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Developing Efficient Regional Seismic Risk and Resilience Assessment Frameworks for
Large-Scale Building Inventories

A dissertation submitted in partial satisfaction
of the requirements for the degree
Doctor of Philosophy in Civil Engineering

by

Laxman Dahal

2024

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ABSTRACT OF THE DISSERTATION

Developing Efficient Regional Seismic Risk and Resilience Assessment Frameworks for Large-Scale Building Inventories

by

Laxman Dahal

Doctor of Philosophy in Civil Engineering

University of California, Los Angeles, 2024

Professor Henry J. Burton, Chair

Natural disasters pose significant challenges to the built environment, communities, and economies. The ability to quantify regional-scale risk and resilience of building inventories is one of the critical components needed to address those challenges and bolster community resilience. Historically, the mandated building design codes have been governed by life-safety standards with no emphasis on other metrics such as economic loss and downtime. However, recent advancements in earthquake engineering have put in motion a national-level initiative to explicitly codify functional recovery as a target performance objective. While the importance of this effort has been broadly acknowledged by stakeholders, engineers, and policymakers, there is a need to develop computational workflows to assess the performance and evaluate the cost-benefit implications of these resilience-based standards at the regional scale. It is with this vision in mind that this study develops a suite of efficient computational frameworks. The regional frameworks are grounded in probabilistic performance-based earthquake engineering (PBEE) methodology. First, an end-to-end platform (dubbed “Auto-WoodSDA”) is developed to automate the entire PBEE method-

ology, from code-confirming design to nonlinear structural analyses, and economic loss and function recovery assessment. Utilizing Auto-WoodSDA and advanced statistical analysis, the robustness of the PBEE methodology is evaluated by 1) quantifying the uncertainty induced by probability model misspecification and 2) identifying the optimal ground motion intensity measure for structural response estimation of woodframe structures. Second, a set of scalable computational frameworks is proposed to assess regional risk and resilience of large-scale building inventories. They harness automation, high-performance computing, and optimization to render regional-scale assessments computationally feasible and reduce runtime from months to days. Finally, a case study is presented on a risk-based seismic loss and functional recovery evaluation of more than 15,000 residential woodframe buildings in the City of Los Angeles. The results of a sensitivity study that examines the implications of alternative seismic design parameters suggest that resilience-driven performance objectives are within the realm of possibility.

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2024

*In loving memory of Jason,
our loyal and beloved dog,
who filled our lives with joy,
companionship, and unconditional love for 18 beautiful years.*

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CHAPTER 1

Introduction

1.1 Background

Natural hazards impose a significant risk to the built environment. The catastrophic impact of a major hazard event reverberates across spatially distributed buildings and lifeline infrastructure culminating in disrupted communities, handicapped societal well-being, and rattled economic conditions. To bolster community resilience and safeguard critical infrastructure, it is imperative that we have a comprehensive understanding of the collective vulnerabilities, intra- and inter-system dependencies, and potential consequences across an entire geographical region. Unlike traditional building-specific risk analyses, regional-scale assessments acknowledge the inherent spatial variability of seismic hazards and recognize that the influence of earthquakes transcends individual structures. Having a holistic perspective is instrumental in developing effective mitigation strategies, as it allows for the identification of vulnerable neighborhoods, the diagnosis of structural defects, and the assessment of imminent cascading effects. More importantly, regional seismic risk assessment informs evidence-based decision-making, enabling the formulation of targeted policies, community preparedness, disaster emergency response planning, and the creation of resilience-based building design codes. To this end, regional seismic analysis is well-positioned to serve as a cornerstone of earthquake engineering and risk management strategies.

Regional seismic risk and resilience analysis is a multifaceted and interdisciplinary endeavor. As illustrated in Figure 1.1, it is at the heart of the disaster management continuum

and is applicable in all four phases ([UNDP/UNDRO, 1992](#)). It quantifies earthquake-induced consequences to support risk-informed decision-making in developing disaster preparedness plans, emergency response strategies, and long-term resilience initiatives. As such, it is critical that a risk analysis framework has the following desirable characteristics: 1) a community-centric viewpoint to capture the widespread impact, 2) robustness to quantify and propagate uncertainties, 3) computational efficiency and scalability, and 4) the ability to advance long-term resilience initiatives such as building code amendment. Rigorous quantification of uncertainties in regional scale assessments is critical to successful risk mitigation strategies. However, this explicit treatment of uncertainties comes at a substantial computational cost. For instance, performing an explicit probabilistic risk analysis in accordance with the FEMA P-58 methodology ([FEMA, 2012](#)) is computationally demanding. The P-58-based analysis procedure utilizes site-specific seismic hazards, building-specific numerical structural modeling, and component-level loss and recovery analysis. Scaling it to assess the seismic risk of large inventories is often deemed computationally prohibitive if not impossible without leveraging specific efficiency-enhancement strategies in the workflow.

One of the primary goals in disaster risk management is to attain and promote community resilience, which is defined as a community’s collective ability to withstand, adapt to, and rapidly recover from disruptions. The concept is hard to quantify in its entirety as disaster (natural or man-made) resilience is a complex phenomenon that requires multifaceted considerations including geological, socioeconomic, and physical among others. Recovery times (e.g., reoccupancy, functional recovery) are very closely related to community resilience and are hereafter used as a proxy for community resilience. To achieve community resilience, all aspects of the built environment must be addressed including building inventories, lifeline infrastructure, and critical facilities such as dams and hospitals. In this study, we deal with the risk and resilience of one of the important aspects of the built environment- residential building inventories. Specifically, we study single- and multi-family woodframe buildings because it is the most prevalent residential building class in the United States.

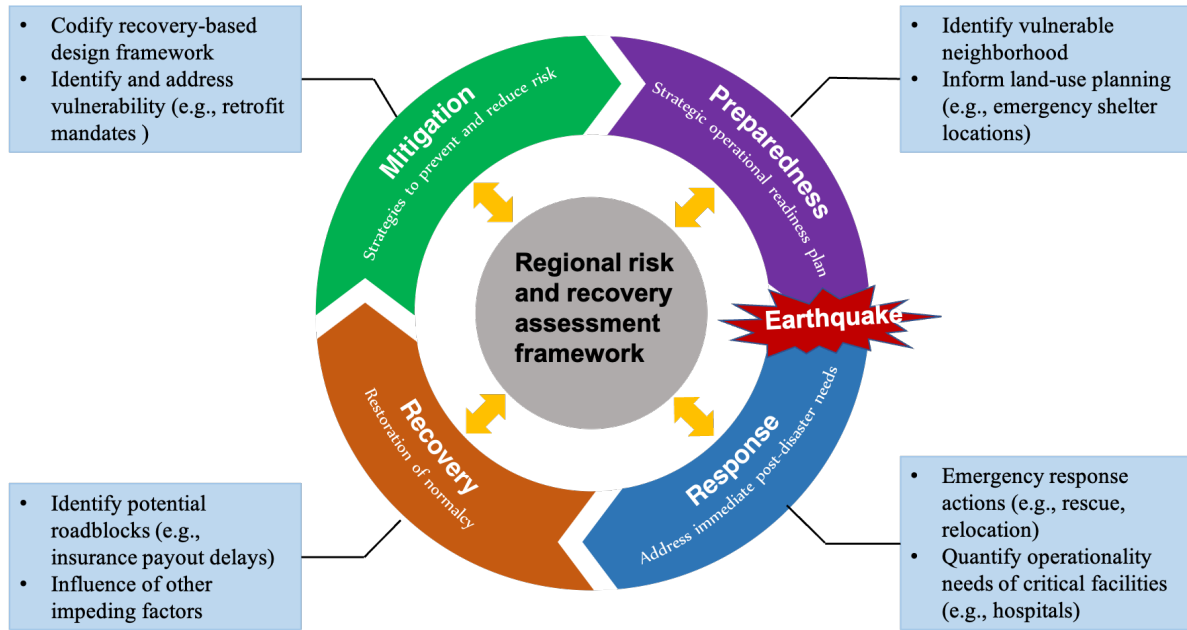


Figure 1.1: Overview of the disaster management continuum and potential role of regional risk and resilience assessment framework in various phases.

It is estimated that the single- and multi-family woodframe buildings sheathed with plywood or other wood-based panels make up over 90 percent of the entire building inventory nationwide (Marcin, 1987). In high seismicity regions such as California, approximately 99 percent of single-family residential buildings are wood construction with light-frame wood shear walls as the primary lateral force resisting system (LFRS) (FEMA, 2020). Given the extent of exposure, it is undeniable that the seismic performance of residential woodframe dwellings has a widespread and lasting impact on community resilience. The performance of the residential building stock in the two significant historical events, the 1989 Loma Prieta (NIST, 1990) and 1994 Northridge earthquakes (NIST, 1994) has underscored the implications to community-scale disruption. From a structural standpoint, woodframe dwellings have fared relatively as the reconnaissance data showed that the collapse rate was comparatively low compared to other structure types (NIST, 1990, 1994). This was in line with the expectation considering that code-conforming buildings are designed to avoid collapse

during a major earthquake. However, the economic and social toll of these earthquakes were substantial, with estimated direct losses reaching \$6 billion in 1989 (Loma Prieta) and \$20 billion in 1994 (Northridge) (NIST, 1990, 1994). Similarly, hundreds of businesses were disrupted while tens of thousands of people were displaced. One study found that it took 10 years to rehabilitate damaged buildings, schools, and bridges after the Loma Prieta earthquake (Comerio and Blecher, 2010). The extensive impact of these two earthquakes underscores the limitations of existing building codes and the need for “beyond life safety” design provisions in woodframe buildings.

The influence of community-wide impeding factors and the lasting effects of socioeconomic disruptions are inevitable after a catastrophe. Researchers and policymakers are beginning to realize that the cascading impact of a catastrophic event can be mitigated through strategic and concerted efforts directed at vital societal functions. More recently, the focus has shifted toward designing structures to achieve recovery-driven performance objectives. This paradigm shift has garnered the attention of practitioners, researchers, and policymakers at both national and international levels. A testament to this transformative momentum is the FEMA P-2090/NIST SP-1254 report (NIST and FEMA, 2021). In 2018, Congress passed the National Earthquake Hazards Reduction Program (NEHRP) Reauthorization Act into law that decidedly stipulated NEHRP to “*gather information on community resilience*.” To comply with the congressional mandate, FEMA and NIST jointly convened a committee comprised of experts from all sectors (technical, policy, and implementation) to identify needs and recommend options to enhance the built environment such that the performance goals guided by reoccupancy and functional recovery time are achieved. The report also describes community resilience from a functional recovery point of view, defines target performance levels, and identifies the potential cost and benefit of resilient-based seismic design.

1.2 Objectives

This study develops a set of efficient computational frameworks and workflows to facilitate regional risk and resilience assessments in support of recovery-based design. At its core, the frameworks are bolstered by an automation platform, high-performance computing (HPC) technologies, and optimization, to effectively scale explicit FEMA P-58- and ATC-138-based risk assessments to large-scale building inventories. The development of these frameworks and workflows is guided by a set of objectives as outlined below:

1. Develop a ready-to-use computational platform, Auto-WoodSDA (WoodSDA in short), to automate code-compliant seismic design, nonlinear dynamic analyses, damage assessment, and component-level loss assessment of woodframe buildings. WoodSDA is modularized and designed to be scalable for large-scale computations. It is intended to significantly reduce the manual and central processing unit (CPU) runtime in performing explicit building-specific economic loss and recovery assessments.
2. Performance-based seismic evaluations inherently involve uncertainties from numerous sources. While record-to-record and modeling uncertainties have been well studied, the uncertainty introduced during parameter estimation has not been examined in research or practice. Considering the significance of fragility curves in seismic risk quantification, the goal is to investigate the effect of parameter estimation uncertainty that might be present due to any assumptions in the fragility function fitting.
3. Selection of an optimal ground motion intensity measure (IM) is one of the preliminary yet integral steps in minimizing uncertainty propagation through the PBEE methodology. In this study, we aim to advance the conventional efficiency and sufficiency-based evaluation by modeling the multivariate relationship between the ground motion shaking intensity measure (IM) and causal parameters such as magnitude, distance, etc. The result from this evaluation informed the ground motion intensity measures that were used in the regional scale assessments.

4. Develop an efficient computational workflow to perform high-fidelity high-resolution risk and resilience assessment at the regional scale. To facilitate risk quantification, the traditional regional risk framework is modified to be applicable in the proposed workflow.
5. Investigate the art and science of balancing fidelity, resolution, and computational efficiency in regional-scale assessments. Propose four additional regional risk assessment frameworks including the use of machine learning-based surrogate modeling as an alternative to the high-fidelity high-resolution approach.
6. Assess the implication of beyond life-safety code provisions by performing sensitivity analyses that ultimately inform the development of recovery-based design procedures.

1.3 Research Significance

We believe this study makes significant contributions in the earthquake engineering domain, both at the macro and micro levels. At the micro level, it enhances the existing methodologies and workflows to support an explicit site-specific component-level analysis of an individual building. The WoodSDA presents itself as a very useful platform that researchers and engineers can use to not only generate code-compliant designs but also iterate until specified performance objectives are met. The successful development of an end-to-end workflow demonstrates that, through careful considerations/assumptions and concerted programming, the PBEE framework can be fully automated. Additionally, the study contributes to advancing statistical robustness in the existing PBEE framework. Namely, the parameter estimation uncertainty and multivariate efficiency and sufficiency studies add new dimensions to quantifying, propagating, and minimizing uncertainty in the implementation of the framework. At the macro level, the study makes a momentous contribution, specifically in the subdomain of regional-scale risk assessment. As discussed in Section 1.1, there is a need for efficient, robust, and scalable computational frameworks to support regional risk

and resilience assessment. To the best of our knowledge, this is the first-of-its-kind study that proposes and implements a fully mechanistic site-specific PBEE assessment on tens of thousands of buildings across a region. The proposed suite of regional workflows focuses on balancing fidelity, resolution, and computational efficiency- a previously unexplored idea. We anticipate that the research community will continue to move toward high-fidelity and high-resolution regional-scale studies and as such, we hope that the frameworks and workflows will be a noteworthy contribution to this end goal.

1.4 Organization

This manuscript consists of seven chapters in total out of which the summary of five chapters is illustrated in Figure 1.2. Chapter 1 provides background information and introduces the research objectives. It also details the motivation behind studying woodframe buildings and establishes the significance of the research work. Chapter 2 describes the technical details of WoodSDA, an end-to-end computational platform, developed to generate code-compliant designs, perform nonlinear dynamic analysis, and assess building and component-level damage and losses. It also presents an example implementation as a proof-of-concept of the end-to-end functionalities as well as to validate the results being generated by the automation framework. Chapter 3 initiates with a discussion on the importance of fragility functions in the overall PBEE methodology. This chapter highlights the classes and types of uncertainties considered in the overall methodology. It then investigates the previously unexplored parameter estimation uncertainty and the effect of probability model misspecification on seismic risk. In Chapter 4, advanced statistical analyses are explored to compare several new and existing approaches to determine the optimality of ground motion intensity measure (IM). Chapter 5 pushes the envelope on the computational feasibility of regional-scale assessment by presenting a high-fidelity high-resolution computational workflow powered by automation, optimization, and distributed computing. It also presents a modified methodology to

quantify the regional risk. Chapter 6 builds on the high-fidelity high-resolution regional risk framework and proposes four additional alternative workflows that seek to balance fidelity, resolution, and computational efficiency. Finally, it presents a sensitivity study on the implications of beyond-code design provisions. Finally, Chapter 7 summarizes the proposed methodologies and frameworks, discusses the major findings of the study, highlights the limitations, and provides guidance on possible future directions of the work.

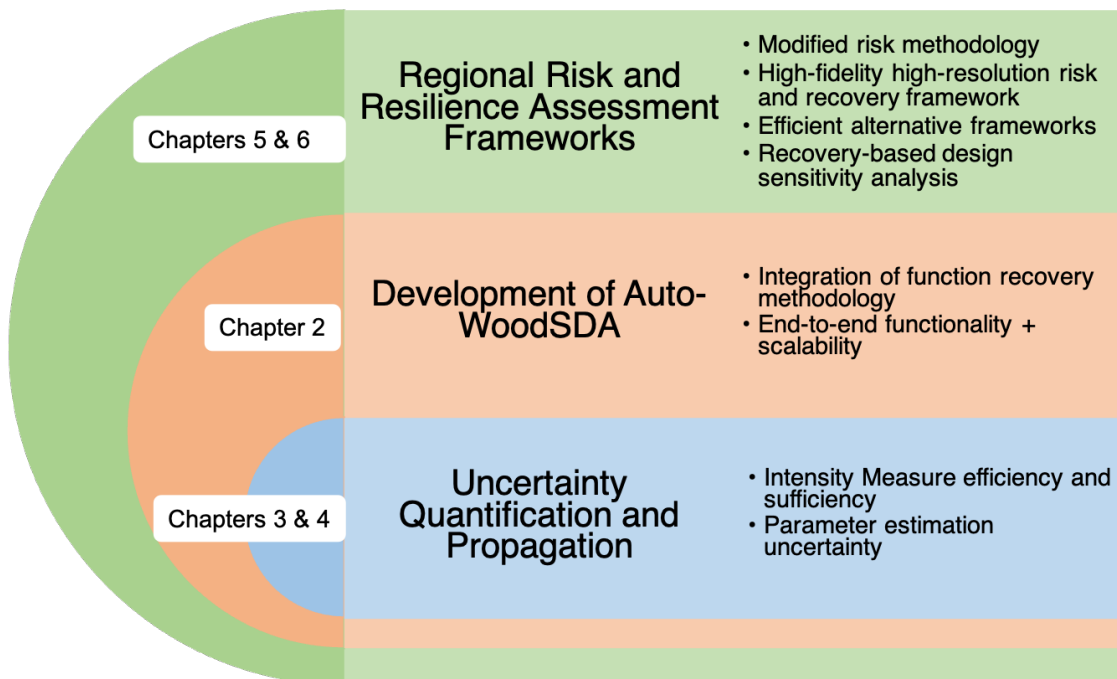


Figure 1.2: Overview of the dissertation and the hierarchy of the chapters.

CHAPTER 2

Auto-WoodSDA: An End-to-End Automation Platform

2.1 Introduction

The United States (US) housing inventory is dominated by woodframe buildings, which comprise approximately 90 percent of all the residences (Marcin, 1987). In high seismic zones such as California, up to 99 percent of single-family residential buildings are constructed with light-frame wood shear walls as the primary lateral force resisting system (LFRS) (FEMA, 2020). Despite the elevated exposure to seismic risk, woodframe buildings have performed “relatively well” in historical events such as the 1989 Loma Prieta (NIST, 1990) and 1994 Northridge earthquakes (NIST, 1994). From a design perspective, the “relatively well” characterization of the seismic performance might be justified because the reconnaissance data showed that the collapse rate was comparatively low in woodframe residential buildings (NIST, 1990, 1994) relative to other structure types. US code-conforming buildings are designed to avoid collapse during a major earthquake, a performance objective that was by and large achieved. However, the economic toll of these earthquakes was substantial, with estimated direct losses reaching \$6 billion in 1989 (Loma Prieta) and \$20 billion in 1994 (Northridge) (NIST, 1990, 1994). The extensive impact of these two earthquakes exposed the “beyond life safety” seismic vulnerabilities of woodframe buildings. In particular, 50 percent of the \$20 billion loss due to the Northridge earthquake was attributed to structural and nonstructural damage in woodframe buildings (NIST, 1994).

In addition to the immediate financial loss, earthquake events have a lasting impact on the

socioeconomic vitality of a community. For instance, the Northridge earthquake disrupted thousands of businesses and displaced an estimated 125,000 people. Residential woodframe buildings are a critical fabric of any community. The functionality of the residential buildings during and after a disaster dictates the short- and long-term impact on the affected region. For a community to be resilient, buildings and all other interconnected lifeline infrastructure need to be designed for resilience-based standards. The substantial losses sustained by the residential dwellings in the last two major earthquakes and their prolonged socioeconomic impacts are a clear indication that 1) designing for life safety standards is not sufficient to safeguard against imminent earthquake-induced losses and 2) we need to understand and quantify the risk to woodframe buildings from a more holistic and community-centric point of view.

In the US, the design of a new building is governed by national codes and standards that establish minimum requirements for providing life safety and collapse prevention ([IBC, 2018](#); [IRC, 2018](#); [ASCE, 2016](#); [AWC, 2015](#)). For instance, new code-compliant residential buildings are governed by the *International Building Code* (IBC) ([IBC, 2018](#)) and *International Residential Code* (IRC) ([IRC, 2018](#)). The modern design codes and standards rely on the latest risk-targeted maximum considered earthquake (MCE_R) ground motion maps. The MCE_R hazard maps supersede the maximum considered earthquake (MCE) maps used in older versions of the IBC, IRC, and other building codes. The MCE map stipulates that the buildings across a region be designed for the same seismic hazard level, i.e. uniform hazard. The MCE_R map, on the other hand, is intended to achieve the same level of seismic performance for all buildings throughout the region. Specifically, the goal is to achieve a uniform collapse risk. While hazard maps and building codes are updated periodically, studies have shown that modern codes significantly enhance collapse safety but only marginally reduce the losses ([Liel and Deierlein, 2013](#); [Hutt et al., 2019](#)). Thus, from a community resilience perspective, the sub-par performance of woodframe buildings in prior earthquakes warrants a shift from prescriptive to resilience-based seismic design codes.

The performance-based seismic design (PBSD) framework enables engineers to design buildings for an explicit performance objective (e.g., life safety, economic loss, or downtime) with explicit consideration of multiple sources of uncertainty. In contrast to the prescriptive design philosophy which seeks to achieve the same seismic performance for all buildings, PBSD supports the design and construction of new buildings with stakeholder-defined performance targets. Although PBSD or some variations of it have been broadly accepted and recognized (e.g., Tall Building Initiative ([PEER, 2017](#))), adoption in woodframe residential design and construction practice has been limited. It is typical and permissible for one-story single-family dwellings (SFD) to not be engineered and constructed based on the prescriptive allowable stress design (ASD) protocol. This embeds an additional layer of uncertainty in their seismic performance. Also, the general lack of knowledge about the expected performance could pose challenges in developing policies for enhanced community resilience.

This study developed a Python-based computational platform to Automate Woodframe building performance-based Seismic Design, and streamline probabilistic risk modeling and Analysis (Auto-WoodSDA). The overarching motivation for developing such a platform is to advance current state-of-the-art computational frameworks. Auto-WoodSDA (hereafter, WoodSDA), is a ready-to-implement program with built-in functionalities to support probabilistic seismic risk and resilience assessment of woodframe buildings. The seismic risk analysis is performed in accordance with the second-generation performance-based earthquake engineering (PBEE) framework ([FEMA, 2012](#)) while the resilience assessment utilizes the beta ATC-138 functional recovery methodology developed as a part of the FEMA P-58 guidelines ([ATC, 2021](#)). Figure 2.1 provides a graphical overview of the overall workflow embedded in WoodSDA, which contains four distinct modules for 1) design, 2) structural modeling and analysis, 3) damage analysis, and 4) performance assessment. It is boosted by an end-to-end programmatic architecture for seamless execution of the four modules. For a given set of user inputs, it systematically and sequentially automates all the computations between facility definitions and decision variables (e.g., collapse fragility, financial loss, func-

tional recovery time, injuries, etc.), thus, effectively creating an end (building inputs) to end (loss metrics) workflow. The end-to-end workflow ensures that the FEMA P58-based computational methodology is implemented efficiently without the need for significant manual intervention.

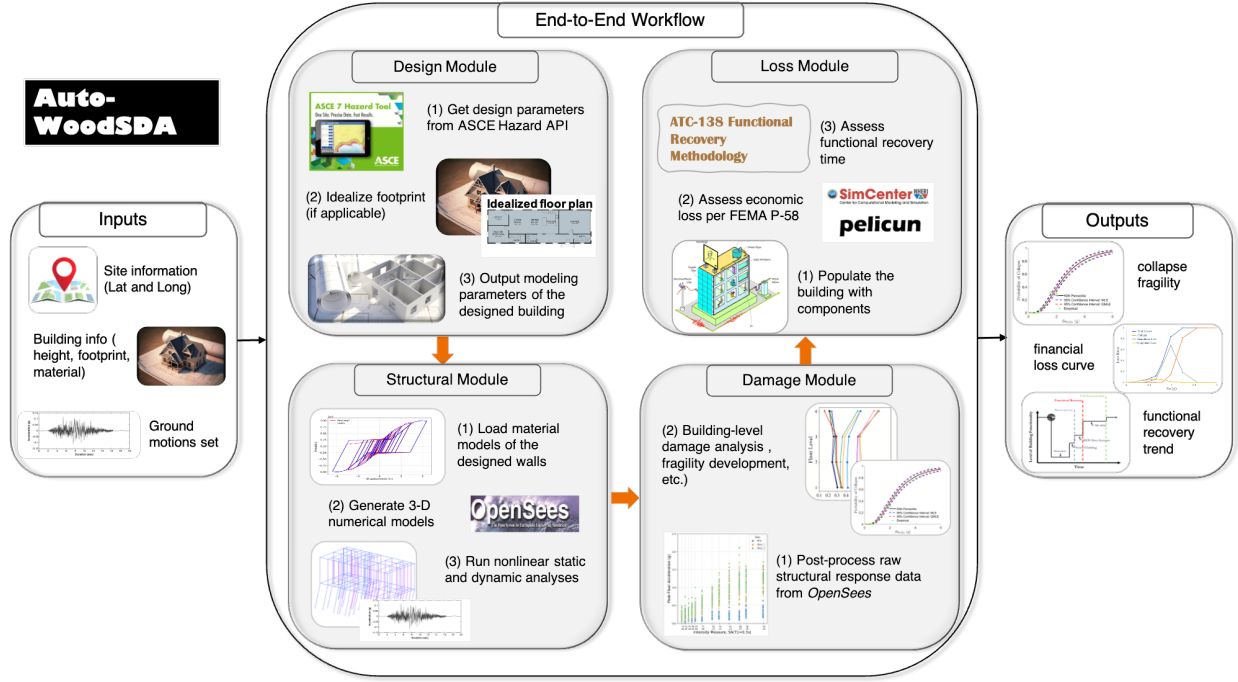


Figure 2.1: Graphical illustration of the end-to-end workflow implemented in WoodSDA.

The modules are structured to align closely (but not exactly overlap) with the four fundamental steps that comprise the FEMA P-58 methodology, as highlighted by the blue box in Figure 2.2. More pointedly, the FEMA P-58 methodology probabilistically determines if a facility (such as a built structure) satisfies the user-specified performance objectives. To do so, the methodology is instantiated with the facility definition which specifies the necessary building characteristics which includes the structural design. This implies that the structural design of a building needs to be readily available before running the PBEE methodology. To this end, the conventional FEMA P-58 methodology is modified to include a design module as shown in Figure 2.2 (in red). The integration of the design module is

a key development that renders the end-to-end computational workflow programmatically viable. Except for the design, the other modules have near one-on-one comparison with their respective analysis steps in the FEMA P-58 methodology. For example, the structural module is closely tied to structural analysis as it creates a numerical model to simulate structural response. Similarly, the damage module quantifies the physical damage to the building due to dynamic excitation (i.e. building-level analysis) and the loss module performs component-level loss analysis. The hazard module is not included in the end-to-end workflow because hazard analysis and the subsequent ground motion selection process require minimal manual work. The ground motion records selected by the hazard module are one of the inputs required by the WoodSDA platform. The ground motion selection strategy adopted in WoodSDA was originally developed by the Natural Hazard Risk and Resiliency Research Institute (Shokrabadi et al., 2020).

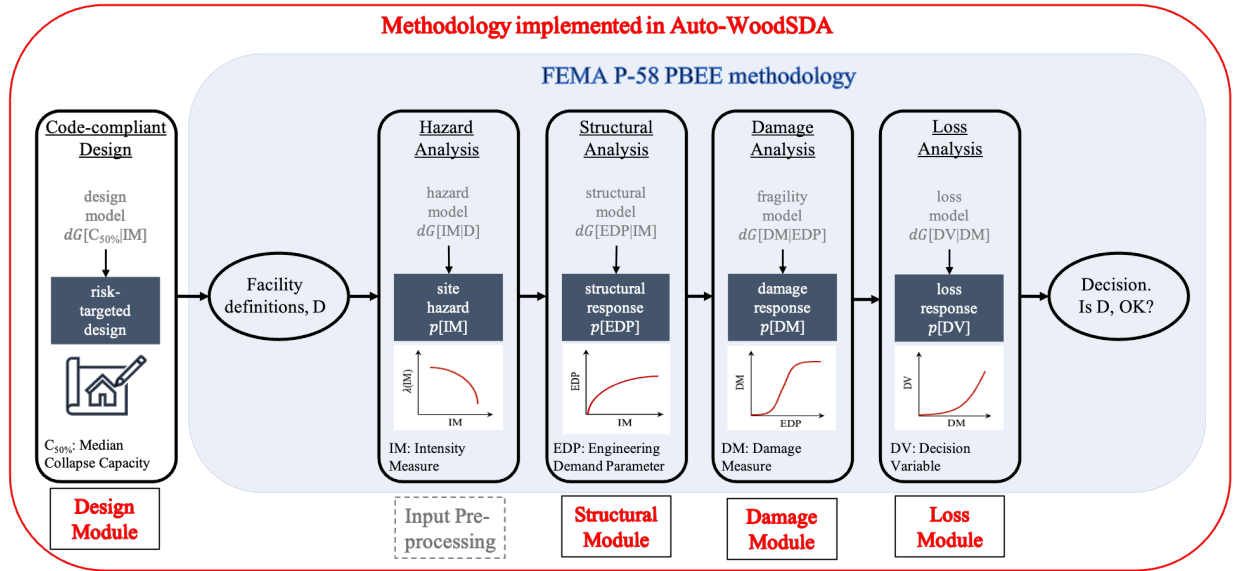


Figure 2.2: An illustration of the proposed methodology in relation to the widely used FEMA P-58-based methodology. The texts in the red represent the different modules implemented in the WoodSDA platform.

2.1.1 Literature review

There have been numerous research efforts focused on automating structural design and analysis processes. [Xu and Grierson \(1993\)](#) proposed a computer-based automation method to design steel frames. The automation engine was used to optimize the design while accounting for the behavior of the semi-rigid connections. [Apostolakis et al. \(2014\)](#) devised a framework to automate the seismic design of steel frames with self-centering connections, [Foley and Schinler \(2003\)](#) utilized an object-oriented computational paradigm to automate the design of steel frames, and [Moharrami and Grierson \(1993\)](#) presented an automation routine to design reinforced concrete frames. There have also been efforts to automate the seismic design of nonstructural elements such as sprinkler piping systems ([Perrone and Filiatrault, 2017](#)). More recently, regional seismic assessment of buildings was automated to conduct a rapid post-disaster assessment using unmanned aerial vehicles ([Xiong et al., 2020](#)). The researchers employed automation as an intermediary engine to achieve a pre-defined goal such as optimal seismic design or rapid post-disaster assessment.

Few studies in the research literature have focused on automating the PBEE framework. [Guan et al. \(2020\)](#) developed an end-to-end computational program to automate the design, two-dimensional nonlinear modeling, and structural analysis of steel moment-resisting frame buildings. The platform was used to iteratively generate code-compliant steel moment frame designs. Similarly, [Yi \(2020\)](#) developed a seismic retrofit framework for woodframe buildings that incorporated nonlinear structural analysis and performance-based assessment. The study focused on the seismic vulnerabilities of buildings with unbraced and/or unbolted cripple walls (in single-family dwellings) and soft, weak, and open front walls (SWOF) (in multi-family dwellings). The goal of this study was to develop a framework for portfolio-scale seismic retrofit. As a part of this work, two standalone tools were developed to perform nonlinear analysis and conduct intensity-based loss assessment ([Yi, 2020](#)). This study adopts the code base of the numerical modeling tool with some specific modifications. It is essential to recognize the parallels and distinguish the differences between the two studies. [Yi \(2020\)](#)

focused solely on the retrofit of existing cripple wall and SWOF buildings while this study focuses on the design and holistic risk and resilience assessment of the new woodframe buildings.

The damage and loss analysis models are two integral parts of the PBEE framework that have been widely studied. Based on the FEMA P-58 methodology ([FEMA, 2012](#)), several research tools and commercial software have been developed to facilitate risk assessment. The seismic performance prediction platform (SP3) is commercial software developed to perform building- and site-specific risk analyses ([SP3, 2014](#)). The SP3 platform is one of the most advanced probabilistic risk models that supports many advanced features such as fully automated P-58 assessment with minimal inputs, an enhanced component fragility database, and ATC-138 functional recovery time ([ATC, 2021](#)). The risk model relies on an analytical structural response prediction engine to perform damage and loss analysis without creating explicit numerical structural models. Researchers have also developed several open-source resources such as PACT ([FEMA, 2012](#)), Pelicun ([Zsarnoczay, 2019](#)), TREADS ([Molina Hutt et al., 2022](#)), and REDi ([Almufti and Willford, 2013](#)) to perform probabilistic financial loss and downtime analysis. These tools are standalone loss assessment programs that require structural response data (e.g., engineering demand parameters (EDPs)) as the input.

The aforementioned research efforts to develop seismic design, analysis, and performance assessment platforms have significantly advanced the field. However, all of the publicly available tools are intended to be standalone and require significant effort to integrate them into the P-58 framework. For instance, if an engineer wants to evaluate the risk and recovery trend of a multi-unit residential building, a typical workflow can be summarized as follows: manually size and detail the shear walls to resist the seismic demand, develop a nonlinear model to simulate the response, process and format the raw structural response data, implement Pelicun to quantify economic loss, and employ REDi to map out the recovery trend. Despite leveraging computer programs, the outlined sequence of tasks requires significant manual effort to pre- and post-process the inputs and outputs from each standalone tool.

Depending on the complexity of the numerical structural model, the “computational time” could be on the order of days to complete the entire process. The computational time is defined as the total manual (or human) time and CPU wall clock time it takes to compile and run a program. The inefficiency of scattered and independent manual procedures is accentuated if one wishes to perform a portfolio-level analysis with tens or hundreds of buildings. The computational time will likely be on the order of weeks but the task would still be viable. However, it would be computationally infeasible to scale the existing set of tools to perform large-scale regional risk assessments with thousands of buildings.

The underlying motivation behind developing WoodSDA is to unify the distinct probabilistic models of the FEMA P-58 methodology for efficient and uninterrupted execution. WoodSDA is developed using the object-oriented paradigm in the Python programming language to promote modularization. This allows the four modules (Figure 2.1) to be implemented independently if needed. It is an open-source tool that can be modified to meet user-specific needs. The key features of WoodSDA are as follows:

1. It streamlines the design process to create code-compliant buildings. Better yet, it facilitates seamless design iterations to develop beyond-code buildings with enhanced resilience-driven performance objectives.
2. It is efficient to implement and requires minimal manual effort.
3. For the specified hazard level, it quantifies different loss metrics (economic, downtime, etc).
4. It can be easily scaled to assess the seismic risk of large building inventories.
5. It can be used to optimize seismic design parameters and guide policy decisions.

This chapter details the technical and programmatic aspects of the WoodSDA platform. It outlines the assumptions encoded in the tool and serves as the technical documentation. The source code is publicly available on the GitHub repository along with the step-by-step

instructions to run the program (Dahal, 2024). To simplify the explanation of this fairly complex and intertwined program, each of the four modules is presented in a separate section. The procedures to generate a code-compliant building are detailed in Section 2.2 while the module that generates a three-dimensional (3D) numerical model and simulates nonlinear structural response is outlined in Section 2.3. Section 2.4 presents the steps undertaken to post-process the raw structural response data and estimate the damage. Finally, Section 2.5 describes how outputs from the damage module are utilized to assess economic loss and recovery time. In addition to explaining the modules in detail, the study also presents an example implementation in Section 2.6 as a proof of concept and validation of the modeling assumptions embedded in the platform. The scripts required to run the example building are also available in the GitHub repository.

2.2 Design Module

The design module is the first to be instantiated in the end-to-end WoodSDA workflow (Figure 2.1). It is developed to produce code-compliant seismic design and output corresponding structural parameters to the structural module. It is able to generate designs for traditional light-frame wood buildings with shear walls as the lateral force-resisting system. Specifically, the module designs and details the shear walls to resist the bi-directional lateral forces acting on the building. The building-level design calculations are based on the *NEHRP Recommended Seismic Provisions for New and Other Structures* (hereafter, the *NEHRP Provisions*) (FEMA, 2009) and the *ASCE/SEI 7-16 Minimum Design Loads for Buildings and Other Structures* (hereafter, ASCE 7-16). Similarly, shear wall-specific calculations such as the detailing and deflection computation are based on the *American Wood Council National Design Specifications (NDS) for Wood Construction 2018 Edition* (AWC, 2018), and *American Wood Council Special Design Provisions for Wind & Seismic (SDPWS) 2015 Edition* (AWC, 2015).

Figure 2.3 shows the workflow and the main steps that comprise the design module. The workflow begins by importing a set of user inputs that include site location, building information, applicable code restrictions, and ground motion records. A complete set of user inputs is critical in preserving the end-to-end functionality of WoodSDA. Section 2.2.1 outlines the steps needed to pre-process and compile the input data. Given the user inputs, the building-level seismic demand is calculated based on the equivalent lateral force (ELF) procedure (ASCE, 2016). The seismic demand is distributed vertically to the story shears, which are distributed to the walls in that story. The procedures used to compute the wall demands are described in Section 2.2.2. The wall-level shear demand is passed through the search algorithm to find the “best” shear wall assembly from a pre-loaded light-frame wood shear wall database. The electronic database consists of various wall assemblies with nominal unit shear capacity and apparent shear stiffness (Ga). It is compiled based on the assemblies available in SDPWS (AWC, 2015). The architecture of the search algorithm is explained in Section 2.2.3. A drift check is performed to ensure that the design meets the code-specific or user-imposed drift limit. If the drift check is not compliant, the design is iterated until the selected shear wall assembly meets all relevant criteria. The underlying equation to compute the shear wall deflection and design iteration options are presented in Section 2.2.4. Ultimately, the shear wall modeling parameters are pipelined to the structural model. In WoodSDA, we use Pinching4 modeling parameters (Lowes et al., 2003) to create numerical models as described in (Section 2.3).

2.2.1 User inputs and data preprocessing

The design of a building is an open-ended problem and is inherently subjective as it depends on the owner’s or stakeholder’s needs and specifications. In engineering practice, subjectivity is addressed by agreeing to a design document and communicating any changes to the client. In WoodSDA, this is accommodated by enabling the user to specify very detailed component-level inputs. For instance, the user can define the panel material type or hold-

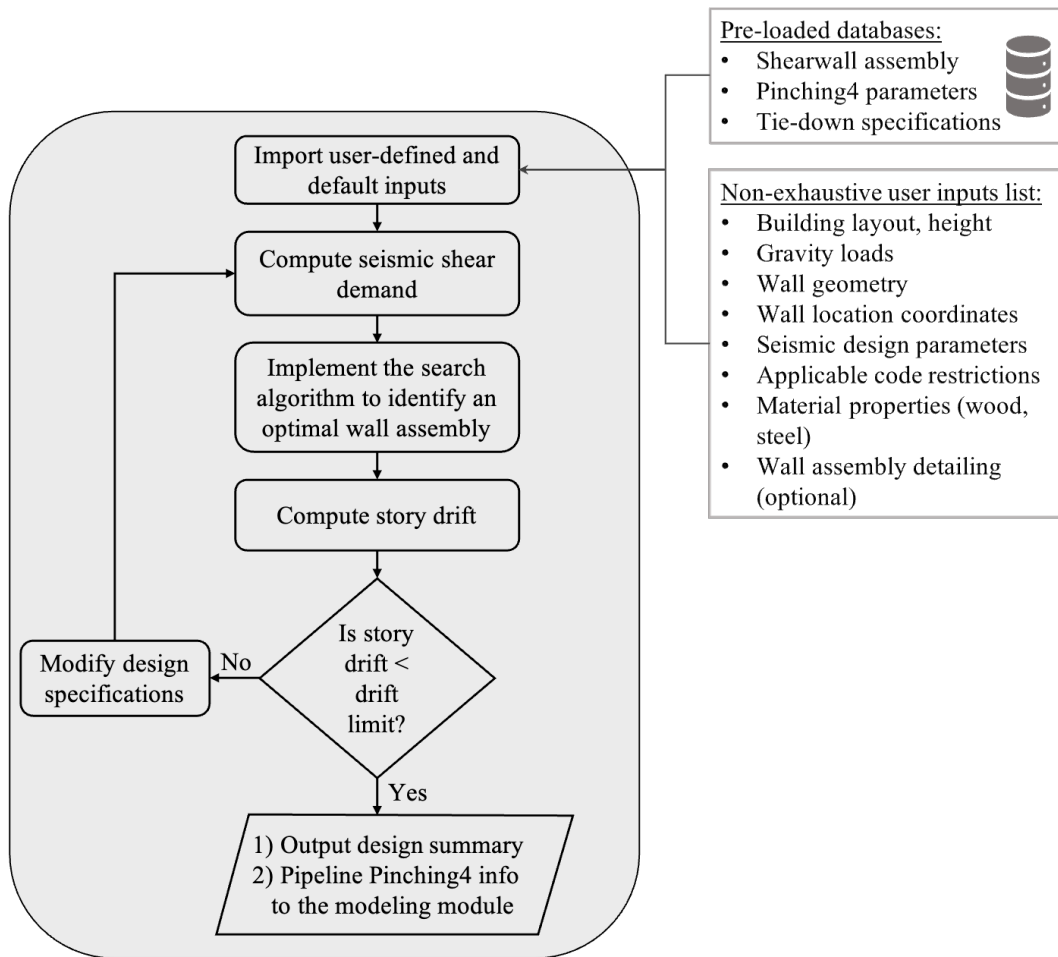


Figure 2.3: Generalized flowchart of the design calculations programmed in the design module of WoodSDA.

down specifications. To facilitate the automated design, the inputs need to be configured in a specific format. Since the tool is equipped to design 3D structures, the inputs must be defined for each principal direction. The building data pre-processing to compile the complete set of user inputs is the only manually intensive task needed to use WoodSDA.

There are several levels of user inputs needed for the design module. The inputs can be broadly categorized into building- and component-level. The building-level information includes geometric properties (e.g., plan dimensions, number of stories), shear wall configuration, gravity loading conditions, and seismic design parameters. Component-level inputs include shear wall length, height, per-lineal gravity loads, moisture content, panel material type, panel thickness, nail size, nail spacing, and hold-down anchorage specification. In practice, the hold-down anchorages are designed by the manufacturing company. The user has the option to specify the pre-designed hold-down properties as input. Alternatively, WoodSDA can size the anchorage based on the tension demand. The building-level inputs are mandatory whereas the detailed component-level inputs are optional. If the component-level inputs are not specified, the default options are utilized. The individualized and detailed shear wall-specific input variables are intended to provide flexibility to the user.

As depicted in Figure 2.1, all input data must be provided before the end-to-end workflow is initialized. The intermediate input files such as the Pinching4 material model parameters and ground motion records utilized by the structural module, and the component list employed by the damage and loss assessment modules are also imported at the beginning. The intermediate input files are loaded from pre-defined databases which might not be extensive for all use cases. For instance, if a desired wall assembly does not have corresponding Pinching4 material parameters in the pre-loaded model database, the user needs to calibrate the parameters for that particular wall. The procedure to calibrate the Pinching4 parameters is detailed in Section 2.3.1. To perform nonlinear dynamic analysis, the 22 pairs of far-field ground motion records proposed in FEMA P-695 (FEMA, 2011b) are made available in WoodSDA as the default option. The ground motion selection tool can also be used to select

and process site-specific records ([Shokrabadi et al., 2020](#)). A component list detailing the type and quantity of structural or nonstructural components on each floor also needs to be specified per the FEMA P-58 guidelines. A default list of components for a typical residential building is included with WoodSDA. For WoodSDA to run successfully, it is imperative to pre-process and specify all the inputs before executing the program.

2.2.1.1 Ground motion selection

The current version of WoodSDA is pre-loaded with the 22 pairs of far-field ground motion records selected as a part of FEMA P-695 Project ([FEMA, 2011b](#)). The ground motion records are scaled by a constant factor to run incremental dynamic analysis (IDA). The scaling process is adopted from the procedures detailed in FEMA P-695 and is repeated for all the pre-defined hazard levels. When simulating the structural response, the directions of the ground motion records are orthogonally switched to consider the impact of directionality. Additionally, WoodSDA also leverages an efficient tool ([Shokrabadi et al., 2020](#)) to facilitate site-specific ground motion selection. The tool is designed to select and consistently scale recorded ground motions from the NGA-West 2 database ([Ancheta et al., 2014](#)). The selection tool is based on a greedy search algorithm that can account for different damping ratios and period-dependent record-to-record variability. Given the target response spectra (either horizontal and/or vertical ground motion components), the tool can select either scaled or unscaled ground motions from the database such that the mean spectra of the selected records match the target spectra. Figure 2.4 shows an example application of the ground motion selection program. The solid blue line represents the site-specific response spectrum and the dashed black line represents the spectrum of the ground motions selected from the NGA-West-2 database. In total, 22 records are selected and scaled using the selection tool. As seen in Figure 2.4, the selection tool can query the records and scale them to match the target. Note that this response spectrum is not used in WoodSDA and is simply presented as an example demonstration.

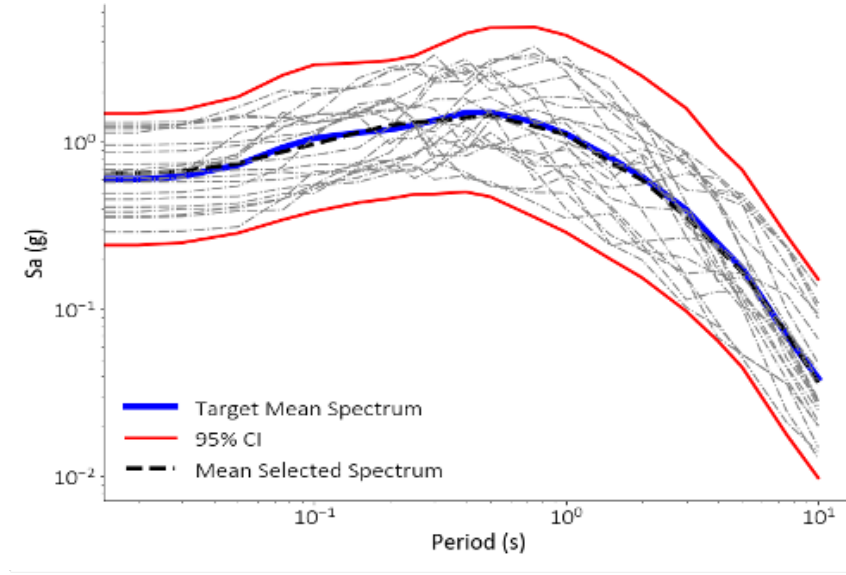


Figure 2.4: Target (blue line) and mean response spectrum for the selected ground motions (black dashed line)

2.2.2 Seismic design

The underlying calculations of the design module are based on the *NHERP Provisions*, which references the ASCE 7-16 standard. The module designs and details for the lateral forces acting in both the transverse and longitudinal directions. The seismic design of the wall is based on the simplified alternative structural design criteria for building frame systems per Section 12.14 of the ASCE 7-16 (ASCE, 2016). The simplified design procedure is mostly applicable to non-cantilevered buildings with symmetric layouts and at least two lines of lateral force-resisting systems in each of the two major axis directions. This procedure is only applicable to Risk Category I and II structures with three or fewer stories above grade and not located in Site Class E or F. In general, a single- or multi-family residential building would meet the limitations specified in Section 12.14 of ASCE 7-16 since they have a simple layout and are usually less than three stories tall. However, if the simplified design criteria are not permitted for any reason such as the building exceeding the three-story limit, analytical

and design procedures outlined in Sections 12.1 through 12.12 of the ASCE 7-16 are adopted. Once the seismic shear is determined for a particular story, the demand is computed for all the shear walls in the story (the number and location of which are specified by the user). The calculated demand is the governing design load used to select the optimal shear wall assembly in Section 2.2.3.

2.2.2.1 Baseline design assumptions

There are several assumptions made while designing a building. Some assumptions are meant to simplify the design process while others are intended as preliminary to be revised or validated. The following assumptions are encoded in the design module:

1. The floor plans are idealized to be a quadrilateral.
2. Diaphragms are assumed to be flexible. This is a preliminary assumption that can be modified to a rigid diaphragm or semi-rigid (envelop design method) with available shear stiffness.
3. No perforated shear walls are considered. This assumption is made for the sake of simplification.
4. Shear walls are assumed to be of the same height and length across the story height. This is a soft assumption that can be easily changed.
5. The load and resistance factor design (LRFD) is used as the default. This is also a soft assumption and can be easily switched to allowable stress design (ASD).

2.2.2.2 Design schemes

The building code ([IBC, 2018](#)) and the *NHERP Provision* ([FEMA, 2009](#)) permit the use of either the LRFD or ASD. As previously discussed in Section 2.1, ASD-based prescriptive

design schemes are routinely used in engineering practice. Unlike steel and reinforced concrete buildings, it is difficult to precisely identify load paths in woodframe buildings. The use of interconnected framing members, redundant elements, anchor bolts, nail sizes, and spacing details can have a measurable influence on performance. The significant contribution of non-structural elements (e.g., dry walls, interior finishes) to seismic response introduces additional uncertainty. To deal with these uncertainties, the buildings are either designed for higher forces (ASD) or detailed more meticulously (LRFD). WoodSDA employs LRFD as the default option which can be easily changed to ASD.

2.2.2.3 Diaphragm flexibility

Diaphragm flexibility is one of the important assumptions in woodframe building design and modeling. Per Section 12.3 of ASCE 7-16 ([ASCE, 2016](#)), one and two-family dwellings are permitted to be idealized as flexible diaphragms whereas buildings with vertical irregularity (e.g., soft story irregularity) are allowed to be designed with a rigid diaphragm assumption. Considering that most light-frame wood buildings have symmetric layouts with at least one shear wall on each axis, a flexible diaphragm assumption is adopted as the default. As such, the loads are distributed to the shear walls based on tributary area. However, to facilitate the design of horizontally or vertically irregular structures, WoodSDA also has built-in functionalities for rigid- or semi-rigid diaphragms. In particular, if the diaphragm is deemed rigid, the story shear demand is distributed based on the relative stiffness of the shear walls in the direction of interest. Similarly, a semi-rigid diaphragm is designed based on an envelope method which is a combination of the stiffness and tributary area-based approaches.

2.2.3 Search algorithm

As discussed earlier, the design of a woodframe building is subjective and often depends on the owner’s specifications and the engineer’s discretion. In addition, constructability and material availability play an important role. It is common for an engineer to design a shear wall based on a pre-selected set of assemblies. For instance, to be code-compliant in fire-prone zones, an engineer has to select fire-rated walls. This would limit the types of shear walls that could be used because not all sheathing materials are fire-rated. To support various user-specific needs, WoodSDA allows users to itemize shear wall assembly details such as material type, sheathing panel thickness, nail size, and nail thickness. The user-specified assembly details along with other design considerations are programmed into a recursive search algorithm as portrayed in Figure 2.5. The search algorithm selects the best possible wall assembly given the shear demand.

The search algorithm selects an “optimal” shear wall assembly that satisfies the code- and user-specified requirements. An optimal (or economical) wall assembly is defined as a wall that has a demand-to-capacity ratio close to one. Figure 2.5 outlines the operations and checks undertaken by the algorithm. It processes information in the top-down and left-right order. It is essentially a greedy search algorithm that is terminated once the best possible assembly is found in the shear wall database. The algorithm first checks for the demand-to-capacity ratio and if specified, the design value is adjusted accordingly. In WoodSDA, a demand-to-capacity ratio of 90% is used as the default value to account for inherent uncertainties in the construction practices. For instance, a shear wall detailed to have 3 inches on center (o.c.) nail spacing might not be constructed with exactly 3 inches spacing. The user-specified shear wall detailing is checked next. If both the demand-to-capacity ratio and detailing are the user inputs, the algorithm first satisfies the former followed by the assembly specifications. The wall assembly with the highest demand-to-capacity ratio is selected from the filtered database as the candidate assembly, which is determined to be the final assembly if it passes the drift check.

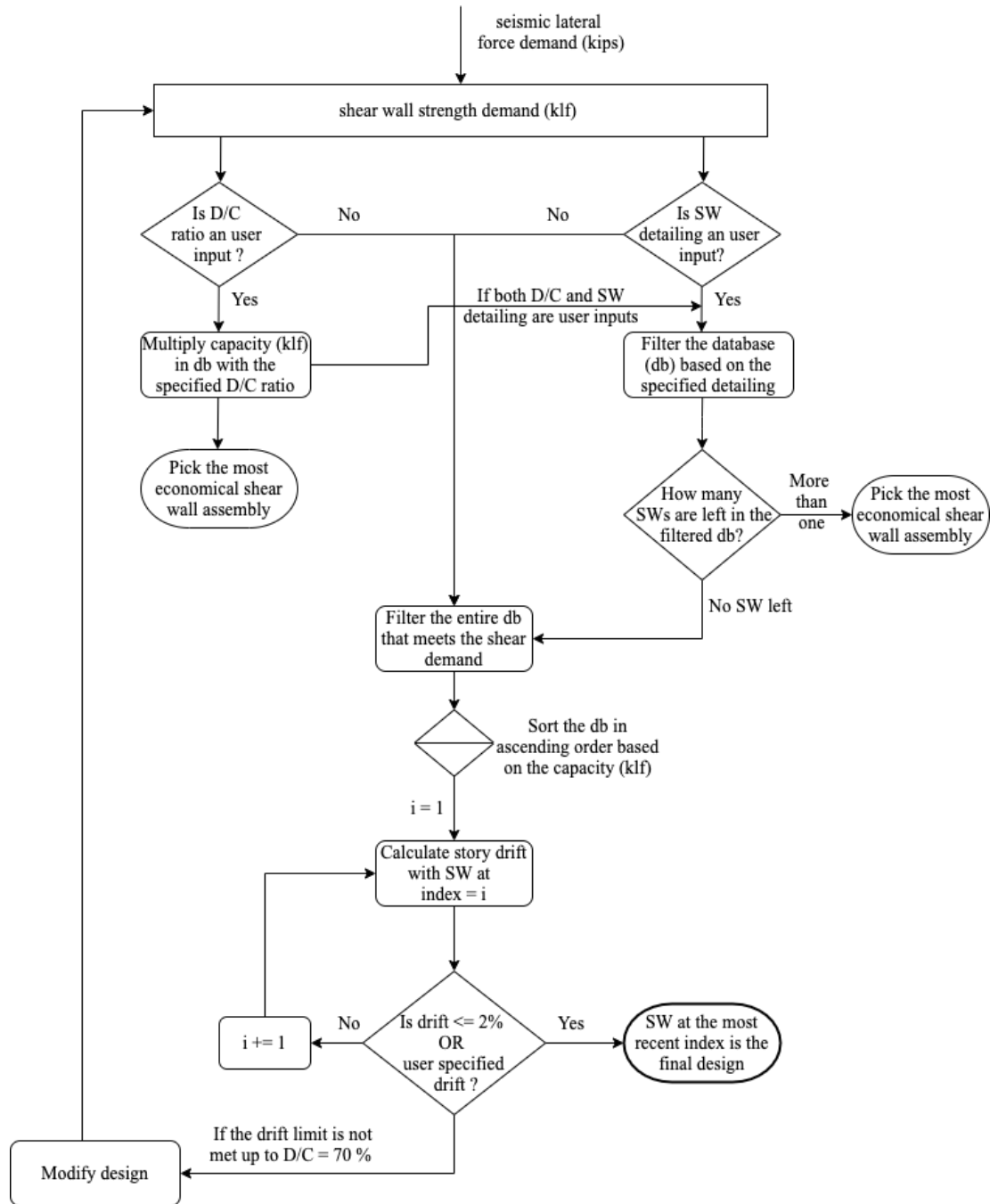


Figure 2.5: Flowchart of the recursive search algorithm.

If for some reason none of the assemblies in the shear wall database satisfy the specifications, the algorithm disregards the user-defined inputs and defaults to selecting the assemblies solely based on the required strength. Since not all strength-compliant assemblies are guaranteed to be drift-compliant, a nested iteration is programmed that loops over all the strength-compliant assemblies and selects the most economical one that also complies with the imposed drift limit. If the algorithm finds at least one assembly within this nested loop then the search is terminated, if not the algorithm exits to the main loop and instantiates an additional iteration by reducing the demand-to-capacity ratio up to a lower limit. However, if none of the assemblies available in the database satisfies the design criteria, the program is terminated along with an error message requesting the user to revise the design.

2.2.4 Drift check and design iteration

In addition to satisfying the strength demand, the design also has to meet the drift requirement for it to be code-compliant. The default drift requirement encoded in WoodSDA is based on Section 12.12 of the ASCE7-16 ([ASCE, 2016](#)). However, a user can override the default drift requirement to define a stricter limit. The drift check is performed based on the shear wall deflection computed using the equation proposed in SDPWS ([AWC, 2015](#)). The deflection is a combination of three different characteristics of the shear wall as shown in Eq.(2.1). The first term quantifies the deflection due to chord bending, the middle term calculates the deflection due to nail slip and panel deformation, and the last term represents the deflection due to shear wall rotation.

$$\delta_{sw} = \frac{8vh^3}{EA_b} + \frac{vh}{1000G_a} + \frac{h\Delta_a}{b} \quad (2.1)$$

where,

δ_{sw} = maximum shear wall deflection determined by elastic analysis (in)

v = shear wall unit shear demand (klf)

h = wall height (ft)

b = wall width (ft)

E = modulus of elasticity of the chord (ksi)

A = area of the chord/ end posts (in²)

G_a = apparent shear stiffness (kip/in)

Δ_a = Sum of the vertical displacements at anchorage and boundary elements or take-up deflection (in)

As previously discussed, the abundance of redundant elements ensures that drift is usually not an issue in woodframe building design. However, to be code-compliant, the drift does need to be checked. Drift check is one of the key aspects of the design iteration built into the WoodSDA design module. Figure 2.5 and Figure 2.3 highlight the trigger point for the design iteration loop within the module. The algorithm is set up to exhaust all possible design scenarios before it requires human intervention. Although not available in the current version, the design module can be extended to automatically adjust the shear wall length based on the demand such that there will be no manual intervention.

2.3 Structural Module

Numerical modeling, structural response simulation, and damage analysis are at the core of the PBEE framework. WoodSDA utilizes three-dimensional (3D) numerical models and explicit nonlinear static and dynamic analysis. The 3D nonlinear structural model construction and response history analysis are the most time-consuming tasks within the PBEE framework. Depending on the complexity of the model, it can take a proficient design engineer hundreds of hours to create the model and run the nonlinear dynamic analysis. However, with automation, the same set of tasks can be completed in hours. In WoodSDA, the structural (model generation and analyses) and damage modules are developed separately but are presented together in Figure 2.6. The structural module takes the model parameters generated by the design module as an input, and the damage module pipelines structural

response data to the loss module.

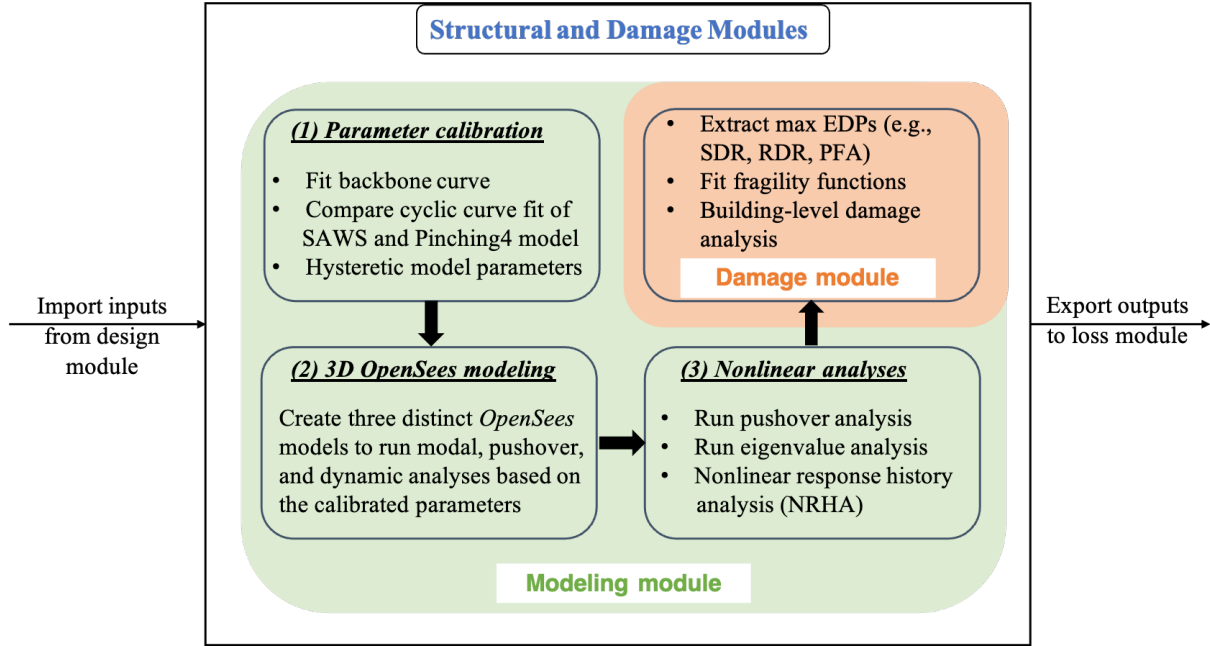


Figure 2.6: Workflow of the structural and damage modules.

Numerous studies have been carried out to develop and investigate analytical models to simulate the seismic response of woodframe buildings. Based on experimental testing, [Folz and Filiatrault \(2002\)](#) proposed a 10-parameter single-degree of freedom system (SDOF) hysteresis model for seismic analysis of woodframe structures (SAWS). The model was developed and incorporated in the “CASHEW” (Cyclic Analysis of SHEar Walls) computer program ([Folz and Filiatrault, 2002](#)). As illustrated in Figure 2.7a, the SAWS model defines hysteretic parameters up to the post-peak strength but does not capture residual strength. A few recent studies (e.g., [Welch and Deierlein \(2020a\)](#); [Yi et al. \(2020\)](#)) have demonstrated that the Pinching4 hysteresis model ([Lowes et al., 2003](#)) can be used to model woodframe structures such as single-family cripple wall dwellings. These studies used two Pinching4 material models in parallel to capture the contribution from both structural and nonstructural wall components. This study also adopts the Pinching4 material in the 3D woodframe

structural model.

2.3.1 Material model parameter calibration

A typical shear wall model assembly is composed of three structural components: rigid frame members, linear elastic sheathing panels, and nonlinear sheathing-to-framing connectors. The hysteretic material model is intended to collectively capture the nonlinear behavior of all three components of the shear wall. In WoodSDA, the Pinching4 model is adopted as an alternative to the SAWS model. Figure 2.7b shows the Pinching4 material backbone curve (solid line) and cyclic load definitions (dashed line) which capture unloading/reloading strength and stiffness degradation.

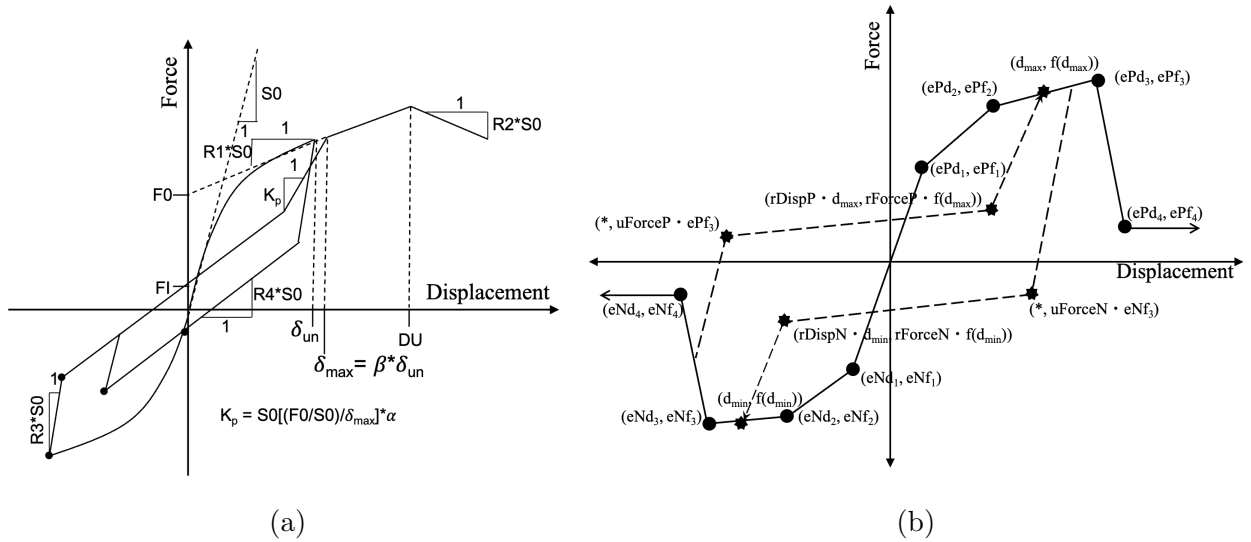


Figure 2.7: a) SAWS hysteretic material model; b) Pinching4 hysteretic material model.

One of the shortcomings of using the Pinching4 material model is the lack of readily available hysteresis parameters in the literature. On the other hand, the SAWS modeling parameters for a limited number of shear wall assemblies are readily available in the literature (Folz and Filiatrault, 2001; Pang et al., 2012; Line et al., 2008). As part of the WoodSDA development, an extensive effort is undertaken to calibrate the Pinching4 param-

eters. Typically, hysteresis parameters are calibrated using experimental data. However, due to the limited availability of test data, the Pinching4 parameters are calibrated based on both experimental data (where available) and the SAWS model (where experimental data is lacking). The calibration process involves two distinct steps: backbone calibration and cyclic calibration. The backbone calibration aims to fit the monotonic response while the cyclic calibration matches the hysteresis energy. The four-point backbone parameters ((ePd₁, ePf₁), (ePd₂, ePf₂), (ePd₃, ePf₃), (ePd₄, ePf₄)) are calibrated based on published monotonic test data (e.g., [Line et al. \(2008\)](#); [FEMA \(2011a\)](#)). Consistent with recent state-of-the-art studies on woodframe buildings (e.g., the FEMA P-2139-2 report on short-period building ([ATC, 1990](#)) and the PEER-CEA Project on cripple wall retrofits ([Welch and Deierlein, 2020a](#))), the residual strength is taken as 30% of the peak force while the residual drift capacity is assumed to be 10%.

As a first step, 128 shear wall assemblies were identified based on popular research experiment projects such as CUREE-CALTECH ([Folz and Filiatrault, 2001](#)) and UCI-COLA ([Line et al., 2008](#)) as the candidate for calibration. However, only 15 out of the 128 assemblies had the complete data (SAWS parameters and experimental data) needed for the calibration process. As such, the final WoodSDA shear wall database only contains 15 assemblies. To calibrate the Pinching4 parameters from the SAWS parameters, two SDOFs are created to simulate the behavior of the two material models. The quasi-static cyclic loading protocol proposed by [Folz and Filiatrault \(2002\)](#) is used to generate the cyclic force-deformation curve. Then, the Pinching4 parameters are iterated until the hysteretic energy dissipated by the two models are reasonably comparable. Figure 2.8 shows the result of a parameter calibration for a single shear wall assembly. It shows that the Pinching4 model can adequately capture the cyclic strength and stiffness degradation. The cyclic curve match is quantified by comparing the hysteresis energy dissipated by the SAWS and Pinching4 models which appear to be nearly identical. In the PEER-CEA Project, the Pinching4 material for the exterior wall (e.g., wood siding and stucco) and interior wall finishes (e.g., gypsum wallboard and plaster

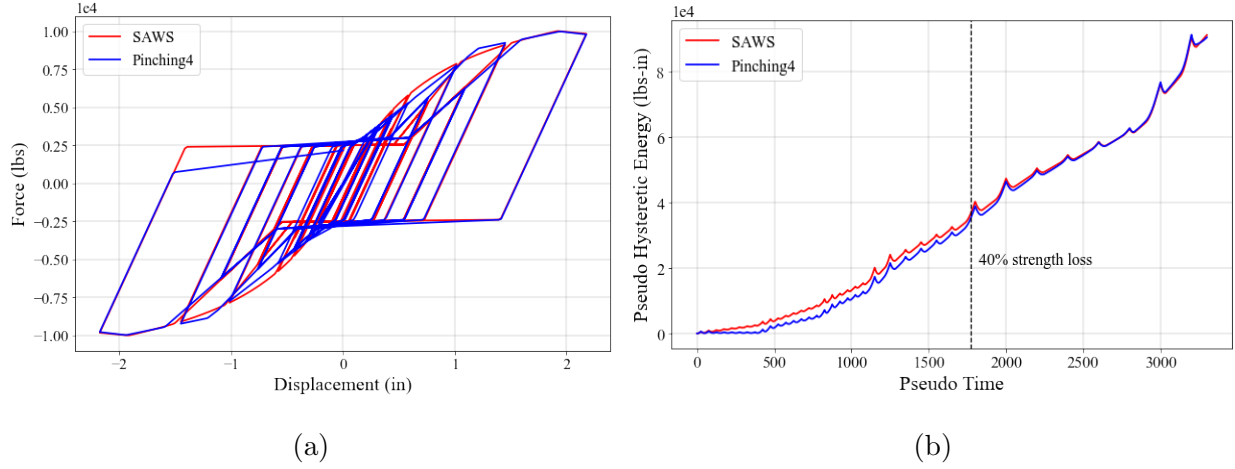


Figure 2.8: a) Comparison of cyclic force-displacement behavior computed using the SAWS (CASHEW) and Pinching4 (OpenSEES) hysteretic models; b) pseudo energy plots based on the dissipated energy.

on lath) were combined by superimposing the two models in parallel. The same strategy is adopted in WoodSDA to model the structural and non-structural walls. The parameter calibration process is repeated for the 15 distinct wall assemblies previously identified. The modeling parameters generated by the design module are the calibrated parameters of the designed shear walls.

2.3.2 OpenSees modeling

The structural module generates a 3D numerical model in OpenSees. It utilizes the modeling parameters from the design module to automatically create three separate 3D numerical models. The three models are intended to perform nonlinear static, modal (eigenvalue), and dynamic analyses. To simplify the modeling process, the floor layout is simplified to a 4-edged shape such as a rectangle or a square. As discussed earlier, the structural and non-structural walls are modeled using a two-node link element with two horizontal springs superimposed in parallel. The idealization of a shear wall into a two-node link element does not capture the overturning response because the contribution of hold-downs is implicitly

accounted for in the Pinching4 material parameters. At each floor level, a total of nine leaning columns are used to capture p - Δ effects: one each at four corners, one each at four mid-points between the corner columns, and one at the center.

2.3.3 Nonlinear analysis

Once the structural module produces the OpenSees model, it automatically performs modal, nonlinear static (or pushover), and dynamic analyses. The analyses can be performed on a local computer or on a high-performance computing (HPC) cluster. For computational efficiency, parallel computing is built into the structural module. An appropriate OpenSees executable (OpenSees for single processor, OpenSeesMP for parallel processing) needs to be properly installed. We have tested the compatibility of the models with OpenSees versions 3.2.0 through 3.6.0 and the pre-built binary OpenSeesMP version 2.5.0. We did not test the compatibility with OpenSeesSP.

2.3.3.1 Eigen and pushover analysis

For the eigenvalue (modal) analysis, the structural module outputs 20 (as a default) fundamental modal periods, mode shapes, and mass participation factors. The nonlinear static or pushover analysis is used to evaluate the strength and deformation capacity of the structure. The pushover analysis is preceded by a static analysis under gravity loads to adequately capture the p - Δ effects. After the gravity analysis, the structure is subjected to a displacement-controlled monotonic lateral load pattern. For a given direction (e.g., longitudinal or transverse), the lateral load is applied to the leaning column at the center of the buildings. Drift and force recorders are used to capture the elastic and inelastic behavior of the structure. The outputs from the nonlinear static analysis are processed to generate a pushover curve to gain insight into the global behavior of the structure. The code to process the outputs is made available in the GitHub repository ([Dahal, 2024](#)).

2.3.3.2 Dynamic analysis

Following the pushover analysis, the structural module runs the dynamic analysis using the ground motion records established in Section 2.2.1. The module is also able to perform IDAs and/or multiple stripe analyses. This requires the user to define the number of hazard levels, ground motion intensity measures, and the number of records to be used at each hazard level. Similar to the pushover, nodal recorders are used to capture force, displacement, and acceleration demands at different floor levels. The simulated dynamic responses of the structure are outputted for all the ground motions and hazard levels. If the pushover analysis is prematurely terminated, the structural module ends the WoodSDA program. In such a scenario, a user should examine the inputs and automated OpenSees models before proceeding with the dynamic analysis.

2.4 Damage Module

The dynamic analysis simulates the structural response and the resulting data is in a time-series format. It is useful to visualize the response history of the structure, however, to perform downstream damage and loss analysis, peak responses are extracted. Specifically, the built-in post-processing functionality extracts peak story drift ratio (PSDR), residual drift ratio (RDR), and peak floor acceleration (PFA) at each floor level. The resulting distribution of structural response parameters (equivalently, engineering demand parameters (EDPs)) are used to assess building- and component-level damage states. The damage module performs building-level damage analysis while the loss module undertakes component-level damage analysis which is subsequently leveraged to estimate the economic loss and recovery time.

2.4.0.1 Fragility function fitting

The processed EDP data is used to fit building-level fragility curves. A fragility curve quantifies the probability of exceeding a damaged state of interest conditioned on an EDP. The fragility functions can be fitted to various damage states. For instance, the collapse fragility function is routinely used in the PBEE framework to quantify seismic collapse risk. Using the collapse data obtained from the dynamic analysis, maximum likelihood estimation (MLE) is used to estimate the fragility function parameters (θ and β). The parameters, θ and β represent the median collapse capacity and the log-standard deviation, respectively. The MLE assumes that the likelihood function is known to follow a specified parametric probability distribution which may not be consistent with the “true” probability distribution of the collapse data. If this is the case, it introduces parameter estimation uncertainty that needs to be estimated using the Huber-White Sandwich estimators instead of the inverse of Fisher’s Information matrix. To account for a potential parameter estimation uncertainty, quasi-maximum likelihood estimation (QMLE) is also programmed into WoodSDA as an alternative to MLE. If probability model misspecification is deemed to be an issue, QMLE is made readily available but MLE is adopted as the default parameter estimation technique. Readers are referred to [Dahal et al. \(2021\)](#) for an in-depth study on the effect of probability model misspecification and parameter estimation uncertainty.

2.5 Loss Module

The loss module is the last to be executed within the WoodSDA end-to-end workflow. Losses are assessed in the form of casualties, repair cost, unsafe placarding, and recovery time among others. The damage and loss are evaluated at the component level. The repair cost evaluation follows the procedures outlined in the FEMA P-58 framework ([FEMA, 2012](#)) and the beta version of ATC-138 is used to assess functional recovery time ([ATC, 2021](#); [Cook et al., 2022](#)). WoodSDA leverages publicly available open-source programs to calculate the losses.

Particularly, Pelicun, a Python package developed by the NEHRI SimCenter ([Zsarnoczay, 2019](#)) is integrated into the loss module to simulate repair costs and casualties. Similarly, a MATLAB-based source code ([Dustin, 2022](#)) released as a part of the beta version of the ATC-138 functional recovery methodology is merged into WoodSDA.

2.5.1 Economic loss estimation

The loss assessment module integrates the hazard model, structural model, and fragility model to evaluate the damage measure. Eq. (2.2) is the governing equation used to compute the intensity-based loss. The expected loss conditioned on a specific EDP is computed by integrating the expected loss given a damage state with the probability of observing that damage state given the EDP. Finally, the expected loss given the EDP is integrated with the conditional probability of exceeding a specified EDP level. The intensity-based loss can be integrated with the hazard curve to compute the annualized expected loss.

$$\mathbb{E}[L_i|IM] = \int_0^\infty \mathbb{E}[L_i|EDP] \cdot |dP(EDP > edp|IM)| \quad (2.2)$$

To consider various sources of uncertainty, the P-58 loss assessment framework adopts a Monte Carlo-based approach. The distribution of simulated losses captures the variability in building performance. The losses are disaggregated to reflect probabilistic contributions from the collapse, demolition, and repairable limit states. For each Monte Carlo realization, losses are computed based on damage to both the structural and nonstructural components. The Monte Carlo samples are generated using the output from the probabilistic seismic demand analysis in Section 2.4. For each realization, the sample is checked against the collapse criteria. If collapse is triggered, the casualties are determined and the repair cost is estimated to be the building value. For non-collapse cases where the building is deemed irreparable, the associated cost equals the building value and an unsafe placard is assigned. However, if the building is found to be repairable, the damage state of each component is determined. As part of the P-58 methodology, FEMA published a component fragility database that

maps a damage state to corresponding decision variables such as repair cost. The building- and component-level decision variables are aggregated to define the distribution of losses. For additional technical background, readers are directed to the Pelicun documentation ([Zsarnoczay, 2019](#)).

2.5.2 Functional recovery time

The loss module also estimates a suite of recovery times based on the ATC-138 methodology ([ATC, 2021](#); [Cook et al., 2022](#)). Specifically, the method distinguishes between the re-occupancy time, functional recovery time, and full repair time. Hereafter, these three are collectively referred to as “recovery times.” The ATC-138 methodology extends the FEMA P-58 framework by the consequence functions with recovery times. Similar to the repair cost analysis, the ATC 138 methodology also uses a Monte Carlo-based simulation approach to probabilistically quantify the recovery times. For each sampled realization, damage to structural and nonstructural components is used to explicitly quantify the functionality level. The functionality levels of all components and systems are aggregated to determine the building-level recovery state.

The functional recovery methodology exploits a number of fault trees to define explicit relationships between component-level damage, system-level operation, and building-level performance. The fault tree logic to assess building function is schematically represented in Figure 2.9. One of the key ideas introduced in the methodology is the concept of tenant units. A tenant unit is defined as a space within a building that serves a unique purpose and may have different requirements to function than other spaces in the same building due to its intended use or ownership ([ATC, 2021](#)). To quantify partial building function, the fault-tree analysis is performed at the tenant unit level. The building-level recovery time is computed by aggregating the recovery times of all the tenant units within the building. There are four sequential stages or checks performed to assess the functionality of a tenant unit. The first three checks identify if the unit can be reoccupied. For each realization of

the damage sample (from Section 2.5.1), the building is checked for safety hazards. If a building is deemed safe to enter, each story is checked for egress and access routes based on the damage to stairways and doors. In Stage 3, tenant safety is assured by checking for interior falling hazards (e.g., damaged ceiling). A tenant unit must satisfy all three checks for it to be reoccupiable. In Stage 4, a series of checks are performed to make sure that an occupant can function in the space and fulfill occupancy-specific requirements. For instance, mechanical, electrical, and plumbing services need to be operational for an apartment unit to be considered functional.

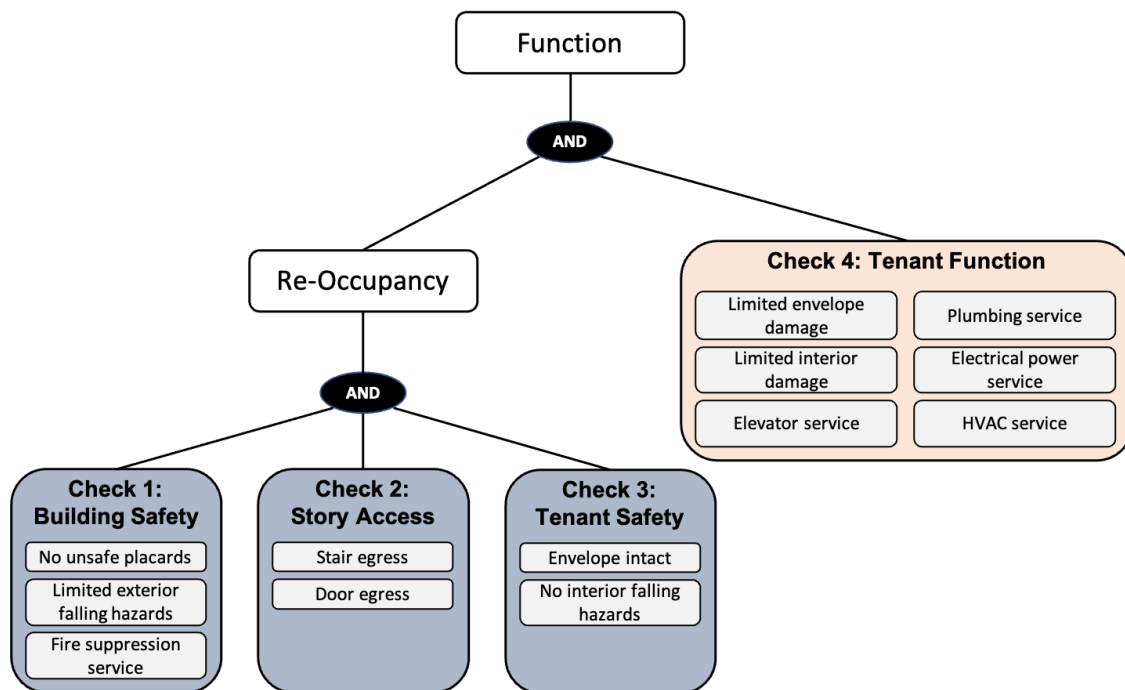


Figure 2.9: The logic tree used to assess tenant-level reoccupancy and function in the ATC-138 methodology.

The recovery trajectory of a building after an earthquake is a complex phenomenon that evolves dynamically. The recovery trend depends on the initialization of damage and the associated repair schedule. Depending on the level of damage, the initialization of repairs could be hindered by impeding factors such as building inspection, design and permitting,

contractor mobilization, temporary clean-up, financing, insurance claims, lack of labor, and supply chain disruptions. The functional recovery methodology introduces temporary repairs as a potential mitigation action. Allowing temporary repairs significantly reduces the re-occupancy time as the repair schedule algorithm can concurrently prioritize systems that cannot be temporarily repaired by the occupants. The algorithm allocates crews of workers to repair the components with the highest priority. Based on the logic tree presented in Figure 2.9, the components that need to be operational for reoccupancy are given the highest priority. To model a more realistic repair sequencing, limits are placed on the number of workers per tenant unit. The output of the functional recovery methodology is the distribution of recovery times for the building. To successfully run the beta ATC-138 codebase in WoodSDA, a Python package named MATLAB Engine API for Python, needs to be installed.

2.6 Example Application

This section implements the WoodSDA platform to test the end-to-end functionality and validate the results where applicable. The test example is adopted from the FEMA P-2139 Volume 2 document ([FEMA, 2020](#)) that was produced as part of the ATC-116 project. In 2012, FEMA funded the ATC-116 project to study the short-period light-frame wood building performance paradox. The paradox stemmed from contradictory seismic collapse performance obtained from numerical simulations that were inconsistent with observations from historical earthquakes since 1964. The numerical models showed a higher collapse risk for short-period buildings as compared to those with a longer period. However, the observed collapses during historical earthquakes did not support the result. To address this discrepancy, enhanced numerical models were developed. The project studied 28 baseline archetypes comprising commercial buildings (COM), single-family dwellings (SFDs), and multi-family dwellings (MFDs) with either one, two, or four stories. The four-story MFD

archetype (archetype ID *MFD6B*) is used to demonstrate the implementation of WoodSDA.

2.6.1 Description of the archetype

To generalize the wide-ranging layouts and properties, it is standard practice to utilize building archetypes (e.g., [FEMA \(2011b, 2009\)](#); [Welch and Deierlein \(2020a\)](#)). An archetype can be defined by grouping buildings based on specific geometric or structural features. The WoodSDA program also exploits the idea of archetypes as the building layouts and floor plans are generalized to be quadrilateral in the input files. The FEMA P-2139-2 report defined archetypes based on the occupancy type and the height of the building. The archetype used in this study is a four-story building with multiple residential units per floor. The *MFD6B* archetype is a 96 ft $\times$ 48 ft layout with shear walls in both the transverse and longitudinal directions. Figure 2.10 shows the typical floor plans for MFD archetypes. The darker lines with labels represent lateral force resisting shear walls. The details of the shear wall schedule are listed in Table 2.1. The nonstructural walls are included in the model but are omitted from the floor plan for simplicity.

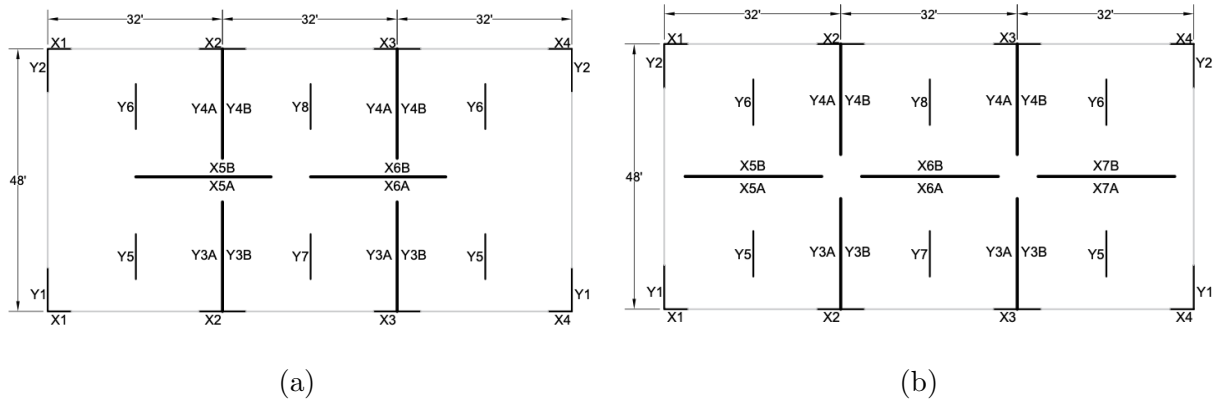


Figure 2.10: (a) Layout of the first and fourth floor; (b) layout of the second and third floor of the archetype MFD6B adopted from [FEMA \(2020\)](#).

Prior to designing the shear walls, the FEMA P-2139-2 investigated the most commonly

used assemblies in residential woodframe construction. Oriented strand board (OSB) and gypsum wallboard (GWB) were identified as the most commonly used wall sheathing. As such, the engineered designs only use three different types of OSB-based shear wall assemblies: OSB-Low, OSB-Med, and OSB-high. The assemblies have a typical 2×4 or 2×6 Douglas fir framing on the edges. The wall specification characteristics are as follows:

1. **OSB-Low:** 7/16-inch structural panels with 8d common nails at 6 inches on center (o.c.). Nominal strength: 520 plf.
2. **OSB-Med:** 7/16-inch structural panels with 8d common nails at 3 inches o.c. Nominal strength: 980 plf.
3. **OSB-High:** 9/32-inch (or 5/8-inch) structural panels with 10d common nails at 2 inches o.c. Nominal strength: 1740 plf.
4. **Non-LFRS:** 7/16-inch OSB, unblocked, with 8d nails at 6 inches o.c., on edges; 1/2 inch GWB, drywall screws at 12 inches o.c.; exterior stucco

The FEMA P-2139-2 project developed seismic designs for the shear walls based on three discrete levels of seismic demand. The engineered designs of the shear wall schedule shown in Table 2.1 are based on MCE_R design parameters. Table 2.1 details the types and lengths of walls designed at each floor level. At the upper story levels, nonstructural walls (Non-LFRS) are assigned because the demands were so low that a shear wall was not deemed necessary. The Non-LFRS walls are not used in the design but are included in the numerical model to simulate realistic structural performance.

The FEMA P-2139-2 project utilized a MATLAB-based analysis program, *Timber3D*, to perform detailed nonlinear structural analysis (Pang et al., 2012). The *Timber3D* program generates a three-dimensional model based on co-rotational formulation and large displacement theory. The walls were modeled as “building blocks” which are intended to capture axial, in-plane, and out-of-plane flexural deformations. The horizontal floor and diaphragm

Table 2.1: Wall schedule for the MFD archetype (FEMA, 2020)

Wall Name	1 st Story		2 nd Story		3 rd Story		4 th Story	
	Wall Type	Length (ft)	Wall Type	Length (ft)	Wall Type	Length (ft)	Wall Type	Length (ft)
X1	OSB-Med	4	OSB-Med	4	OSB-Low	4	OSB-Low	4
X2	OSB-High	8	OSB-Med	8	OSB-Low	8	OSB-Low	8
X3	OSB-High	8	OSB-Med	8	OSB-Low	8	OSB-Low	8
X4	OSB-High	4	OSB-Med	4	OSB-Low	4	OSB-Low	4
X5A	OSB-High	24	OSB-High	24	OSB-Med	24	OSB-Low	24
X5B	OSB-High	24	OSB-High	24	OSB-Med	24	OSB-Low	24
X6A	OSB-High	28	OSB-High	28	OSB-High	28	OSB-Low	28
X6B	OSB-High	28	OSB-High	28	OSB-High	28	OSB-Low	28
Y1	OSB-Med	8	OSB-Med	8	OSB-Low	8	OSB-Low	8
Y2	OSB-Med	8	OSB-Med	8	OSB-Low	8	OSB-Low	8
Y3A	OSB-Med	20	OSB-Med	20	OSB-Med	20	OSB-Low	20
Y3B	OSB-Med	20	OSB-Med	20	OSB-Med	20	Non-LFRS	20
Y4A	OSB-Med	20	OSB-Med	20	OSB-Med	20	OSB-Low	20
Y4B	OSB-Med	20	OSB-Med	20	OSB-Med	20	OSB-Low	20
Y5	OSB-High	8	OSB-Med	8	Non-LFRS	8	Non-LFRS	8
Y6	OSB-High	8	OSB-Low	8	Non-LFRS	8	Non-LFRS	8
Y7	OSB-High	8	OSB-Low	8	Non-LFRS	8	Non-LFRS	8
Y8	OSB-High	8	OSB-Low	8	Non-LFRS	8	Non-LFRS	8

are modeled using a two-node, 12-DOF elastic beam element. A modified SAWS hysteretic model was used to capture the nonlinear strength and deformation degradation. The SAWS modeling parameters for the modeled wall assemblies (OSB-Low, OSB-Med, OSB-High, and Non-LFRS) were calibrated using the experimental test data documented in the FEMA P-750 report (FEMA, 2009). Any missing data needed to calibrate the modeling parameters was substituted by the “best judgment” estimate among the working group members. The modified SAWS parameters were calibrated for two distinct wall building blocks: an 8 ft $\times$ 10 ft and 4 ft $\times$ 10 ft wall shear wall. The project evaluated the nonlinear static and dynamic performance of the woodframe structures. For dynamic analysis, IDA was conducted using the 22 pairs of the FEMA P-695 far-field ground motions (FEMA, 2011b). To account for

the possible influence of directionality on the simulated response, the ground motions were applied in the two orthogonal directions creating response data for 44 dynamic analyses. The spectral acceleration at 0.25 seconds period ($Sa_{T1=0.25s}$) was used as the intensity measure to scale the ground motion records. The records were scaled at an increment of 0.1g until all 44 analyses collapsed the building.

2.6.2 Structural design comparison

As previously discussed, the FEMA P-2139-2 project only considered three candidate shear wall schedules. In WoodSDA, the design module is not restricted to only the three schedules to demonstrate all of the relevant functionalities. For instance, Figure 2.11 presents a snippet of the final design summary of the MFD6B archetype. The ASD method was used and the demand-capacity ratio was not bounded within 0.9 as is default in WoodSDA. Figure 2.11 summarizes the design for each shear wall. Along with the design summary, the module also outputs an *OpenSees Tag*, which essentially maps the designed shear wall to its corresponding Pinching4 modeling parameters.

2.6.3 Nonlinear static analysis result comparison

Table 2.2 summarizes the results from the modal and pushover analyses performed using the WoodSDA structural module. The results from the eigenvalue analysis show that the fundamental periods (T_1) differ on average by 16 percent between the FEMA P-2139-2 and WoodSDA model. The pushover analysis results produced by WoodSDA are also comparable with that of the FEMA P-2139-2 project. The maximum normalized base shear for the MFD6B archetype was found to be 44 and 46 percent of the seismic weight, respectively, from the FEMA P-2139-2 project and WoodSDA. The peak strength in the North-South direction is less than five percent different. The drift capacity at 80% post-peak strength loss is virtually the same between the two models. The maximum drift capacity differs by

		ASD(klf)	D/C Ratio	Drift(in)	Ga(k/in)	OpenSees Tag	Shear Wall Assembly	level
swDesign_gridA_wall1	0	0.100	0.906329	0.928119	5.2	14	Use 1/2in GWB with 5d cooler nails @ 7in o.c. ...	4
	1	0.340	0.799702	0.639139	19.0	8	Use 19/32in WSP on 1 side with 10d nails @ 6o....	3
	2	0.585	0.929568	0.558756	42.0	5	Use 7/16in WSP on 1 side with 8d nails @ 2o.c....	2
	3	0.870	0.887032	0.775445	48.0	9	Use 19/32in WSP on 1 side with 10d nails @ 2o....	1
swDesign_gridA_wall2	0	0.100	0.906492	0.918493	5.2	14	Use 1/2in GWB with 5d cooler nails @ 7in o.c. ...	4
	1	0.340	0.799846	0.630159	19.0	8	Use 19/32in WSP on 1 side with 10d nails @ 6o....	3
	2	0.585	0.929735	0.548572	42.0	5	Use 7/16in WSP on 1 side with 8d nails @ 2o.c....	2
	3	0.870	0.887192	0.750430	48.0	9	Use 19/32in WSP on 1 side with 10d nails @ 2o....	1
swDesign_gridA_wall3	0	0.100	0.906492	0.918493	5.2	14	Use 1/2in GWB with 5d cooler nails @ 7in o.c. ...	4
	1	0.340	0.799846	0.630159	19.0	8	Use 19/32in WSP on 1 side with 10d nails @ 6o....	3
	2	0.585	0.929735	0.548572	42.0	5	Use 7/16in WSP on 1 side with 8d nails @ 2o.c....	2
	3	0.870	0.887192	0.750430	48.0	9	Use 19/32in WSP on 1 side with 10d nails @ 2o....	1
swDesign_gridA_wall4	0	0.100	0.906329	0.928119	5.2	14	Use 1/2in GWB with 5d cooler nails @ 7in o.c. ...	4
	1	0.340	0.799702	0.639139	19.0	8	Use 19/32in WSP on 1 side with 10d nails @ 6o....	3
	2	0.585	0.929568	0.558756	42.0	5	Use 7/16in WSP on 1 side with 8d nails @ 2o.c....	2
	3	0.870	0.887032	0.775445	48.0	9	Use 19/32in WSP on 1 side with 10d nails @ 2o....	1
swDesign_gridB_wall1	0	0.100	0.941271	0.811513	5.2	14	Use 1/2in GWB with 5d cooler nails @ 7in o.c. ...	4
	1	0.340	0.830533	0.504974	19.0	8	Use 19/32in WSP on 1 side with 10d nails @ 6o....	3
	2	0.585	0.965406	0.498604	42.0	5	Use 7/16in WSP on 1 side with 8d nails @ 2o.c....	2
	3	0.870	0.921230	0.560188	48.0	9	Use 19/32in WSP on 1 side with 10d nails @ 2o....	1
	0	0.100	0.941290	0.811837	5.2	14	Use 1/2in GWB with 5d cooler nails @ 7in o.c. ...	4
	1	0.340	0.830550	0.479411	19.0	8	Use 19/32in WSP on 1 side with 10d nails @ 6o....	3

Figure 2.11: A snippet of the final design summary obtained from the design module.

18% (i.e., percent difference) in the Y-direction and is identical in the X-direction. Similar results are obtained for nine other baseline archetypes as outlined in Section A.1. Considering that WoodSDA uses different hysteresis models (Pinching4 vs SAWS) and modeling software (OpenSees vs Timber3D), the overall pushover analysis result verifies that WoodSDA can reliably generate and run nonlinear static analysis.

Table 2.2: Eigen and pushover-analysis result comparison between FEMA P-2139-2 and Auto-WoodSDA

Project Name	E-W Direction (Y-axis)				N-S Direction (X-axis)			
	$T_1(\text{sec})$	$V_{\max}/W$	Drift @ 80% $V_{\max}(\%)$	Max Drift(%)	$T_1(\text{sec})$	$V_{\max}/W$	Drift @ 80% $V_{\max}(\%)$	Max Drift(%)
FEMA P-2139-2	0.55	0.44	0.010	0.04	0.54	0.44	0.010	0.04
WoodSDA	0.48	0.46	0.012	0.033	0.44	0.49	0.011	0.04

2.6.4 Nonlinear dynamic analysis result comparison

Analogous to the FEMA P-2139-2 project, 22 pairs of far-field records from FEMA P-695 are used to run the dynamic analysis. Figure 2.12 shows the collapse fragility curve obtained from WoodSDA. The median collapse capacity of 2.48g reported in the FEMA P-2139-2 report is comparable to 2.58g obtained in WoodSDA. The median collapse capacity has been adjusted for the spectral shape factor. The adjustment factor accounts for the uncertainty in the spectral shape and its value is determined per the FEMA P-695’s recommendations (FEMA, 2011b). The empirical median collapse capacities are 1.85g and 1.93g for FEMA P-2139-2 and WoodSDA, respectively. The comparable collapse performance between the state-of-the-art FEMA P-2139-2 study and the WoodSDA platform demonstrates the platform’s ability to produce reliable nonlinear dynamic analysis results while automating the entire process.

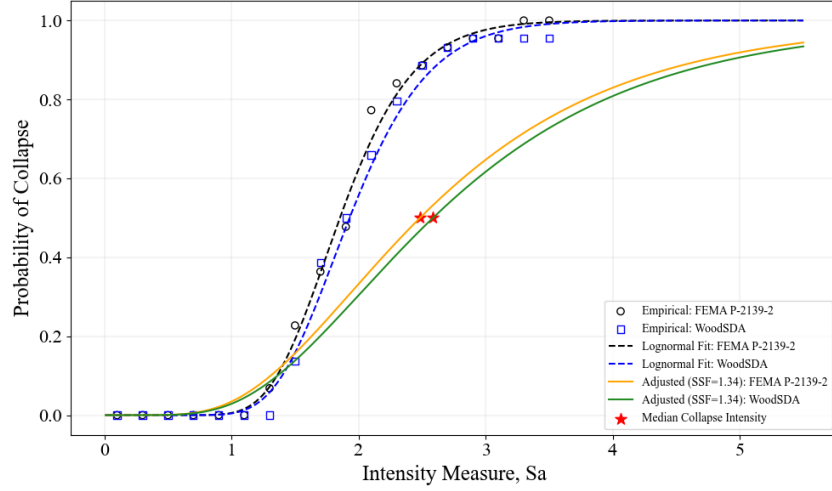


Figure 2.12: Comparison of the collapse fragility curve obtained from the WoodSDA platform with the FEMA P-2139-2 report.

2.6.5 Loss assessment summary

The scope of the FEMA P-2139-2 project was to evaluate the structural performance of the short-period buildings and thus did not assess the losses. To demonstrate the capabilities of WoodSDA, economic losses and recovery time are assessed. The loss module performs component-level damage and loss assessment. The list of components is determined based on the supplemental document published as a part of the FEMA P-58 document series. Specifically, the type and quantities of the components are determined by utilizing the normative database, which assigns each component a unique identifier (i.e., FEMA ID) as well as the governing demand parameter type. Pelicun uses the ID to parse the FEMA fragility database to extract component-level fragility information and perform Monte Carlo simulation-based loss assessment. Installing the Pelicun package automatically downloads the fragility database.

In addition to the EDPs and components list, Pelicun requires a host of input parameters. In this example implementation, the sampling distribution is set to lognormal, the collapse

capacity from Section 2.6.4 is used, the building value is calculated based on a \$387/sqft construction cost, and the replacement time is assumed to be two years. The loss is assessed for 5000 Monte Carlo realizations per intensity level. Figure 2.13 presents the loss curve as a function of the ground motion intensity measure. We can see that beyond the empirical median collapse capacity (1.93g), the replacement cost is triggered because more than 50% of the realizations are flagged as collapse.

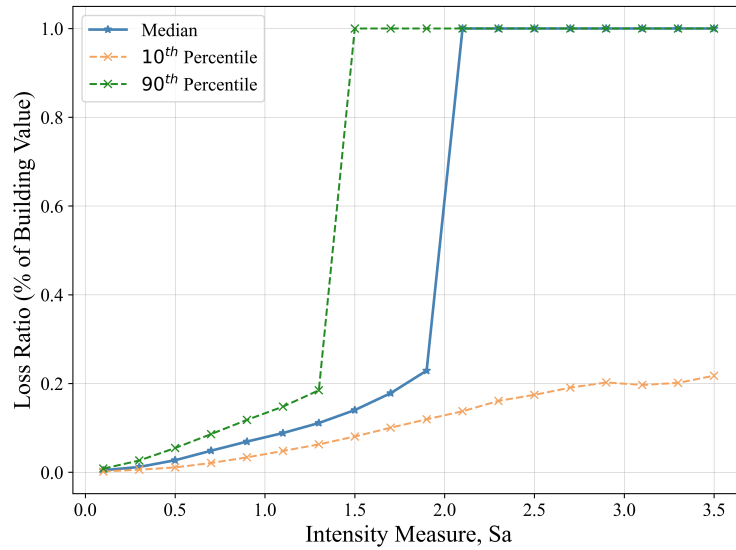


Figure 2.13: Loss curve from AutoWoodSDA

The damage and loss analysis outputs from Pelicun are formatted accordingly and fed into the beta ATC-138 code base. This is an important step because the beta ATC-138 code does not simulate component-level damage states. Since simulated component-level damage states are used, the size of the distribution of recovery time realizations is the same as the repair losses. Figure 2.14 shows the recovery time curve as a function of the ground motion intensity measure. As previously discussed, the ATC-138 functional recovery methodology is considerably extensive and thus requires a significant amount of user input. Some of the inputs include the tenant occupancy type, number of doors and elevators, the inclusion of impedance factors, allowing for temporary repairs, limits on the number of workers per

floor, flooding impact, days to clear a red tag, and the definition of habitability requirements among others. Readers are directed to the GitHub repository for a complete set of user inputs. Figure 2.14 is generated using the default values proposed in the beta ATC-138 source code. Similar to Figure 2.13, the replacement time (2 years) is triggered beyond the empirical median collapse capacity of 1.9g.

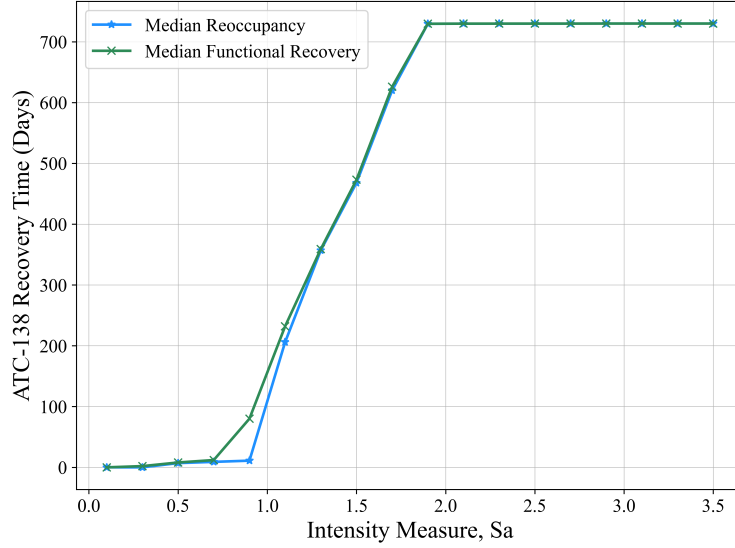


Figure 2.14: Estimated functional recovery time curve for the MFD6B archetype

2.7 Conclusion

This chapter proposed a comprehensive framework for automating seismic design, nonlinear structural analysis, and performance-based assessment. The framework is operationalized as a Python-based computational platform named Auto-WoodSDA (WoodSDA in short). The platform is designed to perform high fidelity (building-, site, and intensity-specific) seismic risk assessment of residential woodframe buildings. It is comprised of four modules: 1) design module, 2) structural module, 3) damage module, and 4) loss module. The modules can be executed independently or sequentially as a part of the end-to-end workflow. Given the

building input information, the design module creates a code-compliant structural design and outputs modeling parameters. Utilizing the modeling parameters, the structural module generates a three-dimensional nonlinear model in OpenSees, simulates nonlinear dynamic structure responses, and processes raw outputs. Subsequently, the damage module performs building-level damage analysis. Finally, the loss module performs component-level damage analysis and assesses loss metrics such as annualized economic loss and time to regain functionality among others. By harnessing automated processes, WoodSDA substantially reduces the overall time (manual time and CPU runtime) it takes to complete a detailed PBEE-type assessment relative to the manual alternative.

The technical and programmatic aspects of WoodSDA are presented in detail. The program is intended to be as generic as possible. It has several useful built-in functionalities such as the ability to specify shear wall assembly details. However, to account for the subjectivity in generating a building design and variability in conducting a PBEE-based design and evaluation, a suite of baseline assumptions is adopted. For instance, real buildings rarely have a perfect quadrilateral footprint. However, for ease of implementation, the WoodSDA footprints are limited to being rectangular or square. To test the end-to-end functionality and validate some of the built-in assumptions, a risk assessment is performed for an example building. The example is adapted from the FEMA P-2139 Volume 2 document that studied the short-period wood light-frame building performance paradox. The results obtained from the WoodSDA program demonstrated that it can reliably implement PBEE-based risk analyses. A comparison between the WoodSDA results and the FEMA P-2139 Volume 2 confirmed that the built-in assumptions are acceptable.

An end-to-end automation program like WoodSDA has tremendous potential and abundant future use cases. From a societal perspective, it is critical for a community to be resilient to natural hazards. Evaluating community resilience requires quantifying seismic risk at a regional scale. Performing large-scale high-fidelity risk assessment without any type of automation is computationally prohibitive, if not impossible. However, an efficient

and scalable tool such as WoodSDA can render high-fidelity regional-scale seismic risk and resilience analysis computationally feasible. Assessing regional seismic impacts is useful for government officials and policymakers in identifying risk-prone neighborhoods and developing programs to support resilience-based objectives. On a national level, WoodSDA has the potential to advance the current state of building codes and standards. By leveraging high-performance computing, WoodSDA can be iteratively executed for large-scale building inventories to investigate the effect of variations in key seismic design parameters (e.g., importance factor (I_e), response modification factor (R) and deflection amplification factor (C_d)) on the ability to achieve resilience-based performance targets.

In this chapter, we have discussed numerous useful features of WoodSDA that will undoubtedly advance the use of automation in computational engineering applications. However, there are some limitations. For instance, WoodSDA designs shear walls by grid lines and as such, requires extensive user inputs. There might be a learning curve in properly defining and formatting the input files. The floor plan is idealized as quadrilateral as the current version cannot deal with buildings that have complex geometry. Due to the lack of experimental data, the shear wall database has a limited number of wall assemblies with corresponding modeling parameters. Finally, the design module cannot deal with perforated walls. While we highlight the limitations, we want to emphasize that the embedded assumptions are in line with state-of-the-art studies such as FEMA P-2139-2.

CHAPTER 3

Quantifying the Effect of Probability Model Misspecification in Seismic Collapse Risk Assessment

3.1 Introduction

Fragility curves are commonly used in modern performance-based earthquake engineering (PBEE) methodologies to quantify probabilistic seismic risk (e.g., ([FEMA, 2012](#))). Component level fragility functions describe the probability of exceeding a damage state of interest conditioned on a response demand (e.g., story drift, peak floor acceleration) level. At the building level, seismic fragility functions relate a ground motion intensity measure (IM) to a limit state of interest (e.g., collapse, post-earthquake structural safety). At either scale, seismic fragility functions are developed using empirical data from experiments, field observations, or data generated from numerical analyses. Regardless of the data generation process, one of several alternative statistical procedures is used to fit an appropriate model. In general, fragility curves can be developed using either parametric or non-parametric approaches. Parametric fragility curves are based on a predefined functional form or probability distribution ([Baker, 2015](#); [Lallemant et al., 2015](#); [Porter et al., 2007](#); [Shinozuka et al., 2000](#)). On the other hand, non-parametric fragilities do not need to conform to a specific functional form or distribution ([Trevlopoulos and Zentner, 2019](#)).

Collapse risk assessment is a central part of the second-generation PBEE procedure. Within this context, fragility functions are used to quantify the probability of collapse conditioned on the IM level. By integrating the fragility function with an appropriate hazard

curve, seismic collapse risk can then be assessed in terms of the mean annual frequency of exceedance or the probability of collapse over some predefined period (e.g., the service life of a building). The lognormal cumulative distribution function (CDF) is commonly used to fit parametric collapse fragilities (Baker, 2015; Lallemant et al., 2015; Bradley and Dhakal, 2008; Porter et al., 2007). The required data can be generated using procedures such as incremental dynamic analyses (IDAs) (Vamvatsikos and Cornell, 2004) or multiple stripe analysis (MSA) (Jalayer, 2003). The IDA procedure incrementally scales each ground motion within a given record set until it causes collapse. The IM level at which collapse occurs for each ground motion is the dataset of interest. The method of moments (Bradley and Dhakal, 2008) is then used to obtain the associated lognormal distribution parameters (θ, β) , where θ defines the median collapse capacity while β is the dispersion or logarithmic standard deviation. The associated CDF is taken as the fragility function. MSA analyzes the structure at pre-defined hazard levels, which are also used as the basis for the ground motion selection. In other words, unlike IDAs, a different suite of motions is selected and used in the analyses at each hazard level. Also, a binary outcome variable (e.g., 0 for non-collapse and 1 for collapse) corresponding to each ground motion and hazard level forms the basis of the MSA collapse data. Maximum likelihood estimation (MLE) is then used to obtain the lognormal distribution parameters that define the collapse fragility. The generalized linear model (GLM) with a Probit link function has been presented as an alternative to the MLE-based approach to estimating fragility parameters (Baker, 2015; Lallemant et al., 2015). However, it is worth noting that the GLM approach also relies on the maximization of the likelihood function. The primary difference between the two procedures is in the definition of the likelihood function. For both methods, a key assumption is that the random variable that describes the number of collapses at each hazard level follows a binomial distribution. In other words, the probability of a certain number of ground motion record(s) causing collapse at a given hazard level is assumed to follow a binomial distribution. This assumption is often made as a matter of mathematical convenience and its implication to the fragility

parameter estimates and the uncertainty around those estimates has never been studied.

Within the PBEE framework, several sources of uncertainty are recognized and, to varying degrees, considered. In collapse risk assessments, record-to-record and modeling uncertainties have been the primary focus of prior research and practice. The former is much more commonly considered by utilizing one or more suites of ground motions for response history analysis (FEMA, 2011b). Modeling uncertainty arises from the limitation in the data and knowledge that is used to develop the numerical model. Bradley (2013) describes four categories of modeling uncertainty denoted as Types I through IV. Type I uncertainty is attributed to a lack of knowledge about the measured values of physical quantities or “basic” parameters (e.g., material strength and modulus). Errors in the models used to relate measured quantities to constitutive models constitute Type II uncertainty. Type III and Type IV modeling uncertainty are related to the chosen constitutive model and system-level idealization. Of the four categories, Types I and II are more commonly addressed in the research literature on seismic collapse risk assessments (Haselton and Deierlein, 2007; Dolsek, 2009; Liel et al., 2009; Asgarian and Ordoubadi, 2016; Gokkaya et al., 2016; Yin and Li, 2010).

A third source of uncertainty that very few studies have addressed is associated with the parameter estimation procedure used to develop fragility functions (denoted as parameter estimation uncertainty in the remainder of the chapter). Building upon previous work, Lallemand and Kiremidjian (2017) derived closed-form confidence intervals for fragility curves based on asymptotic normality. More specifically, uncertainties in the GLM parameter estimates were quantified using the variance-covariance (herein referred to as covariance) matrix of the estimated parameters, which is computed by taking the inverse of Fisher’s information matrix. It is worth noting that this inverse relationship is only valid when the probability model that is attributed to the data is correctly specified (Fisher, 1922). Iervolino (2017) quantified the uncertainty in seismic collapse rates using the Delta method, which is an approximate technique that uses a Taylor series expansion (Oehlert, 1992). Both studies

(Lallemant and Kiremidjian, 2017; Iervolino, 2017) assume the correct specification of the probability model for the collapse data. However, the validity of this assumption and the consequence of model misspecification have not been addressed in the literature in the context of building seismic collapse risk assessments. Other studies (Eads et al., 2013; Pourreza et al., 2021) have implemented various sampling (e.g., Monte Carlo simulation) and re-sampling (e.g., bootstrapping) techniques as a practical approach to quantifying record-to-record and modeling uncertainty in the collapse rate. While sampling is a pragmatic tool to quantify uncertainty, it does not directly address the model misspecification issue. In fact, in the presence of model misspecification, the random samples drawn using the covariance obtained from Fisher’s information matrix are incorrect.

This chapter focuses on the effect of probability model misspecification on collapse fragility parameter estimation and the associated uncertainty. The quasi-maximum likelihood estimator (QMLE) is used to fit collapse fragility functions and quantify the uncertainty in the associated lognormal parameters. We also utilize the fact that QMLE is generally a consistent parameter estimator which minimizes Kullback-Leibler Information Criterion (KLIC) (Kullback and Leibler, 1951). Also known as KL divergence, the KLIC characterizes how far apart the true probability distribution is from the one that is assumed. In other words, minimizing KL divergence ensures that ignorance about the true probability model is minimized. QMLE is sometimes also referred to as the “minimum ignorance” estimator (White, 1982). The uncertainty in the collapse fragility parameters obtained using QMLE is compared to the case where the correct probability model is assumed i.e., using the MLE approach. The next section of the chapter outlines the theoretical properties of QMLE and sandwich estimators. Second, MSA collapse data from four unique single-family wood-frame buildings are used to implement the Information matrix equivalence theorem to identify for misspecification of a parametric model. Each building is analyzed for an existing and retrofitted condition resulting in collapse data for a total of eight buildings. MSA is conducted at 16 different intensity levels with 45 ground motions at each intensity (Yi, 2020).

Collapse risk including the associated parameter estimation uncertainty is quantified using both the MLE and QMLE procedures.

3.2 Huber-White (Robust) Sandwich Estimators

Maximum likelihood is one of the most popular and principled tools used for estimation and inference (Fisher, 1922; Le Cam, 1956). Maximum likelihood relies on a fundamental assumption to ensure its key properties such as consistency (Wald, 1949) and asymptotic normality (Huber, 1967) hold for a broad range of applications. A parameter estimate (for instance, $\hat{\theta}$) is said to be consistent if $\hat{\theta} \rightarrow \theta^0$ as the sample size increases, where θ^0 is the “true” unknown parameter. Similarly, $\hat{\theta}$ is said to be asymptotically normal if $\sqrt{n}(\hat{\theta} - \theta^0)$ converges to a normal distribution with an asymptotic variance of the estimate i.e. $\sqrt{n}(\hat{\theta} - \theta^0) \rightarrow \mathcal{N}(0, \sigma_{\theta^0}^2)$. The assumption in MLE is that the stochastic law that determines the behavior of the phenomena investigated (the “true” probability model) is known to lie within a specified parametric family of probability distributions (herein referred to as the model). In other words, the probability model is assumed to be “correctly specified”. With respect to MLE-based parameter estimation in seismic collapse risk assessments, the lognormal probability distribution is assumed to govern the conditional probability of collapse. In many (if not most) circumstances, there may not be complete confidence in the validity of the assumption. The “Huber Sandwich Estimator” (herein referred to as sandwich estimator(s)) is a framework used to estimate the variance of the QMLE (or parameter estimation uncertainty). When the underlying probability model is incorrect, pseudo-likelihood is being maximized instead of the true likelihood. The estimators are also commonly referred to as pseudo-maximum likelihood estimators or simply QMLE. White (1982) showed that QMLE converges to a well-defined limit and meets the important properties of MLE such as consistency and asymptotic normality (Le Cam, 1956; Huber, 1967; Wald, 1949). It is also shown that, with misspecification, the asymptotic variance matrix of the QMLE no

longer equals the inverse of Fisher's information matrix. It is an important finding because being able to correctly specify the variance matrix is pivotal to data-driven function-fitting approaches. For instance, in parametric bootstrapping, the correctness of the parameters has a direct impact on the accuracy of the result.

When fitting a fragility, the likelihood function defines the probability that a random ground motion record causes collapse at a given IM level. The likelihood is assumed to follow a lognormal probability distribution function. This assumption is sufficient to estimate the mean values of the lognormal distribution parameters (θ, β) . However, the assumption that the probability model is correctly specified can influence the parameter estimation uncertainty.

3.3 Parameter Estimation Uncertainty in Collapse Fragility Functions

3.3.1 Maximum likelihood method

A fragility function defines the conditional probability of collapse as a function of the IM level. It can also be extended to other limit states such as different damage stages but only collapse is considered in the current study. The conditional probability of collapse is described by a lognormal CDF as shown in Eq. (3.1).

$$P(C|IM = im) = \Phi \left(\frac{\ln(im/\theta)}{\beta} \right) \quad (3.1)$$

where $P(C|IM = im)$ is the probability of collapse conditioned on $IM = im$, θ and β are the median and standard deviation of $\ln(IM)$, respectively, and Φ is the CDF of the standard normal distribution. The parameters that define the fragility function are θ and β . Various statistical procedures can be used to obtain the parameter estimates $\hat{\theta}$ and $\hat{\beta}$. A primary goal of the current study is to compare the central tendency values and associated uncertainty when MLE and QMLE are used to determine $\hat{\theta}$ and $\hat{\beta}$. Since the collapse data

is assumed to follow a binomial distribution, the probability of k collapses out of n ground motions at the j^{th} IM level with probability p_j is given by

$$P(k_j \text{ collapses in } n_j \text{ ground motions}) = \binom{n_j}{k_j} \cdot p_j^{k_j} (1 - p_j)^{n_j - k_j} \quad (3.2)$$

Assuming independence in the probability of k collapses out of n ground motions, the likelihood function considering m IM levels is given by

$$L(\theta, \beta) = \prod_{j=1}^m \binom{n_j}{k_j} \Phi \left(\frac{\ln(IM_j/\theta)}{\beta} \right)^{k_j} \cdot \left[1 - \Phi \left(\frac{\ln(IM_j/\theta)}{\beta} \right) \right]^{n_j - k_j} \quad (3.3)$$

Taking log on both sides of Eq. (3.3) gives the log-likelihood function as shown in Eq. (3.4). The log-likelihood function is used because it is easier to maximize using numerical optimization methods. The estimate of the fragility function parameters $(\hat{\theta}, \hat{\beta})$ is obtained by maximizing the log-likelihood function as shown in Eq.(3.5).

$$\ell(\theta, \beta) = \arg \max_{\theta, \beta} \sum_{j=1}^m \left\{ \ln \binom{n_j}{k_j} + k_j \ln \left[\Phi \left(\frac{\ln(IM_j/\theta)}{\beta} \right) \right] + (n_j - k_j) \ln \left[1 - \Phi \left(\frac{\ln(IM_j/\theta)}{\beta} \right) \right] \right\} \quad (3.4)$$

$$\{\hat{\theta}, \hat{\beta}\} = \arg \max_{\theta, \beta} \ell(\theta, \beta) \quad (3.5)$$

To quantify parameter uncertainty, the Score, Hessian, and Information matrix are needed. For optimization and inference of Eq. (3.5), the Score is used. By setting the gradient equal to zero and solving for the parameters of interest, the log-likelihood function is maximized. The Hessian is a symmetric matrix of second-order partial derivatives with respect to the parameters of interest. The negative expectation of the Hessian gives the Fisher's Information matrix. Under correct probability model specification, the inverse of the Information matrix gives the covariance terms of the estimated parameters (Fisher, 1922). In the context of seismic collapse risk assessments, the “probability model” refers to the lognormal distribution. Even though the collapse data is characterized by the binomial distribution, this part of the likelihood function is a constant and therefore does not influence the maximization. However, as shown in Eq. (3.4), the likelihood maximization is affected

by the lognormal distribution with feasible parameter estimates $\hat{\theta}$ and $\hat{\beta}$. In other words, the quantities of interest are the lognormal distribution parameters.

To compute the first and second-order partial derivative of the log-likelihood function, $(\ell(\theta, \beta))$, the Gauss error function ([Andrews, 1998](#)) is needed. The log-likelihood function is rewritten using the error function as shown in Eq. (3.6). The log-likelihood functions in Eqs. (3.4) and (3.6) are numerically equivalent.

$$\ell(\theta, \beta) = \sum_{j=1}^m \left\{ k_j \ln \left[\frac{1}{2} \left(1 + \operatorname{erf} \left(\frac{\ln \left(\frac{IM_j}{\theta} \right)}{\beta \sqrt{2}} \right) \right) \right] + (n_j - k_j) \ln \left[1 - \frac{1}{2} \left(1 + \operatorname{erf} \left(\frac{\ln \left(\frac{IM_j}{\theta} \right)}{\beta \sqrt{2}} \right) \right) \right] \right\} \quad (3.6)$$

In Eq. (3.6), $\ln \binom{n_j}{k_j}$ has been neglected because it is a constant term that “drops out” when taking first and second-order partial derivatives. The Score, $S(\theta, \beta)^\top$, which is computed by taking the first-order partial derivative of Eq. (3.6), is shown in Appendix B.1.1. The complete derivative terms with respect to each parameter can also be found in Appendix B.1.1. Similarly, the Hessian, $H(\theta, \beta)$, is a square matrix obtained by taking the second-order derivative of the log-likelihood function. The matrix formulation and complete second-order derivative terms are shown in Appendix B.1.2. Both the Score and Hessian will later be used to calculate the sandwich estimator. As discussed earlier, Fisher’s Information matrix is given by negative Hessian under correct specification i.e., $I(\theta, \beta) = -\mathbb{E}[H(\theta, \beta)]$. Subsequently, the covariance matrix of the parameter estimates is given by the inverse Information matrix as shown in Eq. (3.7) ([Fisher, 1922](#)).

$$\operatorname{Var}(\theta, \beta) = I^{-1} = \begin{bmatrix} \sigma_\theta^2 & \sigma_{\theta, \beta} \\ \sigma_{\beta, \theta} & \sigma_\beta^2 \end{bmatrix} \quad (3.7)$$

3.3.2 Generalized linear models

A Generalized Linear Model (GLM) with a link function is presented as an alternative to the maximum likelihood method to fitting the fragility function ([Lallemant et al., 2015](#)). The inverse Probit link function links the conditional mean probability of collapse to a linear predictor (π). The inverse Probit uses the standard normal CDF which makes it equivalent

to the methodology outlined in section 3.3.1. Other link functions such as Logit link can also be implemented. The GLM model is presented as an easy-to-implement alternative to maximizing the log-likelihood function with lognormal CDF. The GLM estimator is readily available in popular programming languages such as Python, R, and MATLAB. It fits the fragility function by finding the coefficients of the linear predictor that maximizes the likelihood function. Most programming languages use the iteratively re-weighted least squares (IRLS) ([Green, 1984](#)) optimization algorithm to find the coefficients. IRLS is essentially an L1-norm-based minimization that reduces the contribution of large residuals and improves the data fitting process. Additionally, most programs provide an option to extract the Score and Hessian which makes it an attractive alternative to MLE. Here, “MLE” is loosely used to represent the methodology described in section 3.3.1. It is acknowledged that GLM also uses a maximization (or minimization of negative likelihood) algorithm and could technically be called MLE. The upside of the GLM is that it does not require an initial guess unlike MLE and the downside is that the parameters in the linear predictors (β_0, β_1) as shown in Eq. (3.8) are not as directly descriptive as MLE parameters, θ and β , where θ defines the IM level with 50% probability of collapse and β describes the dispersion around the median. The GLM model is defined as shown in Eq. (3.8)

$$P(C|IM) = g^{-1}(\pi) = \Phi(\beta_0 + \beta_1 \ln(IM)) = g^{-1}(\beta_0 + \beta_1 \ln(IM)) = \Phi\left(\frac{\ln(IM)}{\beta} - \frac{\ln(\theta)}{\beta}\right) \quad (3.8)$$

where, $g(\cdot)$ is the link function that connects $P(C|IM)$ to the linear predictor, π . Using the lognormal CDF formulation of the probability of collapse, the linear predictor parameters, β_0 and β_1 can be transformed into lognormal CDF parameters. The transformation is performed by equating the terms inside the normal CDF, $\Phi(\cdot)$. On the left-hand side in Eq. (3.8), the term with the random variable, $\beta_1 \ln(IM)$, is equated with $\ln(IM)/\beta$ on the right-hand side.

Similarly, equating the intercepts on both sides yields the result as shown in Eqs. (3.9).

$$\theta = e^{\frac{-\beta_0}{\beta_1}} \quad (3.9a)$$

$$\beta = \frac{1}{\beta_1} \quad (3.9b)$$

One of the easy-to-use features of GLM fit is that the Hessian can easily be extracted. To quantify uncertainty in the linear predictor parameters (β_0, β_1) , the inverse of Fisher's information matrix is used. Since the primary focus of this study is to make a comparison between MLE and QMLE, the uncertainty in the linear predictor is transformed into the uncertainty in the median (θ) and standard deviation (β) using first-order Taylor approximation. In addition to transforming the uncertainty from GLM-based parameters to the MLE-based parameters, Eqs. (3.10a and 3.10b) are also used to verify the covariance matrix obtained using the error function.

$$Var[\theta] = \sigma_{\beta_0}^2 \left(\frac{\partial \theta}{\partial \beta_0} \right)^2 + \sigma_{\beta_1}^2 \left(\frac{\partial \theta}{\partial \beta_1} \right)^2 + 2\sigma_{\beta_0, \beta_1} \frac{\partial \theta}{\partial \beta_0} \frac{\partial \theta}{\partial \beta_1} \quad (3.10a)$$

$$Var[\beta] = \sigma_{\beta_1}^2 \left(\frac{\partial \beta}{\partial \beta_1} \right)^2 \quad (3.10b)$$

3.3.3 Uncertainty in collapse risk

The mean annual frequency of collapse (λ_c) is used as a risk-based performance metric. It is calculated either by integrating the continuous fragility function with the ground motion hazard curve or using the Riemann Sum as shown in Eq. (3.11). The Riemann sum is widely used to approximate an integral using a finite sum. To minimize the approximation error, the collapse probability is taken as the mid-point of im_i and im_{i+1} as shown in Eq. (3.11) below

$$\lambda_c = \int_{im} P(C|IM = im) \cdot |d\lambda_{IM}(im)| = \sum_{i=1}^N P(C|im) \cdot |\lambda(im_i) - \lambda(im_{i+1})| \quad (3.11)$$

where im is the mid-point between im_i and im_{i+1} , N is the total number of increments from IM_{min} to IM_{max} , and $\lambda_{IM}(im)$ is the mean annual frequency of exceedance of ground

motion intensity, im . Finally, the variance of the annual collapse rate is estimated as shown in Eq. (3.12) (Lallemant et al., 2015).

$$\sigma_{\lambda_c}^2 = \sum_{i=1}^N \sum_{j=1}^N |\lambda(im_i) - \lambda(im_{i+1})| |\lambda(im_j) - \lambda(im_{j+1})| \rho_{ij} \sigma_{P(C|im)_i} \sigma_{P(C|im)_j} \quad (3.12)$$

where the variance of the probability of collapse is approximated using the first-order Taylor approximation and $\rho_{ij} = 1$.

$$\sigma_{P(C|im_i)}^2 = \frac{\partial \Phi(\pi)}{\partial \pi} \sigma_{\pi}^2(im) \quad (3.13)$$

To approximate the variance of the collapse probability, the variance of the linear predictor is required. Eq. (3.14) (Lallemant et al., 2015) gives the variance of the linear predictor. It is important to note that the covariance in Eq. (3.7) assumes correct model specification. Eq. (3.14), thus, highlights the propagation of parameter estimation uncertainty into collapse risk.

$$\sigma_{\pi}^2(im) = \sigma_{\beta_0}^2 + \sigma_{\beta_1}^2 \ln(im)^2 + 2 \ln(im) \sigma_{\beta_0 \beta_1} \quad (3.14)$$

In a probabilistic sense, the collapse of a building is an event that occurs continuously and independently with a known mean frequency of occurrence (λ_c). In other words, the probability distribution of the time between two events follows a Poisson process. Since it follows a Poisson process, the probability of collapse over T years is based on the cumulative distribution function of the exponential distribution.

3.4 Effect of Model Misspecification

MLE is a flexible tool to estimate the parameters, but the fundamentals are often rooted in assumptions. The likelihood function is based on an underlying assumption that the data is known to lie within a specified parametric family of probability distributions. Misspecification can oftentimes lead to misleading inferences. In the presence of misspecification, standard tests such as the Wald test, Likelihood Ratio test, and Lagrange Multiplier/Score test are invalid. However, if a conditional mean component is correctly specified, QMLE

converges to a well-defined limit and is often consistent for the parameters of interest. The variance around the parameter estimates does not equal the inverse of Fisher's information matrix. The "robust" variance estimator is computed using sandwich estimators. In this section, some of the important properties of QMLE are highlighted. These properties are the basis of MLE and are important to the validity of QMLE. The theoretical results presented in this subsection are based on [White \(1982\)](#).

3.4.1 Existence of maximum likelihood parameters

Assuming that the independent random vector U has a distribution function G on Ω and a measurable Euclidean space with density g , we let f be the density drawn from a family of distribution functions $F(u, \theta)$ for every θ . Since G is unknown, F may or may not contain the true probability distribution. The quasi-log-likelihood of the sample is

$$L(U, \theta) = \sum_{i=1}^n \log f(U_i, \theta) \quad (3.15)$$

Maximizing Eq. (3.15) gives QMLE estimators as parameter estimates. Proof that for all n , there exists a measurable estimator, $\hat{\theta}_n$ can be found in [White \(1982\)](#). θ is a natural estimator for θ^* , the parameter estimate that minimizes the Kullback-Leibler Information Criterion ($I()$) also referred to as KL divergence. KL divergence characterizes how far the assumed distribution (f) is from the true distribution (g). In other words, it measures our ignorance about the true distribution. It is important to note that divergence is not the same as distance. Divergence does not meet the symmetric property of distance. Since the divergence is formulated in log space as shown in Eq. (3.16), the order of f and g matters. The divergence of f from g would not be the same as the divergence of g from f .

$$I(g : f, \theta) = \mathbb{E}[\log(g(U)/f(U, \theta))] = \int \log(g(u))dG(u) - \log(f(u, \theta))dG(u) \quad (3.16)$$

Assuming that $I(g : f, \theta)$ has a unique minimum as θ^* , the QMLE estimate, $\hat{\theta}$ converges to θ^* as $n \rightarrow \infty$. This convergence signifies that QMLE is a strongly consistent estimator for

θ^* . In other words, it ensures we minimize our ignorance about the structure of the true probability model. If the probability model is correctly specified (i.e. $g(u, \theta) = f(u, \theta)$), for some θ^0 , then $I(g : f, \theta)$ achieves its unique minimum at $\theta^* = \theta^0$, so that $\hat{\theta}$ is consistent for the true parameter estimates, θ^0 .

3.4.2 The Information matrix test for misspecification

White (1982) showed that the QMLE is asymptotically normally distributed

$$\sqrt{n}(\hat{\theta} - \theta^*) \sim N(0, A(\theta)^{-1}B(\theta)A(\theta)^{-1}) \quad (3.17)$$

where $A(\theta)$ and $B(\theta)$ are called sandwich estimators and can be computed as

$$A(\theta) = \frac{1}{n} \sum_{t=1}^n \frac{\partial^2 \log f(u_t, \theta)}{\partial \theta_i \partial \theta_j} = H(\theta) \quad (3.18a)$$

$$B(\theta) = \frac{1}{n} \sum_{t=1}^n \frac{\partial \log f(u_t, \theta)}{\partial \theta_i} \cdot \frac{\partial \log f(u_t, \theta)}{\partial \theta_j} = S(\theta)S(\theta)^\top \quad (3.18b)$$

The information matrix equivalence theorem essentially says that when the model is correctly specified, the information matrix can be expressed in either Hessian form, $-A(\theta)$, or the outer product form $B(\theta)$. In other words, the equality condition to identify model misspecification can be formulated simply as

$$A(\theta) + B(\theta) = 0 \quad (3.19)$$

When the equality holds, the asymptotic normality shown in Eq. (3.17) simplifies to

$$\sqrt{n}(\hat{\theta} - \theta^*) \sim N(0, A(\theta)^{-1}) \quad (3.20)$$

When the equality in Eq. (3.19) fails, it is concluded that the model is misspecified. One of the many ways to check the severity of misspecification is to analyze the variance estimator obtained from $A(\theta)^{-1}B(\theta)A(\theta)^{-1}$.

3.5 Case Study

To study the effect of model misspecification, collapse data from the MSA of eight wood-frame buildings are used. The single-family archetypes were developed as part of the Pacific Earthquake Engineering Research (PEER) Center and California Earthquake Authority (CEA) project (Welch and Deierlein, 2020b) on cripple wall residential buildings. The objective of the project was to quantify the benefit of retrofitting unbraced cripple walls in high seismic regions. The overall building dimension was 40ft×30ft. As part of the PEER-CEA project, various structural properties that influence the performance of the building such as cripple wall height, interior panel sheathing material, seismic weight, and the number of stories were considered to create 64 distinct building archetypes (Reis, 2020). Table 3.1 summarizes the characteristics of the four variants considered in the current study. Wood structural panels are used to retrofit the unbraced and unbolted cripple wall, which represents a soft-story vulnerability. For the retrofitted buildings, the wood structural panels are placed at the two ends of each line of cripple walls. The length of the structural panels varies based on the FEMA P-1100 specification (FEMA, 2019). Additional details about the variants and their associated retrofits can be found in Reis (2020) and Welch and Deierlein (2020b).

Table 3.1: Description of wood-frame buildings

Building Name	No. of Stories	Description
B1-Existing	1	Stucco exterior, gypsum wallboard interior with 2ft high stucco cripple wall
B1-Retrofitted	1	B1-Existing retrofitted with 2ft tall wood-frame shear wall
B2-Existing	1	Stucco exterior, gypsum wallboard interior with 6ft high stucco cripple wall
B2-Retrofitted	1	B2-Existing retrofitted with 6ft tall wood-frame shear wall
B3-Existing	2	Stucco exterior, gypsum wallboard interior with 2ft high stucco cripple wall
B3-Retrofitted	2	B3-Existing retrofitted with 2ft tall wood-frame shear wall
B4-Existing	2	Stucco exterior, gypsum wallboard interior with 6ft high stucco cripple wall
B4-Retrofitted	2	B4-Existing retrofitted with 6ft tall wood-frame shear wall

Three-dimensional structural models of one-story and two-story cripple wall buildings are constructed and nonlinear dynamic analyses are performed using the Open System of Earthquake Engineering Simulation (*OpenSEES*) (Mazzoni et al., 2006). Hysteretic shear spring elements are placed at the centroid of the cripple walls to simulate their force-displacement behavior. Two parallel Pinching4 hysteretic springs are used to capture the wide range of cyclic behavior between the near elastic (small displacement) response and the highly nonlinear post-peak behavior at large displacements. Each building was subjected to 16 different hazard levels with 45 ground motions at each individual hazard level. The spectral acceleration corresponding to a period of 0.25 seconds ($Sa_{0.25s}$) is used as the IM. The ground motions were also selected as a part of the PEER-CEA project for a set of ten sites (Mazzoni et al., 2020). The ground motion records used to produce analysis results are based on a San Francisco site with stiff soil (Soil D) and a target upper 30-meter shear wave velocity (V_{S30}) of 270 m/s. Figure 3.1. summarizes the median collapse intensity and dispersion values obtained by implementing MLE. As expected, the retrofitted buildings have higher median collapse capacities. The dispersion, which quantifies record-to-record uncertainty, is generally comparable between the existing and retrofitted cases. It is interesting to note that the median collapse capacity of the retrofitted two-story building with a 6ft tall wood-frame shear wall (B4) is almost the same as the retrofitted two-story building with a 2ft tall shear wall (B3).

Assuming correct specification, variance estimators are computed using Eq. (3.7). The variance around the parameter estimates (i.e., $\text{Var}(\theta)$ and $\text{Var}(\beta)$) is summarized in Figure 3.2. For comparison, a standardized measure of variability, coefficient of variation (CV) is used. The CV is calculated by taking the ratio of standard deviation to the mean values. Comparable CV of the median collapse intensity for the existing and the retrofitted buildings as shown in Figure 3.2a implies that retrofitting the building neither increases nor decreases the relative dispersion around the median value. With the exception of building B2, Figure 3.2b shows that a similar conclusion can be drawn about the relative dispersion

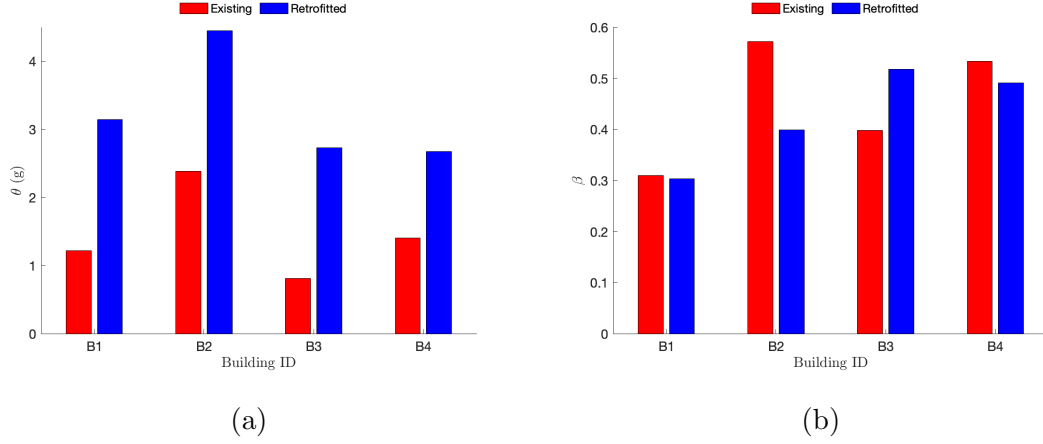


Figure 3.1: (a) Median and (b) log standard deviation of the collapse intensity for all four existing and retrofitted building cases

around the log standard deviation.

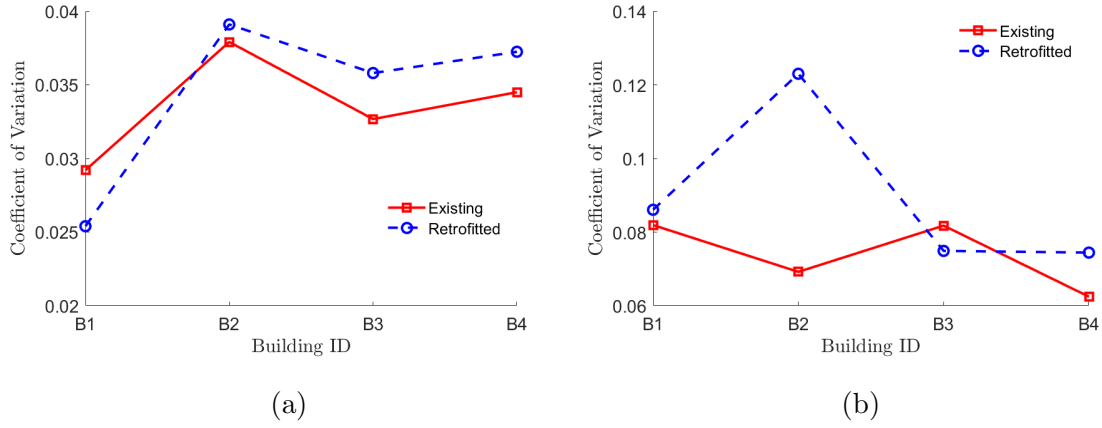


Figure 3.2: Coefficient of variation for (a) the median and (b) log standard deviation under correct specification assumption.

To better understand the uncertainty around the parameter estimates, data from building B2 is used to plot their probability density function (PDF). Figure 3.3a and Figure 3.3b show the PDF of the median and dispersion respectively. The result shows that most of the probability density is concentrated around the mean value in the existing case. For the retrofitted case, the probability density is more distributed implying higher levels of

dispersion, though the increase is not substantive. Similarly, the PDF of the log standard deviation shows a slightly broadened tail for the retrofitted case which explains the higher CV as highlighted in Figure 3.2b. Analogous results were obtained for the rest of the buildings as well where slightly spiked probability density was observed for the median value and more evenly distributed probability density for the log standard deviation. Figure 3.3 also shows the PDF (dashed lines) of the parameter estimates obtained using the sandwich estimators.

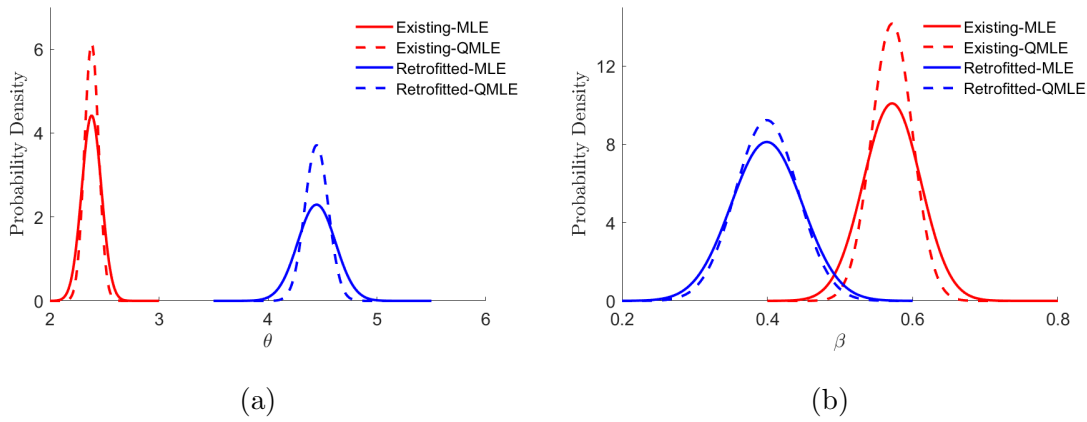


Figure 3.3: Normal PDF showing the distribution of the (a) median and (b) log standard deviation of the collapse capacity for the B2 building.

3.5.1 Effect of model misspecification in fragility function fitting

As shown in Eq. (3.5), MLE is implemented to estimate the lognormal distribution parameters $(\hat{\theta}, \hat{\beta})$. Following the setup outlined in Appendix B.1, the score and the Hessian are computed. Assuming that the lognormal probability distribution is the “true” probability model (i.e., correct specification), an asymptotic covariance matrix is computed. As shown in Eq. (3.20), the covariance matrix equals the inverse of the negative Fisher’s Information matrix. With known variability in the parameter estimates, the uncertainty in the fragility curve is quantified by establishing a confidence interval. Figure 3.4. shows the fitted fragility

curve in black for building B2-Existing along with the empirical probability of collapse data points in green. It is found that the 95% confidence interval provides a good range by bounding almost all of the empirical data.

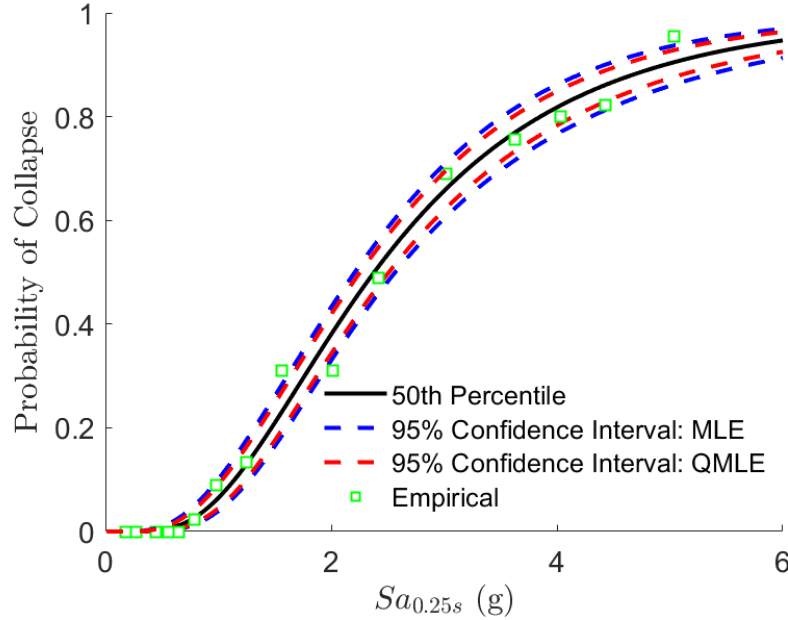


Figure 3.4: Fitted fragility curve for an example building (B2-existing) with 95% confidence interval.

In addition to quantifying the parameter estimation uncertainty, several other techniques are also presented as an alternative to computing the Hessian matrix. The second-order derivative terms of the error function-based likelihood with respect to its parameters are used to formulate the Hessian matrix. The purpose of presenting multiple methods of computing the Score and the Hessian is two-fold: (1) verifying the rigorousness of the error function formulation and (2) presenting an alternative methodology that can be easily implemented in programming languages such as Python, R, and MATLAB. In addition to computing the error function-based covariance matrix, two supplemental methodologies to compute covariances are also presented: (1) Taylor approximation and (2) Numerical integration

using built-in packages.

The Taylor series expansion is used to obtain a first-order second-moment approximation of the parameter estimates. Eqs. (3.10-3.14) shows the steps used to estimate the variance in θ and β . The values obtained should approximately be equal to the variance terms as shown in Appendix B.2.2. Additionally, built-in numerical differentiation tools in programming languages such as Python and R are also used to extract the Hessian. In Python, the “numdifftools” package (Walter and Lehmann, 2013) is used to estimate the Hessian and the Score (Jacobian). Numdifftools uses the complex-step method of numerical differentiation. Similarly, in R, the optimization package “optim” (Nash et al., 2011) returns a numerically differentiated Hessian matrix. For all eight buildings analyzed, the Hessian matrix is found to be consistent regardless of the method, or the built-in package used to compute it.

After the Hessian and the Score are verified to be correct, they are used to assess the equality condition outlined in Eq. (3.19). The sandwich estimators shown in Appendix B.2.1 demonstrate the result obtained for B2-Existing. The results show that the equality condition does not hold, i.e. $A(\theta) + B(\theta) \neq 0$. It is found that none of the eight buildings meet the equality condition. The result signifies the prevalence of model misspecification in the maximum likelihood method used to get the lognormal distribution parameters (θ, β) .

The severity of misspecification is determined by analyzing the values obtained from $A(\theta)^{-1}B(\theta)A(\theta)^{-1}$. Appendix B.2.2 shows the covariance matrix computed based on the inverse of the Fisher’s information matrix (MLE) and the sandwich estimators (QMLE). The comparison shows that the parameter variances obtained using sandwich estimators are approximately half that of the case where the inverse Fisher’s information matrix is used. Figure 3.5 summarizes the CV values for the respective parameter estimates using the sandwich estimators. On average, the CV of the median for the existing building tends to be higher compared to the retrofitted counterpart while the CV of the logarithmic standard deviation does not follow any specific pattern. The results from Figure 3.2a and Figure 3.5a show that the CV of the median collapse capacity obtained from the sandwich estimator

(QMLE) ranges from 42% to 70% that of the MLE case. Similarly, Figure 3.2b and Figure 3.5b indicate that the CV of the log standard deviation computed using QMLE is 48–88% of the corresponding values from MLE. In other words, the parameter estimation dispersion in $\hat{\theta}$ and $\hat{\beta}$ is generally lower when probability model misspecification is considered.

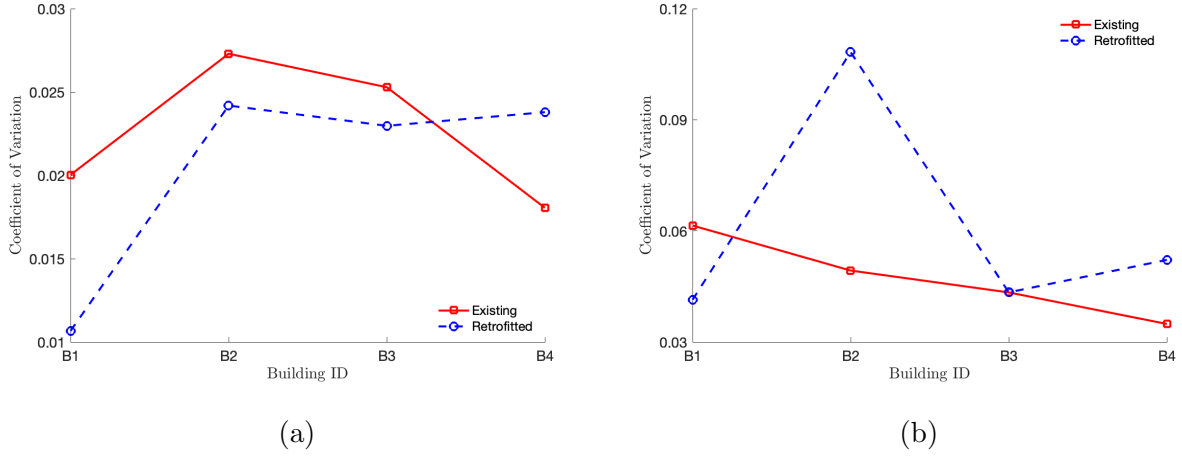


Figure 3.5: Coefficient of variation of the (a) median and (b) log standard deviation computed using sandwich estimators.

3.5.2 Effect of model misspecification in collapse risk

As shown in Eq. (3.11), the mean annual frequency of collapse is computed using the estimated fragility function parameters. Figure 3.6 shows the estimated value of the collapse rate for all buildings (existing and retrofitted). Consistent with our prior knowledge of the physical implications, the retrofitted buildings have lower collapse rates which indicates enhanced performance. We also propagate the parameter estimation uncertainty in the fragility to the collapse rate. More specifically, the covariance matrix corresponding to θ and β obtained from the inverse Fisher's information matrix is used to quantify the parameter estimation uncertainty in the collapse rate (Eqs. 3.12-3.14). To assess the impact of model misspecification, the covariance matrix obtained from the sandwich estimator is also used. Figure 3.7 summarizes the CV values for the collapse rate from MLE and QMLE. Figure 3.7a

shows the results computed assuming the correct specification (MLE) while Figure 3.7b summarizes the results obtained using the sandwich estimator (QMLE). Both figures show that the standardized dispersion in the collapse rate appears to be higher in all the retrofitted cases as compared to the existing buildings. In terms of the effect of misspecification, the net result is that the CV in the collapse rate obtained from QMLE ranges from approximately 40 – 80% of the MLE values.

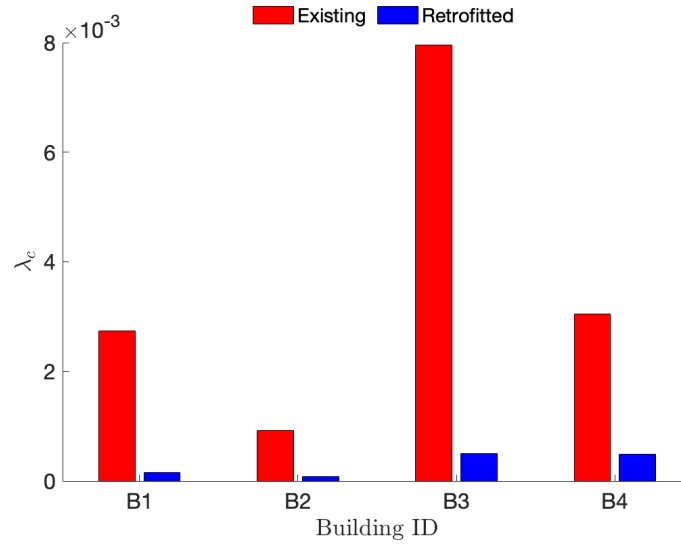


Figure 3.6: Estimated mean annual frequency of collapse for all building cases.

3.5.3 Bootstrapping

In addition to the procedures described in Section 3.3, sampling or resampling techniques are used to quantify the uncertainty in the collapse risk. Monte Carlo simulation is used to draw random samples utilizing fragility parameters and covariance estimates as shown in Eqs. (3.10 and 3.9). The Monte Carlo method can be used as a stand-alone technique. However, in this study, the simulated samples are resampled with replacement. In essence, the random sample generated from Monte Carlo is treated as a population from which a finite number of samples are drawn. It is important to note that the variance is inversely

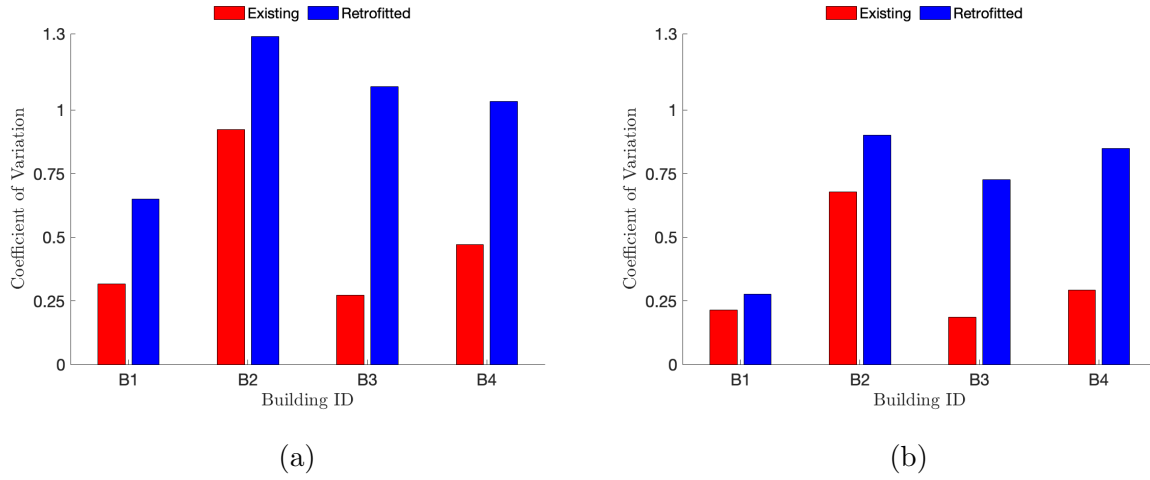


Figure 3.7: Comparison of coefficient of variation of the collapse rate computed using (a) asymptotic variance estimators and (b) sandwich estimators

related to the number of realizations. In other words, it is possible to fine-tune the variability in the random samples by drawing a large number of realizations. To negate subjectivity, 500 samples are drawn as was done in previous studies ([Iervolino, 2017](#); [Trevlopoulos and Zentner, 2019](#)). Figure 3.8a shows the empirical distribution of fragility curves obtained from Monte Carlo simulation for the B2-Existing building and Figure 3.8b presents a comparison for the standard-deviation of the collapse rate for all buildings. In Figure 3.8a, we see that the central tendency of the Monte Carlo samples averages to the empirical fragility curve shown in Figure 3.4. Also, Figure 3.8b highlights that the standard deviation computed using Eq. (3.12) is generally equivalent to the one obtained from the bootstrapping method.

3.6 Conclusion

This chapter discussed the effect of probability model misspecification on fragility function parameter estimates. More specifically, the effect of model misspecification is propagated into seismic collapse performance and risk assessment to study the effect on parameter estimation uncertainty. The successful application of quasi-maximum likelihood estimation

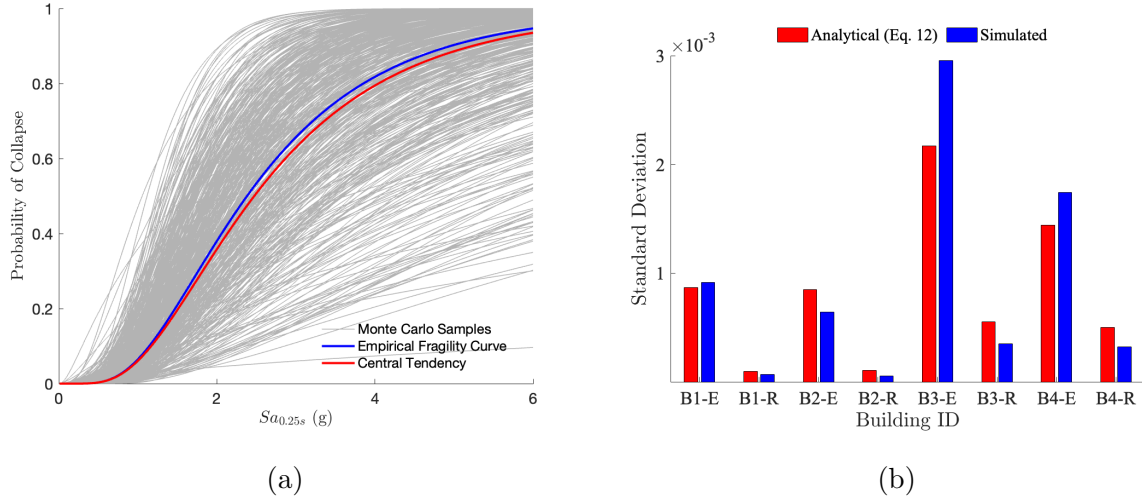


Figure 3.8: (a) Monte Carlo fragility samples for B2-Existing. b) Comparison of standard deviation computed using Taylor approximation and bootstrapping method

(QMLE) requires “sandwich” estimators that rely on the Jacobian (Score) and Hessian of the likelihood function. The Hessian is computed using the error function and is verified using two different approaches (1) Taylor approximation and (2) Numerical integration using a built-in software package. The information matrix equality test performed on collapse data from single-family woodframe buildings showed that model misspecification is present. The implication of the collapse fragility was evaluated by comparing the coefficient of variation (CV) of the median ($\hat{\theta}$) and log standard deviation ($\hat{\beta}$), which represent the parameter estimation uncertainty. For $\hat{\theta}$, the CV obtained from QMLE, was, on average, 38% lower than the case where maximum likelihood estimation (MLE) is used. Similarly, the average ratio between the CV of $\hat{\beta}$ from QMLE and MLE was 64%. The fragility parameter estimation uncertainty was also propagated into the collapse risk assessment using analytical (Reiman Sum) and sampling (Monte Carlo Simulation) approaches, which produced comparable results. Compared to when MLE was used, the CV of the mean annual frequency of collapse due to parameter estimation uncertainty was computed to be 17 – 58% lower in the QMLE case.

MLE and other parameter estimation approaches such as Generalized Linear Models are commonly used in research and practice with the assumption that the probability model is correctly specified which might not always be the case. Oftentimes, the assumption about the "true" model introduces additional uncertainty in the parameter estimates. This chapter demonstrated the use of the Information equality test to identify probability model misspecification and quantify its effect on collapse risk. In the current study, a robust consideration of misspecification was found to generally reduce the parameter estimation uncertainty in collapse risk compared to when the correct probability model is assumed. However, it is important to note that only a single construction type (woodframe residential buildings) and limit state (collapse) was considered. Additional studies are needed where the effect of probability model misspecification on parameter estimation uncertainty for other construction types (e.g., steel and concrete moment frames) and limit states (e.g., demolition, post-earthquake safety, and functionality) is evaluated. If there are situations where a robust consideration of model misspecification leads to an increase in parameter estimation dispersion (e.g., [Fay et al. \(1998\)](#)), this additional uncertainty should be considered in the associated risk assessment.

Table 3.2: Summary of important theorems implemented in QMLE

Theorem	Description
Consistency Theorem	Assuming that (1) the probability density, $f(U_i, \theta)$ is observable and (2) the density is twice continuously differentiable on θ , as $n \rightarrow \infty$, $\hat{\theta}_n \rightarrow \theta^*$. The QMLE is a consistent estimator of the “true” parameter values (θ^*) which minimizes the KL divergence.
Asymptotic Distribution Theorem	As $n \rightarrow \infty$, $\sqrt{n}(\hat{\theta}_n - \theta^*)$ converges to a zero-mean Gaussian distribution with non-singular covariance matrix $A(\theta)^{-1}B(\theta)A(\theta)^{-1}$. If the probability model is correctly specified i.e., $A(\theta) = -B(\theta)$, the covariance matrix is simply represented by $A(\theta)^{-1}$. Hence, the asymptotic distribution is a zero-mean Gaussian with $A(\theta)^{-1}$ covariance matrix.
The Information Matrix Equivalence Theorem	If the Hessian matrix-based covariance matrix ($A^{-1}(\theta)$) and gradient-based covariance matrix ($B^{-1}(\theta)$) are asymptotically different, it indicates the presence of model misspecification. In other words, $A(\theta) + B(\theta) = 0$ can be used as a basis for the identification of the probability model misspecification.

CHAPTER 4

Advanced Statistical Analysis to Identify Optimal Ground Motion Intensity Measures

4.1 Introduction

In modern performance-based earthquake engineering (PBEE) ([FEMA, 2012](#)), seismic hazard analysis is systematically and probabilistically associated with loss estimation by utilizing the total probability theorem:

$$\lambda(DV) = \iiint G(DV|DM)dG(DM|EDP)dG(EDP|IM)d\lambda(IM) \quad (4.1)$$

where $\lambda(DV)$ and $\lambda(IM)$ are the annual exceedance rates for the decision variable of interest and ground motion intensity measure (IM), respectively. The “triple integral” also utilizes the conditional probability of exceeding (i) the decision variable given the damage measure (DM), $G(DV|DM)$, (ii) the damage measure given the engineering demand parameter (EDP), $G(DM|EDP)$, and (iii) EDP given an IM, $G(EDP|IM)$. The latter of the three conditional probabilities is obtained from probabilistic seismic demand analysis (PSDA), which computes the structural response, ideally using nonlinear response history analyses. The formulation shown in Eq. (4.1) is based on an underlying assumption that the EDP of interest is conditionally independent of the ground motion causal parameters such as magnitude (M) and source-to-site distance (R). Preferably, all the predictor variables used in the ground motion model (GMM) (e.g., shear-wave velocity (V_{s30}), fault type, average depth (Z_{TOR}), average dip angle (δ)) would be included as causal parameters. In this study, only M and R are discussed because their contributions are dominant in the GMM and seismic

hazard deaggregation (Luco and Cornell, 2007; Campbell and Bozorgnia, 2014). Hereafter, the term “causal parameters” jointly refers to M and R .

The independence of the conditional distribution of an EDP with respect to the causal parameters can be regarded as a “weak” assumption in the sense that it is not absolutely essential in the PBEE framework. In other words, the dependence on the causal parameters can be explicitly considered by conditioning the EDP on IM , M , and R instead of just the IM . As highlighted in Luco and Cornell (2007) (Equation 12), the explicit consideration of the causal parameters in Eq.(4.1) increases the computational cost as one has to integrate over all the causal parameters in addition to the triple integral, but it is within the realm of possibility. However, while possible, the explicit consideration of causal parameters is not always practical. This approach would require the suite of ground motion records to be consistent with $G(R, M|IM)$, which essentially means that the selected records need to come from the earthquake events that govern the hazard at all the IM levels. Realistically, ground motion suites that are consistent with respect to the causal parameters would be rare because it is unlikely that an event with specific characteristics (e.g., M , R) would dominate the IM s at all hazard levels. It is noted that the consistency issue can be countered by selecting site- and intensity-specific ground motions. The targeted ground motion selection, however, might not be a universal solution to this consistency issue because in applications such as regional studies, cloud analysis might be preferred. The bottom line is that the explicit consideration of conditional dependence imposes an immense limitation on the PBEE framework. Hence, to ease the limitation and increase computational viability, the PBEE framework adopts a simplifying conditional independence assumption. The assumption emphasizes the identification, selection, and evaluation of an “optimal” IM which is the focus of the chapter.

Recognizing the importance of IM selection in quantifying and propagating uncertainty in the PBEE methodology, there has been a body of research work investigating different facets of the optimality of an IM . The most widely accepted metrics to assess the effectiveness of an

IM are “efficiency” and “sufficiency” (Shome et al., 1998; Luco and Cornell, 2007). Efficiency is a measure of an IM’s ability to define the relationship between seismic response and hazard with minimal dispersion. In other words, the efficiency of an IM quantifies the uncertainty of the conditional structural response (EDP | IM). On the other hand, an IM is said to be sufficient if the conditional distribution of the EDP of interest is independent of the causal parameters. This serves as an indication that the IM alone can adequately estimate the structural response with no additional information from the causal parameters. The earliest attempts to quantify efficiency and sufficiency were based on ordinary least squares (OLS) regression (referred to as the “traditional” approach henceforth). Specifically, the conditional distribution of the response demands is estimated by regressing the EDP against the IM. The EDPs are obtained from nonlinear response history analysis (NRHA) under a suite of ground motion records. The standard error obtained from the OLS is then taken as the efficiency measure. The residual of the first OLS model is further regressed on the causal parameter in a one-at-a-time fashion to determine the sufficiency of the IM. The sufficiency criterion relies on statistical significance testing under a pre-specified significance level (α). If the regression coefficient corresponding to the causal parameter is statistically insignificant at the desired confidence level ($p\text{-value} > \alpha$), the IM is deemed sufficient. Other metrics such as “predictability”, “scaling robustness”, “practicality”, and “proficiency” (Bradley et al., 2010; Padgett et al., 2008) have also been proposed, but for generality, this study only focuses on efficiency and sufficiency as the primary evaluation metrics.

An intrinsic assumption in the one-parameter linear model approach to quantifying efficiency is that the EDPs are independent and thus follow a univariate distribution. This assumption, which is usually made as a matter of convenience, has three primary implications: 1) intra-EDP joint distribution (e.g., EDP profile along the story height) cannot be considered, 2) inter-EDP (e.g., peak story drift ratio (SDR) and peak floor acceleration (PFA)) dependence and interactions cannot be incorporated, and 3) multivariate effects of multiple causal parameters cannot be addressed. It is well understood that the nonlinear

behavior of a structure under dynamic loading is a consequence of complex interactions between displacements, velocities, and accelerations of structural and nonstructural components. It is a common practice to assume that EDPs jointly follow a lognormal distribution (FEMA, 2012). Notably, in the PBEE framework, the Monte Carlo algorithm is used to simulate jointly lognormal demand samples to assess losses. The simulated demand samples include direction-dependent EDPs and their profiles along the building height. This enables the framework to conveniently consider intra- and inter-EDP dependence. However, in IM evaluation studies, the optimality of an IM has been investigated assuming that the EDPs follow independent lognormal distributions. Although the majority of prior IM studies (Baker and Allin Cornell, 2005; Aslani, 2005; Eads et al., 2015) have used the maximum value of the EDP profile along the story height, a limited number of studies have utilized three-dimensional models (Kohrangi et al., 2016) and considered the EDP profile (Kazantzi and Vamvatsikos, 2015) in analyzing the effectiveness of an IM. Recent studies have also proposed an entropy-based evaluation metric for site-specific risk assessment (Dhulipala et al., 2018; Du and Padgett, 2021). Du and Padgett (2021) proposed a joint entropy-based procedure to evaluate IMs by considering the multivariate distribution of the demand parameters for a bridge structure. However, to the best of our knowledge, there has not been a similar study for buildings where multiple EDPs are considered.

The univariate OLS approach to quantifying sufficiency relies on a statistical significance test which by definition is a qualitative measure. The hypothesis testing descriptively indicates whether an IM is sufficient with respect to a specific causal parameter or not but it does not quantitatively assess the degree of sufficiency. Additionally, the interpretation of the significance tests becomes challenging if the sufficiency trend is sparse. For instance, in 10 conditional EDP distributions of a 10-story building, suppose R is sufficient in five cases with an average p -value of 0.65 while M is sufficient in six cases with an average p -value of 0.06. In this scenario, the conclusion would be dependent on the researcher's aptitude for the level of significance (α). This induces subjectivity into sufficiency evaluation as it is

common to use 5% (e.g., [Luco and Cornell \(2007\)](#)) or 10% (e.g., [Padgett et al. \(2008\)](#)) as the significance level threshold. To overcome this limitation, [Jalayer et al. \(2012\)](#) proposed a relative sufficiency measure based on information theory. Along the same lines, more recent studies have proposed an entropy-based evaluation metric for site-specific risk assessment ([Dhulipala et al., 2018](#); [Du and Padgett, 2021](#)). [Du and Padgett \(2021\)](#) proposed a joint entropy-based procedure to evaluate IMs by considering the multivariate distribution of the demand parameters for a bridge structure. However, to the best of our knowledge, there has not been a similar study for buildings where multiple EDPs are considered. We cautiously note that the adoption of multivariate EDP distribution in the PBEE framework (Eq. (4.1)) would undoubtedly complicate the loss computation process. The idea behind considering multivariate EDP distribution in an IM evaluation is to ensure that the selected IM is robust against all the implicit simplifying assumptions.

This chapter is guided by two primary motivations: 1) to perform a comparative analysis of the currently available methods and 2) to advance the current methods by explicitly considering multivariate relationships in building structural responses. Figure 4.1 summarizes a host of existing and new methods covered throughout this chapter. First, we present the OLS-based efficiency assessment approach and the joint entropy-based measure as alternative criteria. The joint entropy approach was originally proposed by [Du and Padgett \(2021\)](#) as a singular measure of the optimality of an IM. Under the assumption that EDPs are jointly lognormal, we implement a multi-target generalized additive model (GAM) ([Hastie and Tibshirani, 2017](#)) with smooth functions to effectively capture the multivariate and non-linear relationships between the EDPs and IM. Ultimately, we use the estimated covariance matrix to assess the efficiency of the IM based on joint entropy. Similarly for sufficiency, we start by presenting the univariate OLS approach. Staying within the significance testing domain, we also implement a multivariate GAM to determine sufficiency while accounting for the multivariate relationships within and between EDPs, and causal parameters. We present the relative sufficiency measure as an alternative approach for both the univariate

and multivariate cases. The relative sufficiency measure presented here is inspired by two previous studies ([Jalayer et al., 2012](#); [Dhulipala et al., 2018](#)). Finally, we implement these approaches on a set of 10 residential woodframe buildings consisting of four single-family dwellings (SFD) and six multi-family dwellings (MFD). Although there has been a large body of research on IM evaluation for a variety of structures, woodframe buildings have garnered much less attention. [Heresi and Miranda \(2021\)](#) investigated the efficiency of 10 different IMs for regional-based risk assessment of low-rise woodframe buildings. However, the sufficiency criterion was not considered in their study. To the best of our knowledge, this study is the first of its kind to evaluate IMs for woodframe buildings using entropy-based efficiency and sufficiency measures.

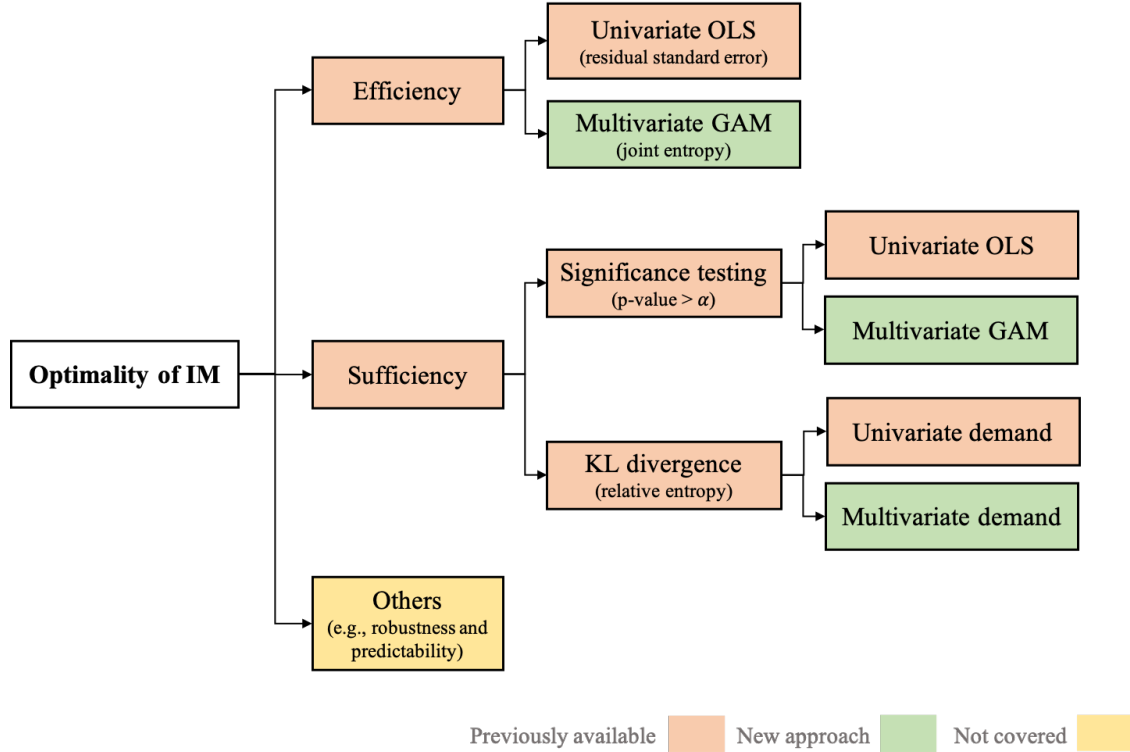


Figure 4.1: Summary of the various methods used to evaluate the effectiveness of IM.

4.2 Quantifying IM Optimality

We perform a comparative assessment of IM optimality using the various metrics shown in Figure 4.1. Acknowledging the availability of other evaluation metrics (e.g., robustness, predictability, etc.), this chapter focuses on efficiency and sufficiency. In the subsequent subsections, a wide variety of methods ranging from univariate OLS to multivariate entropy-based techniques are discussed as measures to evaluate the effectiveness of an IM.

4.2.1 Methods to quantify the efficiency

The efficiency of an IM is a measure of the dispersion of an estimated EDP in PSDA. It is one of the most straightforward evaluation metrics that reflects the predictive performance of the demand model based on the measure of uncertainty in the conditional distribution of the EDP.

4.2.1.1 Univariate OLS-based efficiency

Historically, efficiency has been assessed by evaluating the residual standard error obtained from one-parameter regression of the EDP against the IM (Shome, 1999; Luco and Cornell, 2007). The functional form of the univariate log-log linear model is shown in Eq. (4.2)

$$\ln \text{EDP}|\text{IM} = \beta_0 + \beta_1 \cdot \ln \text{IM} + \ln(\epsilon|\text{IM}) \quad (4.2)$$

where $\ln(\epsilon|\text{IM})$ is a normally distributed noise term with mean zero and standard deviation $\sigma_{\text{EDP}|\text{IM}}$, β_0 is an intercept, and β_1 is a slope in log scale. The use of the log-log model ensures the validity of the normality assumption since the EDP and IM are expected to be linearly related in log space (Shome, 1999; Aslani and Miranda, 2005). The normality enables the residual standard error (RSE), $\sigma_{\text{EDP}|\text{IM}}$, can be directly used as a measure of efficiency. The RSE in Eq. (4.2) does not need to be transformed to log space because it is an estimate of the standard deviation of the residuals in log space. It is evident from Eq (4.2) that an

efficient IM would require fewer NRHAs to estimate the structural response as compared to one that is less efficient.

4.2.1.2 Multivariate entropy-based efficiency

The OLS model is limited to a univariate relationship between the EDP and IM. In reality, different EDPs within a structure follow a joint distribution. Additionally, the relationship between the log-transformed EDP and IM is often more complex than simply linear. To account for this nonlinear multivariate relationship, a multi-target GAM model is proposed. The GAM is a smooth extension of the generalized linear model (GLM) where the linear form in GLM is replaced by a sum of smooth functions ([Hastie and Tibshirani, 2017](#)). These smooth functions are represented via splines and inferred from the data. It is highly flexible and designed to capture the nonlinear relationship between the response and predictor variable via the smooth function ($s(\cdot)$). The smooth functions for each response-predictor variable pair are estimated simultaneously via the maximized penalized likelihood method ([Friedman and Stuetzle, 1981](#)). Ultimately, the smooth functions are all added together to formulate a simple yet powerful GAM model as shown in Eq. (4.3). For detailed mathematical information on the algorithm, the reader is referred to [Hastie and Tibshirani \(2017\)](#) and [Friedman and Stuetzle \(1981\)](#). The model can be expressed as:

$$\ln \mathbf{EDP} | \text{IM} = \mathbf{s}_1(\ln \text{IM}) + \ln(\epsilon | \text{IM}) \quad (4.3)$$

In Eq.(4.3), $\ln \mathbf{EDP}$ is a vector of EDPs within the structure, $\mathbf{s}(\cdot)$ is a vector of non-parametric smooth functions, and $\ln(\epsilon | \text{IM})$ is a multivariate normal error distribution with mean zero and diagonal covariance matrix. The output of the fitted model is RSE in the form of a covariance matrix ($\mathbf{\Sigma}$). To properly account for the covariances between all the EDPs, the concept of joint entropy from information theory is leveraged. The use of joint entropy in the context of IM evaluation was first proposed by [Du and Padgett \(2021\)](#). However, in this study, we reframe entropy as an alternative measure of efficiency because it is a measure

of “surprise” or uncertainty in a random variable’s possible outcomes. Assuming that the EDPs roughly follow a multivariate normal distribution in log space (FEMA, 2012), their joint entropy can be computed using the analytical solution in Eq. (4.4). An IM is regarded as the most efficient if it has the lowest joint entropy among the IMs that are considered. Intuitively, the most efficient IM induces the least uncertainty in PSDA.

$$h(\langle \ln \text{EDP}_1 | \text{IM} \rangle, \langle \ln \text{EDP}_2 | \text{IM} \rangle, \dots, \langle \ln \text{EDP}_n | \text{IM} \rangle) = \frac{1}{2} \log((2\pi e)^d \det(\Sigma)) \quad (4.4)$$

where $\det()$ is the determinant of a matrix. It is noted that this formulation assumes the bias to be zero.

4.2.2 Methods to quantify sufficiency

The idea of sufficiency follows from the assumed independence between the structural response and the ground motion causal parameters after conditioning on the IM. At its core, sufficiency is a measure of the simplifying assumption that an IM is adequate in defining the conditional distribution of the EDP without any additional information from the causal parameters. A sufficient IM also simplifies the ground motion selection process because the suite of selected records does not necessarily need to be consistent with the causal parameters at each hazard level. In other words, a sufficient IM is less reliant on the decisions made during the ground motion selection process. Thus, it can be argued that a sufficient IM results in a more robust EDP distribution (Eads et al., 2015; Heresi and Miranda, 2021).

4.2.2.1 Univariate OLS-based significance testing

Traditionally, the sufficiency of an IM is determined via a null hypothesis significance test characterized by a p -value (Luco and Cornell, 2007). A multiple linear regression model outlining the relationship between an EDP, IM, and a causal parameter is formulated for hypothesis testing. Equivalently, the normally distributed residuals ($\ln(\epsilon | \text{IM})$) obtained from Eq.(4.2) can also be regressed on the causal parameter directly. The two variations of re-

gressions are highlighted in Eq.(4.5) where x represents a causal parameter (either M or R) considered individually. If the observed p -value for the causal parameter (i.e. p -value of β_2 in Eq.(4.5a) or β_1 in Eq.(4.5b)) is higher than the pre-defined significance level (typically $\alpha = 5\%$), then the null hypothesis cannot be rejected, suggesting that the IM is sufficient. However, a p -value lower than the specified threshold signifies that the causal parameter is statistically significant in establishing the conditional distribution of the EDP. The statistical significance of the causal parameter makes an IM insufficient because it implies that the information from the causal parameter is essential in defining the structural response. Interested readers are referred to the following literature ([Luco and Cornell, 2007](#); [Bradley et al., 2010](#)) for a more elaborate description of hypothesis testing and sufficiency.

$$\ln \text{EDP} = \beta_0 + \beta_1 \cdot \ln \text{IM} + \beta_2 \cdot x + \ln(\epsilon|\text{IM}, x) \quad (4.5a)$$

$$\ln(\epsilon|\text{IM}) = \beta_0 + \beta_1 \cdot x + \ln(\epsilon|\text{IM}, x) \quad (4.5b)$$

4.2.2.2 Multivariate GAM-based significance testing

As discussed earlier, the OLS-based sufficiency model disregards the nonlinear and multivariate relationship between the conditional structural response distribution and causal parameters. In GAMs, a scalar IM is derived based on interdependence between various causal parameters. Thus, to render an IM sufficient, a multivariate relationship between the causal parameters should also be considered. The multi-target multivariate GAM presented in Eq.(4.3) can be used to consider the causal parameters as follows

$$\ln \mathbf{EDP}|\text{IM} = \mathbf{s}_1(\ln \text{IM}) + \mathbf{s}_2(\ln M) + \mathbf{s}_3(\ln R) + \ln(\epsilon|\text{IM}, M, R) \quad (4.6)$$

where, $\ln \mathbf{EDP}$ is a vector of EDPs, $\mathbf{s}_i(\cdot)$'s are vectors of non-parametric smooth functions and $\ln(\epsilon|\text{IM})$ is the jointly distributed error. Like the OLS-based significant testing, the sufficiency of an IM is determined based on the significance of the smooth terms for M and R . The GAM can be viewed as a non-parametric extension of OLS as it provides flexibility to consider multivariate EDPs and multivariate causal parameters. Eq (4.6) is a highly flexible

formulation that can be simplified by only considering one causal parameter at a time. On the other hand, it can also be modified to account for two-way or three-way interactions between the IM and the causal parameters as described in Eq(4.7)

$$\ln \mathbf{EDP}|\mathbf{IM} = \mathbf{s}_1(\ln \mathbf{IM}, \ln M) + \mathbf{s}_2(\ln \mathbf{IM}, \ln R) + \ln(\epsilon|\mathbf{IM}, M, R) \quad (4.7a)$$

$$\ln \mathbf{EDP}|\mathbf{IM} = \mathbf{s}_1(\ln \mathbf{IM}, \ln M, \ln R) + \ln(\epsilon|\mathbf{IM}, M, R) \quad (4.7b)$$

4.2.2.3 Univariate entropy-based sufficiency

The GAM-based sufficiency measure addresses the need to consider multivariate relationships within and between the EDPs and causal parameters. It is noted that [Kazantzi and Vamvatsikos \(2015\)](#) proposed dispersion-based metrics that negate subjectivity while staying within the realm of OLS. The idea is to compare the mean and maximum dispersion explained by the causal parameters to determine sufficient IM. This chapter uses the Kullback-Leibler divergence (commonly known as KL divergence) as an alternative measure to quantify the degree of sufficiency. KL divergence (equivalently, relative entropy) has previously been implemented as a measure of sufficiency ([Jalayer et al., 2012](#); [Dhulipala et al., 2018](#)). In particular, [Dhulipala et al. \(2018\)](#) used KL divergence to calculate total information gain by comparing the site-consistent conditional distribution of an IM with and without including a causal parameter i.e. $f_{R \text{ or } M}(\mathbf{IM} | \mathbf{EDP} > \text{edp})$ and $f(\mathbf{IM} | \mathbf{EDP} > \text{edp})$. The conditional distribution of an IM is computed by applying the Bayes rule to the probability of demand exceedance ($P(\mathbf{EDP} > \text{edp}|\mathbf{IM})$). The transformation of the probability of demand exceedance into the conditional distribution of the IM warrants hazard deaggregation. However, since the assumed context in this study is a site-agnostic regional-based assessment, the KL divergence can be computed between the conditional distributions without seismic hazard deaggregation.

Suppose, P and Q are, respectively, the distributions of EDP conditioned on IM with and without the causal parameter (x). Let $p(\ln \mathbf{EDP}|\mathbf{IM})$ and $q(\ln \mathbf{EDP}|\mathbf{IM}, x)$ be the corre-

sponding densities of P and Q . The causal parameter can be considered one at a time (either M or R) or all at once (M and R). Given the univariate conditional distributions, P , and Q , the KL divergence is computed using Eq.(4.8). The KL divergence effectively becomes a sufficiency measure that quantifies the degree to which an IM can render the conditional distribution of the EDP independent of the causal parameter.

$$D_{\text{KL}}(P \parallel Q) = \int p(\ln \text{EDP} | \text{IM}) \log \left(\frac{p(\ln \text{EDP} | \text{IM})}{q(\ln \text{EDP} | \text{IM}, x)} \right) d \ln \text{EDP} \quad (4.8)$$

Under the assumption that P and Q are normally distributed, the KL divergence formulation in Eq. (4.8) simplifies to the analytical solution given by Eq.(4.9). For each IM, the KL divergence between the conditional distribution of the EDP with and without the causal parameter is compared. The IM with the least KL divergence indicates that the causal parameters contribute the smallest amount of additional information in defining the conditional distribution of the EDP (i.e., $P \approx Q$) and is, hence, deemed the most sufficient.

$$D_{\text{KL}}(P \parallel Q) = \log \frac{\sigma_Q}{\sigma_P} + \frac{\sigma_P^2 + (\mu_P - \mu_Q)^2}{2\sigma_Q^2} - \frac{1}{2} \quad (4.9)$$

4.2.2.4 Multivariate entropy-based sufficiency

The relative entropy-based measure presented in subsection Section 4.2.2.3 is an alternative to the significance testing-based approach within the univariate EDP space. In this subsection, we present a generalizable method to consider the multivariate conditional distributions of EDPs with and without causal parameters. Particularly, we compute the KL divergence between residuals obtained by regressing $\ln \text{EDP}$ on $\ln \text{IM}$ (i.e., $\ln(\epsilon | \text{IM})$ from Eq. (4.2)) and residuals obtained by regressing $\ln \text{EDP}$ on $\ln \text{IM}$ and the causal parameters (i.e., $\ln(\epsilon | \text{IM}, x)$ from Eq. (4.5)). The distribution of the residuals is preferred over the predicted conditional distribution of the EDP because the former follows a normal distribution which validates the use of the analytical KL divergence formulation in Eq. (4.9). The results of the normality tests on the residuals have been provided as supplementary material ([Dahal, 2022](#)).

Another advantage of using residuals is the flexibility to incorporate multivariate EDP

distributions. Consistent with the FEMA P-58 framework, the log-transformed SDR and PFA (or equivalently their residuals from Eq. (4.2)) are assumed to follow a multivariate normal distribution (FEMA, 2012). To compute the KL divergence between two jointly normal distributions, let $\mathcal{N}_0 \sim \mathcal{N}(\boldsymbol{\mu}_0, \boldsymbol{\Sigma}_0)$ be the joint conditional distribution of the EDPs without causal parameters and $\mathcal{N}_1 \sim \mathcal{N}(\boldsymbol{\mu}_1, \boldsymbol{\Sigma}_1)$ be the joint conditional distribution of the same EDPs with the causal parameter. The generic formulation of KL divergence is simply an extension of Eq.(4.8) but for normally distributed multivariate distributions, there is a closed-form solution as shown below

$$D_{\text{KL}}(\mathcal{N}_0 \parallel \mathcal{N}_1) = \frac{1}{2} \left\{ \text{tr}(\boldsymbol{\Sigma}_1^{-1} \boldsymbol{\Sigma}_0) - d + (\boldsymbol{\mu}_1 - \boldsymbol{\mu}_0)^T \boldsymbol{\Sigma}_1^{-1} (\boldsymbol{\mu}_1 - \boldsymbol{\mu}_0) + \log \frac{\det(\boldsymbol{\Sigma}_1)}{\det(\boldsymbol{\Sigma}_0)} \right\} \quad (4.10)$$

where $\text{tr}()$ is the trace of a matrix, $\boldsymbol{\mu}_0$ and $\boldsymbol{\mu}_1$ are the mean vectors, d is the dimension of $\mathcal{N}_0$ and $\mathcal{N}_1$, $\boldsymbol{\Sigma}_0$ and $\boldsymbol{\Sigma}_1$ are the correlation matrices. For illustration, suppose SDR and PFA are jointly lognormal. The two multivariate distributions $(\mathcal{N}_0, \mathcal{N}_1)$ then might take the following functional forms:

$$\mathcal{N}_0 \sim \mathcal{N}([\mu_{\ln \text{SDR}|\text{IM}}, \mu_{\ln \text{PFA}|\text{IM}}], \boldsymbol{\Sigma}_0) \quad (4.11)$$

$$\mathcal{N}_1 \sim \mathcal{N}([\mu_{\ln \text{SDR}|\text{IM}, x}, \mu_{\ln \text{PFA}|\text{IM}, x}], \boldsymbol{\Sigma}_1) \quad (4.12)$$

The KL divergence between $\mathcal{N}_0$ and $\mathcal{N}_1$ quantifies the amount of information gained due to the inclusion of a causal parameter (x) in $\mathcal{N}_1$. Identical to the univariate case, the IM with minimal KL divergence is regarded as the most sufficient IM.

4.3 Ground Motion Records and Intensity Measures

For the IM evaluation, 826 pairs of site-agnostic ground motion records from 63 crustal earthquakes recorded by far-field strong motion stations are used. The records were utilized by Heresi and Miranda (2021) to evaluate IMs for low-rise woodframe buildings at a regional scale. The authors originally selected 831 record pairs but due to periodic updates of the PEER NGA-West2 ground motion database (Ancheta et al., 2014), only 826 pairs of records

were available for download at the time of this study. The details about the entire suite of records can be found in [Heresi et al. \(2018\)](#). The 826 ground motion pairs were recorded between 1942 and 2011 and have a minimum, average, and maximum moment magnitude of 5.1, 6.8, and 7.9 respectively. Similarly, the suite of records has a mean Joyner-Boore distance of 77.2 *km* while the minimum and maximum distances were 0, and 315.9 *km*, respectively. The records correspond to NEHRP site class D with 266.7 *m/s* average shear wave velocity. Figure C.2 in Section C.1 shows additional ground motion information such as the pairwise relationship between the causal parameters and response spectrum of the suite of selected ground motions.

The unscaled acceleration histories are used to avoid the possibility of bias being induced due to scaling. Large scale factors have been found to produce a biased estimation of structural response in short-period buildings ([Luco and Bazzurro, 2007](#); [Dávalos and Miranda, 2019](#)). In the PBEE framework, it is customary to scale ground motions to match pre-specified spectral acceleration levels. Moreover, IM-based ground motion scaling would likely produce results that are biased for that specific IM. We acknowledge that the use of unscaled records also has its limitations i) ground motions with higher intensity levels are less common, and ii) two ends of IM distribution might be dominated by a highly specific set of causal parameters. A number of studies ([Luco and Bazzurro, 2007](#); [Dávalos and Miranda, 2019](#); [Tsalouchidis and Adam, 2022](#)) have explored the idea of the capped scale factor to minimize bias induced due to amplitude scaling. The limitations posed by unscaled ground motion are viewed as a trade-off to minimizing bias.

4.3.1 Intensity measures

Over the last couple of decades, a wide range of IMs has been proposed, from vector IMs to advanced frequency-based IMs ([Baker and Allin Cornell, 2005](#); [Bojórquez et al., 2017](#); [Bojórquez and Iervolino, 2011](#); [Heresi and Miranda, 2021](#); [Jamshidiha et al., 2018](#)). However, in this study, a total of 10 IMs that range from acceleration-based to displacement-based are

considered. Each ground motion pair consists of two horizontal time series records (i.e., H1 and H2) with their respective orientation in which the acceleration was recorded. The 50th percentile rotated spectrum (RotD50) is computed (Boore, 2010) by rotating the spectrum through 180 degrees and taking the 50th percentile. The details of the 10 IMs are presented as follows:

1. **Spectral acceleration (Sa_{T1}):** The Sa_{T1} represents the maximum acceleration that a ground motion will cause in a linear oscillator with a specified period (oftentimes the same fundamental period as a building) and damping level. An accurate representation is pseudospectral acceleration which is given by a product of spectral displacement with the squared natural frequency. As discussed in Baker and Cornell (2006), the difference between the spectral and pseudospectral acceleration is negligible which is why the term “spectral acceleration” is used hereafter. The spectral accelerations for all 826 ground motions are computed using a Python library that employs the discrete fast Fourier transformation (Kottke, 2018).
2. **Peak ground acceleration (PGA):** The PGA is a period-independent measure of the maximum acceleration recorded during an earthquake. It is the maximum absolute acceleration from the time series.
3. **Peak ground velocity (PGV):** The PGV is the maximum velocity of an earthquake ground motion. PGV is computed by taking the first-order integral of an acceleration time series with respect to time.
4. **Cumulative absolute velocity (CAV):** The CAV (Reed and Kassawara, 1990) is one of the frequently studied IMs that is intended to capture the cumulative effects of ground motion shaking. Mathematically, it is defined as the integral of the absolute value of the acceleration, $CAV = \int_{t_0}^{t_{max}} |a(t)| dt$.

5. **Average spectral acceleration (Sa_{avg}):** The Sa_{avg} is the geometric mean of the spectral acceleration for a range of periods $[T_{min}, T_{max}]$ (Cordova et al., 2000; Vamvatsikos and Cornell, 2005; Eads et al., 2015). Sa_{avg} aims to capture ground motion effects in cases where the structure responds to a range of frequencies due to period elongation during inelastic response or multi-modal response. Conceptually, it is an ideal IM for regional assessment where the fundamental periods of the buildings are bounded within T_{min} and T_{max} . It is computed as,

$$Sa_{avg}(T_{min}, T_{max}) = \left[\prod_{t=T_{min}}^{T_{max}} Sa(T=t) \right]^{\frac{1}{N}} \quad (4.13)$$

where N is the total number of periods between equally spaced values between T_{min} and T_{max} . The period range is taken as $[0.1T_{1,min}, 2T_{1,max}]$ where $T_{1,min}$ and $T_{1,max}$ are the minimum and maximum fundamental periods among 10 archetypes.

6. **Spectrum intensity (SI):** The SI, also commonly known as response spectrum intensity is computed by taking the area under the velocity spectrum curve between periods 0.1 and 2.5 seconds (Housner, 1959). SI was proposed to characterize the response of a broad class of structures whose fundamental periods are expected to be between 0.1 and 2.5 seconds. SI is computed using $SI = \int_{0.1}^{2.5} SV(T)dT$ where, $SV(T)$ is the spectral velocity at period, T .
7. **Acceleration spectrum intensity (ASI):** The ASI is conceptually similar to SI, but it is most widely used as an intensity measure in stiff structures (e.g., dams) where the first-mode fundamental period is typically less than 0.5 seconds (Von Thun, 1988). Although residential woodframe buildings are not stiff by design, ASI, in principle, would be a very appropriate measure considering the fundamental period typically ranges from 0.1 to 0.5 seconds. To the best of our knowledge, ASI has not been considered in the IM optimality literature discussed above. It is computed by, $ASI = \int_{0.1}^{0.5} Sa(T)dT$

8. **Displacement spectrum intensity (DSI):** The DSI is a spectral displacement-based measure that is intended to capture the impact of the long-period content of a ground motion on structural performance (Bradley, 2011). It is computed as the area under the spectral displacement curve between periods of 2 and 5 seconds using $DSI = \int_2^5 SD(T)dT$ where $SD(T)$ is the spectral displacement at period T .
9. **Significant duration (DS):** The DS is a measure of the cumulative energy dissipated by the acceleration time series. The energy dissipation, also commonly known as Arias Intensity (AI) (Arias, 1970), is captured by integrating the squared acceleration time series, i.e., $AI(t) = \int_0^{t_{max}} a(t)^2 dt$. DS defines the time a ground motion takes to dissipate a pre-specified amount of energy. For instance, DS_{5-95} is the time it takes to dissipate 90% of the total energy ($AI(t)/AI_{max}$) between 5% and 95% intervals. The two most widely used duration ranges, DS_{5-75} and DS_{5-95} are considered as IMs.

4.4 Building Description

A total of 10 woodframe building archetypes are used. They were developed as a part of the FEMA P-2139-2 project (FEMA, 2020) to study the short-period (fundamental period < 0.5 seconds) wood light-frame building performance paradox. The paradox was a contradictory seismic collapse performance obtained from numerical simulations that did not support the actual performance observed during historical earthquakes. Based on the numerical models, short-period buildings were believed to have a higher collapse risk than long-period buildings. However, the observed collapse risk from historical earthquakes was much lower than what was predicted by structural response simulation. To address this discrepancy, enhanced numerical models were employed in a bid to create a realistic representation of the observed performance. The FEMA P-2139-2 project studied 28 baseline archetypes that comprised commercial (COM), single-family dwellings (SFD), and multi-family dwellings (MFD) with either one, two, or four-story variants.

Table 4.1 outlines the naming convention and general design information about the archetypes. As shown, the 10-building set contains four SFDs and six MFDs. The buildings are designed for “High” and “Very High” seismic design levels. The “High” design level corresponds to the seismic design category (SDC) $D_{\max}$ with a seismic response coefficient C_s value of 0.154. It is intended to mimic the seismic demand produced by MCE_R -level ground motions in regions with high seismicity. Table 4.1 contains the complete set of response coefficients, floor layouts, and story heights of all the archetypes. The interested reader is referred to the FEMA P-2139-2 document([FEMA, 2020](#)) which contains design details including the graphical renderings of the archetypes.

Table 4.1: Summary of the basic building information for the set of considered archetypes.

Archetype ID	No of Stories	Seismic Weight(kips)	Design Level	SDC	C_s	Plan Layout (ft)	Story Height (ft)
SFD1B	1	[51]	High	$D_{\max}$	0.154	32×48	10
SFD3B	1	[51]	Very High	$1.5 \times D_{\max}$	0.231	32×48	10
SFD2B	2	[53, 70]	High	$D_{\max}$	0.154	32×48	10
SFD4B	2	[53, 70]	Very High	$1.5 \times D_{\max}$	0.231	32×48	10
MFD1B	1	[141]	High	$D_{\max}$	0.154	48×96	10
MFD4B	1	[141]	Very High	$1.5 \times D_{\max}$	0.231	48×96	10
MFD2B	2	[182, 144]	High	$D_{\max}$	0.154	48×96	10
MFD5B	2	[182, 144]	Very High	$1.5 \times D_{\max}$	0.231	48×96	10
MFD3B	4	[237, 237, 237, 149]	High	$D_{\max}$	0.154	48×96	10
MFD6B	4	[237, 237, 237, 149]	Very High	$1.5 \times D_{\max}$	0.231	48×96	10

4.4.1 Numerical modeling and analysis

Three-dimensional (3D) OpenSees ([Mazzoni et al., 2006](#)) models are constructed for all 10 archetypes where X- and Z- axes are used to denote the two horizontal directions. In FEMA P-2139-2, a modified seismic analysis of woodframe structures (SAWS) ([Folz and Filiatrault,](#)

2001) hysteresis material model is used to capture the nonlinear behavior of different components of the building including the light-frame wood shear wall and nonstructural partitions. The 10-parameter SAWS material model is limited in its ability to capture the residual strength and stiffness of the panels. The residual capacity is one of the key contributing factors in determining the performance of structures that undergo large deformations (e.g., woodframe buildings). To overcome these shortcomings, a versatile 22-parameter Pinching4 hysteresis model is used. Originally developed to model the highly nonlinear behavior of two-dimensional beam-column joints (Lowes et al., 2003), the Pinching4 hysteretic model has since been adopted to model the cyclic degradation of strength and stiffness in a variety of components such as the cripple wall, light-frame wood wall, and steel moment frames (Welch and Deierlein, 2020a; Dahal et al., 2022b; Guan et al., 2020).

4.4.1.1 Pinching4 material parameter calibration

One of the drawbacks of using the Pinching4 model is that the parameters are not readily available in the literature as compared to the SAWS parameters. The 22-parameter Pinching4 hysteresis model is composed of eight backbone and 14 cyclic parameters that can be calibrated based on either the experimental data or the SAWS parameters. The detailed procedure implemented in calibrating the Pinching4 parameter is discussed in Chapter 2.

4.4.2 Nonlinear static analysis

To verify the OpenSees models, Table 4.2 compares the results from nonlinear static analysis against the values documented in the FEMA P-2139-2 report. As outlined in the Table 4.2, the fundamental periods for all 10 archetypes are in alignment with the FEMA P-2139 results. On average, the periods differ by 7% which is expected when two entirely different modeling software are used (Timber3D in FEMA P-2139 and OpenSees in this study). Similarly, the normalized base strengths (maximum base shear normalized by the seismic weight) are

Table 4.2: Comparison of eigenvalue and pushover analysis results between FEMA P-2139-2 and the current study.

Archetype ID	Fundamental Period (sec)		Base Strength ($V_{\max}/W$)		Drift @ 80% $V_{\max}/W$ (%)		Ductility Demand
	FEMA P-2139	OpenSees	FEMA P-2139	OpenSees	FEMA P-2139	OpenSees	
SFD1B	0.14	0.13	2.10	2.28	3	3.54	0.22
SFD3B	0.13	0.13	2.33	2.53	3	3.52	0.16
SFD2B	0.24	0.22	0.90	1.04	2	1.89	0.26
SFD4B	0.24	0.22	0.95	1.14	2	1.94	0.28
MFD1B	0.18	0.16	1.39	1.51	3	3.08	0.99
MFD4B	0.18	0.16	1.48	1.75	3	3.51	0.69
MFD2B	0.27	0.26	0.70	0.67	1	1.99	1.22
MFD5B	0.27	0.26	0.73	0.72	2	2.21	1.14
MFD3B	0.51	0.49	0.39	0.39	1	1.31	2.28
MFD6B	0.54	0.49	0.44	0.48	1	1.41	1.74

comparable with an average difference of 9%. The ultimate drift capacity (drift at 80% peak strength) was found to differ by 24% on average. Again, considering the fact that two different hysteresis models were used to represent the cyclic strength degradation, a 24% variability is considered acceptable. The table also reports the displacement ductility demand ([Miranda and Bertero, 1994](#)) as a measure of inelastic deformation experienced by the building under dynamic excitation. Note that the ductility demand was not computed in the FEMA P-2139-2 report.

4.4.3 Nonlinear dynamic analysis

After verifying the nonlinear static analysis results, site-agnostic NRHAs are performed by subjecting the 3D models to the full suite of 826 ground motion pairs. Two sets of structural responses are generated. First, the two horizontal acceleration time series are applied simultaneously assuming H1 and H2 of the ground motion orientation correspond to the X- and Z-direction of the model, respectively. Consequently, the second set of responses

is obtained by subjecting the model to orthogonally rotated record pairs. The two sets of orientation-dependent responses are combined into one by computing the geometric mean. The output of the NRHA is an orientation-independent EDP (SDR and PFA) profile along the story height in both the X- and Z-direction. The EDP profile for a two-story SFD and a four-story MFD is highlighted in Section C.2. Additionally, the EDP profiles for all archetypes are also provided as supplementary material ([Dahal, 2022](#)).

4.5 Case Studies

This section provides a detailed comparative analysis of the various IM evaluation methods described in Section 4.2. The analysis is performed at two levels of granularity. In the first part, the pros and cons of each method are discussed based on the EDP data from an individual building. In the second half, results from all 10 archetypes are aggregated and discussed.

4.5.1 IM evaluation for a single building

For an in-depth IM evaluation, the four-story MFD (archetype ID: MFD6B) is chosen. The bi-directional (X- and Z-axis) SDR and PFA profiles are leveraged to investigate the effectiveness of the 10 IMs considered.

4.5.1.1 Investigating the multivariate distribution assumption

The methods detailed in Section 4.2 rely on foundational assumptions that the EDPs, IMs, and causal parameters can be modeled by univariate or multivariate distributions that can be defined by a fixed set of parameters. The first step in implementing the outlined methods is validating or equivalently quantifying the degree of invalidity of the parametric assumptions. This ensures that the probability models are not misspecified. If they are misspecified, the

uncertainty propagated due to an invalid assumption should be quantified to make accurate inferences (Dahal et al., 2022a). For the majority of this study, EDPs, IMs, and causal parameters are assumed to follow a multivariate lognormal distribution. In statistics, normality tests such as the Kolmogorov-Smirnov test and Shapiro-Wilk test are widely used to evaluate this type of hypothesis. However, previous authors have noted that normality tests for large datasets might be irrelevant (Ghasemi and Zahediasl, 2012). Specifically, the authors argued that for a moderately large enough dataset ($n > 40$), the violation of normality would not cause major problems. Conceptually, it is trivial that for a large sample size, even the slightest deviation from normality will result in failed normality tests. Considering that the EDPs, IMs, and causal parameters have some degree of randomness, they are not empirically expected to follow a perfectly multivariate lognormal relationship. This can be rationalized by using as a measure the Kullback-Leibler divergence between the two closest Gaussian distributions to the actual distributions, rather than the distributions themselves. Rather, it is appropriate to gauge the relative measure of dependence between multiple random variables in terms of mutual information. Mutual information is a measure of information obtained about one random variable by observing the other. Mutual information between two random variables, X and Y , is computed as

$$I(X; Y) = D_{\text{KL}}(P_{X,Y} \parallel P_X \otimes P_Y) = \int_Y \int_X P_{X,Y}(x, y) \log \left(\frac{P_{X,Y}(x, y)}{P_X(x)P_Y(y)} \right) dx dy \quad (4.14)$$

As noted in Eq. (4.14), mutual information relies on KL divergence to determine how much the joint distribution ($P_{X,Y}$) differs from the product of two marginal distributions (P_X and P_Y). When the joint distribution coincides with the product of the marginals, the mutual information equals zero, thus, effectively indicating that the two random variables are independent. It also implies that observing X provides no information about Y . Mutual information is a non-negative number and is symmetric (i.e., $I(X; Y) = I(Y; X)$). Figure 4.2 presents a heat map of mutual information between SDR_X and PFA_X at story 1 of MFD6B, Sa_{T1} , M, and R. The non-zero mutual information across the board implies the existence of dependence between the respective pairs. The mutual information, however, cannot be

easily interpreted solely based on its value because it is not a standardized quantity like the correlation coefficient. To infer a sense of the degree of dependence, self-information can be used as a baseline reference point. In a special case where the two random variables follow a bivariate normal distribution, mutual information has a closed-form relationship to the correlation coefficient (ρ), i.e. $I(X, Y) = -\frac{1}{2}\log(1 - \rho^2)$. A random variable would be perfectly correlated ($\rho = 1.0$) to itself, but for the purposes of computation, we will assume a near-perfect correlation $\rho = 0.999$ because $\log(0)$ is undefined. The self-information between two perfectly correlated random variables equals 3.10 bits. In Figure 4.2, the diagonal terms are expected to be close to 3.10 bits. The off-diagonal terms can be compared to their respective diagonal term to gauge the degree of joint relationship. As expected, log-transformed SDR_X , PFA_X , and Sa_{T1} share the highest information. Among the causal parameters, mutual information for R is roughly double compared to M suggesting that R has relatively stronger mutual dependence with SDR_X , PFA_X , and Sa_{T1} . It is noted that the conclusion drawn here is valid for the specific set of considered ground motions and the findings may vary if the record-set is changed.

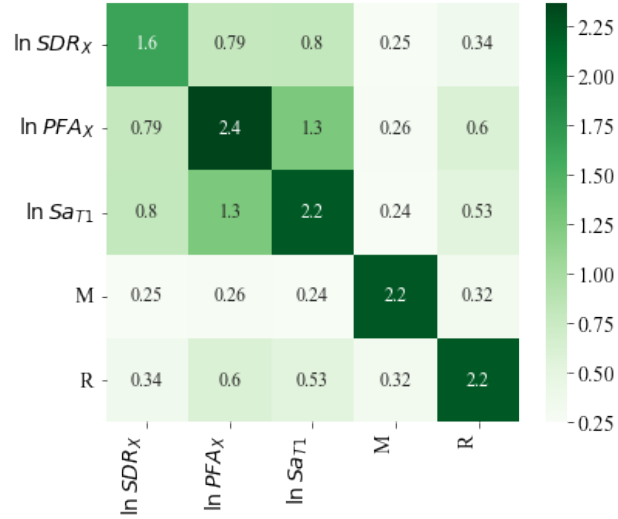


Figure 4.2: Mutual Information between SDR and PFA at floor 1 in X-direction, Sa_{T1} , magnitude, and distance.

4.5.1.2 Efficiency comparisons

Figure 4.3 shows the story-based efficiency profile of all 10 IMs for the four-story building (MFD6B). Although the figure represents efficiency profiles, it is obtained by implementing the traditional OLS method. In other words, the direction-dependent EDPs are individually regressed on all the IMs. For 16 EDPs (8 SDRs and 8 PFAs) and 10 IMs, the RSEs obtained from 160 OLS are represented in the plot. The efficiency profiles for SDR and PFA are

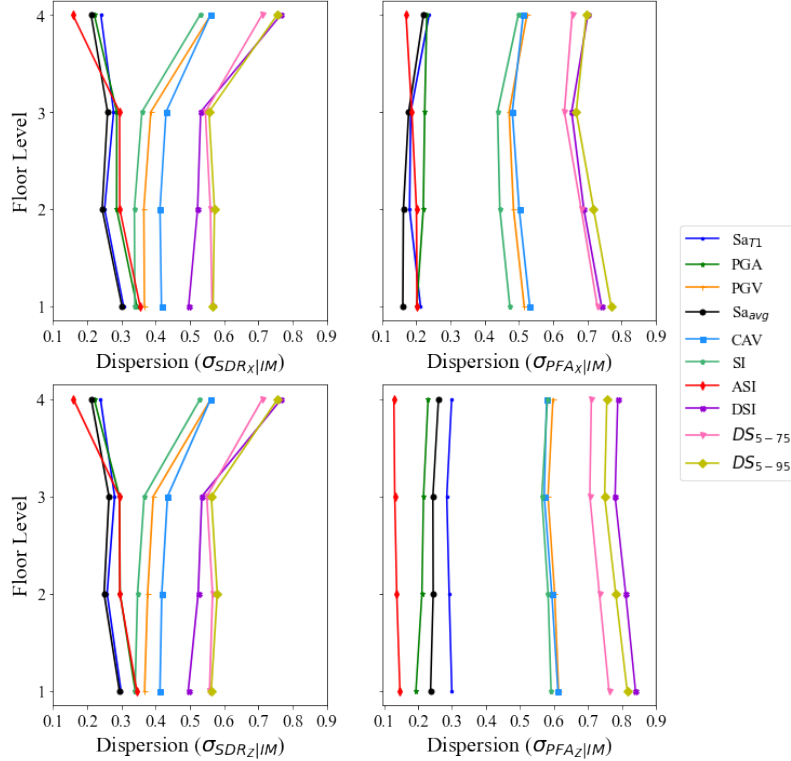


Figure 4.3: Story-level efficiency ($\sigma_{EDP|IM}$) of SDR and PFA of a four-story multi-family building (MFD6B).

nearly symmetrical in the X- and Z-direction. This is indicative of a similar wall density along the X- and Z-direction. For SDR, the dispersion profile along the story height suggests Sa_{avg} and Sa_{T1} to be the most efficient IMs. In predicting PFA along the X-direction, all the acceleration-based IMs showcase similar predictive ability with Sa_{avg} performing slightly

better on average over the height. However, in the Z-direction, the dispersion is constant over the height and ASI is distinctly the most efficient IM followed by PGA. It is interesting to note that acceleration, velocity, and displacement-based intensity measures are roughly grouped together with the same dispersion profile and progressively higher dispersion values.

Based on the discussion above, it is challenging to pinpoint a single “most efficient” IM for all the EDPs. Of course, one could take the average of dispersions, or only consider the maximum EDP instead of the profile to summarize the results but these approaches have two shortcomings 1) the summarized data will potentially lose some information, and 2) it would not be able to account for mutual dependence. Figure 4.4 compares the entropy for each IM obtained by implementing a multivariate GAM model that incorporates all 16 EDPs. When the nonlinear and multivariate relationship is explicitly modeled, ASI is the most efficient IM. ASI was introduced to study short-period structures such as dams. It is therefore not surprising that it has the least uncertainty in estimating the seismic demands of a four-story building with a first-mode period of 0.49 seconds. Appropriately, Sa_{avg} is more efficient than Sa_{T1} because Sa_{avg} naturally contains more information than an elastic spectral intensity (Sa_{T1}). Similar to Figure 4.3, it is apparent in Figure 4.4 that acceleration-based IMs are relatively more efficient than velocity- and displacement-based IMs.

4.5.1.3 Sufficiency comparisons

As detailed in Section 4.2.2, sufficiency can be characterized using either a p -value or relative entropy. This section provides a detailed implementation of univariate and multivariate cases for both the traditional OLS-based and entropy-based methods. Table 4.3 summarizes the p -values obtained by regressing the residuals ($\ln(\epsilon|IM)$) independently against the causal parameters per Eq(4.5). In total, 32 univariate OLS models and two 16-dimensional multivariate GAM models are fitted for each IM of interest. To limit the number of models, Table 4.3 only documents the results for SDR and PFA in the X-direction on the fourth floor. The p -values for the majority of causal parameters and IM pairs are well below the

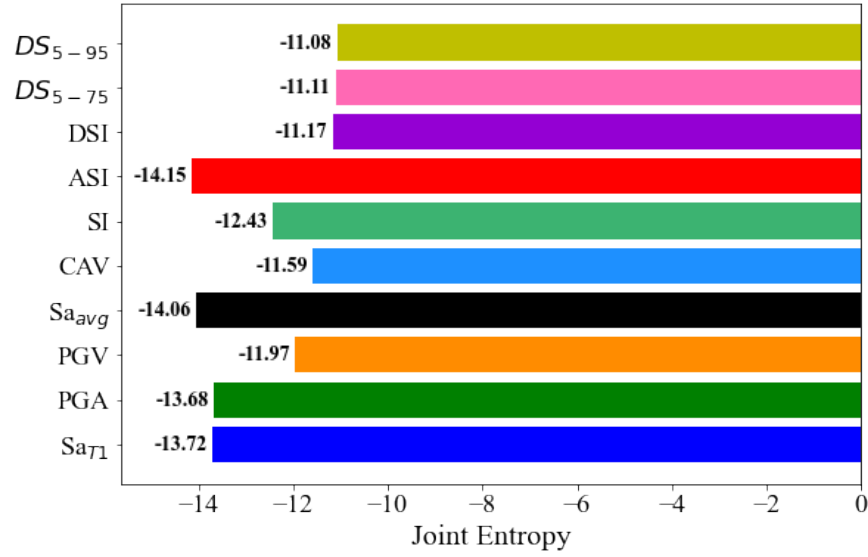


Figure 4.4: Multivariate entropy-based efficiency for the four-story multi-family building (MFD6B).

5% threshold, indicating that most of the IMs are not sufficient in defining the structural response. For both OLS and GAM, it can be argued that PGA is the most sufficient IM.

To better summarize a large number of possible p -values in significance testing, a sufficiency rate is introduced as an aggregate measure. The sufficiency rate is defined as the fraction of sufficient cases within all EDPs against a specific causal parameter. For instance, in Table 4.3, Sa_{T1} is sufficient with respect to R in one out of the two possible OLS models. In this case, the sufficiency rate is 50%. Similarly, the sufficiency rate for the GAM model is 0% because Sa_{T1} is not sufficient against any causal parameters. Table 4.4 lists the sufficiency rates for all 10 IMs. For the univariate OLS, Sa_{T1} is the most sufficient with respect to M while PGA is the most sufficient for R. On aggregate, PGA appears to be the most sufficient IM considering all causal parameters. Similarly, for the multivariate GAM (Eq.(4.6)), PGV is the most sufficient with respect to M while Sa_{avg} is the most sufficient for R. On average, PGV is the most sufficient IM. As noted earlier, the multivariate GAM can be modified to consider two-way or three-way interactions between the IM and causal parameters (i.e., Eq.

Table 4.3: Comparison of p -values obtained from univariate OLS and multivariate GAM models. The residuals, $\ln(\epsilon|IM)$, are regressed on the causal parameters (M and R) independently.

IM Type	OLS: SDR		GAM: SDR		OLS: PFA		GAM: PFA	
	Against M	Against R	Against M	Against R	Against M	Against R	Against M	Against R
Sa _{T1}	< 0.0001	< 0.0001	< 0.0001	< 0.0001	< 0.0001	0.69	< 0.0001	< 0.0001
PGA	0.89	0.86	0.05	0.008	0.17	< 0.0001	0.59	0.17
PGV	< 0.0001	< 0.0001	< 0.0001	< 0.0001	< 0.0001	< 0.0001	< 0.0001	< 0.0001
Sa _{avg}	< 0.0001	0.34	< 0.0001	< 0.0001	< 0.0001	< 0.0001	< 0.0001	< 0.0001
CAV	< 0.0001	< 0.0001	< 0.0001	< 0.0001	< 0.0001	< 0.0001	< 0.0001	< 0.0001
SI	< 0.0001	< 0.0001	< 0.0001	< 0.0001	< 0.0001	< 0.0001	< 0.0001	< 0.0001
ASI	< 0.0001	0.10	< 0.0001	< 0.0001	< 0.0001	< 0.0001	< 0.0001	0.04
DSI	< 0.0001	< 0.0001	< 0.0001	< 0.0001	< 0.0001	< 0.0001	< 0.0001	< 0.0001
DS ₅₋₇₅	< 0.0001	< 0.0001	< 0.0001	< 0.0001	< 0.0001	< 0.0001	< 0.0001	< 0.0001
DS ₅₋₉₅	< 0.0001	< 0.0001	< 0.0001	< 0.0001	< 0.0001	< 0.0001	< 0.0001	< 0.0001

(4.7)). In Table 4.4, only the sufficiency rate from a two-way interaction GAM (Eq. (4.7a)) is presented because the sufficiency rate for three-way interactions (Eq. (4.7b)) is zero for all cases. The multivariate GAM has a higher overall sufficiency rate for velocity-based IMs as compared to the OLS-based approach. This could be because the GAM is designed to account for nonlinear relationships through the spline function. The alternate GAM, on the other hand, has higher sufficiency for acceleration-based IMs and is exclusively sufficient against R. This implies that the two-way interaction between IM and M is more significant than IM and R.

As highlighted in Table 4.3, PGA is considered marginally sufficient (p -value = 0.0467) against M when the GAM model is implemented. Although, given that the p -value is less than 5%, it can also be argued that PGA is marginally insufficient. The judgment would rely on the researcher's choice of the level of significance (α). Table 4.5 compares the KL divergence (relative entropy) for the univariate and multivariate cases. In the univariate case,

Table 4.4: Sufficiency rate (%) based on the number of sufficiency cases for OLS and GAM-based sufficiency checks. The sufficiency rate for the multivariate GAM is computed using Eq.(4.6) while the alternate GAM is computed using Eq.(4.7a)

IM Type	Univariate OLS			Multivariate GAM- Eq.(4.6)			Alternate GAM- Eq.(4.7a)		
	Against M	Against R	Overall	Against M	Against R	Overall	Against M	Against R	Overall
Sa _{T1}	31.25	12.5	21.88	12.5	0	6.25	0	0	0
PGA	25	43.75	34.38	12.5	37.5	25	0	37.5	18.75
PGV	0	0	0	93.75	0	43.75	0	0	0
Sa _{avg}	18.75	37.5	28.22	12.5	43.75	28.13	0	56.25	28.13
CAV	0	0	0	18.75	0	9.38	0	0	0
SI	0	0	0	81.25	0	40.63	0	0	0
ASI	25	37.5	31.25	18.75	18.75	18.75	0	18.75	9.38
DSI	0	0	0	0	0	0	0	0	0
DS ₅₋₇₅	0	0	0	0	0	0	0	0	0
DS ₅₋₉₅	0	0	0	0	0	0	0	0	0

P is the distribution of the EDP conditioned on the IM in the form of residuals ($\ln(\epsilon|IM)$) while Q is the distribution of the EDP conditioned on the IM and a causal parameter x (either M or R) in the form of residuals (i.e., $\ln(\epsilon|IM, x)$). Concurrently, $\mathcal{N}_0$ and $\mathcal{N}_1$ are the jointly normal distribution of maximum SDR and PFA with and without a causal parameter, respectively. For simplification, all KL divergence calculations hereafter utilize the maximum EDPs in each direction instead of the EDP profile. In the univariate relative entropy, KL divergence for SDR and PFA are added to make an equivalent comparison with its multivariate counterpart. It can be seen that Sa_{avg} typically has the lowest KL divergence implying that, relatively speaking, it is the most sufficient IM. The four-story residential building used in this example is known to have nonlinear behavior controlled by multiple modes (FEMA, 2020). It is not surprising that Sa_{avg}, which encompasses spectral acceleration information for a range of periods is the most sufficient in rendering the conditional distribution of EDP independent of the causal parameters. Several past studies have found Sa_{avg} to be sufficient for structures known to undergo highly nonlinear behavior under dynamic loading (Eads

Table 4.5: The univariate relative entropy computed based on residuals from the OLS and the multivariate relative entropy computed based on estimated residuals from the GAM model. The relative entropy is the measure of relative sufficiency. The KL divergence values are scaled by a factor of 1×10^3

IM Type	Univariate Entropy $D_{\text{KL}}(P \parallel Q)$			Multivariate Entropy $D_{\text{KL}}(\mathcal{N}_0 \parallel \mathcal{N}_1)$		
	Including M	Including R	Total	Including M	Including R	Total
Sa _{T1}	1.58	4.54	6.12	2.88	6.64	9.53
PGA	2.29	3.53	5.81	2.66	4.99	7.65
PGV	5.18	19.9	25.1	6.05	19.7	25.7
Sa _{avg}	2.77	1.81	4.58	4.00	2.02	6.01
CAV	31.4	90.3	121	31.8	95.18	127
SI	2.40	13.2	15.6	3.30	13.9	17.3
ASI	3.64	5.04	8.68	3.84	6.68	10.5
DSI	0.47	150	150	1.45	118	119
DS ₅₋₇₅	33.8	199	233	23.9	149	173
DS ₅₋₉₅	16.4	203	220	13.1	152	166

et al., 2015; Du and Padgett, 2021).

4.5.2 IM evaluation for the complete archetype set

The efficiency and sufficiency results for the 10 archetype woodframe buildings are summarized in this section.

4.5.2.1 Efficiency summary

OLS-based efficiency

For the set of 10 archetype woodframe buildings, the OLS-based dispersion is averaged at two stages. First, the average dispersion is computed for an individual building (considering all stories/floor levels and directions) which is then averaged among all the relevant buildings.

Figure 4.5a shows that Sa_{T1} is the most efficient IM in estimating SDR because it has the lowest average dispersion among both the SFD and MFD buildings. In Figure 4.5b, a near identical trend was observed for PFA where Sa_{T1} was found to be the most efficient followed by Sa_{avg} . It is apparent from Figure 4.5 that acceleration-based IMs (Sa_{T1} , PGA, Sa_{avg} , and ASI), velocity-based IMs (PGV, CAV, SI), and displacement-based IMs (DSI, DS_{5-75} , and DS_{5-95}) cluster together and tend to have progressively higher average dispersion across the building groups. Recall that a similar pattern was also observed in the individual building assessment discussed in Section 4.5.1.2. It is also notable that the average dispersion for Sa_{T1} , PGA, and ASI, is lower in predicting PFA as compared to SDR. On the other hand, the dispersion of the velocity- and displacement-based IMs is higher in PFA than SDR.

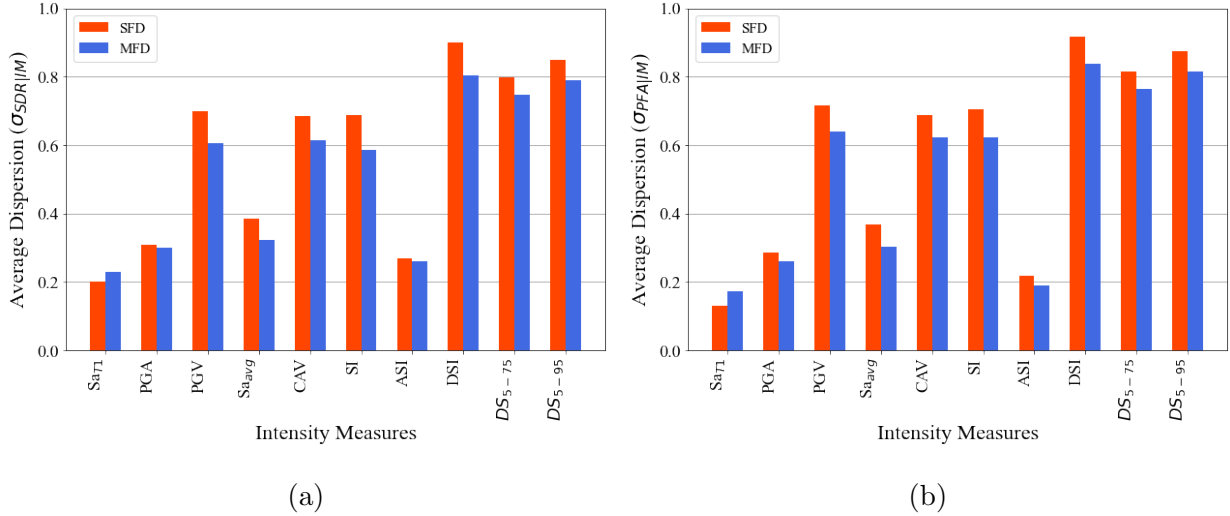


Figure 4.5: Average efficiency of (a) SDR ($\sigma_{SDR|IM}$) and (b) PFA ($\sigma_{PFA|IM}$) among four SFDs (red) and six MFDs (blue) for all 10 IMs considered.

Joint entropy-based efficiency

Figure 4.6 displays the average joint entropy across the four SFDs (in orange) and six MFDs (in green) for each of the 10 IMs. For both categories of buildings, acceleration-based IMs such as Sa_{T1} , PGA, Sa_{avg} , and ASI outperform velocity- and displacement-based IMs. Evi-

dently, Sa_{T1} is the most efficient IM among SFDs while ASI edges Sa_{T1} by a slight margin to be the most efficient for the MFDs. This observation conforms to the expected structural behavior of the archetypes. Meaning, it is reasonable for an elastic, period-dependent Sa_{T1} to be efficient for highly ductile SFDs that are not expected to collapse for a relatively large displacement. MFDs, on the other hand, are moderately ductile and tend to have multi-modal inelastic responses. Thus, it is plausible to observe ASI, which is an aggregate of Sa_{T1} from 0.1 to 0.5 seconds, to be the most efficient as compared to Sa_{T1} and other IMs. This pattern indicates that when the EDPs are assumed to be multivariate, more complex IMs such as ASI perform better in defining the demand model for buildings dominated by multiple modes. Recall that the univariate OLS-based method (Figure 4.5) established Sa_{T1} to be the most efficient for all 10 buildings regardless of the level of ductility of the building. Interestingly, the trend across different IMs for SFD and MFD is identical irrespective of the univariate or multivariate assumption. This implies that both the univariate and multivariate approaches can distinguish the performance of different IMs. This comparison also suggests that additional studies are needed (especially for other types of lateral force-resisting systems) to further investigate the implications of the univariate versus multivariate assumption.

4.5.2.2 Sufficiency summary

As highlighted in Section 4.2.2, there are various methods for determining if the distribution of an EDP conditioned on the IM is independent of the causal parameters. The merits of each method have been previously discussed at length. For the complete archetype set assessment, univariate and multivariate relative entropy-based methods are presented.

Univariate relative entropy

Table 4.6 summarizes the KL divergence between the univariate conditional EDP distribution with and without causal parameters. Each value is the sum of KL divergence between all the

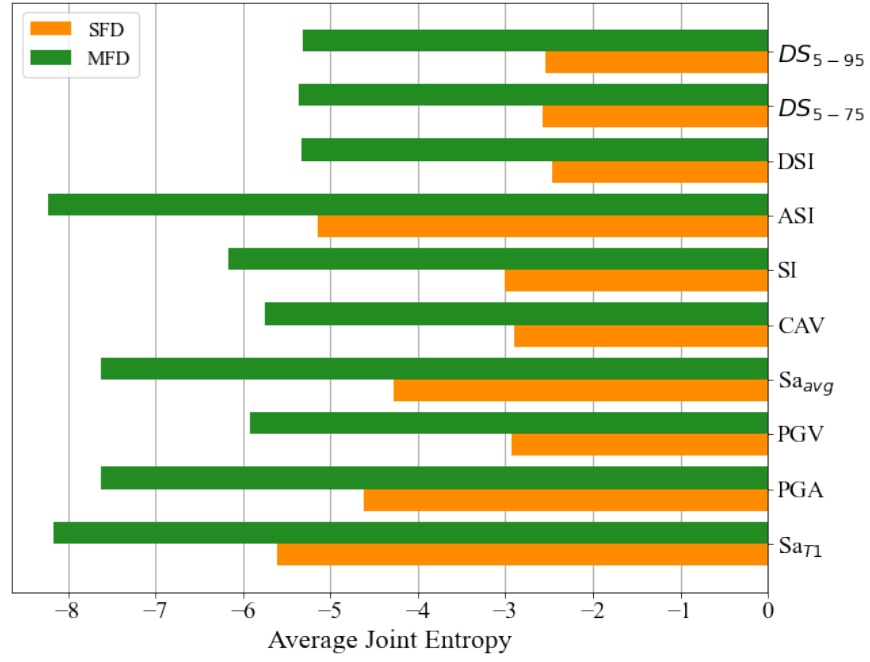


Figure 4.6: Average joint entropy of SDR and PFA ($\sigma_{SDR,PFA|IM}$) among four SFDs (orange) and six MFDs (green) for all the IMs.

causal parameters and EDPs. For instance, the values for MFD6B are the same as the total value presented in Table 4.5. The least relative entropy in each row is highlighted in bold font thus indicating the most sufficient IM. It is seen that the sufficiency trend is a function of the building's fundamental period and/or the displacement ductility demand. S_{aT1} is sufficient for one-story buildings while PGA is sufficient for two-story buildings. In both the one- and two-story buildings, ASI is the second most sufficient IM. The one- and two-story buildings have first-mode fundamental periods less than 0.26 seconds and an average displacement ductility demand of 0.62. To this end, it is logical that IMs such as S_{aT1} , PGA, and ASI are sufficient in general. However, for the four-story buildings that undergo highly nonlinear behavior and are also subjected to higher mode responses, S_{avg} is the most sufficient IM. Among the archetypes, the four-story buildings (on average) have a ductility demand of 2.01 which indicates that they experience much higher inelastic deformations compared to their one- and two-story counterparts. This result highlights the ability of S_{avg} to capture ground motion effects on a structure that responds to a range of frequencies due to period elongation and/or higher mode effects.

Multivariate relative entropy

Table 4.7 shows the KL divergence when the max SDR and PFA are assumed to follow a bivariate lognormal distribution. Each value represents the total KL divergence for all causal parameters. For instance, the values for archetype MFD6B are the same as the total value previously presented in Table 4.5. The sufficiency trend is more distinct as compared to Table 4.6. Under the bivariate assumption, S_{aT1} , PGA, and ASI appear to be the most sufficient for the one-story and two-story buildings while S_{avg} is the most sufficient for the four-story buildings.

Table 4.6: Total KL divergence (relative entropy) among EDPs and across causal parameters computed assuming the univariate relationship between EDPs. The KL divergence values are scaled by a factor of 1×10^3

Archetype ID	Period (T_1)	Sa_{T1}	PGA	PGV	Sa_{avg}	CAV	SI	ASI	DSI	DS_{5-75}	DS_{5-95}
SFD1B	0.13	3.80	10.9	85.0	34.5	309	61.9	6.26	276	225	235
SFD3B	0.13	2.45	10.7	86.6	34.5	319	62.8	5.81	280	234	243
MFD1B	0.16	8.25	9.44	94.3	30.2	302	72.1	8.30	298	235	245
MFD4B	0.16	11.9	10.9	103	31.9	314	80.1	11.1	318	252	263
SFD2B	0.22	15.5	7.85	90.3	25.0	282	70.1	11.3	294	241	250
SFD4B	0.22	25.9	16.0	107	30.2	294	87.6	21.4	333	280	290
MFD2B	0.26	31.6	14.2	95.5	23.6	293	74.5	21.4	319	300	305
MFD5B	0.26	11.7	5.50	56.4	11.2	207	43.3	7.23	236	252	257
MFD3B	0.49	21.4	14.9	44.8	12.8	183	31.4	21.6	211	290	279
MFD6B	0.49	6.13	5.81	25.0	4.58	122	15.6	8.68	150	233	220

4.6 Conclusions

This chapter presented a comparative assessment of alternative methods for evaluating and selecting the most appropriate ground motion intensity measure (IM) for nonlinear response history analyses. Specifically, efficiency and sufficiency are discussed as the two primary evaluation metrics. Historically, univariate linear regression (OLS) has been used for both types of evaluations, which disregards the nonlinear multivariate relationships between the engineering demand parameters (EDPs), IMs, and causal parameters. Recently, entropy-based measures have been proposed that address the limitations of the OLS-based methods but the relevant studies still relied on the univariate assumption.

In this study, the currently available univariate OLS-based methods are expanded to explicitly consider the multivariate distribution of EDPs. In particular, a multi-target generalized additive model (GAM) is proposed as an alternative to the OLS approach. The GAM appropriately captures the complex relationship within a given EDP (i.e., the response along

Table 4.7: Total KL divergence (relative entropy) among EDPs and across causal parameters computed assuming the multivariate relationship between EDPs. The KL divergence values are scaled by a factor of 1×10^3

Archetype ID	Period (T_1)	Sa_{T1}	PGA	PGV	Sa_{avg}	CAV	SI	ASI	DSI	DS_{5-75}	DS_{5-95}
SFD1B	0.13	6.35	10.9	62.0	24.8	183	49.8	8.14	179	141	145
SFD3B	0.13	4.15	9.75	57.7	23.0	182	45.3	6.55	169	141	144
MFD1B	0.16	8.70	10.3	66.1	25.3	186	54.6	9.88	193	147	151
MFD4B	0.16	12.4	12.8	73.0	29.0	201	60.8	12.9	208	163	167
SFD2B	0.22	18.4	13.2	76.8	27.6	209	62.8	16.7	226	186	189
SFD4B	0.22	26.4	19.8	87.1	33.4	232	73.2	23.9	247	216	219
MFD2B	0.26	32.2	17.1	79.8	27.0	234	63.8	22.3	240	231	230
MFD5B	0.26	12.6	7.39	43.8	11.5	167	34.2	8.30	160	179	180
MFD3B	0.49	27.8	17.8	47.1	13.5	191	35.2	25.8	178	238	228
MFD6B	0.49	9.53	7.65	25.7	6.01	127	17.3	10.5	119	173	166

the building height in the two orthogonal directions), between EDPs (e.g., story drift ratio (SDR) and peak floor acceleration (PFA)), and between the IM and EDPs. The GAM is implemented to compute the joint entropy as an alternative measure of efficiency and the p -value of the spline function as a measure of sufficiency. The EDP data generated from 10 woodframe buildings using a site-agnostic set of 826 pairs of ground motion records is leveraged to evaluate 10 different IMs. The results from both the univariate OLS and multivariate GAM suggest that Sa_{T1} and acceleration spectrum intensity (ASI) are the most efficient IMs across all building types. Also, for all IMs, greater efficiency was obtained for the single-family dwellings (SFDs) compared to the multi-family residences. The higher ductility demands in the multi-family dwellings (MFDs) was used to explain this result.

A comparative analysis between the existing and proposed relative entropy-based sufficiency methods is also performed using the set of aforementioned building archetypes and IMs. In the univariate case, Sa_{T1} appeared to be the most sufficient for all but one of the 1-story buildings, whereas, peak ground acceleration (PGA) and Sa_{avg} were found to be the

most sufficient for the 2- and 4-story buildings, respectively. In the multivariate case, the sufficiency trend was even more distinguished such that Sa_{T1} was found to be the most sufficient for all 1-story buildings, PGA the most sufficient for all 2-story buildings, and Sa_{avg} the most sufficient for all four-story buildings. Overall, it is seen that Sa_{avg} is sufficient for structures that respond to a range of frequencies whereas Sa_{T1} , PGA, and ASI are sufficient for shorter buildings with a fundamental period less than 0.26 seconds.

The results from this study suggest that capturing the multivariate EDP distribution in IM evaluations has non-negligible implications, especially for multi-story woodframe buildings. However, both the univariate and multivariate methods demonstrated that a single universally optimal IM likely does not exist for a set of building archetypes. Rather, there was clear evidence that the efficacy of an IM is a function of the level of nonlinearity (or ductility demand) in the response of the structure. To facilitate future applications of the various evaluation methods, the source code developed as a part of this research work is made publicly available in a GitHub Repository ([Dahal, 2022](#)). The repository includes code for the GAM- and univariate OLS-based approaches.

While the alternative methods presented thus far are sound approaches to evaluating the effectiveness of an IM, there are several limitations. Ground motion models often utilize a host of causal parameters such as soil type, fault type, and shear-wave velocity, which were not considered in this study. There is an opportunity for future IM evaluation studies to investigate these often-ignored causal parameters. The current study used a suite of unscaled ground motion records to negate the possibility of bias being induced due to amplitude scaling. However, it is noted that the use of unscaled records comes with its own challenges as the two extreme ends of the IM distribution could be dominated by a very specific set of causal parameters (low M and large R in low-intensity IMs, and high M and low R in high-intensity IMs). Finally, most of the alternative methods rely on the assumption that the EDPs, IMs, and causal parameters for a theoretical multivariate distribution (usually lognormal) which should be further investigated for different classes of structures.

CHAPTER 5

High-Fidelity High-Resolution Regional Risk and Resilience Assessment Framework

5.1 Introduction

Natural hazards impose a significant risk to the built environment. The catastrophic impact of such an event reverberates across spatially distributed buildings and lifeline infrastructure culminating in disrupted communities, handicapped societal well-being, and rattled economic conditions. To bolster community resilience and safeguard critical infrastructure, it is imperative that we have a comprehensive understanding of the collective vulnerabilities, intra- and inter-system dependencies, and potential consequences across an entire geographical region. Unlike traditional building-specific risk analyses, regional-scale assessments acknowledge the inherent spatial variability of seismic hazards and recognize that the influence of earthquakes transcends individual structures. Having a holistic perspective is instrumental in developing effective mitigation strategies, as it allows for the identification of vulnerable neighborhoods, the diagnosis of structural defects, and the assessment of imminent cascading effects. More importantly, regional seismic risk assessment informs evidence-based decision-making, enabling the formulation of targeted policies, community preparedness, disaster emergency response planning, and the creation of resilience-based building design codes. To this end, regional seismic analysis is well-positioned to serve as a cornerstone of earthquake engineering and risk management strategies.

A regional seismic risk and resilience analysis is a multifaceted and interdisciplinary

endeavor. It quantifies earthquake-induced consequences to support risk-informed decision-making in developing disaster preparedness plans, emergency response strategies, and long-term resilience initiatives. As such, it is pivotal for the risk analysis framework to have the following desirable characteristics: 1) a community-centric viewpoint to capture the widespread impact, 2) robustness to quantify and propagate uncertainties, 3) computational efficiency and scalability, and 4) the ability to advance long-term resilience initiatives such as building code amendment. Rigorous quantification of uncertainties in regional scale assessments is critical to successful risk mitigation strategies. However, this explicit treatment of uncertainties comes at a substantial computational cost. Performing an explicit probabilistic risk analysis in accordance with the FEMA P-58 methodology ([FEMA, 2012](#)) is computationally demanding. The P-58-based analysis procedure utilizes site-specific seismic hazards, building-specific numerical structural modeling, and component-level loss and recovery analysis. Scaling it to assess the seismic risk of large-scale inventories is bound to be computationally prohibitive if not impossible without leveraging specific efficiency-enhancement strategies in the workflow.

In this chapter, we present a generalizable computational framework to facilitate high-fidelity, high-resolution, and fully mechanistic regional assessment (HiFi FMRA) (note that “Hi-Fi” jointly represents high-fidelity and resolution) of building inventories. The term “high-fidelity” reflects the level of detail used for the nonlinear structural models, which is consistent with typical building-specific assessments. By “high-resolution”, we mean that each building and site in the inventory is explicitly represented. This can be contrasted with HAZUS-based (or similar) regional assessments ([FEMA, 2011](#)) which groups buildings and sites at the census-block or census-tract scale. The fully mechanistic assessment (FMA) implies that the component-based FEMA P-58-based procedure is utilized for all buildings and sites in lieu of, for example, surrogate models. The level of fidelity and resolution as well as the use of fully mechanistic assessments have a proportional influence on the computational cost, with higher levels requiring increased demands. One of the

key contributions of the proposed framework is the ability to maintain the rigorousness of building-specific performance-based assessments at the regional scale while balancing computational efficiency. In literature, the current state-of-the-art procedures ([Elhaddad et al., 2019](#); [McKenna et al., 2024](#); [Lu et al., 2020](#)) exploit the trade-off between fidelity and resolution to increase the computational feasibility of regional scale assessments. For example, the widely used HAZUS methodology sacrifices both fidelity and resolution to make regional risk analysis computationally tractable ([FEMA, 2011](#)). The HiFi FMRA is a departure from the conventional methods and presents a computationally viable approach to performing high-fidelity high-resolution regional risk assessment of large-scale building inventories. Additionally, a new approach to performing stochastic event set-based risk assessment of building portfolios is presented that is consistent with the HiFi FMRA. Ultimately, our intended goal is to contribute to the advancement of state-of-the-art regional risk assessment methods. The framework is demonstrated using a case study that performs economic loss and functional recovery assessments for more than 15,000 woodframe buildings in the City of Los Angeles. In addition to showcasing the computational workflows and results, the case study highlights the challenges and potential pitfalls of running a regional-scale HiFi FMRA.

5.1.1 Background

The damage caused by a large-scale earthquake not only contributes to billions of dollars in direct economic losses but also significantly disrupts community functionality by interrupting businesses and displacing households. Recent major events such as the 1989 Loma Prieta, California ([NIST, 1990](#)), 1994 Northridge, California earthquake ([NIST, 1994](#)), 2010 Maule, Chile ([Zareian et al., 2012](#)), 2011 Christchurch, New Zealand ([Allen et al., 2010](#)), and 2015 Gorkha, Nepal ([Rai et al., 2016](#)) earthquakes, have underscored the fact that it could take years for the affected communities to recover and get back to (a new) normal. For instance, it took 10 years to rehabilitate damaged buildings, schools, and bridges after the Loma Prieta earthquake ([Comerio and Blecher, 2010](#)). The same study also found that

it took Stanford University three years to repair and restore functionality in the 25 damaged buildings. Identical trends have been repeatedly observed for other United States and global earthquake events. The recurring theme of longer-than-acceptable recovery trajectory has instigated a national-level effort aimed at exploring the prospect of “beyond life safety” building code [EERI \(2019\)](#).

The extent and magnitude of losses endured in historical earthquakes is a testament that life safety and collapse prevention should be a baseline performance objective but not an end goal. Although the mandated building codes are amended periodically, the updates have focused on local or global structural enhancements. Recent studies have found that modern code updates significantly enhance collapse safety but only marginally reduce losses ([Liel and Deierlein, 2013](#); [Hutt et al., 2019](#)). As a result of the periodic building code updates, it is undeniable that if an event equivalent to the Loma Prieta earthquake occurs today, the overall devastation will be much lower. However, the consequences (e.g., direct loss, indirect loss, business disruption, household displacement, etc.) of such an event will likely be much greater because of a significant increase in assets and exposure. The performance of buildings designed to “modern” design codes in Christchurch, New Zealand supports this hypothesis. In the central business district near Christchurch, even the non-collapsed buildings took months to resume operation ([Chang et al., 2014](#)). The extended recovery was attributed to limited access due to cordons around the damaged buildings, lack of labor, delays in the decision to demolish repairable buildings, and challenges with funding the large-scale rehabilitation and reconstruction efforts (e.g., insurance payouts). The post-event surveillance data revealed the intricacies and complexities of recovery through a community-centric lens. For instance, a significant portion of the business district was cordoned off for more than two years ([Chang et al., 2014](#)) which displaced 50,000 city jobs and created ripple effects putting in question the long-term viability of a concentrated city center.

The influence of community-wide impeding factors and the lasting effects of socioeconomic disruptions are inevitable after a catastrophe. Researchers and policymakers are

starting to realize that the cascading impact of a catastrophic event can be mitigated through strategic and concerted efforts directed at vital societal functions. More recently, the focus has shifted toward designing structures to achieve recovery-driven performance objectives. This paradigm shift has garnered the attention of practitioners, researchers, and policymakers at both national and international levels. A testament to this transformative momentum is the FEMA P-2090/NIST SP-1254 report (NIST and FEMA, 2021). In 2018, Congress passed the National Earthquake Hazards Reduction Program (NEHRP) Reauthorization Act into law that decidedly stipulated NEHRP to “*gather information on community resilience*.” To comply with the congressional mandate, FEMA and NIST jointly convened a committee comprised of experts from all sectors (technical, policy, and implementation) to identify needs and recommend options to enhance the built environment such that the performance goals guided by reoccupancy and functional recovery time are achieved. The report also describes community resilience from a functional recovery point of view, defines target performance levels, and identifies the potential cost and benefit of resilient-based seismic design.

Three out of seven recommendations in the FEMA P-2090/NIST SP-1254 report (namely Recommendations 2, 3, and 4) emphasized the need to design and retrofit new and existing buildings and lifeline infrastructure to meet recovery-based objectives. The report specifically states that “... *new buildings should be designed for specific recovery-based objectives that will support reliable reoccupancy and acceptable functional recovery times following a major earthquake*”. Evaluation and characterization of recovery-based design is an active area of research and policy discussions. In particular, as a part of the 2026 NEHRP Provisions update, the Building Seismic Safety Council (BSSC) has established the functional recovery task committee to investigate and quantify the implications of recovery-based design updates. The committee is tasked to develop technical proposals to codify the recovery-based design updates into the current building codes and standards. Established in 1979, BSSC develops and maintains the NEHRP Recommended Seismic Provisions for New Buildings

and Other Structures. The Provisions serve as the primary resource to the ASCE/SEI 7 design standard (ASCE, 2016). Conceptually, a resilience-based design framework would involve identifying recovery-targeted design parameters (e.g., response modification factor (R), importance factor (I_e)) that enhance the performance of both the structural and nonstructural components. The “optimal” recovery-targeted design parameters would then replace the design parameters in current codes.

In concept, the HiFi FMRA approach is well-positioned to make tangible contributions to the development of safe, sustainable, and resilient societies. However, to the best of our knowledge, there is a lack of efficient computational frameworks for achieving such an assessment. Historically, regional risk has been performed based on pre-defined building fragility curves (e.g., HAZUS). Such a method is useful for representing aggregated loss at the zip code or neighborhood level but is severely limited in guiding policy decisions to help achieve recovery-based performance objectives. To address the glaring need for an efficient and practical computational workflow, HiFi FMRA is proposed to facilitate high-fidelity high-resolution, and fully mechanistic regional risk and resilience simulation. The HiFi FMRA can serve various purposes within the disaster risk management spectrum but for the scope of this work, the framework is presented in the context of 1) evaluating the functional recovery of buildings under existing codes and 2) investigating the influence of recovery-based design. The HiFi FMRA is designed to perform site- and building-specific risk and resilience analysis at a regional scale by explicitly considering spatial variability. It can also be used as an engine to iterate alternative recovery-based designs. In this study, we implement HiFi FMRA to assess the spatially distributed risk and resilience of more than 15,000 single- and multi-family woodframe buildings within the City of Los Angeles. To fully understand the implications of recovery-based design, it is also important to perform cost-benefit analyses, evaluate the feasibility from an implementation standpoint, and identify potential challenges. However, such HiFi FMRA use cases that can potentially support building code updates, are beyond the scope of this chapter.

5.2 Proposed Computational Framework

The proposed computational framework is formulated specifically for spatially distributed buildings and is thus suitable for regional seismic risk assessment. The overarching motivation of the procedure is to efficiently scale the implementation of site-specific component-level FEMA P-58 methodology to large-scale building inventories. The goal is to be able to accommodate both single (or a few) scenario assessments and stochastic event set-based evaluations. We focus on the latter in the formulation of the overall workflow because it has (by far) the highest computational demand. The high fidelity is achieved by utilizing explicit three-dimensional (3D) finite element models generated in OpenSees ([Mazzoni et al., 2006](#)). The model is employed to simulate the structural performance of the building and perform probabilistic seismic demand analysis (PSDA). PSDA is one of the four key components of the FEMA P-58 methodology and, by far, the most computationally demanding aspect. Numerous research studies have proposed simplified single-degree- or multi-degree-of-freedom systems as an alternative to a detailed structural model ([Lu et al., 2020](#); [Elhaddad et al., 2019](#)), particularly for use in regional scale assessments. The simplified structural analysis model reduces the computational cost but does so by sacrificing building-level fidelity. In the traditional regional analysis approach (e.g., HAZUS), it is typical to aggregate risk at the neighborhood or census tract level. Aggregating risks across a neighborhood is an efficient approach but it loses the granularity which could be crucial in disaster risk management and identifying vulnerable areas. The proposed framework adopts high-resolution simulations where building- and site-specific (including ground motion selection) risk analyses are considered.

Figure 5.1 illustrates the computational workflow of the HiFi FMRA approach. It is composed of six distinct procedural steps as indicated by the orange circles in the graphics. The first task is delineating the region and identifying the geo-locations of the building sites of interest. Once the sites are identified, a building is assigned to each site based on a pre-defined

inventory database. As described earlier, one of the intended goals of the HiFi FMRA is to evaluate the implications of changes to different seismic performance parameters (e.g., R , I_e) to regional functional recovery performance. With this goal in mind, the strategy described in Section 5.2.3 includes an automated design of woodframe buildings. The designs are governed by the geometric (e.g., number of stories, floor plan) and loading (e.g., roof weight) characteristics of the building as well as the site-specific hazard. In other words, the assigned building is designed for site-specific design parameters to maintain a high resolution. To enable these site-specific designs, we adopt the concept of a “design variant” (Welch and Deierlein, 2020c), which is an archetypal skeleton-like building structure with a fixed layout and building properties (e.g., number of stories, roof loading) but without a designed lateral-force-resisting structural system. Table 5.2 outlines the design variant database assembled for this study. Section 5.4.1 details the design variant database is leveraged to model the spatially distributed building inventory.

The third step characterizes the seismic hazard across the region of interest. Recall that the adopted context is a stochastic event set-based assessment. Therefore, hazard modeling entails probabilistically simulating a suite of hazard-consistent stochastic ground motion maps. These maps represent the joint spatial distribution of ground motion shaking intensity along with the associated uncertainty. The details of this step are described in Section 5.3. Following the exposure and hazard modeling, the site-specific building and hazard specifications are screened to remove redundant assets with similar hazards. In other words, if two sites have the same building design and are expected to see a “similar” hazard distribution, an explicit analysis of only one of the buildings is sufficient to define consequences for both buildings. The hazard similarity is determined by comparing the first and second moments of the distribution of the ground motion intensity measure (IM) of interest. The distribution of IM at a site corresponds to the distribution of stochastic maps. Two sites are deemed similar only if both the first and second moments of the IM are numerically the same. Section 5.4.2 details an example implementation of such characterization. Filtering

such redundancies serves as an initial curtailment of the computational demand without sacrificing resolution. The final step is to execute an automated workflow in a distributed computing environment to run large-scale FMAs. The proposed framework takes advantage of Auto-WoodSDA (WoodSDA in short), an end-to-end computational platform developed to perform an explicit FEMA P-58-based assessment (Dahal et al., 2022b). As discussed in Section 5.2.3, the output of the framework is the building-level distribution of the consequences (e.g., repair cost, reoccupancy time, and functional recovery time) conditioned on the site-specific shaking intensity distribution for the entire inventory.

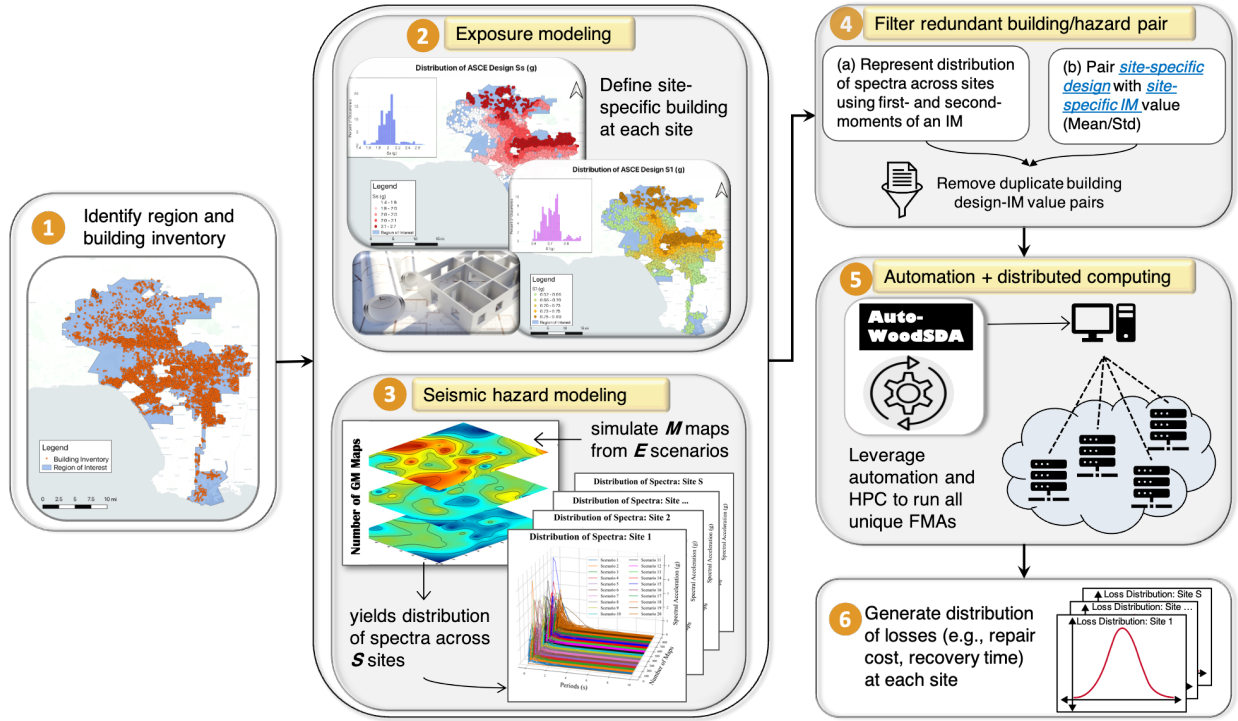


Figure 5.1: Graphical illustration HiFi FMA.

5.2.1 Traditional regional assessment

In traditional regional loss assessment studies (e.g., Jayaram and Baker (2010); Han and Davidson (2012); Miller and Baker (2015)), the set of stochastic maps have corresponding

loss maps. The one-on-one mapping between the intensity and loss map preserves the spatial correlation which allows the losses of spatially distributed assets to be aggregated for a given loss map. The distribution of total loss is used to quantify the annual rate of exceeding some loss threshold. [Jayaram and Baker \(2010\)](#) proposed Eq. (5.1) to compute the annual loss exceedance rate at a given loss value x

$$\lambda_{X \geq x} = \left(\sum_{i=1}^E \lambda_i \right) \cdot P(X \geq x) \quad (5.1)$$

where X is the distribution of total loss, E is the number of earthquake scenarios, λ_n is the annual rate of occurrence of n^{th} scenario, and $P^i(L \geq x)$ is the empirical loss exceedance probability as given by Eq. (5.2),

$$\hat{P}(X \geq x) = \frac{1}{M} \sum_{m=1}^M I(l_m \geq x) \quad (5.2)$$

where M is the number of stochastic intensity maps, l_m is the loss corresponding to the m^{th} map, and $I(l_m \geq x)$ is an indicator function which equals to 1 if $l_m \geq x$, 0 otherwise.

The traditional regional risk framework is not directly applicable to the HiFi FMRA approach because the stochasticity introduced by the Monte Carlo-based loss samples simulated in WoodSDA makes it impossible to link a ground motion map to a corresponding loss map. Recall that site-specific loss distribution is simulated via Monte Carlo simulation in Pelicun, a FEMA P-58-based loss assessment tool developed by NHERI SimCenter ([Zsarnoczay, 2019](#)). The randomly generated loss samples can not be aggregated across sites because it will result in central tendency. In this study, we modify the traditional risk framework to propose an algorithm that retains the spatial correlation and enables one-on-one mapping between consequence and ground motion maps. algorithm 1 outlines the step-by-step operation to establish a one-to-one link between the ground motion and damage/loss map, aggregate losses of spatially distributed inventory, and computes the regional loss curve.

Algorithm 1 Modified Regional Loss Assessment Methodology

- 1: **Input:** Distribution of site-specific loss ($N_{MC} \times 1$) across all sites I and M ground motion maps i.e $N \times I \times N_{MC}$.
- 2: Use the WoodSDA-generated loss samples ($N_{MC} \times 1$) to calculate site-specific loss curves (as a function of an intensity measure (IM))
- 3: Initialize an empty vector $\mathbf{L}$ to store the total loss **for** n *in range*(N) **do**
- 4: Compute the total regional loss L_R

$$L_R = \sum_{i=1}^I L_n(IM_i)$$

where $L_n^i(IM = im)$ is the loss corresponding to an IM value im at site i for ground motion map n . It is computed based on the loss curve computed in Step 2.

- 5:
- 6: Compute an empirical exceedance probability

$$\hat{P}(L_R \geq x) = \frac{1}{N} \sum_{n=1}^N I(l_n \geq x)$$

where $I(l_n \geq x)$ is an indicator function which equals to 1 if $l_n \geq x$, 0 otherwise

- 7: Compute regional loss exceedance rate

$$\lambda_{L \geq x}^{total} = \left(\sum_{n=1}^N \lambda_n \right) \cdot P(L_R \geq x)$$

where λ_n is the recurrence rate of ground motion map n

- 8: **Output:** Annual exceedance rates as a function of total regional loss values L_R
-

5.2.2 Regional Recovery Assessment

algorithm 1 addresses the issue of intensity-to-loss map mapping. However, it still cannot be used to compute the regional functional recovery exceedance curve because recovery times (reoccupancy and functional recovery time) are not additive in nature. In other words, the recovery time of building inventory cannot be aggregated because the recovery trend of buildings is parallel as they can regain functionality simultaneously. To the best of our knowledge, there has not been a regional-scale study that quantified the recovery exceedance curve. To that end, we modify Eq. (5.1) to compute building-level recovery exceedance curve utilizing the Monte Carlo-based recovery time samples ($N_{MC} \times 1$) simulated using the beta ATC-138 functional recovery methodology (ATC, 2021). In this study, we simulate two recovery times, reoccupancy, and functional recovery, and generate $N_{MC} \times 1$ samples where N_{MC} is the number of Monte Carlo sample size, which is set to 5000. The annual exceedance rate of exceeding a recovery time t is given by

$$\lambda_{T \geq t}^i = \left(\sum_{n=1}^N \lambda_n \right) \cdot P^i(T \geq t) \quad (5.3)$$

where N is the number of ground motion maps used in the hazard characterization, λ_n is the annual rate of occurrence of the ground motion map n , and $P^i(T \geq t)$ is the empirical recovery exceedance probability at site i which is estimated by Eq. (5.4),

$$\hat{P}^i(T \geq t) = \frac{1}{N_{MC}} \sum_{n=1}^{N_{MC}} I(t_n^i \geq t) \quad (5.4)$$

where N_{MC} is the number of Monte Carlo samples, t_n is the recovery time corresponding to the n^{th} sample, and $I(t_n \geq t)$ is an indicator function which equals to 1 if $t_n \geq t$, 0 otherwise.

5.2.3 Leveraging automation

To combat scalability challenges, we have developed a computational program equipped to perform high-fidelity FMA per the FEMA P-58 methodology. Figure 5.2 shows the end-to-end workflow of different modules implemented in the automation tool, WoodSDA. The

tool consists of four modules that can be executed independently or sequentially. Given the suite of user inputs such as building information and site-specific ground motion records, the design module creates a code-compliant design and outputs material modeling parameters to the structural module, which generates a 3D numerical model in OpenSees and simulates the nonlinear static and/or dynamic response under the pre-selected ground motions. It also post-processes the raw structural response data to compute the relevant (to the damage assessment) response parameters including the peak story drift ratio (PSDR), peak floor acceleration (PFA), and maximum (across all stories) residual drift ratio (RDR). The processed structural response parameters are pipelined to the damage module where building-level damage analysis is performed. Finally, the loss module simulates component-level damage states and assesses consequence metrics such as economic loss and time to regain function among others. By harnessing the automated workflow, the overall “computational time” required to complete an FMA is substantially reduced. The computational time is defined as the combination of manual (human) and CPU wall clock time it takes to complete an FMA. WoodSDA is one of the two key components of the proposed regional-scale computational workflow. It significantly reduces the total computational time and renders large-scale assessments computationally feasible. The reader is referred to ([Dahal et al., 2022b](#)) for a more comprehensive overview and implementation guide of the platform.

5.2.4 Leveraging distributed computing

High-performance computing (HPC) resources and technologies are an integral part of the proposed framework. HPC resources are utilized in a variety of ways to tackle the high computational demand of performing HiFi FMRA. In particular, distributed computing is used to execute the WoodSDA program while parallel computing is adopted to perform regional seismic hazard analysis. At a high level, distributed and parallel computing appear to be similar because both make use of multiple processors simultaneously to enhance computing

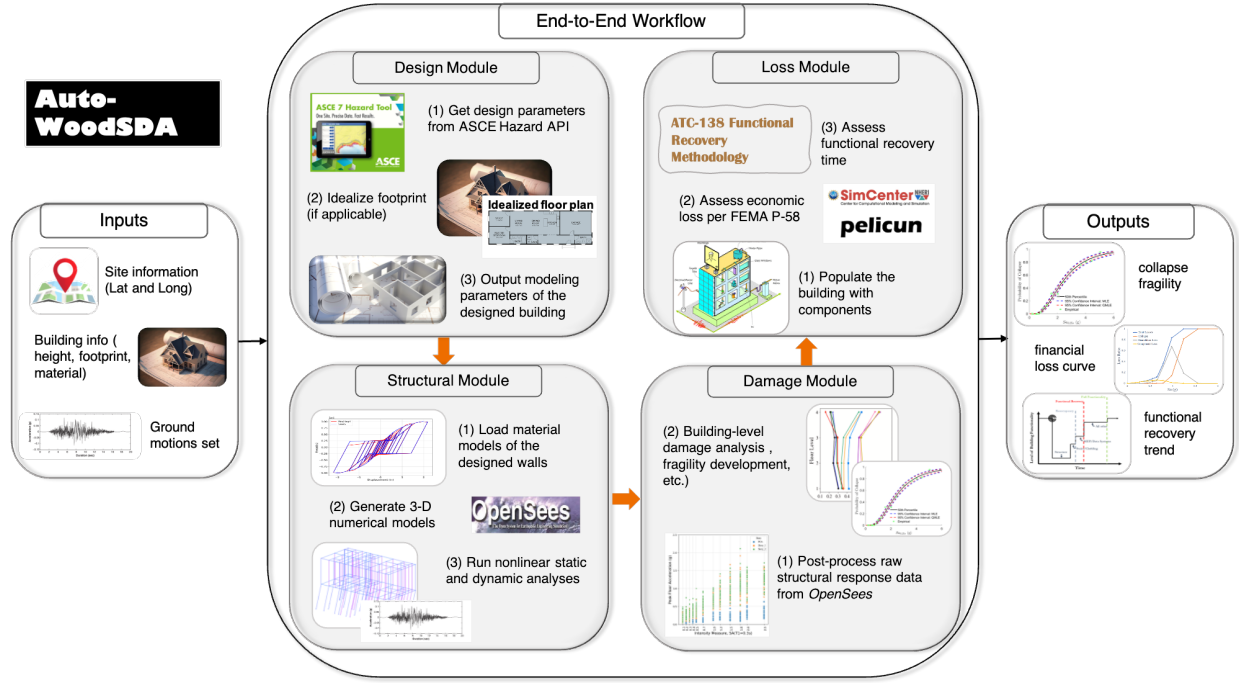


Figure 5.2: Graphical illustration of the end-to-end workflow implemented in WoodSDA.

capacity. However, there are differences in how each approach exploits the HPC resources. In parallel computing, tasks are divided into sub-tasks which are executed concurrently in a set of processors connected via a shared memory space inside one computer. Distributed computing, on the other hand, involves a network of processors with independent memory that work together to execute large-scale computations across multiple machines. Distributed computing is instantiated at Step 5 of the framework as demonstrated in Figure 5.1. Once the exposure and hazards are characterized, the unique FMA runs are identified and executed in a cluster of processors as highlighted in Figure 5.3. The four modules of the WoodSDA platform cannot be executed in parallel because the input of each module is pipelined from the preceding one. The sequential nature of the computation makes it suitable for distributed computing where each processor has an allocated memory and can complete the risk assessment of individual buildings without any data transfers from the neighboring processors. The computational efficiency of distributed computing depends on the number of FMAs,

available processors, and the job scheduling algorithm. In this study, we use an adaptive job scheduler that assigns a job (i.e., an FMA run in WoodSDA) to available processors until all the jobs are completed. The adaptive scheduler aims to maximize processor utilization by dynamically allocating additional jobs to processors that demonstrate faster job completion times. It ensures that all the processors remain active and help balance the workload. This differs from the traditional scheduling algorithm which assigns a fixed number of jobs to a particular processor. The traditional scheduler is likely to result in some idle processors because if one processor completes the assigned jobs faster than the other it will not be assigned additional jobs. The number of concurrent instantiations of WoodSDA (or jobs) is capped by the number of available processors.

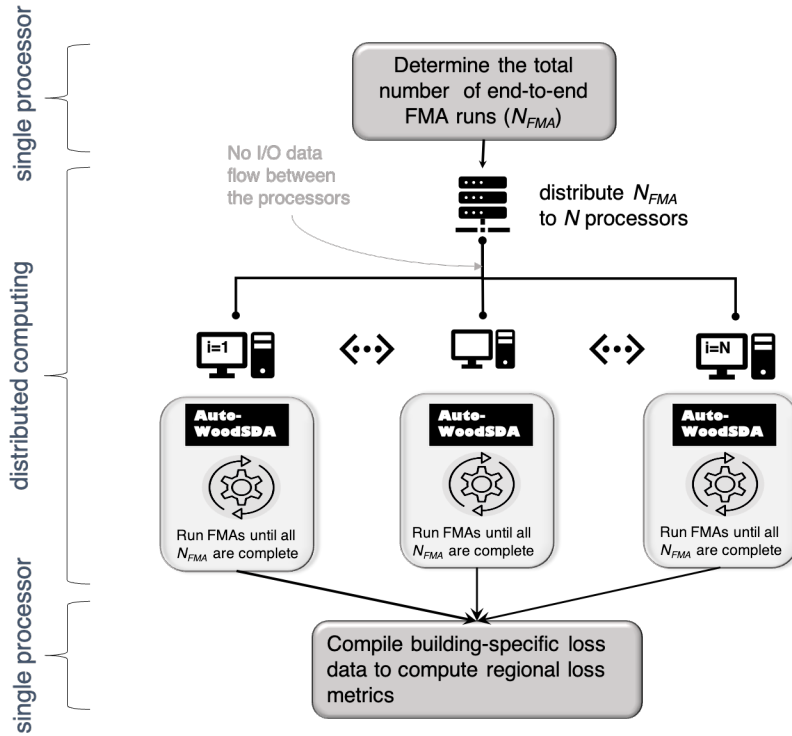


Figure 5.3: Overview of distributed computing.

5.3 Regional Seismic Hazard Analysis

To quantify the seismic risk and resilience of spatially distributed structures, the seismic hazard characterization must be consistent across the region. Conventionally, site-specific seismic hazard analysis (i.e. probabilistic seismic hazard analysis (PSHA)) is performed to develop hazard maps. The site-specific PSHA is applicable to an individual building but it is not suitable for regional assessments because 1) PSHA quantifies the probability distribution of the ground motion intensity independently between the sites and 2) spatially correlated inter- and intra-event residuals cannot be incorporated into the site-specific PSHA. The independent treatment of the probability densities implies that the set of rupture scenarios and their associated magnitudes and distances used in the ground motion attenuation relationship might be different for two sites within a region. It creates hazard inconsistency and is not suitable for regional risk assessment.

In theory, one could consider every possible rupture scenario that is likely to occur within the region to quantify hazard. However, it will be computationally prohibitive, if not impossible, to integrate the hazard curve of potentially hundreds of thousands of rupture scenarios with tens of thousands of sites within a region. Thus, to make the regional risk analysis computationally viable and practical, the catalog of thousands of probable earthquake events is down-sampled to a “manageable” set. Several studies ([Han and Davidson, 2012](#); [Jayaram and Baker, 2010](#); [Manzour et al., 2016](#); [Wang et al., 2023](#)) have proposed efficient approaches to regional seismic hazard characterization as part of the risk analysis workflow for distributed infrastructure.

There are two major aspects of regional seismic hazard analysis 1) simulating hazard-consistent probabilistic earthquake scenarios ([Chang et al., 2000](#); [Campbell and Seligson, 2003](#)) and 2) simulating probabilistic ground motion intensity maps ([Jayaram and Baker, 2010](#); [Vaziri et al., 2012](#)). The overall procedure of implementing the two aspects is similar for both the scenario-based and stochastic event sets. In the scenario-based hazard

analysis, the stochastic ground motion maps are simulated based on the magnitude recurrence relationship. The underlying purpose of scenario-based assessment is to study risk to distributed infrastructure under specific earthquake scenarios. It can be used to appraise losses across a region after a real earthquake event or to investigate the potential risks under specific earthquakes that might dominate the hazard in the region. While this approach is computationally tractable, it cannot capture uncertainties that are otherwise represented in a stochastic event set-based framework. Furthermore, identifying an earthquake scenario that will uniformly dominate the hazard across a region is not trivial. Conceptually, a large enough fault rupture might dominate the hazard in a small region (e.g., neighborhood or small town) but the same cannot be said for larger geographical areas (e.g., city or county) because shaking intensity attenuates with distance. A more robust and comprehensive approach involves probabilistically generating a stochastic set of ground motion intensity maps by considering all possible earthquake scenarios that have a measurable impact on the hazard within the region i.e., stochastic event set-based assessment. This study only implements the stochastic event set-based risk assessment procedures.

Regional seismic hazard analysis involves several layers of high-dimensional computations as outlined in algorithm 2. It poses significant computational challenges because of the need to characterize the joint (spatially) distribution of shaking intensities across a large number of sites. Additionally, the need to quantify uncertainty in predicting the ground motion shaking intensity compounds the complexity. Regional seismic hazard analysis is an active area of research. This study adopts the algorithm presented in [Han and Davidson \(2012\)](#) with appropriate modifications to fit our use case. The regional hazard simulation is performed using the regional risk determination tool (R2D), a software developed by the NHERI SimCenter ([McKenna et al., 2024](#)). Specifically, the back-end code of the *Hazard Simulation* within R2D is used to simulate regional ground motion maps. To facilitate nonlinear response history analysis in WoodSDA, ground motion records are selected for the set of site-specific spectra corresponding to the set of maps. The ground motion selection is

completed externally, outside R2D. The following subsections describe each algorithm step in detail.

5.3.1 Region and site delineation

Identifying and modeling exposure is relatively straightforward in the context of this study. The WoodSDA platform is specifically developed to automate the component-level FEMA P-58-based consequence analysis of residential woodframe buildings. One of the key features of WoodSDA is the built-in module that generates code-complaint new designs. As such, new residential woodframe buildings are identified as the asset class of interest. The asset class is then utilized to identify the region of interest. The United States housing inventory is dominated by woodframe residential buildings. The pattern is consistent across states, counties, and cities. In particular, low-rise residential dwellings account for more than 90 percent of the housing inventory in the City of Los Angeles (LA) ([Marcin, 1987](#)). To this end, the city of LA is identified as the region of interest.

To model the identified exposure within the region of interest, data is gathered from the LA city data portal ([Portal](#)). The portal is an open-source repository that hosts a wide array of data catalogs including the new residential building permits issued by the Department of Building and Safety for the construction, remodeling, and repair of buildings and attached structures. The dataset is periodically updated and when it was last accessed on November 11, 2022, it had 24,544 rows. The dataset contains the permits issued from 2013 until 2022. The raw dataset was cleaned to remove incomplete and irrelevant parts. The following filtering criteria are applied:

1. The rows with missing geolocation coordinates (latitude and longitude) are removed.
2. The permits for an attached structure, retrofit, or remodeling are removed because the asset class of interest is the new single- and multi-family residential buildings.
3. The occupancy type of a trace number of buildings is commercial. The dataset is

Algorithm 2 Regional Seismic Hazard Analysis

- 1: **Input:** Geographical locations for sites $i \in \{1, \dots, I\}$ [Section 5.3.1]
 - 2: Generate or identify earthquake scenarios. E.g., Mean UCERF3 model [Section 5.3.2]
 - 3: Down-sample scenarios in Mean UCERF3 model into a smaller earthquake set (J) [Section 5.3.3]
 - a: Filter by source-to-site distance
 - b: Filter by hazard contribution
 - c: Mixed integer optimization-based subsampling **for** j *in range*(J) **do**
 - └ [Section 5.3.4]
 - 4: Simulate M_j correlated ground motion maps per scenario based on Monte Carlo Simulation (MCS)
 - 5:
 - 6: Sample a reduced number of ground motion maps N from the total set of $J * M$ MCS maps using one of the three approaches [Section 5.3.5]
 - a: OPS-based method
 - b: Random sampling and minimizing KL divergence
 - c: KMeans clustering
 - 7: Perform checks to ensure down-sampled MCS maps recover the hazard curve **for** i *in range*(I) **do**
 - └ [Section 5.3.6]
 - 8: Select N_i ground motion records by matching the site-specific spectra from N maps
 - 9:
 - 10: Select ground motions to represent the spectrum of the MCS maps [Section 5.3.6]
-

filtered for non-residential occupancy types.

4. The data is also filtered for duplicate geolocation coordinates, and permit numbers.

After data cleansing, the final dataset consists of 15,336 data points representing 15,336 unique sites permitted to construct single- or multi-family residences as depicted in Figure 5.4a. The permits were issued between 2013 and 2022. Figure 5.4b highlights the breakdown of 15,336 total permits per issued year. It appears that new residential building construction peaked in 2017 and has since been on a downtrend. The numbers are the lowest for 2022 because the database, when accessed in November 2022, did not have data for the full year.

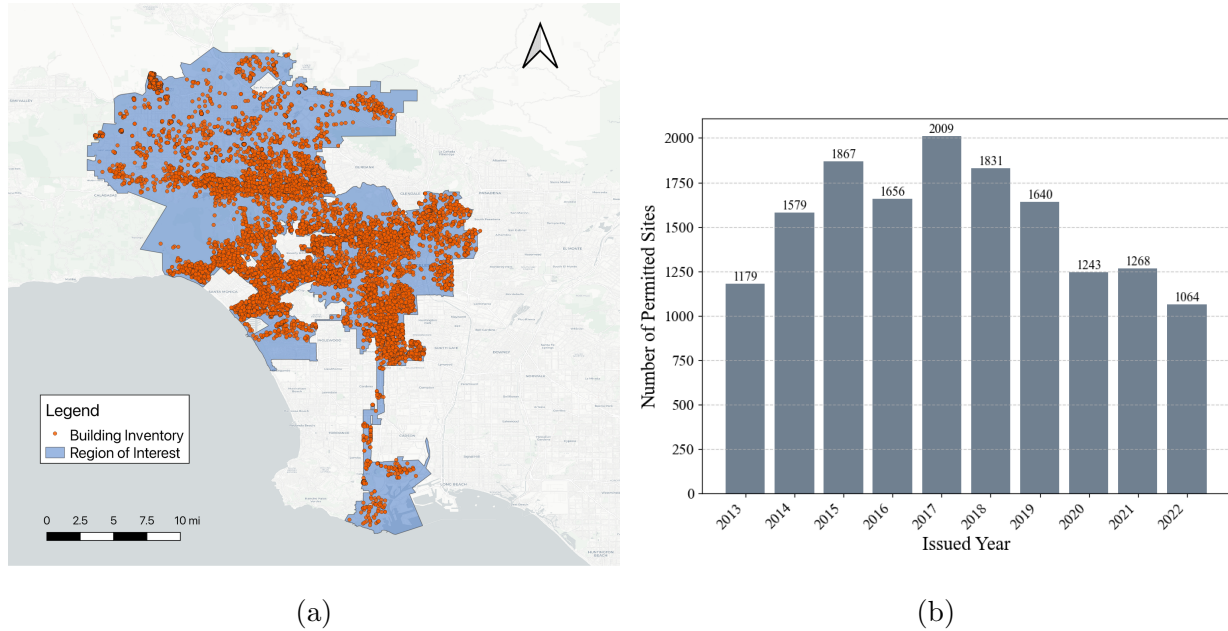


Figure 5.4: a) Region and site delineation; b) Breakdown of LA City permits issued between 2013 and 2022.

5.3.2 Generating candidate earthquake scenarios

Generating a candidate set of earthquake scenarios is the first step of regional hazard simulation. In the conventional MCS-based approach, earthquakes on any given active fault are randomly sampled from the distribution of probable earthquake magnitudes. The Gutenberg-Richter recurrence law characterizes the distribution of earthquake magnitudes. This study leverages the uniform California earthquake rupture forecast, version 3 (UCERF3) model (Field et al., 2014) developed by the working group jointly established between the United States Geological Survey (USGS), the California Geological Survey, the Southern California Earthquake Center, and the California Earthquake Authority. The UCERF3 is the latest forecast model that gives the probability of all possible, damaging (e.g., $M > 5$) earthquakes over a specified time-span. The UCERF3 considers more than 350 active faults across California and its various models (e.g., FM3.1, FM3.2, and FM Mean) comprise more than 300,000 unique fault-based earthquakes. To account for various sources of model uncertainty (epistemic and aleatory), a logic tree structure is established based on the two primary fault models (FM3.1 and FM3.2) and other model components such as deformation models and earthquake rate models. The working group also released the Mean UCERF3 model (equally weighted FM3.1 and FM3.2 models) which consists of 355,084 viable earthquake rupture scenarios with a corresponding annual probability of occurrence. The 355,084 earthquakes are the initial candidate scenarios.

5.3.3 Down-sampling earthquake scenarios

Simulating stochastic ground motion maps based on the initial candidate set of 355,084 earthquake scenarios is computationally prohibitive. For instance, if we only simulate 10 ground motion maps per scenario, it would result in 3.5 million maps. The subsequent operations would be in the order of billions. Thus, to render the ground motion map simulation computationally feasible, the initial earthquake set is reduced to a “manageable” size. Sev-

eral research studies ([Han and Davidson, 2012](#); [Miller and Baker, 2015](#); [Manzour et al., 2016](#); [Wang et al., 2023](#)) have investigated numerical optimization schemes to efficiently sample the earthquake scenarios. The approach implemented in algorithm 2 combines engineering judgment with the optimization-based probabilistic scenario (OPS) method ([Han and Davidson, 2012](#)). In total, three reduction techniques are executed in sequence to reduce the initial candidate set with 355,084 possible earthquake scenarios to 20. The three techniques are discussed in the following sections.

5.3.3.1 Filtering by distance

The first reduction technique is essentially a filtration process and is trivial. The 355,084 earthquakes in the Mean UCERF3 model represent possible earthquakes all over California. However, as demonstrated in Figure 5.4a, the region of interest is the City of Los Angeles. We know that the ground motion intensity attenuates with site-to-source distance. Therefore, we can remove earthquake sources that are far away from the region. The earthquake sources that are farther than 150 kilometers from the centroid of all the building locations are sampled out.

5.3.3.2 Downsample by contribution

In theory, the USGS Hazard Tool ([USGS, 2023](#)) considers all possible earthquakes in the region to calculate the “true” hazard curve. The true hazard curve is utilized as a benchmark. The objective of the sub-sampled set of earthquakes is to match the true hazard curve as closely as possible. Since a set of earthquake scenarios is used to match the hazard, the contribution of an earthquake scenario, j , in matching the true hazard curve across the region is quantified by Eq. (5.5). Ultimately, a scenario set, J , is selected with the highest cumulative contribution to the hazard curve. This approach was proposed by [Han and](#)

Davidson (2012).

$$C_j = \frac{1}{I \cdot R} \sum_{i=1}^I \sum_{r=1}^R \left[\frac{P_j \cdot P(y_{ij} \geq Y_{ir})}{\sum_{j=1}^J P_j \cdot P(y_{ij} \geq Y_{ir})} \right] \quad (5.5)$$

In Eq. (5.5), I is the number of sites, J is the number of earthquake scenarios, R is the total return periods, P_j is the annual occurrence probability of earthquake scenario j , Y_{ir} is the ‘true’ ground motion intensity measure for the return period r at site i , and y_{ij} is the ground motion intensity at site i due to earthquake j . Note that the annual occurrence probability of selected earthquakes needs to be normalized such that their sum is unchanged and still represents the original hazard level.

5.3.3.3 OPS method

The final step is to select a subset of events that will recover the hazard curve for all sites and return periods via a mixed-integer linear optimization routine termed the optimization-based probabilistic scenario (OPS) method. The objective function of the OPS method is to minimize the sum of errors over all sites (I) and return periods (R), between the ‘true’ hazard curves and the hazard curves recovered by the reduced set of earthquakes. The mathematical formulation of the objective function is defined in Eq. (5.6)

$$\text{Min} \sum_{i=1}^I \sum_{r=1}^R w_{ir} (e_{ir}^+ + e_{ir}^-) \quad (5.6)$$

where w_{ir} is the user-defined weight to the error term at site i and return period r , e_{ir}^+ is the error due to overestimating the hazard curve while e_{ir}^- is the error due to underestimating the hazard curve. As recommended by Han and Davidson (2012), for a given return period, equal weights ($w_{ir} = r$) are assigned to all the sites. The reasoning behind assigning error weights proportional to the true annual exceedance probability ($1/r$) is to ensure that the discrepancy in the error terms associated with different hazard levels (i.e., return periods) are properly considered.

The error terms in Eq. (5.6) are calculated as the difference between the “true” annual

exceedance probability ($1/r$) and the annual exceedance probability estimated using the subset of earthquake events as formulated in Eq.(5.7)

$$\sum_{j=1}^J \{P_j \cdot P(y_{ij} \geq Y_{ir})\} - e_{ir}^+ + e_{ir}^- = \frac{1}{r} \quad \forall i, r \quad (5.7)$$

where J is the number of candidate earthquake events, P_j is the hazard-consistent annual occurrence probability for earthquake event $j \in (1, \dots, J)$ as determined by the OPS method, and e_{ir}^+ and e_{ir}^- are estimation errors as described above. The OPS method outputs hazard-adjusted occurrence probabilities as well as errors. A constrained optimization formulation that utilizes the following constraints (Equations (5.8)-(5.12)) guarantees that the errors are minimized. Eq. (5.8) and Eq. (5.9) are two user-defined constraints that specify the desired number of earthquake scenarios (J^{red}) in the reduced set. Per Eq. (5.9), the optimal number of earthquake scenarios (J) selected by the OPS method will not exceed the user-specified number (J^{red}). The constraint is implemented through an indicator function, z_j which equals 1 if scenario j is included in the subset and 0 otherwise.

$$P_j \leq z_j \quad \forall j \quad (5.8)$$

$$\sum_{j=1}^J z_j \leq J^{red} \quad (5.9)$$

The mixed-integer optimization routine imposes additional constraints on some parameters as follows:

$$z_j \in \{0, 1\} \quad \forall j \quad (5.10)$$

$$e_{ir}^+, e_{ir}^- \geq 0 \quad \forall i, r \quad (5.11)$$

$$0 \leq P_j \leq 1 \quad \forall j \quad (5.12)$$

The objective function (Eq. (5.6)) is intended to minimize the sum of error over all sites (I) and return periods (R). The nested loop structure of the optimization routine is known

to lead to convergence issues, especially for larger numbers of sites [Wang et al. \(2023\)](#). In this study, we attempted to implement the OPS method for all 15,336 sites but the optimization was not tractable, even with a cluster of 320 processors. Another challenge was the unstable performance of the USGS Hazard API ([USGS, 2023](#)). Continuously extracting site-specific hazard curves for each site resulted in a “time-out” error. To address the issue, we implement the K-means clustering algorithm ([Lloyd, 1982](#); [MacQueen, 1967](#)) using the *Scikit-learn* Python package ([Pedregosa et al., 2011](#)) to group the 15,336 sites into 108 clusters. The site-specific design parameters parsed from the USGS Hazard API are used as the feature vectors. From each cluster, one centroid geolocation is selected to represent all the geolocations within that cluster. The sub-sampled 108 centroidal geolocations replace I in Eq. (5.6). Following ([Han and Davidson, 2012](#)), $R = [100, 475, 1000, 2500]$ years is used to match the hazard curves. The reduction of sites was a critical step in guaranteeing the convergence of the optimization routine. The OPS method sampled 20 rupture scenarios as mapped in Figure 5.5. In the UCERF3 Mean model, a fault can rupture in multiple ways resulting in distinct rupture scenarios. For instance, inversion sources 259281, 346208, and 156802 are three different earthquake scenarios as a consequence of full or partial rupture of the Northridge fault source. The 20 sampled scenarios represent 18 different faults.

5.3.4 Simulating ground motion maps

Simulating a stochastic set of probabilistic ground motion intensity maps involves simulation-based computational techniques such as Monte Carlo Simulation (MCS). The most widely used MCS-based approach to simulate intensity maps was initially proposed by [Crowley and Bommer \(2006\)](#). Several studies ([Jayaram and Baker, 2010](#); [Vaziri et al., 2012](#); [Han and Davidson, 2012](#)) have extended the conventional MCS to develop more robust and computationally efficient approaches. The fundamental idea of MCS is to probabilistically generate stochastic ground motion intensity maps by considering all probable earthquake fault rupture scenarios. An earthquake scenario/event is defined in terms of a fault rupture-magnitude

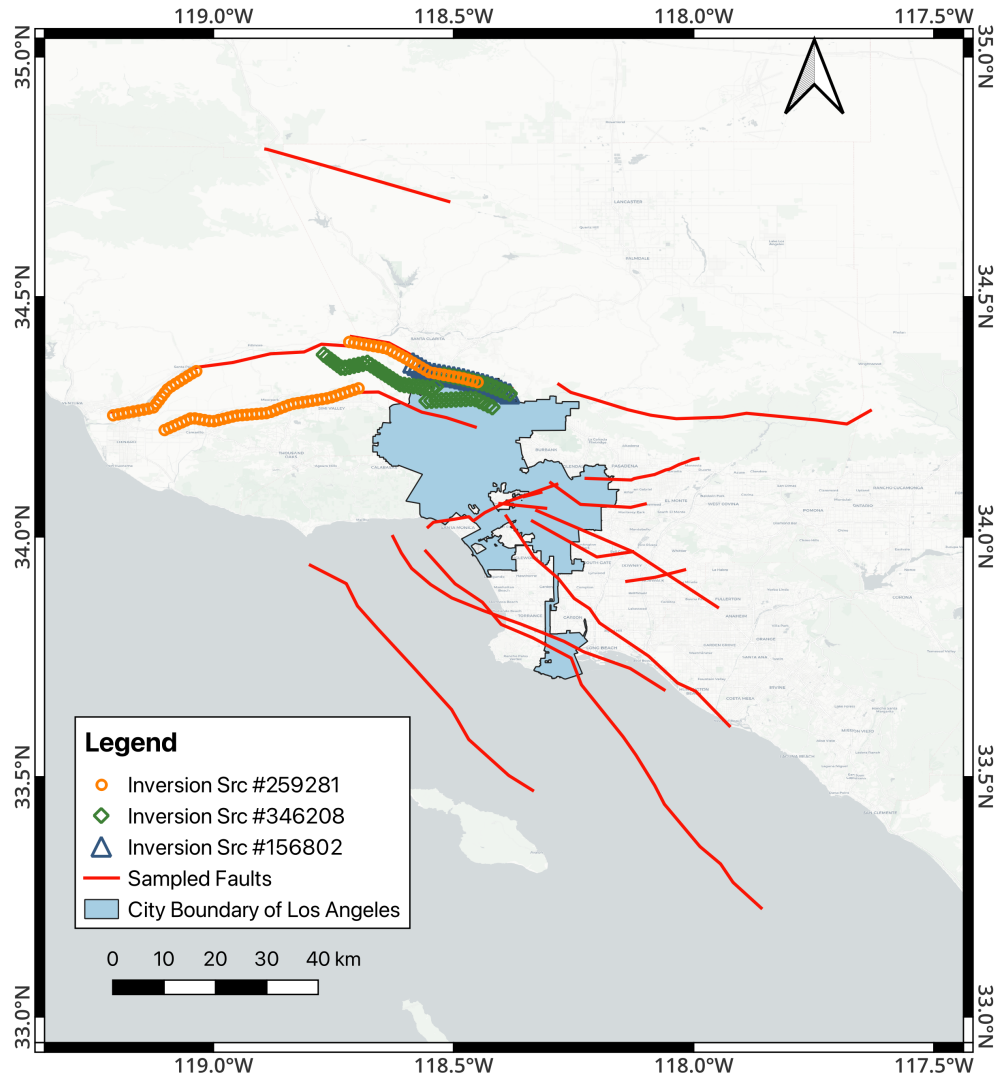


Figure 5.5: Mapped rupture projection of the 20 sampled scenarios using OPS method.

pair with an associated annual occurrence probability of the rupture. A fault rupture scenario in itself is a random event that can happen anywhere on a fault line. Moreover, the rupture mechanism at any given fault segment is also random (e.g., strike-slip, reverse, blind thrust, etc). Different rupture mechanisms release various amounts of energy thus resulting in earthquakes with varying magnitudes. The uncertainty in rupture scenarios is addressed by considering a distribution of earthquake magnitude, characterized by the Gutenberg-Richter recurrence law.

Once the source-magnitude combination (or an earthquake scenario) is defined, ground motion intensities are generated using existing ground motion models ([Jayaram and Baker, 2010](#)). Mathematically, the ground motion intensity at a site is formulated as

$$\ln Y_{ij} = \ln \hat{Y}_{ij}(M_j, R_{ij}, V_{s30,i}) + \sigma_{ij}\epsilon_{ij} + \tau_{ij}\eta_{ij} \quad (5.13)$$

where Y_{ij} is a ground motion intensity measure (IM) (e.g., spectral acceleration, peak ground acceleration (PGA), acceleration spectrum intensity (ASI), etc) at site i due to earthquake j , $\ln \hat{Y}_{ij}(M_j, R_{ij}, V_{s30,i})$ is the IM predicted by empirical ground motion models (GMMs), σ_{ij} denotes intra-event standard deviation, τ_{ij} denotes inter-event standard deviation, ϵ_{ij} is normalized intra-event residual, and η_{in} is the normalized inter-event residual. The standard deviation terms (σ_{ij} and τ_{ij}) are estimated by the GMMs while the normalized residual terms (ϵ_{ij} , η_{in}) follow a standard normal distribution. All GMMs depend on causal parameters such as earthquake magnitude, source-to-site distance, site properties, and fundamental period of the structure. If two hypothetical sites have identical causal parameters but are assigned structures with different spectral periods, they will experience different shaking intensities. This highlights the importance of pairing sites and buildings in defining various regional risk engines. For the remainder of the manuscript, the term $\sigma_{ij}\epsilon_{ij}$ is called the intra-event residual and the term $\tau_{ij}\eta_{ij}$ is referred to as the inter-event residual. It is noted that for any given earthquake, the inter-event residual is a constant within the region of interest. Eq. (5.13) is the centerpiece of the conventional MCS approach presented in [Crowley and Bommer \(2006\)](#).

The traditional MCS method (Crowley and Bommer, 2006) is conceptually straightforward but has several limitations. First, sampling magnitude based on recurrence law cannot account for complex rupture mechanisms including aftershocks. As such, to ensure that the ground motion maps simulated based on the traditional MCS method are probabilistically robust, a fairly large number of MCS-based maps need to be generated to account for variability in shaking intensities. In other words, to generate a stochastic map set that is spatially and temporally complete, a large number of residual samples need to be simulated. Additionally, the conventional MCS method does account for spatial correlation in the intra-event residual terms. Several studies have demonstrated that the residuals are spatially correlated (Jayaram and Baker, 2009; Loth and Baker, 2013) and need to be quantified for risk assessment of spatially distributed infrastructure. Jayaram and Baker (2009) demonstrated that the normalized intra-event residuals (ϵ_j) of an earthquake j follow a multivariate normal distribution with zero mean and unit standard deviation of ϵ_{ij} .

Jayaram and Baker (2010) modified the traditional MCS-based method (Crowley and Bommer, 2006) to incorporate spatial correlations. The modified step-by-step procedures to simulate correlated ground motion maps are presented as follows:

1. Considering appropriate magnitude-recurrence relationships (e.g., Gutenberg-Richter relationship), stochastically simulate earthquakes of varying magnitudes on the considered active faults. In our study, we determine the earthquake scenarios by sampling from the Mean UCERF3 model.
2. For every simulated earthquake scenario, estimate median shaking intensity and corresponding standard deviation terms at all the sites. The shaking intensity is estimated by calling OpenSHA within the R2D software. Developed by USGS, OpenSHA is an open-source tool for conducting seismic hazard analysis (Field et al., 2003).
3. Randomly sample normalized residual terms from $\mathcal{N}(0, 1)$ with importance sampling. The number of samples (N_j) determines the number of MCS intensity maps.

4. Incorporate appropriate spatial correlations into the residual terms. A predictive model for inter-event correlation ([Baker and Jayaram, 2008](#)) developed using the NGA West2 database is also incorporated in the correlation computation.
5. Combine median intensities, correlated intra-event residual, and inter-event residual for each earthquake scenario per Equation 5.13 to obtain the ground motion maps.
6. The probability of each sampled correlated map is $P_m = P_j/M_j$, where P_j is the annual occurrence probability of earthquake j and M_j is the number of simulated maps for scenario j .

Following the aforementioned operations, the ground motion maps are simulated using the hazard simulation module of the R2D software. The software has several useful features such as built-in correlation models (inter- and intra-event), specifications of weighting schemes for several GMMs, and the ability to specify the number of simulated maps per scenario. The current version specifies two correlation models ([Jayaram and Baker, 2009](#); [Markhvida et al., 2018](#)), adopts the NGA-West2 GMM weighting scheme ([Ancheta et al., 2014](#)), and defines 40 MCS (M_j) ground motion maps per scenario. Additionally, a total of 14 periods ranging from 0.01 seconds to 10 seconds are defined to facilitate ground motion selection.

Simulating multi-period spectra instead of scalar spectral acceleration values unquestionably increases the computational complexity. For one, the multi-period spectral accelerations are correlated. The principal component analysis-based correlation model proposed by [Markhvida et al. \(2018\)](#) handles the cross-period correlograms. It also increases the memory requirement as the amount of data that must be stored increases linearly with the number of spectral periods. In other words, the memory demand for 14-period spectra is 14-fold higher as compared to the scalar spectral value. While there are undeniable challenges in simulating multi-period spectra, we argue that it is essential for regional analysis because the response of a structure to dynamic excitation is dependent on the dominant modal periods of the structure. The multi-period spectra also present the flexibility to consider alterna-

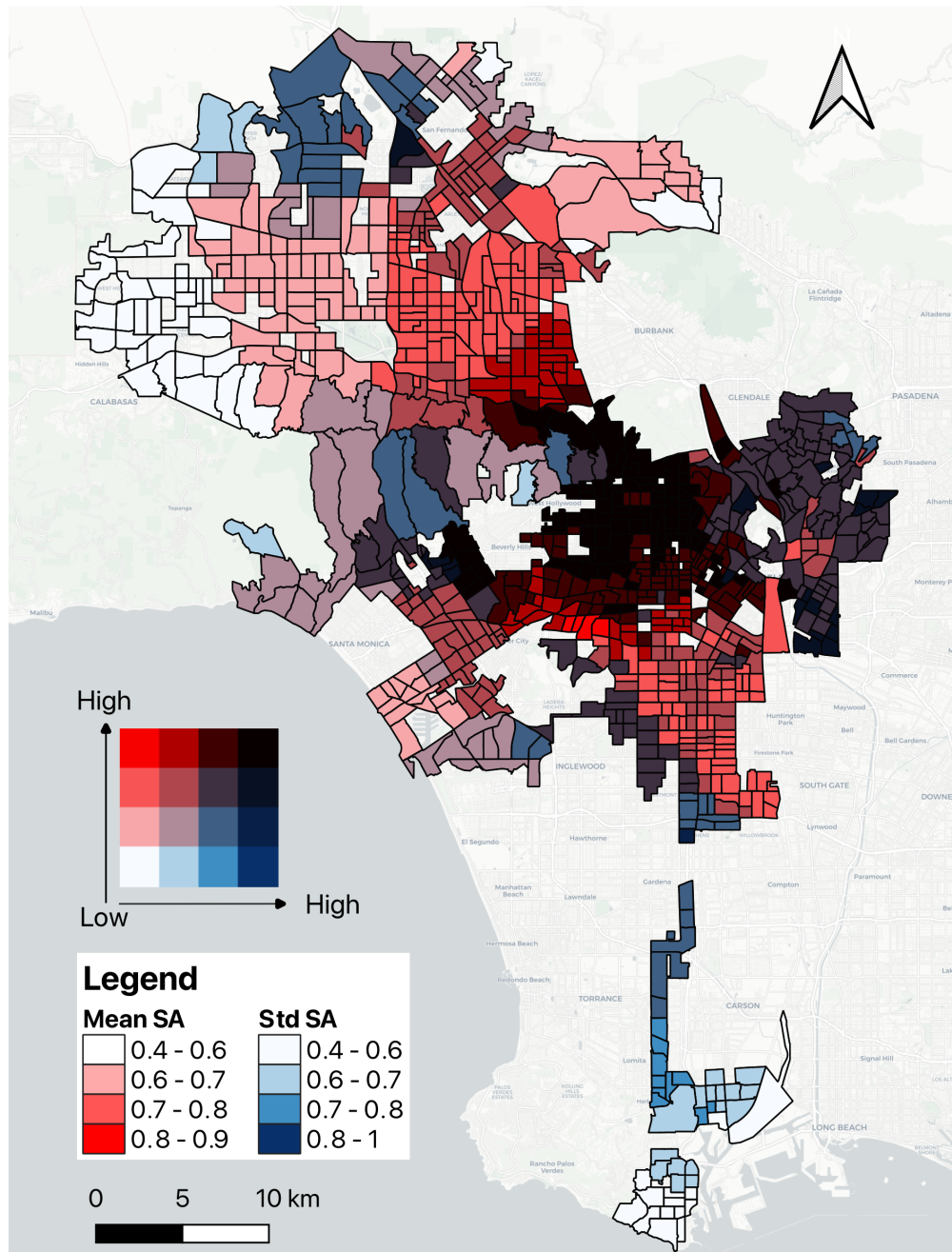
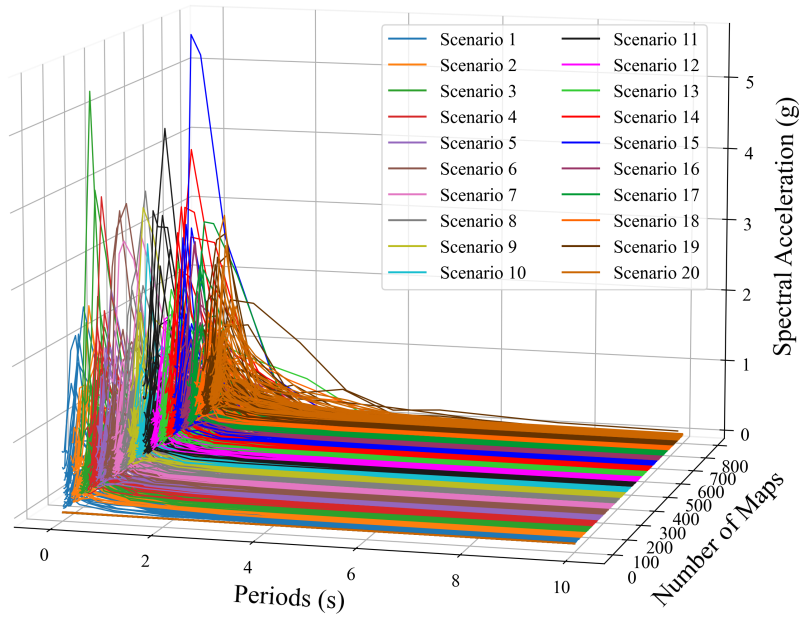
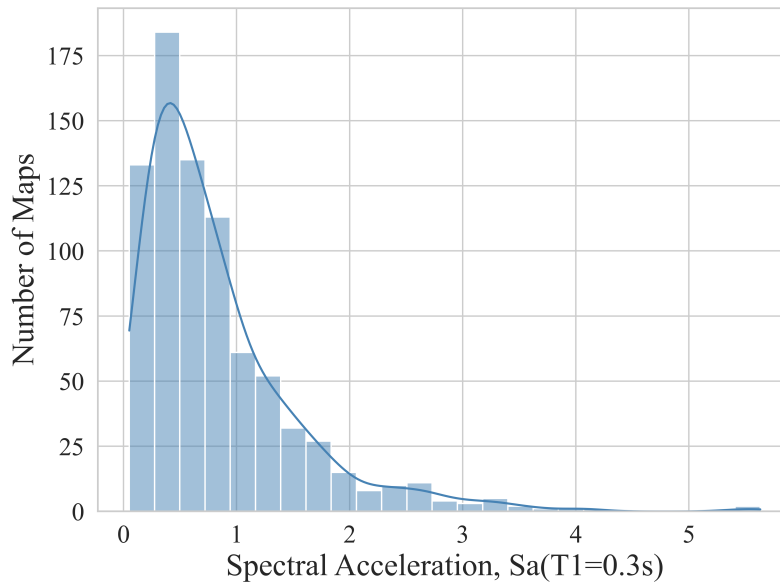


Figure 5.6: Bivariate choropleth of the mean of 800 ground motion maps simulated from 20 scenarios.

tive ground motion intensity measures. For instance, this study uses acceleration spectrum intensity (ASI) as an alternative IM.



(a)



(b)

Figure 5.7: a) Distribution of spectra from 800 maps; b) histogram of $Sa(T_1=0.3s)$.

5.3.5 Down-sample ground motion maps

The number of probabilistic ground motion intensity maps generated in Section 5.3.4 is usually large. In this study, we generate 40 correlated ground motion maps (M_j) for each of the 20 candidate earthquakes (J) in the reduced set resulting in 800 total ground motion maps. As discussed earlier, one ground motion record is selected for each map to simulate building nonlinear structural response. To this end, performing a nonlinear dynamic analysis of 15,336 buildings using 800 ground motion records imposes a significant computational burden. To address this computational challenge, the full stochastic set of 800 ground motion maps is down-sampled to a “relatively” small but representative set with K maps. The map reduction concept is well-known and has been implemented in numerous research studies ([Jayaram and Baker, 2010](#); [Miller and Baker, 2015](#); [Manzour et al., 2016](#); [Wang et al., 2023](#)). Researchers have proposed various methods to down-sample the full set of stochastic ground motion maps. We investigated three popular methods and selected one based on a comparative assessment. The following sections describe each of the methods in detail.

5.3.5.1 OPS-based downsampling

[Manzour et al. \(2016\)](#) extended the OPS-based optimization routine to optimize the down-sampling of ground motion maps. As noted earlier, the OPS method was initially proposed by [Han and Davidson \(2012\)](#) to probabilistically downsample earthquake scenarios while minimizing the hazard curve error. The overarching idea of the OPS-based ground motion map downsampling is similar to the approach used to reduce the number of earthquake scenarios except for a few. The objective function of the optimization model remains the same Eq. (5.6) because the reduced ground motion maps aim to reproduce the “true” hazard curve with as minimal error as possible.

Similarly, the equation that defines the error terms and adjusted occurrence probability is identical to Eq. (5.7) except that instead of summing over the number of candidate scenarios

(i.e., $j \in (1, \dots, J)$), the Eq. (5.14) sums over the number of candidate ground motion maps (i.e., $n \in (1, \dots, N)$). Note that the number of ground motion maps to be sampled (N) is a user input. The output P_n represents the hazard-adjusted occurrence probability of the intensity map n . The probability of exceedance of ground motion shaking intensity, $P(y_{in} \geq Y_{ir})$ is represented by a binary indicator function because there is no uncertainty in the exceedance of the ground motion intensity measure at site i in ground motion map n . In other words, if the intensity measure of map n at site i is greater than the intensity measure due to true hazard then 1 is assigned otherwise 0 is assigned. Eq. (5.17) represents the binary indicator function.

$$\sum_{n=1}^N \{P_n \cdot P(y_{in} \geq Y_{ir})\} - e_{ir}^+ + e_{ir}^- = \frac{1}{r} \quad \forall i, r \quad (5.14)$$

The remaining constraints are also identical to the ones previously discussed except that they are defined in terms of candidate ground motion maps instead of candidate earthquake scenarios. Similar to J^{red} , the optimal number of ground motion maps selected by the optimization routine, N^{red} , is constrained by the user-specified number of ground motion maps (N).

$$P_n \leq z_n \quad \forall n \quad (5.15)$$

$$\sum_{n=1}^N z_n \leq N^{red} \quad (5.16)$$

$$P(y_{in} \geq Y_{ir}) \in \{0, 1\} \quad \forall n \quad (5.17)$$

$$z_n \in \{0, 1\} \quad \forall n \quad (5.18)$$

$$e_{ir}^+, e_{ir}^- \geq 0 \quad \forall i, r \quad (5.19)$$

$$0 \leq P_n \leq 1 \quad \forall n \quad (5.20)$$

The implementation of the OPS-based downsampling of ground motion maps is equally as challenging as the OPS method for scenario selection (Section 5.3.3). The objective function loops over all sites (I), return periods (R), and the number of reduced ground motion maps

(N). The scale of computation coupled with the inherent stochasticity in the ground motion maps significantly impedes the convergence of the optimization routine. We implemented the optimization routine to downsample 800 maps to 100 maps (N) while considering all 15,336 sites. However, it failed to converge even when the computations were parallelized in 320 processors. To make the optimization tractable, we implemented the algorithm for only 108 sites representing the centroid of the 108 spatial clusters. The OPS-based downsampling method is one of the built-in functionalities of the R2D tool. Following the simulation of ground motion maps, the R2D tool is designed to automatically instantiate the OPS-based downsampling method. To discretize the computational load, the MCS-based method to simulate probabilistic ground motion maps and the OPS-based method to downsample the maps are executed individually and sequentially. With this modification, we were able to ensure convergence. To determine the appropriate number of downsampled maps, we investigated three distinct sizes: $N = [40, 50, 100]$. Figure 5.8 compares the response spectra of 800 maps (full stochastic set), 49 maps (left), and 96 maps (right) samples for an example site. For the two instances, 50 and 100 maps were specified as the user inputs but the OPS method converged with 49 and 96 maps, respectively. As expected, the median, 10th, and 90th percentile of 96 sampled spectra have a better match with the full stochastic set compared to the 49 maps.

5.3.5.2 Random sampling

An alternative to the OPS-based downsampling is random sampling. The approach is rather straightforward. We randomly sample a suite of N ground motion maps and select the set that has the minimum Kullback-Leibler (KL) divergence compared to the full set with 800 maps. KL divergence measures the distance between two probability distributions ([Kullback and Leibler, 1951](#)). In information theory and statistics, KL divergence is used to determine how similar one distribution is to the other. This approach requires two inputs, the number of ground motion maps to be selected (N) and the number of iterations (N_{iter}) for which

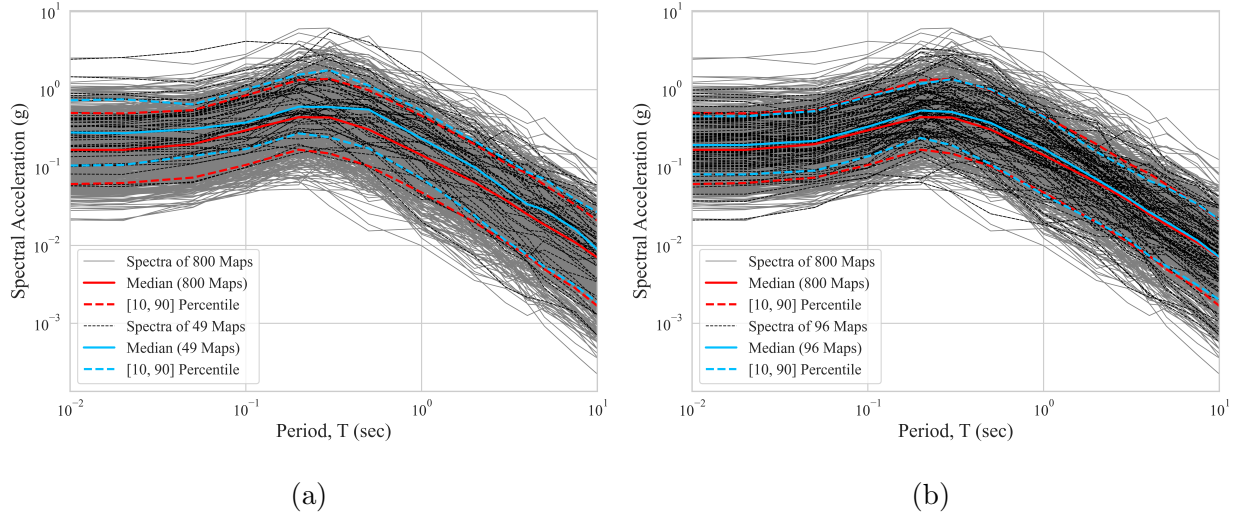


Figure 5.8: a) Comparison of spectra at an example site corresponding to the full stochastic maps set (800 maps) and 49 spectra sampled using OPS-based method; b) Spectra comparison at the same site against 96 sampled spectra.

the random sampling is repeated. As noted earlier, each ground motion map preserves the multi-period spectral acceleration vector of size $N_p \times 1$. Thus, the iterative sampling output results in $N_{iter} \times N \times N_p$ ground motion maps. To ensure that we match the entire spectrum, multivariate KL divergence is computed between the full ground motion set ($800 \times N_p$) and the suite of randomly sampled maps ($N_{iter} \times N \times N_p$). This results in an array of KL divergence values with the same dimension as the number of iterations. The final downsampled map set is selected from the suite of N_{iter} ground motion maps that has the lowest KL divergence value. The minimized KL divergence signifies that the distribution of spectra of the downsampled maps best represents the distribution of spectra of the full set of maps.

Considering the densities, P and Q , the KL divergence of P with respect to Q is given by Eq. (5.21).

$$D_{KL}(P \parallel Q) = \int p(\mathbf{x}) \frac{p(\mathbf{x})}{q(\mathbf{x})} d\mathbf{x} \quad (5.21)$$

The formulation requires a functional form of the multivariate distribution which is not

available. The closed-form solution is available if the two distributions follow a multivariate normal distribution. To compute KL divergence based on the closed-form solution, it is first imperative to statistically demonstrate the normality of the distributions. In research, it is broadly acknowledged that the distribution of a scalar ground motion intensity measure is lognormal. However, there is a lack of substantive research that conclusively demonstrates that the distribution of the multi-period spectrum is lognormal. To negate making extended assumptions, we estimate KL divergence based on k -nearest-neighbor density estimation as proposed by (Pérez-Cruz, 2008).

$$\widehat{D}_k(P \parallel Q) = \frac{1}{n} \sum_{i=1}^n \log \frac{\widehat{p}_k(\mathbf{x}_i)}{\widehat{q}_k(\mathbf{x}_i)} = \frac{d}{n} \sum_{i=1}^n \log \frac{r_k(\mathbf{x}_i)}{s_k(\mathbf{x}_i)} + \log \frac{m}{n-1} \quad (5.22)$$

$$(5.23)$$

where

$$\widehat{p}_k(\mathbf{x}_i) = \frac{k}{(n-1)} \frac{\Gamma(d/2+1)}{\pi^{d/2} r_k(\mathbf{x}_i)^d} \quad (5.24)$$

$$\widehat{q}_k(\mathbf{x}_i) = \frac{k}{m} \frac{\Gamma(d/2+1)}{\pi^{d/2} s_k(\mathbf{x}_i)^d} \quad (5.25)$$

where $r_k(\mathbf{x}_i)$ and $s_k(\mathbf{x}_i)$ are the Euclidean distances to the k^{th} nearest-neighbour of $\mathbf{x}_i$ and $\pi^{d/2}/\Gamma(d/2+1)$ is the volume in $\mathbb{R}^d$. The authors mathematically proved that the estimated KL divergence converges to the true divergence. Readers are referred to Pérez-Cruz (2008) for the in-depth mathematical background and proofs.

To the best of our knowledge, this approach has not yet been proposed in the literature. As such, it is not yet available in R2D. algorithm 3 presents the step-by-step operations as a pseudo-code. The algorithm is coded and implemented in Python, external to the R2D tool.

The desired number of reduced ground motion maps (N) is a key input parameter of algorithm 3. N can be defined based on judgment, pre-defined constraints, or by setting a threshold on the minimum KL divergence value. Figure 5.9 demonstrates that the approximated KL divergence value decreases as the size of downsampled ground motion maps

Algorithm 3 Random Sampling and Minimizing KL Divergence

- 1: **Input:** Distribution of M ground motion maps. Specify the desired number of reduced maps (N) where $N \ll M$
- 2: Initialize empty vectors $\mathbf{X}$ and $\mathbf{W}$ to store the sampled maps and total KL divergence, respectively **for** i *in range*(N_{iter}) **do**
- 3: Randomly sample N ground motion maps from M total maps
- 4: Compute and aggregate the KL divergence between the distribution of sampled maps (P_N) and the total maps (Q_M) across all I sites

$$KLD_{region} = \sum_{i=1}^I \hat{D}_k (P_N \parallel Q_M)$$

- 5:
 - 6: Identify the index w at which the minimum value occurs in $\mathbf{W}$
 - 7: Select w^{th} ground motion map set from $\mathbf{X}$ as the final sub-sampled set
 - 8: **Output:** Distribution of N ground motion maps
-

increases. As expected, if all M maps are selected in the downsampled set, the KL divergence converges to zero implying that the two distributions are the same.

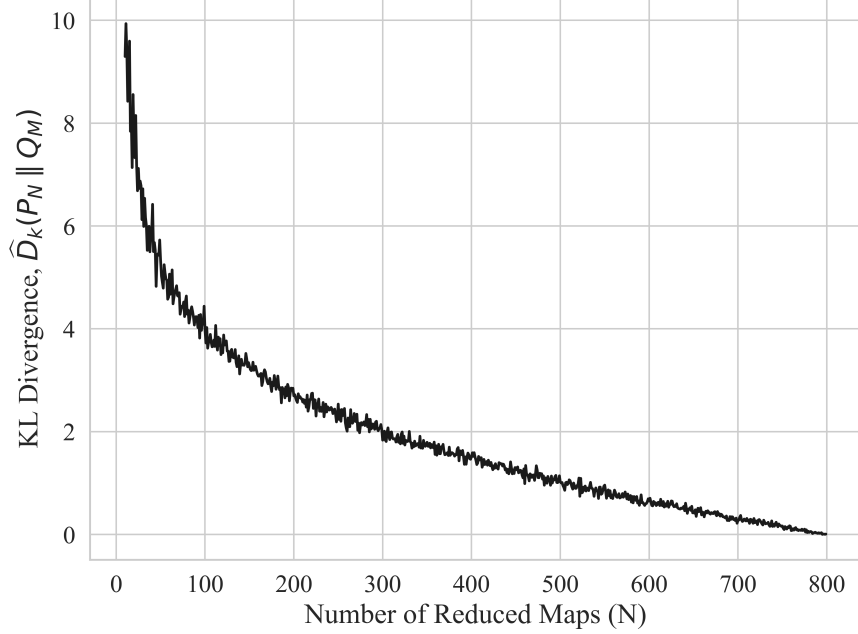


Figure 5.9: KL divergence as a function of the size of reduced ground motion maps.

5.3.5.3 K-Means clustering

Jayaram and Baker (2010) implemented K-means clustering as an efficient data reduction technique to reduce ground motion maps. K-means clustering is an unsupervised machine learning algorithm widely used for clustering. It is an optimization algorithm that aims to minimize within-cluster variance by partitioning M candidate ground motion maps into N clusters. Each map is assigned to one of the k clusters. The clustering operation is performed on a multi-dimensional vector ($M \times I$) where $M = 800$ is the total ground motion maps and $I = 15,336$ is the number of sites. The values in the input vector represent the ASI of the m^{th} map at the i^{th} site. Similar to Jayaram and Baker (2010), we also use a scalar IM per map/site to cluster the maps. They also mathematically proved that the exceedance rates

obtained using K-means are unbiased. For technical details, readers are referred to [Jayaram and Baker \(2010\)](#). In this study, the K-means clustering is implemented using the *Scikit-learn* Python package. The output of the clustering is N clustered ground motion maps. As a part of the study, we investigated cluster sizes of 40, 60, and 100. Figure 5.10 shows the spatial distribution of mean and standard deviation of $Sa(T_1=0.3s)$ across 60 clustered maps.

The three approaches to downsampling the ground motion maps are compared to determine the final selection method to be used in the study. Table 5.1 compares the KL divergence value for the three approaches with varying numbers of reduced maps. Based on the comparative assessment, K-means clustering with 60 clusters is selected. The selection of the number of ground motion maps has direct implications on the computational cost of the regional analysis framework. The number of maps is directly proportional to the number of dynamic analyses. Increasing the number of maps increases the computational expense linearly at the very least if not more rapidly. The 60 ground motion maps (equivalently 60 ground motion records) are judged to be the right trade-off between the computational cost and sufficiently representing the full distribution.

5.3.6 Ground motion records selection

The final step of the regional seismic hazard analysis is selecting site-specific ground motion records, which are used for high-fidelity risk modeling with explicit structural response simulation and downstream loss assessment. In Section 5.3.5, we sampled 60 representative maps from 800 MCS maps. At each site, 60 ground motion records are selected from the NGA-West2 database ([Ancheta et al., 2014](#)) by matching the response spectra of 60 maps. The adequacy of the match is determined by evaluating the sum of squared errors (SSE) ([Jayaram et al., 2011](#)). The SSE quantifies the total dissimilarity between the target spectrum ($\hat{S}a(T)$) and the pseudo-acceleration spectrum ($Sa(T)$) of the selected ground motion

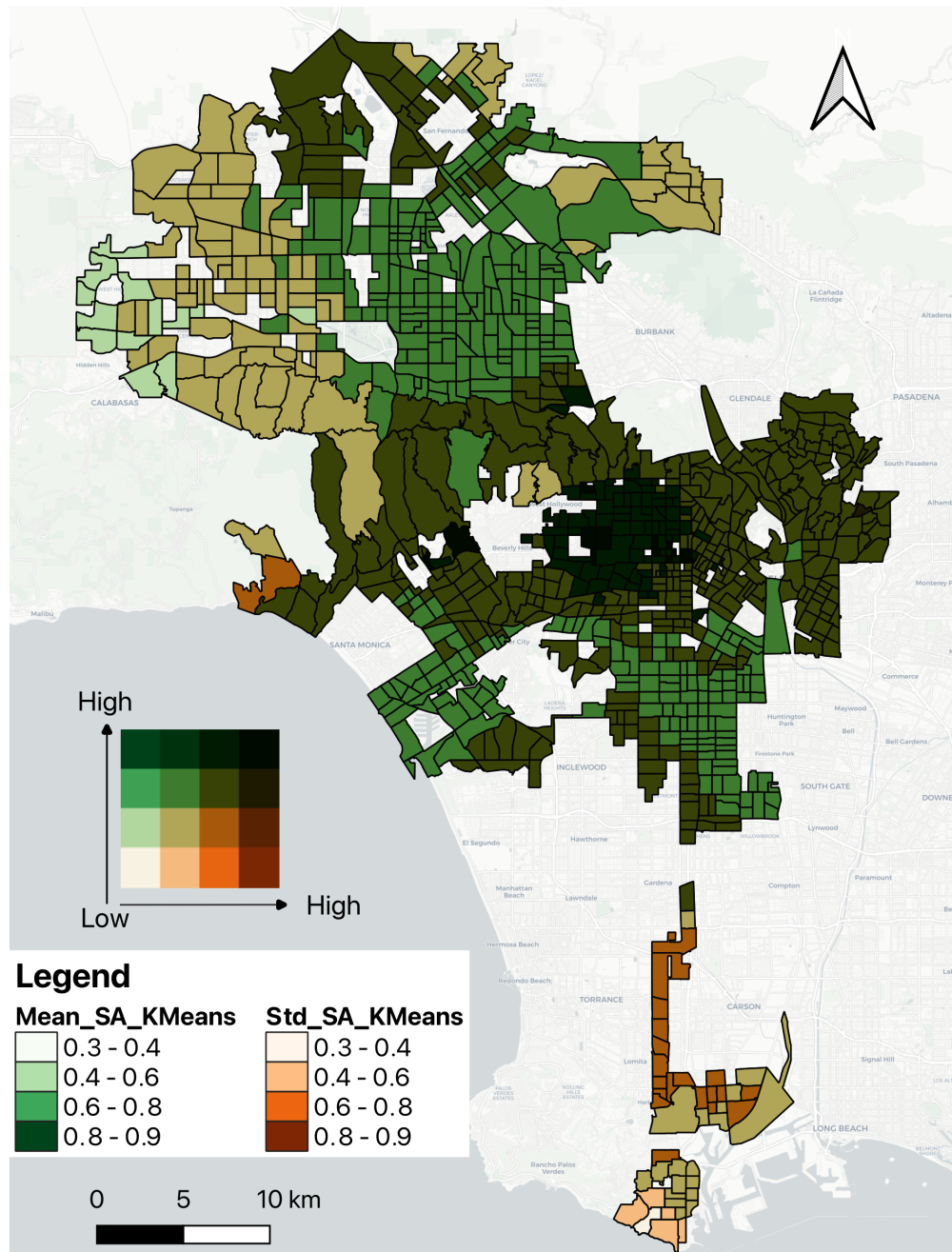


Figure 5.10: Bivariate choropleth map of the mean of 60 KMeans ground motion maps.

Table 5.1: Comparison of KL divergence between the full set ($M = 800$) and reduced ground motion maps downsampled using various approaches.

Approach	No. of Reduced Maps	KL Divergence	Description
OPS	40 (35)	5.76	$N = 40$ was specified but OPS selected 35
OPS	50 (49)	5.23	$N = 50$ was specified but OPS selected 49
OPS	100 (96)	3.96	$N = 100$ was specified but OPS selected 96
Random sampling	40	4.64	10,000 iterations
K-means	40	4.03	K-means performs better
K-means	60	3.37	Final selection
K-means	100	2.50	The closest to the actual distribution

record. It is computed as

$$SSE = \sum_{n=1}^{N_p} \left(\ln S_a(T_n) - \ln \hat{S}a(T_n) \right)^2 \quad (5.26)$$

where N_p is the number of periods. To select a ground motion, Eq. (5.26) is iteratively implemented for all the ground motions in the NGA-West2 database, and the ground motion record with the minimum SSE is selected. To guarantee that the selected ground motion has the least SSE among all the available records in the database, one needs to compute the SSE of all the records in the database. In other words, it is essentially an exhaustive search algorithm. Eq. (5.26), in itself, is efficient so the exhaustive nature of the computation does not noticeably influence the overall efficiency when selecting ground motion records for a single site. However, scaling the SSE-based approach to select site-specific ground motions across a region exacerbates the inefficiencies of performing an exhaustive search.

To boost the efficiency, we present a modified version of the conventional selection technique in algorithm 4. Specifically, we impose a filtering criterion based on the efficient and/or sufficient IM. We use ASI to filter the database because a previous study (Dahal et al., 2023) suggested that ASI is one of the two most optimal IMs for woodframe structures. We assembled a database of 7,000 NGA-West2 unscaled ground motion records. We extend the database to 49,000 entries by considering seven scaling factors ranging from 0.5 to 3. The algorithm is generic as one can specify the IM type, bounds, or scaling factors.

Algorithm 4 Ground Motion Record Selection

- 1: **Input:** Distribution of target spectra ($N \times N_p$ where N is number of spectra and N_p is the number of periods per spectrum.
- 2: Load NGA-West2 database with the spectrum of 49,000 scaled ground motion records
- 3: Compute acceleration spectrum intensity (ASI) for all the records in the database

$$ASI = \int_{0.1}^{0.5} S_a(T) dT$$

for n in range(N) **do**

4:

 Compute the target ASI (T_{ASI}) for the n^{th} target spectrum.

- 5: Filter the DB for records that are within $\pm 2\%$ of the target ASI i.e. $0.98 * T_{ASI} \leq DB(ASI) \leq 1.02 * T_{ASI}$. This substantially reduces the database from 49,000 entries to ≈ 200
 - 6: Calculate SSE between the target spectrum and all the records in the filtered database using Equation 5.26
 - 7: Select the record with the least SSE.
 - 8: Remove the record from the database to avoid duplicates
 - 9:
 - 10: **Output:** A suite of N scaled ground motion records
-

We implement algorithm 4 to select ground motion records for all 15,336 sites. Figure 5.11

demonstrates the distribution of the target spectrum and the spectrum of the selected scaled ground motion records for an example site. As shown in the figure, the median, 10th, and 90th percentile of the target spectrum (black solid line) match well with the spectrum of selected records (red dotted lines). The match is exact between 0.1 and 0.5 seconds, which is the period bound of ASI.

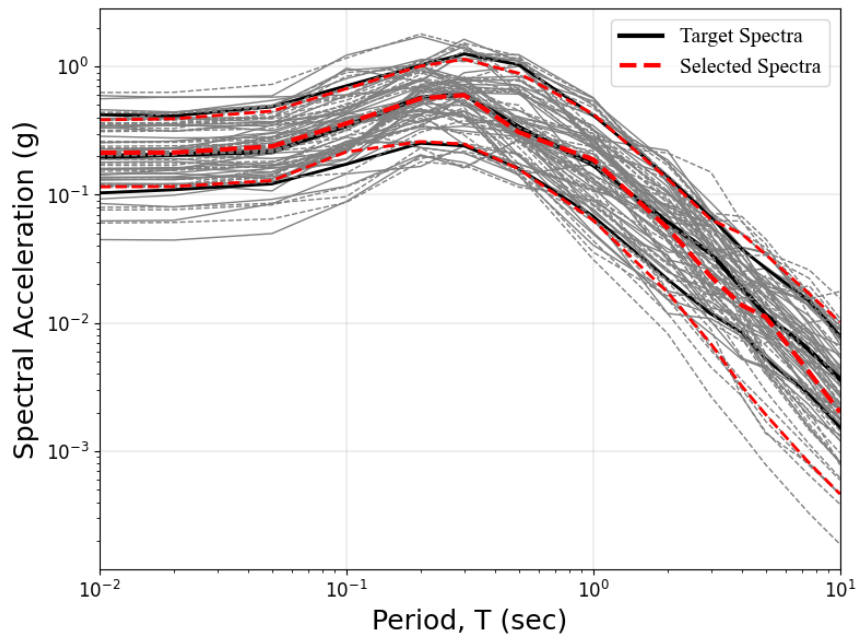


Figure 5.11: Comparison of target and selected spectra of an example site. The plot shows median, 10th, and 90th percentiles

5.4 Case Study

The high-fidelity high-resolution computational framework for regional risk and recovery assessment presented in Section 5.2 is implemented. The region of interest, building inventory, and corresponding site locations have previously been established in Section 5.3.1. Section 5.3 described the regional seismic hazard analysis. This section utilizes the results

from seismic hazard analysis to assess the risk and resilience of 15,336 woodframe residential buildings in the City of Los Angeles. We demonstrate how the computation of large-scale building inventories can be made “viable” by leveraging automated workflows and HPC resources. In addition to presenting the results, we highlight the challenges encountered in running a large-scale Hi-Fi regional risk simulation.

5.4.1 Exposure modeling

As previously discussed, the building inventory of interest comprises single- and multi-family woodframe residential buildings in the City of LA. The site locations of the buildings are determined using the permit dataset available in the LA open data portal. Ideally, the individual designs and structural models should be based on the information contained in the dataset. However, the portal data lacks building-specific details such as the floor plan layout, building geometry, shear wall configurations, and material type. To circumvent this issue, we developed a database of baseline design variants. The design variants are archetypical building layouts with pre-defined information such as the shear wall locations, material type, story height, and footprint dimensions. Table 5.2 summarizes 108 total design variants with four distinct footprint layouts. The variants with smaller footprint areas (i.e., 40×30 and 48×32) represent single-family dwellings (SFD) while the larger variants represent multi-family dwellings (MFD). To account for variability in buildings across a region, the archetype database includes buildings with different numbers of stories, material types, and seismic weights. Only 1- and 2-story variants are included for SFDs. For MFD, four different variants based on the number of stories are considered. Similarly, three distinct material types are included, which are prevalent in the existing and new woodframe construction. Three levels of seismic weight are used to distinguish light, normal, and heavy-weight buildings. The seismic weight presented in the FEMA P-2139-2 report ([FEMA, 2020](#)) is utilized as the benchmark weight.

The information in Table 5.2 is used to define the high-resolution building inventory.

Table 5.2: Summary of the five different parameters considered in the design variant database.

Floor Layout (ft×ft)	No. of Stories	Material Type	Seismic Weight	No. of Variants	Reference
96×48	1-, 2-, 3-, and 4-story	(Stucco+GWB), (HWS+GWB), and (Stucco+Plaster)	Light (0.8*ATC), Normal (ATC), and Heavy (0.8*ATC)	36	FEMA P2139-2 (FEMA, 2020)
60×32				36	CUREE CALTECH (Folz and Filiatrault, 2002)
48×32	1-, 2-story			18	FEMA P2139-2 (FEMA, 2020)
40×30				18	PEER CEA (Welch and Deierlein, 2020b)

Figure 5.12 shows the procedure used to model the exposure. For each site, we randomly assign a variant and design it with the site-specific parameters. Note that the variants in Table 5.2 are merely a skeleton-type structure with no designed lateral seismic force resisting system. The site-specific building design is generated using the design module of WoodSDA, which automatically extracts design parameters (e.g., S_{aMS} , S_{aM1}) from the USGS Hazard API ([USGS, 2023](#)) and designs the shear walls to resist the seismic demand. This process is repeated for all 15,336 sites identified in the region. With a pre-defined database and an automated design workflow in WoodSDA, the exposure modeling becomes computationally efficient and can be completed within minutes using only one processor. Figure 5.12 presents the procedures implemented to model the exposure along with a breakdown of the designed buildings across the city of LA. The random distribution of design variants ensures that the layout types are distributed uniformly.

5.4.2 HiFi FMRA implementation

After defining the exposure (Section 5.4.1) and hazard (Section 5.3), the HiFi FMRA is implemented by leveraging WoodSDA and a high-performance computing cluster. The results from exposure modeling show that we created 15,336 building designs but only 2,267

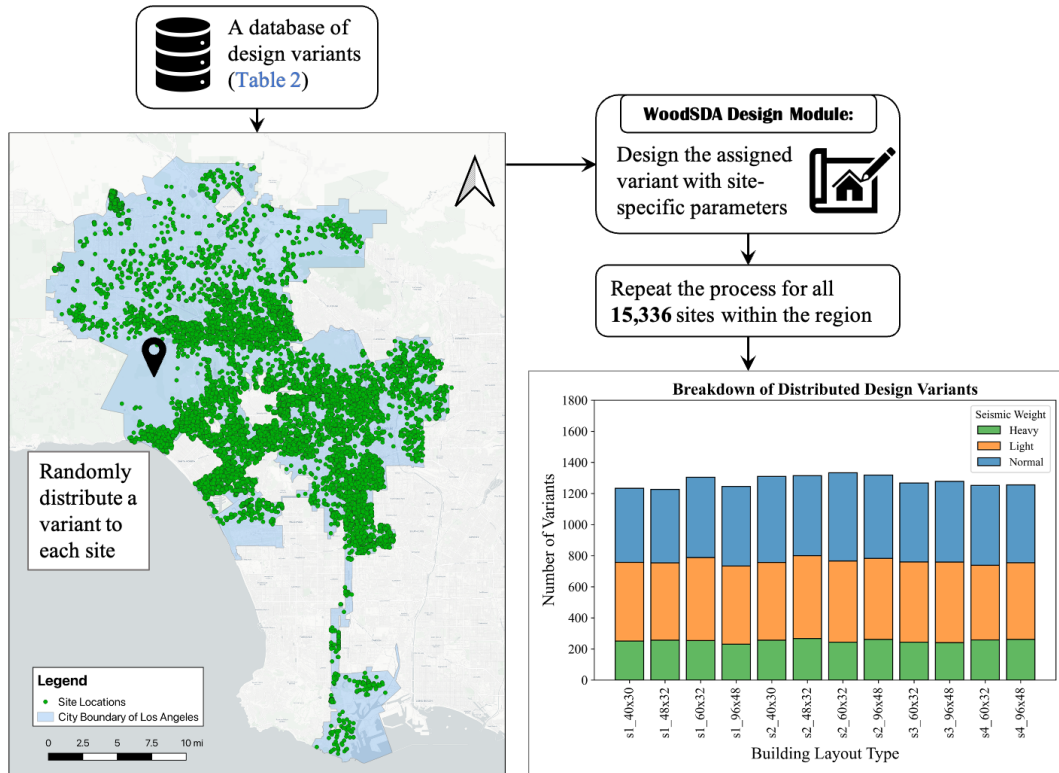


Figure 5.12: Overview of the procedures implemented to define the high-resolution building inventory.

designs were unique across the region. A building is said to have a “unique design” if it has a unique combination of five characteristics (number of stories, building layout, material type, seismic weight, and base shear). For instance, consider a 2-story design variant with a 40×30 layout, stucco and gypsum wallboard as external and internal material, respectively, and normal seismic weight (naming convention: *s2_40x30_Stucco_GWB_Normal*). Further, if the variant is designed for two different seismic base shears (rounded to the nearest integer), the result will be two unique building designs. If two identical variants are designed for different base shear, the designed shear walls will likely have different structural properties.

The regional hazard simulation outputs a site-specific distribution of N spectra representing N sampled ground motion maps. The distribution of spectra at each site is characterized by the first and second moments of the distribution of an IM of interest. Of the 15,336 sites, 3,854 have unique ASI mean and standard deviation (std) value pairs. The mean and standard deviation (STD) are rounded to two decimal places. The total number of fully mechanistic assessments (FMA) across a region is determined by combining the 2,267 unique designs and 3,854 unique mean/STD ASI pairs and removing the redundant cases. For instance, three sites in the region have the same building (*s2_40x30_Stucco_GWB_Normal_Vs42*) and the same spectra distribution (mean ASI = 0.93, ASI std = 0.68). In this case, instead of assessing losses at three redundant sites, we only assess losses at one and use that to inform the losses at all three sites. The combination of designed variants and ASI mean and STD requires 15,205 end-to-end FMAs to represent performance at 15,336 sites without sacrificing fidelity or resolution. In general, running HiFi FMAs for 131 fewer buildings might not noticeably reduce the computational cost but the idea of combining site-specific building design with the ASI first and second moments offers an attractive technique to balance resolution and computational efficiency. For example, if we characterize the spectra distribution using the mean and std of ASI rounded to one decimal place, then the total number of unique FMAs reduces by roughly 50% to 10,564. This would represent a significant reduction in computational cost.

5.4.3 Result discussion

Figure 5.13 presents the scatter, contour plots, and kernel densities for the key input and output parameters in WoodSDA. The plots highlight the spatial variability among the 15,336 sites as depicted by the diagonal kernel densities. The median spectral acceleration ($Sa(T1=0.3s)$) is based on $N = 60$ downsampled stochastic ground motion maps that are provided as an input parameter to WoodSDA. The four other parameters are outputs of WoodSDA. The distributional shape (based on the kernel density plot) of the PSDR (peak story drift among all story levels) looks lognormal and appears to have two peaks. The bimodal-looking shape is attributed to higher drifts in the two-story single-family dwellings (i.e., buildings with $s2.48 \times 32$ and $s2.60 \times 32$ layouts). The contour plot of PSDR and median $Sa(T1=0.3s)$ indicates that the gradient is steeper at higher $Sa(T1=0.3s)$ values and lower PSDR. This is consistent with the distribution shape of $Sa(T1=0.3s)$ which roughly looks like a lognormal distribution. The distributional shapes of the three plotted loss metrics (median loss ratio, median reoccupancy time in days, and median functional recovery time in days) also appear lognormal. The scatter plot between the loss ratio and recovery times exhibits a somewhat nonlinear trend suggesting that the buildings with a higher loss ratio tend to have higher recovery times.

The pair plot provides valuable insights by visualizing median spatial trends in the empirical data. However, it cannot facilitate risk-informed decision-making as it lacks probabilistic information. We utilize Eq. (5.3) to transform the site-specific distribution of consequence parameters exceedance curves as shown in Figure 5.14. Each grey line represents the consequence curve of an individual building. Figure 5.14a presents the annual exceedance rate of the repair cost of 15,336 sites while Figure 5.14d highlights the exceedance rate of functional recovery time. Figure 5.14d shows that the dispersion of time to regain functionality increases as the exceedance rate decreases. A similar trend is evident for the reoccupancy time as depicted in Figure 5.14c.

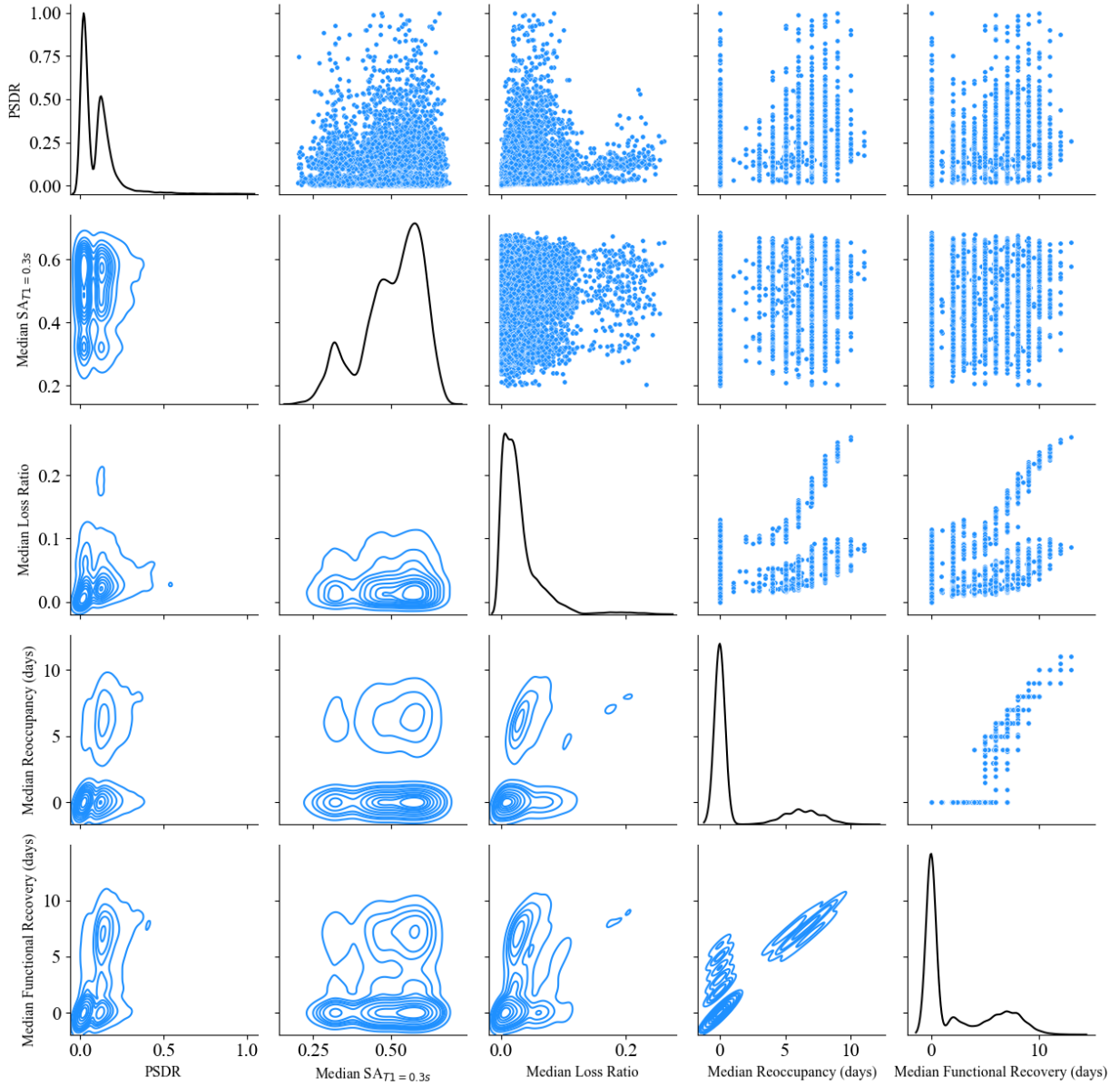
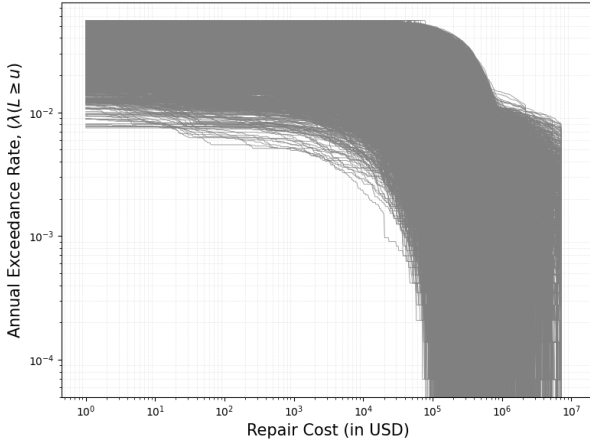
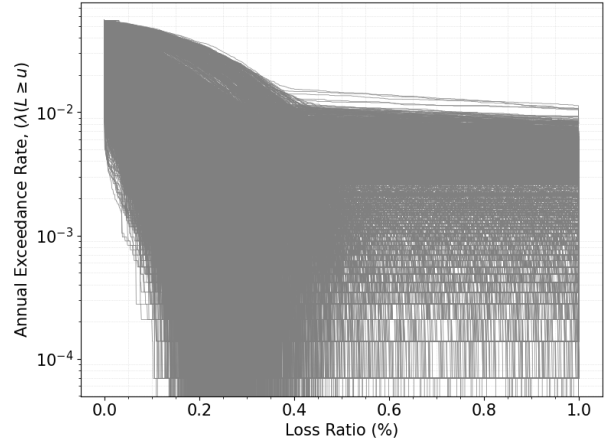


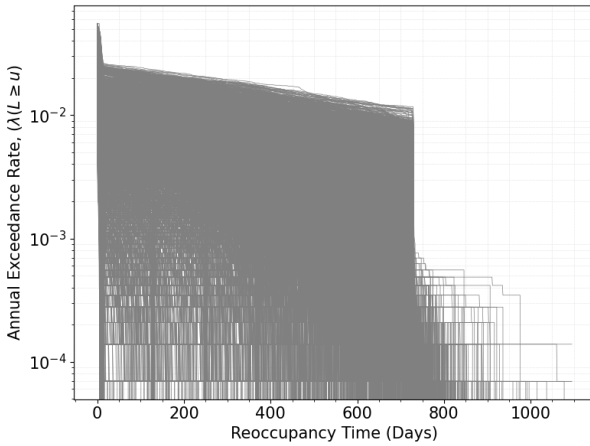
Figure 5.13: Pair plot of median shaking intensity, EDP, and Loss metric.



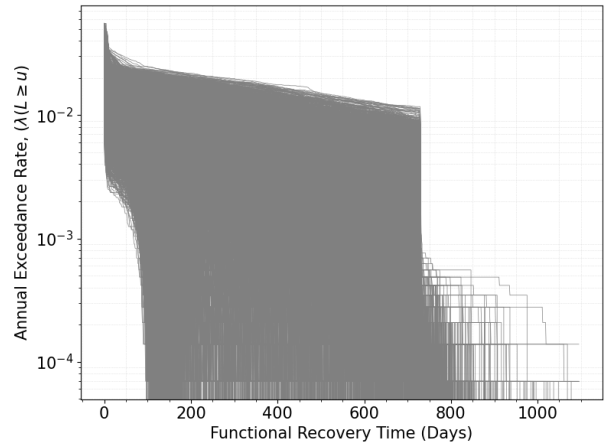
(a)



(b)



(c)



(d)

Figure 5.14: a) Exceedance curve of repair costs of all sites; b) exceedance curve of loss ratio (normalized repair cost) all sites; c) Exceedance curve of reoccupancy time at all sites; b) exceedance curve functional recovery time.

To quantify the extent of loss across the region, the loss of individual buildings can be aggregated to compute the total regional loss. As discussed in Section 5.2, the aggregation of site-specific loss distribution is not trivial due to the inherent randomness in the Monte Carlo-based loss assessment methodology. To be probabilistically consistent, we aggregate losses by implementing algorithm 1. Figure 5.15 presents the aggregated regional loss curve. It shows that the expected regional direct loss for an event with a 475-year return period is roughly around 7 billion dollars. Similarly, the estimated direct loss for a 2475-year event is closer to 10 billion dollars. The total exceedance curves cannot be computed for other consequence parameters because recovery times are not additive because the recovery of spatially distributed assets is parallel and complex.

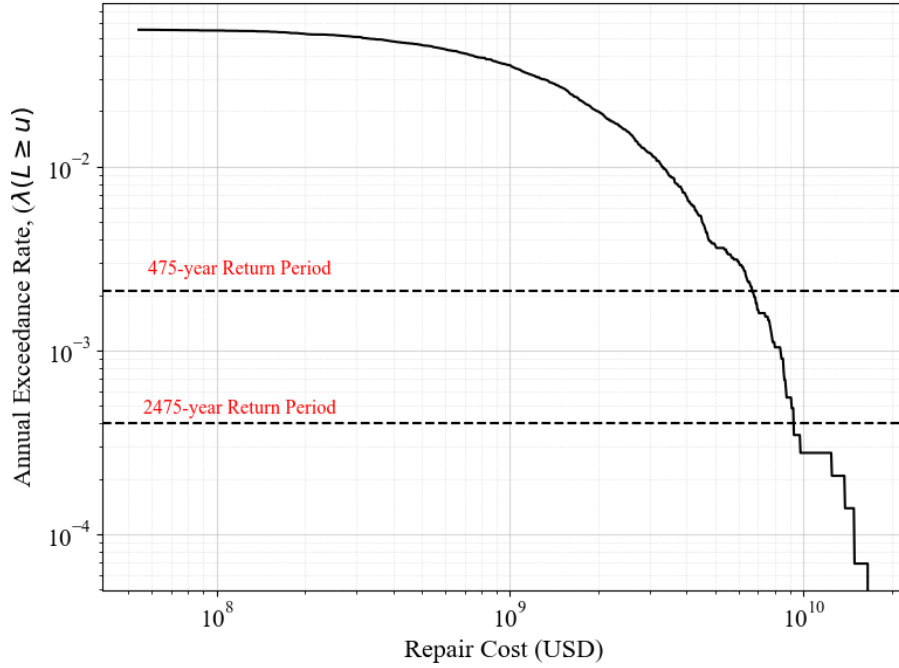


Figure 5.15: Total regional exceedance curve representing the aggregated loss of 15,336 buildings.

We utilize Figure 5.14 to extract hazard rate-dependent spatial distribution of consequence values. Figure 5.16 maps spatial variability of loss ratio across the region for a

475-year event (rate = 0.0021). The loss ratio represents the repair cost as the percentage of the building value. Consistent with the spatial distribution of shaking intensity (Figure 5.6) and the respective fault ruptures (Figure 5.5), central LA has the higher concentration of sites with a higher loss ratio.

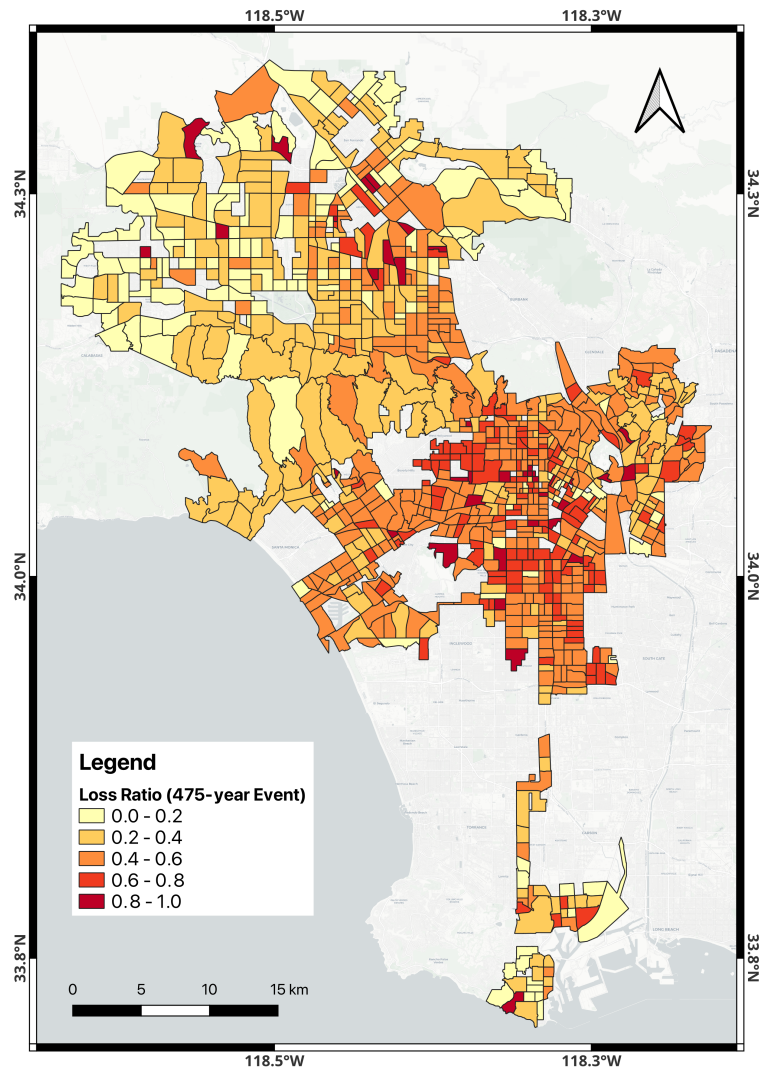


Figure 5.16: Spatial distribution of loss ratio for a 475-year return period event.

Similarly, Figure 5.17 visualizes spatial variability of reoccupancy time (left) and functional recovery time (right). The recovery times appear to have a noticeable spatial correlation

tion as the reoccupancy and functional recovery time concentrate in the same region. This implies that the recovery time is governed by the components that impact reoccupancy time.

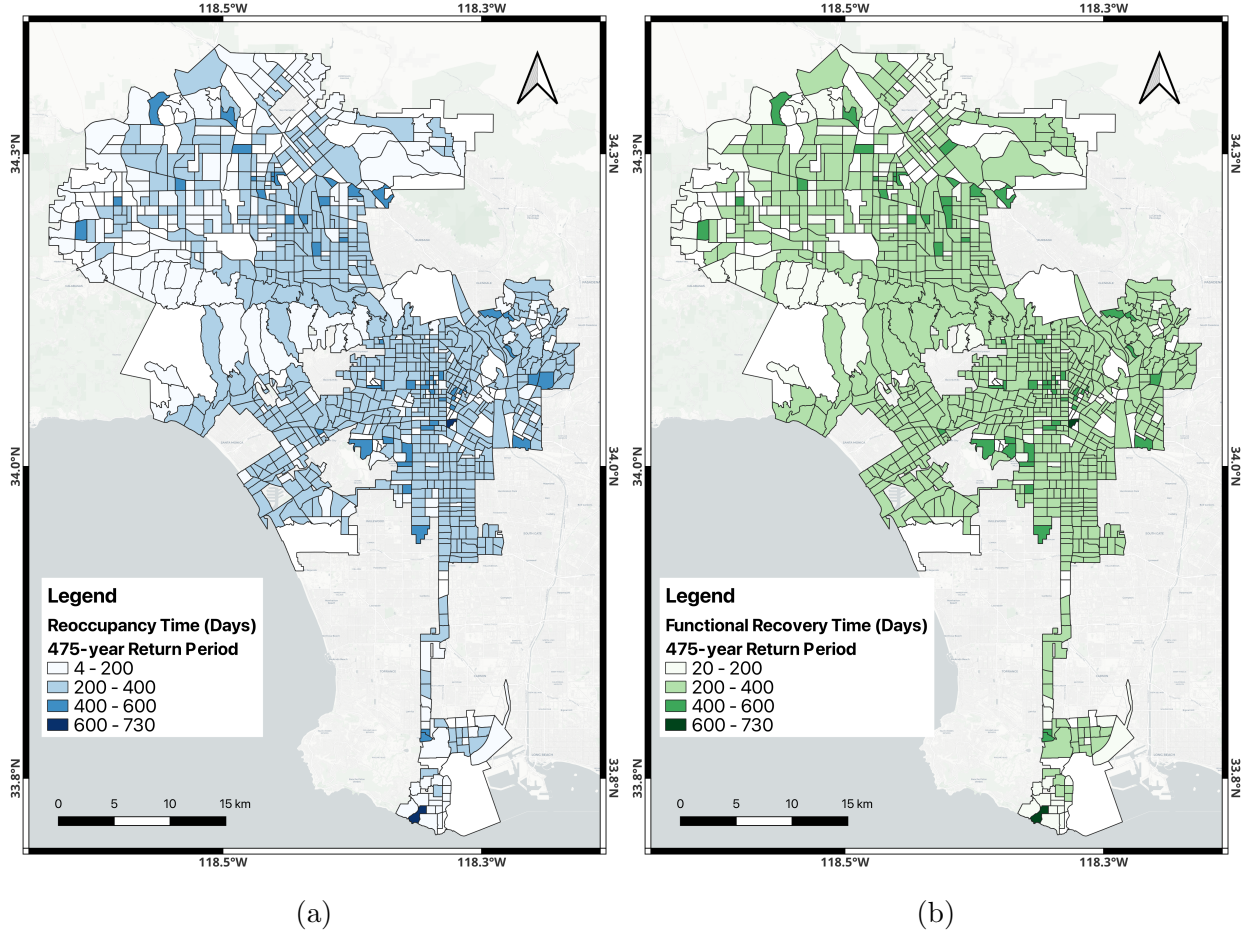


Figure 5.17: Spatial distribution of a) reoccupancy time and b) functional recovery time for a 475-year return period event.

5.4.4 Computational resources and challenges

To address the substantial computational demand in performing regional risk and recovery assessment, we leverage high-performance computing (HPC) clusters. The computations are performed in *Hoffman2*, an HPC cluster operated by the Institute for Digital Research

and Education (IDRE) at the University of California Los Angeles. Table 5.3 presents the summary of HPC resource usage for the case study. The bulk of the computational demand is concentrated on performing regional seismic hazard analysis and selecting ground motion records. Particularly, simulating correlated ground motion maps and downsampling the full set of stochastic maps to a smaller representative size are the two most computationally demanding operations. The computations are parallelized using a Python package, *MPI for Python* (Dalcín et al., 2005), in R2D’s backend code. HiFi FMRA is executed by distributing WoodSDA-based automated risk assessments across 600 processors.

Table 5.3: Summary of estimated total time (human time and CPU time) per building to perform fully mechanistic PBEE-based loss assessment.

Computation Type	No. of Processors	Wallclock time (hours)	Description
Generate Scenarios	320	72	Implemented using R2D’s backend code
Downsample scenarios			
Simulate ground motion maps			
Downsample maps	400	32	R2D and external code for K-means
Select ground motion records	120	3	Parallelized using OpenMPI
HiFi FMRA	600	45	WoodSDA and distributed computing
HiFi FMRA post-processing	1-20	2-5	single and distributed processing

Running first-of-its-kind large-scale assessments of thousands of buildings came with a

unique set of challenges. Notably, regional seismic hazard maps simulation was the most computationally expensive and challenging part as it involved several interconnected steps. To make regional hazard analysis computationally tractable, we made several adjustments to the commonly used techniques to generate and downsample rupture scenarios and ground motion maps. Specifically, we implemented the OPS-based downsampling technique ([Han and Davidson, 2012](#); [Manzour et al., 2016](#)) on just 108 centroid locations instead of 15,336. This was one of the important modifications required to achieve convergence in sampling 20 representative scenarios from 350,055 scenarios in the Mean UCERF3 model. Simulating correlated ground motion maps with multi-period spectral acceleration was a memory-intensive task. For 15,336 sites and 20 scenarios, we simulated 800 total maps with spectral acceleration values at 14 distinct periods. The correlation ground motion maps were simulated in the R2D software by leveraging parallel computations through OpenMPI. The parallelization relies on the control-compute node programming structure and thus requires the high-dimensional data matrix to be transferred between the nodes. This created a memory bottleneck because the control node did not have enough memory capacity to store the outputted data from each of the compute nodes. We addressed this bottleneck issue by dividing the hazard simulation into four different fragments with each chunk simulating 200 correlated ground motion maps representing 5 scenarios. Once the ground motion maps were simulated and downsampled, ground motion records were selected for each site. The record selection algorithm does not require data flow between sites which makes it is reflected by the relatively low computational time as compared to other hazard simulation tasks. Similar to the ground motion selection, WoodSDA is also executed independently across sites because there is no data flow between loss assessments of spatially distributed assets. Another challenge was managing the significant amount of raw structural response time history data generated by WoodSDA. The memory demand for storing the raw response data compounded and exceeded the allocated memory quota of 3,000 gigabytes. We resolved this issue by extracting the engineering demand parameter profiles and retroactively deleting

the raw response history data.

5.4.4.1 Strategies to improve efficiency

The proposed computational framework provides a generic workflow to perform regional seismic risk and resilience assessment. Although the case study implements the framework to evaluate the performance of single- and multi-family residential woodframe buildings, it can be adapted for other building inventories with appropriate modifications to WoodSDA. By harnessing automated workflow and distributed computing, we demonstrate that high-fidelity high-resolution risk assessment is feasible for large-scale building inventories. Computational cost is often the only restrictive factor in large-scale regional risk assessment. We have identified governing factors that determine the computational expense of running regional-scale assessment. Following are the five most computationally demanding aspects and potential solutions to address them:

1. This is trivial but the number of sites in the region is directly proportional to the computational expense. Depending on the scope of the work, the sites can be aggregated at a neighborhood, zip code, or census tract level to reduce the number of sites. Undoubtedly, this trades off computational efficiency for the level of resolution.
2. The number of ground motion records (or equivalently the number of sampled ground motion maps) has a linear relationship with the computational demand. In our case study, we investigated 40 and 60 ground motion maps and found that 60 maps represent the full set of 800 maps “well enough.” While fewer ground motion map increases efficiency, it reduces the robustness of risk analysis and weakens the ability to quantify and propagate uncertainty.
3. The computational time reduces at least linearly with the increasing number of available processors.

5.5 Conclusions

We presented a generalizable and efficient computational framework to facilitate high-fidelity high-resolution risk and recovery assessment of spatially distributed assets. The framework leverages automated workflow and distributed computing to perform an explicit FEMA P-58-based risk analysis. The overarching goal of the framework is to efficiently scale building- and site-specific FEMA P-58-based fully mechanistic assessment (FMA) to large-scale building inventory. One of the key components is WoodSDA, an end-to-end computational platform developed to automate the implementation of FEMA P-58 methodology. Utilizing WoodSDA and high-performance computing technologies, we demonstrated through a case study that high-fidelity high-resolution risk assessment of large-scale building inventory is computationally feasible. In the context of this study, “high-fidelity” defines the level of fidelity in assessing risk, specifically, the fidelity level of structural numerical modeling. The framework utilizes a three-dimensional (3D) structural model to evaluate the performance of a building under seismic excitation. The regional risk assessment is performed on a per-site basis thus maintaining a high resolution. The site-specific analysis is the highest possible resolution in regional assessment.

The proposed framework is implemented to assess the loss, reoccupancy, and functional recovery time of single- and multi-family woodframe buildings in the City of Los Angeles. The site locations are identified based on open-source data on new building construction permits issued by the city. The building exposure is modeled using the geolocations and a pre-defined design variant database. The regional seismic hazard analysis is undertaken by sampling representative earthquake scenarios from the catalog of 355,084 viable scenarios in the Mean UCERF3 model. The nuances and challenges of simulating a stochastic set of ground motion shaking intensity maps are presented. More importantly, we implement techniques to address the computational challenges of simulating and downsampling regional ground motion maps.

CHAPTER 6

Efficient Alternative Regional Frameworks and Resilience-based Design Sensitivity Analysis

6.1 Introduction

In Chapter 5, we presented a regional-scale computational framework to perform high-fidelity high-resolution risk and recovery assessment of building inventories. The framework is formulated to efficiently scale an explicit fully mechanistic assessment (FMA) to large-scale inventories. An FMA is referred to as a detailed component-level probabilistic performance assessment of an individual building based on the FEMA P-58 methodology ([FEMA, 2012](#)). As the name suggests, the key aspect of FMA is that the risk computation is mechanistic and does not use surrogate or meta-modeling techniques. The framework promotes the idea of high-fidelity (HiFi) high-resolution (HiRes) fully mechanistic regional assessment (FMRA) as the benchmark regional risk assessment strategy. Within the scope of this study, it is intended to maintain the highest level of fidelity and resolution. Recall that the term “fidelity” is used to represent the level of detail used to represent the structural numerical model while the term “resolution” refers to the granularity with which spatially distributed assets are assessed. In a regional setting, the highest attainable level of resolution is a site-specific analysis. Performing high-resolution HiFi FMRA is computationally demanding. To render loss simulations of large-scale building inventory computationally feasible, HiFi FMRA leverages automation and distributed computing as discussed in Chapter 5. Specifically, we developed WoodDSA to automate the entire FEMA P-58 methodology and paired it with distributed

computing technologies. We implemented it to quantify regional risk and recovery of 15,336 buildings in the City of Los Angeles.

The case study in Chapter 5 made it abundantly clear that HiFi HiRes FMRA imposes a substantial computational demand, even with automated workflows and high-performance computing (HPC) resources. The computational burden is bound to proliferate for applications where design iterations and optimization are involved, as is the case with evaluating functional recovery-based design procedures. As such, there is a need for more efficient computational frameworks and strategies to facilitate regional risk and resilience simulations. In this study, we propose four efficient risk assessment frameworks as alternatives to the benchmark HiFi FMRA approach, which are based on varying the levels of fidelity and resolution. Figure 6.1 provides a schematic illustration of how different levels of fidelity and resolution are combined to produce the alternative approaches. Fidelity is characterized into three levels. The term "high-fidelity" is used to represent detailed three-dimensional (3D) structural modeling and component-level performance analysis whereas "low fidelity" describes the use of structural surrogate models. Resolution is sub-categorized into building and hazard representation with three levels each. Hereafter, the term "resolution" is jointly used to indicate the resolution of building and hazard definition.

A regional-scale assessment is at the core of the disaster management continuum. It has several use cases and can be implemented in various contexts. Undoubtedly, different use cases have different computational demands. For instance, evaluating recovery-based design parameters requires a high-fidelity high-resolution approach because the prospect of amending existing building code warrants that level of detail. On the other end of the spectrum, if the goal is to identify vulnerable neighborhoods to inform emergency preparedness programs, the HiFi HiRes approach might not be necessary. As such, a one-size-fits-all regional risk solution is not advisable. The proposed alternative risk frameworks address the complexity of regional-scale assessment while keeping a close eye on efficiency, fidelity, and resolution. They are presented as a mechanism to balance computational efficiency, fidelity, and reso-

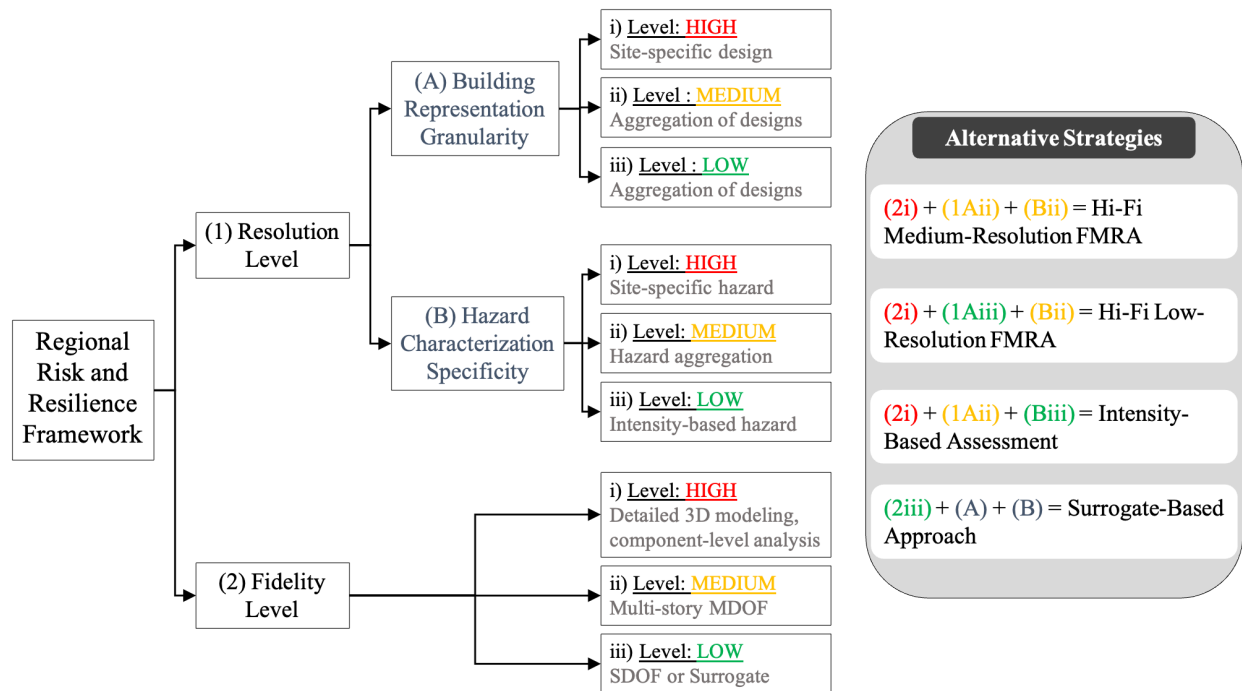


Figure 6.1: Characterization of fidelity and resolution levels used in alternative risk assessment frameworks.

lution. As listed below, the alternative strategies are intended to be flexible, generalizable, and extendable to any region of interest or building inventory.

1. HiFi high-resolution fully mechanistic regional assessment (HiFi FMRA, Chapter 5)
2. HiFi medium-resolution fully mechanistic regional assessment (MedRes FMRA, Section 6.2.1)
3. HiFi low-resolution fully mechanistic regional assessment (LowRes FMRA, Section 6.2.2)
4. Medium-fidelity event-agnostic intensity-based method (Section 6.2.3)
5. Low-fidelity surrogate-based method (Section 6.2.4)

This chapter is divided into two parts. The first part describes the four alternative risk frameworks. They are then implemented on the building inventory established in Chapter 5 to benchmark against HiRes FMRA. The implementation highlights the trade-off between computational efficiency, fidelity, and resolution. In the second half, one of the alternative strategies is selected to investigate “beyond-code” design provisions. In particular, a sensitivity analysis is conducted for a range of importance factors to determine their implications to achieving resilience-based performance objectives.

6.1.1 Controlling fidelity

The probabilistic seismic demand analysis (PSDA) is one of the most important aspects of the FEMA P-58 methodology. PSDA relies on nonlinear response history analysis to simulate the structural response of a building subjected to ground motion records. It quantifies the structural responses using engineering demand parameters (EDPs) such as story drift ratio (SDR), peak floor acceleration (PFA), and residual drift ratio (RDR). The EDP data is used to determine the extent of building damage and perform downstream loss assessment.

The quality of the EDP data has a direct and vital role in determining the robustness of the loss analysis and establishing confidence in the overall results. The fidelity level refers to the quality of the EDP data as well as the explicitness of the loss assessment methodology. In this study, we adopt three levels of fidelity (high, medium, and low) as highlighted in Figure 6.1. In high fidelity, we create detailed three-dimensional numerical models, perform dynamic analysis, and assess component-level loss by populating structural and nonstructural components per floor level. The medium fidelity approach develops and implements building-level consequence curves. Although the development of consequence curves is high-fidelity, their implementation on spatially distributed buildings is categorized as medium fidelity. Additional details on this approach are provided in Section 6.2.3. Finally, the low-fidelity approach circumvents performing explicit analysis or developing building-specific consequence curves. Instead, data-driven surrogate models are developed to estimate the structural response and/or loss distribution. For the scope of this work, we categorized fidelity into three levels but multi-fidelity is an active area of research. Numerous studies have investigated the utility of a spectrum of fidelities ranging from a single-degree-of-freedom (SDOF) system to a three-dimensional (3D) finite element numerical model (Kyrioti and Taflanidis, 2021; Patsialis and Taflanidis, 2021; Deierlein et al., 2010).

6.1.2 Controlling resolution

As illustrated in Figure 6.1, the granularity of building- and hazard representation is treated as two levers to control the level of resolution in regional-level assessment. Recall that the resolution dictates the level of spatial detail with which we assess the risk to buildings across a region. This is critical because the FMA P-58 PBEE methodology relies on site-specific information. For instance, facility and seismic hazards are defined on a per-site basis to assess the performance of a building. Studies have proposed assessing risk using aggregated geographic scales such as neighborhood, zip code, census tract, and city. The HAZUS multi-hazard risk assessment tool (FEMA, 2011) is one such example where risk simulation can be

done at an aggregated level. Taking motivation from HAZUS, we propose that the level of resolution of a regional-scale assessment can be managed by controlling 1) the precision of building representation and 2) the granularity of hazard characterization across the region. Similar to fidelity, we categorize building- and hazard characterization into three levels: high, medium, and low. A high resolution signifies that both the building and hazard are defined at each site. As we move to the lower-resolution options, we either aggregate the building and/or hazard definition.

6.1.2.1 Building Representation

In real life, individual buildings across a region have a unique makeup whether it be distinct based on their plan geometry, size, number of stories, material type, and age. However, there are classes of residential buildings (e.g. townhouses) that are similar enough to warrant grouping. The idea behind building representation is to do exactly that i.e. present a highly generalizable scheme to define building information with the desired level of detail. Figure 6.1 outlines three levels of building representation: high, medium, and low. At the highest level, a unique variant (as defined in XX) is assigned to each site and designed for the site-specific parameters. For medium and low levels, site-specific design parameters are aggregated by binning the design intensities and creating spatial clusters, respectively. The building representation is analogous to the facility definition, which is the first step of the FEMA P-58 methodology.

6.1.2.2 Hazard Characterization

Once the building is defined at the desired scale, to run the end-to-end risk assessment we need to quantify the seismic hazard. As highlighted in Figure 6.1, hazard characterization is the second lever used to control the resolution level in regional-scale assessments. Hazard characterization seeks to provide a generalizable scheme to identify the sites that are

expected to experience similar hazard intensities. As previously discussed, a stochastic set of hazard-consistent ground motion intensity maps is simulated to model the region hazard. The traditional probabilistic seismic hazard analysis (PSHA) is not appropriate because it relies on site-specific hazard deaggregation and cannot incorporate spatial correlation (e.g., inter- and intra-event correlations (Baker and Jayaram, 2008; Jayaram and Baker, 2009)) in the simulated hazard. Therefore, the distribution of simulated intensity maps is used to characterize hazards. High resolution hazard characterization implies site-specific shaking intensity definitions whereas medium resolution implies some spatial aggregation. In this study, low resolution implies that the spatial variation of shaking intensities is implicitly represented by conducting incremental dynamic analyses (IDAs) or multiple stripe analyses (MSAs) using the suite of ground motions. In other words, site-specific ground motion selection is not performed based on the distribution of shaking intensities at the individual sites. This approach is also described as site- and event-agnostic intensity-based hazard characterization.

6.2 Alternative Regional Risk Frameworks

6.2.1 HiFi Medium-resolution FMRA

The first alternative strategy is the HiFi medium-resolution FMRA. It deviates from the baseline strategy based on the degree of granularity of building and hazard representation. In HiFi FMRA, buildings are designed for site-specific intensities. In other words, the spatial distribution of the design intensities is continuous. The main idea of the current approach is to partition the continuous distribution into bins and design buildings for discrete design levels instead of site-specific parameters. Let $X \in \{x_1, x_2, \dots, x_N\}$ represent the design intensity (S_s or S_1) for N sites in a region, and z be user-specified bin size. The number of bins (N_B) is computed as

$$N_B = \left\lceil \frac{\max(X) - \min(X)}{z} \right\rceil \quad (6.1)$$

where $\lceil \cdot \rceil$ denotes the ceiling function that rounds up N_B to the nearest integer. For each value x_i in X , determine its corresponding bin index y_i as

$$y_i = \left\lfloor \frac{x_i - \min(X)}{z} \right\rfloor + 1 \quad (6.2)$$

where $\lfloor \cdot \rfloor$ denotes the floor function that rounds down the bin index to the nearest integer. The array of bin indices becomes $Y \in \{y_1, y_2, \dots, y_N\}$ where y_i is an integer and its values range from 1 to N_B . Now, the design level of j^{th} bin is computed as the conditional median of X assigned to j^{th} bin

$$DL_j = \text{median}(\{X|Y = j\}) \quad \forall \quad j = 1, 2, \dots, N_B \quad (6.3)$$

which ensures that only x_i assigned to the j^{th} bin is used to compute the median value. Figure 6.2 presents a visual depiction of the binning process and an example of the spatial distribution of binned design intensities. By designing buildings based on a smaller number of intensity levels, we are able to reduce the number of unique designs across the region.

In Figure 6.2, the five different colors on the map represent five discrete design levels. To model the exposure, buildings are designated to individual sites- similar to HiFi FMRA. However, unlike HiFi FMRA, they are designed based on bin-specific intensities. For instance, all the buildings assigned to the green bin are designed for a short-period spectral (S_s) design intensity of 2.07g (median between 1.95 and 2.21g) and its corresponding 1-second design intensity (S_1). The idea of intensity-based binning is extended to seismic hazard characterization as well. The distribution of stochastic ground motion intensity maps is grouped to identify sites with similar shaking intensity distributions. The recommended discretization bin size is 0.1g which is equivalent to rounding the floating point intensity measure value to one significant decimal point. By binning both the design and hazard-shaking intensities, we are able to identify buildings with comparable hazard exposure and vulnerability. Recall that one of the steps in the proposed regional framework (Chapter 5) is filtering out redundant sites/buildings to enhance efficiency. The filtration involves combining unique building designs and shaking-intensity bins and only keeping the unique pairs. The total

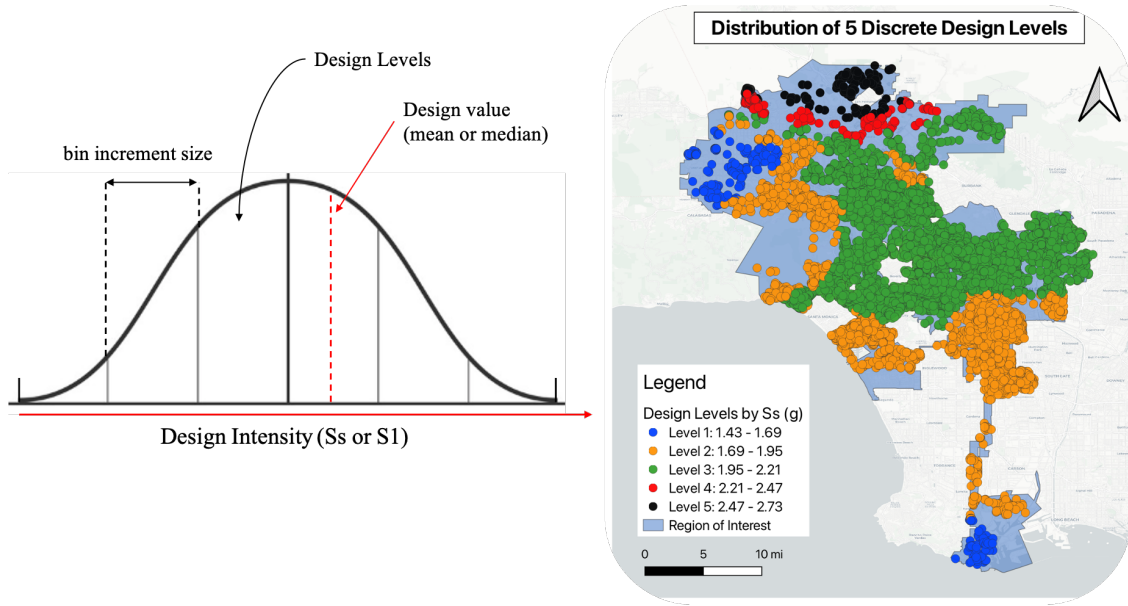


Figure 6.2: Graphical illustration of a design intensity binning (left) and the spatial distribution for an example bin increment of 0.2g (right).

number of unique pairs determines the number of explicit WoodSDA-based analyses needed to represent losses across the region. Depending on the geographic area of the considered region, the building inventory size, the number of design levels, and the shaking intensity bin increment size, this approach is expected to increase the computational efficiency by at least 50%. Section 6.3 presents a case study where this strategy reduced the number of explicit risk simulations by 57%. Note that, the efficiency gain is a direct consequence of the trade-off between resolution and computational expense.

6.2.2 Low-resolution FMRA

In real communities, it is very common to find neighborhoods (or areas within a neighborhood) with identical houses. Real estate developers often build residential houses in bulk which implies that buildings tend to have similar layouts, design, material quality, and construction practices. Even if the houses are not commercially developed, the design and

construction of houses in a neighborhood are likely dominated by a certain group of contractors and builders. To this end, it is fair to assume that the building inventory across a region can collectively be represented by a set of spatially clustered buildings. The low-resolution (LowRes) FMRA seeks to exploit this spatial similarity to gain computational efficiency while maintaining high fidelity. This approach distinguishes itself from the MedRes strategy in two major ways: 1) the design intensities are grouped together based on spatial clusters that are expected to have similar site-related features such as S_s , S_1 , Vs30, and site class and 2) a design variant is not assigned more than once to a cluster.

Creating representative clusters is a key aspect of the LowRes strategy. While there are multitudes of clustering algorithms available in the literature we implement K-means clustering ([MacQueen, 1967](#)) because of its flexibility, relative efficiency, and the fact that it is readily implementable for large-scale data. As the name suggests, it aims to partition n sites into k clusters such that each site belongs to the cluster with the nearest mean distance. The objective function seeks to minimize the within-cluster variance as shown in Equation. (6.4)

$$\arg \min \sum_{j=1}^k \sum_{i=1}^n \|x_i^{(j)} - \mu_j\|^2 \quad (6.4)$$

where each observation has a d -dimensional feature vector, μ_j represents the centroid for cluster j . K-means minimizes the within-cluster sum of square or “interia” until all sites are assigned to a cluster. The number of clusters n is a user input and it determines the number of unique WoodSDA-based risk assessments. One of the advantages of k-means is that we can use the widely used “elbow method” to identify the optimal number of spatial clusters in the region ([Thorndike, 1953](#)). There is no mathematical formulation behind the elbow criterion but it is a common heuristic in optimization to choose a cut-off number such that additional clusters do not have a meaningful impact on the inertia.

The second aspect of LowRes is identifying distinct classes of buildings in each cluster. As discussed above, this is implemented by not duplicating the variant assignment in independent clusters. The idea here is to use one variant to represent the various classes of

buildings in a given cluster. For instance, if a pre-1970 one-story woodframe dwelling with stucco and plaster is considered a building class, explicit risk analysis of one such building would be sufficient to inform decisions at all other sites with the same building class. This level of representation significantly reduces the number of WoodSDA-based loss analyses because one building can represent thousands of similar buildings within a cluster. Similar to MedRes, the hazard is characterized at a bin level with an increment of 0.1g. While the reduced number of WoodSDA-based analyses boosts efficiency, cluster-level building, and bin-level hazard characterization undoubtedly reduce the resolution. The case study presented in Section 6.3 demonstrates that the efficiency gain could be in the factor of 5x compared to MedRes and up to 10x compared to HiFi FMRA. The exact scale of efficiency gain and level of resolution would depend on the number of spatial clusters and the number of design variants per cluster.

6.2.3 Event-agnostic intensity-based approach

The event-agnostic intensity-based approach draws inspiration from traditional regional assessment frameworks such as HAZUS (FEMA, 2011) but also leverages the fully mechanistic simulation. Specifically, the idea is to 1) generate building-level fragility or consequence curves (otherwise referred to as loss curves) tailored to the building inventory and region of interest and 2) use the consequence curves to infer loss of spatially distributed assets and for a given set of stochastic maps. The curves are intensity-based in that the consequence parameter (e.g., repair cost, loss ratio, and recovery times) is quantified as a function of the ground motion intensity measure. Figure 6.3 demonstrates five major steps in this strategy. The regional hazard simulation (Step 3) is similar to the three previously discussed FMRA strategies.

One of the key advantages of the LowRes strategy is that the consequence curves are generated based on a high-fidelity risk assessment methodology. Additionally, the curves are event and site-agnostic which implies that they will remain relevant regardless of the

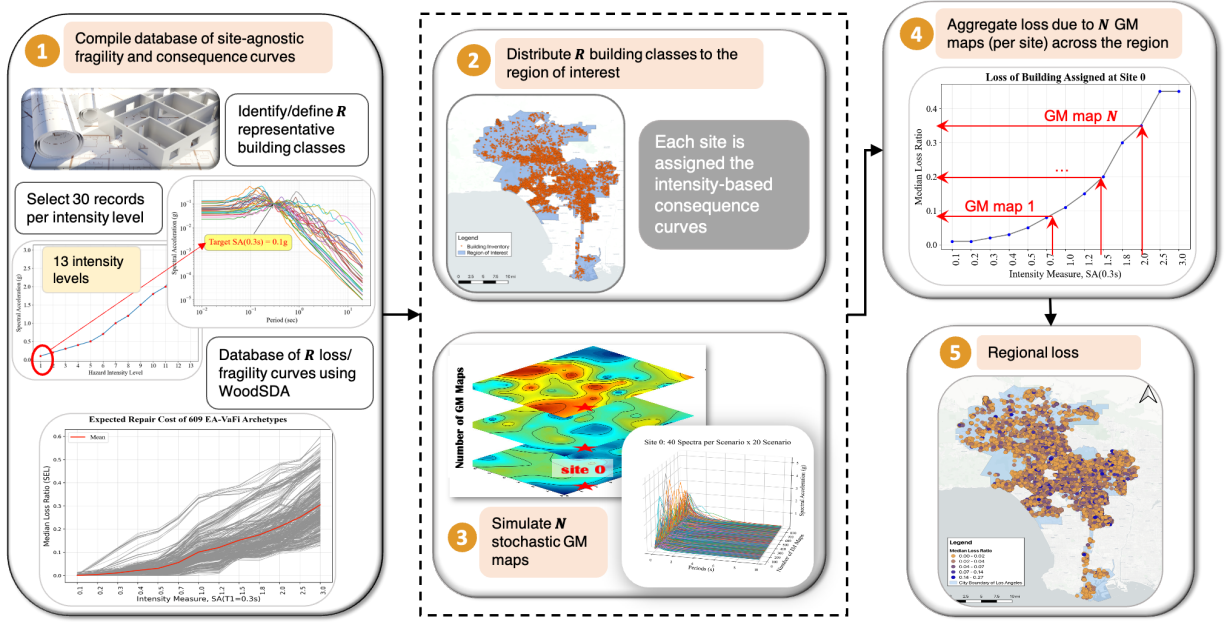


Figure 6.3: A detailed illustration of major steps involved in the intensity-based strategy.

stochasticity in the simulated ground motion maps. This is not the case for the three aforementioned strategies as the WoodSDA-based assessment needs to be re-run for different sets of simulated ground motion maps. It is noticeably efficient because once the curves are generated, inferring losses across the region does not involve complex computations. There are also obvious disadvantages such as the lack of probabilistic robustness and the inability to quantify and propagate uncertainty. In other words, for a given building and intensity, a scalar consequence parameter value is produced instead of a distribution. Additionally, by inferring losses based on the consequence curve, we are assuming that losses and ground motion intensity measure have a perfect relationship which is not entirely valid as building-specific factors would also play an important role.

The following subsections describe the procedures used to assemble the consequence curves database. The first step is to compile a database of fragility and consequence curves for R representative building classes identified across the region. The building classes can be defined based on expertise, publicly available inventory data, or by using computer vision

tools such as BRAILS (Cetiner et al., 2024) to catalog the relevant information. In this study, we leverage the design variant database (discussed in Chapter 5) to define 609 (R) buildings. The 609 buildings are intended to represent the building inventory of single- and multi-family residential woodframe buildings in the City of Los Angeles. Table 6.1 presents a breakdown of the 609 buildings based on four key properties. To account for variability in buildings across a region, the database includes buildings with different numbers of stories, material types, seismic weights, and design intensity levels. Since the majority of single-family houses are one or two stories, only 1- and 2-story variants are included. For multi-family dwellings, four different types of story variants are considered. Similarly, three distinct material types are used to represent those that are prevalent in the existing and new construction. Three levels of seismic weight are used to distinguish light, normal, and heavy-weight buildings. The seismic weight presented in the FEMA P-2139-2 report (FEMA, 2020) is utilized as the benchmark weight. Finally, the buildings are designed for six discrete design intensity levels. The values of the design levels are determined based on the spatial distribution of design intensities across the region as discussed in Section 6.2.1.

Table 6.1: Summary of the five different parameters considered in the design variant database.

Floor Layout (ft×ft)	No. of Stories	Material Type	Seismic Weight	Design Levels (S_s , S_1)g	No. of Buildings
96×48	1-, 2-, 3-, and 4-story	(Stucco+GWB), (HWS+GWB), and (Stucco+Plaster)	Light (0.8*ATC), Normal (ATC), and Heavy (0.8*ATC)	(1.54, 0.6) (1.84, 0.65), (2.03, 0.72), (2.29, 0.8), (2.51, 0.86), (2.7, 0.89)	204
60×32					196
48×32	1-, 2-story				102
40×30					107

6.2.3.1 Ground motion selection

To perform an end-to-end assessment in WoodSDA, the structural module requires ground motion records to simulate the nonlinear response under dynamic excitation (Chapter 5).

For events-specific strategies such as HiFi, MedRes, and LowRes FMRA, the ground motion records are selected for individual sites by matching the response spectra from the stochastic ground motion maps. For those strategies, the final downsampled stochastic map set contained 60 intensity maps, and correspondingly 60 pairs of ground motion records were selected per site. For the current approach, 13 discrete intensity levels are defined and 30 ground motion records are selected for each intensity level. Figure 6.4a presents the 13 amplitude-based intensity measures while Figure 6.4b shows the response spectra of 30 the ground motion records that were selected by matching the spectral acceleration at the fundamental period of 0.3 seconds at the lowest intensity level. The first-mode spectral period of

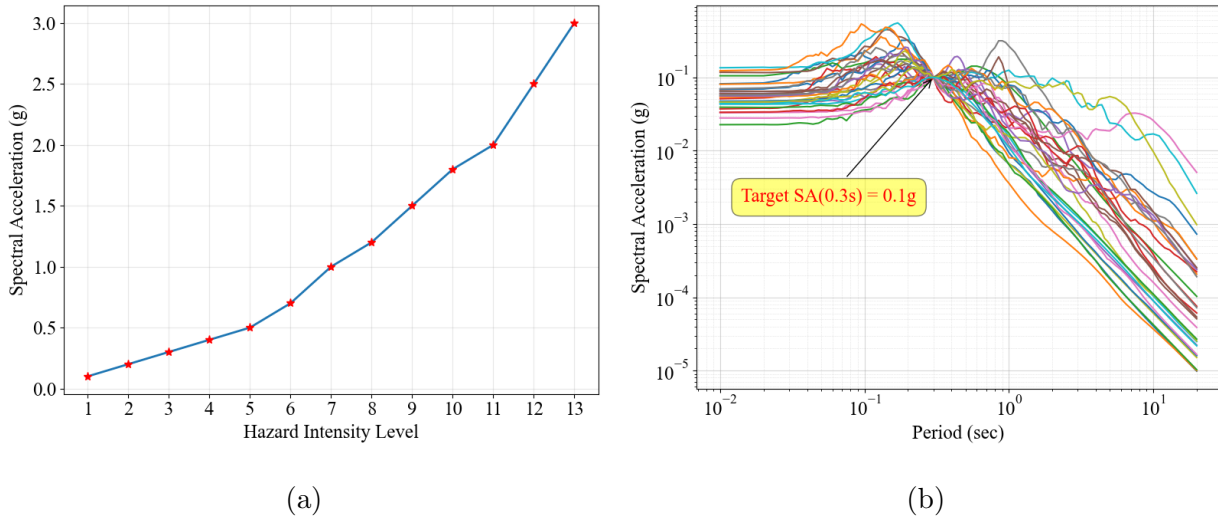


Figure 6.4: (a) Discrete amplitude-based hazard levels and (b) an example response spectra of 30 randomly sampled ground motion records for hazard intensity level 1. The target 0.3 second spectral acceleration at intensity level 1 is 0.1g.

0.3 seconds is used because the average period among the 108 baseline archetypes previously discussed in Chapter 5 is roughly 0.3 seconds. The ground motions are selected from NGA-West2 Database ([Ancheta et al., 2014](#)) by simply matching the spectral acceleration for the specified intensity level. Figure 6.4b shows the response spectra of the 30 selected ground motion records with an $Sa_{T1=0.3s}$ of 0.1g. To include ground motions with a wide range

of frequency contents, unique records are selected across all intensity levels. The selection procedure prioritizes unscaled (as-recorded) ground motions. Scaling is only performed if there are not enough records to fulfill the specified spectral intensity. Several studies ([Luco and Bazzurro, 2007](#); [Dávalos and Miranda, 2019](#); [Tsalouchidis and Adam, 2022](#)) have worked on reducing bias induced in the downstream risk analysis due to high ground motion scaling factor. To minimize the scaling bias, the scale factor is capped at 3.

6.2.3.2 Development of consequence curves database

Given the building database and intensity-based ground motions, we implement WoodSDA to compile the database of building-level fragility and consequence curves. For each building, we consider four consequence/loss parameters: repair cost, loss ratio, reoccupancy time, and functional recovery time. Figure 6.5 plots the median repair cost and median loss ratio as a function of the 13 discrete intensity levels. Recall that the WoodSDA platform outputs Monte Carlo-based loss distribution and the data points plotted in Figure 6.5 represent the median values of those loss distributions. The red line, however, plots the mean values of the 609 buildings. Figure 6.5b shows that the median loss ratio, on average, does not exceed 20% until the shaking intensity measure exceeds 2g.

Consequence curves are also generated for the recovery times. Figure 6.6 shows the median reoccupancy and functional recovery time for the 609 buildings. The recovery times are simulated in WoodSDA by leveraging the beta ATC-138 functional recovery methodology. The ATC-138 methodology also relies on the Monte Carlo approach and thus outputs a distribution of recovery time samples ([ATC, 2021](#)). Figure 6.6 shows that on average the median reoccupancy time for the 609 buildings is near zero up to 1.2g, indicating that most residential buildings are estimated to remain occupiable immediately for low- to medium-intensity shaking. However, it appears that most of these occupiable buildings will have some loss of functionality as the mean functional recovery time is roughly three months. At higher intensities, the reoccupancy and functional recovery time are significant, implying that

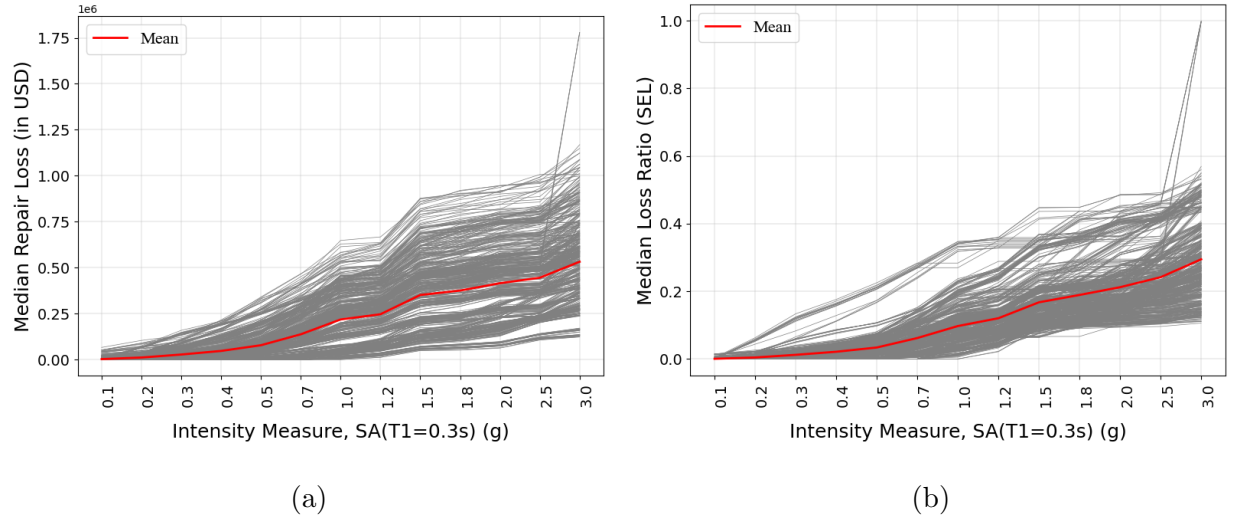


Figure 6.5: a) Economic loss curves of 609 buildings in absolute dollar amount; b) loss ratio curves of 609 buildings as a function of the intensity measures.

some critical components sustain substantial damage and require extensive repair. Impeding factors such as contractor delays, labor shortages, and inspection delays, among others, are included in the methodology, which would undoubtedly increase the estimates. The baseline assumptions used in the recovery time estimates are documented in (ATC, 2021).

6.2.4 Surrogate-based approach

The surrogate-based regional risk and resilience assessment framework is the final approach in the suite of efficiency-seeking strategies. Figure 6.7 illustrates the overall workflow where two tiers of surrogate models are developed. It aims to replace the most computationally intensive part of the FEMA P-58 methodology, nonlinear dynamic structural response analysis, with surrogate models. The predicted structural response is then pipelined into the relevant WoodSDA modules to perform damage and loss analysis, respectively. The prediction task is building-specific and the operation is repeated for all buildings in the region. The second approach directly predicts the loss parameters for the spatially distributed assets without explicit simulation of any of the FEMA P-58 steps. The approaches offer varying levels of

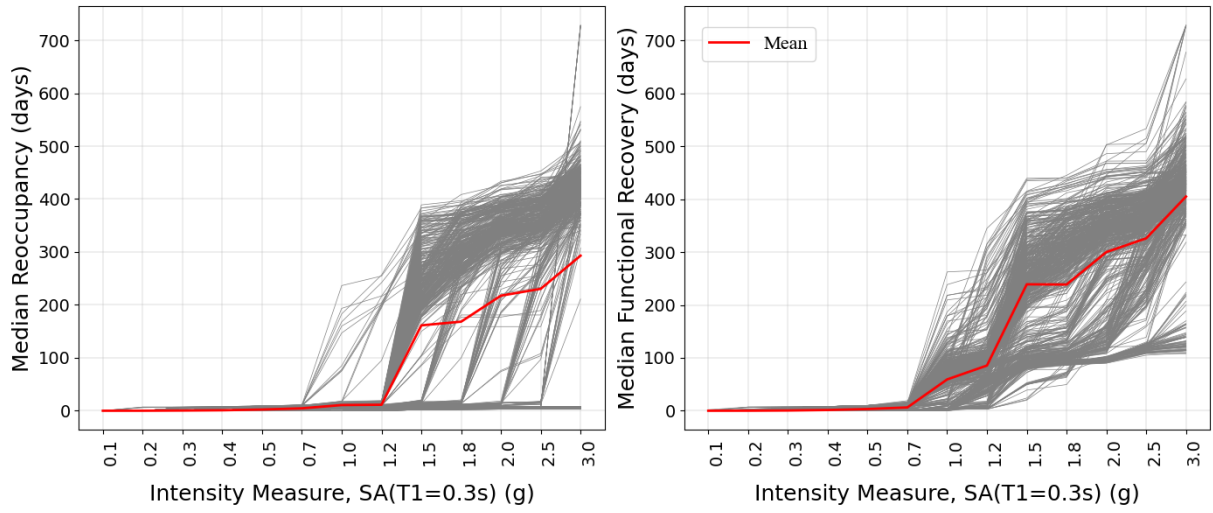


Figure 6.6: Median reoccupancy and functional recovery time of 609 buildings computed based on the beta ATC-18 functional recovery time.

explainability, fidelity, and efficiency in simulating the spatially distributed losses.

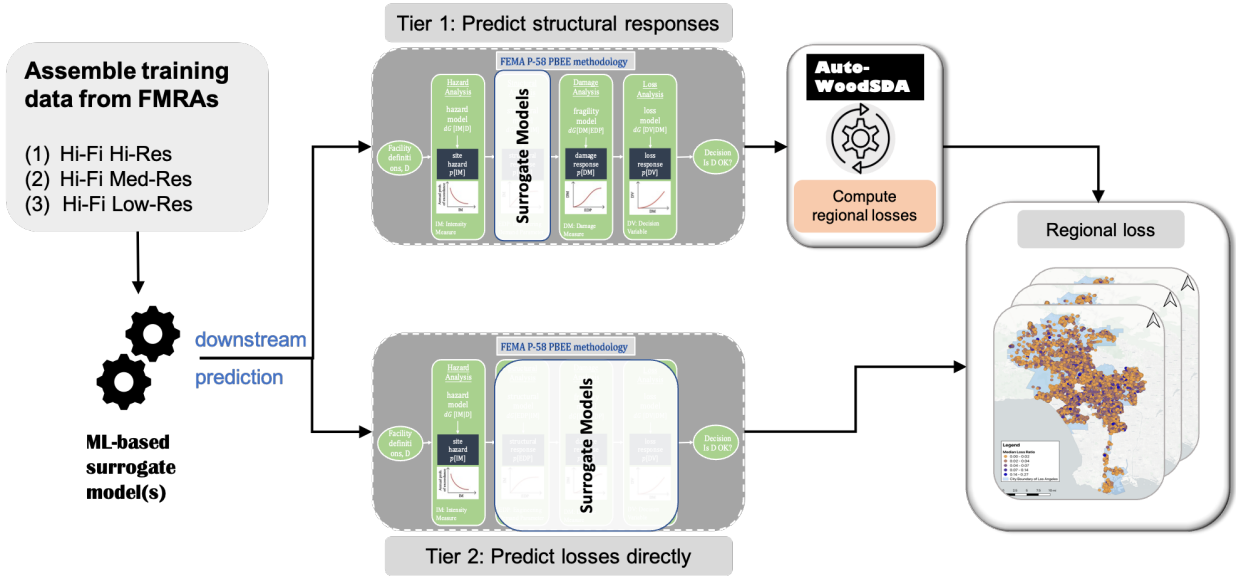


Figure 6.7: Graphical illustration surrogate model-based approach.

6.2.4.1 Structural surrogate model

The development of surrogate models to predict the structural response has been an active area of research for the better part of the last two decades. From machine learning (ML) (Sun et al., 2021) to probabilistic learning (Zhong et al., 2023), studies have explored a wide array of methods. A few of the well-documented challenges in developing structural surrogate models include: 1) they do not generalize well for “unseen” samples, 2) predicting the multivariate distribution of engineering demand parameters (EDP) is incredibly challenging, and 3) it does a poor job of predicting for out-of-range feature parameters. However, in recent years, the Gaussian Process (GP) (Williams and Rasmussen, 1995) model has been shown to perform “well” when predicting multivariate distributions. The GP model has been implemented in *quoFEM*, an open-source software developed by NEHRI SimCenter (McKenna et al., 2022). The *quoFEM* is intended to be a general-purpose uncertainty quantification application and has built-in functionalities for GP modeling. The procedures presented hereafter are adapted from *quoFEM*’s documentation page.

The primary objective of developing a structural surrogate model is to replace the computationally expensive PSDA component of the FEMA P-58 methodology. In the mechanistic regional strategies (HiRes FMRA, MedRes FMRA, and LowRes FMRA), PSDA relied on nonlinear response history analysis (NRHA) to generate the engineering demand parameters (EDPs) needed for the component- and building-level damage analysis. Since NRHA is based on a 3D numerical model, the EDPs are multivariate in the number of stories and two orthogonal directions. For a four-story building, the distribution of SDR, for example, is 8-dimensional. With that in mind, let $\mathbf{Y} \in \{\mathbf{y}_1, \mathbf{y}_2, \dots, \mathbf{y}_P\}$ represent the P –dimensional multivariate data where $\mathbf{y}$ is a vector of EDP values of size N . The EDP surrogate model can be formulated as

$$\mathbf{Y} \simeq g^{sur}(\mathbf{x}) = \tilde{g}(\mathbf{x})^T \beta + z(\mathbf{x}) \quad (6.5)$$

where $\mathbf{x}$ is an input feature matrix of size $N \times M$, M is the number of input features, g^{sur}

is the surrogate model. g^{sur} performs two tasks: 1) it captures the global trend based on global basis functions ($\tilde{g}(\cdot)$) and linear combination coefficients (β) and 2) models the residual term ($z(\mathbf{x})$) as a centered second-order stationary Gaussian process. It is mathematically represented as

$$z(\mathbf{x}) \sim GP(\mathbf{x}; 0, K(\mathbf{x}_i, \mathbf{x}_j)) \quad (6.6)$$

where $K(x_i, x_j)$ is the kernel function. Given this setup, the goal of surrogate modeling is to find the optimal stochastic parameters $\hat{\beta}$, and kernel function $\hat{K}(x_i, x_j)$ that best matches the “true” distribution. In most practical applications, the exact kernel is not known so it is typical to assume the mathematical form of a kernel and calibrate the applicable parameters based on the observed data. The Matérn kernel, also known as the Matérn covariance function ([Genton, 2001](#)) is adopted in this study. Mathematically, it is represented as

$$k(\mathbf{x}_i, \mathbf{x}_j) = \sigma \prod_{d=1}^D g_d(h_d) \quad (6.7)$$

where $h_d = x_{i,d} - x_{j,d}$ and

$$g_{d, \frac{5}{2}}(h_d) = \left(1 + \frac{\sqrt{5}|h_d|}{l_d} + \frac{5h_d^2}{3l_d^2} \right) \exp \left(- \frac{\sqrt{5}|h_d|}{l_d} \right) \quad (6.8)$$

$$g_{d, \frac{3}{2}}(h_d) = \left(1 + \frac{\sqrt{3}|h_d|}{l_d} \right) \exp \left(- \frac{\sqrt{3}|h_d|}{l_d} \right) \quad (6.9)$$

Once the kernel is selected, the parameters are calibrated to maximize the likelihood of the observations. We implement the GP-based surrogate model using an open-source Python package, *GPpy* ([GPpy, 2012](#)). The training data is compiled based on the results from the HiFi FMRA strategy. Recall that in the HiFi strategy, we had 15,336 buildings but we only ran end-to-end simulations for 15,205 sites/buildings using 60 ground motion records per site. Of the 15,205 sites, there were 2,267 that had unique building designs. As a first iteration, the training data was compiled based on individual ground motion records, resulting in $2267 * 60 = 136,020$ observations. The GP model was not computationally feasible for this size data set because it required 88.2 gigabytes (GB) of memory to store

the high-dimensional matrix of size 136020×136020 . Specifically, we were not able to run the GP model, even on the Hoffman2 cluster, which has a per-processor memory capacity of 32-64 GB. To resolve the memory issue, we reduced the training data by only considering the median EDP value instead of the distribution based on the 60 ground motion records. This enabled us to include data from all 15,205 buildings. In this instance, we were able to train the GP model but its performance was subpar. In particular, the r-squared, which measures how the variance in Y is accounted for by x , was 0.26.

one possible reason for the underwhelming performance of the structural response surrogate model could be the training dataset. The 15,205 data points include one-, two-, three-, and four-story buildings which means that the dimensions of an EDP array (e.g., SDR in two orthogonal directions) are 1×2 , 1×4 , 1×6 , and 1×8 , respectively. This raises data incompatibility issues because stacking the EDP data of dimension 1×2 on 1×8 means that the missing values in the latter six entries of 1×2 data dimensions are replaced with zeros. To address this disparity, we separated the training data by the number of stories to train the GP model. The number-of-stories-specific GP model improved the r-squared to 0.5 on average, but it is nowhere near the acceptable range. For this reason, we did not pursue the structural surrogate model further nor implemented it to assess regional risk in Section 6.3. However, we believe there were some valuable lessons learned about the challenges of creating a structural surrogate model that can reliably predict multivariate EDPs and generalize for several building parameters.

6.2.4.2 Loss surrogate model

The loss surrogate model aims to directly predict the distribution of building-specific consequences within the inventory (e.g., repair cost, loss ratio, reoccupancy time, functional recovery time) by bypassing all the intermediate FEMA P-58 steps. In other words, given a set of intensity maps, the surrogate model would predict the corresponding loss maps. Figure 6.7 gives a schematic overview of the workflow which is predicated on training machine

learning-based surrogate models. The objective is to develop surrogate models that can predict regional losses. From a computational perspective, loss surrogate models are the most efficient among all other strategies presented in this study. Except for the one-time upfront cost of training the models, it is extremely efficient to implement and scale them to make predictions. Although the efficiency is undeniable, it comes at the cost of low fidelity and resolution, and (some) loss of explainability (e.g., relative influence of different components on the consequences).

Extreme Gradient Boosting (XGBoost)

The eXtreme Gradient Boosting and is a decision tree-based algorithm (XGBoost) is one of the most popular machine-learning models for regression ([Chen and Guestrin, 2016](#)). There are two key aspects of the model: 1) the decision tree ensemble and 2) the gradient-boosted optimization. Figure 6.8 presents a schematic flowchart of the algorithm that leverages tree ensemble models to train the objective function $f()$ and find the optimal set of parameters θ that best fits the training data X . The algorithm is designed to recursively partition the data space to create K decision trees. For each consecutive tree, the residual from the previous tree is utilized to enhance the performance of the next tree. Each tree learns a new function $f_k(X, \theta_k)$. The final XGBoost model is determined by adding the learned parameters of the individual trees.

Ultimately, the response predictions are made by using the K additive functions,

$$\hat{y}_i = \sum_{k=1}^K f_k(x_i), f_k \in F \quad (6.10)$$

where K is the number of decision trees, $f_k(x_i)$ is the learning function of the $k - th$ decision tree, $\hat{y}_i$ is the predicted output value, and F is the set of all possible trees.

The objective function of XGBoost, as presented by [Chen and Guestrin \(2016\)](#), is outlined

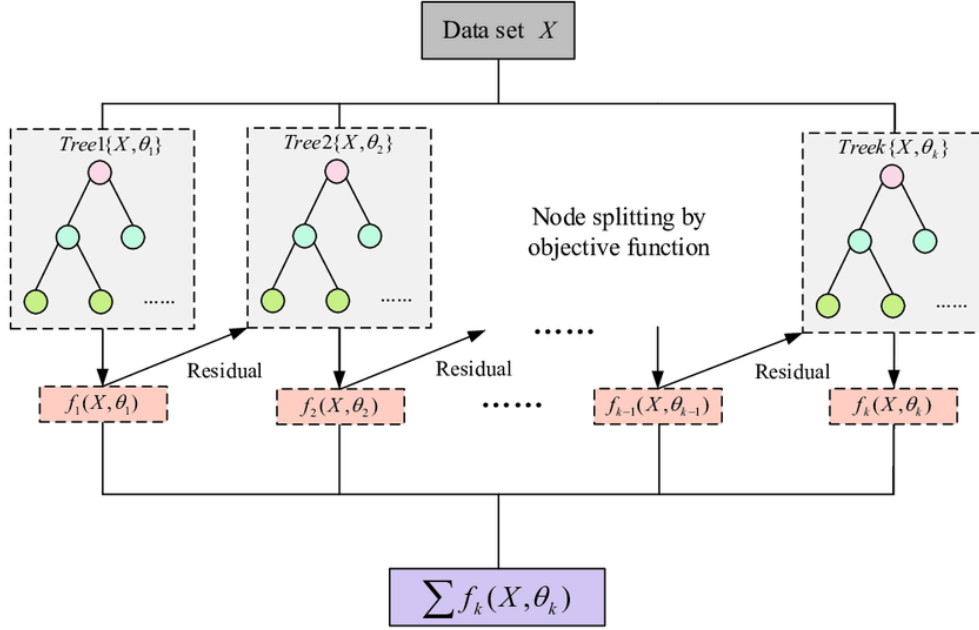


Figure 6.8: A schematic flowchart of the XGBoost model (Guo et al., 2020).

in Eq. (6.11)a

$$\mathcal{L} = \sum_{i=1}^n l(y_i, \hat{y}_i) + \sum_{k=1}^K \Omega(f_k) \quad (6.11)$$

where the first part, $\sum_{i=1}^n l(y_i, \hat{y}_i)$, is the training error that measures the difference between the true (y_i) and predicted ($\hat{y}_i$) values. $\sum_{k=1}^K \Omega(f_k)$ is the regularization term that controls the complexity of the model and plays a critical role in avoiding overfitting. A common choice of $l(\cdot)$ is the mean squared error (MSE). The regularization term is computed as

$$\Omega(f) = \gamma T + \frac{1}{2} \lambda \sum_{j=1}^T w_j^2 \quad (6.12)$$

where T is the number of leaf nodes, w is the scores of the leaf nodes, γ is the leaf penalty coefficient, and λ ensures that the scores of leaf nodes are not exceedingly large.

The gradient boosting algorithm recursively adds one new tree at a time and utilizes the residual to learn the function in each consecutive iteration step as formulated in the following

set of equations.

$$\begin{aligned}
\hat{y}_i^{(0)} &= 0 \\
\hat{y}_i^{(1)} &= f_1(x_i) = \hat{y}_i^{(0)} + f_1(x_i) \\
\hat{y}_i^{(2)} &= f_1(x_i) + f_2(x_i) = \hat{y}_i^{(1)} + f_2(x_i) \\
&\dots \\
\hat{y}_i^{(K)} &= \sum_{k=1}^K f_k(x_i) = \hat{y}_i^{(K-1)} + f_K(x_i)
\end{aligned}$$

combining the learning function and Eq.(6.11), we get

$$\mathcal{L}^{(K)} = \sum_{i=1}^n l(y_i, \hat{y}_i^{(K-1)} + f_K(x_i)) + \sum_{i=1}^K \Omega(f_i) \quad (6.13)$$

Based on the work on the second-order tree method by [Friedman \(2001\)](#), the XGBoost makes use of the second-order approximation to efficiently optimize as well as consider the curvature in the gradient-based optimization. The objective function now becomes

$$\mathcal{L} = \sum_{i=1}^n \left[l \left(y_i, \hat{y}_i^{(K-1)} + g_i f_K(x_i) + \frac{1}{2} h_i f_K^2(x_i) \right) \right] + \sum_{i=1}^K \Omega(f_i) \quad (6.14)$$

where g_i h_i are the first and second derivatives given by

$$g_i = \partial_{\hat{y}_i^{(K-1)}} l(y_i, \hat{y}_i^{(K-1)}) \quad (6.15)$$

$$h_i = \partial_{\hat{y}_i^{(K-1)}}^2 l(y_i, \hat{y}_i^{(K-1)}) \quad (6.16)$$

We can remove all the constant terms from the objective function in Eq. (6.14) and re-formulate as

$$\mathcal{L} \approx \sum_{i=1}^n [g_i w_{q(x_i)} + \frac{1}{2} h_i w_{q(x_i)}^2] + \gamma K + \frac{1}{2} \lambda \sum_{j=1}^K w_j^2 \quad (6.17)$$

$$= \sum_{j=1}^K \left[\left(\sum_{i \in I_j} g_i \right) w_j + \frac{1}{2} \left(\sum_{i \in I_j} h_i + \lambda \right) w_j^2 \right] + \gamma K \quad (6.18)$$

where I_j is the set of data point indices assigned to the j^{th} leaf. The optimal w and objective function is simplified to

$$w_j = -\frac{G_j}{H_j + \lambda} \quad (6.19)$$

$$\mathcal{L} = -\frac{1}{2} \sum_{j=1}^K \frac{G_j}{H_j + \lambda} + \lambda K \quad (6.20)$$

where $G_j = \sum_{i \in I_j} g_i$ and $H_j = \sum_{i \in I_j} h_i$. the above equation

The equations presented above provide a mathematical understanding of the algorithm and how it is optimized. Before we get to optimization, the algorithm needs to split the data space, create trees, and determine nodes to separate the tree and stop iteration. That is done based on the *Gain* metric.

$$Gain = \frac{1}{2} \left[\frac{G_L^2}{H_L + \lambda} + \frac{G_R^2}{H_R + \lambda} - \frac{(G_L + G_R)^2}{H_L + H_R + \lambda} \right] - \gamma \quad (6.21)$$

For the algorithm to recursively generate additional branches to the trees, the gain should be higher than when a branch is not added.

Model evaluation metrics

To evaluate the performance of a regression surrogate model, the following evaluation metrics are utilized. The mean squared error (MSE) quantifies the average squared differences between the true (y) and predicted ($\hat{y}$) values. It is computed as

$$MSE = \frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2 \quad (6.22)$$

where n is the number of data points, y is true values, and $\hat{y}$ is predicted values. Another popular metric is the root mean squared error (RMSE) which is simply the square root of MSE. RMSE is interpretable because it is measured in the same unit as the target variable. MSE is sensitive to outliers because the squaring operation magnifies the large errors. The mean absolute error (MAE) aims to address that issue. MAE is more commonly used when

dealing with datasets with extreme values. It is given by

$$\text{MAE} = \frac{1}{n} \sum_{i=1}^n |y_i - \hat{y}_i| \quad (6.23)$$

The R-squared (R^2), also known as the coefficient of determination, measures the proportion of the variance in the dependent variable that is explained by the independent variables. It ranges from 0 to 1 and, with higher values indicating better model fit. It is calculated as

$$R^2 = 1 - \frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{\sum_{i=1}^n (y_i - \bar{y})^2} \quad (6.24)$$

where $\bar{y}$ is the mean of the observed values y_i .

Model development

We develop individual surrogate models for each of the four consequence parameters, namely repair cost, loss ratio, reoccupancy time, and functional recovery time. The training data is assembled from the benchmark strategy (i.e., HiRes FMRA) and includes building- and site-specific features. The building-specific features include footprint area, number of stories, material type, and design base shear whereas the site-specific features include spectral acceleration at various periods (0.2-, 0.3-, and 0.5-seconds) ASI, and Vs30. These features are measured in different units and thus have values with different scales. Since the objective function (Eq.(6.11)) takes real values to fit the parameters, the scale of the input features will have a disproportional influence on the learned parameters. To negate this issue, we normalize the input features using a standard scalar. The standard scalar transforms the data as follows,

$$\tilde{X}_i = \frac{X_i - \text{mean}(X)}{\text{std}(X)} \quad (6.25)$$

The training data is compiled based on the results from the HiFi FMRA strategy. Recall that in the HiFi strategy, we had 15,336 buildings but we only ran the explicit analysis for 15,205 sites/buildings. The 15,205 runs represent 2267 unique building designs. As discussed in Chapter 5, 800 maps are generated with the consequences to the spatially

distributed buildings. Since the goal of the surrogate model is to predict losses at the map level, the training data is stacked by maps. In other words, each building has 800 entries in the training dataset. While assembling training data at a map level allows it to model and capture the uncertainties, it increases the size of the data as well as the complexity of training and testing the models. We intended to train the models using the data from 15,205 buildings. However, with 800 maps, our training/testing dataset exceeded 12 million entries which posed a significant computational challenge as the XGBoost model did not converge within 24 hours and 16 processors on the Hoffman2 cluster. The model was trained using the *XGBoost* Python package (Chen and Guestrin, 2016). The training was terminated at the 24-hour mark because the Hoffman2 cluster imposes a runtime limit of 24 hours per job. To make model training tractable, we reduced the number of buildings from 15,205 to 2,267. Thus, the new training data consists of 1,813,600 entries which takes about 8 hours to train each surrogate model with 16 processors.

Hyperparameter tuning is essential for optimizing the performance of the XGBoost models. The *XGBoost* package offers numerous tunable hyperparameters as a means to control model complexity, increase predictive accuracy, and boost generalization ability. We perform extensive hyperparameter tuning by using the grid search technique. Specifically, an exhaustive search over the specified hyperparameter grid is performed to determine the best parameters. The following is the list of tuned parameters and their significance

1. **No. of estimators:** The number of estimators refers to the number of trees in the XGBoost ensemble. Increasing the number of trees can improve the predictive performance, but it also increases the complexity of the model as well as the risk of overfitting. The default value is 100 and the grid used in tuning was [50, 150, 300].
2. **Learning rate:** The learning rate controls the step size at each iteration during gradient descent optimization. A lower learning rate requires more iterations but can lead to better convergence. The default value is 0.1 and the grid used in tuning was

[0.05, 0.1, 0.2].

3. **Maximum depth:** The maximum depth of a tree in the ensemble. A deeper tree can capture more complex relationships in the data but may also increase the risk of overfitting. Conversely, a shallower tree may lead to underfitting. The default value is 6 and the grid used in tuning was [3, 7, 11].
4. **Minimum child weight:** It is the minimum sum of instance weights (Hessian) needed in a child node of the tree. It helps prevent splitting nodes that contain too few instances, thereby reducing overfitting. The default value is 1 and the grid used in tuning was [1, 3, 5]

Model performance

Table 6.2 summarizes the model training, testing, and prediction performance. A 70-30 training and testing split is applied to the data. The metrics for training and testing are computed based on the split data. For prediction, an “unseen” dataset is compiled based on the exposure and hazard information from the medium-resolution strategy. Recall that we ran explicit analyses for 6,606 buildings in the MedRes FMRA strategy so we have the true value to compute the evaluation metrics as shown in Table 6.2. The surrogate model is iteratively implemented for 6,606 buildings one at a time. The evaluation metrics for prediction shown in Table 6.2 represent the average of 6,606 prediction instances. The near-perfect training R-squared (R^2) value of 0.98-0.99 demonstrates that the loss models captured variability in the training set extremely well. There is not a drop in R^2 for the testing set which signifies that the models likely did not overfit the training data. It, however, decreases significantly for the unseen prediction dataset, suggesting that the models do not generalize for the unseen observations. A similar trend is observed for other loss metrics and loss parameters. The training RMSE of repair cost is about 41,000 USD which inflates to 99,000 USD for the prediction set implying that on average the predicted repair cost is off by about

99,000 USD.

Table 6.2: Evaluation metrics summary of loss surrogate model trained with data from HiRes FMRA and predicted on MedRes FMRA.

Metric	Task	Data Source	Repair Cost	Loss Ratio	Reoccupancy	Functional Recovery
R^2	Training	HiRes	0.98	0.99	0.99	0.99
	Testing	HiRes	0.91	0.97	0.97	0.98
	Prediction	MedRes	0.81	0.79	0.73	0.84
MSE	Training	HiRes	1.7E9	7.1E-5	41	31
	Testing	HiRes	8.4E9	6.1E-4	274	166
	Prediction	MedRes	9.8E9	1.76E-3	1918	1285
RMSE	Training	HiRes	41231	0.0084	6.4	5.54
	Testing	HiRes	91651	0.025	17	12.87
	Prediction	MedRes	99099	0.042	44	34.85
MAE	Training	HiRes	9330	0.0023	1.7	1.9
	Testing	HiRes	13058	0.0041	3.8	3.5
	Prediction	MedRes	19595	0.0099	13	12

6.2.5 Sensitivity to training data size

The training data size in the loss surrogate model presented above is quite large with nearly two million observations, which could explain the strong predictive power. To investigate the potential impact of training data size, we reversed the training/testing and prediction data sets. We created a second set of loss surrogate models with training/testing data from the MedRes FMRA, which has 594 unique buildings and 800 maps which results in a total of 475,200 training observations. The four trained models are used to make predictions on the Hi-Res buildings. Table 6.3 provides evaluation metrics from training, testing, and prediction. The prediction score is averaged across the 15,205 buildings in the Hi-Res strategy. Compared to Table 6.2, the training and testing performance reduces marginally which is to

be expected because the training data size is significantly lower. The prediction scores, however, surprisingly increase signifying that the model generalizes well. Similar to the earlier model, the reoccupancy time has the lowest prediction score because a sizeable number of buildings have zero reoccupancy days, which is not well-captured by the model. The good overall performance of the models on the prediction dataset suggests that a larger training dataset does not guarantee better performance.

Table 6.3: Summary of performance evaluation metrics for the surrogate model trained with the Med-Res data and used to predict the Hi-Res consequences.

Metric	Task	Data Source	Repair Cost	Loss Ratio	Reoccupancy	Functional Recovery
R^2	Training	MedRes	0.92	0.97	0.94	0.97
	Testing	MedRes	0.87	0.90	0.88	0.94
	Prediction	HiRes	0.85	0.78	0.76	0.86
MSE	Training	MedRes	4.3E9	4.4E-5	436.2	293.86
	Testing	MedRes	6.1E9	1E-3	922	560
	Prediction	HiRes	12E9	1.96E-3	1893	1172
RMSE	Training	MedRes	63246	0.021	21	17.14
	Testing	MedRes	78358	0.031	30	23.66
	Prediction	HiRes	108251	0.037	37	34
MAE	Training	MedRes	13755	0.0052	4.3	1.9
	Testing	MedRes	14735	0.0065	6.0	3.5
	Prediction	HiRes	20571	0.0099	11	10

6.3 Implementation and Comparison

The four alternative strategies presented in Section 6.2 are implemented and benchmarked against the HiFi FMRA. The strategies are implemented to assess the losses for the previously identified 15,336 single- and multi-family residential woodframe buildings in the City of Los Angeles. The exposure is modeled by randomly distributing the 108 design variants to

15,336 sites and designing the assigned buildings. To ensure a consistent comparison across the different strategies, the seed of the random distribution is fixed such that any given site has the same design variant for all the strategies. Once the exposure is modeled, we perform regional hazard simulation to generate a stochastic set of ground motion intensity maps as discussed in Chapter 5. The simulated site-specific intensity maps are used to perform strategy-specific hazard characterization. The use of the same exposure and hazard guarantees that the comparison of the proposed suite of strategies is consistent.

6.3.1 Exposure modeling

The building designs are created based on the spatially distributed design variants and the design intensity aggregation adopted by each strategy. Recall the variants are skeleton-type buildings that do not have a designed lateral force-resisting system. The building designs are created using the design module in woodSDA. Although 108 design variants are sampled with replacement to populate the 15,336 sites, the uniqueness of the individual buildings is defined by their base shear. Formally, a design is deemed unique if it differs from the rest of the inventory in any one of the five following properties: 1) number of stories, 2) layout dimension, 3) material type, 4) seismic weight, and 5) base shear (rounded to the nearest integer). Note that the first four properties are defined by a design variant while the base shear is calculated by the design module of WoodSDA. If a design variant (e.g., *s2_48×32_Stucco_GWB_Normal*) is assigned to two different sites and designed for two different base shears (30 and 31 kips) then the two buildings (naming convention: *s2_48×32_Stucco_GWB_Normal_Vs30* and *s2_48×32_Stucco_GWB_Normal_Vs31*) are identified as two unique designs. Similarly, a unique hazard is defined as the number of sites that have unique pairs of mean and standard deviation of an intensity measure (IM). The mean and standard deviation are computed based on the set of stochastic intensity maps. Finally, the number of end-to-end E2E WoodSDA runs is determined by combining the unique designs and unique hazards. It represents the number of sites that have unique designs and

unique shaking intensity distribution.

Table 6.4 summarizes the number of unique designs, the number of sites with unique hazards, and the total number of E2E WoodSDA runs for all five strategies. For Hi-Res FMRA, we know from Chapter 5 that out of 15,336 sites, there are 2,267 total unique designs. Since it is the ground truth, there is no design or hazard aggregation in the Hi-Res FMRA. The assigned variants are designed for site-specific intensities obtained from the ASCE hazard API ([ASCE, 2016](#)). Similarly, the Hi-Res FMRA has 1,462 sites with unique pairs of mean and standard deviation (std) acceleration spectrum intensity (ASI). We use ASI as the intensity measure because Chapter 4 showed that ASI is one of the most optimal IMs for woodframe structures. The total number of E2E WoodSDA runs implies that only 131 sites (out of 15,336) have unique design and hazard combinations. Also, by filtering redundant sites with the same exposure and hazard, we reduce the computation cost, however small, without sacrificing the fidelity or resolution.

Table 6.4: Summary of the total number of WoodSDA runs based on exposure and hazard characterization.

Strategy	Unique Designs	Unique Hazards	No. of WoodSDA runs
HiRes FMRA	2267	1462	15205
MedRes FMRA	594	70	6606
LowRes FMRA	1063	16	1693
Intensity-based	609	NA	609 runs with 13 intensity levels per building
Surrogate model	Depends	Depends	0

6.3.1.1 MedRes FMRA Strategy

In this strategy, the exposure and hazard are aggregated to reduce the number of E2E computations and enhance efficiency while trading off the level of resolution. As outlined in Section 6.2.1, the design intensities established in the HiRes approach are discretized into 6 bins of increment size 0.25g as depicted in Figure 6.9a. This resulted in 594 unique designs which is roughly a four-fold decrease compared to the HiRes approach. Figure 6.9a presents the sensitivity of the number of design levels to the bin size. As we increase the bin size, the number of design levels decreases to one implying that the entire region is a single bin. Based on our study, we found that a bin size of 0.2-0.4g is appropriate for moderately reducing the resolution. For the hazard, we bin the mean and std ASI at an increment of 0.1g which reduces the sites with unique hazards to 70. Figure 6.9b shows the total number of E2E runs as a function of the design intensity bin while keeping the hazard intensity bin constant at 0.1g. As expected, increasing the bin size reduces the number of WoodSDA runs needed to represent the regional loss. For a bin size of 0.25g, 6,606 runs are needed which is roughly 2.5 times lower than the benchmark strategy.

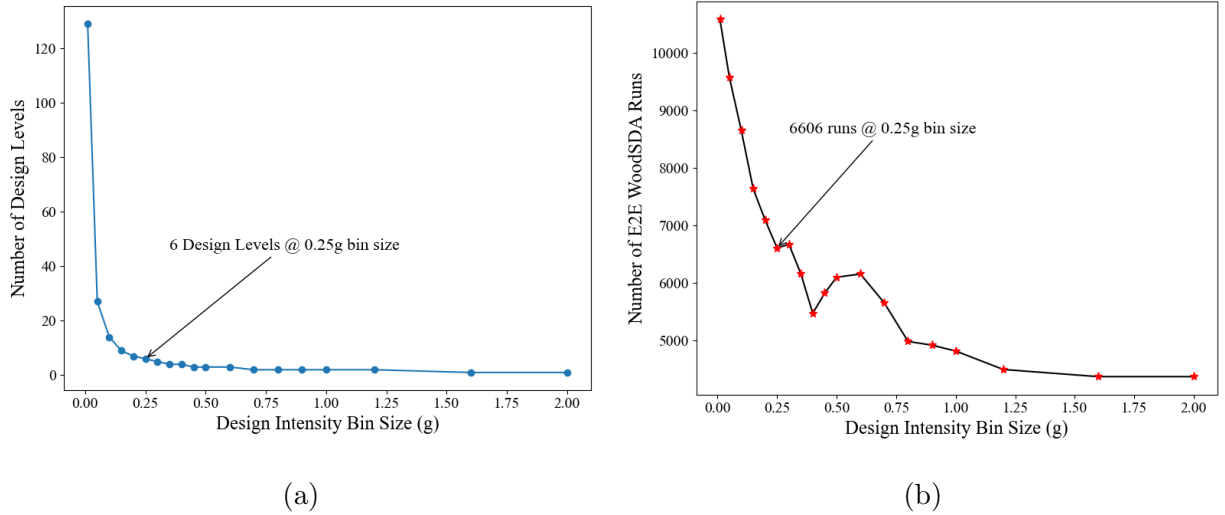


Figure 6.9: a) Sensitivity of the number of discrete design levels to the design intensity bin size; b) the number of E2E WoodSDA runs as a function of design intensity bin size.

6.3.1.2 LowRes FMRA Strategy

As discussed in Section 6.2.2, the exposure modeling in the LowRes strategy leverages the spatial similarity in the buildings and hazards. The spatial clusters are based on features such as the design intensities, Vs30, and seismic design category (SDC). All of the building properties are categorical which is why it is not directly used in the K-Means algorithm (MacQueen, 1967). Instead, we capture spatial similarity in the building by imposing that the design variants are not repeated in any cluster. In other words, a cluster can have a maximum of 108 designs. The designs are generated based on a cluster-specific intensity which is taken as the average for that cluster. To determine the number of clusters, we implemented the elbow rule as described earlier. Figure 6.10a demonstrates the decrease in inertia with the increased number of clusters. The inertia is computed using Eq.(6.26),

$$\text{Inertia} = \sum_{i=0}^n \min_{\mu_j \in C} (\|x_i - \mu_j\|^2) \quad (6.26)$$

where n is the number of data points, C is the number of clusters, x_i is the i^{th} data point, μ_j is the center of the j^{th} cluster, and $\|x_i - \mu_j\|^2$ is the squared Euclidean distance between x_i and μ_j . The optimal number of clusters is determined to be 16, which approximately corresponds to the location of the elbow point. The 16 clusters imply that we have 16 design intensity levels, which yields 1,063 unique designs. The increase in the number of unique designs compared to MedRes is attributed to the higher number of discrete design levels.

The hazard is aggregated such that all sites in a cluster are assumed to experience the “same” hazard. Combining unique designs and hazards, the total number of unique runs needed to represent the regional loss is 1,693. Although the number of unique designs was higher than the MedRes, the lower number of E2E runs is a result of a significant reduction in the number of unique hazard distributions. Figure 6.10b summarizes the number of WoodSDA runs for a variety of cluster sizes. At 16 clusters, the 1,693 runs represent a nine-fold reduction compared to the benchmark strategy.

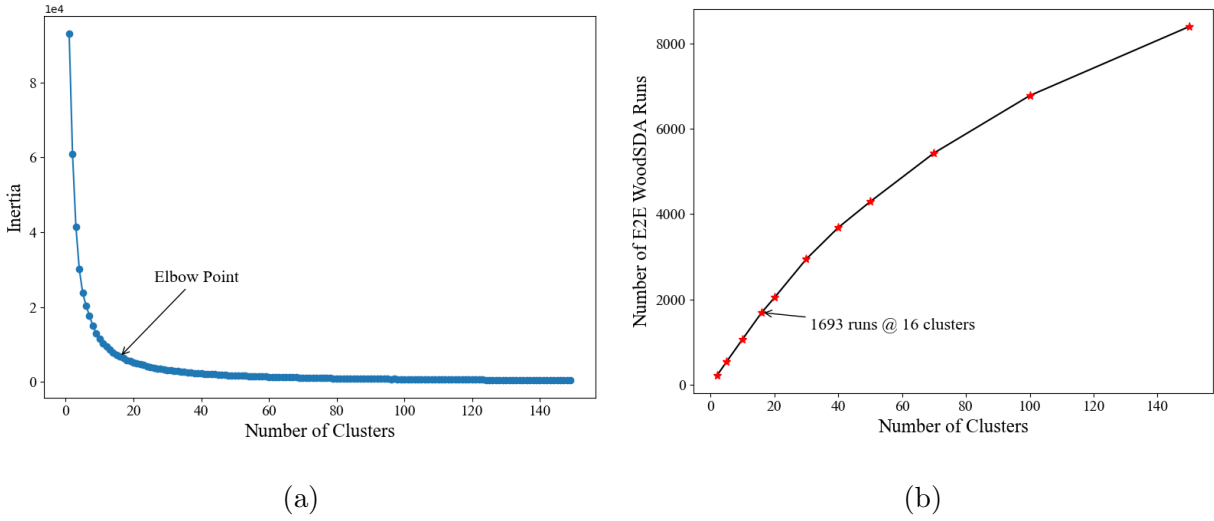


Figure 6.10: a) Graphical illustration of elbow method indicating the optimal number of clusters to be 16; b) the number of E2E WoodSDA runs as a function of cluster size.

6.3.2 Runtime comparison

Once the number of E2E runs is determined, they are executed in a distributed computing setting via WoodSDA. We utilize Hoffman2, a campus-wide cluster located at the University of California, Los Angeles, and maintained by the Institute for Digital Research and Education (IDRE). It consists of more than 21,000 cores across 1,300 high-performance compute nodes and has an aggregate memory of 76 terabytes (TB). Given the scale, we exclusively used the Hoffman2 cluster to complete the computations. Table 6.5 lists the HPC resources utilized to run various strategies. It highlights the resolution-efficiency trade-off as it is evident that reducing the level of resolution (while keeping fidelity constant) increases computational efficiency. For the same number of processors, LowRes reduces the computational efficiency by a factor of 2.7. It is important to note however that the same number of processors does not necessarily equate to the same computing power as the Hoffman2 consists of processors with various computing capacities. To negate the disproportionate impact of slower processors, the type of processor is specified as the “intel-gold” class. This ensures that all the processors have comparable computing powers.

Table 6.5: Summary of HPC resource utilization and runtime comparison.

Strategy	No. of WoodSDA runs	No. of Processors	Wallclock Time (hours)
HiRes FMRA	15,205	600	45
MedRes FMRA	6,606	400	28
LowRes FMRA	1,693	400	9.5
Intensity-based	609	256	48
Surrogate model	0	16	8 (training and testing), 2 (prediction)

6.3.3 Results discussion

Figure 6.11 compares the loss exceedance curves computed based on various strategies presented thus far. The x-axis represents the total aggregated loss from the 15,336 buildings in the region. It is important to note that, although we ran different numbers of explicit analyses for different strategies, losses at the redundant sites are represented using those explicit analyses. Figure 6.11a shows that the exceedance rates for the three variations of FMRA (HiRes, MedRes, LowRes) are nearly identical up to the 2475-year return period. On the contrary, the exceedance curve from the intensity-based approach begins to diverge from the benchmark at very low hazard levels. Figure 6.11b presents the loss exceedance curves from the two versions of surrogate models. As previously discussed in Section 6.2.4, the performance of the surrogate model with big data (i.e., training data from HiRes, predicted on MedRes) was comparable with the one trained on “low” data (i.e., training data from MedRes, predicted on HiRes). The same observation is reflected here as the loss exceedance curves from the two surrogate models also appear to be identical to HiRes. As outlined in Table 6.6, the surrogate curves are roughly 4% on average when compared to HiRes, while the surrogate curves themselves are less than 2% different.

In addition to the visual inspection, we quantify the difference using mean performance

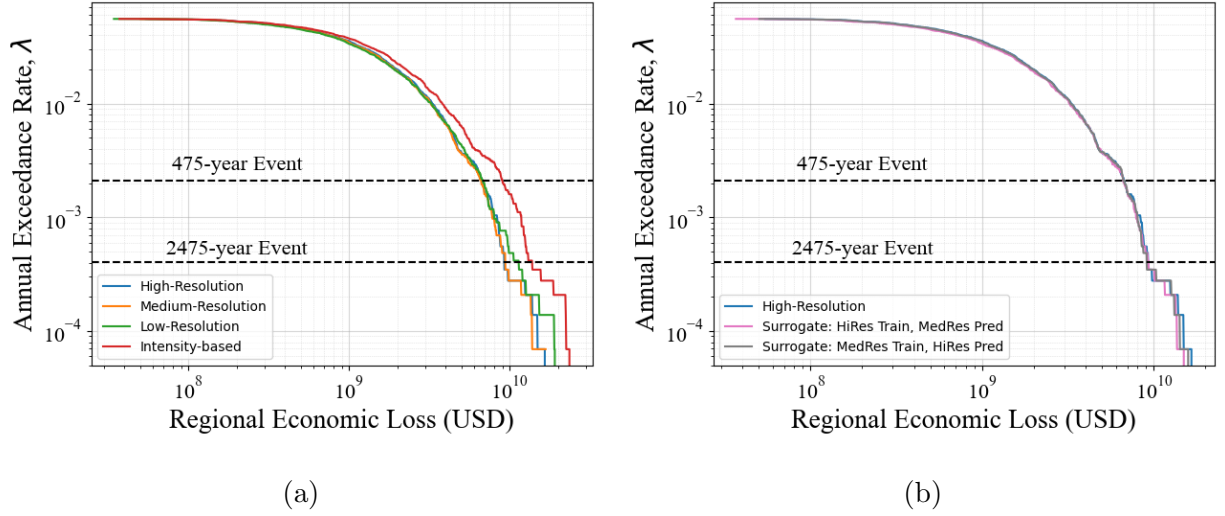


Figure 6.11: a) Regional loss curve comparison of three FMRA-based strategies (namely HiRes, MedRes, and LowRes) and intensity-based approach; b) comparing regional loss exceedance curve obtained from surrogate-based strategies against HiRes FMRA.

measure curve error (MPMCE) proposed by [Miller and Baker \(2015\)](#). The MPMCE measures on average how much the curves differ from one another. It is computed as

$$\text{MPMCE} = \frac{1}{R} \sum_{r=1}^R \left| \frac{x_r - \hat{x}_r}{x_r} \right| \quad (6.27)$$

where R is the number of return periods, x_r is the benchmark regional loss at the r^{th} return period, and $\hat{x}_r$ is the regional loss for the alternative strategies.

Table 6.6 summarizes the MPMCE metric for six strategies. The MPMCE values are computed by considering strategies on the left (or rows) as the baseline and those on the column (or top) as the alternative. For instance, the MPMCE of 3.52% indicates that the regional loss curve obtained from the MedRes FMRA is on average 3.5% different from the one obtained from the HiRes FMRA. In comparison, the MPMCE obtained from comparing the HiFi FMRA to the LowRes FMRA and intensity-based approaches are 12.95% and 51.41%, respectively. This result indicates that decreasing the resolution reduces the relative “accuracy” of the strategy as compared to the HiFi FMRA. The MPMCE of the two surro-

gate models is lower than the LowRes and intensity-based approach signifying reducing the resolution to gain efficiency is only worthwhile up to a certain point. Additionally, this result also highlights the potential of surrogate-based methods in regional-scale studies. Table 6.6 has no values in the lower diagonal elements because MPMCE compares the benchmark against the alternative approach and is thus not a symmetric metric. In other words, the MPMCE value for HiRes against MedRes would not be the same as the one for MedRes against HiRes. Most importantly, the MPMCE of MedRes against HiRes is not applicable in comparison because MedRes is not the benchmark.

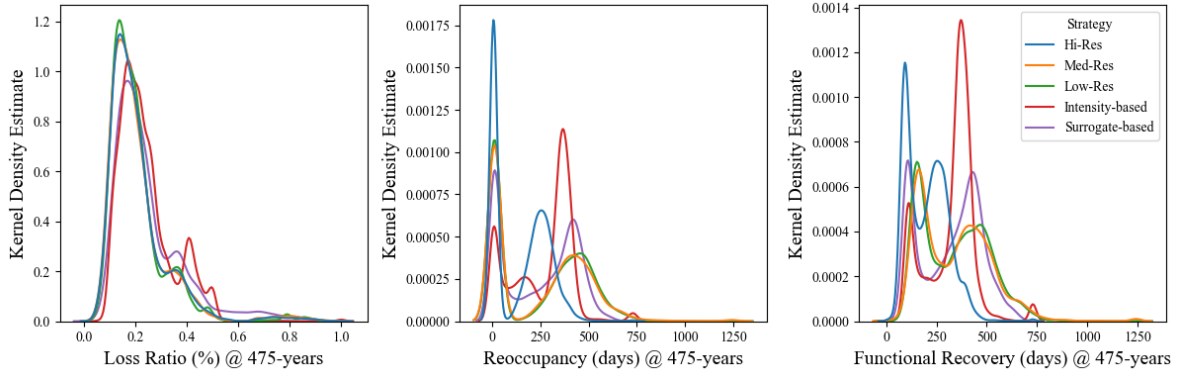
Table 6.6: Matrix comparing mean performance measure curve error (MPMCE) between various regional strategies.

MPMCE (%)	HiRes FMRA	MedRes FMRA	LowRes FMRA	Intensity- Based	Surrogate MedRes Pred	Surrogate Hi-Res Pred
HiRes FMRA	0	3.52	12.95	51.41	4.34	3.93
MedRes FMRA	NA	0	16.78	56.94	2.68	2.98
LowRes FMRA	NA	NA	0	34.58	14.40	13.88
Intensity- based	NA	NA	NA	0	36.23	35.72
Surrogate HiRes Pred	NA	NA	NA	NA	0	1.81
Surrogate MedRes Pred	NA	NA	NA	NA	NA	0

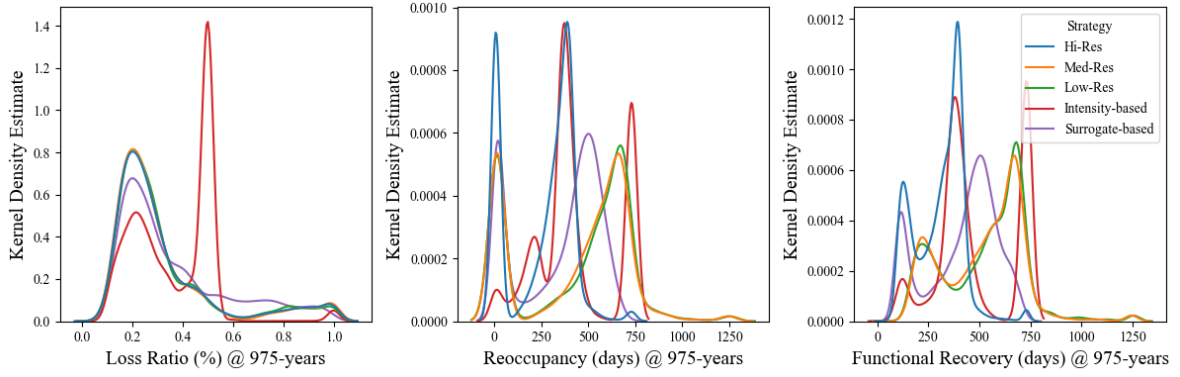
6.3.3.1 Spatially distributed losses

Regional-scale aggregated loss curves are useful for providing a single-value summary of the losses. However, the spatial distribution of losses should also be examined. Moreover, not all loss measures can be aggregated spatially. For instance, reoccupancy and functional recovery times cannot be aggregated because impacted buildings recover in parallel. Figure 6.12 presents the spatial distribution of the loss ratio, reoccupancy time, and functional recovery time for 475-, 975-, and 2475-year return periods. Figure 6.12a demonstrates that the distribution of loss ratio is comparable for all five strategies at a 475-year event. As we compare the same distribution for higher return periods, it is a clear trend that the intensity-based approach follows a central tendency with a peak of around 0.5 while the peak of the other strategies is to the right. The central tendency has a center of 0.5 because the loss ratio curves developed in Section 6.2.3 do not exceed 0.5 except for a couple of buildings. Similarly, the distribution shift to the right also makes sense because, in the intensity-based approach, the buildings are subjected to the maximum Sa_{T1} of 3.0g. However, the explicit analyses in FMRA are not constrained within the spectral acceleration of 3.0g. At a higher return period, the IM tends to be higher which translates to a rightward distribution peak shift.

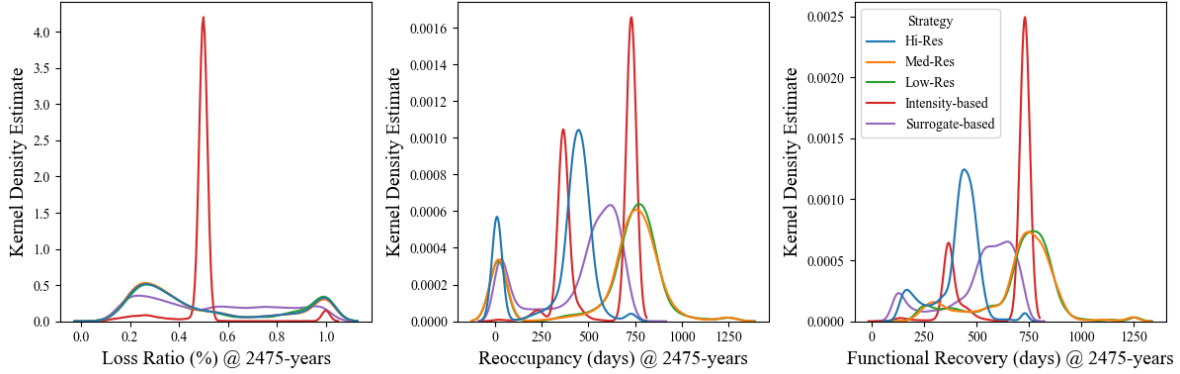
A similar trend is observed for reoccupancy and functional recovery time. As we move from the 475- to 2475-year return period, we notice that the density mass at 0 days shrinks while the mass at longer times increases. Another prominent trend is that the MedRes and LowRes tend to overestimate recovery times as their distribution is often always on the farthest right. To investigate further, Figure 6.13 maps the functional recovery time at a 475-year return period. Figure 6.13b and Figure 6.13c give a clear visual illustration that MedRed and LowRes tend to overestimate the functional recovery time as compared to the benchmark strategy (Figure 6.13a). This is likely because the building used to represent the losses for an entire bin or a cluster of buildings is actually reporting losses at the higher quantile. If the representative building has higher losses, it can have a compounding effect,



(a)



(b)



(c)

Figure 6.12: Spatial distribution of loss ratio, reoccupancy time, and functional recovery time obtained from five various regional frameworks at a) 475-year return period; b) 975-year return period; c) 2475-year return period.

and the entire cluster/bin will have higher overall losses. As discussed earlier, this is a direct repercussion of the resolution-efficiency trade-off.

6.4 Recovery-based Design: Sensitivity Study

Recommendations 2, 3, and 4 of the FEMA P-2090/NIST SP-1254 report ([NIST and FEMA, 2021](#)) emphasized the need to design and retrofit new and existing buildings and lifeline systems to meet recovery-based objectives. The report specifies that “... *new buildings should be designed for specific recovery-based objectives that will support reliable reoccupancy and acceptable functional recovery times following a major earthquake*”. There are ongoing national-level efforts to evaluate the feasibility of a recovery-based seismic design code. In particular, as a part of the 2026 NEHRP Provisions update, the Building Seismic Safety Council (BSSC) has established the functional recovery task committee (FRTC) to develop technical proposals and other resources regarding the design of new buildings to meet post-earthquake functional recovery performance objectives ([BSSC, 2022](#)). Established in 1979, BSSC develops and maintains the NEHRP Recommended Seismic Provisions for New Buildings and Other Structures. The Provisions serve as the primary resource to the professional design standard ASCE/SEI 7 Minimum Design Loads for Buildings and Other Structures ([ASCE, 2016](#)). In this study, we contribute to the evaluation of recovery-based design by investigating the implication of alternative design provisions such as “beyond-code” design parameters as illustrated in Figure 6.14. In particular, we evaluate the impact of global (e.g., Importance factor (I_e)) and component-level (e.g., component importance factor (I_p)) design parameters on the recovery time.

A sensitivity analysis is performed by varying the I_e and I_p factors. The I_e factor is directly proportional to the base shear or seismic demand used to design the LFRS. The default value used in the life-safety-based design of non-critical facilities is 1.0. Similarly, the I_p factor is proportional to the seismic demand used to design nonstructural components,

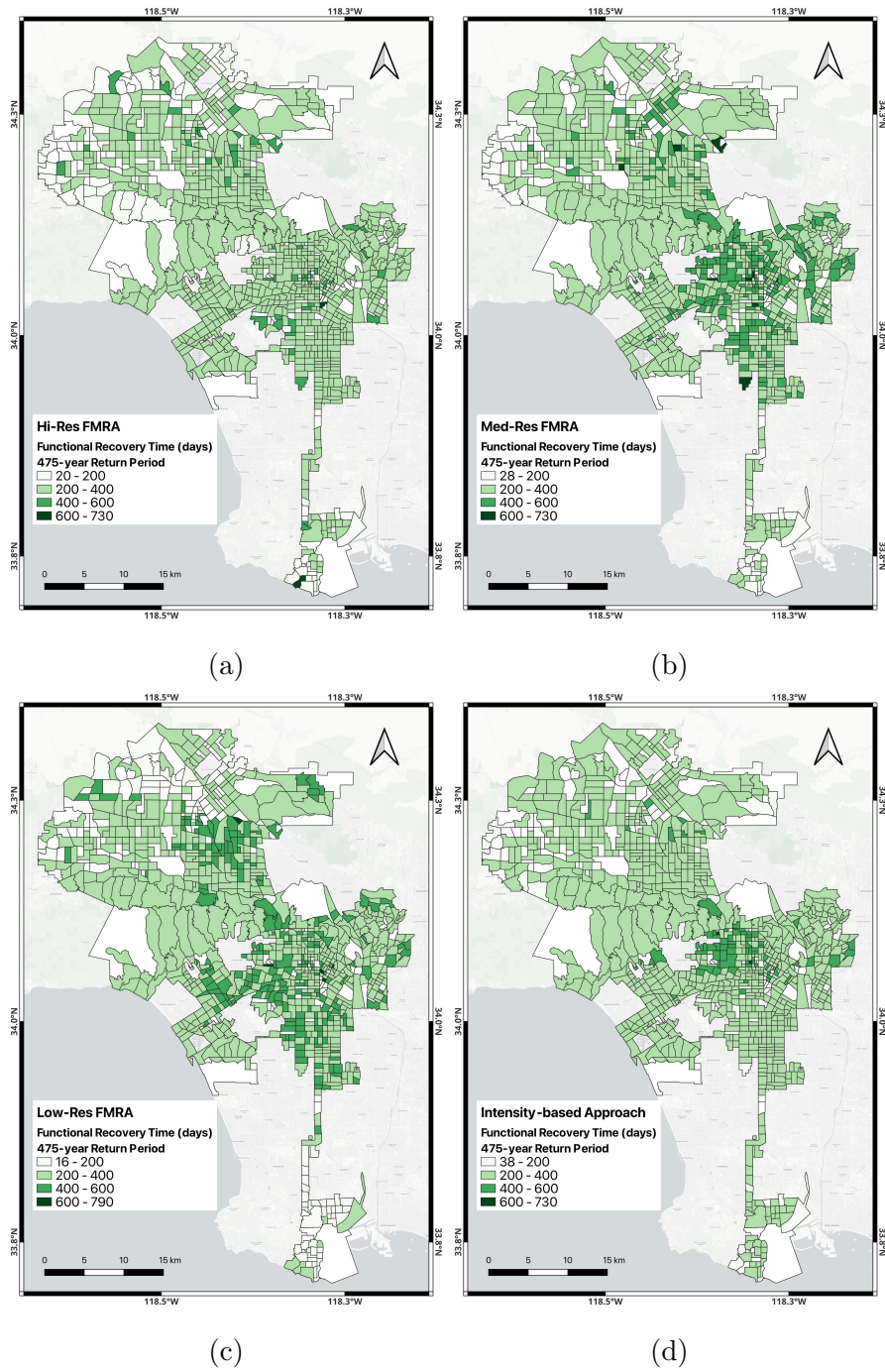


Figure 6.13: Mapped spatially distributed functional recovery time for a 475-year return period computed based on a) HiRes FMRA; b) Med-Res FMRA; c) LowRes FMRA, and d) intensity-based method.

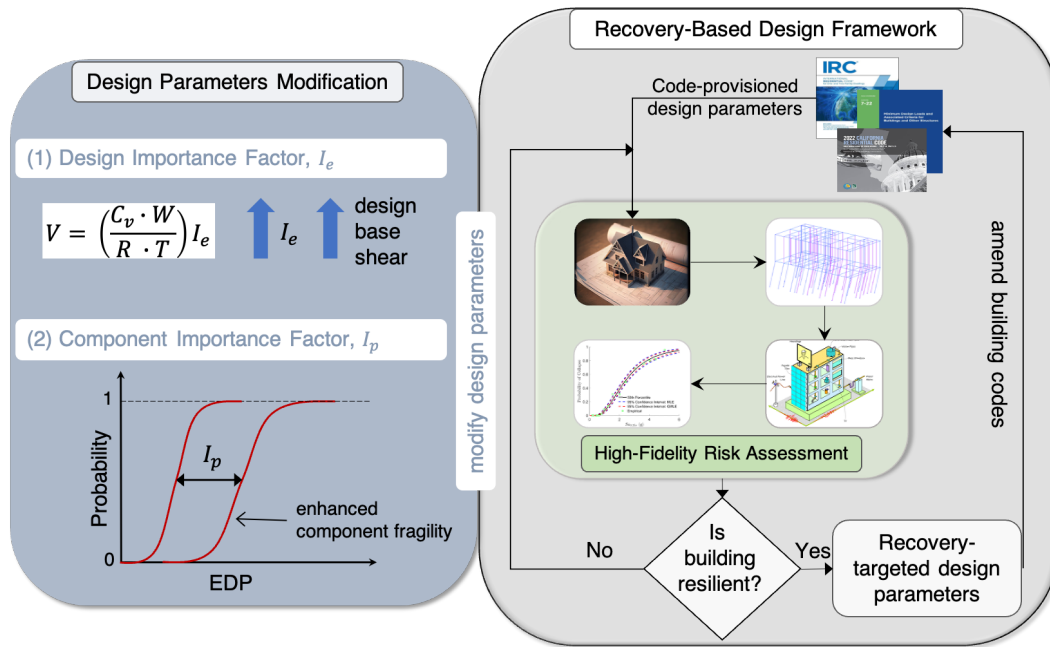


Figure 6.14: Graphical illustration of the recovery-based design framework and potential code modifications.

including architectural, electrical, mechanical, plumbing, and heating systems and equipment (*Chapter 13* of [ASCE \(2016\)](#)). The baseline requirement is that I_p shall be taken as 1.5 for components critical to life safety such as fire sprinkler systems and egress stairways. Additionally, I_p shall be taken as 1.5 for components in the Risk Category IV buildings. *Chapter 13 Section 1* provides additional conditions and exceptions. In this study, we redefine I_p as a component fragility adjustment factor because we do not explicitly design the nonstructural components or their anchorage systems. Specifically, I_p is used to scale the median component capacity, which shifts the fragility curve to the right. In other words, for the same demand (e.g., peak floor acceleration), the probability of exceeding a specific loss level is reduced, which in turn lowers the associated repair costs.

Three different structural design importance factors (i.e., $I_e \in \{1.0, 1.5, 2.0\}$) and five different component fragility adjustment factors (i.e., $I_p \in \{1.0, 1.5, 2.0, 2.5, 3.0\}$) are considered in the sensitivity analysis. These values are adopted from a study by [Issa et al. \(2023\)](#). A total of 15 different combinations of I_e and I_p are implemented, ranging from the default values ($I_e = 1.0$ and $I_p = 1.0$) to an extreme case where the two parameters are taken as the maximum value ($I_e = 2.0$ and $I_p = 3.0$). These alternative design provisions are implemented on buildings defined in the LowRes FMRA strategy. We selected LowRes (as opposed to MedRes or HiRes) to strike a balance between the accuracy and computation expense of repeating the explicit analyses for 15 cases. For this reason, the 1,693 buildings from the LowRes are determined to be the initial building inventory. As a first step, the feasibility of the designs produced by the range of I_e factors is evaluated for the 1,693 buildings. Specifically, the viability of a given design (based on the I_e) is controlled by the shearwall database compiled in Chapter 2, which has a limited number of assemblies with the highest design shear capacity being 1.9 klf. For larger multi-family dwellings (e.g., 96×48) and higher I_e factor, the shear demand exceeds the capacity in the database which renders the design unfeasible. To maintain consistency in building inventory across all different I_e factors, the buildings that do not have feasible designs are removed from the inventory. Thus, the final

inventory for the sensitivity analysis consists of 1,558 buildings.

6.4.1 Sensitivity results discussion

Figure 6.15 compares the loss exceedance curves for three cases with different design importance factors. The baseline importance factor is 1.0 which is also equivalent to risk category II. Figure 6.15 shows that designing residential buildings for higher seismic demand shifts the exceedance curve to the left. This signifies that the frequency of exceeding a certain level of loss reduces as we increase I_e . It is important to note that the x-axis represents the total repair cost for the 1,558 buildings. The losses are not adjusted for comparison with the HiFi inventory as was done in Section 6.3. A single value comparison for the three I_e values can be obtained by considering the total losses associated with specific hazard levels (e.g., 475-year and 2475-year). For instance, relative to the baseline case ($I_e = 1.0$), the 475-year return period losses are reduced by 33% and 44%, respectively for $I_e = 1.5$ and 2.0. At the 2475-year return period, the reduction is 23% and 36%, respectively for $I_e = 1.5$ and 2.0. Interestingly, the margin of loss reduction going from $I_e = 1.5$ to $I_e = 2.0$ (33% at the 475-year return period) is less than the case where we move from $I_e = 1.0$ to $I_e = 1.5$ (23% at the 475 year return period). This reduction in benefit is explained by the increase in the proportion of losses due to non-structural components which is not affected by the I_e parameter.

At lower return periods (less than 100 years), there is a reverse trend where there is an increase in the losses at higher I_e values. This is because designing for higher I_e reduces drift demand but increases peak floor accelerations. As shown in Figure 6.16, the median peak story drift ratio (PSDR) of the building inventory reduces almost linearly as we increase I_e from 1.0 to 2.0. The median peak floor acceleration, on the other hand, increases with the same change in I_e but does not have as strong of a linear trend. The increase in PFA for $I_e = 2.0$ appears to be lower than the increase for $I_e = 1.5$. Note that the loss exceedance rate is a product of the total hazard exceedance rate and the probability of loss exceedance.

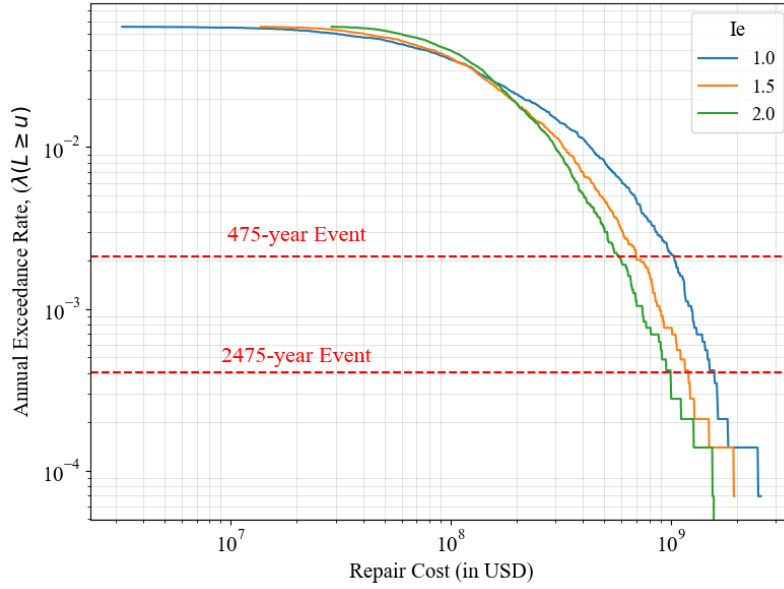


Figure 6.15: Comparison of total loss exceedance rate for three importance factors (I_e). The component fragilities are not adjusted.

The higher exceedance rate implies that the probability of exceeding the loss is also higher at lower loss levels. The increased probability of loss exceedance can be attributed to the higher EDP demand, which has a direct relation to the component-level damage state that is triggered and the subsequent loss.

Figure 6.15 established the influence of I_e on losses. For each I_e we examined the sensitivity of the losses to the five different I_p values. Figure 6.17 shows the exceedance curve for the regional loss in all 15 cases. Figure 6.17a, Figure 6.17b, and Figure 6.17c compare five different I_p cases individually for I_e values of 1.0, 1.5, and 2.0, respectively. As expected, increasing I_p reduces the loss for all cases of I_e . However, there is a pretty clear trend of diminishing returns for higher I_p values. There could be a multitude of factors contributing to this trend which needs to be studied and remains a good candidate for future research. Given the time and scope of the current work, a detailed investigation of the trend was not undertaken. However, a plausible hypothesis could be that the lower I_p factors are sufficient

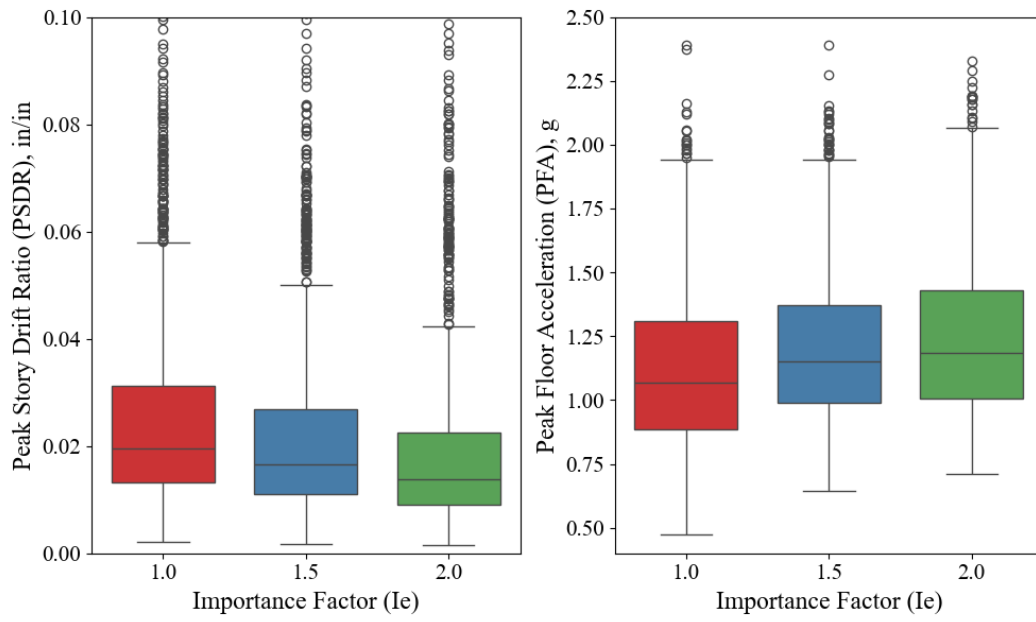
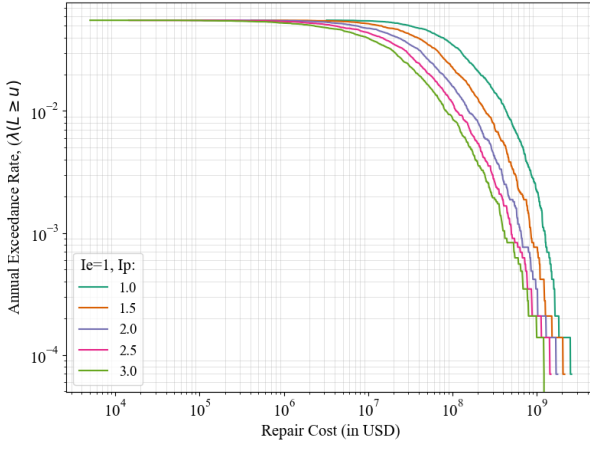


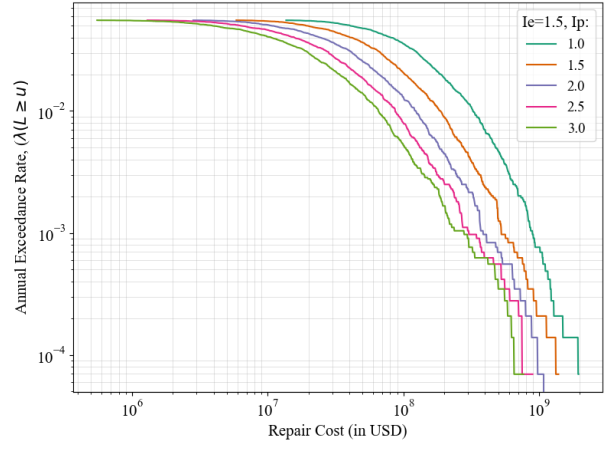
Figure 6.16: Boxplot of median PSDR (left) and PFA (right) of 1,558 buildings. The colors represent three design importance factors (I_e).

to shift the component-level damage states (e.g., from damage state 0 to 1, 1 to 2, and so forth) which would consequently reduce the losses. However, at higher I_p values, it is likely that the shift in damage states does not translate to the same degree of loss reduction as it did for lower I_p . Consider a nonstructural component, FEMA P-58 component ID: B1071.001 that corresponds to light framed wood walls with structural panel sheathing, gypsum wallboards, and no hold downs. The component has three damage states (DS1, DS2, DS3) with median fragility capacities of 0.01, 0.0175, and 0.025 which correspond to slight, moderate, and severe damage, respectively. Consider, for illustration, the drift of a hypothetical building designed for $I_e = 1.0$ is 0.019 inch/inch which will trigger DS2. Now consider we amplify the fragility by $I_p = 1.5$ resulting in the modified median capacities of 0.015, 0.026, and 0.0375 for the three respective damage states. In this instance, DS1 will be triggered instead of DS2 which has downstream repair cost implications such as major repair in DS2 and minor repair in DS1. Instead, if we amplify the component by 2.0 (or higher factor), the probability of DS1 being triggered will be a lot lower but will not benefit from repair action/repair cost implications as the component in DS1 will always need to be repaired just with a lower probability. A similar argument can be made for higher I_e and higher I_p . We saw in Figure 6.16 that higher I_e reduces PSDR. Let us assume $I_e = 2.0$ reduces the drift from 0.019 to 0.014. In this case, if we $I_p = 1.5$, DS1 will not be triggered because the demand (0.014) will be lower than the capacity (0.015). This explains the wider reduction margins for $I_e = 2.0$.

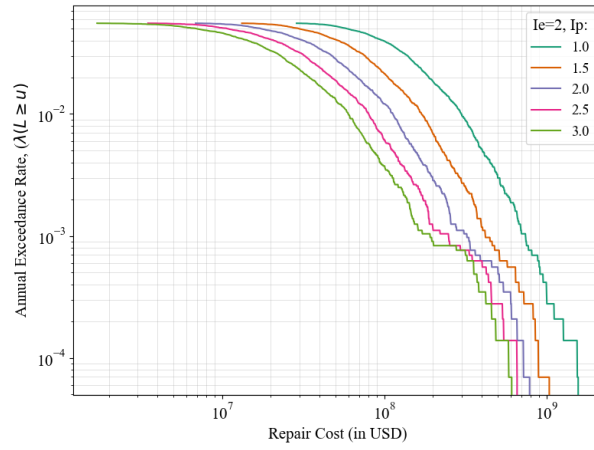
Figure 6.18 presents the breakdown of building inventory performance by I_p factor. The plots show a subsequent reduction in the loss ratio with increasing I_p for the 475-year (Figure 6.18a) and 2475-year return periods (Figure 6.18b). At the 475-year return period, the median loss ratio of the building inventory reduces by a bigger margin when I_p is increased to 1.5 compared to when I_e is increased to 1.5. However, for the 2475-year return period, the reverse is true i.e., increasing I_e to 1.5 leads to a bigger reduction compared to when I_p is increased to 1.5.



(a)



(b)



(c)

Figure 6.17: a) Sensitivity of five levels of I_p for $I_e = 1.0$; b) sensitivity of five levels of I_p for $I_e = 1.5$; c) sensitivity of five levels of I_p for $I_e = 2.0$.

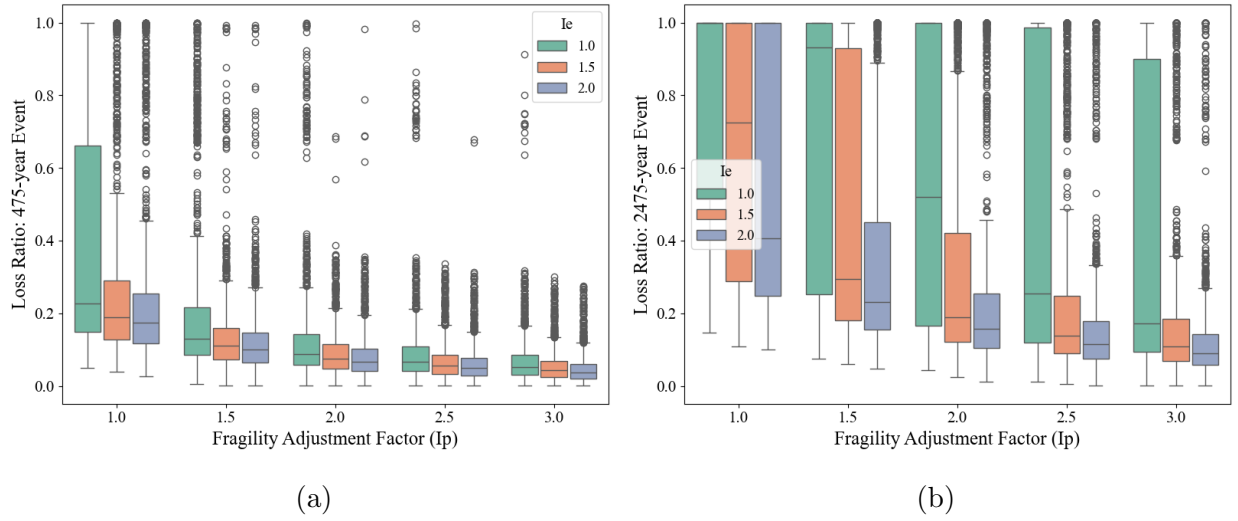


Figure 6.18: Sensitivity of the distribution of loss ratio of 1,558 buildings across various levels of I_e and I_p for the a) 475-year event and b) 2475-year event.

Figure 6.19 presents the breakdown of reoccupancy and functional recovery time at the 475-year return period. Figure 6.19a shows that increasing I_e to 2.0 and leaving I_p unchanged would yield median reoccupancy days close to zero, albeit with a 75th-percentile reoccupancy time close to 600 days. However, increasing I_p to 2.0 ensures that the majority of the buildings in the inventory, excluding some outliers, have near zero time to reoccupancy. Increasing I_e , in general, has a minor impact on functional recovery time because the functionality of a building is mostly determined by the operability of the non-structural components. For the 475-year return period, it appears that I_p needs to be scaled by a factor of 2.5 for the building inventory to achieve negligible functional recovery time.

6.4.2 Recovery-based surrogate model

Performing sensitivity analysis can be a computationally intensive task. To this end, a surrogate model that can predict the influence of I_e and/or I_p on building performance can enhance the efficiency of the recovery-based design procedure evaluation. With this goal in mind, we developed a set of four XGBoost models- one for each loss measure. The models

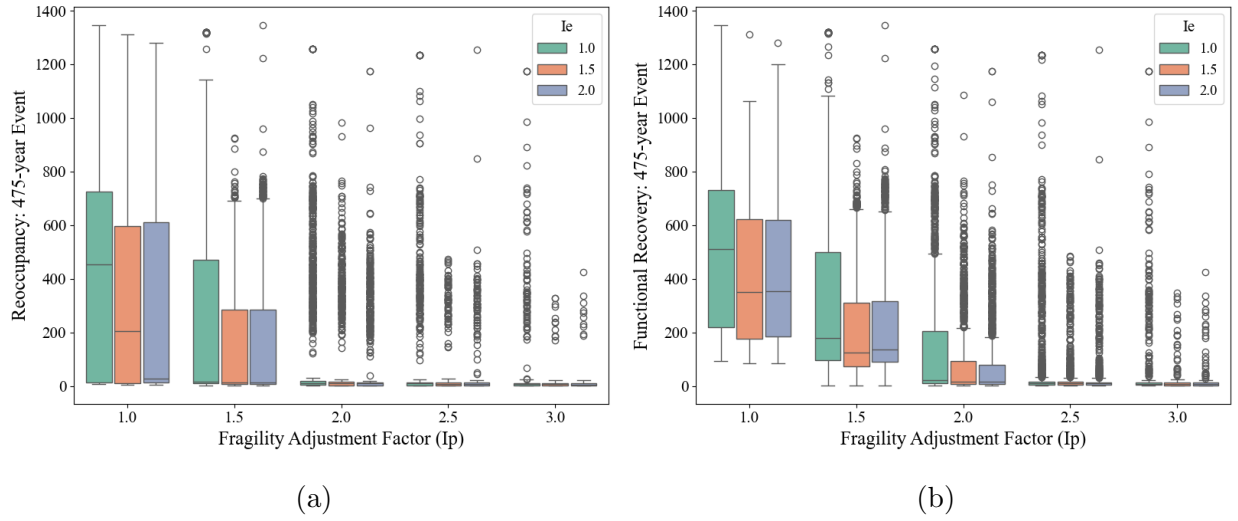


Figure 6.19: a) Reoccupancy time trend across various levels of I_e and I_p for the 475-year event and b) Functional recovery time trend across various levels of I_e and I_p for the 475-year event.

are trained and tested using the data assembled from the 15 sensitivity case studies. Their objective is to predict the repair cost with I_e and I_p as the input features. The training data was split into 70-30 training and testing splits. Table 6.7 summarizes the model performance. The near-perfect training and testing R^2 indicate that the models do a good job of capturing the trend without overfitting. The RMSE for the repair cost is almost double for testing as compared to training which suggests that there is room for improvement. It is interesting to note that, compared to the surrogate models developed in Section 6.2.4, (i.e., Table 6.2 and Table 6.3), the metrics are noticeably lower in Table 6.7. This is likely because the models are able to capture trends within each I_e and I_p which enhances their ability to make predictions. While this is a promising result, it would be interesting to see how the models perform on unseen data. The unseen data would ideally consist of I_e and I_p that are not included in the training data. This is a candidate for future studies.

Table 6.7: Summary of performance evaluation metrics for the surrogate model trained to predict the consequences for alternative design parameters.

Metric	Task	Repair Cost	Loss Ratio	Reoccupancy	Functional Recovery
R^2	Training	0.98	0.98	0.99	0.99
	Testing	0.96	0.94	0.97	0.97
MSE	Training	1.1E9	1.9E-4	77	62
	Testing	3.7E9	5.3E-3	226	170
RMSE	Training	33800	0.014	8.8	7.8
	Testing	61487	0.023	15	13
MAE	Training	4825	0.0025	1.4	1.5
	Testing	6836	0.0034	2.2	2.2

6.5 Conclusion

Based on the previously proposed high-fidelity (HiFi) high-resolution regional risk and resilience framework, this study presented four efficient alternative frameworks targeted for regional-scale assessments. The alternative frameworks are developed on the fundamental idea that the level of resolution and/or fidelity can be traded off to enhance efficiency. The proposed alternative frameworks are as follows: 1) HiFi medium-resolution fully mechanistic regional assessment (MedRes FMRA), 2) HiFi Low-resolution FMRA (LowRes FMRA), 3) medium-fidelity intensity-based method, and 4) low-fidelity surrogate-based approach. MedRes FMRA maintains high fidelity while moderately sacrificing resolution to boost efficiency. Binning is used to aggregate the building and hazard characterization compared to site-specific in HiRes FMRA. Similar to MedRes FMRA, LowRes FMRA maintains a high fidelity but reduces resolution further by aggregating building and hazard based on spatial clusters. The intensity-based method first develops a region-specific database of consequence curves and uses that to inform losses at each site. Finally, the surrogate-based approaches are intended to enhance efficiency by developing data-driven models to directly

predict consequences (e.g., loss, recovery time) of spatially distributed assets.

The alternative frameworks are implemented on a building inventory consisting of 15,336 single- and multi-family dwellings in the City of Los Angeles. Based on different levels of aggregation, the number of explicit analyses needed to represent the losses for HiRes, MedRes, LowRes, and intensity-based strategies are 15,205, 6,606, 1,693, and 609 (13 intensity levels per building), respectively. The subsequent reduction in the number of explicit analyses directly translates to computational efficiency as the runtime for LowRes was lower by a factor of more than 5. As expected, reducing resolution reduced the framework’s ability to replicate the ground truth result (i.e. HiRes FMRA). Specifically, we found that MedRes can replicate the benchmark regional loss curve with an average error of 3.5% while the error rate was 13% for LowRes, 51% for the intensity-based method, and 4% for the surrogate-based approach.

The second part of this chapter studied the implications of “beyond-code” design provisions. In particular, a sensitivity analysis was performed to investigate the impact of amplified global design parameters such as importance factor (I_e) and component-level design parameters such as I_p . The sensitivity analysis included 15 different cases representing three levels of I_e (i.e., $I_e \in 1.0, 1.5, 2.0$) and five levels of I_p (i.e., $I_p \in 1.0, 1.5, 2.0, 2.5, 3.0$). The sensitivity study was implemented on the 1,558 buildings from LowRes FMRA. The results indicated that to achieve a resilience-driven performance objective, increasing I_e or I_p independently is not sufficient. The losses (e.g., economic loss, recovery time, etc.) of a building are governed by the performance of both the structural and nonstructural components, and as such it is critical to strengthen both.

CHAPTER 7

Conclusions

7.1 Summary

Throughout the long history of building design and construction, engineers, policymakers, and stakeholders have predominantly concentrated on fortifying individual buildings to withstand collapse and protect lives during and after an earthquake. However, recent disasters have revealed two realities: 1) the impact of such events transcends individual buildings and 2) collapse prevention and/or life-safety building standards are not sufficient in reducing the socioeconomic impacts. To foster community resilience, it is imperative to have a comprehensive understanding of the collective vulnerabilities of the built environment and formulate proactive strategies to address these risks effectively. It is increasingly clear that embracing a holistic, regional-scale seismic risk and resilience assessment framework is the next frontier in earthquake engineering and disaster risk management. This interdisciplinary endeavor aims to facilitate informed decision-making, support the development of robust emergency preparedness plans, and ensure that existing building codes evolve to prioritize resilience-driven performance objectives.

Acknowledging the need for a comprehensive, efficient, and scalable regional risk and resilience assessment framework, this dissertation develops a suite of regional-scale frameworks with varying levels of fidelity, resolution, and computational efficiency. The frameworks are operationalized by leveraging advanced technologies such as automation, distributed computing, optimization, and machine learning. Finally, they are implemented to assess the

performance of 15,336 spatially distributed single- and multi-family woodframe structures in the City of Los Angeles. Furthermore, a sensitivity analysis is conducted to explore the implications of enhanced “beyond-code” design provisions on recovery-based design.

The mainstream probabilistic performance assessment method, namely the performance-based earthquake engineering (PBEE) methodology, developed by the Federal Emergency Management Agency (FEMA), is one of the most popular building-level risk assessment frameworks ([FEMA, 2012](#)). By systematically quantifying building-level performance measures through hazard, structural, damage, and loss analyses, it offers a comprehensive understanding of seismic vulnerabilities. It is grounded in a probabilistic formulation that enables rigorous treatment of various sources of uncertainties. However, its implementation demands significant manual effort. To address this challenge, Chapter 2 developed an end-to-end computational platform named Auto-WoodSDA (WoodSDA in short) to automate the implementation of the FEMA P-58 methodology. The conventional P-58 methodology requires the facility definition as an input which includes designs of lateral force-resisting systems. To materialize a true end-to-end workflow, which meant WoodSDA needed to output performance measures (e.g., economic losses, downtime, and injuries) given a set of user inputs, the existing P-58 methodology is expanded. Specifically, a design module is incorporated to facilitate on-demand code-compliant design generation. The ATC-138 methodology is also integrated to quantify building-specific recovery time. Comprising four modules—design, structural, damage, and loss—WoodSDA allows for independent or sequential execution, enhancing flexibility. The design module generates code-compliant designs and modeling parameters, which are then utilized by the structural module to create three-dimensional nonlinear models, simulate dynamic responses, and analyze raw outputs. Subsequently, the damage module assesses building-level damage, followed by the loss module, which evaluates component-level damage and key loss metrics such as annualized economic loss and time to regain functionality. Through its automated processes, WoodSDA significantly reduces the total time (manual and CPU runtime) required to complete a detailed PBEE-type assessment

compared to the manual alternatives.

Chapter 3 investigated the probability model misspecification in fitting the fragility curves. In the PBEE procedure, fragility functions are a key part of damage and loss assessment. The building-level fragility functions are used to quantify the probability of a limit state (e.g., collapse and demolition) conditioned on the IM level while component-level fragility functions describe the probability of exceeding a damage state of interest conditioned on a response demand (e.g., story drift, peak floor acceleration). They are developed using empirical data from experiments, field observations, or data generated from numerical analyses. Regardless of the data generation process, the fragility curves can be fitted using either parametric or non-parametric approaches. Maximum likelihood estimation (MLE) is one of the popular parametric statistical approaches that rely on a likelihood function formulated based on a predefined functional form or probability distribution. To investigate the uncertainty induced by potential probability model misspecification, we implemented quasi-maximum likelihood estimation (QMLE) to quantify the fragility estimates. It presents a probabilistic procedure (information matrix equality test) to identify model misspecification and quantify the uncertainty (sandwich estimators) in the estimated median (θ) and dispersion (β) parameters. It is noted that the parameter estimation uncertainty is different from other sources of uncertainties that have been typically considered in the PBEE framework such as record-to-record and modeling uncertainty.

In pursuit of further enhancing the robustness of the FEMA P-58 methodology, Chapter 4 applied advanced statistical techniques aimed at two key objectives: 1) relaxing the univariate assumption in determining the optimal ground motion intensity measure (IM), and 2) identifying the optimal IM for woodframe structures. Traditionally, the optimality of an IM is assessed using efficiency and sufficiency measures, assuming a univariate log-linear relationship between seismic demand and IM. However, recognizing the limitations of such assumptions, this study proposed an alternative method based on a generalized additive model (GAM) to capture nonlinear multivariate relationships among engineering demand

parameters (EDPs), IMs, and causal parameters such as magnitude and source-to-site distance. Additionally, taking motivation from (Dhulipala et al., 2018), relative entropy is presented as a qualitative measure to determine sufficiency.

Chapter 5 discusses research gaps in regional-scale studies and presents a high-fidelity high-resolution regional-scale risk and resilience assessment framework, which fuses the tools and methods developed in the previous three chapters. Specifically, it pairs automation (i.e., WoodSDA) with distributed computing to scale FEMA P-58-based performance assessment of large-scale building inventories. To accommodate the proposed regional risk framework, the computations of the traditional approaches are modified. It also describes the procedures implemented in regional seismic hazard simulation. The hazard simulation is executed in R2D, an open-source software developed by NEHRI SimCenter (McKenna et al., 2024). It involves five distinct steps, including 1) candidate earthquake generation, 2) earthquake scenarios downsampling (Han and Davidson, 2012), 3) generating correlated ground motion intensity maps (Jayaram and Baker, 2009), 4) downsampling simulated maps (Jayaram and Baker, 2010) 5) selecting site-specific ground motion records for the downsampled maps. The selected ground motion records are directly used in WoodSDA to perform the FEMA P-58-based performance assessment. The proposed framework is implemented to evaluate the risk of 15,336 single- and multi-family woodframe dwellings in the City of Los Angeles. Large-scale computation is made feasible by leveraging automation and distributed computing.

Chapter 6 is a direct continuation of Chapter 5. It develops alternative strategies based on the fundamental idea that fidelity and resolution can be traded off to boost computational efficiency. Taking the high-fidelity high-resolution framework as the benchmark, the four alternative risk frameworks are developed: 1) high-fidelity medium-resolution fully mechanistic regional assessment (MedRes FMRA), 2) high-fidelity low-resolution fully mechanistic regional assessment (LowRes FMRA), 3) Event-agnostic intensity-based approach, and 4) surrogate-based methods. The MedRes FMRA maintains a high level of fidelity but sacrifices resolution to gain efficiency as it performs risk assessment at an aggregated bin level. The

LowRes FMRA also maintains a high fidelity level but further reduces the resolution to enhance efficiency. The event-agnostic takes inspiration from traditional regional frameworks such as HAZUS (FEMA, 2011) and develops a database of building-level loss parameters as a function of intensity measures. The database consists of consequence curves from 609 single- and multi-family woodframe buildings that were generated using 13 intensity levels with 30 ground motion records per intensity level. The fourth strategy involves creating generalizable surrogate models to predict the losses across a region.

In the second half of Chapter 6, a sensitivity analysis is performed to study the implications of “beyond-code” building design provisions. This and several other studies (Issa et al., 2023; Cook et al., 2022; ATC, 2021) have found that economic losses and recovery times are governed by damage to structural and nonstructural components. To this end, the sensitivity study evaluates the implication of global design parameters (e.g., Importance factor (I_e)) and component fragility adjustment (e.g., component importance factor (I_p)) on the recovery time. As one of the first problem-driven applications of the regional-scale risk assessment framework presented in the first half of the dissertation, the sensitivity analysis is carried out by varying I_e and I_p factors. The I_e factor aims to enhance global performance by designing the building for higher seismic demands. Similarly, the I_p factor is intended to enhance the capacity of nonstructural components which includes architectural, electrical, mechanical, plumbing, and heating systems and equipment. We consider three different design importance factors (i.e., $I_e \in \{1.0, 1.5, 2.0\}$) and five different component fragility adjustment factors (i.e., $I_p \in \{1.0, 1.5, 2.0, 2.5, 3.0\}$) to perform sensitivity analysis for the total of 15 cases. Finally, utilizing the data from the sensitivity analysis, we developed a machine-learning model to predict the degree of enhancement a building might require to attain resilience-driven performance objectives.

7.2 Findings

The very first objective of this research endeavor was to develop a ready-to-use computational platform that would automate the FEMA P-58- and ATC-138-based risk assessments of individual buildings. The successful development of WoodSDA demonstrated that a fully automated risk framework is achievable. More importantly, it showed that the automated workflow significantly reduces the total computational time (manual and wallclock time) of performing FEMA P-58 loss assessment. The implementation of WoodSDA on an example building from the FEMA P-2139-2 document validated the assumptions made in WoodSDA. The FEMA P-2139-2 is viewed as a state-of-the-art study that conducted a thorough investigation to benchmark the structural performance of short-period woodframe structures. Thus, the fact that WoodSDA was able to replicate the structural analysis results within a 10% margin of error underscores its reliability. Considering the FEMA P-2139-2 and WoodSDA used two completely different modeling software, a 10% differential is deemed acceptable.

To evaluate the effect of probability model misspecification on fragility function parameter estimates, we used collapse performance data from eight single-family woodframe buildings. The information matrix equality test performed on the collapse data revealed that model misspecification was present in all the cases. We fitted the fragility parameters using MLE and QMLE with the goal of comparing the coefficient of variation (CV) of the median ($\hat{\theta}$) and log standard deviation ($\hat{\beta}$), which represent the parameter estimation uncertainty. For $\hat{\theta}$, the CV obtained from QMLE, was, on average, 38% lower than the case where maximum likelihood estimation (MLE) is used. Similarly, the average ratio between the CV of $\hat{\beta}$ from QMLE and MLE was 64%. The fragility parameter estimation uncertainty was also propagated into the collapse risk assessment using analytical (Reimman Sum) and sampling (Monte Carlo Simulation) approaches, which produced comparable results. Compared to when MLE was used, the CV of the mean annual frequency of collapse due to parameter

estimation uncertainty was computed to be 17 – 58% lower in the QMLE case.

The multivariate GAM and relative entropy-based evaluation of IMs is implemented on EDP data of 10 woodframe buildings generated using a regional ground motion set with 826 record pairs. The results suggested that capturing the multivariate EDP distribution in IM evaluations has non-negligible implications, especially for multi-story woodframe buildings. The comparative analysis of univariate and multivariate methods demonstrated that a single universally optimal IM likely does not exist for a set of building archetypes. Rather, there was clear evidence that the efficacy of an IM is a function of the level of nonlinearity (or ductility demand) in the response of the structure. Overall, it was found that $S_{a_{avg}}$ is sufficient for structures that respond to a range of frequencies whereas $S_{a_{T1}}$, PGA, and ASI are sufficient for shorter buildings with a fundamental period less than 0.26 seconds.

The suite of five regional risk and resilience assessment frameworks, including the benchmark HiFi HiRes FMRA, is employed to assess the seismic risk of 15,336 residential wood-frame buildings. It is found that automation and distributed computing significantly reduce the computational time of performing FEMA P-58-based performance assessment of large-scale building inventories. The total computation time for the benchmark approach came in at 45 hours with 600 concurrent processing units. As expected, the alternative approaches boosted computational efficiency while sacrificing some level of resolution. Compared to Hi-Res FMRA, Med-Res FMRA boosted efficiency by a factor of 2.5 while Low-Res by a factor of 5. A direct one-on-one comparison of efficiency gain cannot be made against the event-agnostic and surrogate-based methods because the majority of computational resources consumed by these methods are utilized to develop either a consequence curves database or train machine-learning models. If we are to consider those computational costs as overhead expenses and solely compare the time to implement those methods, the efficiency gain was found to be roughly 30 and 20-fold for intensity-based and surrogate-based methods, respectively. The mean performance measure curve error (MPMCE) ([Miller and Baker, 2015](#)), which quantifies the average degree of difference between two regional loss exceedance

curves, was used to quantify the impact of reduced resolution. The MPMCE for MedRes, when computed against HiRes, was found to be 4%. It was found to be 13% for the LowRes, 51% for the intensity-based approach, and 5% for the surrogate-based approach.

7.3 Limitations and Future Work

This dissertation has pushed the envelope on regional assessments and proposed a suite of computational frameworks to make large-scale risk analysis computationally feasible. However, in doing so, several assumptions were made that need to be acknowledged and further investigated in future studies.

To realize a true end-to-end functionality, WoodSDA makes several simplifying assumptions. The design module is only equipped to handle quadrilateral (e.g., square or rectangular) building layouts. The WoodDA utilizes an object-oriented programming structure. This allows future studies to generalize WoodSDA to other geometries without rewriting the entire codebase. It is intended to create a detailed building design and allows users to specify shear wall characteristics such as panel thickness, panel material type, nail size, and nail thickness. This level of detail requires a significant number of input files. A future study could look into ways to streamline the input generation and formatting. Due to the lack of modeling parameters, the number of shear wall assemblies in the shear wall database is relatively low. While it might not be feasible to run physical experiments to calibrate the modeling parameters, an analytical method to calibrate the modeling parameters using limited data would add tremendous value to the research community.

In this study, we quantified the potential effect of parameter estimation uncertainty on only one limit state (collapse) using data from a single construction type (woodframe residential buildings). Additional studies are needed where the effect of probability model misspecification on parameter estimation uncertainty for other construction types (e.g., steel and concrete moment frames) and limit states (e.g., demolition, post-earthquake safety, and

functionality) is evaluated. Moreover, the fragility estimation technique based on quasi-maximum likelihood estimation (QMLE) can be extended to fit component-level fragilities for various damage states. The updated fragility can then be used to quantify and propagate the uncertainty in the simulated losses. In Chapter 4, we relaxed the univariate assumption often used in evaluating the optimality of an IM. To do so, we studied 10 IMs using the structural response data obtained from cloud-based analysis. It will be worthwhile to study the effectiveness of other types of IM and use data from intensity-based structural analysis.

The regional risk and resilience presents itself as the first-of-its-kind computational framework. However, undertaking such a large-scale computational body of work came with its own set of challenges. One of the biggest limitations is that the number of downsampled earthquake scenarios and their corresponding ground motion records are not big enough to reliably capture the uncertainties inherent in hazard simulation. It is imperative that future studies investigate the sensitivity of the number of downsampled scenarios/maps in capturing the uncertainties in the simulated losses. Due to the lack of rich inventory data, we established a database of design variants. Although the database encompasses a wide variety of common woodframe building types, it is not extensive enough to represent the real world. A future study could implement a computer vision tool such as BRAILS ([Cetiner et al., 2024](#)) to catalog the buildings and assemble the building inventory. Even with this approach, one would have to make assumptions about the shear wall configurations within the buildings because it is likely that for security reasons a detailed layout of buildings will not be made publicly available. Nonetheless, the risk assessment would be based on the actual building at a particular location instead of an arbitrary building archetype. Although the ground motion maps are generated for each site within the region of interest, because of convergence issues, the downsampling of 350,055 viable earthquake scenarios to 20 candidate scenarios was based on only 108 sites. This can be viewed as a limitation because we cannot quantify the goodness of the hazard curve match at all 15,336 sites. Some researchers are starting to navigate the complexities of sampling a representative set ([Wang et al., 2023](#)), but

more intellectual resources and attention to this problem would immeasurably contribute to advancing regional studies.

With the belief that the regional-scale risk assessment frameworks are the next frontiers of earthquake engineering, this dissertation accentuates numerous future research opportunities. Future studies should make an effort to validate the estimated recovery times. If historical recovery data is not available, conducting a thorough sensitivity analysis on the various assumptions in recovery time simulation would give a better understanding of the result. From an owner's or stakeholder's perspective, the cost of recovery-based design is an important consideration in amending the building code. An extensive cost-benefit analysis of recovery-based design would shed light on the possibility of it making its way into the building code and widespread adoption. In the recovery-based sensitivity study, we amplified the fragility capacity of all the components regardless of their contribution to the losses and functional recovery time. However, enhancing the capacities of every single component in a building might not be realistic. A concerted effort to identify the most common damage-prone components could help building code officials make targeted provisions. The sensitivity study included older construction materials (e.g., plaster on wood lath), that are no longer used. To inform code changes, it is paramount to ensure that the buildings being analyzed include components currently used in construction. Finally, the development of a structural surrogate model could provide yet another alternative to computationally intensive mechanistic frameworks.

APPENDIX A

Appendix: Auto-WoodSDA

A.1 Extended Pushover Result Comparison

Table A.1 outlines the summary pushover results for all 10 baseline archetypes from the FEMA P-2139-2 study. As we can see, the pushover results generated by WoodSDA are very comparable to the FEMA P-2139-2 document for all 10 archetypes.

Table A.1: Comparison of eigenvalue and pushover analysis results between FEMA P-2139-2 and the current study.

Archetype ID	Fundamental Period (sec)		Base Strength ($V_{\max}/W$)		Drift @ 80% $V_{\max}/W$ (%)	
	FEMA P-2139	OpenSees	FEMA P-2139	OpenSees	FEMA P-2139	OpenSees
SFD1B	0.14	0.13	2.10	2.28	3	3.54
SFD3B	0.13	0.13	2.33	2.53	3	3.52
SFD2B	0.24	0.22	0.90	1.04	2	1.89
SFD4B	0.24	0.22	0.95	1.14	2	1.94
MFD1B	0.18	0.16	1.39	1.51	3	3.08
MFD4B	0.18	0.16	1.48	1.75	3	3.51
MFD2B	0.27	0.26	0.70	0.67	1	1.99
MFD5B	0.27	0.26	0.73	0.72	2	2.21
MFD3B	0.51	0.49	0.39	0.39	1	1.31
MFD6B	0.54	0.49	0.44	0.48	1	1.41

APPENDIX B

Appendix: QMLE

B.1 Maximum Likelihood Equations Using the Error Function

$$\text{Let, } E = e^{-\frac{\ln\left(\frac{IM_j}{\theta}\right)^2}{2\beta^2}} \quad ; \quad Q = e^{-\frac{\ln\left(\frac{IM_j}{\theta}\right)^2}{\beta^2}} \quad ; \quad P = \text{erf}\left(\frac{\ln\left(\frac{IM_j}{\theta}\right)}{\sqrt{2}\beta}\right)$$

B.1.1 Score

$$\begin{aligned} \frac{\partial \ell(\theta, \beta)}{\partial \theta} &= \frac{\sqrt{2}}{\sqrt{\pi}\theta\beta} \sum_{j=1}^m -k_j \frac{E}{1+P} + (n_j - k_j) \frac{E}{1-P} \\ \frac{\partial \ell(\theta, \beta)}{\partial \beta} &= \frac{\sqrt{2}}{\sqrt{\pi}\beta^2} \sum_{j=1}^m -k_j \frac{\ln\left(\frac{IM_j}{\theta}\right)E}{1+P} + (n_j - k_j) \frac{\ln\left(\frac{IM_j}{\theta}\right)E}{1-P} \\ S(\theta, \beta)^\top &= \left[\frac{\partial \ell(\theta, \beta)}{\partial \theta}, \frac{\partial \ell(\theta, \beta)}{\partial \beta} \right] \end{aligned}$$

B.1.2 Hessian

$$\begin{aligned} \frac{\partial^2 \ell(\theta, \beta)}{\partial \theta^2} &= \frac{1}{\theta^2\beta} \sum_{j=1}^m k_j \frac{\sqrt{2}E}{\sqrt{\pi}(P+1)} - k_j \frac{2Q}{\beta\pi(P+1)^2} - k_j \frac{\sqrt{2}\ln\left(\frac{IM_j}{\theta}\right)E}{\beta^2\sqrt{\pi}(P+1)} \\ &\quad - (k_j - n_j) \frac{\sqrt{2}E}{\sqrt{\pi}(P-1)} + (k_j - n_j) \frac{2Q}{\beta\pi(P-1)^2} \\ &\quad + (k_j - n_j) \frac{\sqrt{2}\ln\left(\frac{IM_j}{\theta}\right)E}{\beta^2\sqrt{\pi}(P-1)} \end{aligned}$$

$$\begin{aligned}\frac{\partial^2 \ell(\theta, \beta)}{\partial \theta^2} &= \frac{1}{\beta^3} \sum_{j=1}^m k_j \frac{2\sqrt{2}E}{\sqrt{\pi}(P+1)} - k_j \frac{2 \ln \left(\frac{IM_j}{\theta} \right)^2 Q}{\beta \pi (P+1)^2} - k_j \frac{\sqrt{2} \ln \left(\frac{IM_j}{\theta} \right)^3 E}{\beta^2 (P+1)} \\ &\quad - (k_j - n_j) \frac{2\sqrt{2} \ln \left(\frac{IM_j}{\theta} \right) E}{\sqrt{\pi}(P-1)} + (k_j - n_j) \frac{2 \ln \left(\frac{IM_j}{\theta} \right)^2 Q}{\beta \pi (P-1)^2} \\ &\quad + (k_j - n_j) \frac{\sqrt{2} \ln \left(\frac{IM_j}{\theta} \right)^3 E}{\sqrt{\pi} \beta^2 (P-1)}\end{aligned}$$

$$\begin{aligned}\frac{\partial^2 \ell(\theta, \beta)}{\partial \theta \partial \beta} &= \frac{1}{\theta \beta^2} \sum_{j=1}^m k_j \frac{\sqrt{2}E}{\sqrt{\pi}(P+1)} - k_j \frac{2 \ln \left(\frac{IM_j}{\theta} \right) Q}{\beta \pi (P+1)^2} - k_j \frac{\sqrt{2} \ln \left(\frac{IM_j}{\theta} \right)^2 E}{\beta^2 \sqrt{\pi}(P+1)} \\ &\quad - (k_j - n_j) \frac{\sqrt{2}E}{\sqrt{\pi}(P-1)} + (k_j - n_j) \frac{2 \ln \left(\frac{IM_j}{\theta} \right) Q}{\beta \pi (P-1)^2} \\ &\quad + (k_j - n_j) \frac{\sqrt{2} \ln \left(\frac{IM_j}{\theta} \right)^2 E}{\beta^2 \sqrt{\pi}(P-1)}\end{aligned}$$

$$H(\theta, \beta) = \begin{bmatrix} \frac{\partial^2 \ell(\theta, \beta)}{\partial \theta^2} & \frac{\partial^2 \ell(\theta, \beta)}{\partial \theta \partial \beta} \\ \frac{\partial^2 \ell(\theta, \beta)}{\partial \beta \partial \theta} & \frac{\partial^2 \ell(\theta, \beta)}{\partial \beta^2} \end{bmatrix}$$

$$\frac{\partial \theta}{\partial \beta_0} = \frac{-e^{\frac{-\beta_0}{\beta_1}}}{\beta_1} \quad \frac{\partial \theta}{\partial \beta_1} = \frac{\beta_0 e^{\frac{-\beta_0}{\beta_1}}}{\beta_1^2}$$

$$\frac{\partial \beta}{\partial \beta_1} = -\frac{1}{\beta_1^2}$$

B.2 An Example Implementation of the Equality Test

MLE and QMLE are implemented using the collapse data of the building B2-Existing.

B.2.1 Sandwich estimators

The sandwich estimators ($A(\theta)$ and $B(\theta)$) are computed using Eq. (3.18)

$$A(\theta) = \begin{bmatrix} 122.7572 & -5.5052 \\ -5.5052 & 638.9830 \end{bmatrix} \quad B(\theta) = \begin{bmatrix} 63.6039 & -14.1952 \\ -14.1952 & 324.0924 \end{bmatrix}$$

B.2.2 Variance estimators

The following matrices represent the variance estimators. $A(\theta)^{-1}$ is the variance estimator under correct specification (MLE). $A(\theta)^{-1}B(\theta)A(\theta)^{-1}$ is the variance estimator for QMLE.

$$A(\theta)^{-1} = \begin{bmatrix} 8.1493e^{-03} & 7.0211e^{-05} \\ 7.0211e^{-05} & 1.5655e^{-03} \end{bmatrix}$$

$$A(\theta)^{-1}B(\theta)A(\theta)^{-1} = \begin{bmatrix} 4.2240e^{-03} & -6.9977e^{-08} \\ -6.9977e^{-08} & 7.9438e^{-04} \end{bmatrix}$$

APPENDIX C

Appendix: IM Study

C.1 Ground Motion Information

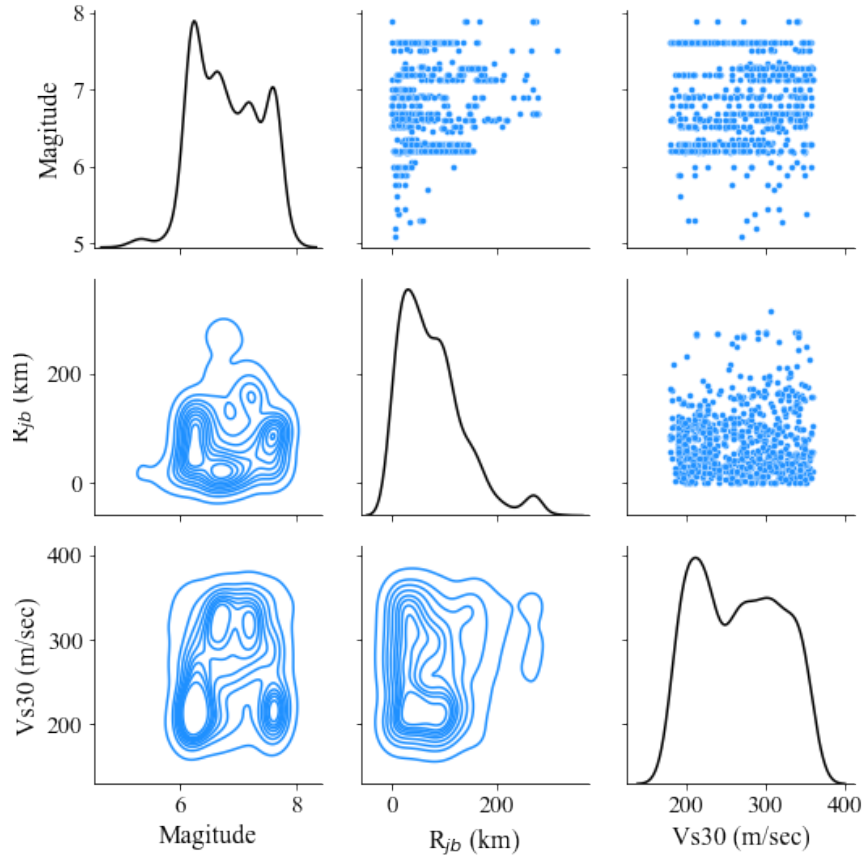


Figure C.1: A three-way grid plot showing individual (diagonal) and pairwise (off-diagonals) relationships between three causal parameters, magnitude, distance (R_{jb}), and shear-wave velocity (V_{s30}).

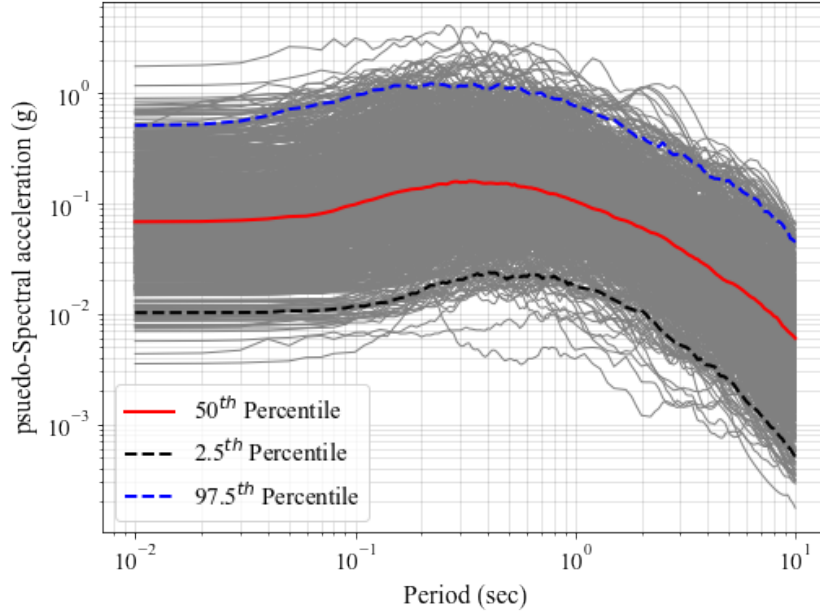


Figure C.2: Rotated response spectrum (RotD50) of all 826 ground motion pairs (in grey) and the median of all the records (in red).

C.2 Engineering Demand Parameters

Figure C.3 highlights the EDP profiles along the building height for a two-story single-family dwelling (Figure C.3a) and a four-story multi-family dwelling (Figure C.3b). The figures show the peak story drift ratio and peak floor acceleration in the X-direction experienced by the archetypes when subjected to 826 pairs of ground motion records. It can be seen that the four-story archetype experiences a higher story drift ratio as compared to its two-story counterpart.

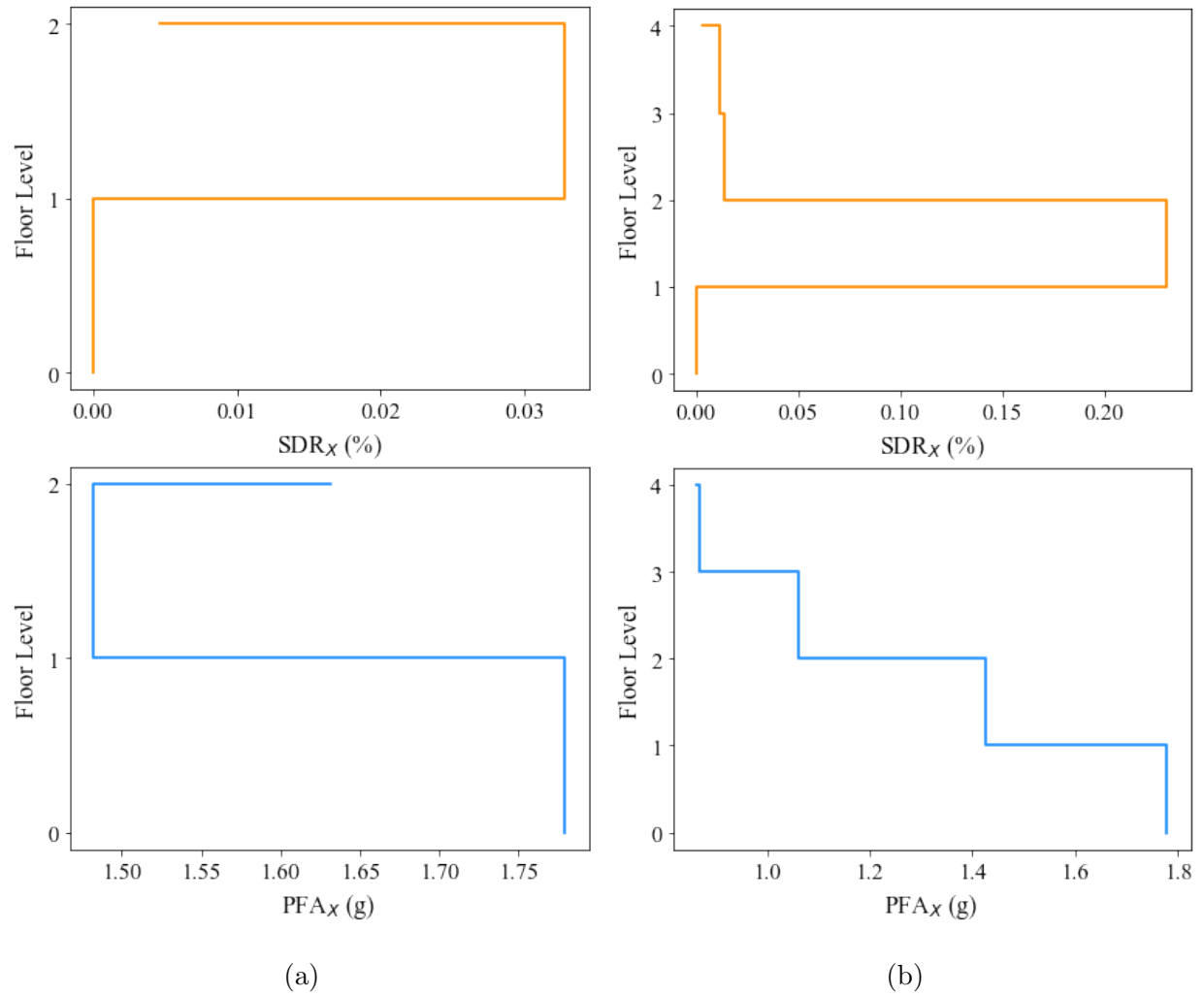


Figure C.3: a) EDP profile of a two-story archetype (SFD2B) and b) EDP profile of a four-story archetype (MFD3B).

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