quantification; (8) ***Cloud*** that communicates with remote computing and data service providers; (9) ***DL Data*** that stores available fragility curves for various types of facilities; and (10) ***Exp/Sim Data*** that stores experimental/computational data for machine learning ***SAM*** applications and code validation [295]. These workflow tools were recently employed in a testbed application to assess the damage and loss of 1.84 million buildings in the San Francisco Bay Area due to a Mw 7.0 earthquake rupture on the Hayward fault [295]. This testbed assessment was conducted through the cloud-based high-performance computing resources at the Texas Advanced Computing Center, which is facilitated by SimCenter's regional Workflow for Hazard and Loss Estimation (rWHALE) [299]. In general, SimCenter's rWHALE stands out by its computational capability that directly interacts with existing advanced simulation tools (e.g., OpenSees, remote computing, etc.), as well as the implementation of machine learning tools that facilitates regional exposure modeling.

4.4. IN-CORE

Developed by the Center of Excellence for Risk-Based Community Resilience Planning, IN-CORE [300] is an open-source platform with seamlessly integrated databases for community resilience assessment against natural hazards through a risk-informed approach that covers regional damage modeling, recovery modeling, and quantitative comparisons of different resilience strategies. IN-CORE features a collective effort from engineering, economics, data science, and social science. The platform combines physics-based models of inter-dependent physical systems with socio-economic systems; it also deals with multiple hazards, including earthquakes, floods, tornados, hurricanes, wildfires, tsunamis, storm surges, etc. A noted merit in IN-CORE is an online library termed ***Web Tools*** that enable users to search, browse, and download available datasets for individual modules in RSRiA and RSReA, such as hazard models, fragility curves, restoration curves, etc. In addition, IN-CORE allows users to import data obtained from external software or platforms. For instance, two options are available for seismic hazard analyses in IN-CORE, i.e., one is to execute the analysis using the incorporated scenario-specific rupture models (e.g., [301]), and the other is to import ground kinematic data produced through external simulations. Another advantage compared with other mentioned workflows is the integration of several readily available testbeds that can be conveniently used for research and education purposes. Owing to this feature, IN-CORE has become an emerging and promising workflow for both RSRiA and RSReA.

4.5. Other platforms

Besides the aforementioned workflows, it should be noted that many other platforms have also been developed and applied by agencies worldwide. Some examples include (but not limited to) CAPRA [302] supported by World Bank, the Inter-American Development Bank and the International Strategy of United Nations for Disaster Reduction; and SELINA [303] (Seismic Loss Estimation using a Logic Tree Approach) supported by the Norwegian Seismic Array.

5. Future research needs

While past research has made significant strides in advancing the field of RSRiA and RSReA, several major research gaps still exist and require future investigation. Discussions on the challenges and possible future directions are elaborated subsequently.

5.1. Regional seismic hazard simulation

While the IM-based ground motion simulation (GMS) has been the mainstream method for regional seismic hazard simulation, the state-of-the-art GMPEs still embody a large amount of epistemic and aleatory uncertainties that dominate the uncertainty propagation [127,304]. The large IM prediction uncertainties largely stem from the ergodic assumption and the unexplained source complexity and 3D path effects [305,306], which is largely due to the limited number of recorded ground motions in conjunction with the conventional functional forms adopted in the development of the GMPEs. Recent studies have steered toward leveraging advanced machine learning techniques in developing data-driven GMPEs [307–311], to better characterize the sophisticated input-output relationships and to further reduce the prediction bias and uncertainties. The merit of these data-driven GMPEs can be better appreciated should more abundant synthetic ground motions are made available. A more comprehensive review on machine learning implementation in ground motion prediction can be found in Khosravikia and Clayton [312]. In addition, the current GMPEs typically lack co-development of corresponding IM correlation models, which are crucial to modeling the spatially correlated IM random field, with only few exceptions of emerging studies [308,313] that have provided GMPEs with compatible correlation models. Furthermore, additional features such as ground motion duration and near-fault effects are yet to be incorporated into the IM-based GMS. On the other hand, although the physics-based GMS offers high-fidelity seismic hazard simulation, compared with the IM-based GMS, the availability of physics-based GMS is comparatively limited. Due to the high computational demand as well as sophisticated model development and calibration process, most of the research and development efforts have been limited to a few seismically active regions such as California [58,314], the Cascadia Subduction Zone [315], New Zealand [316], and Europe [129,317–320]. Moreover, due to the computational burden and the lack of knowledge of the source and crustal properties at the high frequency range, fully physics-based broadband GMS is yet to be achieved. Currently, a hybrid approach is typically employed instead, where the low frequency content is obtained from deterministic physics-based simulation and the high frequency content is derived from stochastic simulations [321].

5.3. Regional seismic response and fragility assessment

Regional seismic response modeling incorporates regional ground motion intensities and structure-specific variability by means of statistical sampling of uncertain hazard and modeling parameters. However, it should be noted that the generated seismic response data is also sensitive to the adopted finite element modeling strategy. As listed in Table 2, the fidelity of existing seismic response modeling approaches varies significantly – the induced modeling fidelity/uncertainty issue has been considered a key research area for future studies [322]. In fact, rigorous modeling strategies have been utilized in developing fragility models for individual structures under complex seismic conditions, such as aging and deterioration (e.g., [182,323]), soil-structure interaction (e.g., [324,325]), and cyclic degradation (e.g., [326]). However, these high-fidelity approaches have not been widely adopted in RSRiA due to their high computational cost and stringent data requirement. To this end, Silva et al. [327] evaluated the impact of different modeling schemes on the resultant fragility and risk outputs for RC building frames. Their study concluded that static modeling approaches could somewhat yield similar fragility outcomes compared with THAs. However, it remains unclear whether such a conclusion is still valid should the mentioned complex phenomena are taken into account in the THAs. Recently, Xiong et al. [328] proposed a multi-level modeling approach for urban-scale building portfolios that can potentially solve this issue. In their study, fragility functions for non-engineered buildings were developed through an empirical approach; regular engineered buildings were dealt with using SDOF or MDOF modeling schemes; yet irregular complex special buildings were simulated using refined finite element models that can capture component damage at material levels. There is also a compelling need to explore statistical and machine learning techniques for fragility model development. As illustrated in Fig. 4, the widely applied IDA, MSA, and *cloud* approaches often cannot converge, and thus remain questionable in capturing the true fragility of a structural system. Using advanced data science approaches (e.g., kernel smoothing [329], Bayesian inference [330], surrogate modeling [331], etc.) can relax some of the strong assumptions associated with each conventional method, reflect the actual latent structure of the data, and thereby yield statistically more stable fragility results. These approaches also bear the promise to deal with complex structural systems that consist of multiple correlated EDPs (e.g., [188]).

Moreover, spatially distributed structures and infrastructure systems in earthquake-prone regions are continuously exposed to aging-induced deterioration. In the meantime, they may also experience sequential earthquake excitations and other types of natural hazards (e.g., hurricanes and floods) together with routine maintenance and repair actions throughout their entire lifecycle. Although past research has made significant advancements in probabilistic assessment of seismic damage potential by means of fragility models, they mostly considered pristine structures subjected to a single earthquake event [142,182,188,332–336]. For this reason, there has been emerging research attention in seismic fragility modeling of aging structures [182,337,338] or Markovian state-dependent fragility modeling considering sequential seismic hazard [339–346] to account for the effect of damage accumulation. Still, there is a lack of fragility models that can synergistically account for the compound impacts from multiple different and potentially recurrent external threats over a prolonged time horizon. Furthermore, beyond fragility modeling of structural integrity, which has traditionally been the major research focus, there is also a lack of seismic fragility models depicting the functionality of structure and infrastructure systems. Such models are vital to estimating the post-earthquake functionality and recovery process, hence the estimation of indirect losses. To correlate ground motion intensity, structure-specific parameters, and the availability of external resources with structural functionality estimates, future research is needed to facilitate fragility or functionality modeling considering the role of non-structural components (e.g., equipment and building utility systems) [347–352] and system operation. Particularly, several recent studies have already started investigating the impact of seismic hazard on the functionality and operation of structural and infrastructure systems such as building portfolios [262,352], schools [10], and hospitals [347,353–355].

5.3. Data availability

A rigorous examination of regional fragility, risk, and resilience products often leads to this critical question – do we have sufficient measured data that can be utilized to validate our models? This question traditionally pertains to GMPE development and GM selection, where the ever-increasing recorded (e.g., the NGA-West2 database) and synthetic ground motions have greatly alleviated the data availability issue. However, the problem still persists in regions that lack sufficient recorded data. In general, data availability remains a substantial concern that permeates RSRiA and RSReA. For example, publicly available exposure data is generally lacking to accurately describe the features of regional structural portfolios and lifeline infrastructure systems. The state of experimental research mainly focuses on testing structural elements under cyclic loadings to obtain their specific modeling parameters and seismic capacity limit-state values. Although such experimental data can help understand the physical properties and damage behaviors of individual structural components, they fail to provide validation in a broader context, such as system-level structural modeling and regional-scale variability. On the other hand, only a handful of studies have calibrated seismic fragility models against real-world earthquake data or large-scale experimental tests (e.g., [356–358]). Given the scarcity of field measured data and the high costs of initiating new large-scale experimental campaigns, it is crucial to establish a community-driven cyberinfrastructure where everyone can share, integrate, and exploit diverse data sets related to RSRiA and RSReA. One such cyberinfrastructure platform is the NHERI DesignSafe Cyberinfrastructure (https://www.designsafe-ci.org/) [359] that supports natural hazards engineering research, through which various recently generated data sets have been archived and shared.

In addition, compared with the sheer number of existing studies and models on seismic hazard, demand, and fragility modeling, which are traditionally more closely related to the realm of engineering, there has been significantly less available data for socioeconomic consequence modeling. The dearth of credible data to accurately support the estimation of direct and indirect losses is further compounded with the fact that such data typically differs across different geographic regions and countries. Due to the general scarcity of relevant data and models, the HAZUS [232] default loss data, which is largely based on expert judgment and empirical estimates and provides information for a comprehensive list of building and lifeline systems, and indirect loss cases, has been widely adopted by many past studies. Although the HAZUS data can serve as a starting point to enable RSRiA and RSReA, for more accurate and tailored loss estimation, detailed data pertinent to the studied problems should be developed and employed [232]. Therefore, future collaborative and multi-disciplinary research is still needed to more synergistically integrate expertise in economics and sociology into RSRiA and RSReA.

5.4. Epistemic uncertainties and model compatibility

The PEER convolutional risk integral under the conditional independence assumption has allowed researchers from different disciplines to contribute their respective expertise in tackling the broad challenge of regional seismic risk and resilience assessment. As a result, numerous models have been developed for the different analysis modules. However, the decomposition of the convolutional risk integral into standalone modules may also incur inconsistency during the uncertainty propagation and may lead to biased risk estimates. First of all, currently, it is barely possible to conduct uncertainty propagation from seismic hazard all the way to the risk estimates of decision variables, while also ensuring consistency within all the employed intermediate models. For example, the adopted seismic fragility models may not necessarily pertain to the regional seismic hazard or structural features of interest. Moreover, there also exists inconsistency in how the different models are developed, where the sources of data, the explanatory power of the regression models, as well as the selection of predictors all matter. All the above issues will impose obstacles in actual applications, as the researchers and practitioners should be fully aware of the compatibility and consistency of all the models involved, which is often not the case. Convoluting the associated epistemic uncertainties may lead to significant bias in the risk estimates, thereby misinforming decision-making. To date, due to the lack of recorded post-earthquake damage and recovery data as well as the high dimensionality, complexity, and stochasticity involved in the problem, there has been limited research in validating the regional-level risk estimates. Among the few existing regional-level risk and resilience validation efforts, Tomar et al. [360]

compared the simulated and empirical restoration trajectories of the Napa water system after the 2014 South Napa earthquake; Du and Padgett [37] employed an information theoretical approach to investigate the influence of IM selection on the credibility of regional seismic risk estimation based on spatially distributed highway bridge portfolios.

5.5. Fidelity vs. scalability

Although it is anticipated that the convolution of a series of high-fidelity simulations (e.g., physics-based ground motion simulation, 3-D nonlinear finite element analysis, complex network-level analysis) can lead to the most credible and accurate risk and resilience estimates, the computational burden of such high-fidelity analyses can easily become intractable due to the large number of required Monte-Carlo simulations in conjunction with the numerous individual structures involved. Currently, there is a lack of studies aiming at comparing the results from the RSRiA and RSReA pipelines when adopting intermediate analysis modules with different levels of fidelity. In addition, the issue of fidelity is also related to the issue of scalability. This is because the curse of dimensionality permeates throughout RSRiA and RSReA. For example, the computational complexity of Cholesky decomposition commonly employed in IM co-simulation, finite element analyses, and graph theory typically scales in cubic with the problem dimension; and the mixed integer linear programming for post-earthquake restoration optimization is typically solved in exponential time. Several recent studies [33, 361–363] have also explored methods to reduce the number of ground motion random maps while still achieving satisfactory accuracy on the risk estimates. Still, future research is needed to explore dimensionality reduction or surrogate modeling approaches to reduce the complexity of the problem, while still delivering satisfactorily reliable risk estimates.

5.6. Toward proactive long-term seismic resilience

The current state of research in resilience-driven restoration planning and RSReA largely falls into reactive, short-term recovery, while lacking proactive consideration of the long-term threats (e.g., recurring hazard events coupled with prolonged aging-induced deterioration). As a result, the resulting mitigation plans or restoration strategies may not be able to fully exploit and leverage the opportunity of recovery to adapt to future threats in a sustainable fashion, and significant losses may again be incurred should other subsequent disasters take place. Future research efforts are needed in extending the resilience-driven planning horizon to more proactively adapt the built environment against future long-term threats.

5.7. Social consequences and equity issues

Past RSRiA and RSReA studies mainly focused on quantifying the damages and economic losses incurred by earthquake hazard, while there is a lack of research efforts in societal wellbeing and equity issues, despite a few recent studies [364–367]. Earthquakes can cause disporportional impact to the low-income, marginalized, and colored population and community, who typically lack enough resources and capacity to withstand and recover from the consequences caused by earthquakes. How to more strategically allocate the limited resources for seismic risk mitigation or post-earthquake recovery while taking the equity issue into consideration requires joint efforts involving civil engineers, social scientists, infrastructure stakeholders, community members and leaders, and policy makers.

6. Conclusion

This study conducts a comprehensive review of the state of research in regional seismic risk and resilience assessment (i.e., RSRiA and RSReA), offering insights into the research advancements of each of the analysis modules as well as their interconnections under the general seismic risk and resilience assessment framework. The methodological development, constitutive components, and assessment capability of several existing analysis workflows, such as HAZUS, OpenQuake, SimCenter, IN-CORE, CAPRA, etc., are introduced to promote their real-world applications. Moreover, future research needs are further elaborated to advance the scientific research in the fields of RSRiA and RSReA.

CRediT authorship contribution statement

Ao Du: Conceptualization, Writing – original draft, Writing – review & editing. **Xiaowei Wang:** Conceptualization, Writing – original draft, Writing – review & editing. **Yazhou Xie:** Conceptualization, Writing – original draft, Writing – review & editing. **You Dong:** Writing – original draft, Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

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