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A report for the California Seismic Safety Commission
Prepared by Colorado State University



Beyond Earthquake Damage

*Innovative Metrics
for Economic
and Community
Recovery*



State Of
California



California Office of
Emergency Services



California Seismic
Safety Commission



Beyond Earthquake Damage: Innovative Metrics for Economic and Community Recovery

Project Report

www.in-core.org

This report was prepared by Colorado State University for the California Seismic Safety Commission within the California Governor's Office of Emergency Services.

June 2025



Credits and Acknowledgements

IN-CORE Team and Colorado State University

This project was performed at Colorado State University. IN-CORE's objective is to apply IN-CORE capabilities to provide technical assistance and scenario-based modeling to develop resilience strategies for hazards.

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Preface

The Alfred E. Alquist Seismic Safety Commission (SSC) is pleased to present the report entitled “*Beyond Earthquake Damage: Innovative Metrics for Economic and Community Recovery*,” prepared by Colorado State University in partnership with the IN-CORE research team. This report is part of the SSC’s continued commitment to advancing seismic safety and community resilience across California.

Audience and Purpose

This report is intended for a broad range of users and decision-makers involved in disaster recovery and resilience planning. It is particularly relevant for those focused on equitable disaster assistance, long-term recovery investments, and integrated planning across physical infrastructure and socio-economic systems.

How This Report Can Be Used

This study introduces a powerful new approach to understanding the full impact of earthquakes — not just the physical damage to buildings and infrastructure, but also how entire economies respond and recover. By combining advanced engineering tools with cutting-edge economic modeling, this framework offers critical insights that can help communities, governments, and policymakers make smarter, faster decisions to strengthen resilience and speed up recovery after disasters. By analyzing three representative California communities—Rio Dell, Monte Sereno, and East Richmond Heights—the report highlights how pre-existing socioeconomic vulnerabilities can influence recovery trajectories and identifies metrics to measure resilience more holistically.

The SSC encourages readers to use this report to:

- **Understand disparities** in disaster recovery outcomes between affluent and underserved communities;
- **Support data-informed planning** for community recovery funding prioritization;
- **Develop and evaluate policies** that promote equitable access to FEMA and other disaster aid programs;
- **Incorporate new metrics** for resilience into hazard mitigation plans and recovery strategies;
- **Advance pre-disaster planning** by modeling scenarios that integrate engineering and economic data.

The SSC believes this work provides actionable insight to help California build not only back—but forward—by promoting resilient, inclusive, and economically stable communities after seismic and natural disastrous events.



The SSC thanks Colorado State University and the IN-CORE team for their expert analysis and thoughtful recommendations; our CalOES colleagues from the Response and Recovery Directorates for their robust review and insights; and the ad hoc committee of Commissioner Debra Barnes and Commissioner Kit Miyamoto for working with IN-CORE and staff to ensure a comprehensive and polished product.

For readers seeking a non-technical overview, the following Plain Language Executive Summary provides the key findings and implications of this study. The full technical report follows.

Plain Language Executive Summary

Beyond Earthquake Damage: Innovative Metrics for Economic and Community Recovery

1. Why This Study Matters

When earthquakes hit, they don't just crack buildings — they shake entire communities. Families may lose homes, jobs, and savings. Schools and hospitals may close. Some towns bounce back quickly, while others struggle for years.

This study asks two key questions:

1. Why do some communities recover faster than others? And how much faster?
2. What policies could make recovery more equitable and faster for everyone?

Key finding: Wealthy towns recover years sooner than working-class or rural communities, even when the earthquake damage is the same. Aid programs can shorten recovery for low-income families by more than 42 months — but only if they reach the people who need them most and in a timely manner.

This is important because disasters should not widen the gap between rich and poor. If we want resilient California communities, recovery policies must support those with the fewest resources.





Photo Credit: California Earthquake Authority

2. What We Did

We used an earthquake + local economy simulator (the IN-CORE, which is a community resilience modeling tool plus a Spatial Computable General Equilibrium economics model, or SCGE model).

Think of it as a “what if” machine:

- It starts with earthquake damage to homes, businesses, and schools.
- It then shows how that damage ripples into the economy — jobs lost, wages cut, businesses slowed, families displaced.
- It tracks how long it takes households at different income levels to get back to “normal” conditions.

We tested this simulator on three California towns with very different income profiles:

- Rio Dell—rural, working-class (median income ~\$46,000).
- East Richmond Heights—middle-income suburb (median ~\$112,000).
- Monte Sereno—affluent community (median ~\$250,000).

We modeled the same earthquake—the 2022 Ferndale earthquake — in all three towns.

Then we tested how recovery changes:

- Without FEMA aid
- With FEMA aid at 6 months (immediate)
- With FEMA aid at 18 months (delayed)

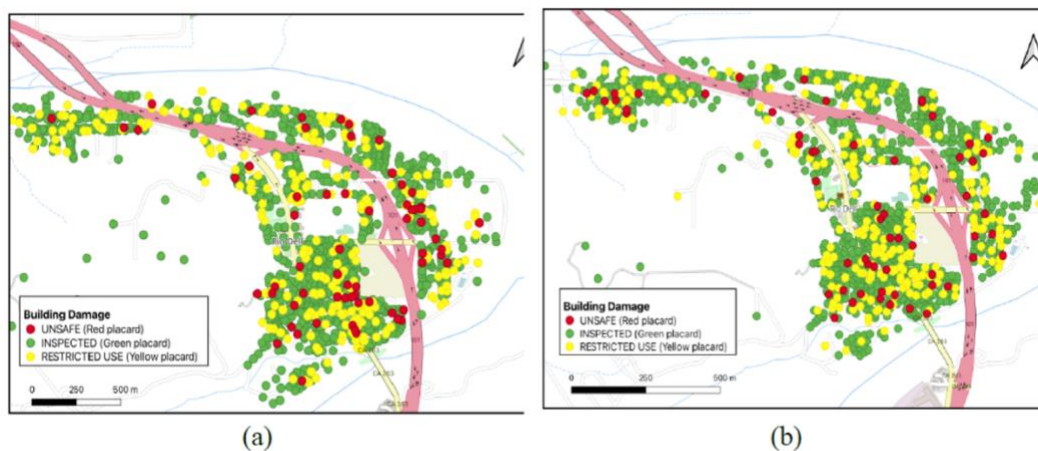


Figure 3-7: Spatial distribution of post-earthquake posting for buildings of Rio Dell in: (a) actual inspected buildings, and (b) developed building data set

3. What We Found

A) Poorer towns recover much slower

- Rio Dell (lowest income group, HH1 <\$30K):
 - No aid: income recovery in 17 periods (~102 months)
 - Immediate aid: 10 periods (~60 months) → 42 months faster
 - Delayed aid: 11 periods (~66 months) → 36 months faster than no aid
- Monte Sereno (wealthy):
 - Economy stabilizes by period 8 (~48 months), with or without aid.
 - Large household savings mean families recover quickly on their own.

B) Aid matters more than aid timing

- The presence of aid drives the biggest gains: cutting recovery times by 2–3 years for low-income families.
- Aid timing (6 months vs 18 months) shifts recovery only slightly (~6 months difference).

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C) Recovery looks different across the three towns

- Rio Dell: Heavily dependent on aid, longest recovery without it.
- East Richmond Heights: Middle ground — aid shortens recovery, but wealthier households still recover faster.
- Monte Sereno: Fastest recovery regardless of aid.

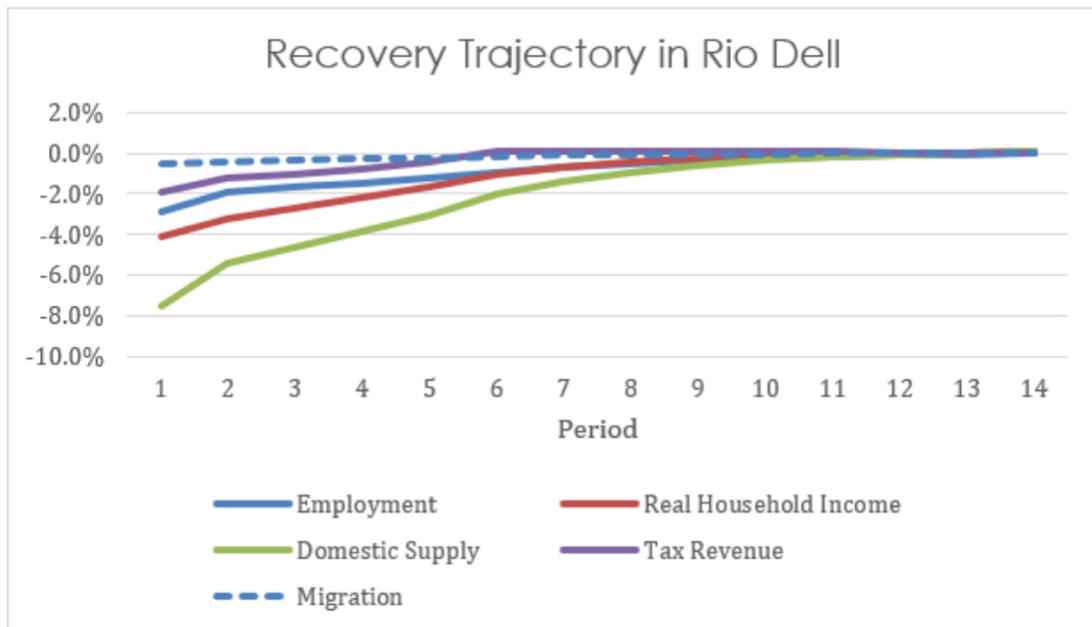


Figure 3-13: Recovery trajectory in Rio Dell across simulated periods

4. How This Affects Families

The numbers tell us more than just economic theory—they describe what happens to people’s lives.

- In Rio Dell, without aid, a family living on <\$30K could wait over 8 years to regain their income. With aid, they might be back on their feet 3 years sooner.
- For a middle-income family in East Richmond Heights, aid shortens recovery by around 12–24 months.
- In Monte Sereno, most families never fall as far behind because savings cushion the shock.

Why this matters:

- Delays in recovery mean families can't pay rent, buy food, or stay healthy.
- Children miss school and routines.
- Stress leads to higher risks of crime, poor mental health, and community breakdown.

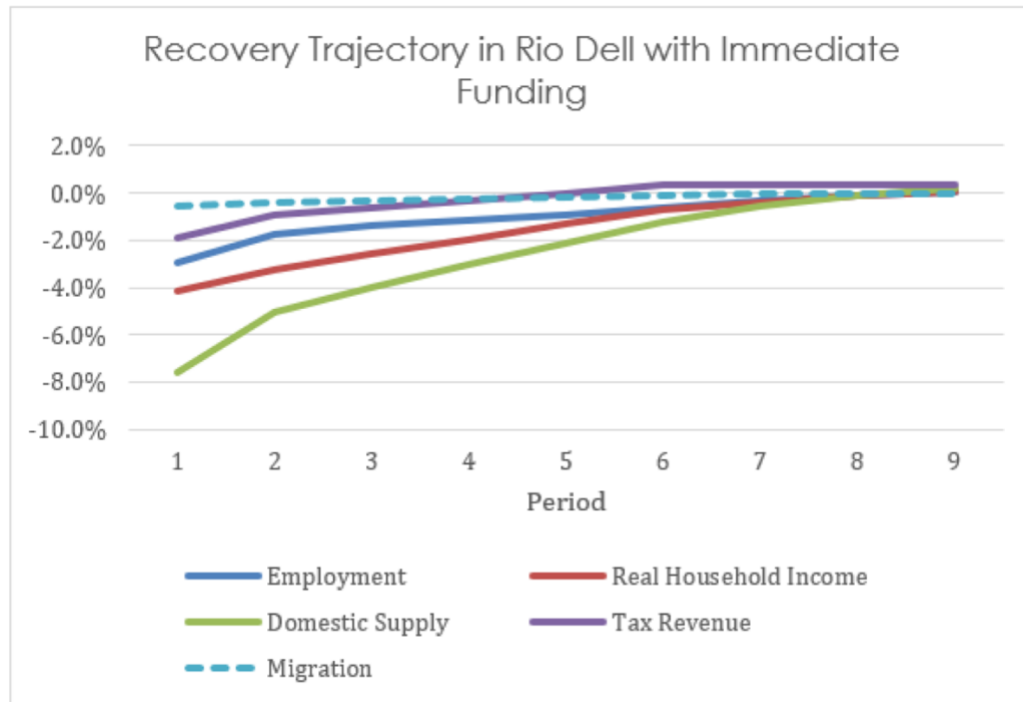


Figure 3-19: Recovery trajectory in Rio Dell with immediate funding

5. What Should Be Done

This study shows that recovery is not just about fixing buildings. It's about helping people, especially those with the fewest resources. Based on the findings:

A) Ensure aid reaches those in need

- The availability of aid is more important than exact timing. For Rio Dell's poorest households, aid cut recovery time by ~36 months compared to no aid.

B) Target families who struggle most

- Low-income households benefit the most from aid. Directing funds first to these groups can shorten their hardship by 2–3 years.

C) Adjust aid rules to reflect real barriers

- FEMA rules use state-level economic measures that can overlook rural towns. Criteria should also consider poverty, commuting patterns, overcrowding, and lack of transport.

6. The Bigger Picture

This study makes one thing clear:

- Wealthy communities recover years sooner because they have more savings and resources.
- Lower-income communities need aid and targeted policies to close this recovery gap.

The plain conclusion: To make California communities safer and recover more equitably from earthquakes, we must:

1. Deliver aid to families who need it most.
2. Make sure recovery programs don't leave rural or low-income towns behind.
3. Plan ahead with both engineering and economic tools — not just damage estimates, but full community impacts.

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EXECUTIVE SUMMARY

Disaster assistance funding is essential to reducing both the immediate and long-term consequences of earthquakes, and offering critical assistance to affected populations. However, the distribution of these funds often perpetuates and intensifies pre-existing social inequalities. Vulnerable groups, including low-income households, racial and ethnic minorities, and individuals with limited access to education and healthcare, frequently experience the greatest disparities in disaster recovery. The inequity of FEMA approved disaster aids between the eligible affluent communities and the eligible underserved communities is highlighted in Figure 1-1, excerpted from an OES study in 2021 that shows the disparity in aid approvals. The inequality issue on eligibility itself can be best summarized in that there are specific elements of the IA criteria that indirectly inhibit the recovery of a rural community. Specifically, FEMA relies on a state's Total Taxable Resources (TTR) which results in a lack of equitable support for rural communities within large states. This study shows that rural underserved communities like Rio Dell have disproportionately longer recovery times compared with more affluent communities. Low-income households within the rural community have the longest recovery period. To address this shortcoming, this study utilizes the economic characteristics of communities using an integrated, simulation-based approach, to make recommendations for more resilient communities. This approach models the interdependencies between the physical aspects of a community—represented by earthquake-induced damage and the functionality of buildings—and its economic system, which is evaluated through factors such as employment shifts, domestic supply by sector, and household income distribution using a spatial computable general equilibrium (SCGE) model. A SCGE model is a robust model of the economy of a community and is described further below.

Figure E-1 provides an overview of the IN-CORE simulation framework, which is utilized herein and designed to be highly modular, multidisciplinary, and interconnected. Each community system is represented by a series of analyses, with input parameters exchanged among the different analyses within the framework. The modular design allows for easy modification or scaling, as analyses can be adjusted or expanded as needed. In this framework, two systems are considered: the building system and the economic system, as shown in Figure E-1. The modular structure also facilitates scalability, allowing new systems to be incorporated by adding corresponding analyses. For instance, integrating the electric power system would involve adding new analyses for electric power network damage and functionality and linking these modules into the existing framework. All analyses are developed and executed within the open-source Interdependent Networked Community Resilience Modeling Environment (IN-CORE).

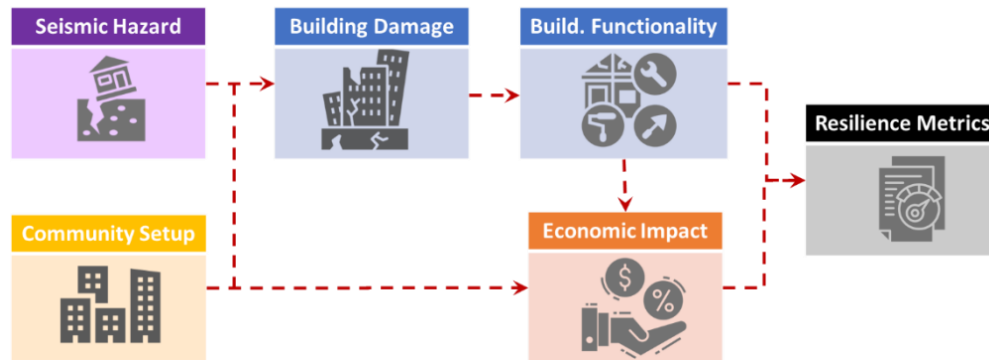


Figure E-1: IN-CORE framework overview

As illustrated in Figure E-1, the community setup analysis provides all the analyses with information related to the buildings in the community such as building material, structural system, occupancy, number of stories, seismic design code level, etc. Whereas the seismic hazard analysis supplies earthquake parameters (such as peak ground acceleration) at various community locations to the building damage analysis. The damage analysis then assesses the probability of different damage across the components of the building system. The resulting damage states are utilized by the building functionality analysis to evaluate the post-earthquake functionality state in each building in the studied community. This building functionality is then passed to the economic model and an economic impact analysis then evaluates the economic impact of building damage on the different sectors in the community. The output of all of the analyses described is then collected to represent resilience metrics in order to evaluate the final resilience metrics of the community.

This study presents a novel approach to evaluating community resilience and speed of recovery by proposing several pre-event actions that can help accelerate recovery of at-risk communities. A multidisciplinary simulation-based framework was utilized in IN-CORE which links the physical aspects of resilience, such as post-earthquake damage to buildings and infrastructure functionality, with the economic impacts, including shifts in employment, sectoral supply changes, and household income distributions. This integration is assessed using a spatial computable general equilibrium (SCGE) model. The proposed framework is applied to three representative towns in California, Rio Dell, Monte Sereno, and East Richmond Heights subjected to the equivalent damage imposed by the 2022 Ferndale earthquake on Rio Dell. These towns were chosen to highlight the differences in socioeconomic conditions across communities, in order to examine how these inequities interact with the engineering challenges of infrastructure damage. The study offers a more holistic understanding of resilience, capturing both the physical and socioeconomic vulnerabilities that influence recovery and long-term resilience in disaster-prone

areas.

A Computable General Equilibrium (CGE) model serves as a robust tool for analyzing economic impacts, especially valuable in developing policies for disaster resilience. Grounded in core microeconomic theories, it provides a detailed evaluation of economic disruptions caused by natural hazards, including earthquakes, hurricanes, tornadoes, and floods. The model effectively replicates the impact on both commercial and residential assets within a community, detailing the economic consequences of physical damage. CGE models assess not only the immediate effects, such as workforce reductions and property losses but also explore the broader indirect effects that alter behavioral patterns and affect the interconnected market dynamics. Consequently, CGE modeling has become a preferred method for studying disaster effects and supporting the development and assessment of strategies for both pre-disaster preparedness and post-disaster recovery.

CGE models provide a detailed representation of the interactions between different economic sectors by utilizing a series of equations that illustrate the dynamics resulting from these interactions. Figure E-2 demonstrates the structure of CGE model illustrating the flow of resources among four principal economic actors: households, firms, the government, and the neighboring economies referred to as the 'rest of the world' (ROW), emphasizing their integral roles within the economy. Households aim to maximize their utility by consuming products and services from firms and utilizing housing services. As price-takers, they make decisions based on complete information about prices in both goods and production factor markets. Their economic contribution includes providing labor and capital, with their primary income coming from wages and secondary income derived from returns on capital investments in businesses and real estate. Firms are driven by profit maximization and respond to market price signals as price-takers. They utilize labor and capital as their main inputs, quantified in terms of workforce numbers and the real dollar value of capital. The flexibility in adjusting these inputs, according to relative price changes, allows for some substitutability based on their elasticity. The government collects taxes from sales, income, and property, allocating this revenue to fund essential public services, including law enforcement and fire protection. It adheres to a balanced budget policy, ensuring that its spending equals its income, thus maintaining no surplus or deficit. The ROW interacts with the local economy by facilitating trade, which includes both imports and exports. This sector merges trade activities with both nearby and overseas economies, influencing resource flows. Exports from the local economy result in resource outflows, whereas imports contribute to resource inflows. The economy's gross investment is supported by both domestic savings and capital inflows from the ROW.

The CGE model evaluates changes from both the supply and demand sides of an economy.

Supply-side modifications are driven by variables like wages, input prices, technological innovations, and taxes. On the demand side, variations may arise from shifts in local household consumption, business investments, government spending, and regional exports. Dynamic CGE (DCGE) models extend these analyses over multiple time periods, which enables the exploration of economic variables' trajectories through time and the gradual adaptation of economies to new equilibria. Developing a dynamic CGE model enables the study of dynamic economic resilience by integrating disaster recovery policies, such as resource infusions that can accelerate the recovery process. Due to these features, DCGE models have been extensively employed by researchers to simulate the economic recovery following disasters and to assess the effectiveness of various recovery interventions. These analyses have contributed significantly to understanding post-disaster economic dynamics and policy impacts.

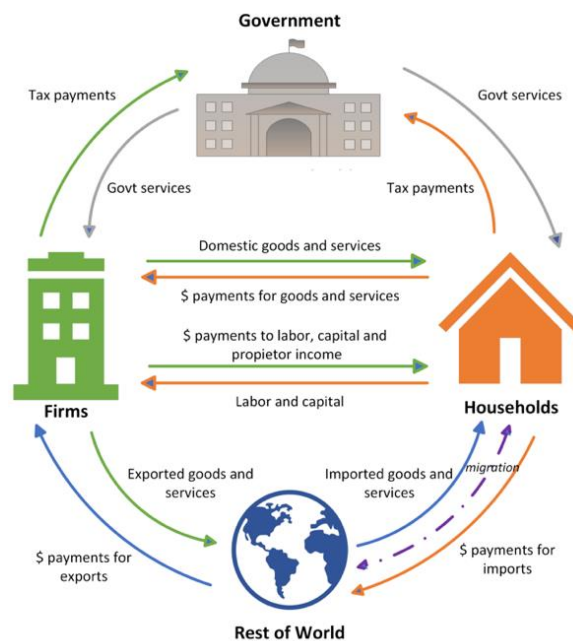


Figure E-2: Structure of Computable General Equilibrium Model (Amini et al., 2023)

As mentioned above in Figure E-2, when the engineering model outputs include building functionality probabilities, which represent the likelihood of each building within a community remaining operational post-disaster, based on damage to critical infrastructure. Capital stock impacts at the building level are calculated by multiplying these functionality probabilities by the capital values of the buildings. These impacts are then aggregated to the relevant two-digit NAICS sectors and housing services, introduced into the model as exogenous shocks in the form of capital

stock percentage reductions. For instance, when a commercial building sustains damage, its tenants may cut back or halt production temporarily. A significant outcome of this reduction is a decrease in labor demand, leading to wage losses. Consequently, households affected by these wage reductions experience a drop in income, which then lowers local consumer spending. Additionally, physical damage to residential properties adversely affects home equity. This decline in household wealth can result in reduced income and may prompt some residents to relocate from the area.

As part of this project, simulations were conducted to assess the impact of external financial assistance from FEMA on recovery efforts. According to the California Office of Emergency Services (Cal OES), in 2023 the average FEMA IA grant awarded for disasters in California was \$7,618. It was assumed that all damaged housing units receive these grants. The simulation included two scenarios: one with FEMA funds distributed at 6 months (period-2), signifying immediate assistance, and another with funds allocated at 18 months (period-4), indicating delayed assistance. It is noted that all housing units sustained damage across three simulated communities, and the projected FEMA funding allocations.

It was assumed that FEMA funds are distributed uniformly across all housing units since data on distribution is not available to the project, so the lower-value housing sectors in the three communities have seen a significant portion of their capital stock losses covered by these funds. Notably, in Rio Dell, the FEMA funds cover a substantial portion of the losses for the lowest - value of housing units, HS1, with 57% of its losses compensated. In contrast, higher-value properties receive comparatively less FEMA funding. For example, the FEMA coverage ratio for the highest-value of housing units, HS3, in Monte Sereno is only 9%. This highlights that properties with lower values are more impacted, when funds are allocated, than their more affluent counterparts to help aid in recovery from the FEMA funds.

It was also noted that while immediate aid may not drastically shorten the recovery period, it is especially crucial for lower-income households, helping them stabilize more quickly. Lower-income households often face greater difficulties in meeting basic needs such as housing, food, and healthcare during recovery periods. Delays in income recovery can extend hardship and instability, adversely affecting their overall health and well-being. Additionally, prolonged financial challenges can lead to broader social issues, such as increased crime rates, mental health problems, and disruptions in children's education, undermining community stability and cohesion. It is important to note that the model assumes no change in the wage income earned outside the city. However, in reality, wage income for commuters may decrease following a disaster, particularly because lower-income jobs typically offer less security and fewer benefits like paid leave or health insurance. This makes these workers more vulnerable during economic downturns, potentially leading to significantly longer recovery times for lower-income households than the

analysis suggests. Overall, the findings indicate that financial aid is particularly critical for communities that are less affluent or more severely affected by disasters.

Several recommendations to help improve the resilience of communities to natural hazards such as earthquakes include (1) direct cash transfers for direct financial assistance to low-income households following an event; (2) introduction of a low-interest loan program; (3) IA criteria should include a review of the totality of circumstances with consideration of recovery-relevant factors such as poverty, lack of access to transportation, displacement of education and work, and overcrowded housing; (4) Disaster aids such as IA should prioritize low-income households since they take the longest to recover.

1. INTRODUCTION

Earthquakes continue to have devastating effects on both human populations and the environment. As far back as 1556, catastrophic earthquakes led to significant destruction, such as the massive earthquake in Shaanxi, China, which resulted in the deaths of approximately 830,000 people and caused widespread societal upheaval (Hou et al., 1998). The economic cost of such events is difficult to translate into modern figures. More recently, on February 6, 2023, a Mw 7.8 earthquake struck Türkiye and Syria, followed by a Mw 7.6 aftershock. This disaster led to more than 45,000 deaths in Türkiye alone, as reported by the Disaster and Emergency Management Authority (AFAD), with the combined death toll, including Syria, exceeding 52,000 (Dal Zilio and Ampuero, 2023). The economic impact of the earthquake series was estimated to surpass 160 billion USD (Dal Zilio and Ampuero, 2023). More recently, a Mw 7.3 earthquake struck the offshore area of Hualien County, Taiwan on April 3, 2024. It claimed the lives of at least 18 people and left over 1,100 injured. It stands as the most powerful earthquake in Taiwan since the 1999 Jiji earthquake, with three notable aftershocks surpassing a magnitude of Mw 6.0 (Qiu et al., 2024).

Additionally, the 2024 Noto Peninsula earthquake and tsunami in Japan, which had a magnitude of 7.6, severely impacted roughly 160 hectares in Suzu City and Noto Town. It also caused a significant fire in Kawai-machi, Wajima City, which destroyed more than 200 buildings, including homes and businesses (Itatani et al., 2024). The earthquake also led to disruptions in electricity, water, and communications, while over 1,000 aftershocks, some exceeding Mw 5.0, occurred within a week, forcing over 20,000 residents to evacuate. The total damage from this event was estimated to exceed 157 billion USD (Itatani et al., 2024).

Disaster relief funding (DRF) is critical in responding to earthquakes, as it provides immediate relief and long-term support to impacted areas, helping communities recover and rebuild. It serves as the main source of funding for the federal government's general disaster relief programs. Federal disaster relief grants or loans for individuals were initially implemented in the US in 1915. However, in subsequent years, many local officials hesitated to seek federal assistance, expressing concerns that such support might carry a stigma for recipients (Barry 1997). From the inception of the United States until 1950, Congress passed 128 disaster relief acts, each addressing a particular disaster. Most of these acts focused on providing "in-kind" support, such as medical personnel, supplies, and transportation, rather than direct financial assistance to individuals.

A shift toward establishing permanent disaster relief programs began in 1949 when Congress

introduced what would eventually become the U.S. Department of Agriculture's (USDA) Farm Service Agency (FSA) emergency disaster loan program. This program was designed to offer low-interest loans to farmers and ranchers impacted by natural disasters (Barry 1997). Later in the 1990s, DRF in the United States saw significant changes, driven by the increasing frequency and severity of natural disasters. The Federal Emergency Management Agency (FEMA), which had been established in 1979, became the primary agency responsible for coordinating federal disaster response and providing financial assistance (Knapp 2020). Throughout the decade, the federal government increasingly used DRF not only to respond to immediate emergencies but also to support long-term recovery efforts. Since the year 2000, FEMA's role in disaster funding has evolved to address the increasing scale, complexity, and frequency of natural and man-made disasters. The agency has been called upon more frequently to provide direct financial assistance to both individuals and communities following large-scale events such as hurricanes, wildfires, floods, and terrorist attacks. Key milestones in FEMA disaster funding include the aftermath of the catastrophic Hurricane Katrina in 2005, which caused over \$125 billion in damage (EM-DAT, 2019; Knabb et al., 2005) and prompted an unprecedented response from FEMA. In the wake of Katrina, FEMA allocated more than \$48 billion in disaster relief to support recovery efforts in affected regions (Raker and Woods, 2023). In the years following Hurricane Katrina, FEMA's funding strategies were expanded and improved to address both immediate recovery needs and long-term mitigation goals including building back better. For instance, in 2012, Hurricane Sandy caused over \$60 billion in damage (de Moel et al., 2013), and FEMA allocated more than \$25 billion for recovery efforts (Lieberman-Cribbin et al., 2017), which included rebuilding homes, businesses, and critical infrastructure.

The FEMA budget has continued to increase, with billions of dollars allocated to disaster response each year. In 2017, following Hurricanes Harvey, Irma, and Maria, FEMA's funding obligations exceeded \$100 billion, including both direct assistance to individuals and public infrastructure repair (Lee 2021). The growing number of severe weather events, compounded by the impacts of climate change, has led to a marked rise in disaster-related funding. By 2020, FEMA had allocated more than \$50 billion in federal grants to help communities prepare for, respond to, and recover from disasters, while also addressing the ongoing effects of the COVID-19 pandemic, which added an additional layer of complexity to disaster relief efforts (FEMA 2020).

Despite the rising amount of Disaster Relief Funding (DRF) in the US and worldwide, the manner in which DRFs are allocated and distributed often highlights and deepens pre-existing social inequities. Disasters don't affect all populations equally, and marginalized groups, particularly low-income families, racial and ethnic minorities, and those with limited access to healthcare and education, are disproportionately impacted both during and after these events.

These vulnerable groups often live in regions with inadequate infrastructure, such as buildings that are less resistant to seismic activity, making them more susceptible to severe damage and injury during an earthquake. Furthermore, limited financial resources can prevent these individuals from relocating to safer areas or from undertaking the costly repairs needed to make their homes resilient against future disasters. Several researchers have attempted to study this matter for earthquake hazards specifically and for natural disasters in general.

Muñoz and Tate (2016) adopted a distributive justice framework to assess how disaster recovery funds for property acquisition were allocated following the 2008 severe flooding in Iowa. Using spatial econometric modeling, the study compared recovery outcomes between two federal programs that financed the acquisitions and evaluated disparities among different vulnerable population groups. The findings reveal significant distributive and temporal inequalities in federal recovery fund allocation. Notably, recovery rates were lower among Latino and elderly populations, highlighting potential inequities in the distribution of federal assistance.

Emrich et al. (2019) emphasized the important yet underexplored role of social characteristics in influencing recovery support. They provide detailed quantitative analysis of U.S. disasters across a large, affected area. The results revealed that while flood recovery assistance is generally closely linked to physical damage, this connection is less pronounced in areas with higher social vulnerability. The findings suggest that incorporating both physical damage and social vulnerability into future disaster recovery programs could lead to more equitable outcomes. Emrich et al. (2022) examined the county-level Federal Emergency Management Agency's (FEMA) Individuals and Households Program (IHP) assistance data provided between 2010 and 2018, focusing on the relationship between fund allocation and social vulnerability indicators while controlling for total disaster damages. Ordinary least squares regression analysis was applied to evaluate connections between Total Assistance, Housing Repair/Replacement Assistance, and Other Needs Assistance with specific social vulnerability factors derived from the Social Vulnerability Index (SoVI) framework. The findings identified race and ethnicity-related variables as significant determinants, often negatively associated with the amount of aid received. These results indicate that federal disaster aid is influenced by socio-economic disparities, underscoring the need for greater consideration of social vulnerability in disaster relief programs.

Waters et al. (2024) investigated the factors that influence federal disaster coverage at the county level, focusing on hurricanes that received Presidential Disaster Declarations between 2008 and 2017. The results showed that counties receiving aid despite no reported damage are more likely to have higher storm intensity and greater exposure to hazards, suggesting that the damage may not be properly documented in these areas. These counties also tend to have greater social

vulnerability, which could impact their ability to recover effectively. Among counties that reported damage, it was observed that the level of federal disaster coverage tends to decrease as the severity of the disaster and per capita damage increase, implying that more severe disasters might receive proportionally less assistance. More research on allocation of DRFs for different disasters can be found at (Domingue and Emrich, 2019; Drakes et al., 2021; Han et al., 2023; Ghaedi et al., 2024).

Vulnerable groups, including low-income households, racial and ethnic minorities, and individuals with limited access to education and healthcare, frequently experience the greatest disparities in disaster recovery. The inequity of FEMA approved disaster aids between the eligible affluent communities and the eligible underserved communities is highlighted in Figure 1-1, excerpted from an OES study in 2021 that shows the disparity in aid approvals. The inequality issue on eligibility itself can be best summarized in that there are specific elements of the IA criteria that indirectly inhibit the recovery of a rural community. Specifically, FEMA relies on a state's Total Taxable Resources (TTR) which results in a lack of equitable support for rural communities within large states. This study shows that rural underserved communities like Rio Dell have disproportionately longer recovery times compared with more affluent communities. Low-income households within the rural community have the longest recovery period. To address these shortcomings, this study presents a novel approach to evaluating community resilience by proposing comprehensive resilience metrics that take into account the socioeconomic features of the communities which reflect the true costs of earthquakes. A multidisciplinary simulation-based framework is developed which links the physical aspects of resilience, such as post-earthquake damage of buildings and infrastructure functionality, with the economic impacts, including shifts in employment, sectoral supply changes, and household income distributions. This integration is assessed using a spatial computable general equilibrium (SCGE) model. The proposed framework is applied to three representative towns in California, Rio Dell, Monte Sereno, and East Richmond Heights subjected to the 2022 Ferndale earthquake. These towns were chosen to highlight the differences in socioeconomic conditions across communities in order to examine how these inequities interact with the engineering challenges of infrastructure damage. The study offers a more holistic understanding of resilience, capturing both the physical and socioeconomic vulnerabilities that influence recovery and long-term resilience in disaster-prone areas.

Social Vulnerability Category	Average FEMA Verified Loss \$'s Per Applicant	Average Individuals & Households (IHP) Program \$'s Allocated Per Eligible Applicant	% of Individuals & Households (IHP) Program Eligible Applicants	Average Rental Award \$'s Per Eligible Renter Applicant	% of Renter Applicants That Received Rental Award	Average Other Needs Assistance \$'s Per Eligible Applicant	% of Applicants Eligible for Other Needs Assistance
20% Least Vulnerable Census Tracts	\$2,385.99	\$3,974.37	23.18%	\$4,714.42	23.88%	\$962.77	19.91%
20% Most Vulnerable Census Tracts	\$301.57	\$2,707.20	4.74%	\$2,933.20	4.25%	\$1,127.71	3.98%

Figure 1-1: Cal OES review of FEMA approvals for California Wildfire events DR-4558 and DR-4569

2. IN-CORE ANALYSIS

2.1 IN-CORE Framework Overview

Figure 2-1 provides an overview of the IN-CORE simulation framework, which is designed to be highly modular, multidisciplinary, and interconnected. Each community system is represented by a series of analyses, with input parameters exchanged among the different analyses within the framework. The modular design allows for easy modification or scaling, as analyses can be adjusted or expanded as needed. In this framework, two systems are considered: the building system and the economic system, as shown in Figure 2-1. The modular structure also facilitates scalability, allowing new systems to be incorporated by adding corresponding analyses. For instance, integrating the electric power system would involve adding new analyses for electric power network damage and functionality and linking these modules into the existing framework. All analyses are developed and executed within the open-source Interdependent Networked Community Resilience Modeling Environment (IN-CORE) (van de Lindt et al., 2023).

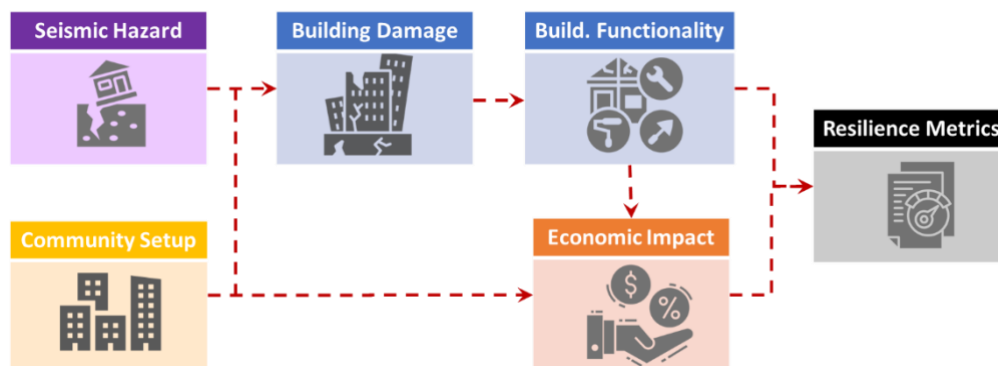


Figure 2-1: IN-CORE framework overview

As illustrated in Figure 2-1, the community setup analysis provides all the analyses with information related to the buildings in the community such as building material, structural system, occupancy, number of stories, seismic design code level, etc. Whereas the seismic hazard analysis supplies earthquake parameters (such as peak ground acceleration) at various community locations to the building damage analysis. The damage analysis then assesses the probability of different damage across the components of the building system. The resulting damage states are utilized by the building functionality analysis to evaluate the post-earthquake functionality state in each building in the studied community. On the economic aspect, the economic impact analysis

evaluates the economic impact of building damage on the different sectors in the community. The output of all of the analyses described is then collected to represent resilience metrics in order to evaluate the final resilience metrics of the community.

The interdependencies between various systems within the community are depicted by arrows linking the analyses across different systems. Figure 2-1 highlights a primary interdependency in the proposed simulation framework which links the building system to the economic system, indicated by an arrow from the building damage analysis to the economic impact analysis. Further details on how these interdependencies are modeled within each analysis will be discussed later in this report.

2.2 Community Setup

The initial phase involves gathering data and information essential for resilience modeling, following a two-step approach. This begins by identifying data sources and then collecting relevant information. Once collected, building datasets are used to create shapefiles for each community, which capture details such as structural type, layout, number of stories, height, and location. Taxation databases provide further information on property characteristics, including location, land value, improvement value, land use designation, tenure, construction year, and square footage. Additional building attributes, such as usage, construction type, configuration, and content value, may also be identified.

For the building dataset, the National Structure Inventory (NSI 2024) database is used to collect essential information about the studied communities. The NSI databases are designed to support assessments and analyses of natural hazards by providing detailed information on the exposure and vulnerability of structures across the country, with each point typically representing an individual structure. By combining this inventory with hazard data, the NSI enables the evaluation of potential impacts from various natural hazards. Although flood damage analysis has been the primary application, the data available for each structure is also suitable for calculating damages from other hazard types.

NSI databases provide detailed attributes for all the buildings nationwide on the state level in the format of GeoPackage. Geopackage is an open, standardized platform-independent, portable, self-describing, and compact format designed for transferring geospatial data. The NSI database is extracted on the state level not the city level. Therefore, more processing is needed to extract the data for each community separately. Figure 2-2 shows an overview for the development process of the building dataset from NSI state-level database to a shapefile that can be run within

the IN-CORE framework. The first step is to define the boundaries of the studied community which is done through Google Maps (Google 2025). The boundaries are converted to a matrix in MATLAB software (Simulink 2022) with the rows representing the corner points of the community boundary and the columns representing the latitude and longitude of the corner points.

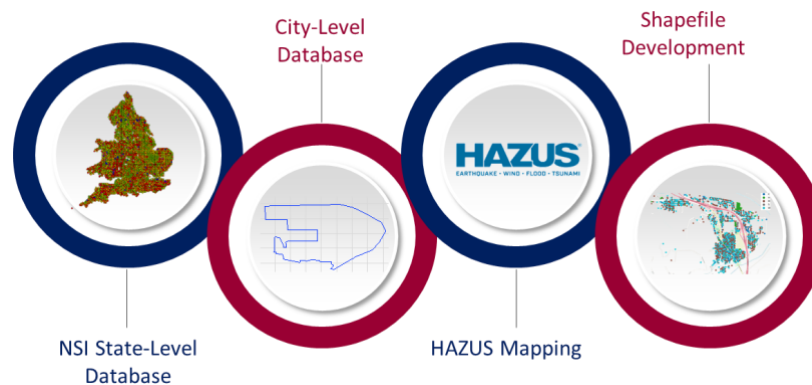


Figure 2-2: Overview of development of building dataset

After defining the boundaries of each of the three cities being studied herein, the information for buildings inside each boundary is extracted from the original NSI GeoPackage database through a MATLAB script (Simulink 2022). Though NSI dataset provides a multitude of attributes for the buildings in the US, it was designed for flood hazards. Therefore, most of the attributes are not related to the lateral load resisting system of the structure, as listed in

Table 2-1, which is a key attribute needed for assessing the seismic resilience of communities. The only attribute related to the structural system of the structure is the “bldgtype” attribute which only gives information about the material of the building (i.e., wood, masonry, concrete, mobile, or steel). The building type coded as: “W” means wood buildings, “C” means concrete buildings, “M” refers to masonry buildings, “H” refers to mobile homes, and “S” refers to steel buildings. The building type attributes in NSI dataset along with the number of stories, age of building, and occupancy type are then used to map each building in the three cities to one of the 34 building archetypes specified by HAZUS (FEMA 2022a) based on the approach specified in Appendix A in HAZUS Inventory Technical Manual (FEMA 2022b).

Table 2-2 lists the description of each of the 34 HAZUS archetypes.

Table 2-1: Description of attributes for NSI database

Attribute	Description
fd_id	A number that should be unique for all structures
bid	A building ID
x	X coordinate of each structure in GCS WGS84
y	Y coordinate for each structure in GCS WGS84
cbfips	Census Block that contains the structure
st_damcat	Damage category of the structure
occtype	Damage Function or Occupancy Type of the structure
bldgtype	Building type of the structure
source	The source of the initial iteration of the structure
sqft	The estimated Square footage of the structure
ftprntid	An identifier of the building footprint record used for estimating fields such as sqft and num_story
ftprntsrc	The source of the utilized footprint
found_type	Describes the type of foundation on the structure
found_ht	Describes the foundation height of the structure in feet from the ground elevation
num_story	The number of stories of the structure
val_struct	Value in dollars of the structure
val_cont	Value in dollars of the contents of the structure
val_vehic	Value in dollars of the cars at the structure
med_yr_blt	Describing the median year built of structures within the Census Block
pop2amu65	Population at night for the structure of people under the age of 65
pop2amo65	Population at night for the structure of people over the age of 65
pop2pmu65	Population during the day for the structure of people under the age of 65
pop2pmo65	Population during the day for the structure of people over the age of 65
students	Number of students attending the school as estimated by the source NCES data
o65disable	The percent of the county population over the age of 65 that is expected to have an ambulatory disability
u65siable	The percent of the county population under the age of 65 that is expected to have an ambulatory disability
firmzone	Estimated 2021 flood zone for the structure
grnd_elv_m	Ground elevation (in meters, NAVD88) at the structure
ground_elv	Ground elevation (in feet, NAVD88) at the structure

Table 2-2: Description of HAZUS building archetypes

Material	HAZUS Archetype	Description	Height
Wood	W1	Wood, Light Frame ($\leq 5,000$ sq. ft.)	All
	W2	Wood, Commercial & Industrial ($> 5,000$ sq. ft.)	All
Steel	S1L	Steel Moment Frame	Low-Rise
	S1M		Mid-Rise
	S1H		High-Rise
	S2L		Low-Rise
	S2M	Steel Braced Frame	Mid-Rise
	S2H		High-Rise
	S3		All
	S4L	Steel Light Frame Steel Frame with Cast-in-Place Concrete Shear Walls	Low-Rise
	S4M		Mid-Rise
	S4H		High-Rise
	S5L	Steel Frame with Unreinforced Masonry Infill Walls	Low-Rise
	S5M		Mid-Rise
	S5H		High-Rise
Concrete	C1L	Concrete Moment Frame	Low-Rise
	C1M		Mid-Rise
	C1H		High-Rise
	C2L	Concrete Shear Walls	Low-Rise
	C2M		Mid-Rise
	C2H		High-Rise
	C3L	Concrete Frame with Unreinforced Masonry Infill Walls	Low-Rise
	C3M		Mid-Rise
	C3H		High-Rise
	PC1	Precast Concrete Tilt-Up Walls	All
	PC2L	Precast Concrete Frames with Concrete Shear Walls	Low-Rise
	PC2M		Mid-Rise
	PC2H		High-Rise
Masonry	RM1L	Reinforced Masonry Bearing Walls with Wood or Metal Deck Diaphragms	Low-Rise
	RM1M		Mid-Rise
	RM1H		High-Rise
	RM2L	Reinforced Masonry Bearing Walls with Precast Concrete Diaphragms	Low-Rise
	RM2M		Mid-Rise
	RM2H		High-Rise
	URML	Unreinforced Masonry Bearing Walls	Low-Rise
	URMM		Mid-Rise
Others	MH	Mobile Homes	All

For economic analysis, this study employs a dynamic computable general equilibrium (DCGE) model. Central to the DCGE model is the Social Accounting Matrix (SAM), which documents the economic interactions among households, firms, and the government. Figure 2-3 provides a visual representation of the SAM and includes succinct descriptions of its crucial elements. The model assesses the demand for intermediate input using input-output coefficients for two-digit NAICS sectors, which are based on IMPLAN data. Employment data within four wage brackets are integrated into the corresponding two-digit NAICS sectors using the Census Bureau's Longitudinal Employer-Household Dynamics (LEHD) dataset and Public Use Microdata Sample (PUMS).

	Economic sector	Labor groups	Capital	Households	Housing services	Taxes	Government	ROW
Economic sector	Intermediate purchases			Household expenditure			Government expenditure	Export
Labor groups	Wage payments by firms						Wage payments by government	
Capital	Capital payments				Capital payments			
Households		Wage transfer to households						
Housing services				Housing expenditure				
Taxes	Tax payments			Tax payments				
Government						Tax transfer to government		
ROW	Imports							

Figure 2-3: Detailed SAM for a community

The model also simulates wage distributions by businesses and government agencies using income data from PUMS, organized by sector. These wages are distributed to various household groups, demonstrating the income flow within the economy. Additionally, household demographics and income data are sourced from PUMS, with spending patterns estimated from IMPLAN data and adjusted by the Bureau of Labor Statistics Consumer Expenditure Survey. Note that the income data from PUMS represent broader regional averages and might not accurately reflect the specific economic conditions in each community.

Capital stock values for buildings are derived from the National Structure Inventory (NSI) managed by the U.S. Army Corps of Engineers, which offers comprehensive information on property types, building values, and locations. To obtain more precise estimates of building values in Rio Dell, we use data from both the Humboldt County Assessor and the NSI.

Government financial operations, including tax revenues and expenditures, are extracted from the Annual Comprehensive Financial Reports of Rio Dell, Monte Sereno, and Contra Costa County. The import and export matrices illustrate the financial interactions between sectors and households in a community and other regions, emphasizing the economic impacts of relative price differences between the local community and the rest of the world (ROW).

2.3 Building Damage and Functionality Analyses

Equation (1) determines the likelihood that a building will experience a particular damage state i ($P_{DS,i}$) by applying fragility functions ($F_{r_{DS,i}}$) designed for each building archetype and its associated damage state (DS_i). These fragility functions are modeled as logarithmic cumulative distribution functions (CDFs), which are governed by two parameters: the median (λ) and the standard deviation (ξ). Essentially, these functions describe the probability of a building exceeding damage thresholds (e.g., slight, moderate, extensive, or complete) depending on the intensity measure (IM, such as peak ground acceleration or PGA in this case). Figure 2-4 visually represents this relationship. In the framework shown in Figure 2-1, the HAZUS (FEMA 2022a) equivalent-PGA structural fragility curves are utilized to compute $P_{DS,i}$ for buildings throughout the community.

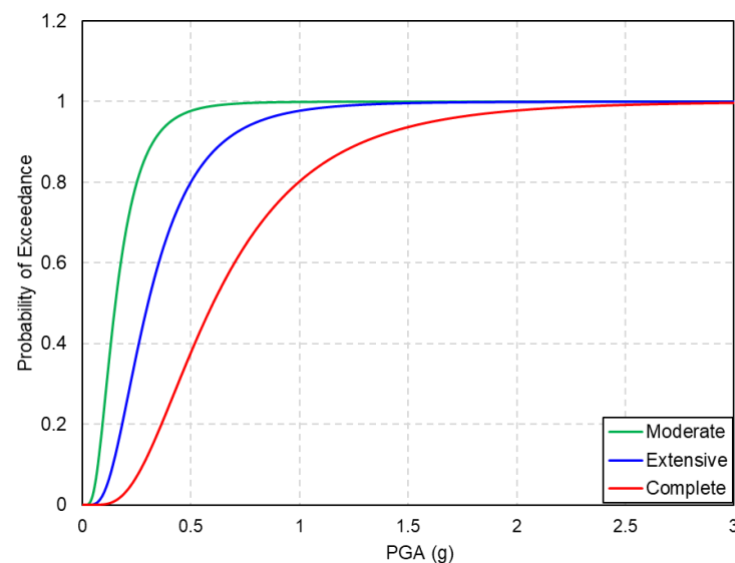


Figure 2-4: Fragility curves for low-rise unreinforced masonry buildings from HAZUS (FEMA 2022a)

In each iteration of a Monte Carlo (MC) simulation for an earthquake event, a random

variable R_j , which is uniformly distributed between 0 and 1, is generated. This variable is then compared to the probabilities of a building experiencing one of three damage states: moderate, extensive, or complete. If the generated random value indicates that the building would sustain at least moderate damage, the building is considered to lose its functionality for that iteration (as described in Eq. 2). In seismic damage assessments, a moderate damage state refers to yielding and cracking of structural components and moderate harm to nonstructural elements. While such a building may still be inhabitable and capable of being repaired, it is generally impractical to continue business operations within it.

The building's functionality status, denoted as $I_{fun,j}^k$, is determined for each iteration and takes a value of either 1 (functional) or 0 (nonfunctional). Here, j denotes each iteration in the MC simulation, ranging from 1 to N , for each building k . The probability of a building remaining functional ($P_{build,fun}^k$) is then estimated using Eq. (3). To assess the overall post-earthquake functionality of buildings in the community, a building is classified as nonfunctional if the likelihood of experiencing moderate or greater damage is more than 0.5, as outlined in Eq. (4). The community's post-earthquake functionality is subsequently expressed as the proportion of buildings that remain functional, calculated using Eq. (4).

$$P_{DS,i}^k = Fr_{DSi}^k(IM = x) \quad (1)$$

$$I_{fun,j}^k = \begin{cases} 1, & R_j > Fr_{DS1} \\ 0, & R_j \leq Fr_{DS1} \end{cases} \quad (2)$$

$$P_{build,fun}^k \approx \frac{N_{fun}^k}{N} = \frac{\sum_{j=1}^N (I_{fun,j}^k = 1)}{N} \quad (3)$$

$$F_{build}^k = \begin{cases} 1, & P_{build,fun}^k > 0.5 \\ 0, & P_{build,fun}^k \leq 0.5 \end{cases} \quad (4)$$

2.4 Economic Impact Analysis

A Computable General Equilibrium (CGE) model serves as a robust tool for analyzing economic impacts, especially valuable in developing policies for disaster resilience. Grounded in core microeconomic theories, it provides a detailed evaluation of economic disruptions caused by natural hazards, including earthquakes, hurricanes, tornadoes, and floods (see studies by Rose and Liao, 2005; Rose et al., 2011, 2016; Cutler et al., 2016; Chen and Rose, 2018; Roohi et al., 2020, 2024; Attary et al., 2020; Wang et al., 2021; Amini et al., 2023). The model effectively replicates the impact on both commercial and residential assets within a community, detailing the economic consequences of physical damage. CGE models assess not only the immediate effects, such as workforce reductions and property losses but also explore the broader indirect effects that alter behavioral patterns and affect the interconnected market dynamics. Consequently, CGE modeling has become a preferred method for studying disaster effects and supporting the development and assessment of strategies for both pre-disaster preparedness and post-disaster recovery (e.g., Chen et al., 2017; Attary et al., 2020; Koc et al., 2020).

CGE models provide a detailed representation of the interactions between different economic sectors by utilizing a series of equations that illustrate the dynamics resulting from these interactions. Figure 2-5 demonstrates the structure of CGE model illustrating the flow of resources among four principal economic actors: households, firms, the government, and the neighboring economies referred to as the 'rest of the world' (ROW), emphasizing their integral roles within the economy. Households aim to maximize their utility by consuming products and services from firms and utilizing housing services. As price-takers, they make decisions based on complete information about prices in both goods and production factor markets. Their economic contribution includes providing labor and capital, with their primary income coming from wages and secondary income derived from returns on capital investments in businesses and real estate. Firms are driven by profit maximization and respond to market price signals as price-takers. They utilize labor and capital as their main inputs, quantified in terms of workforce numbers and the real dollar value of capital. The flexibility in adjusting these inputs, according to relative price changes, allows for some substitutability based on their elasticity. The government collects taxes from sales, income, and property, allocating this revenue to fund essential public services, including law enforcement and fire protection. It adheres to a balanced budget policy, ensuring that its spending equals its income, thus maintaining no surplus or deficit. The ROW interacts with the local economy by facilitating trade, which includes both imports and exports. This sector merges trade activities with both nearby and overseas economies, influencing resource flows. Exports from the local economy result in resource outflows, whereas imports contribute to resource inflows. The economy's gross

investment is supported by both domestic savings and capital inflows from the ROW.

The CGE model evaluates changes from both the supply and demand sides of an economy. Supply-side modifications are driven by variables like wages, input prices, technological innovations, and taxes. On the demand side, variations may arise from shifts in local household consumption, business investments, government spending, and regional exports. Dynamic CGE (DCGE) models extend these analyses over multiple time periods, which enables the exploration of economic variables' trajectories through time and the gradual adaptation of economies to new equilibria. Developing a dynamic CGE model enables the study of dynamic economic resilience by integrating disaster recovery policies, such as resource infusions that can accelerate the recovery process. Due to these features, DCGE models have been extensively employed by researchers to simulate the economic recovery following disasters and to assess the effectiveness of various recovery interventions (Xie et al., 2014, 2015; Cutler et al., 2016; Okiyama and Tokunaga, 2017; Fan and Davlasheridze, 2019; Shibusawa 2020; Li et al., 2022). These analyses have contributed significantly to understanding post-disaster economic dynamics and policy impacts.

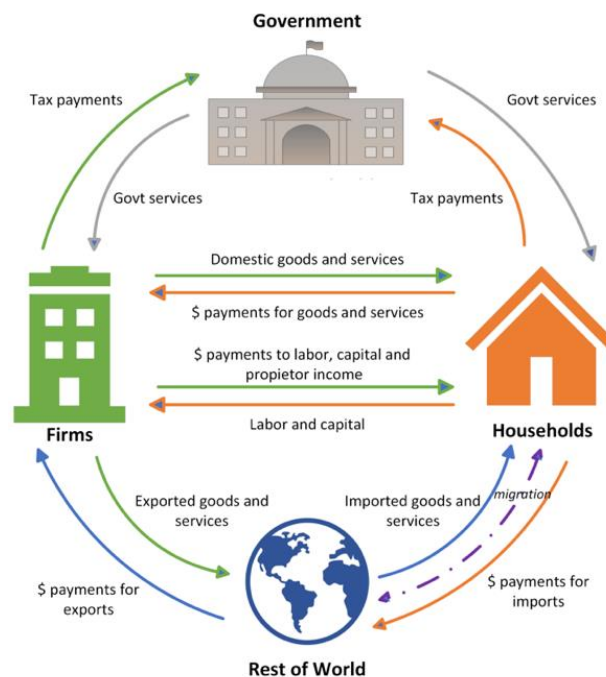


Figure 2-5: Structure of Computable General Equilibrium Model (Amini et al., 2023)

2.5 Proposed Multi-Disciplinary Resilience Metrics

Integrating the developed post-hazard functionality model with the CGE model enables an exploration of disaster impacts on the quality, quantity, and functionality of various structures and infrastructures. Essentially, by incorporating outputs from engineering models as external shocks, the CGE model can assess employment effects, sector-specific domestic supply, and variations in household income levels and distribution. This helps explore the diverse impacts of disasters on regional economies. The engineering model outputs include building functionality probabilities, which represent the likelihood of each building within a community remaining operational post-disaster, based on damage to critical infrastructure. Capital stock impacts at the building level are calculated by multiplying these functionality probabilities by the capital values of the buildings. These impacts are then aggregated to the relevant two-digit NAICS sectors and housing services, introduced into the model as exogenous shocks in the form of capital stock percentage reductions. For instance, when a commercial building sustains damage, its tenants may cut back or halt production temporarily. A significant outcome of this reduction is a decrease in labor demand, leading to wage losses. Consequently, households affected by these wage reductions experience a drop in income, which then lowers local consumer spending. Additionally, physical damage to residential properties adversely affects home equity. This decline in household wealth can result in reduced income and may prompt some residents to relocate from the area.

Cutler et al. (2016) introduced a dynamic spatial CGE model designed to evaluate the effects of earthquakes on economic, demographic, and fiscal dimensions. Their methodology integrates engineering hazard simulations into the CGE model via three pathways: (1) reductions in capital stock, (2) losses in intermediate inputs, and (3) decreases in total factor productivity. Their research offers an extensive examination of the immediate, widespread repercussions stemming from simulations targeting localized shocks that impact Centerville's buildings and transport systems. Roohi et al. (2020) applied building damage estimates within a CGE model to assess the macroeconomic impact of an earthquake in the Memphis Metropolitan Statistical Area, Tennessee, U.S. Attary et al. (2020) integrated building damage assessments into a CGE model, exploring various recovery scenarios and underscoring the differences in recovery aid timing. Amini et al. (2023) developed a method to evaluate the effects of multiple simultaneous hazards on economic resilience metrics, which cover both direct losses such as reductions in capital stock and broader economic impacts like changes in employment, domestic financial losses, and local tax revenues.

3. ANALYSIS AND DISCUSSION

3.1 Community Data Collection

For the current study, we selected three bedroom communities characterized by varying levels of household income: Rio Dell, East Richmond Heights, and Monte Sereno. Drawing on data from the U.S. Census Bureau, the Center for Economic Studies, LEHD, and Headwaters Economics, our findings indicate distinct demographic and economic profiles for each. Rio Dell has a population of 3,386, with 93.8% of its workforce commuting out, and a median household income of \$45,703. East Richmond Heights, with a population of 3,285, has an even higher rate of out-commuters at 98.8%, and a median household income of \$112,344. Monte Sereno, slightly larger, has a population of 3,444, 98.1% out-commuters, and a significantly higher median household income of \$250,001.

Bedroom communities primarily serve as residential hubs for individuals who work in adjacent urban or industrial zones. These areas are predominantly residential, featuring minimal commercial or industrial activities. Consequently, local job opportunities are scarce, compelling many residents to commute to larger cities for work. As outlined in Table 3-1, Rio Dell, East Richmond Heights, and Monte Sereno exemplify such communities with limited local employment. Rio Dell's workforce of 271 is mainly distributed across lower to middle income levels. East Richmond Heights, despite having the smallest workforce of 152, spans a higher income spectrum than Rio Dell. Meanwhile, Monte Sereno, with the largest number of workers at 368, predominantly occupies higher income levels, reflecting its status as the most affluent of the three communities.

The household income distribution data from Rio Dell, East Richmond Heights, and Monte Sereno, as shown in Table 3-2, display clear economic distinctions among these communities. Rio Dell's 1,371 households primarily fall in the sub-\$30K income bracket, with the fewest households earning between \$50K and \$90K. In contrast, East Richmond Heights, with a similar total number of households (1,373), has its largest group earning between \$100K and \$200K, indicating a generally higher income level compared to Rio Dell. Monte Sereno shows an even wealthier profile, with 1,270 households and the majority earning above \$350K, which is significantly higher than the top income brackets in the other two communities.

Table 3-3 offers a comparative overview of economic sectors and capital stock across three communities. Table 3-3 clearly demonstrates that all three communities' function primarily as bedroom communities with limited business sectors. Rio Dell lists 1,301 buildings with a capital

stock value of roughly \$150.6 million, predominantly consisting of lower-priced residential properties alongside modest commercial and service sectors. East Richmond Heights, with 1,460 buildings, shows more variety and higher property values, amounting to \$370.8 million, and includes a larger number of upscale residential properties than Rio Dell. Monte Sereno, the most affluent of the three, comprises 1,251 buildings with the highest total capital stock valued at \$595.2 million, incorporating premium residential properties.

Table 3-1: Characteristics of employment in three communities

Rio Dell		East Richmond Heights		Monte Sereno	
Labor groups	# of Workers	Labor groups	# of Workers	Labor groups	# of Workers
L1 <\$15K	70	L1 <\$30K	38	L1 <\$30K	89
\$15K ≤ L2 <\$30K	53	\$30K ≤ L2 <\$80K	50	\$30K ≤ L2 <\$100K	113
\$30K ≤ L3 <\$70K	94	\$80K ≤ L3 <\$130K	35	\$100K ≤ L3 <\$200K	92
\$70K ≤ L4	54	\$130K ≤ L4	29	\$200K ≤ L4	74
Total	271	Total	152	Total	368

Table 3-2: Characteristics of households in three communities

Rio Dell		East Richmond Heights		Monte Sereno	
Household groups	# of households	Household groups	# of households	Household groups	# of households
HH1 <\$30K	326	HH1 <\$50K	351	HH1 <\$130K	382
\$30K ≤ HH2 <\$50K	295	\$50K ≤ HH2 <\$100K	262	\$130K ≤ HH2 <\$250K	333
\$50K ≤ HH3 <\$90K	335	\$100K ≤ HH3 <\$200K	433	\$250K ≤ HH3 <\$350K	143
\$90K ≤ HH4	415	\$200K ≤ HH4	327	\$350K ≤ HH4	412
Total	1,371	Total	1,373	Total	1,270

Table 3-3: Characteristics of building inventory data in three communities

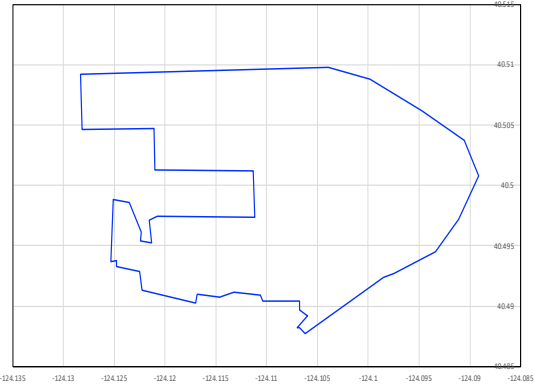
Rio Dell			East Richmond Heights			Monte Sereno		
Econmic sector	# of build-ings	Capital Stock Value (\$M)	Econmic sector	# of build-ings	Capital Stock Value (\$M)	Econmic sector	# of build-ings	Capital Stock Value (\$M)
HS1<\$100K	447	29.66	HS1<\$200K	503	81.2	HS1<\$400K	403	136.2
\$100K≤HS2<\$150K	590	70.08	\$200K≤HS2<\$300K	636	154	\$400K≤HS2<\$500K	447	200.1
\$150K≤HS 3	195	42.46	\$300K≤HS 3	287	108.5	\$500K≤HS3	354	222.3
Commercial	58	6.6	Commercial	13	6.8	Commercial	22	12.3
Education	2	0.7	Education	4	18.1	Education	1	14.4
Health	1	0.4	Professional	11	1.35	Health	3	1.2
Retail	8	0.8	Repair	6	0.9	Professional	21	8.7
Total	1,301	150.6	Total	1,460	370.8	Total	1,251	595.2

Note: "HS" represents housing services.

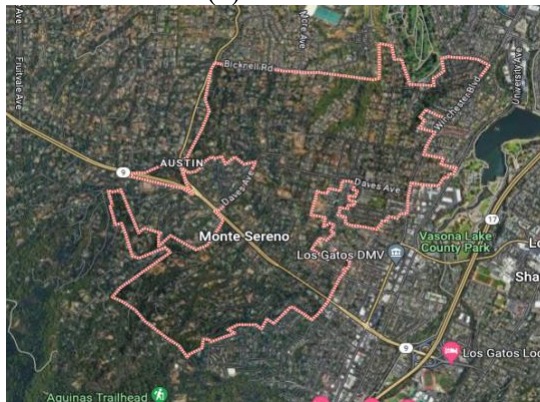
For buildings in Rio Dell, East Richmond Heights and Monte Sereno, the methodology described in Figure 2-2 is modified to incorporate the building data available from CSSC (2024) and generate the datasets for the buildings in the three communities. The main modification in the methodology described in Figure 2-2 is associated with masonry buildings. According to NSI (2024), the classification of the building type is based on the material commonly associated with exterior walls and structural stability (i.e., M = Masonry, W = Wood, H = Manufactured, S = Steel). For Rio Dell, around 38% of the buildings are masonry buildings according to NSI data. Though, the actual inspection of the buildings show that no more than 7% are masonry buildings while most the buildings are wood buildings. The reason for this discrepancy is that many buildings have exterior brick walls, leading NSI to classify them as masonry, even though the primary structural system is wood frame. Therefore, the methodology described in Figure 2-2 is modified to address this discrepancy.



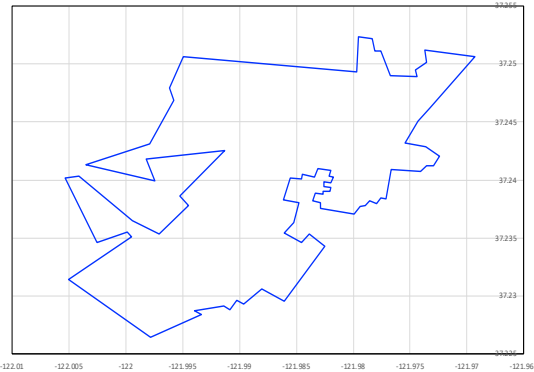
(a)



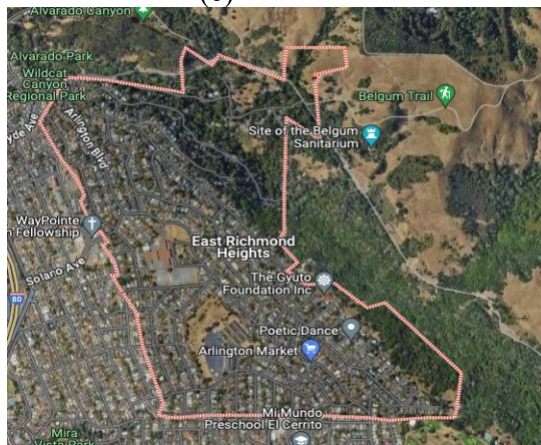
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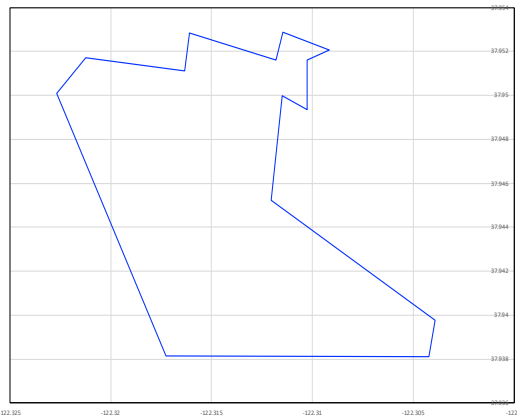
(c)



(d)



(e)



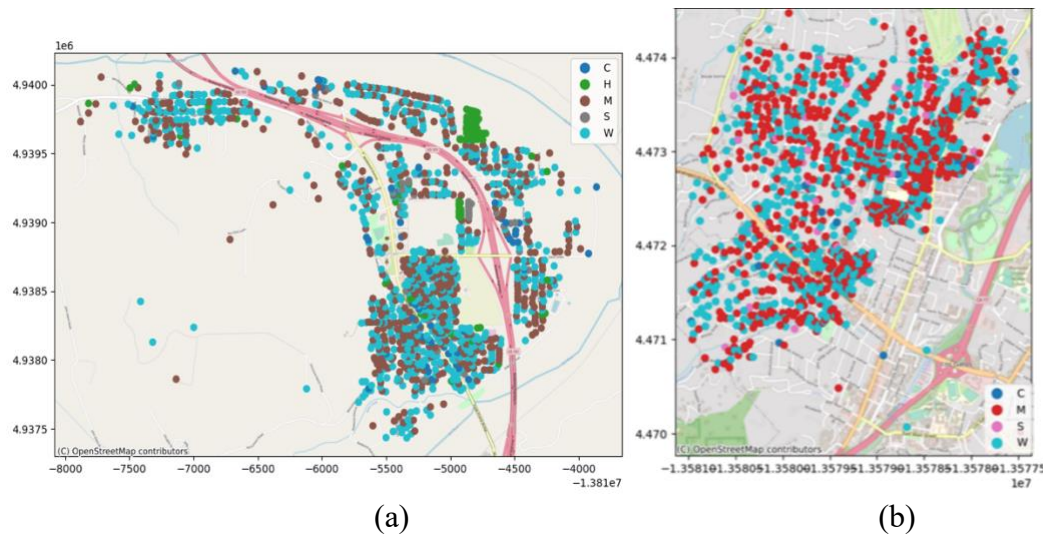
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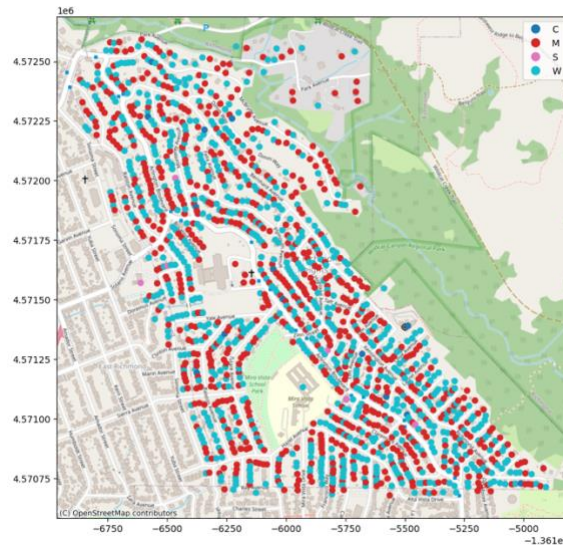
Figure 3-1: Boundaries of: (a) Rio Dell on Google Maps, (b) Rio Dell in MATLAB, (c) Monte Sereno on Google Maps, (d) Monte Sereno in MATLAB, (e) East Richmond Heights on Google Maps, and (f) East Richmond Heights in MATLAB

Table 3-4 lists the number of each building type in the three studied cities. In the three cities, most of the buildings are wood buildings (around 87% on average) which is typical in US communities with similar characteristics or size.

Table 3-4: Building types in three studied cities

	Rio Dell	Monte Sereno	East Richmond Heights
Wood	1128 (85.3%)	1090 (86.6%)	1090 (86.6%)
Concrete	61 (4.6%)	19 (1.5%)	19 (1.5%)
Steel	41 (3.1%)	38 (3.0%)	38 (3.0%)
Masonry	92 (7.0%)	111 (8.9%)	111 (8.9%)
Total	1322	1258	1460

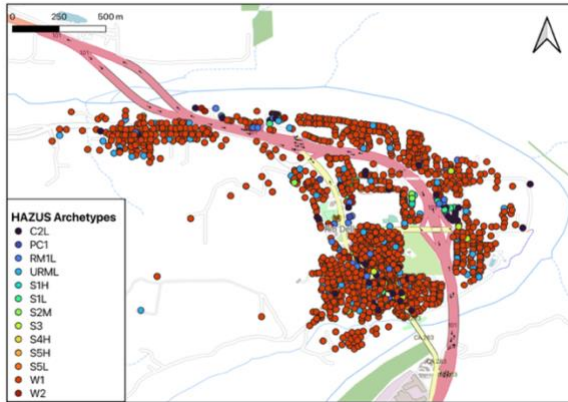




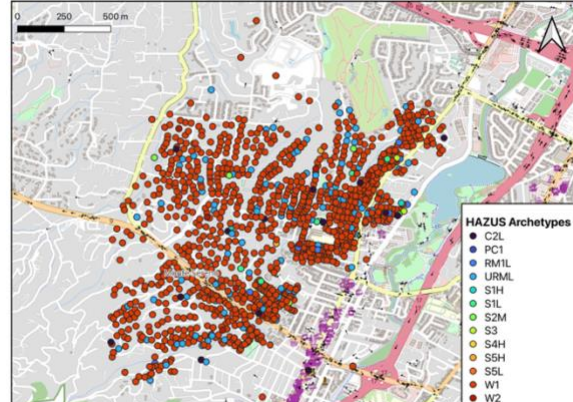
(c)

Figure 3-2: Building types from NSI database for: (a) Rio Dell, (b) Monte Sereno, and (c) East Richmond Heights

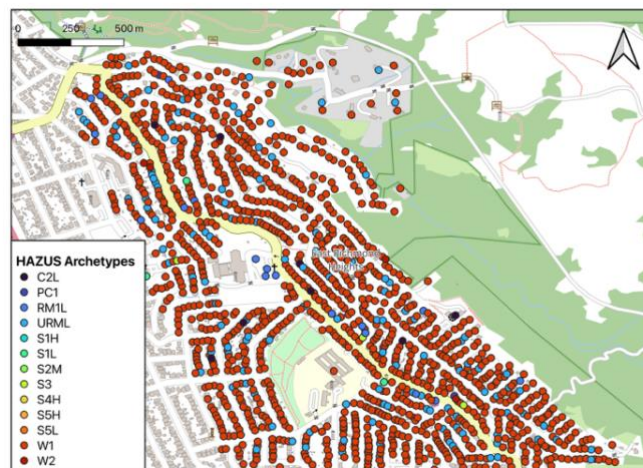
Figure 3-3 shows the spatial distribution of the mapped HAZUS archetypes of the buildings in the three cities. Whereas Table 3-5 lists the number of each HAZUS building archetype in the three cities studied. As shown, for the three cities, most of the buildings (around 91% on average) are either “W1” which are wood light frame buildings with area less than 5000 sq. ft. or “URML” which are unreinforced masonry bearing wall buildings. After mapping the data extracted from NSI dataset to HAZUS archetypes, the building attributes are then converted into shapefiles for the three cities to be able to be used in the INCORE analysis framework shown in Figure 2-1 as will be discussed in more detail in subsequent sections.



(a)



(b)



(c)

Figure 3-3: Mapped HAZUS archetypes for buildings in: (a) Rio Dell, (b) Monte Sereno, and (c) East Richmond Heights

Table 3-5: HAZUS building archetypes of the three studied cities

HAZUS Archetype	Rio Dell	Monte Sereno	East Richmond Heights
W1	1105 (83.5%)	1081 (85.9%)	1303 (89.2%)
W2	23 (1.7%)	9 (0.7%)	7 (0.5%)
S1L	10 (0.8%)	7 (0.6%)	3 (0.2%)
S1M	--	4 (0.3%)	--
S1H	7 (0.5%)	2 (0.2%)	0 (0%)
S2L	--	1 (0.1%)	--
S2M	8 (0.6%)	5 (0.4%)	0 (0%)
S3	13 (1.0%)	4 (0.3%)	3 (0.2%)
S4L	--	4 (0.3%)	--
S4M	--	7 (0.6%)	--
S4H	1 (0.1%)	--	--
S5L	1 (0.1%)	--	--
S5M	--	2 (0.2%)	0 (0%)
S5H	1 (0.1%)	2 (0.2%)	0 (0%)
C2L	59 (4.5%)	17 (1.4%)	13 (0.9%)
PC1	2 (0.2%)	2 (0.2%)	4 (0.3%)
RM1L	40 (3.0%)	12 (1%)	20 (1.4%)
URML	52 (3.9%)	99 (7.6%)	107 (7.3%)
Total	1322 (100%)	1258 (100%)	1460 (100%)

3.2 Seismic Hazard

The seismic hazard considered in the current report is the 2022 Ferndale earthquake which took place on December 20, 2022, at 10:34 UTC (2:34 p.m. local time), with the epicenter situated near the northern coast of California, roughly 15 km southwest of Ferndale and 30 km south of Eureka, California. While California is no stranger to earthquakes, this one was particularly severe for the area and was quickly followed by aftershocks, heightening the anxiety of residents and local authorities. This recent quake was caused by strike-slip faulting along a fault plane that likely oriented either southeast or southwest. According to the United States Geological Survey, its depth, focal mechanism, and location suggest it originated within the subducting Gorda plate. Although the epicenter was offshore, the fault moved onshore and ruptured in a northeastward direction.

The earthquake left many homes without power and led to disruptions in daily life across

Humboldt County. In the days following the main 6.4-magnitude earthquake near Ferndale on December 20, 2022, the region experienced numerous aftershocks, intensifying the challenges faced by residents and responders. These aftershocks ranged in magnitude, with several measuring between 3.0 and 4.0, and one notable aftershock having a magnitude of 5.4, adding to the structural strain on already compromised buildings and infrastructure.

The earthquake caused extensive structural damage in Ferndale and surrounding towns, leaving some buildings and homes uninhabitable. Cracks appeared in bridges, and roadways buckled, creating challenging conditions for emergency responders attempting to assess the damage and assist those affected. The aftershocks significantly complicated the response and recovery operations in Humboldt County. Emergency teams working to restore power, clear debris, and provide medical assistance had to proceed with extra caution, as ongoing tremors threatened to destabilize roads, buildings, and power lines further.

3.3 Building Damage and Functionality

Rio Dell experienced a comprehensive assessment of its buildings to measure the extent of damage caused by the earthquake (CSSC, 2024). The inspections adhered to ATC-20 guidelines, titled "Procedures for Post-Earthquake Safety Evaluation of Buildings," which offer a standardized and efficient method to evaluate structural safety. Trained inspectors performed rapid visual assessments, documenting their observations in a database for further analysis. The evaluations categorize building conditions into three levels: Minor/None, Moderate, and Severe. Based on the inspection and the judgment of the evaluation team, a posting is assigned as follows:

- Unsafe ("red tag"): Assigned when "Severe" conditions threaten the overall structural integrity of the building, making it unsafe for occupancy.
- Restricted Use ("yellow tag"): Applied when there are localized "Severe" issues, but the overall condition is "Moderate," allowing limited and controlled use of the building.
- Inspected ("green tag"): Given when "Minor/None" conditions are observed, meaning no immediate hazards are present. While some repairs may be necessary, there are no restrictions on the use or occupancy of the building.

Evaluations were conducted following the earthquakes on December 20, 2022, and January 1, 2023. Much of this information was documented in the California Governor's Office of Emergency Services (CA-OES) database. The assessments performed after the December earthquake did not include all the buildings in Rio Dell (only 590 buildings). Whereas the assessments performed after the January quake included revisiting buildings evaluated in

December, as the latter tremor could have caused additional damage, warranting adjustments to previous postings. These follow-up evaluations took place from Tuesday, January 3, to Wednesday, January 11, resulting in a database of 1346 building tags as will discussed in more detail later on. For the remainder of the report, the December 2022 seismic event is referred to as mainshock while the January 2023 seismic event is referred to as aftershock. The data used in this study were initial Safety Assessment Program (SAP) estimates obtained immediately following the 2022 Ferndale Earthquake and 2023 Aftershock. Later updates show that the actual number of red-tagged buildings is lower than originally recorded. However, because the same damage proportion was consistently applied across all three communities, the overall simulation results and conclusions remain unaffected.

Figure 3-4 and Table 3-6 summarize the posting of the buildings in Rio Dell following both the mainshock and aftershock. As shown, for both earthquakes, most of the inspected buildings are in the “green tag” state (79% of inspected buildings for mainshock and 77% of inspected buildings for aftershock). Whereas the percentage of buildings in the “yellow tag” state has increased from 16% of the inspected buildings after the mainshock to 19% of the inspected buildings following the aftershock. The percentage of the red tagged buildings is kept the same following the aftershock. Some of the reasons of the “red tag” posting in some of the buildings include but not limited to shifted exterior walls, falling chimneys, significant foundation movement, considerable interior shifting, shifted porch, and severe cracking.

Figure 3-5 shows the spatial distribution of the different building postings in Rio Dell following both earthquakes (i.e., mainshock and aftershock). As mentioned earlier and shown in Figure 3-5, only 590 buildings were included in the inspection after the mainshock. The focus of the current project is to study the effect of both the mainshock and aftershock on Rio Dell and potentially on similar communities (i.e., Monte Sereno and East Richmond Heights). Therefore, the damage data following the aftershock event is adopted throughout the remainder of the report. Also, the framework shown in Figure 2-1 is modified to employ the actual database resulted from the inspection effort performed on Rio Dell city instead of predicting the damage probabilistically using fragility curves as described earlier.

As mentioned earlier, the main aim of the current study is to investigate the effect of earthquake damage on the economic behavior of the communities. Therefore, the damage observed after both the mainshock and the aftershock in Rio Dell city is analyzed based on the economic sector each building belongs to. The buildings in Rio Dell are categorized into six categories based on their occupancies: commercial, residential, government, industrial, offices, and public assembly.

Figure 3-6 summarizes the postings of buildings in Rio Dell based on their occupancies. As shown, all of the red-tagged buildings are residential buildings (mostly single-family houses). Whereas 67% of the government buildings in Rio Dell are yellow tagged. The relatively large percentage of yellow tagged buildings in the government sector of Rio Dell is attributed to the small number of government buildings in Rio Dell. Rio Dell has three government buildings which are USPS building, City of Rio Dell wastewater treatment plant, and utility powerhouse. Two of these government buildings (i.e., Rio Dell wastewater treatment and utility powerhouse) were yellow tagged after the mainshock and aftershock event. Also as shown in

Figure 3-6, all commercial and office buildings were not affected by the seismic event (i.e., green tagged).

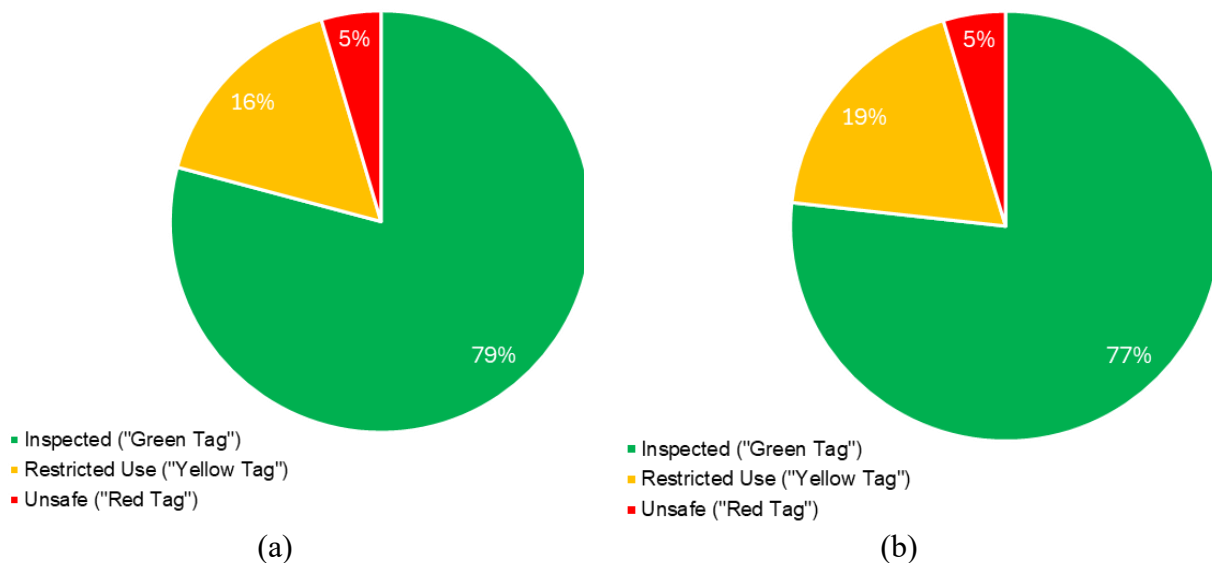
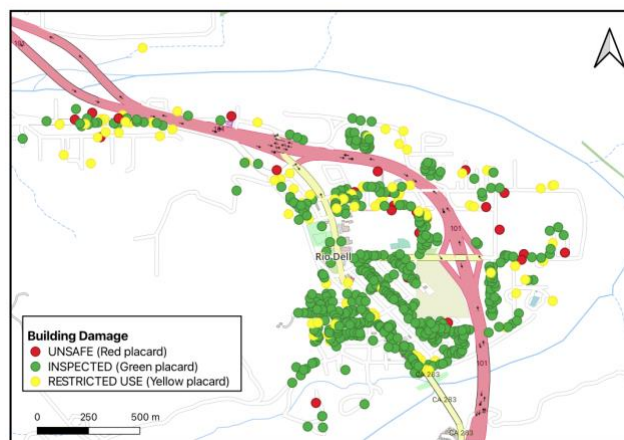


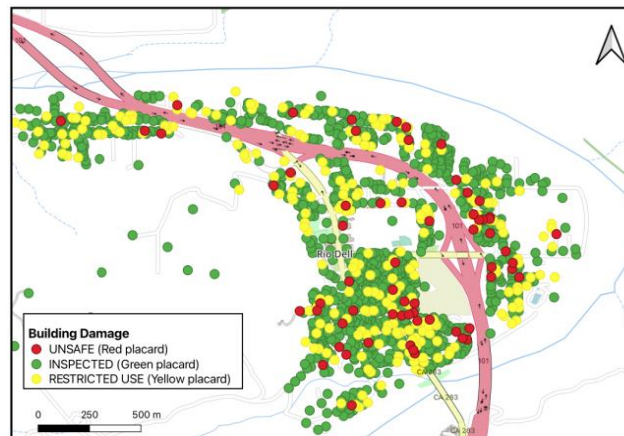
Figure 3-4: Distribution of post-earthquake posting for buildings of Rio Dell following the earthquake: (a) on December 20, 2022, and (b) on January 1, 2023

Table 3-6: Post-earthquake posting for buildings of Rio Dell

	After December, 20; Mainshock	After January, 1; Aftershock
Inspected ("Green Tag")	467 (79%)	1033 (77%)
Restricted Use ("Yellow Tag")	96 (16%)	250 (19%)
Unsafe ("Red Tag")	27 (5%)	63 (5%)



(a)



(b)

Figure 3-5: Spatial distribution of post-earthquake posting for buildings of Rio Dell following the earthquake: (a) on December 20, 2022, and (b) on January 1, 2023

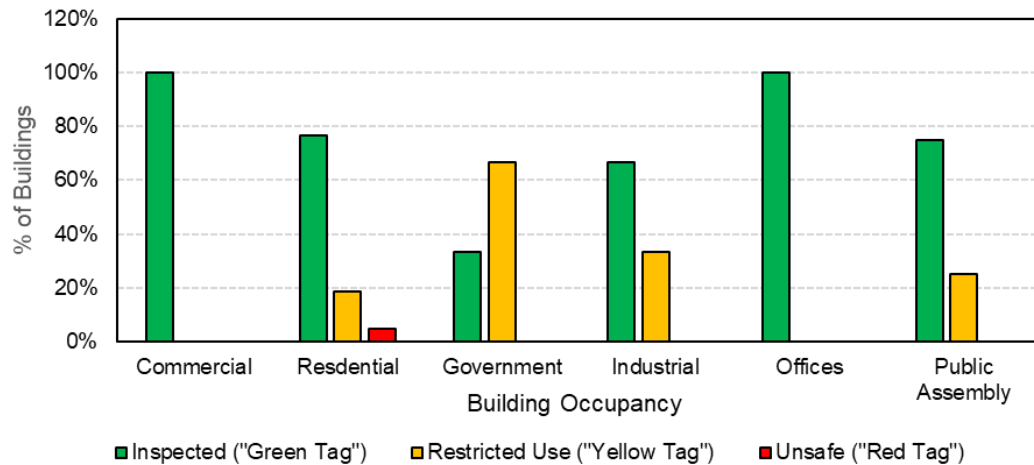


Figure 3-6: Distribution of postings of buildings in Rio Dell based on buildings occupancies

To be able to compare the economic impact of post-earthquake damage on the three communities, the damage distribution among the economic sectors in the three communities should match to have a parallel comparison. To do so, the post-earthquake damage in Rio Dell was distributed randomly among the buildings in the dataset for Rio Dell as discussed earlier. Figure 3-7 compares the spatial post-earthquake damage distribution for both the actual inspected buildings and the buildings in the developed dataset for Rio Dell. As shown, there is an overall agreement between the damage pattern in the actual inspected city (i.e., surveyed) and the developed dataset (i.e., modeled).

Figure 3-8 compares the post-earthquake damage distribution for both the actual inspected buildings and the buildings in the developed dataset for Rio Dell among the six sectors described earlier. As shown, there is an overall agreement between the damage pattern in the actual inspected city (i.e., surveyed) and the developed dataset (i.e., modeled) in all sectors. The differences observed in some sectors are due to the relatively small number of buildings belonging to these sectors (e.g., three buildings in the government sector as discussed earlier) making it infeasible to match the exact damage distribution probabilistically. Though, the impact of these differences will be accounted for probabilistically in a Monte Carlo simulation as will be discussed later on in this report.

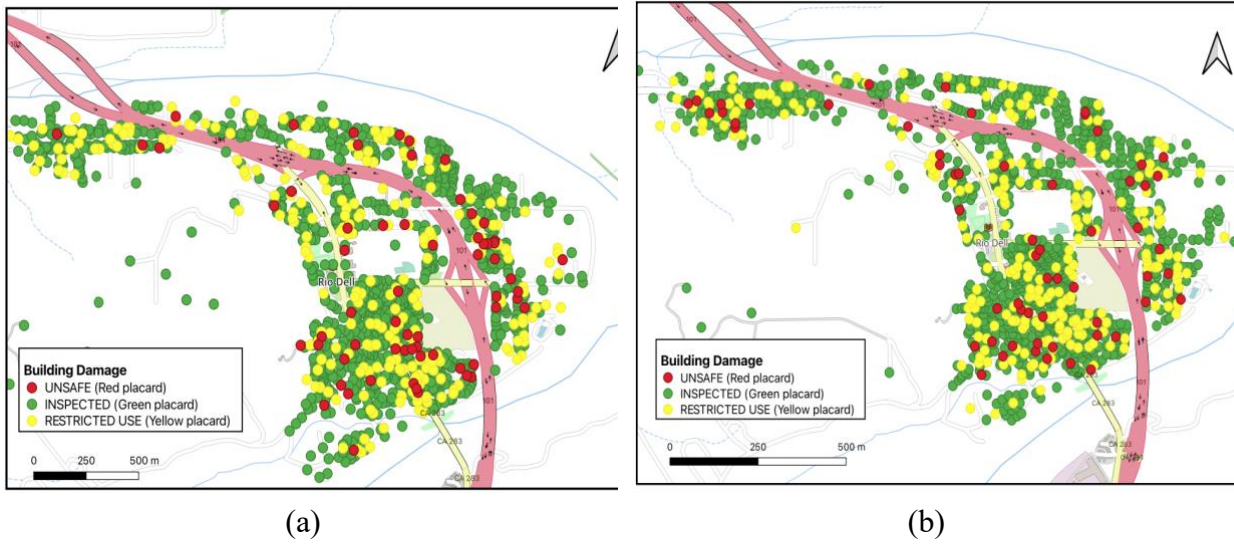
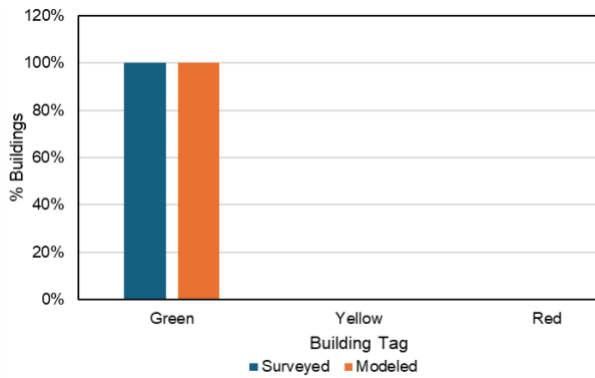
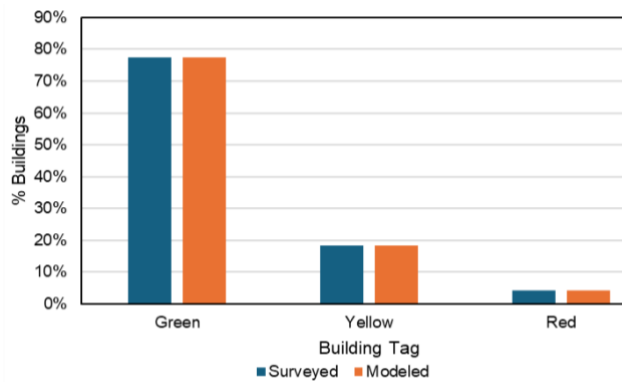


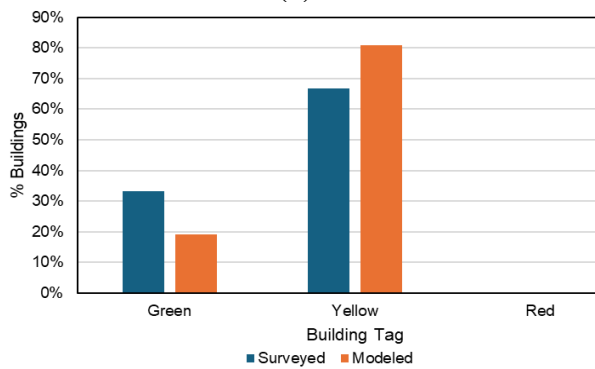
Figure 3-7: Spatial distribution of post-earthquake posting for buildings of Rio Dell in: (a) actual inspected buildings, and (b) developed building dataset



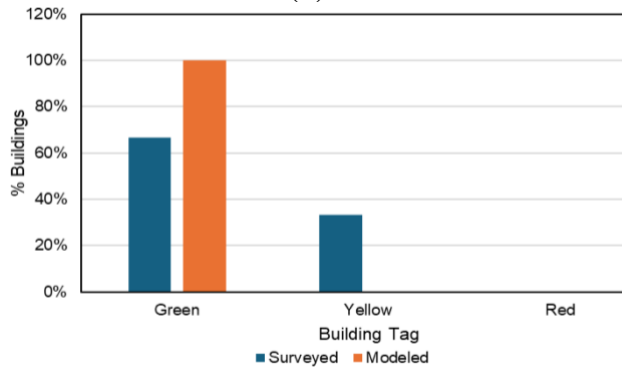
(a)



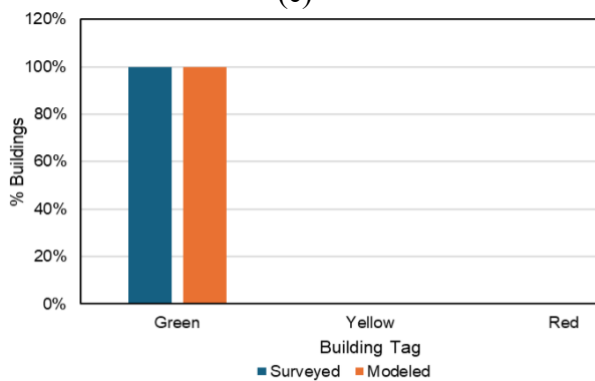
(b)



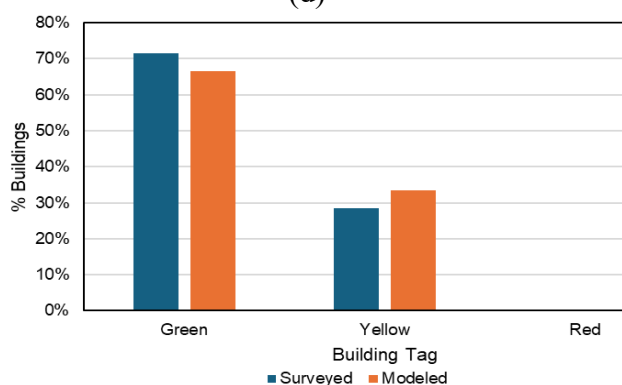
(c)



(d)



(e)



(f)

Figure 3-8: Comparison of post-earthquake posting of the buildings in Rio Dell for: (a) commercial, (b) residential, (c) government, (d) industrial, (e) offices, and (f) public assembly sectors

After applying the damage distribution of the buildings in the developed dataset for Rio Dell, the same distribution is applied randomly to all the buildings in both Monte Sereno and East Richmond Heights. It should be noted that the damage distribution among the six sectors described earlier is matched with the distribution of the surveyed buildings in Rio Dell. Figure 3-9 shows the spatial distribution of the post-earthquake posting for buildings of both Monte Sereno and East Richmond Heights.

Figure 3-10 and Figure 3-11 compare the post-earthquake tagging distribution of the actual surveyed buildings in Rio Dell and the modeled buildings in Monte Sereno and East Richmond Heights, respectively, among all six sectors. As shown, there is a general agreement between the post-earthquake tagging of the actual surveyed buildings for Rio Dell and the modeled buildings. Some differences are observed in certain sectors due to the relatively low number of buildings in these sectors as discussed earlier. The shown comparison provides confidence in the adopted approach for building damage and functionality modeling which will be used later to evaluate the economic impact on the three studied cities.

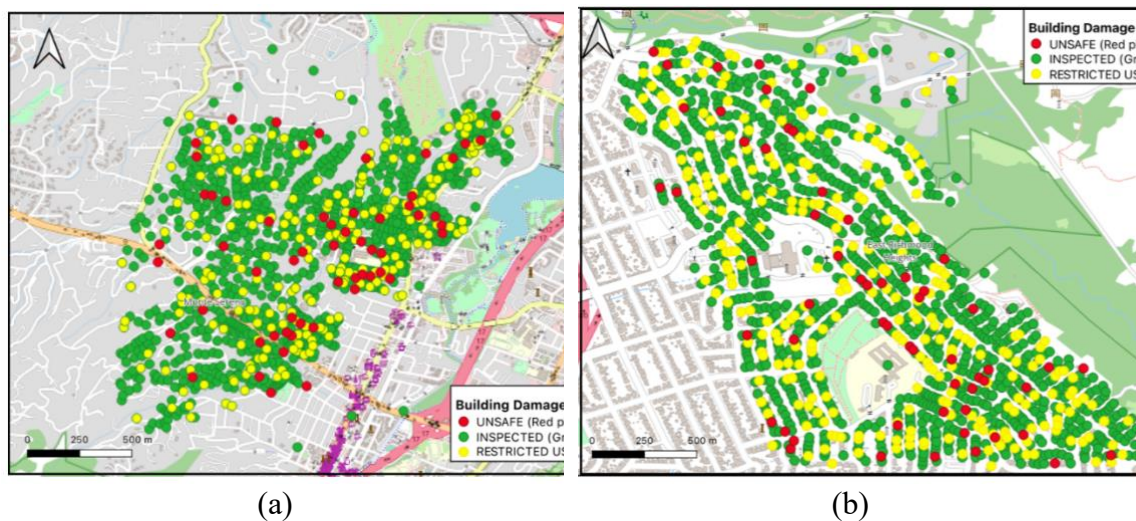
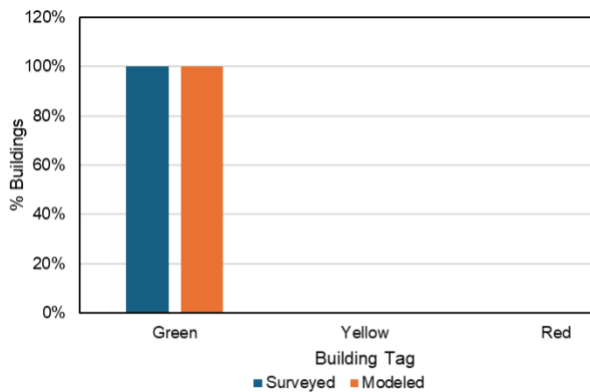
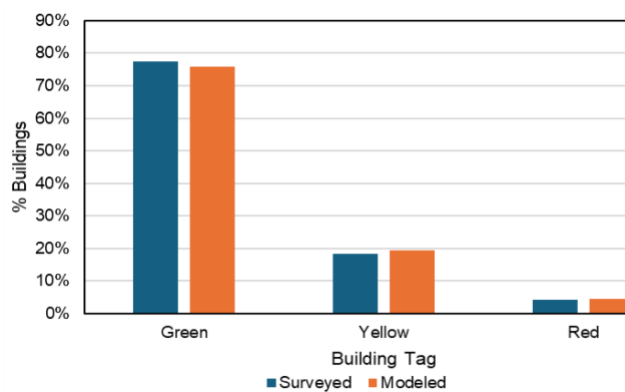


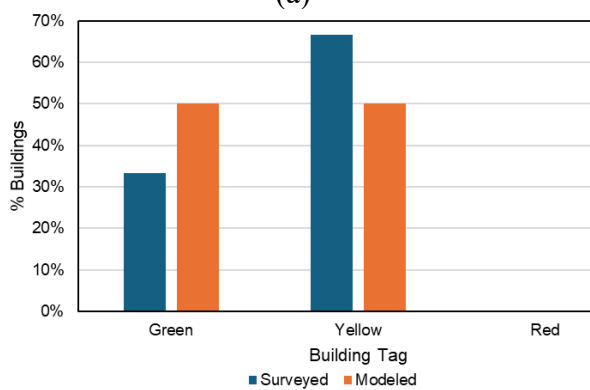
Figure 3-9: Spatial distribution of post-earthquake posting for buildings in: (a) Monte Sereno, and (b) East Richmond Heights



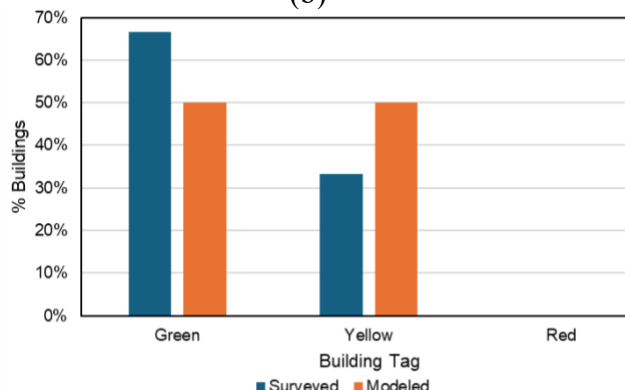
(a)



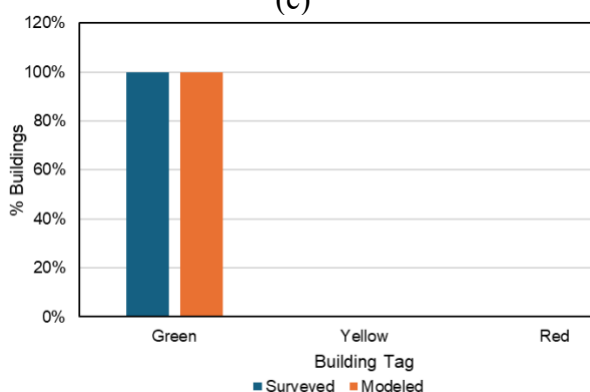
(b)



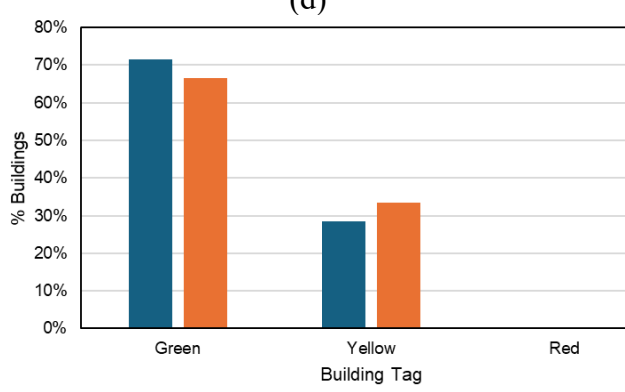
(c)



(d)



(e)



(f)

Figure 3-10: Comparison of post-earthquake posting of the actual buildings in Rio Dell and modeled buildings in Mont Sereno for: (a) commercial, (b) residential, (c) government, (d) industrial, (e) offices, and (f) public assembly sectors

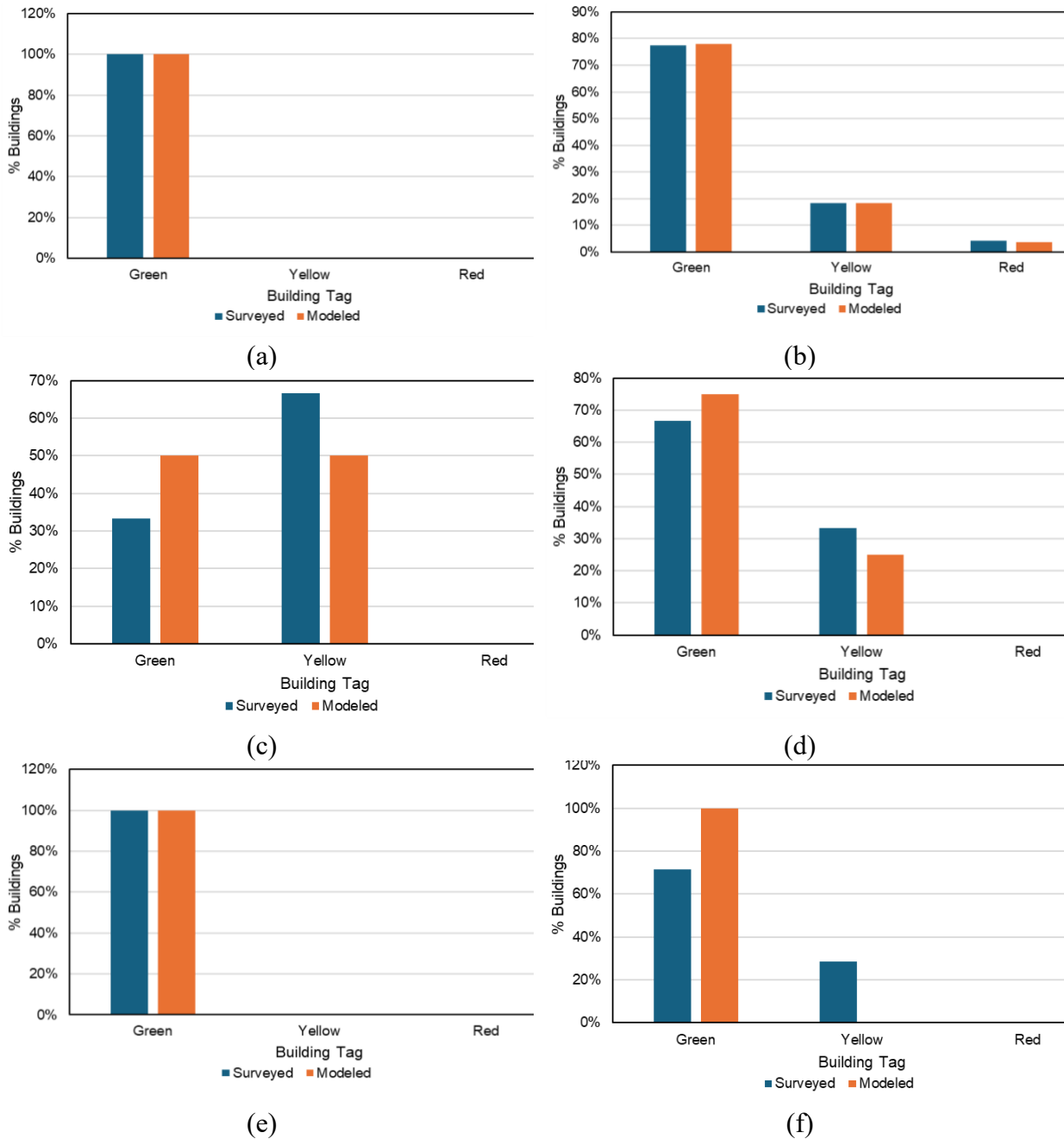


Figure 3-11: Comparison of post-earthquake posting of the actual buildings in Rio Dell and modeled buildings in East Richmond Heights for: (a) commercial, (b) residential, (c) government, (d) industrial, (e) offices, and (f) public assembly sectors

The six economic sectors described earlier (i.e., commercial, residential, government, industrial, offices, and public assembly) are based on the data received from the survey of the buildings in Rio Dell after the January aftershock event. These sectors are then refined more for the purpose of economic analysis to include more socioeconomic aspects of the community (e.g., household income). The economic sectors of the three communities are listed in Table 3-3.

The economic analysis requires the capital shock of each sector in the community. To do so, the capital shock of each sector is aggregated from the building level to the sector level by evaluating the probability of failure of each building in the community through a Monte Carlo simulation. Due to the special case of the current study where real data is available after a mainshock-aftershock event, the framework shown in Figure 2-1 is modified to be able to have perfect comparison between the three studied communities from all prospective (i.e., engineering, social, and economic).

Eq. 5 to 7 summarize the Monte Carlo simulation approach of evaluating the failure probability (which is translated into economic capital shocks as discussed later) of the economic sectors of the three studied cities. In each Monte Carlo simulation realization j ($j = 1$ to N), a uniformly distributed random number R_j is generated. The index j represents each iteration of the Monte Carlo simulation ($j = 1$ to N) for each building k . The generated random number is then compared with three post-earthquake posting probabilities for each building k in the community (i.e., P_{Green}^k , P_{Yellow}^k , and P_{Red}^k). These failure probabilities are based on the modeled percentage of the buildings in each posting category in the economic sector the building belongs to. These values are shown in Figure 3-8, Figure 3-10, and Figure 3-11 for Rio Dell, Monte Sereno, and East Richmond Heights, respectively.

Three states of failure are identified for each building k in the community based on the generated random number discussed earlier: 0 for the green tag posting, 0.5 for the yellow tag posting, and 1 for the red tag posting. These values correspond to the predicted functionality of the buildings based on their post-earthquake postings. It should be noted that these values are arbitrary and can be adjusted easily by the decision maker based on the community under investigation. Consequently, the probability of the building ($P_{build,fail}^k$) can be estimated using Eq. (6). The building failure probability is then aggregated to the economic sector level through Eq. (7)

$$I_{fail,j}^k = \begin{cases} 0, & R_j \leq P_{Green}^k \\ 0.5, & P_{Green}^k < R_j \leq P_{Yellow}^k \\ 1, & P_{Yellow}^k < R_j \leq P_{Red}^k \end{cases} \quad (5)$$

$$P_{build,fail}^k = \frac{\sum_{j=1}^N I_{fail,j}^k}{N} \quad (6)$$

$$P_{sector,fail}^m = \frac{\sum_{j=1}^{nbuild_m} P_{build,fail}^k}{nbuild_m} \quad (7)$$

Table 3-7 lists the probability of losing functionality throughout each sector in the three studied cities. As shown for Rio Dell, the most affected sector is the housing sector with low-income level (i.e., HS1 < \$100K) with a probability of failure of 0.201. On the other hand, the health and retail sectors are not affected. The commercial sector in Rio Dell is slightly affected by the seismic event with a probability of failure of 0.014. For East Richmond Heights, the most affected sector is the educational sector with a probability of failure of 0.147. This is attributed to the relatively low number of buildings in this sector making the damage of one building very effective in the whole sector. Another observation is that the probability of failure of the three housing sectors (low-, moderate-, and high-income sectors) are almost the same with a probability of failure of 0.134 for all of them. On the other hand, the professional and repair sectors are not affected by the seismic event.

The most affected sector in Monte Sereno is the healthcare sector with a probability of failure of 0.168. Similar to the educational sector in East Richmond Heights, the healthcare sector in Monte Sereno comprises a relatively low number of buildings leading to the relatively high probability of failure. The same trend in the housing sector observed in East Richmond Heights is seen in Monte Sereno with all the housing sectors having the same probability of failure of 0.134. Whereas the professional sector in Monte Sereno is not affected by the seismic event. Figure 3-12 shows a histogram for the probability of failure of all the buildings in the three studied cities which will be used later to evaluate the economic impact of the seismic event on the three communities.

Table 3-7: Sector failure probability in studied cities

Rio Dell			East Richmond Heights			Monte Sereno		
Econmic sector	# of build-ings	Failure Probab-ility	Econmic sector	# of build-ings	Failure Probab-ility	Econmic sector	# of build-ings	Failure Probab-ility
HS1<\$100K	447	0.201	HS1<\$200K	503	0.134	HS1<\$400K	403	0.134
\$100K≤			\$200K≤			\$400K≤		
HS2<\$150K	590	0.134	HS2<\$300K	636	0.134	HS2<\$500K	447	0.134
\$150K≤			\$300K≤			\$500K≤		
HS 3	195	0.141	HS 3	287	0.134	HS3	354	0.134
Commercial	58	0.014	Commercial	13	0.038	Commercial	22	0.064
Education	2	0.138	Education	4	0.147	Education	1	0.141
Health	1	0.000	Professional	11	0.000	Health	3	0.168
Retail	8	0.000	Repair	6	0.000	Professional	21	0.000

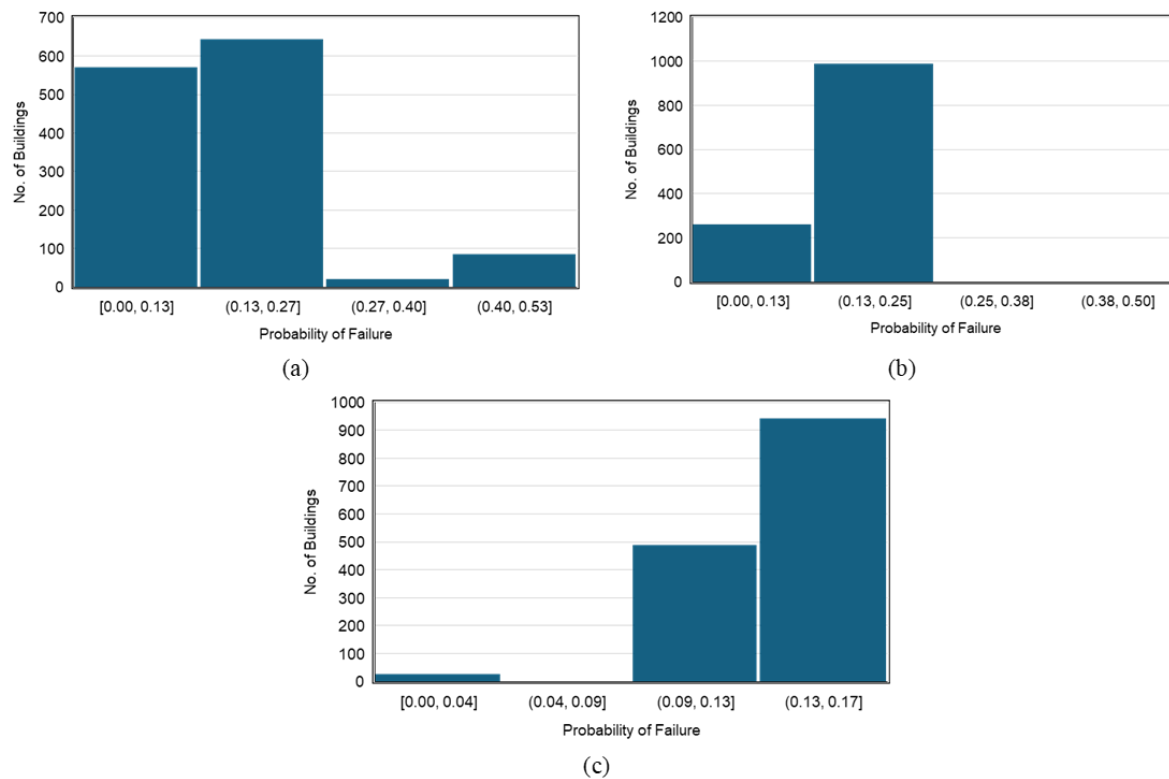


Figure 3-12: Probability of failure of the buildings in: (a) Rio Dell, (b) Monte Sereno, and (c) East Richmond Heights

3.4 Economic Impact and Recovery Between the three Sample Communities– No External Financial Assistance

This section provided the technical content of the computable general equilibrium (CGE) model and readers are referred to the executive summary for an overview in more general terminology.

In the economic model, a firm uses labor and capital to produce goods and services, represented by the generalized Constant Elasticity of Substitution (CES) production function defined as:

$$Y_{it} = \gamma_{it} \left[\sum_j \alpha_{ij} X_{ijt}^{\rho_i} \right]^{1/\rho_i} \quad (8)$$

where Y_{it} represents the total output for the sector i at time t and γ_{it} denotes the total factor productivity for that sector at time t . α_{ij} is a distribution parameter for input j in sector i . These parameters for each sector i must sum up to 1. X_{ijt} represents input j used in sector i at time t . ρ_i denotes substitution parameter specific to sector i , which influences the elasticity of substitution among inputs within that sector.

We assume a concave production function characterized by diminishing marginal returns, meaning that each subsequent unit of input yields progressively less output. As a result, when the same quantity of input is continuously added (assuming a constant cost per unit), each additional unit generates less output, despite the cost of each unit remaining unchanged.

In the simulation, we explore how variations in capital stock, influenced by building damage assessments and subsequently the loss of functionality of the buildings due to that damage, affect the local economy. This includes aspects such as domestic supply, employment, household incomes, local tax revenues, and household migration. Hazard-induced destruction leads to a reduction in capital stock across affected sectors. Specifically, the relationship between capital stock levels before and after a disaster can be described as:

$$K_{it} = \gamma_i K_{it-1}(1 - \delta) + N_{it} \quad (9)$$

where K_i represents the post-disaster capital stock for the sector i and K_{it-1} denotes the initial/pre-disaster capital endowment for the sector i at time t . N_{it} denotes gross investment in sector i at time t , and δ is the depreciation rate ($0 \leq \delta \leq 1$). γ_i can be externally defined, indicating the direct economic loss ratio of the sector i .

Damage to capital stock, an essential element for production, severely impacts the regional economy's ability to produce goods and services. When damage occurs to commercial and industrial buildings, it leads to a reduction in firms' production capacities, resulting in lower output. As capital grows scarce and more costly, companies adapt by reducing their capital investments and increasing their use of alternative resources, such as labor. These adjustments can escalate production costs and undermine a business's competitive edge in domestic and international markets. To counteract these financial burdens, companies often implement cost-saving measures,

including layoffs and reduced hiring, which contribute to higher unemployment and job losses. Consequently, affected households face income declines, reducing their spending power for goods and services. This decrease in consumer spending can weaken local businesses further, creating a cycle that deepens economic recessions and could lead to additional job losses.

Also, damage to capital stock directly affects household income by impacting wages, capital, and labor income. For example, households with substantial investments in local businesses see a decrease in capital income when commercial capital stock is damaged, which lowers overall household income. Similarly, damage to residential capital negatively impacts home equity, leading to further declines in household income and spending. These economic hardships might compel some residents to move in search of better economic opportunities.

When housing units are damaged or become uninhabitable, housing prices typically increase. This leads to higher household expenditure on housing services such as repairs or rent. Lower-income households, which often spend a larger share of their income on housing, are disproportionately affected by these price hikes. For example, in Rio Dell, the lowest income households (HH1) spend 46% of their income on rent (PUMS). Increased rental costs directly reduce these households' real income, limiting their spending on other goods and services. Moreover, the scarcity of affordable housing may lead to out-migration as individuals unable to afford the escalating costs leave the area. This outflow of residents can hinder economic recovery and resilience by diminishing the labor pool and lowering productivity. As a result, this may intensify the economic slump, continuing a cycle of decline that is challenging to overcome.

In response to capital damage, there is often increased investment in rebuilding and repairing damaged capital. This shift in resources can boost demand for construction, possibly reducing capital prices by increasing capital supply. Over time, as the capital stock is rebuilt, the capacity to produce goods and services returns, potentially leading to stabilization once supply reaches pre-damage levels.

Table 3-8 provides an overview of capital stock losses in various business sectors within Rio Dell, East Richmond Heights, and Monte Sereno. Rio Dell recorded a capital stock loss of \$21.5 million, accounting for 14.3% of its total capital, with the most severe losses occurring in its less expensive residential sectors, including a 20% loss in its lowest housing category. East Richmond Heights experienced greater losses, totaling \$49 million or 13.2% of its capital, with notable reductions spread across residential and educational sectors. As a wealthy community, Monte Sereno suffered the most considerable dollar loss at \$77.8 million, but it represents the lowest capital loss at 13.1% of its total, with significant decreases noted in the more expensive residential and health services sectors.

Table 3-8: Capital stock losses for the earthquake in three communities

Rio Dell			East Richmond Heights			Monte Sereno		
Business sector	Capital Stock Loss (\$M)	Capital Stock Loss (% of total)	Business sector	Capital Stock Loss (\$M)	Capital Stock Loss (% of total)	Business sector	Capital Stock Loss (\$M)	Capital Stock Loss (% of total)
HS1<\$100K	-5.93	-20.0%	HS1<\$150K	-10.8	-13.3%	HS1<\$400K	-18.1	-13.3%
\$100K≤	-9.39	-13.4%	\$150K≤	-20.6	-13.4%	\$400K≤	-26.8	-13.4%
HS2<\$150K			HS2<\$300K			HS2<\$500K		
\$150K≤HS3	-5.99	-14.1%	\$300K≤HS3	-14.5	-13.4%	\$500K≤HS3	-29.8	-13.4%
Commercial	-0.09	-1.4%	Commercial	-0.3	-3.9%	Commercial	-0.8	-6.6%
Education	-0.1	-14.8%	Education	-2.8	-15.3%	Education	-2.0	-14.2%
Health	0	0	Health	0	0	Health	-0.2	-16.6%
Retail	0	0	Retail	0	0	Professional	0	0
Total	-21.5	-14.3%	Total	-49.0	13.2%	Total	-77.8	-13.1%

This study not only examines the immediate economic impacts of the earthquake but also investigates how different communities progress in their recovery efforts. Previous studies highlight the critical role of insurance, savings, and loans in helping households rebound after disasters. (Collier and Ellis, 2024) surveyed 474 people impacted by severe hurricanes from 2017 to 2021, discovering that half of these households relied on savings to address uninsured damages, while around 20% used credit cards. On the other hand, (Ratcliff et al., 2022) found that about a quarter of consumers do not have emergency savings, and roughly 40% have saved less than one month's income for emergencies. Although many depend on savings for disaster-related costs, these funds often do not fully cover expenses. (Brevoort et al., 2021) pointed out that households may also withdraw from less accessible assets, such as retirement accounts, which come with tax advantages but also penalties for early access. Concerningly, about one-quarter of working adults do not have any retirement savings, and of those who do, two-thirds are not saving adequately. While the role of insurance, savings, and loans in supporting disaster recovery is well recognized, there is still a substantial lack of research on how households across different income levels utilize private loans under these circumstances.

We analyzed data from the California Department of Insurance which revealed that earthquake insurance coverage among households varies significantly across communities: 5% in Rio Dell, 13% in East Richmond Heights, and 23% in Monte Sereno. We established a criterion

that only households earning more than \$100,000 annually are considered capable of affording earthquake insurance. Using this income threshold, we estimated that 69 households in Rio Dell have earthquake insurance. Based on household expenditure patterns on housing services across different income brackets, we calculated that 3 residential buildings in HS1, 14 in HS2, and 52 in HS3 are insured. To calculate the estimated insurance payments, we used the average square footage for each housing service sector combined with a replacement cost of \$275 per square foot, which reflects the average construction cost in California. The formula for the deductible is calculated as square footage multiplied by replacement cost and a percentage set in the policy. For the insurance payment, it is square footage multiplied by failure probability and replacement cost in excess of the deductible. Additionally, with a deductible set at 15%, only those housing service sectors that sustain damage exceeding 15% will receive an insurance payout. Consequently, it was found that only a select number of residential units in HS1 qualify for insurance benefits described in Table 3-9.

Table 3-9: Estimated insurance payments for housing service sectors in Rio Dell

	HS1	HS2	HS3
Average sqft	1,226	1,958	2,866
Average failure Probability	20%	13%	14%
Replacement Cost	275	275	275
15% Damage Threshold (\$)	50,573	80,768	118,223
Average Damage Value (\$)	67,430	69,999	110,431
Insured Units	3	14	52
Total Insurance Payments (\$M)	\$0.051	0	0

To estimate the use of personal savings and retirement plans for recovery efforts, we established thresholds according to annual income levels: 5% for those from \$150K to \$200K and 10% for incomes above \$200K. Table 3-10 displays the estimated total amount of savings drawn from personal savings and retirement plans across the three communities.

Table 3-10: Estimated savings utilized from personal savings and retirement plans

Community	Income Threshold	Annual Income (\$M)	Saving Threshold	Utilized Saving (\$M)
Rio Dell	150K<HH<\$200K	9.53	5%	0.48
	HH>200K	15.85	10%	1.59
East Richmond Heights	150K<HH<\$200K	25.57	5%	1.28
	HH>200K	93.51	10%	9.35
Monte Sereno	150K<HH<\$200K	69.22	5%	3.46
	HH>200K	879.66	10%	87.97

Considering spending patterns, we calculated the total savings used for reconstructing damaged residential housing units, as outlined in Table 3-11.

Table 3-11: Estimated savings utilized for each housing service sector across three communities

Housing Sector	Capital Stock Loss (\$M)	Utilized Saving (\$M)	Ratio of Savings to Capital Stock Loss
Rio Dell			
HS1<\$100K	-5.93	0.10	2%
\$100K≤HS2<\$150K	-9.39	0.41	4%
\$150K≤HS3	-5.99	1.55	26%
East Richmond Heights			
HS1<\$150K	-10.8	1.19	11%
\$150K≤HS2<\$300K	-20.6	4.25	21%
\$300K≤HS3	-14.5	5.19	36%
Monte Sereno			
HS1<\$400K	-18.1	5.26	29%
\$400K≤HS2<\$500K	-26.8	27.43	102%
\$500K≤HS3	-29.8	58.74	197%

We assume that both savings and insurance payments are utilized six months after the earthquake. In the simulation, adjustments are made to key elasticities to reflect short- and long-term periods. These adjustments include the elasticity of substitution in the production function, domestic share price elasticities, and land elasticity. Consequently, each period in the simulation represents a timeframe of six months (Kajitani and Tatano, 2018).

The simulations in DCGE model describes how the economy responds to damage from earthquake and savings and insurance payments to start rebuilding or replacing the damaged capital stock. The investment, capital stock equations are central here:

$$N_{it} = N_{it-1} \left(\frac{R_{it}}{R_{it-1}} \right)^{ETAIX} \quad (10)$$

$$K_{it} = \rho_i K_{it-1} (1 - \delta) + N_{it} \quad (11)$$

where N_{it} represents the investment in sector i during period t . N_{it-1} refers to the baseline data derived from the SAM, reflecting the value from the previous period. R_{it} indicates the current rate of return on investments at the sector level, while R_{it-1} denotes the rate of return in the base period. Consequently, $\left(\frac{R_{it}}{R_{it-1}} \right)$ captures the relative rate of return. ETAIX is a positive elasticity parameter, which is assumed to have a value of one. At $t = 1$, the model represents the state of the economy immediately following the earthquake.

To model the impact of savings and insurance six months after the event, we exogenously increase, N_{it-1} in the housing services sectors. This adjustment operates through two channels. First, it generates a short-term aggregate demand effect by increasing the need for intermediate inputs and labor to produce the new capital. Second, once the new capital is in place, it becomes an input in the production function, leading to a subsequent boost in economic output.

The figures below, Figure 3-13 to Figure 3-15 illustrate the recovery trajectories of three communities, highlighting significant differences in economic recovery patterns after the simulated earthquake scenarios. These variations are observed across key metrics, including employment, real household income, domestic supply, tax revenue, and migration.

In Rio Dell, the recovery trajectory shows a slow and gradual improvement. Both employment and tax revenue increase steadily over the simulation periods, but the recovery of real household income lags behind. This slower improvement in household income, despite rising employment, points to ongoing issues with household financial stability, largely driven by increased expenses on housing services. Although some residents rely on savings and insurance payouts to repair damaged homes, these resources make up only 9.7% of the total capital lost in all housing sectors of Rio Dell. As a result, the local economy struggles to return to its pre-earthquake levels. By period 14, the economy exhibits signs of stabilizing, suggesting that the

recovery could be approaching an equilibrium. It is important to note that the City of Rio Dell¹ reports a decrease in local government tax rates by 2.14% from FY 2021-2022 to FY 2022-2023. Simulations also show a corresponding reduction in local tax revenue by 1.93%. This coherence between reported data and simulated outcomes not only validates the accuracy of our models but also reinforces the reliability of our analysis. The consistency of the simulation results with real-world data provides a robust foundation for our conclusions, suggesting that the assumptions regarding economic behavior and policy impact are well-founded. Furthermore, the City of Monte Sereno reported a 5.10% increase in local government tax revenues during the same period, while Contra Costa County saw a 3.48% increase². This contrast supports the conclusion that the earthquake contributed significantly to the decline in tax revenue for Rio Dell.

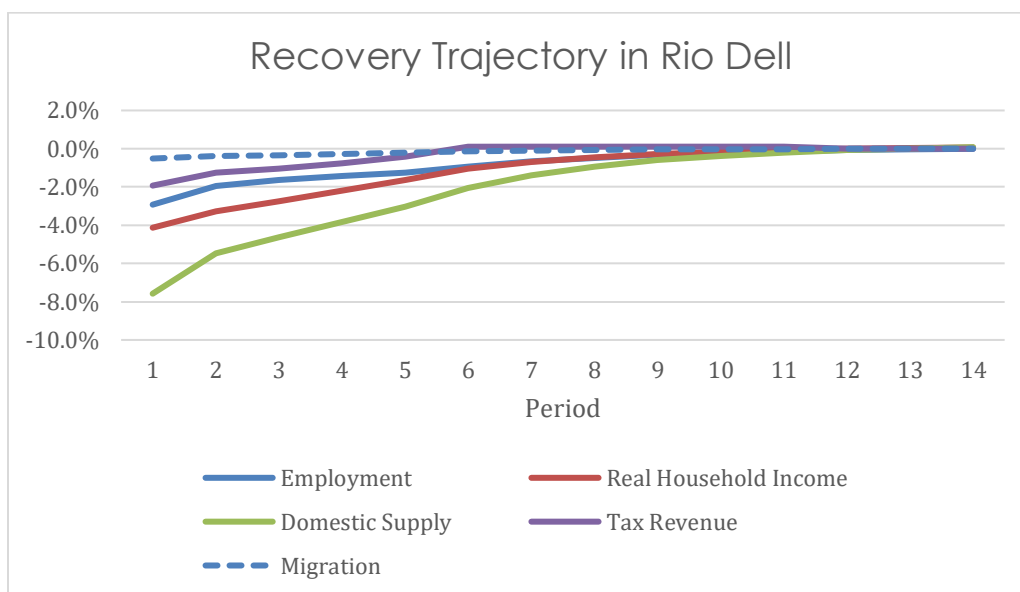


Figure 3-13: Recovery trajectory in Rio Dell across simulated periods

In East Richmond Heights, the initial reduction in domestic supply within the housing services sectors is less severe compared to Rio Dell. Furthermore, approximately 23.2% of the total capital stock loss in the housing services sectors is supported by utilized savings. This contributes to a moderate recovery, particularly in domestic supply and real household income.

¹ <https://www.cityofriodell.ca.gov/transparency/pages/city-budgets>

² Annual Comprehensive Financial Reports from City of Monte Sereno (<https://www.montesereno.org/2187/Finance-Department>) and Contra Costa County (<https://www.contracosta.ca.gov/770/Budget-Documents>)

Moreover, migration and local tax revenue trends stabilize more quickly than in Rio Dell, highlighting the community's greater overall resilience in economic and social recovery. By the 13th period, indications of economic stabilization suggest that the economy could be nearing a recovery to its equilibrium levels.

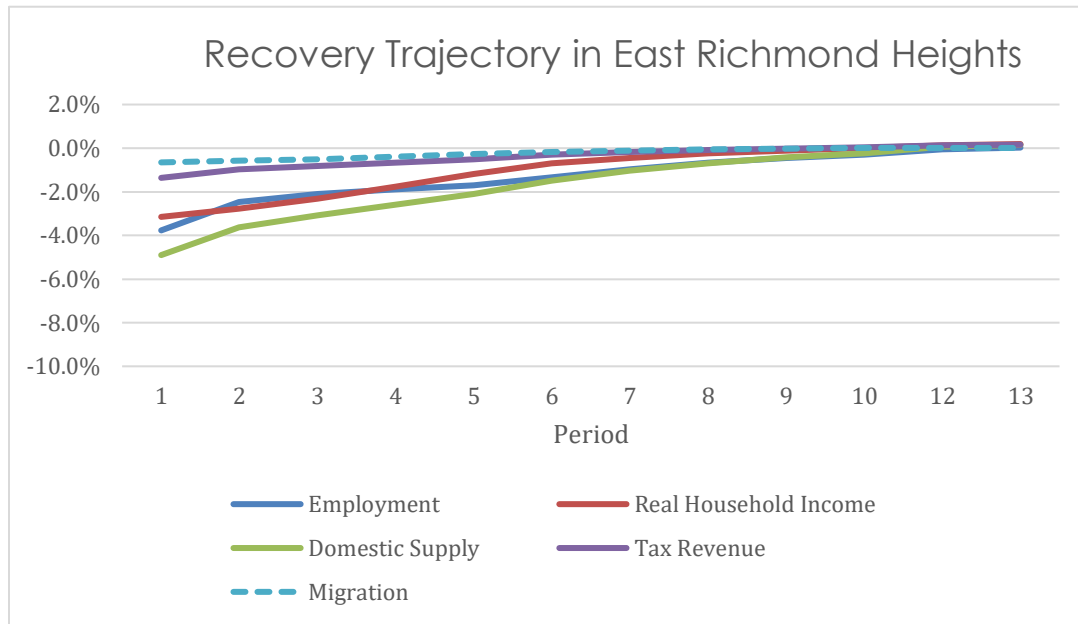


Figure 3-14: Recovery trajectory in East Richmond Heights across simulated periods

It is important to note that the earthquake causes comparatively less damage to the housing sectors in East Richmond Heights than in Rio Dell, and more savings were deployed in response. In East Richmond Heights, Education is the predominant economic sector in terms of employment. Unlike the other two communities, over 42% of local workers are employed in this sector. Therefore, the slower recovery in the Education sector significantly influences the overall economic recovery, resulting in no notable differences in economic rebound when compared to Rio Dell.

Monte Sereno demonstrates the fastest recovery among the three communities, with employment, real household income, and tax revenue nearing or even surpassing pre-earthquake levels during the simulated periods. Although the initial damage, particularly in the housing sectors, was as severe as in East Richmond Heights, the community's wealth played a crucial role in recovery. Personal savings equivalent to 122.4% of the total capital stock loss in housing service sectors were utilized, significantly aiding recovery efforts. This allowed Monte Sereno's domestic

supply to rebound more effectively than in East Richmond Heights and Rio Dell, indicating a stronger production recovery capacity. Furthermore, migration trends in Monte Sereno stabilized more quickly, highlighting the community's robust resilience to the earthquake's economic challenges. By period 7, there are indications that the economy is stabilizing, suggesting that it might be nearing a state of equilibrium.

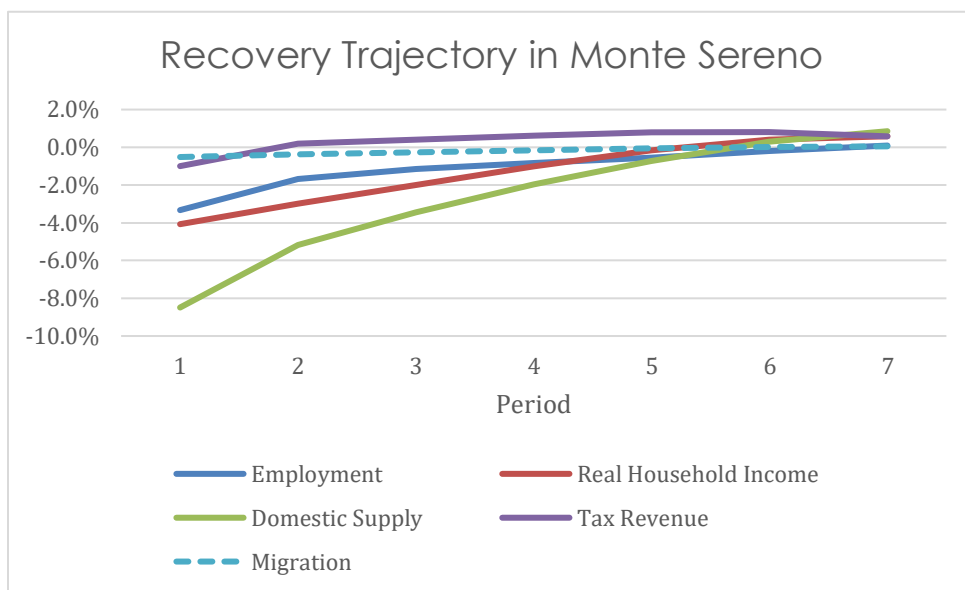


Figure 3-15: Recovery trajectory in Monte Sereno across simulated periods

Additionally, although East Richmond Heights and Monte Sereno both suffered similar damage in their housing service sectors, Monte Sereno experienced a significant reduction in domestic supply after the earthquake. This was largely due to the substantial influence of its high-value housing service sector on the local economy, which encompasses construction and real estate activities. Furthermore, Monte Sereno could promptly deploy personal savings, exceeding the total capital stock losses in these sectors. However, the housing sector is typically labor-intensive, meaning capital and labor tend to complement rather than substitute each other. Effective output enhancement requires proportional increases in both. Thus, any delay in labor adjustments can impede the efficient utilization of new investments and slow the recovery process.

The next three figures, Figure 3-16 to Figure 3-18 depict the recovery trajectories of domestic supply for housing sectors HS1 through HS3 in three different communities over the

course of the simulation periods. In Rio Dell, a clear divergence is observed among the three housing sectors throughout these periods. Initially, HS1 undergoes a markedly sharper decline than HS2 and HS3, indicating that HS1 is more adversely affected and experiences a slower recovery in Rio Dell. As detailed in Table 3-12, only 2% of the capital stock losses in HS1 are covered by savings, in contrast to 4% in HS2 and 26% in HS3. Variations in initial damage and the allocation of savings for reconstruction result in significantly different recovery paths, with HS1 exhibiting the slowest recovery trajectory among the three sectors in Rio Dell. In detail, the domestic supply for HS1 and HS2 reach equilibrium by periods 18 and 17, respectively, while HS3 achieves equilibrium by period 11. East Richmond Heights presents a contrasting situation where the domestic supply for all housing sectors begins simultaneously and maintain close alignment throughout the simulation. They ultimately achieve equilibrium by period 14 for HS1, period 12 for HS2, and period 10 for HS3. This pattern suggests a consistent impact or response to the prevailing conditions across the domestic supply for housing sectors in this community.

Monte Sereno displays distinct recovery dynamics, particularly with faster recovery patterns. As previously observed, Monte Sereno efficiently utilizes available savings for reconstruction, particularly in HS3. This accelerates the recovery process and generates a temporary boost in economic activity before stabilizing at the long-run equilibrium. Specifically, the domestic supply for HS3 attains equilibrium by period 5, while HS1 and HS2 reach equilibrium by periods 9 and 7, respectively. Compared to other communities, domestic supply for all three housing service sectors in Monte Sereno demonstrates a quicker recovery.

Despite the ability to fully utilize their savings, recovery times do not necessarily accelerate. This can be attributed to the characteristics of the production function in the model, where the low elasticity of substitution between labor and capital in the labor-intensive housing sector causes them to act more as complements than substitutes. This requires proportional increases in both to boost output. Furthermore, delays in labor adjustment can impede the efficient utilization of new investments. Housing reconstruction demands specific materials and skilled labor, which may highlight rigidities in local labor markets such as skill mismatches and mobility constraints. Even in affluent communities with sufficient financial resources, the local availability of critical construction resources like labor and materials may still face limitations, particularly if demand surges unexpectedly following a disaster.

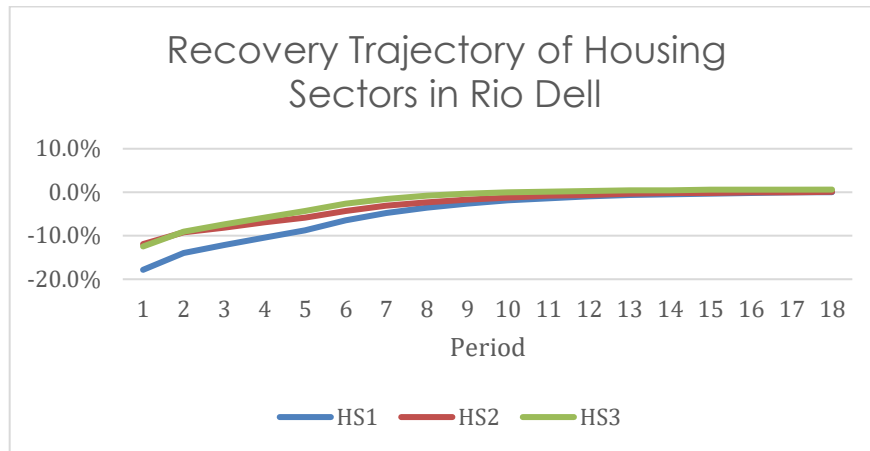


Figure 3-16: Recovery trajectory of housing sectors in Rio Dell across simulated periods

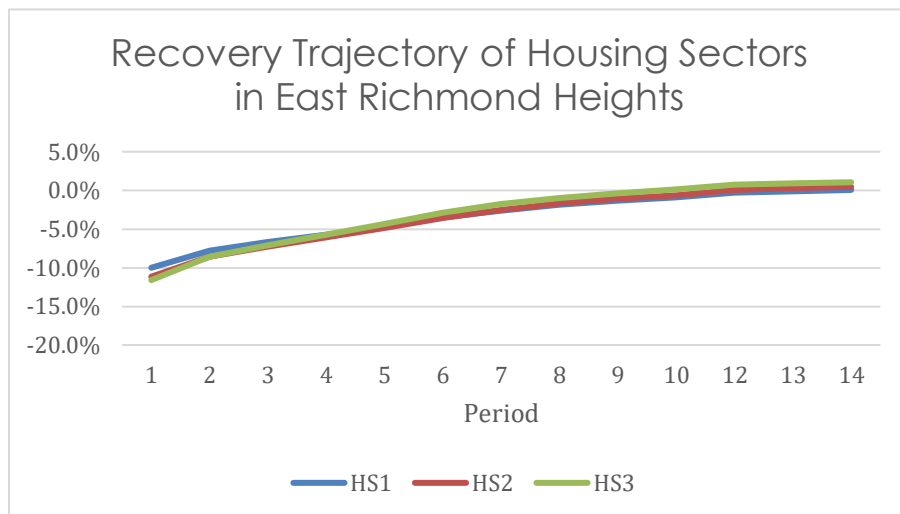


Figure 3-17: Recovery trajectory of housing sectors in East Richmond Heights across simulated periods

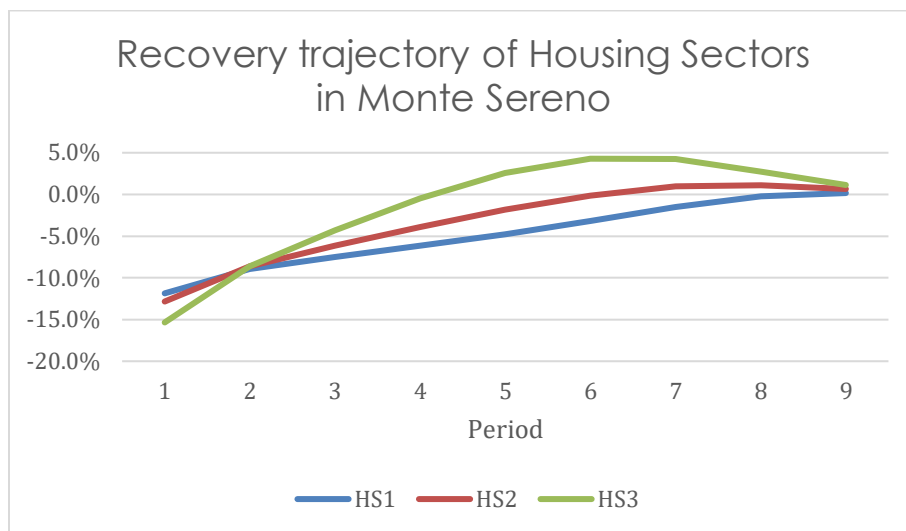


Figure 3-18: Recovery trajectory of housing sectors in Monte Sereno across simulated periods

3.5 Economic Impact and Recovery – External Financial Assistance from FEMA

In this section, we conduct simulations to assess the impact of external financial assistance from FEMA on recovery efforts. According to the California Office of Emergency Services (Cal OES), in 2023 the average FEMA IA grant awarded for disasters in California was \$7,618. FEMA IA has two primary components, Housing Assistance (HA) and Other Needs Assistance (ONA), depending on homeowner or renter status. However, we assume that all damaged housing units regardless ownership status receive these grants across all three communities. Our simulation includes two scenarios: one with FEMA funds distributed at 6 months (period-2), signifying immediate assistance, and another with funds allocated at 18 months (period-4), indicating delayed assistance. It is noted that all housing units sustained damage across three communities, and the projected FEMA funding allocations are detailed in Table 3-12.

Although FEMA funds are assumed distributed uniformly across all damaged housing units, the lower-value housing sectors in the three communities have seen a significant portion of their capital stock losses covered by these funds. Notably, in Rio Dell, the FEMA funds cover a substantial portion of the losses in HS1, with 57% of its losses compensated. In contrast, higher-value properties receive comparatively less FEMA funding. For example, the FEMA coverage ratio for HS3 in Monte Sereno is only 9%. This highlights that properties with lower values receive more significant financial support and aid in recovery from the FEMA funds.

Table 3-12: Summary of capital stock loss and financial assistance allocation by housing sector across three communities

Housing Sector	Damaged Housing Units	Capital Stock Loss (\$M)	FEMA Fund (\$M)	Ratio of FEMA Fund to Capital Stock loss
Rio Dell				
HS1<\$100K	447	-5.93	3.41	57%
\$100K≤HS2<\$150K	590	-9.39	4.49	48%
\$150K≤HS3	195	-5.99	1.49	25%
East Richmond Heights				
HS1<\$150K	503	-10.8	3.83	35%
\$150K≤HS2<\$300K	636	-20.6	4.85	24%
\$300K≤HS3	287	-14.5	2.19	15%
Monte Sereno				
HS1<\$400K	403	-18.1	3.07	17%
\$400K≤HS2<\$500K	447	-26.8	3.41	13%
\$500K≤HS3	354	-29.8	2.7	9%

The next figures, Figure 3-19 to Figure 3-24 show the recovery trajectories of three communities, comparing immediate and delayed funding over the course of the simulation periods. In Rio Dell, the impact of financial assistance is more significant than in the other two communities. Immediate funding in the housing sectors could lead to quicker improvements in domestic supply and real household income, shown in Figure 3-19. The total fund accounts for 44.1% of the capital lost across all housing sectors in Rio Dell. Given their lower values, housing units receive a substantial portion of the damage coverage from FEMA funds. As a result, the local economy returns to equilibrium more quickly compared to the scenario without financial assistance. By period 9, the economy approaches equilibrium, signaling stabilization of the local economy. With delayed funding, Figure 3-20, the recovery trajectory exhibits a pattern similar to that observed with immediate funding. Although the funds arrive with a two-period delay, recovery still approaches equilibrium by the 10th period, only one period behind the immediate funding scenario. This suggests that the timing of financial assistance does not significantly impact the shortening of recovery time; rather, the presence of financial assistance is crucial. Particularly, as Rio Dell is predominantly a bedroom community, most of its wage income may remain unaffected by the earthquake. Essentially, the community initiates its recovery by utilizing existing savings and wage income early on, with substantial FEMA funds subsequently enhancing the pace of recovery.

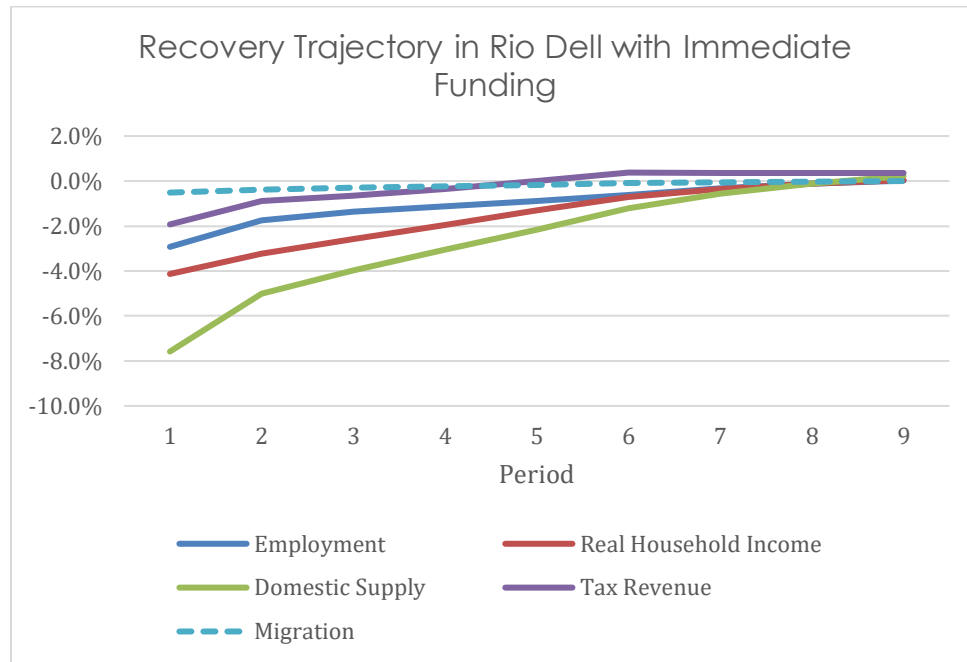


Figure 3-19: Recovery trajectory in Rio Dell with immediate funding

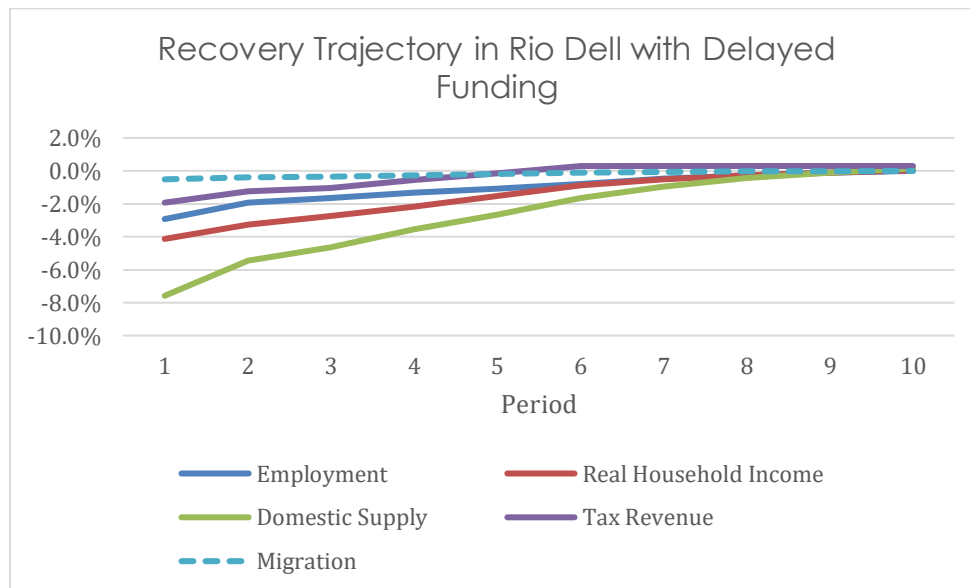


Figure 3-20: Recovery Trajectory in Rio Dell with delayed funding

In East Richmond Heights, 23.7% of the total capital loss in all housing sectors is covered by FEMA funds. These funds, combined with personal savings, play a crucial role in covering damage early on. Similar to Rio Dell, East Richmond Heights recovers more quickly with financial aid than without. By the 9th period, the local economy nears equilibrium, signaling stabilization and recovery. Recovery timing in East Richmond Heights is consistent with that in Rio Dell, regardless of when funding is received, demonstrating the typical resilience of a commuter town. With fewer commercial sectors and most residents working outside the area, the community starts its recovery by using existing savings and wage income, with substantial FEMA funds further expediting the process.

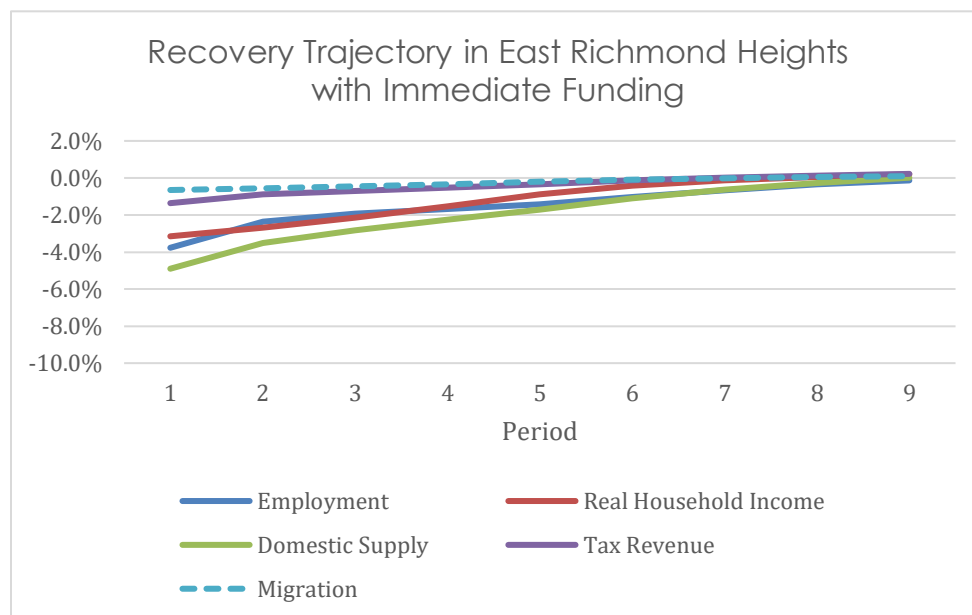


Figure 3-21: Recovery trajectory in East Richmond Heights with immediate funding

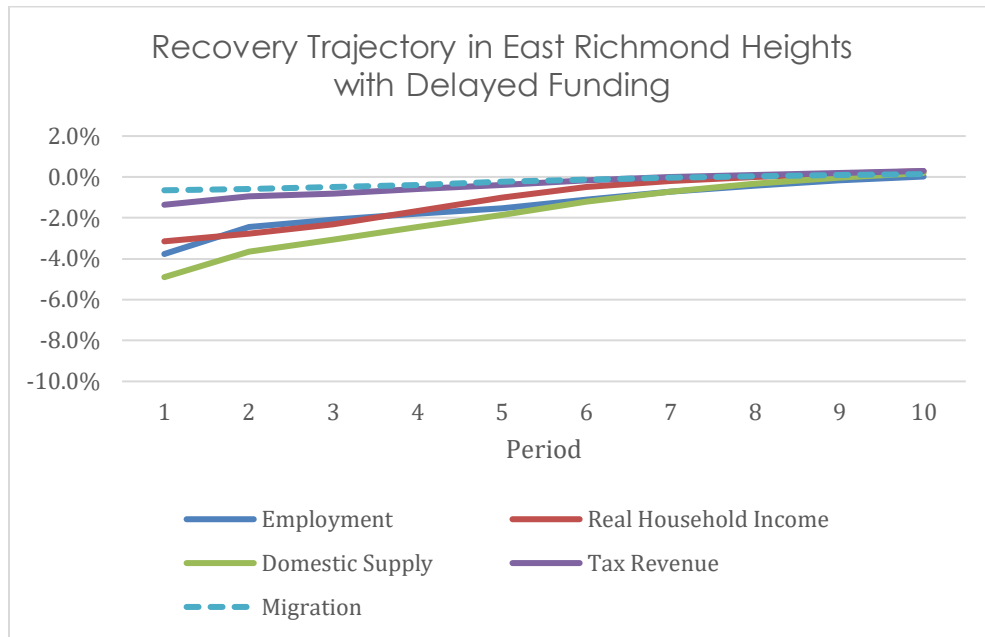


Figure 3-22: Recovery trajectory in East Richmond Heights with delayed funding

Monte Sereno exhibits distinctive recovery patterns, showing no significant differences in outcomes between scenarios with funding, without funding, or even with variations in the timing of funding. This pattern suggests that Monte Sereno, as a wealthier community, has considerable resilience and can effectively recover using its own resources, such as personal savings. Consequently, the local economy initiates a swift recovery primarily through the use of these local funds. The FEMA funds, covering only 12.3% of the total capital stock loss, do not significantly influence the recovery process.

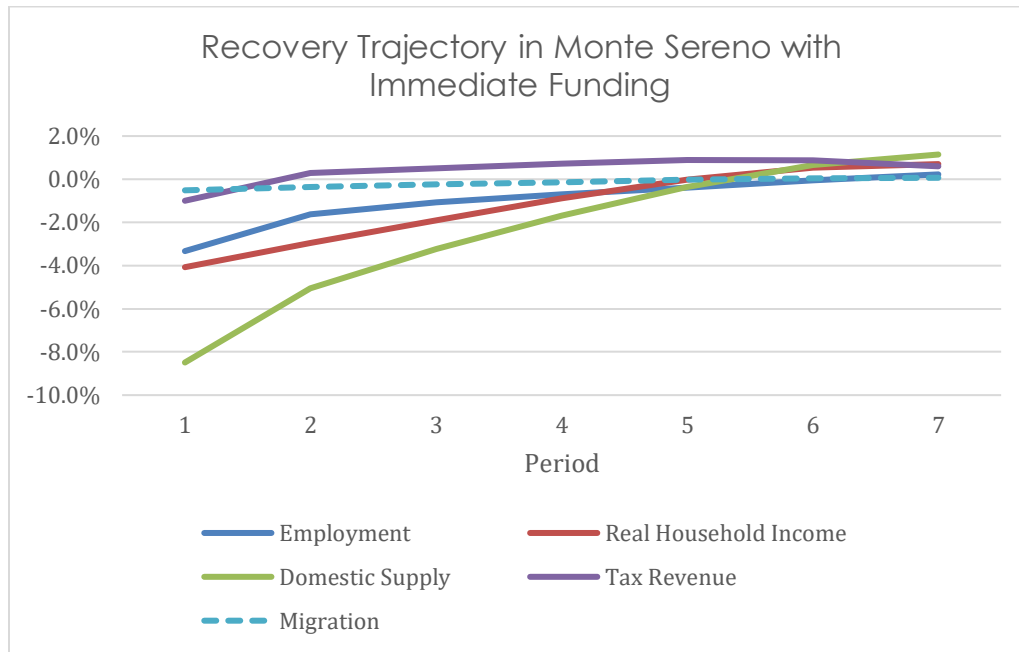


Figure 3-23: Recovery trajectory in Monte Sereno with immediate funding

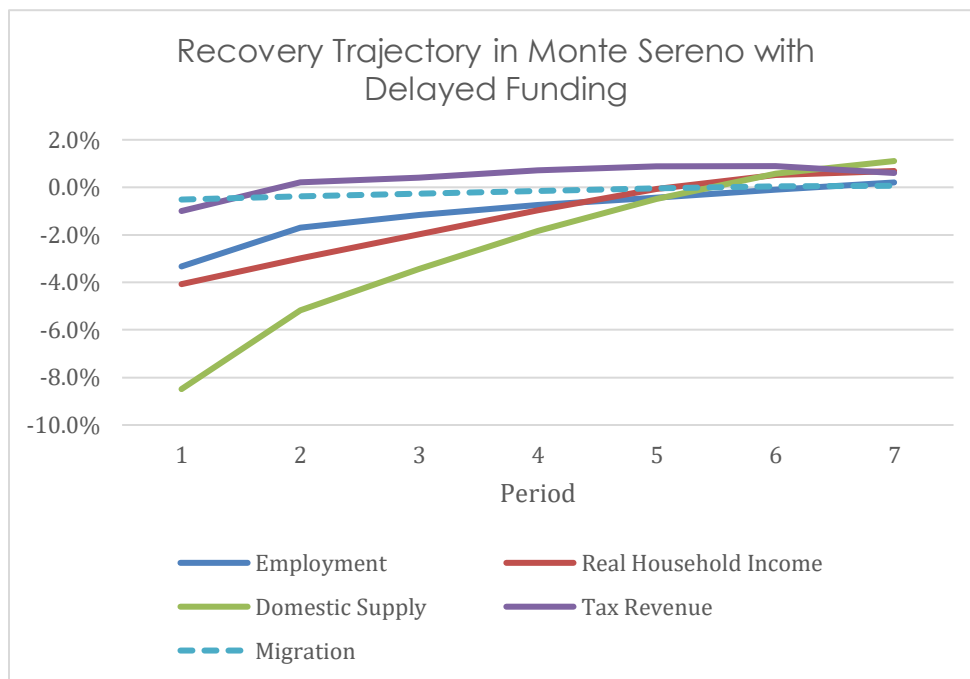


Figure 3-24: Recovery trajectory in Monte Sereno with delayed funding

Table 3-13 summarizes the recovery timelines for real household income across various household groups in three communities under different scenarios: no assistance, delayed assistance, and immediate assistance. In both Rio Dell and East Richmond Heights, immediate financial assistance markedly reduces recovery times compared to scenarios without aid, especially for lower-income household groups. For example, in Rio Dell, the recovery time for real household income in the HH1 group is shortened from 17 periods without assistance to just 10 periods with immediate assistance. Moreover, delayed assistance typically extends recovery times by one to two periods compared to immediate aid. Conversely, as a wealthier community, Monte Sereno shows no significant differences in recovery times with or without aid. In Monte Sereno, the availability of FEMA funds does not markedly speed up the recovery process.

While immediate aid may not drastically shorten the recovery period, it is especially crucial for lower-income households, helping them stabilize more quickly. Lower-income households often face greater difficulties in meeting basic needs such as housing, food, and healthcare during recovery periods. Delays in income recovery can extend hardship and instability, adversely affecting their overall health and well-being. Additionally, prolonged financial challenges can lead to broader social issues, such as increased crime rates, mental health problems, and disruptions in children's education, undermining community stability and cohesion. It is important to note that the model assumes no change in the wage income earned outside the city. However, in reality, wage income for commuters may decrease following a disaster, particularly because lower-income jobs typically offer less security and fewer benefits like paid leave or health insurance. This makes these workers more vulnerable during economic downturns, potentially leading to significantly longer recovery times for lower-income households than the analysis suggests. Overall, the findings indicate that financial aid is particularly critical for communities that are less affluent or more severely affected by disasters.

Table 3-13: Summary of recovery periods for real household income across three communities under three different scenarios

	Recovery Period for Real Household Income		
	No Assistance	– Delayed Assistance	– Immediate Assistance
Rio Dell			
HH1 <\$30K	17	11	10
\$30K≤HH2 <\$50K	14	11	9
\$50K≤HH3<\$90K	13	10	9
\$90K≤HH4	11	10	9
East Richmond Heights			
HH1 <\$50K	13	9	9
\$50K≤HH2 <\$100K	12	9	9
\$100K≤HH3<\$200K	10	8	8
\$200K≤HH4	9	8	8
Monte Sereno			
HH1 <\$130K	8	8	8
\$130K≤HH2 <\$250K	7	6	6
\$250K≤HH3<\$350K	6	6	6
\$350K≤HH4	5	5	5

4. CLOSURE AND RECOMMENDATIONS

This study presents a novel approach to evaluating community resilience by introducing advanced metrics that account for the economic characteristics of various communities, thereby offering a more accurate representation of the multifaceted costs associated with earthquakes. The proposed method employs a multidisciplinary simulation-based framework that integrates both physical and economic dimensions of resilience. Specifically, the framework captures physical impacts such as post-earthquake structural damage and infrastructure functionality, while also addressing economic factors, including fluctuations in employment, disruptions in sectoral supply chains, and variations in household income distribution. This holistic analysis is conducted using a spatial computable general equilibrium (SCGE) model, which allows for a detailed assessment of the interdependencies between physical infrastructure and economic systems.

To demonstrate the capabilities of the proposed framework, it is applied to three distinct towns in California—Rio Dell, Monte Sereno, and East Richmond Heights—that were affected by the 2022 Ferndale earthquake. The selection of these towns was deliberate, as it highlights the diverse socioeconomic conditions present in different communities, with particular attention to rural and economically disadvantaged areas. By focusing on these communities, the study underscores how pre-existing socioeconomic inequities exacerbate the challenges posed by post-earthquake recovery, thereby emphasizing the importance of addressing both engineering and social factors in resilience planning.

In order for at-risk communities such as Rio Dell to become more resilient and recover more rapidly from hazard events such as earthquakes several key recommendations are provided below:

Direct Cash Transfers: Propose direct financial assistance in the form of cash transfers to low-income households that have been affected by the disaster. This immediate provision of funds aims to quickly restore the purchasing capabilities of these families, enabling them to acquire essential goods and services. Such assistance is crucial not only for meeting immediate, day-to-day needs such as food, clothing, and shelter, but also for invigorating the local economy. By injecting cash directly into disaster-stricken areas, these households can spend in local markets, thereby supporting local businesses and fostering a faster economic recovery. This method is an effective way to ensure that aid reaches its intended recipients promptly and efficiently, helping to stabilize the community in the aftermath of the disaster.

Low-Interest Loans: Introduce a program offering low-interest loans targeted at homeowners and businesses affected by disasters, aimed specifically at aiding in the repair and reconstruction

of damaged properties. Additionally, the program should allow for the refinancing of existing high-interest debt as an eligible use. This financial support is designed to ease the burden on property owners who face the daunting task of rebuilding in the aftermath of a disaster. By providing access to capital at reduced interest rates, the initiative not only accelerates the physical rebuilding process but also alleviates the economic pressures often associated with large-scale repairs.

Individual Assistance: IA criteria should include a review of the totality of circumstances with consideration of recovery-relevant factors such as poverty, lack of access to transportation, displacement of education and work, and overcrowded housing.

Low Income Prioritization: Disaster aids such as IA should prioritize low-income households since they take the longest to recover.

In order to determine better metrics for disbursement of disaster assistance, a number of additional analysis are recommended for a broader range of communities using IN-CORE, e.g. approximately 12-16, should eventually be conducted to develop trends. These would need to have additional variables such as population size and race/ethnicity included beyond the current study. Then, either a new qualification defined as a function of these variables could be determined or a factor that accounts for these demographic variables combined with a household deviation from the median.

This research offers a more holistic perspective on community resilience by combining physical vulnerabilities with socioeconomic disparities, which are critical in determining the pace and extent of recovery after a disaster. The findings suggest that effective resilience strategies must move beyond merely restoring infrastructure and should also consider broader socioeconomic factors that influence long-term recovery and sustainability. Consequently, the study provides valuable insights into improving disaster preparedness, response, and equitable recovery planning in earthquake-prone regions.

REFERENCES

- Amini, M., H. Jeon, D.R. Sanderson, D.T. Cox, A.R. Barbosa, and H. Cutler. (2023). Integrated Engineering–Economic Analysis for Multihazard Damage and Loss Assessment. *Journal of Infrastructure Systems*, 29(4), 04023031.
- Attary, N., H. Cutler, M. Shields, and J.W. van de Lindt. (2020). The economic effects of financial relief delays following a natural disaster. *Economic Systems Research*, 32(3), 351-377.
- Barry, J.M. (1997). *Rising Tide: The Great Mississippi Flood of 1927 and How it Changed America*. Simon & Schuster, New York.
- Brevoort, K., S. Canilang, K. Jones, J. Larrimore, A. Lloro, E. Merry, and M. Zabek. (2021). Economic well-being of US households in 2020. *Board of Governors of the Federal Reserve System* May, 2021.
- Chen, Z., A.Z. Rose, F. Prager, and S. Chatterjee. (2017). Economic consequences of aviation system disruptions: a reduced-form computable general equilibrium analysis. *Transportation Research Part A: Policy and Practice*, 95, 207-226.
- Chen, Z. and A. Rose. (2018). Economic resilience to transportation failure: a computable general equilibrium analysis. *Transportation*, 45, 1009-1027.
- Collier, B. and C. Ellis. (2024). A demand curve for disaster recovery loans. *Econometrica*, 92(3), 713-748.
- CSSC (2024). “Ferndale Earthquake Sequence: Understanding Impediments to Local Recovery in Rio Dell, California”. Californai Seismic Safety Commission, Report SSC No. 24-02.
- Cutler, H., M. Shields, D. Tavani, and S. Zahran. (2016). Integrating engineering outputs from natural disaster models into a dynamic spatial computable general equilibrium model of Centerville. *Sustainable and Resilient Infrastructure*, 1(3-4), 169-187.
- Dal Zilio, L., and J.P. Ampuero. (2023). Earthquake doublet in Türkiye and Syria. *Commun Earth Environ* 4, 71.
- de Moel, H., W. Botzen, and J. Aerts. (2013). Economic and direct losses from Hurricane Sandy. In: *Annals of the New York Academy of Sciences*. 2013 ; Vol. 1294. pp. 81-89.
- Domingue, S. J., and C.T. Emrich. (2019). Social Vulnerability and Procedural Equity: Exploring the Distribution of Disaster Aid Across Counties in the United States. *The American Review of Public Administration*, 49(8), 897–913. <https://doi.org/10.1177/0275074019856122>.

Drakes, O., E. Tate, J. Rainey, and S. Brody. (2020). Social vulnerability and short-term disaster assistance in the United States. *International Journal of Disaster Risk Reduction*, 53, 102010. <https://doi.org/10.1016/j.ijdrr.2020.102010>.

EM-DAT. (2019). Retrieved June 10, 2019, from EM-DAT, The international Disaster Database website: <https://www.emdat.be/>.

Emrich, C.T., E. Tate, S.E. Larson, and Y. Zhou (2019). Measuring social equity in flood recovery funding. *Environmental Hazards*, Vol 19 (3), 228 – 250, <https://doi.org/10.1080/17477891.2019.1675578>.

Emrich, C. T., S.K. Aksha, and Y. Zhou. (2022). Assessing distributive inequities in FEMA’s Disaster recovery assistance fund allocation. *International Journal of Disaster Risk Reduction*, 74, 102855. <https://doi.org/10.1016/j.ijdrr.2022.102855>.

Fan, Q. and M. Davlasheridze. (2019). Economic impacts of migration and brain drain after major catastrophe: The case of Hurricane Katrina. *Climate Change Economics*, 10(01), 1950004.

FEMA. (2020). FEMA’s Budget and Disaster Funding: 2020 Update. Federal Emergency Management Agency.

FEMA (2022a). Earthquake loss estimation methodology: *Technical manual*. National Institute of Building for the Federal Emergency Management Agency, Washington, DC.

FEMA (2022b). Hazus Inventory Technical Manual: *Technical manual*. National Institute of Building for the Federal Emergency Management Agency, Washington, DC.

Ghaedi, H., K. Best, A. Reilly, and D. Niemeier. (2024). Statistical learning to identify salient factors influencing FEMA public assistance outlays. *Natural Hazards*, 120(12), 10559–10582. <https://doi.org/10.1007/s11069-024-06620-2>.

Google. (2025). www.google.com

Han, Y., H. Jia, C. Xu, M. Bockarjova, C. Van Westen, and L. Lombardo. (2023). Unveiling spatial inequalities: Exploring county-level disaster damages and social vulnerability on public disaster assistance in contiguous US. *Journal of Environmental Management*, 351, 119690. <https://doi.org/10.1016/j.jenvman.2023.119690>.

Hou, J. J., M.K. Han, B.L. Chai, and Y. Han. (1998). Geomorphological observations of active faults in the epicentral region of the Huaxian large earthquake in 1556 in Shaanxi Province, China. *Journal of Structural Geology*, 20(5), 549–557. [https://doi.org/10.1016/S0191-8141\(97\)00112-0](https://doi.org/10.1016/S0191-8141(97)00112-0).

IN-CORE. (2025). www.IN-CORE.org

Itatani, T., M. Kojima, J. Tanaka, R. Horlike, K. Sibata, and R. Sasaki. (2024). Operational Management and Improvement Strategies of Evacuation Centers during the 2024 Noto Peninsula Earthquake – A Case Study of Wajima City. *Safety*, 2024, 10(3), 62; <https://doi.org/10.3390/safety10030062>.

Kajitani, Y., and H. Tatano. (2018). Applicability of a spatial computable general equilibrium model to assess the short-term economic impact of natural disasters. *Economic Systems Research*, 30(3), 289-312.

Knabb, R. D., J.R. Rhome, and D.P. Brown. (2005). Tropical Cyclone Report, Hurricane Katrina, 23-30. August, 2005 (p. 43). Retrieved from National Hurricane Center website: https://www.nhc.noaa.gov/data/tcr/AL122005_Katrina.pdf.

Knapp, H. (2020). Managing an administrative emergency: establishing FEMA as an independent agency. *Colorado Natural Resources, Energy and Environmental Law Review*. 31(1). pp. 231–264.

Koc, E., B. Cetiner, A. Rose, L. Soibelman, E. Taciroglu, and D. Wei. (2020). CRAFT: Comprehensive resilience assessment framework for transportation systems in urban areas. *Advanced Engineering Informatics*, 46, 101159.

Lee, J. (2021). The economic aftermath of Hurricanes Harvey and Irma: The role of federal aid. *International Journal of Disaster Risk Reduction*, 61, 102301. <https://doi.org/10.1016/j.ijdrr.2021.102301>.

Li, H., E. Xu, H. Zhang, and S. Zhong. (2022). A dynamic disastrous CGE model to optimize resource allocation in post-disaster economic recovery: post-typhoon in an urban agglomeration area. *China. Environmental Research Letters*, 17(7), 074027.

Lieberman-Cribbin, W., B. Liu, S. Schneider, R. Schwartz, and E. Taioli. (2017). Self-Reported and FEMA Flood Exposure Assessment after Hurricane Sandy: Association with Mental Health Outcomes. *PLoS ONE*, 12(1), e0170965. <https://doi.org/10.1371/journal.pone.0170965>.

MathWorks. (2022). MATLAB version: 9.13.0 (R2022b), Natick, Massachusetts: *The MathWorks Inc.* <https://www.mathworks.com>.

Muñoz, C. and E. Tate. (2016). Unequal Recovery? Federal Resource Distribution after a Midwest Flood Disaster. *International Journal of Environmental Research and Public Health*, 13(5), 507. <https://doi.org/10.3390/ijerph13050507>.

National Structure Inventory (NSI). 2025. <https://www.hec.usace.army.mil/confluence/nsi>.

Okiyama, M., & Tokunaga, S. (2017). Economic analysis of fiscal measures for reconstructing the Tohoku Region after the Great East Japan Earthquake: Using a dynamic two-regional CGE model. *Spatial Economic Modelling of Megathrust Earthquake in Japan: Impacts, Reconstruction, and Regional Revitalization*, 123-161.

PUMS. Public Use Microdata Sample, <https://www.census.gov/programs-surveys/acs/microdata/access.html>.

Qiu, J., L. Ji, L. Zhu, C. Liu, and Z. Zhao. (2024). Coseismic deformation and seismogenic structure of the 2024 Hualien Earthquake measured by InSAR and GNSS. *Earthquake Research Advances*, 100328. <https://doi.org/10.1016/j.eqrea.2024.100328>

Raker, E. J., and T. Woods. (2023). Disastrous Burdens: Hurricane Katrina, Federal Housing Assistance, and Well-Being. RSF the Russell Sage Foundation. *Journal of the Social Sciences*, 9(5), 122–143. <https://doi.org/10.7758/rsf.2023.9.5.06>.

Ratcliff, C., B. Middlewood, M.A. Knoll, G. Guillory, and M. Davies. (2022). Emergency Savings and Financial Security: Insights from the Making Ends Meet Survey and Consumer Credit Panel. *Consumer Financial Protection Bureau Office of Research Reports Series*, (22-1).

Roohi, M., J. W. van de Lindt, N. Rosenheim, Y. Hu, and H. Cutler. (2020). Implication of building inventory accuracy on physical and socio-economic resilience metrics for informed decision-making in natural hazards. *Structure and infrastructure engineering*, 17(4), 534-554.

Roohi, M., S. Ghasemi, O. Sediek, H. Jeon, J.W. van de Lindt, M. Shields, and H. Cutler. (2024). Multi-disciplinary seismic resilience modeling for developing mitigation policies and recovery planning. *Resilient Cities and Structures*, 3(2), 66-84.

Rose, A. and S.Y. Liao. (2005). Modeling regional economic resilience to disasters: A computable general equilibrium analysis of water service disruptions. *Journal of regional science*, 45(1), 75-112.

Rose, A., S. Y. Liao, and A. Bonneau. (2011). Regional economic impacts of a Verdugo scenario earthquake disruption of Los Angeles water supplies: a computable general equilibrium analysis. *Earthquake Spectra*, 27(3), 881-906.

Rose, A., I. S. Wing, D. Wei, and A. Wein. (2016). Economic impacts of a California tsunami. *Natural Hazards Review*, 17(2), 04016002.

Shibusawa, H. (2020). A dynamic spatial CGE approach to assess economic effects of a large earthquake in China. *Progress in Disaster Science*, 6, 100081.

Simulink, (2022). MATLAB version: 9.13.0 (R2022b), Natick, Massachusetts: *The MathWorks Inc.* <https://www.mathworks.com>.

van de Lindt, J. W., J. Kruse, D.T. Cox, P. Gardoni, J.S. Lee, J. Padgett, T.P. McAllister, A. Barbosa, H. Cutler, S. Van Zandt, N. Rosenheim, C.M. Navarro, E. Sutley, and S. Hamideh. (2023). The interdependent networked community resilience modeling environment (IN-CORE). *Resilient Cities and Structures*, 2(2), 57–66.

Wang, W., J.W. van De Lindt, N. Rosenheim, H. Cutler, B. Hartman, J.S. Lee, and D. Calderon. (2021). Effect of residential building wind retrofits on social and economic community-level resilience metrics. *Journal of Infrastructure Systems*, 27(4), 04021034.

Waters, L., K. Best, Z. Miao, M. Davlasheridze and A. C. Reilly. (2024). Under-reported and under-served: Disparities in US disaster federal aid-to-damage ratios after hurricanes. *International Journal of Disaster Risk Reduction*, Vol 106, May 2024, 104430.

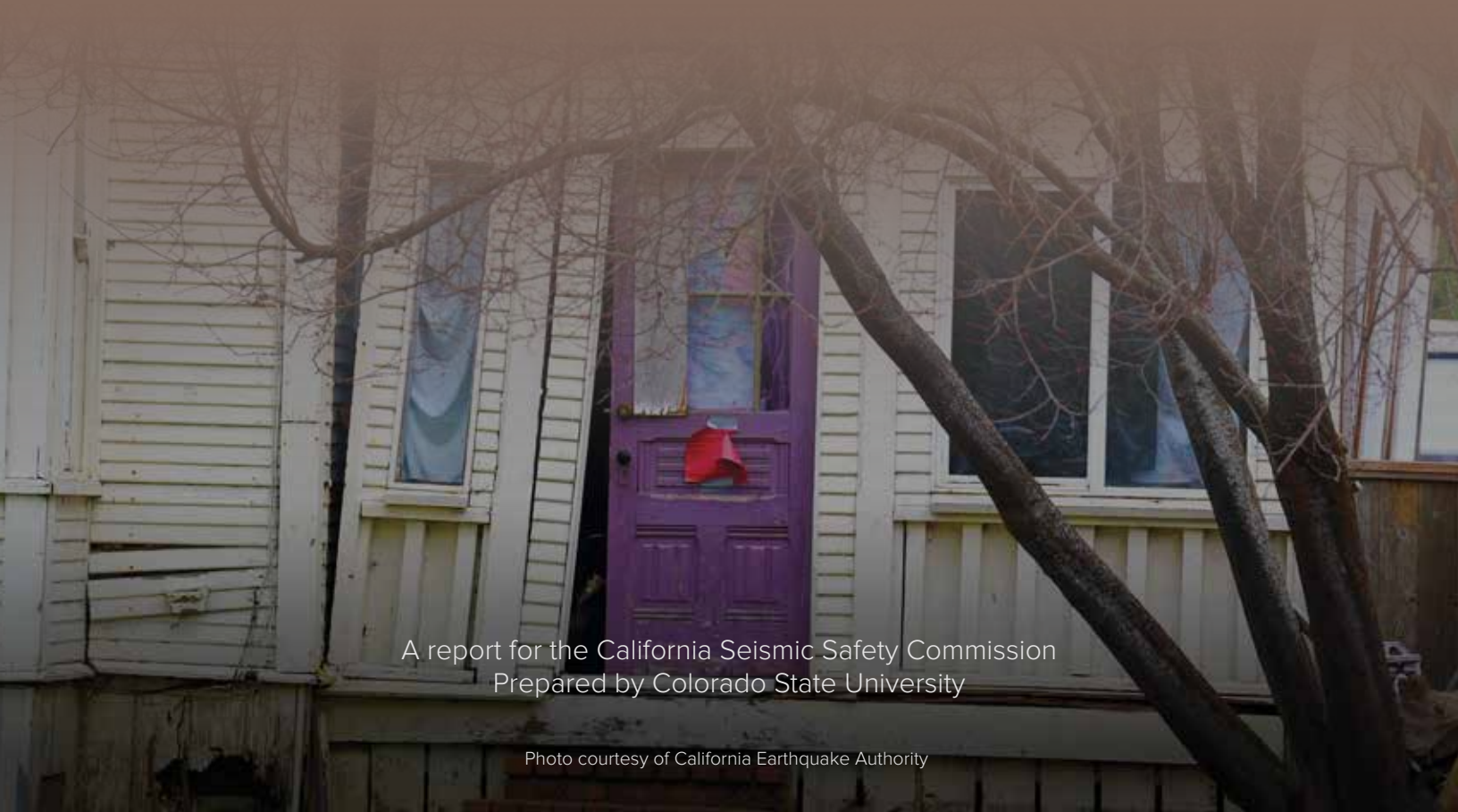
Xie, W., N. Li, J.-D. Wu, and X.-L. Hao. (2014). Modeling the economic costs of disasters and recovery: analysis using a dynamic computable general equilibrium model. *Natural Hazards and Earth System Sciences*, 14(4), 757-772.

Xie, W., N. Li, J. Wu, and X. Hao. (2015). Disaster risk decision: a dynamic computable general equilibrium analysis of regional mitigation investment. *Human and Ecological Risk Assessment: An International Journal*, 21(1), 81-99.



Beyond Earthquake Damage

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Prepared by Colorado State University

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