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MULTI-OBJECTIVE OPTIMIZATION OF BUILDING MITIGATION STRATEGIES TO ADDRESS MULTIPLE HAZARDS

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MULTI-OBJECTIVE OPTIMIZATION OF BUILDING MITIGATION STRATEGIES TO ADDRESS MULTIPLE HAZARDS

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BY THE COMMITTEE CONSISTING OF

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To my family, my mentors, all OU-CORE members, and my friends

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Abstract

This study develops a decision support framework for community resilience planning in the context of multiple hazards. The ability to prepare for and adjust to changing circumstances, as well as to withstand and recover from future hazards, is referred to as community resilience planning. Although different mitigation strategies have been established for each form of hazard, it is critical to choose the right plan for the community considering the combined risk of multiple hazards. Coastal areas are particularly vulnerable to deadly earthquakes and tsunamis. Communities must create a new vision for their post-disaster existence in order to successfully address the devastating effects of these multiple events, this analysis will aid community leaders in making these critical decisions. The study was carried out in Seaside, Oregon to address resilience planning under multiple hazards. This framework has the potential to optimize economic, social, and physical viability of the community by identifying the most effective mitigation strategies for a given budget. The approach describes in depth how to integrate models built by specialists in the fields of social science and civil engineering to construct a multi-objective optimization model.

1. Introduction

Communities around the world are prone to natural hazards and are oftentimes not just subject to a single hazard, but to multiple hazards (Kappes et al. 2012). Nuances in the definition of multiple hazards exist. For example, cascading hazards refer to one event triggering another, such as earthquakes triggering landslides and tsunamis (Gasparini et al. 2014;De Risi and Goda 2016; Park, Cox, Alam, et al.); whereas compounding hazards refer to one event posing multiple threats, such as hurricanes resulting in high winds, heavy rainfall, and storm surge (Li et al. 2012; Sebastian et al. 2017). The impact that these hazards have on communities can be devastating. Not only do natural hazards pose threats to life safety, but damage to infrastructure can disrupt communities. The effects of which can last years following the initial event (Cutter et al. 2006);, Costa, Haukaas, and Chang 2021).

Megathrust earthquakes and subsequent tsunamis, such as the 2004 Indian Ocean tsunami, the 2010 Chile tsunami, and the 2011 Tohoku tsunami, have resulted in devastating casualties and damage to the developed and natural ecosystems over the last two decades. Post-disaster assessments of building damage demonstrate the need for measures to improve community resilience in order to plan for potential tsunami disasters and reduce structural damage and losses. Planning for tsunami-prone areas face significant challenges since tsunami danger is unclear in most coastal areas along the Pacific basin, and the likelihood of occurrence and recurrence periods are unknown in most areas. Unlike the earthquake, winter storm surge, or general flood danger, where recurrence data is used to guide planning decisions, the science of tsunami probability can be summarized as an attempt to measure a very low probability yet extremely high impact threat.

Assessing and quantifying the probability of natural disasters is beyond the reach of this study. However, the information is accessible from a variety of other outlets. Many natural disasters have occurred often enough in the past that researchers have established estimates of regional probabilities of possible natural disaster events. Maintaining the performance of infrastructure following extreme events is critical for post-event rescue and response operations as well as long-term community recovery. However, in comparison to single-hazard assessments, examining multiple hazards presents a number of additional difficulties due to the differences in process characteristics. This relates to the evaluation of the losses, as well as the exposure to specific processes and the resulting risk level. Since the comparability of single-hazard outcomes is critical, an equivalent method must be chosen that allows for the estimation of the overall hazard and consequent risk level. (Kappes et al. 2012) and (Park et al. 2019) have presented study on probabilistic seismic and tsunami damage analysis (PSTDA) due to earthquake shaking and tsunami inundation caused by tsunamigenic earthquake events in a coastal community. The PSTDA assesses the cumulative impacts of earthquake and tsunami using a stochastic approach that considers accumulated damage from seismic shaking and eventual tsunami inundation. Because of the relative simplicity of quantifying the damage for selected scenarios versus the difficulty associated with probabilistic-based danger and damage assessment, deterministic scenario-based hazard and damage assessment has become a common approach to predict potential threats of a tsunamigenic earthquake occurrence. This motivates us to include multiple hazards in our decision-making process for improving community resilience.

Community resilience is characterized as a community or society's ability to adapt in the face of hazards by acting to achieve and sustain an appropriate level of operation and structure. In light of multi-hazards, mitigation strategies that reduce the damages can be employed. These are dependent on a number of factors including hazards, economic and time constraints, and community values. Differences in mitigation strategy by hazard include retrofitting buildings and bridges against earthquakes (Zhang and Nicholson 2016; Wen, Nicholson , González', 2021; Kameshwar et al. 2019), vs. relocating structures from tsunami inundation zones and strengthening buildings to be more resistant to tsunami forces (Goltz et al. 2020).

To improve how communities respond to hazards, resilience planning has emerged as an area of study to both quantify and reduce these negative impacts (What et al. 2009; Oregon Seismic Safety Policy Advisory Commission (OSSPAC) 2013; NYC Emergency Management 2019). Although the concept of resilience can be applied across diverse fields such as ecology, psychology, and economics, the work of (Bruneau et al. 2003)is often credited with first applying this concept to communities in the context of natural hazards.

In the remainder of thesis, Section 2 summarizes background of previous research. Section 3 describes the methodology and solution approach. Section 4 is the case study on seaside community and Section 5 discusses the results and analyses for seaside community. Finally, Section 6 presents the conclusion and future work.

2. Background

The literature on resilience in the context of natural hazards is extensive and multiple review papers summarizing the status of the field have been published. These range broadly between the current status of community resilience modeling (Koliou et al. 2020) to definitions of resilience (Hosseini, Barker, and Ramirez-Marquez 2016), and down to specifics such as resilience metrics within transportation systems (Sun, Bocchini, and Davison 2020). The study of community resilience is, by default, interdisciplinary. Subsequently, resilience planning should aim to sit at the intersection of the natural, built, and socioeconomic environments (Rosenheim et al. 2019; Koliou et al. 2020) identify that, despite ongoing research efforts in various disciplines, the integration of multidisciplinary elements of community resilience is scarcely completed. Two examples of this convergence include: (1) (Guidotti, Gardoni, and Rosenheim 2019) who considered population dislocation following a natural hazard and the ability of a water network to meet demands and (2) (Franchin and Cavalieri 2015), who consider population dislocation and road damage using a Bayesian network.

Whereas resilience research has often aimed to quantify and increase how resilient communities are, both parallel and supplementary to the field of resilience is the study of decision support systems. Applied to natural hazards, decision support systems aim to reduce risks and/or increase resilience of communities. In a comprehensive review of decision support systems for natural hazards (Newman et al. 2017) evaluated 101 papers and devised a decision support system classification system. According to (Newman et al. 2017), decision support systems can relate to: (1) exploring risks associated with natural hazards under present-day conditions (Kappes et al. 2012; Park et al. 2019), (2) manually evaluating risk-reduction alternatives via “what-if” scenarios (Kameshwar et al. 2019), and (3) developing models that determine optimal solutions and automatically develop risk reduction plans (Frangopol and Bocchini 2011; Gomez and Baker 2019). Each of which, according to Newman et al., exhibit increasing levels of “decision support”. According to this review, the field of decision support systems has largely focused on the former areas, evaluating risk and resilience, whereas fewer works have been focused on optimization of mitigation strategies; however, this is nonetheless becoming increasingly popular.

Within this subdiscipline of decision support systems applied to natural hazards, optimization can relate to either pre-emptive mitigation strategies or restoration strategies. Considering the former, Zhang and Nicholson developed a multi-objective optimization model considering the performance of interdependent physical, social, and economic systems under disruption from earthquake hazards and (Wen, Nicholson, González', 2021) extended that works by implementing new objectives to the optimization framework. On the other hand, considering optimization of restoration strategies, (González et al. 2016; Gomez et al. 2019) posed the Interdependent Network Design Problem (INDP), which is concerned with determining the least-cost reconstruction strategy for a partially destroyed system of interdependent infrastructure networks. In a similar vein, (Zhang, Wang, and Nicholson 2017) considered post-disaster recovery of road and bridge transportation networks.

Given that: (1) communities are often prone to multiple hazards, and (2) successful resilience planning sits at the intersection of the natural, built, and socioeconomic environments, the intention of this thesis is to present an optimization model that considers both of these facets. Namely, a multi-objective optimization framework for building mitigation strategies subject to multiple hazards is proposed. While multi-objective optimization models for resilience have been developed (Zhang and Nicholson 2016) (Yunjie Wen , Charles Nicholson , Andrés González', 2021), the novelty of this paper lies in that multiple hazards are considered and the solutions provided are at individual building level. As such, mitigation options that target either both or one of the underlying hazards are included in the model. Further, the multi-objective aspect of this framework provides avenues to consider the impact that hazards, have not only on buildings, but also on the population and repair time. Thus, the optimization framework presented herein sits at the intersection of the natural, built, and socioeconomic environments.

3. Optimization Model Formulation

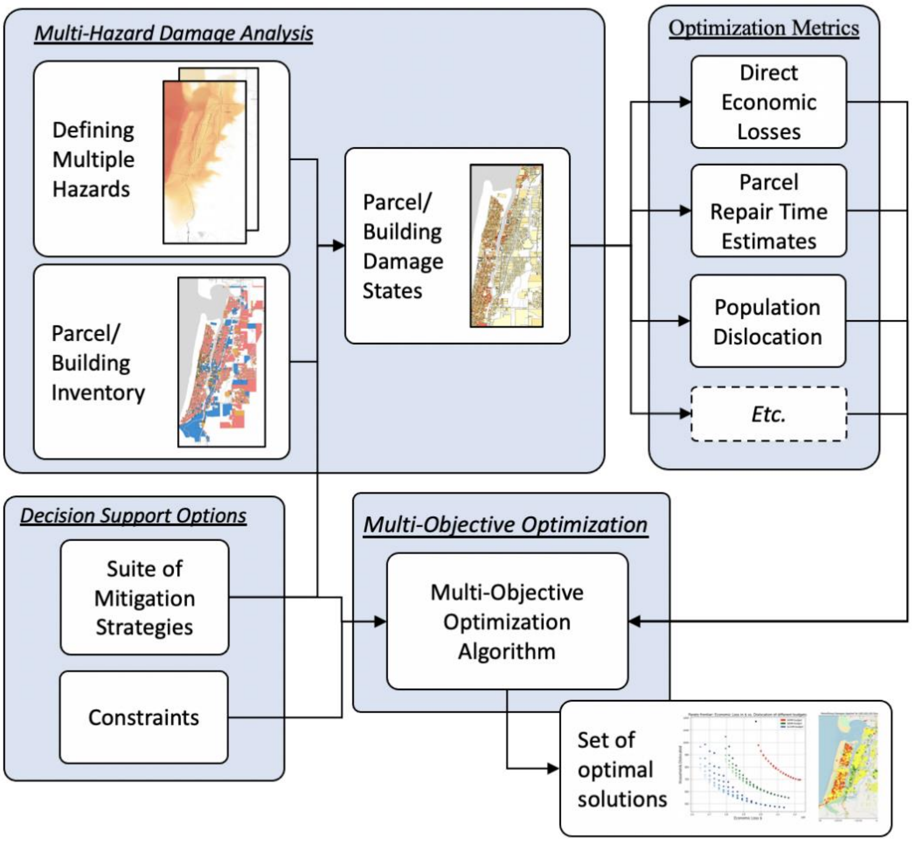


Figure 1: Framework demonstrating the multi-objective optimization of parcel mitigation strategies subject to multiple hazards

The multi-objective optimization of building mitigation strategies subject to multiple hazards is shown in Figure 1. The framework consists of four primary steps: (1) defining decision support options, (2) performing the multi-hazard damage analysis, (3) extracting metrics from the multi-hazard damage analysis to be used in the optimization model, and (4) performing the multi-objective optimization. The following subsections outline each of these steps in detail.

3.1. Decision Support Options

The first step in this framework is to define decision support options, which consists of identifying: (1) a suite of mitigation strategies to consider, and (2) constraints that are employed in the optimization model. In the context of disasters, the former can consist of either proactive or reactive strategies. Costs of implementing each of the mitigation strategies should be defined. The latter consists of identifying constraints that are employed in the optimization model and can consist of items such as budgetary or resource limits.

This analysis assumes a community with one or more distinct zones. A community zone is any defined geographic region that contains structures of interest. Such zones could be based on census tracts, topographically distinct regions, or areas of relative homogeneity in structure types or purposes. Furthermore, it is believed that the community has information related to structure type, retail market value, and population at the parcel level.

3.2.Multi-Hazard Damage Analysis

Following the identification of decision support options, a multi-hazard damage analysis is then performed to determine the probability of being in damage states for each individual parcel. This step consists of mapping spatially explicit hazard intensity measures of the underlying individual hazards to the built environment. This is shown in Figure 1 via the connections between the multiple hazards and parcel/building inventory box. Methods to employee a multi-hazard damage analysis are numerous and can range from the use of fragility surfaces to assuming the underlying hazards and damages are statistically independent (‘FEMA’,2015; ‘FEMA’, 2013; Park *et al.*, 2019). For a comprehensive review of multi-hazard risk and damage analyses, readers are directed to (Kappes et al. 2012).

The multi-hazard damage analysis consists of overlaying hazard maps on the parcel inventory to get parcel-level damage state probabilities. The earthquake and tsunami hazards employed in this work were defined from the PSTHA performed by (Park et al. 2017). The PSTHA resulted in earthquake and tsunami hazard maps for Seaside associated with 7 discrete recurrence intervals (100-, 250-, 500-, 1,000-, 2,500-, 5,000- and 10,000-year). The parcel inventory was collected by (Park et al. 2017) and follows the same methodology that was originally outlined in (‘FEMA’, 2013)

Within this framework, the multi-hazard damage analysis is informed by the mitigation strategies that were defined as decision support options. These strategies have an impact on the damage state probabilities of each individual parcel. The damage state probabilities then inform a set of optimization metrics that are to be minimized (or maximized) across the entire community. Examples of optimization metrics include direct and/or indirect economic losses, individual parcel repair times, and residential population dislocation. Additional metrics can be defined to meet community needs. The end result is a set of optimal solutions that minimize (or maximize) the objectives under the given constraints.

In this work pyIncore, an open-source community resilience modelling environment, is used to perform structural damage analysis (van de Lindt *et al.,* 2018; (Gardoni et al. 2018). HAZUS fragility models were used to determine the probability of being in or exceeding a given damage state (‘FEMA, 2013; ‘FEMA’, 2015) and are characterized by a lognormal distribution given as:

$$P[ds|D] = \Phi[\frac{1}{\beta_{ds}} \ln\left(\frac{D}{\overline{D}_{ds}}\right)] \tag{1}$$

Where ds is the damage state, D is the demand on the structure, β_{ds} is the lognormal standard deviation, and $\overline{D}_{ds}$ is the median of the lognormal distribution associated with damage state *ds*. This parameterization of lognormal distributions is used for both the earthquake and tsunami fragility curves. For earthquake hazards, spectral displacement is employed as the demand type, whereas momentum flux is employed for the tsunami hazard.

$$\begin{aligned} P_{comb}[DS = C] \\ &= P[DS = C|Eqke] + P[DS = C|Tsu] - P[DS = C|Eqke] \\ &\cdot P[DS = C|Tsu] + (P[DS \geq H|Eqke] - P[DS = C|Eqke]) \\ &\cdot (P[DS \geq H|Tsu] - P[DS = C|Tsu]) \end{aligned} \tag{2}$$

$$\begin{aligned} P_{comb}[DS \geq H] \\ &= P[DS \geq H|Eqke] + P[DS \geq H|Tsu] - P[DS \geq H|Eqke] \\ &\cdot P[DS \geq H|Tsu] + (P[DS \geq M|Eqke] - P[DS \geq H|Eqke]) \\ &\cdot (P[DS \geq M|Tsu] - P[DS \geq H|Tsu]) \end{aligned} \tag{3}$$

$$\begin{aligned} P_{Comb}[DS \geq M] \\ &= P[DS \geq M|Eqke] + P[DS \geq H|Tsu] - P[DS \geq M|Eqke] \\ &\cdot P[DS \geq H|Tsu] \end{aligned} \tag{4}$$

The lognormal fragility parameterization depends on the structure type and seismic code. As previously mentioned, mitigation option 1 corresponds to retrofitting the structure to the highest seismic code, thus shifting the seismic fragility curves. Example fragility curves for a reinforced concrete structure under high seismic code is shown in Figure 2.

PyIncore uses four damage states (none/insignificant, moderate, heavy, complete), thus the above results in the probability of being in each of the four damage states for both earthquake and tsunami hazard. There is a cumulative building damage module in pyIncore that combines the damage state probabilities of individual hazards to a cumulative damage state probability assuming statistical independence. The probability of being in each damage state considering both the earthquake and tsunami hazard is given as

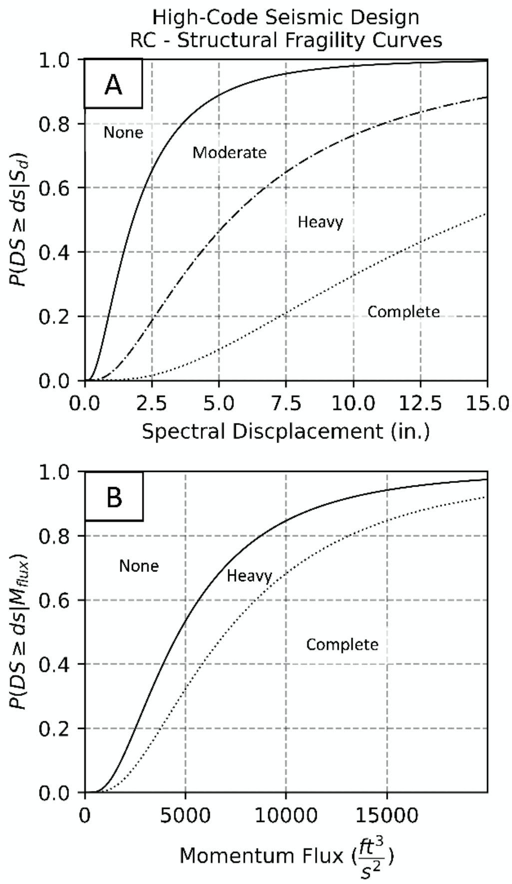


Figure 2: Example fragility curves for a reinforced concrete structure under high seismic code.

The multi-hazard damage analysis results in damage state probabilities at each parcel under each of the mitigation options.

3.3. Optimization Metrics

Let l_{ik} denote the expected economic loss due to a multi-hazard scenario for building in parcel $i \in \mathcal{Z}$ and mitigation option $k \in \mathcal{K}$. The direct economic losses are computed using damage ratios and each parcel's real market value. Here it is assumed that the four damage states of none/insignificant, moderate, heavy, and complete have damage ratios of 0.005, 0.155, 0.55, and 0.90, respectively these damage ratios vary for each hazard and since the current research is done for earthquake and tsunami, the constants used by (Kameshwar et al. 2019) are followed in this model as well . The expected economic loss is a function of retail market value of the building and probability of being in a damage state.

$$l_{ik} = RMV_{ik}(\sum_{ds} P_{ds} * DR_{ds}) \quad (5)$$

Where RMV_{ik} is the retail market value of the building in parcel $i \in \mathcal{Z}$ and mitigation option $k \in \mathcal{K}$, DR_{ds} is the damage ratio associated with the damage state (ds) of building in parcel $i \in \mathcal{Z}$ and mitigation option $k \in \mathcal{K}$,. For this study, 4 damage state probabilities are considered and each of it has a damage factor depending on a hazard.

The damage state probabilities are additionally used for the calculation of population dislocation, the second community resilience metric in our research, was computed by (Rosenheim et al. 2019). The human systems response, household dislocation, was modeled using data and results from housing unit and household surveys conducted in the aftermath of Hurricane Andrew (Girard 1997).Based on the loss of property value, the model forecasts the likelihood of household dislocation. During an off-season earthquake, the population dislocation study predicts that Seaside, Oregon will have 4,628 households dislocated, accounting for roughly 80% of total households. This shows that it is vital for the integration of social science and engineering data opens up previously unexplored avenues for coupling engineering and social science modeling, as well as enhancements to post-hazard resilience models.

Let d_{ik} be the expected population dislocation due to a multi-hazard scenario for building in parcel $i \in \mathcal{Z}$ and mitigation option $k \in \mathcal{K}$. The dislocation is computed from four dislocation probabilities based on a random beta distribution of the four damage factors provided by (Bai, Hueste, and Gardoni 2008). These four damage factors correlate to a loss of value. The likelihood of dislocation is calculated as the sum of the four probabilities multiplied by the four probabilities of damage states. The probability of dislocation is calculated using the logistic regression equation given below,

$$PrDis_{ik} = \frac{1}{1 + e^{-(b_0 + b_1 ploss_{ik} + b_2 dsf_k + b2pblack_k + b_2 phisp_k)}} \quad (6)$$

Once we have the information of probability of dislocation, we calculate the expected value of population dislocation by multiplying probability of dislocation with number of people living in each building at parcel $numprec_{ik}$ $i \in \mathcal{Z}$.

$$d_{ik} = PrDis_{ik} * numprec_{ik} \tag{7}$$

The final community resilience metric is the amount of time it will take to restore each community to their former natural state, i.e. restoration time, which has been studies in detail by (Kameshwar et al. 2019). HAZUS provides median repair time estimates for each building type and damage state. Here it is assumed that the four damage states none/insignificant, moderate, heavy, and complete have median repair times of 0.5, 60, 360, and 720 days, respectively. Following (Kameshwar et al. 2019), it is assumed that these median repair time estimates correspond to a lognormal distribution, each with a dispersion of 0.5. The mean associated with each lognormal repair time curve is determined ($u_{r_{ds}}$), and the expected repair time at each parcel is computed as:

$$R_{ik} = \sum_{ds} P_{ds} * u_{r_{ds}} \tag{8}$$

The average repair time of the community will be,

$$T_{ik} = \frac{R_{ik}}{\Sigma\, b_{ik}} \tag{9}$$

3.4. Multi-Objective Optimization

The set of objectives can be chosen as any metric of community resilience. The information of the metric must be available at building level. For this research we consider the objectives based on the scenario is Seaside, Oregon. After a catastrophe, the economic loss from building damage in Seaside, Oregon, can reach $1.2 billion (Wiebe and Cox 2014), This value is obtained using a methodology for estimating building damage on a community scale using fragility curves. A fragility curve is a statistical function that reflects a given demand's performance (or damage state). The curves are usually S-shaped, indicating uncertainty in the system's ability to withstand a loading condition (Schultz et al. 2010). Fragility curves are usually created using one of four methods: judgmental, empirical, analytical, and hybrid (Schultz et al. 2010). Fragility curves for tsunami performance have historically been constructed empirically through field observations, laboratory experiments, and numerical simulations. The use of fragility curves has the advantage of incorporating all of the risks and uncertainty into a single function. (Wiebe and Cox 2014). The methodology has the capability to calculate damage at individual building level. Only the direct tangible economic loss, which is building damage, was assessed for this paper. Direct intangible loss, such as death, and indirect tangible loss were not considered. Though this may be evident, the most significant economic losses caused by hazards are to buildings and their contents.

Once, we have calculated these three metrics at parcel level, we convert the information to community level by multiplying the number of buildings in each parcel. The number of buildings in each parcel $i \in \mathcal{Z}$ and mitigation option $k \in \mathcal{K}$ can be defined as b_{ik}.

The expected economic loss, population dislocation and repair time of the community is given by eq 10,11,12 respectively,

$$\sum_{i \in \mathcal{Z}} \sum_{k \in \mathcal{K}} l_{ik} b_{ik} \tag{10}$$

$$\sum_{i \in \mathcal{Z}} \sum_{k \in \mathcal{K}} d_{ik} b_{ik} \tag{11}$$

$$\sum_{i \in \mathcal{Z}} \sum_{k \in \mathcal{K}} T_{ik} b_{ik} \tag{12}$$

The mitigation strategy/policy used on the community would be the difference between x_{ik} and b_{ik}. The objective functions for the model would simply be replacing b_{ijk} with x_{ijk} from the equations 10,11,12 and adding whether we want to minimize or maximize the metrics. It is evident in the current case that these metrics need to be minimized to reach optimum values.

Therefore, the objective functions will be,

$$min \sum_{i \in \mathcal{Z}} \sum_{k \in \mathcal{K}} l_{ik} x_{ik} \tag{13}$$

$$min \sum_{i \in \mathcal{Z}} \sum_{k \in \mathcal{K}} d_{ik} x_{ik} \tag{14}$$

$$min \sum_{i \in \mathcal{Z}} \sum_{k \in \mathcal{K}} T_{ik} x_{ik} \tag{16}$$

The optimization approach, in turn, strategically allocates scarce resources to retrofit as many buildings as possible by mitigation options while simultaneously attempting to mitigate direct loss, population dislocation, and repair time at the community level.

Given the scarce in resources to retrofit the buildings, it is considered that we have a total maximum budget B. The cost of improving from mitigation option $k \in \mathcal{K}$ to mitigation option $k' \in \mathcal{K}$, in parcel $i \in \mathcal{Z}$ is $SC_{ikk'} y_{ikk'}$. The optimization model is informed with the constraint (17) to maintain the retrofit building to be below the total available budget.

$$\sum_{i \in \mathcal{Z}} \sum_{k \in \mathcal{K}} \sum_{k' \in \mathcal{K}} SC_{ikk'} y_{ikk'} \leq B \tag{17}$$

Another constraint is making sure that the total number of building after retrofitting from mitigation option $k \in \mathcal{K}$ to mitigation option $k' \in \mathcal{K}$ in parcel $i \in \mathcal{Z}$ is equal to the total number of buildings before retrofitting.

$$x_{ik} = \sum_{k':(k',k) \in \mathcal{L}} y_{ik'k} + b_{ik} - \sum_{k':(k,k') \in \mathcal{L}} y_{ikk'} \quad \forall i \in \mathcal{Z}, \forall\, k \in \mathcal{K} \tag{18}$$

The next constraint is to maintain a balance in number of buildings in each parcel $i \in \mathcal{Z}$ before and after retrofitting.

$$\sum_{k \in \mathcal{K}} x_{ik} = \sum_{k \in \mathcal{K}} b_{ik} \quad \forall i \in \mathcal{Z}, k \in \mathcal{K} \tag{19}$$

Finally the last set of logical constraints are to have non-negative values.

$$x_{ik} \geq 0 \quad \forall i \in \mathcal{Z}, k \in \mathcal{K} \tag{20}$$

$$y_{ikk'} \geq 0 \ \forall i \in \mathcal{Z}, (k, k') \in \mathcal{K} \tag{21}$$

3.5.Data Preparation using IN-CORE

The Center of Excellence for Risk-Based Community Resilience Planning (CoE) (Cooperative Agreement 70NANB15H044) was funded by the National Institute of Standards and Technology (NIST) to improve measurement science to help community resilience assessment. The measurement science is applied on the Interdependent Networked Community Resilience Modeling Environment framework (INCORE). It integrates a risk-based decision-making methodology that allows for quantitative comparisons of alternative resilience strategies. Data from the community can be easily incorporated on the IN-CORE platform, allowing users to intelligently refine community disaster resilience planning and post-disaster recovery strategies using physics-based models of inter-dependent physical structures coupled with socio-economic systems. For this analysis we are utilizing IN-CORE's models to develop the required data to integrate into optimization model. IN-CORE is used to create a virtual community, then the fragility mappings are developed for the selected community, using which the damage analysis are conducted and then economic loss, population dislocation and repair times are computed using the output from damage analysis. Finally the data is aggregated as required input for the optimization model as shown in Figure 3.

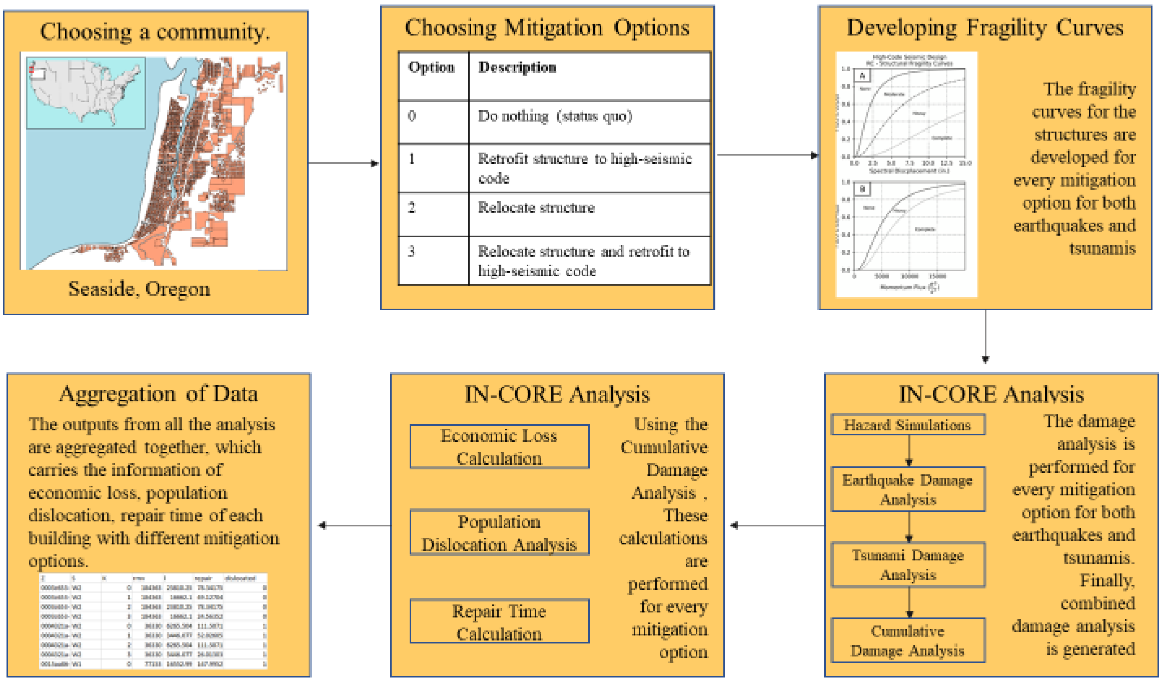


Figure 3: Flow Chart of INCORE Analysis

4. Case Study – Multi-hazard analysis for Seaside, Oregon

The methodology outlined in section 2 is employed at Seaside, Oregon, and a multi-hazard earthquake-tsunami. Seaside is a small coastal community located in the North American Pacific Northwest and is subject to the rupture of the Cascadia Subduction Zone (CSZ). The CSZ is an approximately 1,000km. long fault that stretches from Cape Mendocino, California to Vancouver Island, British Columbia and is formed by the Juan de Fuca, Explorer, and Gorda plates converging beneath the North American Plate (Goldfinger *et al.* 2012). Rupture of the CSZ will result in a multi-hazard earthquake and tsunami.

4.1. Seaside Community

Seaside is selected as a testbed community because it is particularly vulnerable to the CSZ. Some studies estimate that approximately 87% of the developed land is within the inundation zone (N. Wood 2007). Furthermore, among Oregon coastal communities, Seaside has the largest number of residents with a high social vulnerability index (N. J. Wood, Burton, and Cutter 2010) Given this exposure to the CSZ, Seaside has been used as a testbed community in numerous additional studies (Park et al. 2017; Park, Cox, and Barbosa 2017; Guidotti, Gardoni, and Rosenheim 2019; Kameshwar et al. 2019; Rosenheim et al. 2019). Figure 4 shows the city of Seaside and its location within the North American Pacific Northwest.

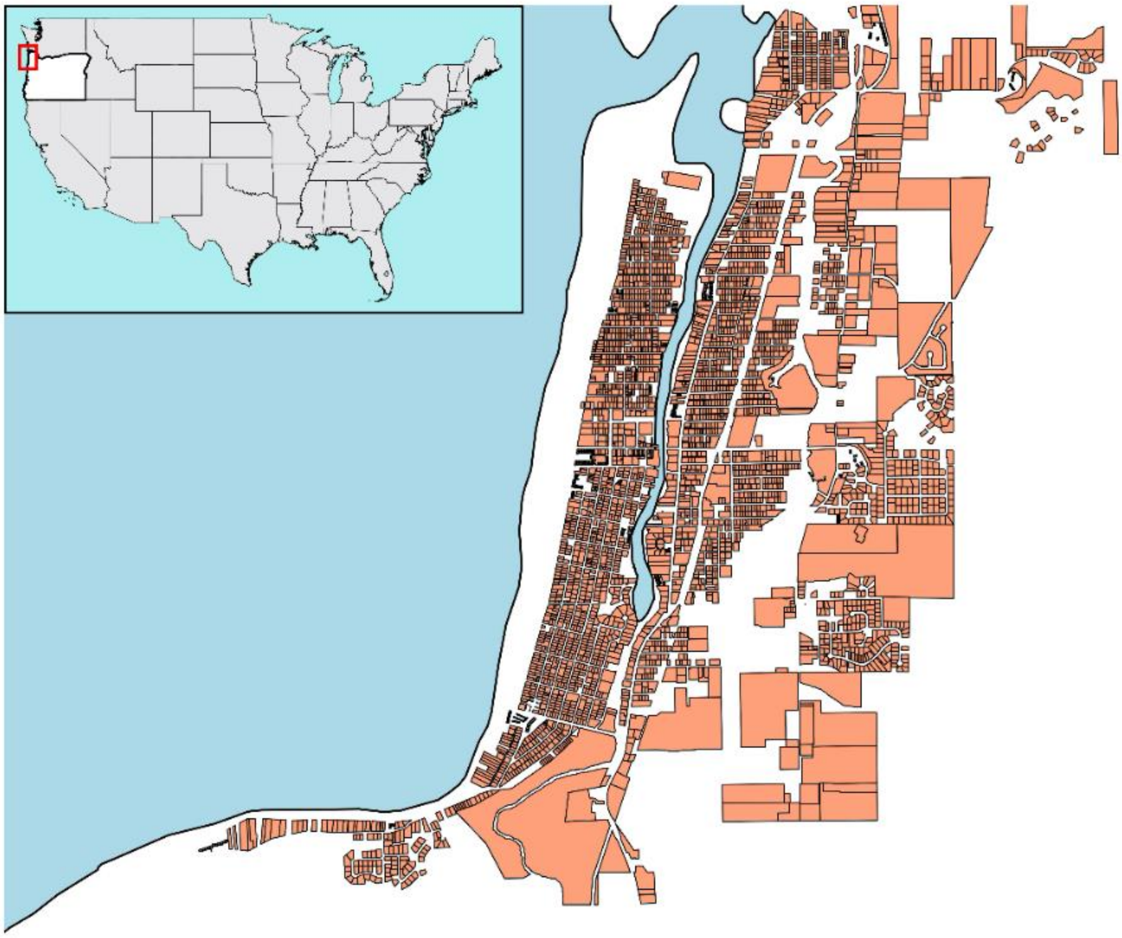


Figure 4: City of Seaside, Oregon, and location within the North American Pacific Northwest

4.2.Data Availability

The first step consists of defining the decision support options. For the case study, four mitigation strategies are considered and summarized in Table 1. The mitigation options outlined herein are employed to demonstrate the multi-objective optimization framework applied to multiple hazards. Costs associated with each strategy are not exact and can be refined in future work.

All parcels are initially considered under status quo conditions (Option 0). (Park et al. 2017) classified the buildings' into HAZUS typologies and depend on building construction type (wood, reinforced concrete, *etc.*) and the seismic code.

The first mitigation option (Option 1) is to retrofit the building located on a parcel to the highest seismic code. Retrofitting a structure to a higher seismic code improves its performance to the earthquake; however, it is assumed that this has no impact on the tsunami damage. It is assumed that the costs associated with retrofitting a structure are 30% of the structure's real market value.

The second mitigation option (Option 2) is to relocate the building on a parcel outside of the tsunami inundation zone. Here, it is assumed that the building is relocated to a location that is near to Seaside but is safe from the tsunami. Given that Seaside covers a small geographic area and there is little variation in the earthquake hazard intensity measure over the study domain, it is assumed that Option 2 does not modify the earthquake damage that a building sustains. It is further assumed that the costs associated with relocating a building are 100% of the buildings real market value.

The final mitigation option (Option 3) is to both relocate the structure and retrofit it to the highest seismic code. Whereas Options 1 and 2 are targeted towards a specific hazard, Option 3 is targeted towards both the earthquake and tsunami hazards. It is assumed that this mitigation options costs 130% of the structures real market value.

Table 1: Mitigation options available at each parcel

Option	Description	Targeted Hazard	Cost (%RMV)
0	Do nothing (status quo)	-	-
1	Retrofit structure to high-seismic code	Earthquake	30%
2	Relocate structure	Tsunami	100%
3	Relocate and retrofit to high-seismic code	Earthquake and Tsunami	130%

Assuming these figures, we can now quantify the expense of a mitigation strategy at the building stage. The cost of improving from mitigation option $k \in \mathcal{K}$ to mitigation option $k' \in \mathcal{K}$, in parcel $i \in \mathcal{Z}$ is $Sc_{ikk'}$.

$$Sc_{ikk'} = RMV_{ik}(P_{kk'}) \tag{22}$$

Where, RMV_{ik} is the retail market value of the building in parcel $i \in \mathcal{Z}$ and $P_{kk'}$ is cost percentage of RMV_{ik} to improve from mitigation option $k \in \mathcal{K}$ to mitigation option $k' \in \mathcal{K}$.

Since there is no clear budget for resilience planning as stated in (Oregon Seismic Safety Policy Advisory Commission (OSSPAC) 2013) an assumption of three budgets $40 million , $80 million and $120 million are used. Using these budgets, we examine how mitigation options can be implemented at the building level to decrease the community's economic loss, population dislocation, and repair times in two scenarios: 500-year return period multi-hazard and 1000-year return period multi-hazard.

4.3.Solution Approach

Using the ϵ-constraint approach which is widely implemented by researchers (Ji et al. 2018; Pike-burke, n.d.; Zhang and Nicholson 2016), the optimization model displays many solutions on Pareto front in terms of direct economic loss, population dislocation and average repair time as shown in Figure 4 and Figure 5 with different budget levels, the highlighted color red represents the solutions with a $40 Million budget whereas green and blue represents optimal solutions with $80 Million and $120 Million budget, respectively. The proposed budgets are selected to show the variety of solutions with change in money invested and since the available budget is unknown and (Oregon Seismic Safety Policy Advisory Commission (OSSPAC) 2013) discusses that the Oregon legislature has authorized seismic grants for different sectors ranging from $1.5 million to $150 million, we assume these budgets reasonable. These Figures also show details of 3 points on each surface as Plan 1, Plan 2 and Plan 3 which represent the least value in economic loss, population dislocation and repair time, respectively. Figure 5 depicts solutions for a 500-year multi-hazard event, while Figure 6 depicts solutions for a 1000-year multi-hazard event. These two events are chosen as for analysis from a list of 8 events as (Kameshwar et al. 2019) already proved that 500-year event and 1000-year event have the highest economic risk.

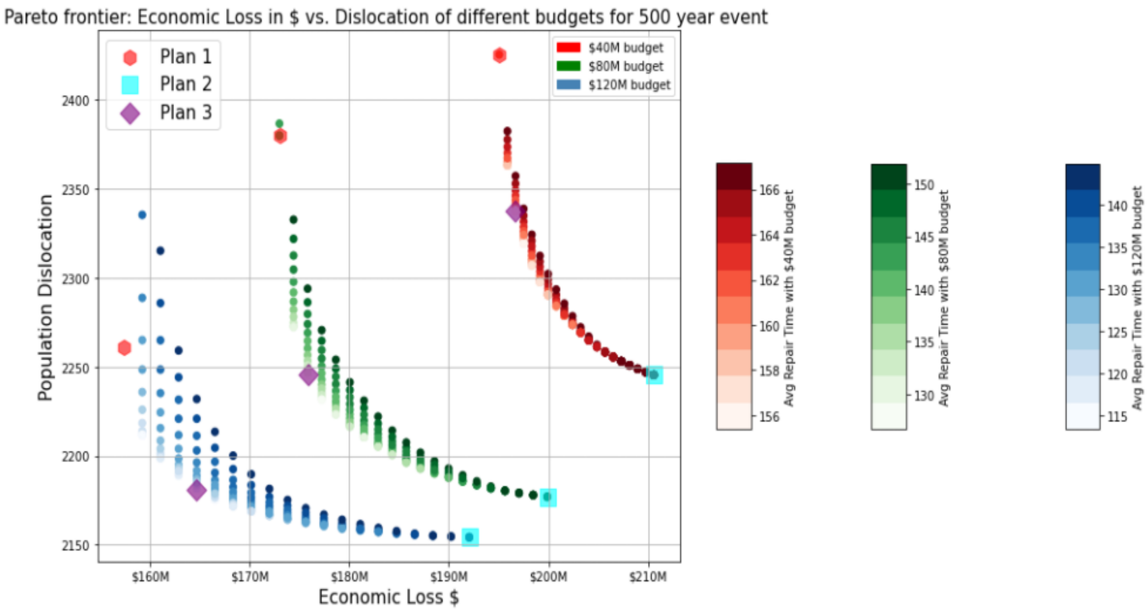


Figure 5: Pareto Frontier: 500-Year Event

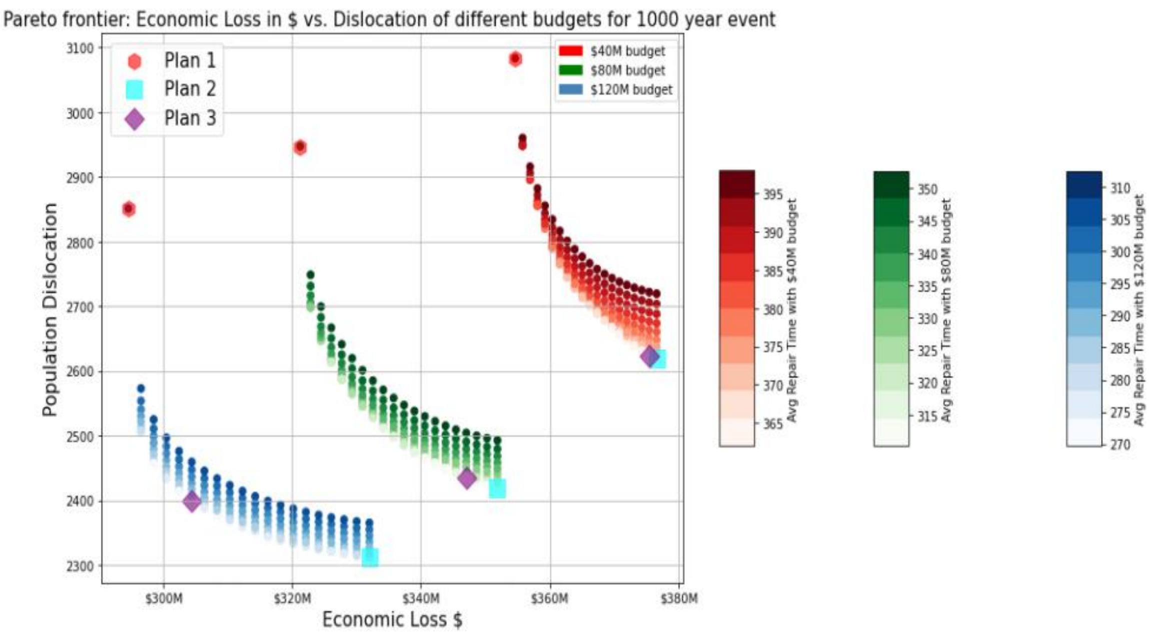


Figure 6: Pareto Frontier: 1000-year Event

One is capable of selecting a plan from among all available choices that has the best course of action that can be taken to prepare for the event. Three plans are chosen for this case study. Plan 1 has the least economic loss whereas Plan 2 and Plan 3 have the least population dislocation and least repair times, respectively. The trade-offs of these conflicting metrics at each plan are being explored further at each budget level.

Table 2: Trade-off Analysis between the objectives at $40 million budget

Budget $40,000,000	Economic Loss	Population Dislocation	Repair Time (Days)	Number of Buildings not Retrofitted	Number of Buildings Retrofitted to Option 1	Number of Buildings Retrofitted to Option 2	Number of Buildings Retrofitted to Option 3
500 Year Event Plan 1	$195,058,236	2425	162	3425	1028	0	0
500 Year Event Plan 2	$210,578,945	2245	167	3005	1366	3	79
500 Year Event Plan 3	$196,691,995	2338	155	3133	1309	5	6
1000 Year Event Plan 1	$354,645,723	3083	398	3840	613	0	0
1000 Year Event Plan 2	$376,626,929	2618	363	3433	684	169	167
1000 Year Event Plan 3	$375,470,024	2623	362	3420	706	187	140

Table 3: Trade-off Analysis between the objectives at $80 million budget

Budget $80,000,000	Economic Loss	Population Dislocation	Repair Time (Days)	Number of Buildings not Retrofitted	Number of Buildings Retrofitted to Option 1	Number of Buildings Retrofitted to Option 2	Number of Buildings Retrofitted to Option 3
500 Year Event Plan 1	$172,991,856	2380	142	2899	1528	26	0
500 Year Event Plan 2	$199,877,619	2177	152	2482	1705	2	264
500 Year Event Plan 3	$175,821,937	2246	127	2208	2171	23	51
1000 Year Event Plan 1	$321,260,048	2947	353	3079	1317	57	0
1000 Year Event Plan 2	$351,891,052	2419	312	2914	922	237	380
1000 Year Event Plan 3	$347,054578	2435	310	2902	955	269	327

Table 4: Trade-off Analysis between the objectives at $120 million budget

Budget $120,000,000	Economic Loss	Population Dislocation	Repair Time (Days)	Number of Buildings not Retrofitted	Number of Buildings Retrofitted to Option 1	Number of Buildings Retrofitted to Option 2	Number of Buildings Retrofitted to Option 3
500 Year Event Plan 1	$157,399,834	2261	116	1823	2565	10	55
500 Year Event Plan 2	$192,044,756	2154	145	2239	1746	4	465
500 Year Event Plan 3	$164,693,502	2181	113	1759	2453	20	221
1000 Year Event Plan 1	$294,555,902	2851	313	2808	1290	355	0
1000 Year Event Plan 2	$332,005,862	2311	279	2581	1042	136	694
1000 Year Event Plan 3	$304,411,154	2399	270	2412	1363	344	334

To examine the trend of the above plans further, the economic damage, population dislocation, and repair times for 500-year and 1000-year incidents in the absence of a retrofitting strategy were estimated.

Table 5: Community metrics with no mitigation strateg–y

Investment ($0)	Economic Loss	Population Dislocation	Avg Repair Time (Days)
500-year return period	$237,244,445	2574	220
1000-year return period	$405,304,927	3157	455

5. Results and Analysis

We should investigate the returns on - budget level further to determine which budget level would provide us with the best financial return for the money invested. In the first plan for 500-year event, we seek the solution with the least amount of economic loss. Let us compare how the invested capital benefits us in terms of avoiding economic loss. At a budget amount of $40 million, the economic loss has decreased from $237,244,445 to $195,058,236 for a 105% return on investment. In terms of economic loss, other budget amounts of $80M and $120M yield 80% and 66% returns, respectively. While the return-on-investment capital to money could be lower in these situations, when looking at the increase of the community's repair time, the $40Millon investment has a 40% improvement, while the $80 and $120M investments have a 73% and 94% improvement, respectively. Comparing outcomes across budget levels can help to enhance decision making even more. For example, with the least budget, the minimum population dislocation is 2245 households. This can be reduced by 121 predicted dislocations for an extra $40M. This more expensive drastic approach also results in a $61.6M reduction in direct economic loss.

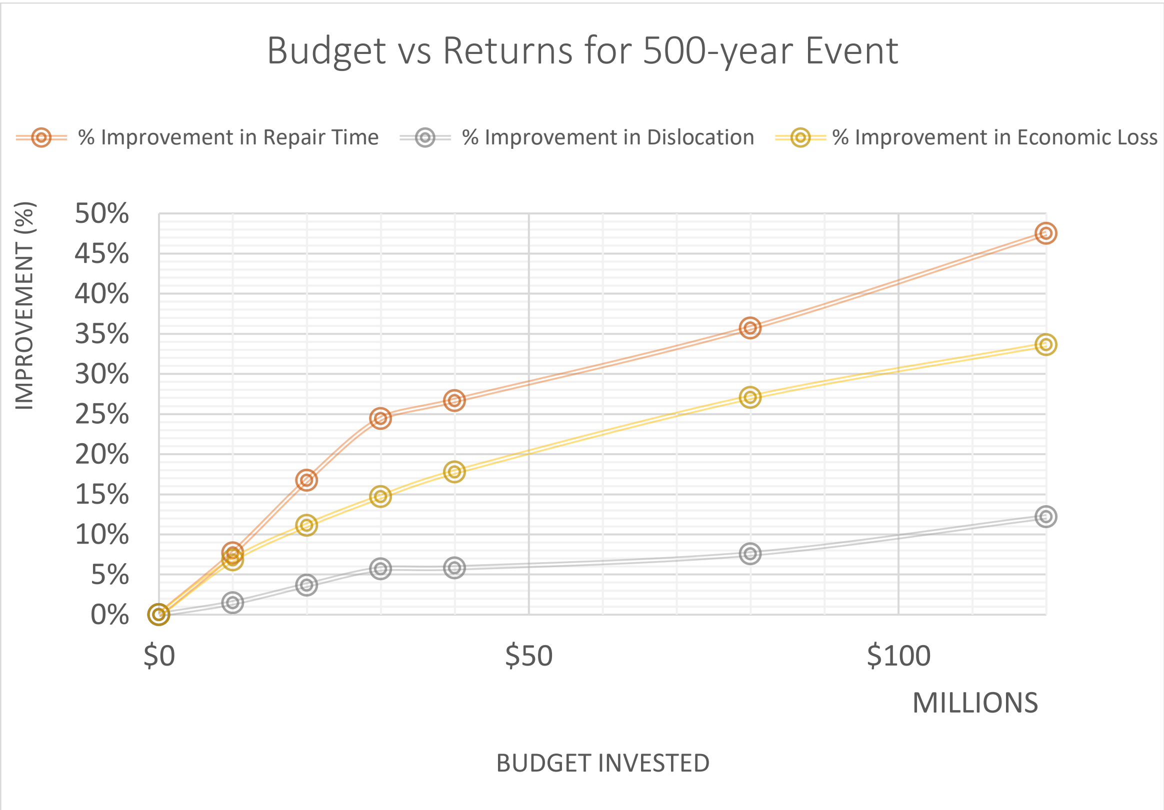


Figure 7: Improvements in Objectives for 500-year Event

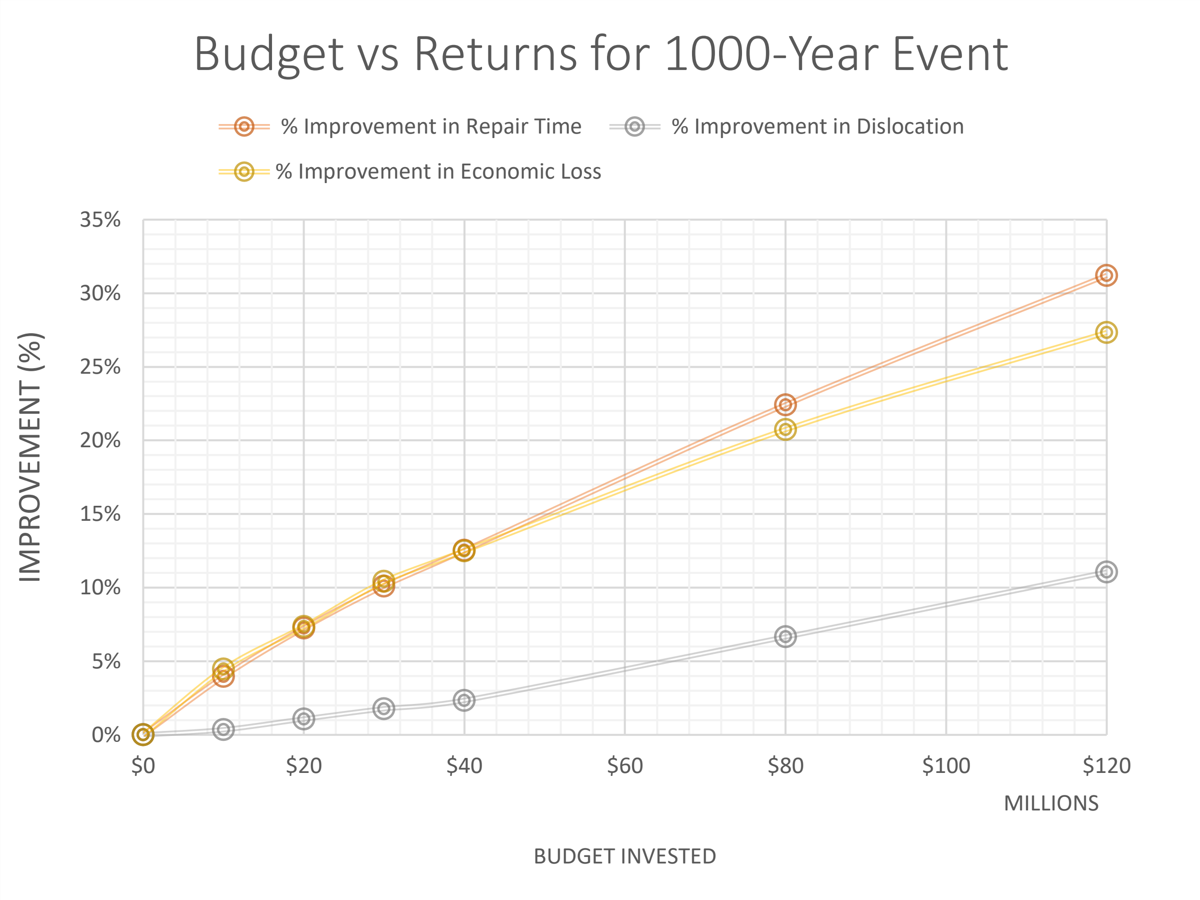


Figure 8: Improvements in Objectives for 1000-year Event

The trade-offs are numerous, and the outcomes produced by the optimization model can be used in a variety of analyses, allowing the decision maker to choose the best plan for their community based on these insights. This model's capability ranges from providing an overall optimum value on how much we can save in economic loss, population dislocation, and repair times to informing the user with which building needs to be retrofitted with which strategy to achieve these values within a variety of budgets.

Looking at the spatial analysis, we can see why these results support some regions in different plans. The mitigation strategies for different plans and different budget levels are shown below in Figure10. The top row of Figure 10, panels 10a-c, show the 500-year event under different budget levels, ranging from $40M to $120M. The bottom row, panels 10d-f, show the 1,000-year event under the same budget levels. In 10a-c, each plot shows the plan 2 solution, that is minimizing population dislocation. Conversely, panels 10d-f shows plans 2, 3, and 1 respectively, or minimize population dislocation, repair time, and economic losses.

Considering panels 10a-c, it be seen that as the budget increases, an increasing number of parcels are show that the optimal solution is to relocate and retrofit to the highest seismic code. It is interesting note that few, if any, parcels are simply relocated (option 2). This akin to saying that if a structure is relocated, it is worthwhile for the owners to invest in retrofitting the structure to the highest seismic code. Panels 10a-c further show that Seaside's urban corridor, the centrally located seaward-most parcels remain under mitigation option 0 regardless of budget level. This is due to the strategy being to decrease population dislocation, Plan 2, and this area is not residential as seen in Figure 9

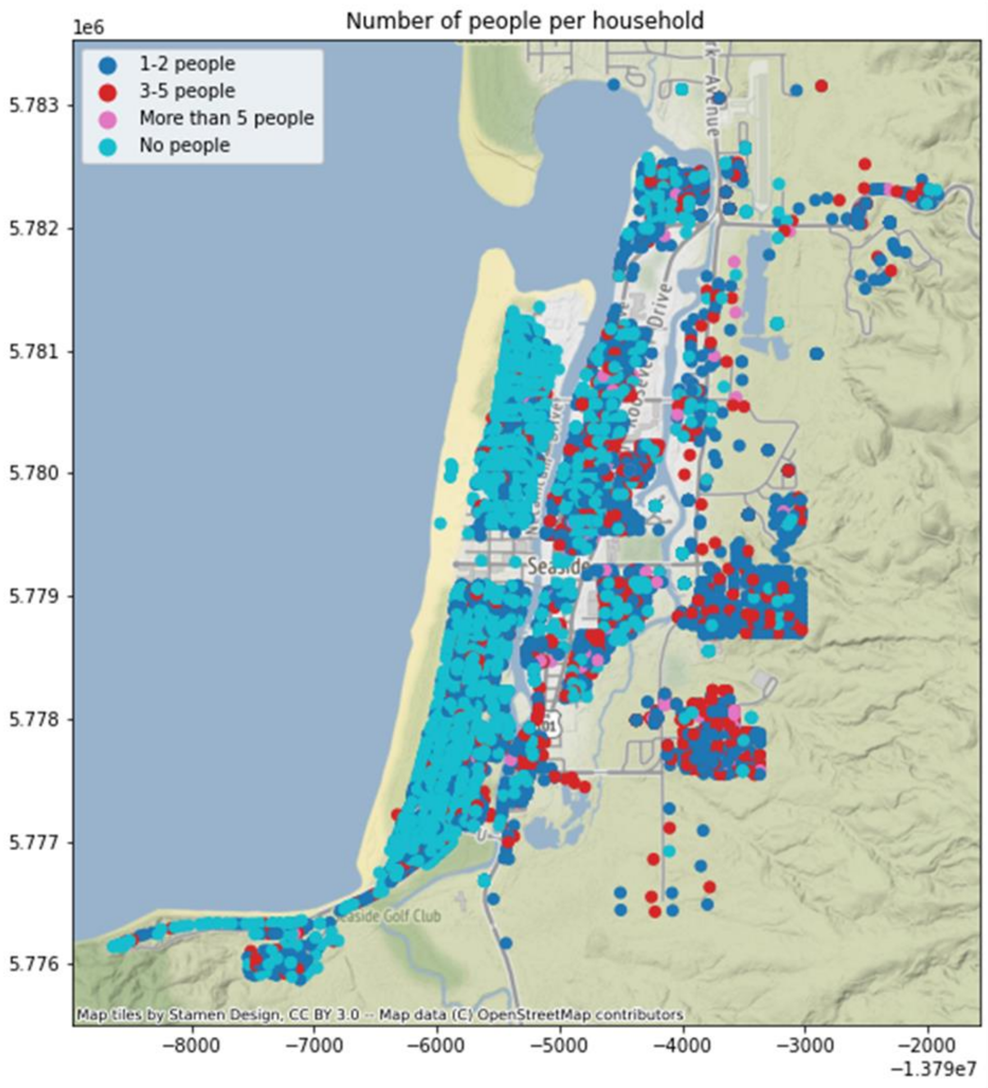


Figure 9: Seaside Community Analysis: Population Spread

Considering panels 10d-f, these show the 1,000-year event under different budgets and mitigation plans. Similar to the top row of Figure 10, where the plan is to minimize population dislocation, panel 10d shows that the urban corridor remains in status quo conditions whereas the surrounding residential areas are either retrofitted or relocated, options 1 and 2, respectively. Comparing panels 10a and 10d, it can be seen that with an increased recurrence interval, but under the same budget, a significant number of seaward parcels shift from retrofitting to relocating. This is due to the increased threat the tsunami plays as the recurrence interval increases. Panel 10f shows that when the objective is to minimize the economic losses, the urban corridor begins to shift from mitigation option 0 to either retrofitting or relocating.

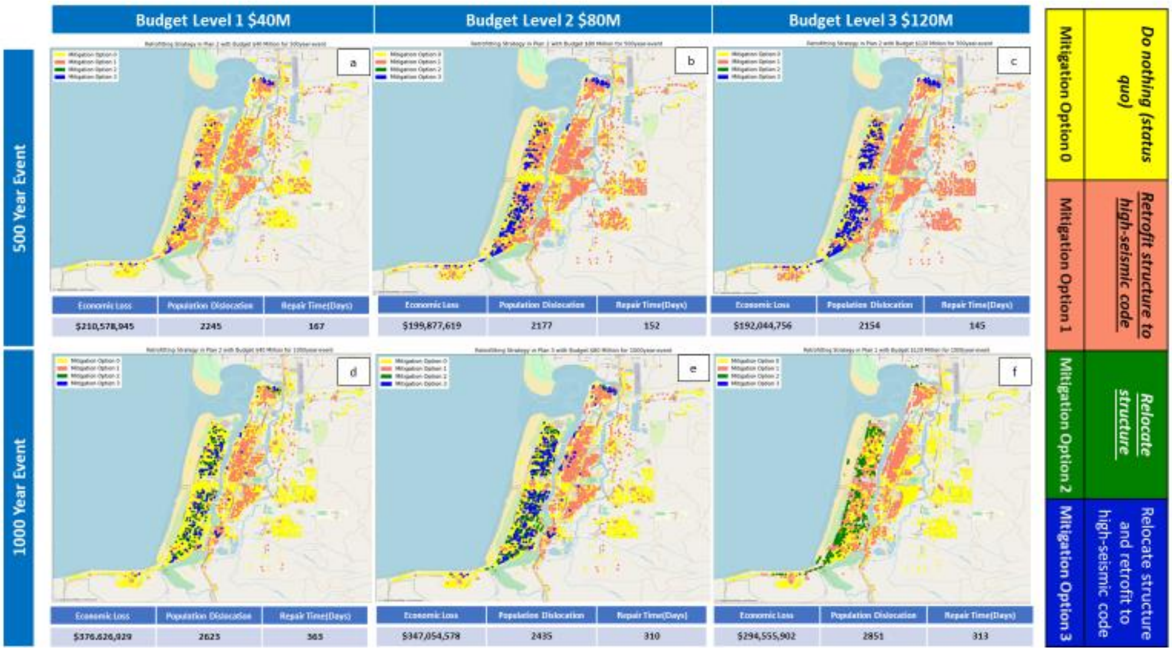
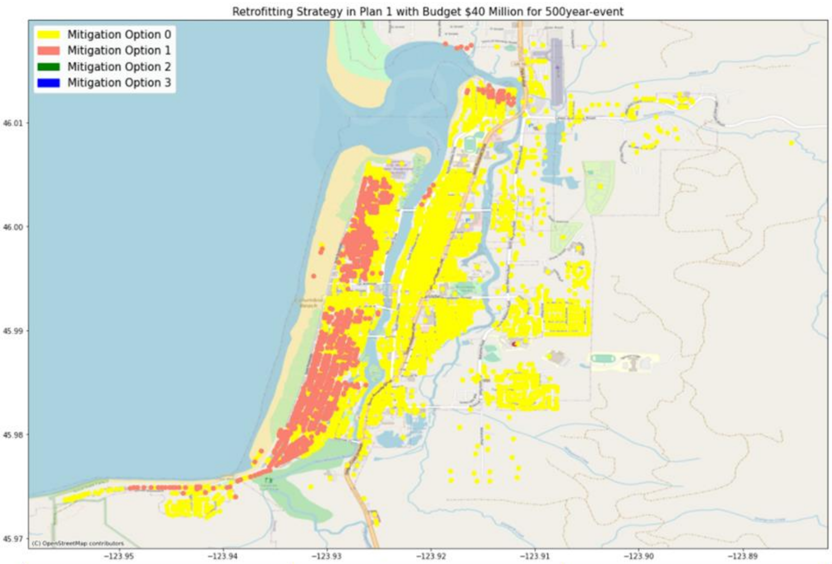
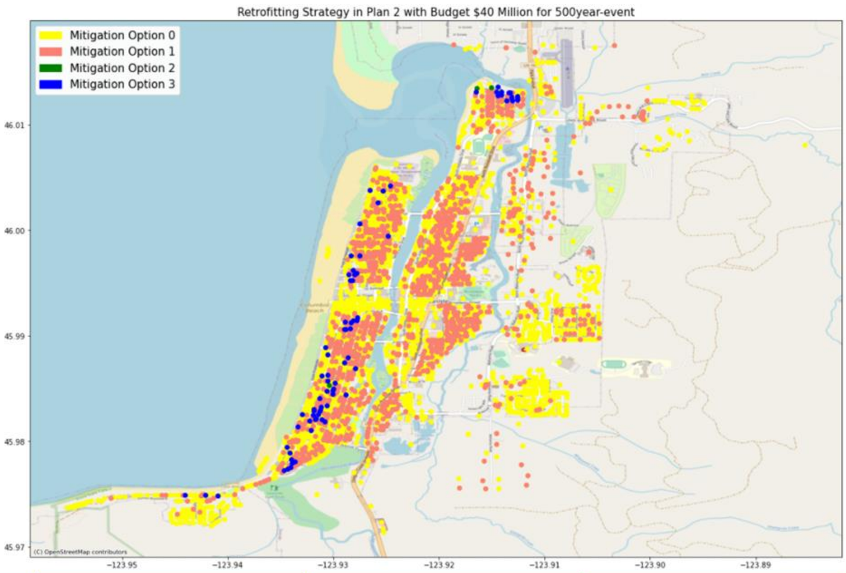


Figure 10: (a-f): Retrofitting Plans for 500-year event & 1000-year event



Economic Loss	Population Dislocation	Repair Time(Days)
$195,058,236	2425	162

Figure 11: Plan 1 with $40Million for 500-year event



Economic Loss	Population Dislocation	Repair Time(Days)
$210,578,945	2245	167

Figure 12: Plan 2 with $40Million for 500-year event

Figure 11 depicts Plan 1 and Figure 12 shows Plan 2 for the 500-year scenario with a $40M budget. In Plan 1, where we have the least economic loss, the model selects the coastal area with mitigation strategy 1, which is the region with the most costly buildings used for seasonal and recreational use. The model's tendency to retrofit the most expensive buildings in order to incur the least economic loss demonstrates the model's preferences in terms of optimal tradeoffs. Similarly, we can see in Figure 10 that the population is broadly distributed in the middle area, and in Plan 2 from Figure 12 we can see that the spread of strategies is even around the map to help get the least population dislocation while still making sure to minimize the total economic loss by proposing relocated buildings in coastal regions, i.e. mitigation strategy 3.

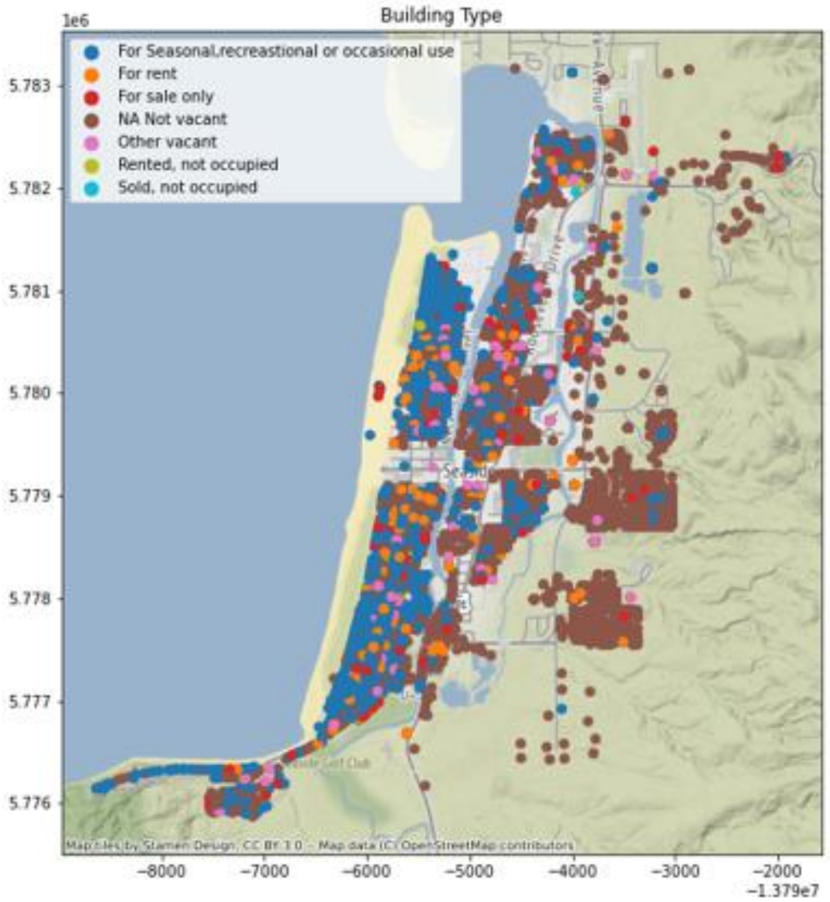


Figure 13: Seaside Community Analysis, Building Type

The transition in mitigation strategy visible in the three chosen plans represents the model's broader pattern of moving investments from residential to non-residential structures. When these are compared to the competing repair times, the decision maker gets an unique perspective.

6. Conclusion

The model considers mitigation options for both tsunami and earthquake, broadening resilience preparation, and the results specifically select retrofitting for which hazard provides the best optimum metrics in the future. Community leaders, emergency managers, and local authority representatives face difficult decision problems and conflicting priorities when it comes to community resilience. This study's multi-objective optimization model for multiple hazards is intended to serve as a decision-making mechanism for those members as they analyze how investments can affect community vulnerability and planning for multiple events. We cannot prevent future disasters, but we can choose a future in which post-disaster losses are manageable. Preparing now by assessing infrastructure, developing, and implementing a long-term retrofit and redesign plan to make Oregon more resilient to future disasters should be considered. One approach to improve the resilience of community is by retrofitting the infrastructure with multiple mitigation options by making optimal investments, which is not so simple. Understanding the benefits of resilience investments in one or more mitigation strategies is difficult when dealing with multiple hazards and a variety of assets with varying values. Community leaders will face difficult decisions as they attempt to address the economic, social, cultural, and environmental values of multiple community assets. It is critical to have access to reliable data in order to support these types of decisions. This research helps to ensure that city leaders have accurate information about the investments they can make while considering multiple events.

Even though investments are made in some communities for securing the vital services and running operations, they are useful only if they provide a well-established rate of return on investment and provide insight into trade-offs that can help identify value. Trade-offs between population dislocation and the community's ability to recover in time and economic loss of the community is inadequate. Hence, we determine the community's resilience based on the assessment of these three metrics. Considering these as key characteristics we were inspired to research on seeing how investments can go toward improving these three metrics. For which, the multi-objective optimization framework was built to handle several competing objectives. The framework considers multiple future hazards which can occur concurrently and is informed of the community's economic losses, population dislocation, and repair time, as well as the community's available mitigation strategies and the cost of implementing these strategies. This has the potential to optimize investments for building retrofitting and generate a variety of solutions within a given budget while ensuring optimum community resilience metrics. Community leaders' approach would most likely be unique to the community. We only provide information in this work to help you decide where to focus your potential investment.

References

Bai, Jong Wha, Mary Beth D. Hueste, and Paolo Gardoni. 2008. “Probabilistic Assessment of Structural Seismic Damage for Buildings in Mid-America.” *AIP Conference Proceedings* 1020 (PART 1): 1685–92. https://doi.org/10.1063/1.2963799.

Bruneau, Michel, Stephanie E. Chang, Ronald T. Eguchi, George C. Lee, Thomas D. O’Rourke, Andrei M. Reinhorn, Masanobu Shinozuka, Kathleen Tierney, William A. Wallace, and Detlof Von Winterfeldt. 2003. “A Framework to Quantitatively Assess and Enhance the Seismic Resilience of Communities.” *Earthquake Spectra* 19 (4): 733–52. https://doi.org/10.1193/1.1623497.

Costa, Rodrigo, Terje Haukaas, and Stephanie E. Chang. 2021. “Agent-Based Model for Post-Earthquake Housing Recovery.” *Earthquake Spectra* 37 (1): 46–72. https://doi.org/10.1177/8755293020944175.

Cutter, Susan L., Christopher T. Emrich, Jerry T. Mitchell, Bryan J. Boruff, Melanie Gall, Mathew C. Schmidtlein, Christopher G. Burton, and Ginni Melton. 2006. “The Long Road Home: Race, Class, and Recovery from Hurricane Katrina.” *Environment* 48 (2): 8–20. https://doi.org/10.3200/ENVT.48.2.8-20.

“FEMA_2013.” Tsunami Methodol ogy Technical Manual.

“FEMA_2015..” Multi-hazard Loss Estimation Methodology.

Franchin, Paolo, and Francesco Cavalieri. 2015. “Probabilistic Assessment of Civil Infrastructure Resilience to Earthquakes.” *Computer-Aided Civil and Infrastructure Engineering* 30 (7): 583–600. https://doi.org/10.1111/mice.12092.

Frangopol, Dan M., and Paolo Bocchini. 2011. “Resilience as Optimization Criterion for the Rehabilitation of Bridges Belonging to a Transportation Network Subject to Earthquake.” *Structures Congress 2011 - Proceedings of the 2011 Structures Congress*, 2044–55. https://doi.org/10.1061/41171(401)178.

Gardoni, P., John W. van de Lindt, Bruce R. Ellingwood, T. McAllister, J.S. Lee, Harvey Cutler, Walter G. Peacock, and Dan Cox. 2018. “The Interdependent Networked Community Resilience Modeling Environment.” *Proceedings of the 16th European Conference on Earthquake Engineering*, 1–10.

Gasparini, Paolo, Infn Istituto, Fisica Nucleare, and Alexander Garcia-aristizabal. 2014. “Encyclopedia of Earthquake Engineering.” *Encyclopedia of Earthquake Engineering*, no. November. https://doi.org/10.1007/978-3-642-36197-5.

Girard, Chris. 1997. “Ethnicity and Segregation: Post-Hurricane Relocation.,” no. March 2020.

Goltz, James, Katsuya Yamori, James Goltz, and Katsuya Yamori. 2020. *Tsunami Preparedness and Mitigation Strategies*. *Oxford Research Encyclopedia of Natural Hazard Science*. https://doi.org/10.1093/acrefore/9780199389407.013.324.

Gomez, Camilo, and Jack W. Baker. 2019. “An Optimization-Based Decision Support Framework for Coupled Pre- and Post-Earthquake Infrastructure Risk Management.” *Structural Safety* 77 (October 2017): 1–9. https://doi.org/10.1016/j.strusafe.2018.10.002.

Gomez, Camilo, Andrés D. González, Hiba Baroud, and Claudia D. Bedoya-Motta. 2019. “Integrating Operational and Organizational Aspects in Interdependent Infrastructure

Network Recovery.” *Risk Analysis* 39 (9): 1913–29. https://doi.org/10.1111/risa.13340.

González, Andrés D., Leonardo Dueñas-Osorio, Mauricio Sánchez-Silva, and Andrés L. Medaglia. 2016. “The Interdependent Network Design Problem for Optimal Infrastructure System Restoration.” *Computer-Aided Civil and Infrastructure Engineering* 31 (5): 334–50. https://doi.org/10.1111/mice.12171.

Guidotti, Roberto, Paolo Gardoni, and Nathanael Rosenheim. 2019. “Integration of Physical Infrastructure and Social Systems in Communities’ Reliability and Resilience Analysis.” *Reliability Engineering and System Safety* 185 (January): 476–92. https://doi.org/10.1016/j.ress.2019.01.008.

Hosseini, Seyedmohsen, Kash Barker, and Jose E. Ramirez-Marquez. 2016. “A Review of Definitions and Measures of System Resilience.” *Reliability Engineering and System Safety* 145: 47–61. https://doi.org/10.1016/j.ress.2015.08.006.

Ji, Jing Yu, Wei Jie Yu, Yue Jiao Gong, and Jun Zhang. 2018. “Multiobjective Optimization with ϵ-Constrained Method for Solving Real-Parameter Constrained Optimization Problems.” *Information Sciences* 467: 15–34. https://doi.org/10.1016/j.ins.2018.07.071.

Kameshwar, Sabarethinam, Daniel T. Cox, Andre R. Barbosa, K. Farokhnia, Hyoungsu Park, Mohammad S. Alam, and John W. van de Lindt. 2019. “Probabilistic Decision-Support Framework for Community Resilience: Incorporating Multi-Hazards, Infrastructure Interdependencies, and Resilience Goals in a Bayesian Network.” *Reliability Engineering and System Safety* 191 (May): 106568. https://doi.org/10.1016/j.ress.2019.106568.

Kappes, Melanie S., Margreth Keiler, Kirsten von Elverfeldt, and Thomas Glade. 2012. “Challenges of Analyzing Multi-Hazard Risk: A Review.” *Natural Hazards* 64 (2): 1925–58. https://doi.org/10.1007/s11069-012-0294-2.

Koliou, Maria, John W. van de Lindt, Therese P. McAllister, Bruce R. Ellingwood, Maria Dillard, and Harvey Cutler. 2020. “State of the Research in Community Resilience: Progress and Challenges.” *Sustainable and Resilient Infrastructure* 5 (3): 131–51. https://doi.org/10.1080/23789689.2017.1418547.

Li, Yue, John W. van de Lindt, Thang Dao, Sigridur Bjarnadottir, and Aakash Ahuja. 2012. “Loss Analysis for Combined Wind and Surge in Hurricanes.” *Natural Hazards Review* 13 (1): 1–10. https://doi.org/10.1061/(asce)nh.1527-6996.0000058.

Newman, Jeffrey Peter, Holger Robert Maier, Graeme Angus Riddell, Aaron Carlo Zecchin, James Edward Daniell, Andreas Maximilian Schaefer, Hedwig van Delden, Bijan Khazai, Michael John O’Flaherty, and Charles Peter Newland. 2017. “Review of Literature on Decision Support Systems for Natural Hazard Risk Reduction: Current Status and Future Research Directions.” *Environmental Modelling and Software* 96: 378–409. https://doi.org/10.1016/j.envsoft.2017.06.042.

NYC Emergency Management. 2019. “Plan for Hazards - Hazard Mitigation - NYCEM.” *NY City Emergency Hazard Mitigation*, no. May. https://www1.nyc.gov/site/em/ready/hazard-mitigation.page.

Oregon Seismic Safety Policy Advisory Commission (OSSPAC). 2013. “The Oregon Resilience Plan: Reducing Risk and Improving Recovery for the next Cascadia Earthquake and Tsunami.” *Report to the 77th Legislative Assembly*, no. February: 2–40. https://doi.org/10.1074/jbc.M703713200.

Park, Hyoungsu, Mohammad S. Alam, Daniel T. Cox, Andre R. Barbosa, and John W. van de Lindt. 2019. “Probabilistic Seismic and Tsunami Damage Analysis (PSTDA) of the Cascadia Subduction Zone Applied to Seaside, Oregon.” *International Journal of Disaster Risk Reduction* 35 (January): 101076. https://doi.org/10.1016/j.ijdrr.2019.101076.

Park, Hyoungsu, Daniel T. Cox, Mohammad Shafiqual Alam, and Andre R. Barbosa. 2017. “Probabilistic Seismic and Tsunami Hazard Analysis Conditioned on a Megathrust Rupture of the Cascadia Subduction Zone.” *Frontiers in Built Environment* 3 (June): 1–19. https://doi.org/10.3389/fbuil.2017.00032.

Park, Hyoungsu, Daniel T. Cox, and Andre R. Barbosa. 2017. “Comparison of Inundation Depth and Momentum Flux Based Fragilities for Probabilistic Tsunami Damage Assessment and Uncertainty Analysis.” *Coastal Engineering* 122 (January): 10–26. https://doi.org/10.1016/j.coastaleng.2017.01.008.

Pike-burke, Ciara. n.d. “Multi-Objective Optimization,” 1–6.

Risi, Raffaele De, and Katsuichiro Goda. 2016. “Probabilistic Earthquake–Tsunami Multi-Hazard Analysis: Application to the Tohoku Region, Japan.” *Frontiers in Built Environment* 2 (October): 1–19. https://doi.org/10.3389/fbuil.2016.00025.

Rosenheim, Nathanael, Roberto Guidotti, Paolo Gardoni, and Walter Gillis Peacock. 2019. “Integration of Detailed Household and Housing Unit Characteristic Data with Critical Infrastructure for Post-Hazard Resilience Modeling.” *Sustainable and Resilient Infrastructure* 00 (00): 1–17. https://doi.org/10.1080/23789689.2019.1681821.

Sebastian, Antonia, Kasper Lendering, Baukje Kothuis, Nikki Brand, Sebastian N. Jonkman, Pieter van Gelder, Maartje Godroij, Bas Kolen, Tina Comes, and Stef Lhermitte. 2017. “Hurricane Harvey Report: A Fact-Finding Effort in the Direct Aftermath of Hurricane Harvey in the Greater Houston Region.” *Delft: Delft University Publishers*, no. October: 102. https://www.researchgate.net/publication/321749153_Hurricane_Harvey_Report_A_fact-finding_effort_in_the_direct_aftermath_of_Hurricane_Harvey_in_the_Greater_Houston_Region.

Sun, Wenjuan, Paolo Bocchini, and Brian D. Davison. 2020. “Resilience Metrics and Measurement Methods for Transportation Infrastructure: The State of the Art.” *Sustainable and Resilient Infrastructure* 5 (3): 168–99. https://doi.org/10.1080/23789689.2018.1448663.

What, Defining, S A N Fr, Needs From, I T S Seism, and Mitigation Policies. 2009. “The Resilient City: Defining What San Francisco Needs From Its Seismic Mitigation Policies Spur Report the Resilient City: Defining What San Francisco Needs From Its Seismic Mitigation Policies.” www.spur.org.

Wood, Nathan. 2007. “Variations in City Exposure and Sensitivity to Tsunami Hazards in Oregon Scientific Investigations Report 2007-5283,” 43.

Wood, Nathan J., Christopher G. Burton, and Susan L. Cutter. 2010. “Community Variations in Social Vulnerability to Cascadia-Related Tsunamis in the U.S. Pacific Northwest.” *Natural Hazards* 52 (2): 369–89. https://doi.org/10.1007/s11069-009-9376-1.

Yunjie Wen , Charles Nicholson, Andrés González. n.d. “A Multi-Objective Optimization

Model for Buildings Retrofit Strategies to Optimize Direct Economic Loss , Population Dislocation , and Building Functionality.”

Zhang, Weili, and Charles Nicholson. 2016. “A Multi-Objective Optimization Model for Retrofit Strategies to Mitigate Direct Economic Loss and Population Dislocation.” *Sustainable and Resilient Infrastructure* 1 (3–4): 123–36. https://doi.org/10.1080/23789689.2016.1254995.

Zhang, Weili, Naiyu Wang, and Charles Nicholson. 2017. “Resilience-Based Post-Disaster Recovery Strategies for Road-Bridge Networks.” *Structure and Infrastructure Engineering* 13 (11): 1404–13. https://doi.org/10.1080/15732479.2016.1271813.