Coupled urban change and natural hazard consequence model for community resilience planning

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Key Points:

- An urban change model is coupled with a hazard consequence model to consider future hazards, population growth, and planning policies.
- The model is applied to a coastal community in the Pacific Northwest considering Cascadia Subduction Zone seismic-tsunami hazards.
- Placing a cap on the number of vacation homes in a community could result in more visitors in damaged buildings.

Abstract

This paper presents a new coupled urban change and hazard consequence model that considers population growth, a changing built environment, natural hazard mitigation planning, and future acute hazards. Urban change is simulated as an agent-based land market with six agent types and six land use types. Agents compete for parcels with successful bids leading to changes in both urban land use – affecting where agents are located – and structural properties of buildings – affecting the building's ability to resist damage to natural hazards. IN-CORE, an open-source community resilience model, is used to compute damages to the built environment. The coupled model operates under constraints imposed by planning policies defined at the start of a simulation. The model is applied to Seaside, Oregon, a coastal community in the North American Pacific Northwest subject to seismic-tsunami hazards emanating from the Cascadia Subduction Zone. Ten planning scenarios are considered including caps on the number of vacation homes, relocating community assets, limiting new development, and mandatory seismic retrofits. By applying this coupled model to the testbed community, we show that: (1) placing a cap on the number of vacation homes results in more visitors in damaged buildings, (2) that mandatory seismic retrofits do not reduce the number of people in damaged buildings when considering population growth, (3) polices diverge beyond year 10 in the model, indicating that many policies take time to realize their implications, and (4) the most effective policies were those that incorporated elements of both urban planning and enforced building codes.

Plain Language Summary

Natural hazards negatively impact communities resulting in significant infrastructure damages. Natural hazard mitigation planning attempts to reduce these damages and modeling can be used to measure how effective different mitigation plans can be. A new modeling framework is presented that accounts for population growth, a changing built environment, natural hazard mitigation planning, and future hazards. The model is applied to a testbed community with a large tourist population that is exposed to earthquake and tsunami hazards. Using this model, we consider different combinations of policies such as limiting the number of vacation homes in the community, relocating community assets, limiting new development, and enforcing building codes. Interestingly, we show that while placing a cap on the number of vacation homes does free up housing for full time residents, this also results in more visitors in damaged buildings. It is also shown how even with building codes in place, population growth contributes to an increased number of people in damaged buildings. Lastly, we show how the most effective policies incorporate elements of both urban planning and building codes.

1 Introduction

With disasters occurring at the nexus of the built-natural-social environments (Mileti, 1999; Peek and Guikema, 2021), recent natural hazards have highlighted the need for disaster resilient communities (Koliou *et al.*, 2018). Increasing community resilience has gained traction in recent years with local stakeholders, national, and global entities alike addressing community resilience and disaster risk reduction (*e.g.*, SPUR, 2009; OSSPAC, 2013; UNDRR, 2015; NIST, 2016). Simultaneously, however, complexities of increasing community resilience in an uncertain future are being identified. These complexities stem from a variety of sources and can include accelerating human activities, increased uncertainty in the built-natural-human environments, and increased complexity of infrastructure systems themselves (Spies *et al*., 2014; Chester *et al.*, 2021). Population growth, urbanization, and a changing climate are expected to further contribute to increased exposure and societal losses associated with natural hazards in both the immediate and long-term future (Neumann *et al*., 2015; Hemmati *et al.*, 2020; Bilskie *et al.*, 2022; Cremen *et al.*, 2022). As a result, the outcomes of hazard mitigation plans are often difficult to fully envision, with biased policies leading to increased vulnerability of marginalized populations (Peek *et al*., 2020).

Given these challenges and complexities, modeling and simulation have been identified as a means to inform disaster theory and understand emerging phenomena (Mostafavi and Ganapati, 2021). Subsequently, the use of simulation has proven effective to evaluate how natural hazard mitigation plans and policy can help improve community resilience (Talebiyan and Mahsuli, 2018; Wang *et al*., 2019; Nofal *et al*., 2021). While many of these simulation efforts provide what-if scenarios for natural hazard mitigation planning, they often consider static, present-day representations of the built-natural-social environments despite their dynamic nature.

There has, however, been a recent shift towards considering disaster resilience under a more dynamic and future-oriented lens (Hemmati *et al*., 2020; Galasso *et al*., 2021; Cremen *et al*., 2022). To this end, there is a need to situate the simulation of disaster resilience within appropriate temporal settings given that both disasters and the adoption of mitigation plans happen over an extended period of time ranging from months to years. The dynamic nature of the built and social environments within disaster resilience simulation can be captured by coupling urban growth and change models with hazard consequence models. Figure 1 shows a conceptual diagram of this coupling. The time scale shown is in decades, and the y-axis shows a "Metric of Interest". Example metrics could include the number of habitable homes, number of residents with electricity, *etc*. Policies influence how these metrics evolve over time and, while not shown here, these metrics could also decrease. At some point in the future, an extreme event may occur resulting in damages, losses, and recovery. The overall goal of the simulation model is to evaluate how policies affect the metric of interest relative to the status quo during non-disaster conditions and how these policies affect the resilience trajectory (initial damage and recovery) following an extreme event.

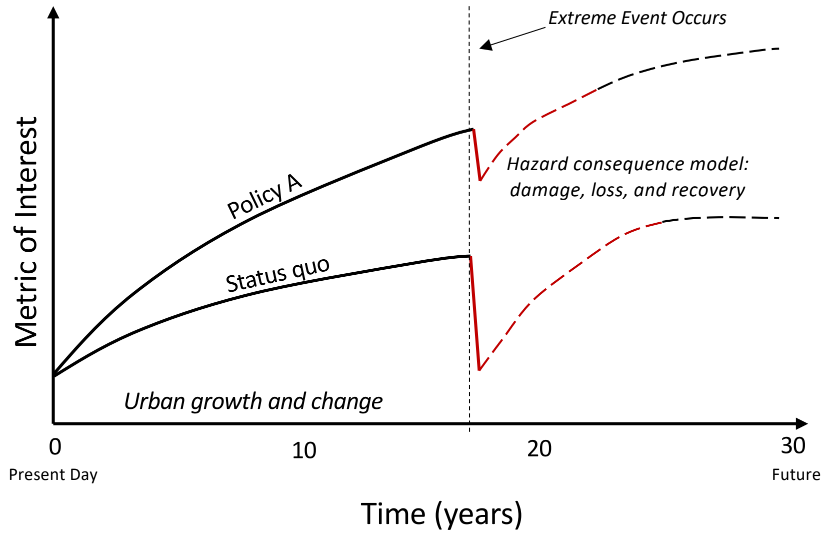

Figure 1: Situating infrastructure resilience within a larger temporal setting by coupling urban growth and change modeling with hazard consequence modeling

While it is common to find models to evaluate policies for either non-disaster growth or damage-recovery following a disaster, there are few comprehensive models that evaluate both in a consistent manner. Table 1 provides a review of models and papers divided into three groups: (1) urban growth and change models, (2) hazard consequence models, and (3) coupled urban change and hazard consequence models.

Table 1: Review of: (1) urban growth/change models, (2) hazard consequence models, and (3) coupled urban change and hazard consequence models

Model Group	Paper	Urban Change	Earthquake	Flood	Hurricane	Tornado	Tsunami	Model Description/Notes	Model name
Urban growth and change	White and Engelen (1993)	✓						Early cellular automata model of urban change	-
	Berry et al. (1996)	✓						Socioeconomic model influences transition probability matrix, influences land use	LUCAS
	Waddell (2002)	✓						Real estate market modeling choices of households, businesses, real estate, etc.	UrbanSim
	Hunt and Abraham (2003)	✓						Used for simulating spatial economic systems; can be applied to urban land use change	PECAS
	Brown and Robinson (2006)	✓						Residential choice where agents select grid space maximizing utility	SLUCE/SOME
	Bolte et al. (2007)	✓						Land use change model for alternative future evaluation of policies	Envision/EvoLand

Model Group	Paper	Urban Change	Earthquake	Flood	Hurricane	Tornado	Tsunami	Model Description/Notes	Model name
	Filatova et al. (2009)	✓						Residential choice with agent buying/selling mechanisms	ALMA
	Filatova et al. (2011)	✓						Residential choice with agent buying/selling mechanisms for coastal area	ALMA-C
	Magliocca et al. (2011)	✓						Coupled housing and land market	CHALMS
	Chaudhuri and Clarke (2013)	✓						Cellular automata model that started out as wildfire spread model	SLEUTH
Hazard Consequence	McLaren et al.(2008)		✓					Early regional-level earthquake risk analysis software	MAEVIS
	van de Lindt et al. (2018)		✓	✓	✓	✓	✓	Regional-level natural hazard damage, loss, and recovery	IN-CORE
	FEMA (2021a)		✓	✓	✓		✓	Regional-level natural hazard damage, loss, and recovery; GIS-based	HAZUS
	Deierlein et al.(2021)		✓	✓	✓		✓	Regional-level natural hazard damage, loss, and recovery	SimCenter - R2D
Urban growth and change + Hazard Consequence	Jain et al. (2005)	✓			✓			Forecast urban change as proportional to population and consider hurricane risk	
	French (2012)	✓	✓					Forecast urban growth using per capita multipliers and focus on nonstructural damages from earthquakes	
	Filatova (2015)	✓		✓				Empirical land market and consider flood risk as in/out of flood zone	RHEA
	Dubbelboer et al. (2017)	✓		✓				Simulate land market for flood insurance evaluation	
	Jenkins et al. (2017)	✓		✓				Agent-based model of land use change for insurance evaluation	
	Sleeter et al. (2017)	✓	✓				✓	Apply LUCAS model and consider earthquake/tsunami exposure at regional scale	
	Mills et al. (2018)	✓		✓				Use Envision model to evaluate coastal hazard policies informed by stakeholder engagement	
	Chang et al. (2019)	✓	✓	✓				Urbanization follows simple rules based on policy; consider both earthquake and flood risk	
	Haer et al. (2019)	✓		✓				Agent-based model of land use change for disaster policy evaluation	
	Haer et al. (2020)	✓		✓				Agent-based model of land use change for exploring safe development paradox	

Model Group	Paper	Urban Change	Earthquake	Flood	Hurricane	Tornado	Tsunami	Model Description/Notes	Model name
	Sarica et al. (2020)	✓	✓					Apply SLEUTH model and consider buildings exposed to earthquake hazard	
	Calderón et al (2021)	✓	✓					Multi-agent system with agents defining preferences for land use to change; consider earthquake damage	
	Cremen et al. (2021)	✓	✓					Number of residences in future projections match population growth; consider earthquake hazards	
	Hemmati et al. (2021a)	✓		✓				Use cellular automata and consider flood hazards	
	Hemmati et al. (2021b)	✓		✓				Use cellular automata + agent-based model and consider flood hazards	
	Mesta et al. (2022)	✓	✓	✓				Apply SLEUTH model and consider earthquake and flood hazard at regional scale	
	Williams et al. (2022)	✓			✓			Urbanization by using a neural network and consider hurricane hazards	

As shown in Table 1, modeling urban change can take on many forms ranging from cellular automata (White and Engelen, 1993; Chaudhuri and Clarke, 2013) to modeling land markets and buyer-seller transactions (Parker and Filatova, 2008; Parker *et al*., 2012; Huang *et al*., 2014). These models are typically used for land use and urban planning to explore alternative futures under various policy scenarios.

On the hazard consequence side, there has been extensive research into simulating the impact that natural hazards have on the built- and social-environments. These can include infrastructure damages and losses, recovery and restoration processes, and/or modeling of social impacts. Recently, there have been efforts to transfer this research into deployable models that communities can utilize for resilience planning (*e.g*., van de Lindt *et al.*, 2018; Deierlein *et al*., 2021).

The coupling of these two groups of models has increased in recent years as researchers are recognizing that future projections of the built- and social-environments are important to consider for mitigation planning. Limitations to many of the previously coupled models include either considering hazards in a minimal way (*i.e*., hazard exposure), or considering urban change in a minimal way (*i.e*., multipliers based on population growth). Only a handful of the modeling approaches in Table 1 focus on the exploration of policies to evaluate hazard risks with both detailed urban change and hazard consequence components (Haer *et al*., 2019; Hemmati *et al.*, 2021a; Hemmati *et al.*, 2021b). These approaches in particular have focused exclusively on flood risks.

This paper thus presents a new coupled urban change and hazard consequence model that considers population growth, a changing built environment, natural hazard mitigation planning, and future acute hazards. Urban change is modeled via simulation of a land market whereas immediate post-disaster damages are modeled using IN-CORE, an opensource software for community resilience (van de Lindt *et al.*, 2018). The coupled model is applied to Seaside, Oregon, a testbed community in the North American Pacific Northwest considering seismic-tsunami hazards associated with the Cascadia Subduction Zone.

2 Coupled Urban Change and Hazard Consequence Model

Figure 2 shows a flowchart of the coupled urban change (grey dash-dot box) and hazard consequence model (blue dash-dot box). IN-CORE is used as the hazard consequence model, and we consider only building damages here. Alternative hazard consequences, including damages to lifelines and social impacts, could be considered using IN-CORE. Each time step in the model represents one year. The overall modeling framework begins with defining an urban change policy or policies that constrain the model simulation (b). These policies could be unrelated to the extreme event, for example to increase tourism, or could be specific to hazard mitigation, for example to incentivize building retrofits. The model is then initiated with a population and housing unit allocation (c), followed by simulating population growth (d). A land market is simulated (e) which updates the community description (f). This process repeats until the hazard event is triggered, at which the community description (f) is passed to IN-CORE. IN-CORE maps spatially explicit hazard intensity measures (g) to the built environment using damage models (h). This results in damages to physical infrastructure (i). This process is then repeated for a user-defined number of iterations. The remainder of this section provides more detail of the coupled model. Additional model documentation and the source code is provided through the data availability statement.

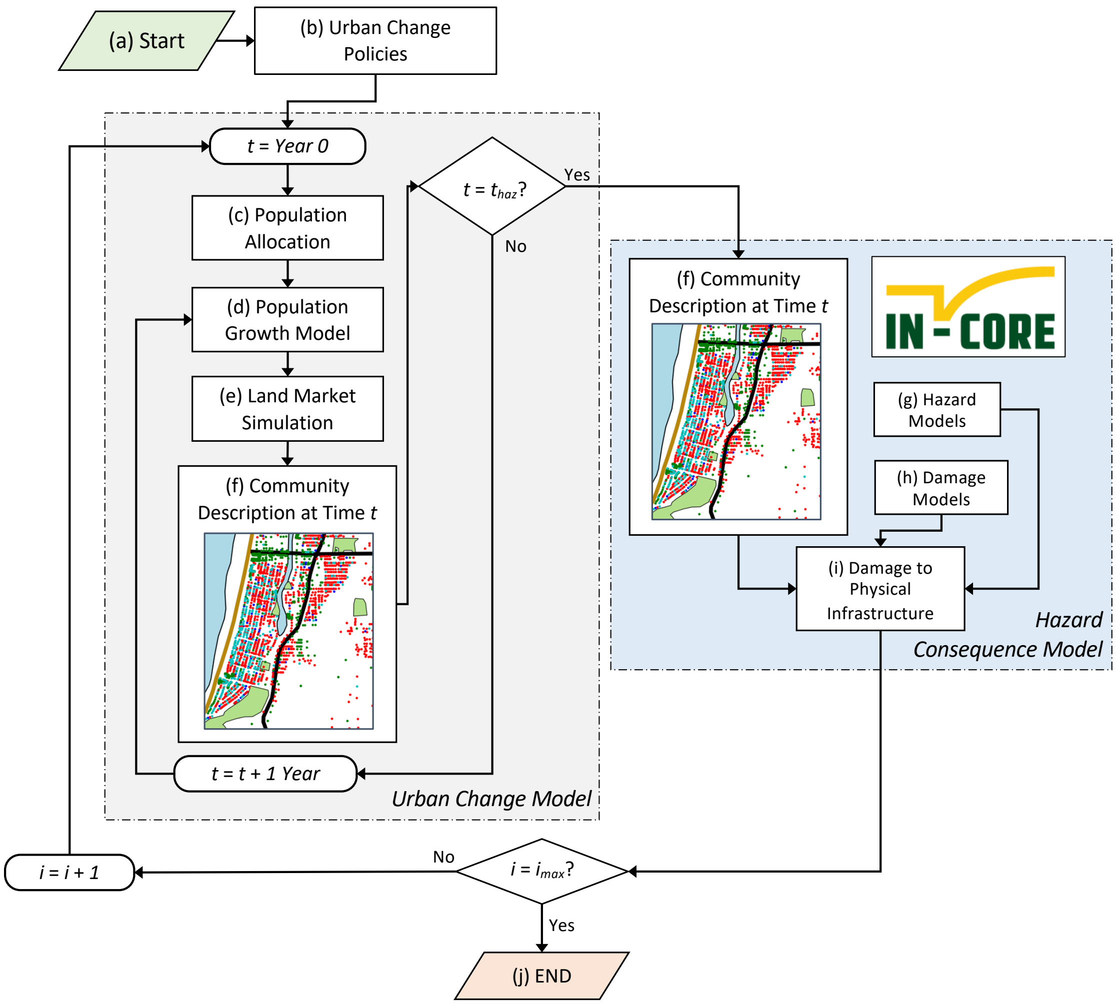

Figure 2: Flowchart of the coupled urban change (grey dash-dot box on left) and hazard consequence model (blue dash-dot box on right).

2.1 Urban Change Policies

A policy, or combination of policies, is first identified shown as *b* in Figure 2. These could include both policies unrelated to hazard mitigation or those that aim to reduce the damages and losses following natural hazards. Many forms of natural hazard mitigation policies exist. In general, these can be classified as modifying the hazard, modifying the building inventory, modifying building structural properties, or decreasing social and economic losses (S. French, personal communication, February 16, 2022).

Modifying the hazard includes implementing both grey and green engineered solutions to reduce the intensity of natural hazards (Feagin *et al.*, 2015; Saleh and Weinstein, 2016). Modifying the hazard can be costly and requires community buy in. In addition, this may result in the "safe-development paradox" in which individuals feel more protected behind engineered structures, leading to increased exposure if the structural protection were to fail (Haer *et al.*, 2020).

Modifying the building inventory includes various urban planning measures such as zoning, acquisition of damaged buildings for repeating hazards, and managed retreat (Han *et al.*, 2020; Hurlimann *et al.*, 2021). Often a charged topic, managed retreat could disrupt the fabric and cohesive structures of communities (Hino *et al*., 2017).

Modifying building structural properties includes building codes for new development, and structural retrofits or elevation of flood-prone structures for existing development (Haer *et al*., 2019; Wang *et al.*, 2021). This can often be difficult to finance and unattainable for low-income groups.

Decreasing social and economic consequences includes hazard insurance mechanisms and recovery financing (Dubbelboer *et al*., 2017; Costa *et al*., 2020; Alisjahbana *et al*., 2021). While these policies could be implemented pre-disaster, actions are often taken as post-disaster responses.

Of these policy classes, this paper focuses on *modifying the building inventory* and *modifying building structural properties*. Note that these policies focus on buildings; however additional policies could be applied to different aspects of the built environment.

2.2 Agent-based modeling of urban land use change

The grey left-most box of Figure 2 is an agent-based model (ABM) of urban change developed in this paper. ABMs have been identified as a "boundary-object" for interdisciplinary disaster research as they can seamlessly integrate knowledge from multiple disciplines (Reilley *et al.*, 2021). As such, an ABM is adopted here to both simulate urban change and couple the hazard consequence model. The ABM is written in Julia using Agents.jl (Datseris *et al.*, 2022). Each time step in the model represents one year. The urban change model is initiated with a population and housing unit allocation to infer the initial land use, types of agents, and number of people in each parcel (*c* in Figure 2). Population projections are employed as input to the model and is updated at each annual time step (*d* in Figure 2). Agents are added to the general model space – *i.e.*, not yet in a parcel – and will be competing in the land market. If at the end of an iteration, the total number of people exceeds the population projection, agents are randomly removed from the model representing out-migration.

To drive land use changes in the model, a land market is simulated (*e* in Figure 2). This is an original model developed herein following the ALMA (Filatova *et al.*, 2009) and ALMA-C (Filatova *et al*., 2011) models with two notable changes. First, the ALMA and ALMA-C models consider two agents (buyers, sellers) and two land uses (vacant, urban). The present work expands on this by considering six agents and six land uses. This is an important addition to account for (1) full time resident and visitor populations, and (2) different types of development including single family homes, rental properties, and high occupancy development. Second, the model developed here considers changes to the structural properties of buildings. This is an important feature of the model because it allows for coupling to the hazard consequence model.

2.2.1 Agent types and relations to land uses

The six agents and land uses are shown in Figure 3. Arrows indicate that an agent can occupy a parcel, whereas the colors indicate an agent owns a parcel. Agents that own parcels can structurally retrofit the building on their property. The six land uses include (a) Unoccupied, (b) Owned Residential, (c) Rental Residential, (d) Low Occupancy Seasonal Rental, (e) High Occupancy Residential, and (f) High Occupancy Seasonal Rental. The six agent types are as follows.

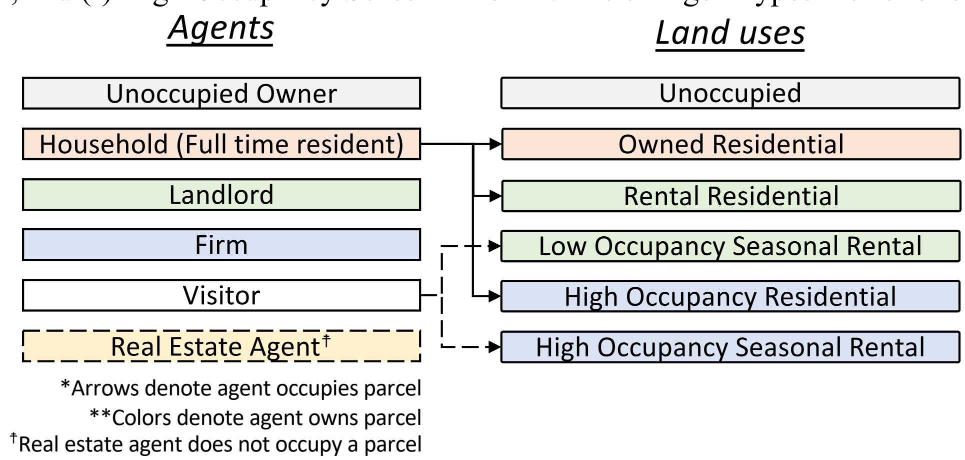

Figure 3: Agents and land uses in the urban growth and change model.

Unoccupied Owner agents are associated with unoccupied parcels and act as "sellers" in the model. As other agents bid on their parcel, they review the bids selecting the maximum if it exceeds their willingness to accept price.

Household agents are associated with full-time residents. They either reside in a parcel or are searching for a place to live. They can own an "owned residential" property (*i.e.*, a single-family home), reside in a rental residential (*i.e.*, a rental home) or reside in a high occupancy residential property (*i.e.*, an apartment/condo). The number of people associated with newly added household agents are randomly drawn from a gamma distribution and rounded to the nearest integer. A single age is randomly assigned to represent the head of the household following a gamma distribution and increases at each time step. Once the head of the household turns 80 years old, the agent is removed, and their place of residence becomes vacant. A household will randomly gain or lose one person following a Poisson process.

Landlord agents own parcels and rent them to household agents as "rental residential" or to visitor agents as "low occupancy seasonal rentals" (*i.e.*, vacation homes) (Vinogradov *et al.*, 2020). At any point in the simulation, landlord agents can choose to switch between these two land uses based on a net utility gain. Like household agents, landlord agents are removed from the model when they turn 80 and their property becomes vacant.

Firm agents purchase properties for development as either "high occupancy residential" (*i.e.*, apartments) or "high occupancy seasonal rental" (*i.e.*, hotels). Firm agents cannot switch between these land uses during the simulation. After a parcel is developed into one of these land uses, it remains as such for the remainder of the simulation. Firm agents do not age and are not removed from the model at any point.

Visitor agents represent a transient seasonal visitor and temporarily reside in either "low occupancy seasonal rental" (*i.e.*, vacation homes) or "high occupancy seasonal rental" properties (*i.e.*, hotels). The number of people associated with a visitor agent is sampled from a gamma distribution. At the start of each annual time step, all visitors in the model are removed and new visitor agents are reassigned to vacant low occupancy or high occupancy seasonal rental parcels on a first-come, first-served basis that maximizes their utility.

The *Real estate* agent sets the market value of every parcel throughout the simulation. This market value is used to inform both the unoccupied owner agents' willingness to accept price and the cost of structural retrofits. The market value of a parcel is based on a user-defined base price of land, the maximum expected utility that either household or visitor agents will get from the parcel, and the overall demand for parcels.

Gamma distributions are used to sample agent age and number of people in the household because they are right-skewed and the support is positive. A Poisson distribution, similarly right-skewed, could alternatively be used to model the number of people in each household (Jarosz, 2021). A Poisson process is used to model the household change rates as they are commonly used to model the occurrence of events. It is assumed that each high occupancy residential parcel can hold up to 20 household agents, and each high occupancy seasonal rental parcel can hold up to 45 visitor agents. These values and distributions can be modified based on study area. The owned residential, rental residential, and low occupancy seasonal rental properties each have space for 1 occupying agent.

2.2.2 Agent bidding and changing land uses

Agents compete in the land market attempting to maximize their utility gained from a parcel. The land market is similar to that of the ALMA model; however, different land uses and agents are considered here. All utilities are computed using a Cobb-Douglas utility function, commonly used in urban economics (Huang *et al.*, 2014), and given by:

$$U = \prod_{i=1}^{n} P_i^{\alpha_i} \tag{1}$$

where P_i is a normalized value (0-100) representing either proximity to a particular feature or market pressure, α_i weights the importance of this feature to the agent representing a preference, and *n* are the number of features considered. Spatial features can include the coast, community assets, and the central business district. The preference weights, α_i, for each agent are uncorrelated, sampled from a normal distribution, and rescaled such that they sum to 1. Proximity is computed using a scaled distance decay function, $P_{dist} = 100 \cdot e^{-dk}$, with *d* being distance to the feature and *k* being a tunable parameter. Market pressure is based on the number of buyers and sellers, $P_{mkt} = 100 \cdot (0.5 \cdot \epsilon + 0.5)$ where ϵ, as in the ALMA model, is computed as $\epsilon = (NB - NS)/(NB + NS)$, with *NB* number of buyers and *NS* number of sellers.

Agents competing in the land market compute their willingness to pay (WTP) for the parcel that maximizes their utility. Here, the WTP is modified to account for structural retrofits as:

$$WTP = \frac{Y \cdot U^2}{b^2 \cdot U^2}(1 + \epsilon) - \rho \cdot m \tag{2}$$

where Y is the agent budget sampled from a normal distribution, U is the utility of the parcel, b represents costs of other goods. The final two terms of equation (2) were not in the ALMA model and were added to account for the additional costs an agent would incur if retrofits were mandatory. Here, ρ is a constant between 0 and 1 parameterized on the transition between structural-code levels, *e.g.,* $\rho = 0.6$ for a building being retrofit to moderate-seismic code. The market value of the parcel as provided by the real estate agent is represented as m.

2.3 Damage and loss modeling

The urban change model simulates annual time steps updating the community description until the time of the hazard event. For this paper, the timing of the event is defined as a specified year in the future, rather than treating the occurrence as random. At the time of the hazard, the community description (*f* in Figure 2) – including structural properties and number of people – is passed to IN-CORE. Initial damages to the built environment are computed using the community description, hazard models, and damage models. Hazard models (*g* in Figure 2) are spatially explicit representations of hazard intensity measures. Damage models (*h* in Figure 2) map the hazard intensity measures to infrastructural damage. Fragility curves are used here as the damage model to determine the probability that each building exceeds a damage state for a given hazard intensity measure. Figure 4 shows an example of structural seismic fragility curves for light-frame wood buildings and four seismic-code levels (pre-, low-, moderate-, and high-code) (FEMA, 2020; FEMA 2021b). The probability of being in a discrete damage state given a hazard intensity is the difference between fragility curves. This is shown in Figure 4 with the text "None/Insignificant", "Moderate", "Heavy", and "Complete". In the case of multiple hazards, cumulative building damage is computed (FEMA, 2020; FEMA 2021b). Using the fragility curves, the expected damage to a building can be determined (*i* in Figure 2).

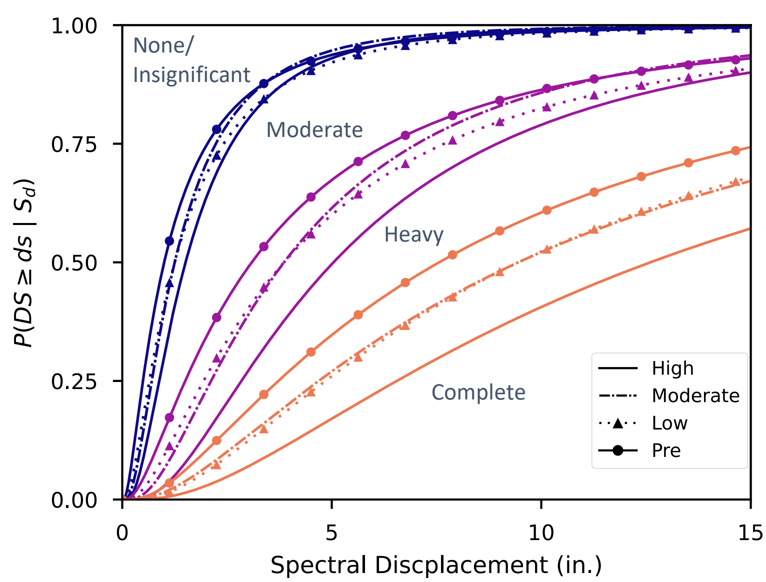

Figure 4: Example structural fragility curves for W1 structures (wood light frame) and four seismic-code levels (pre-, low-, moderate-, and high-code). Fragility curves are shown for

moderate (blue), heavy (purple), and complete (yellow) damage. The probability of being in a discrete damage state given a hazard intensity is the difference between fragility curves.

3 Case Study

3.1 Seaside, Oregon

The city of Seaside, Oregon, is utilized to demonstrate the coupled urban change and hazard consequence model. Seaside – shown in Figure 5 – is a small coastal community in the North American Pacific Northwest, with a population of 7,115 people (US Census Bureau, 2022). Seaside, along with many coastal communities in this region, are under threat of a rupture of the Cascadia Subduction Zone (CSZ). The CSZ is an approximately 1,000 km long subduction fault that extends between Cape Mendocino, California and Vancouver Island, Canada. Evidence suggests that the last full rupture of the CSZ occurred in 1700 and is estimated to have had a moment magnitude between 8.7 and 9.2. Some studies have estimated a 7% to 11% chance that a full-margin rupture will occur between 2010 and 2060 (Goldfinger *et al*. 2012). Additionally, an M9 scenario serves as the basis for the Oregon Resilience Plan (OSSPAC, 2013).

The economy of Seaside is tourist-oriented with large seasonal fluctuations in visitors (Raskin and Wang, 2017), making this an interesting case study for other coastal towns with large tourist populations. The Seaside building inventory used in this work was developed from a combination of 2012 tax assessor data, Google Street view, and a field survey (Park *et al*., 2017). Initial parcel population estimates are generated from a housing unit allocation algorithm that uses 2010 US Census data (Rosenheim *et al*., 2019). Seaside has been used in previous studies to evaluate multi-hazard risks (Park *et al*., 2019; Sanderson *et al*., 2021b), and infrastructure resilience (Kameshwar *et al*., 2019; Sanderson *et al*., 2021a). The Seaside testbed inventory for the built environment and hazard layers is publicly available (Cox *et al*., 2022). A detailed description of the built environment allows for an analysis at the parcel-scale rather than more aggregate levels.

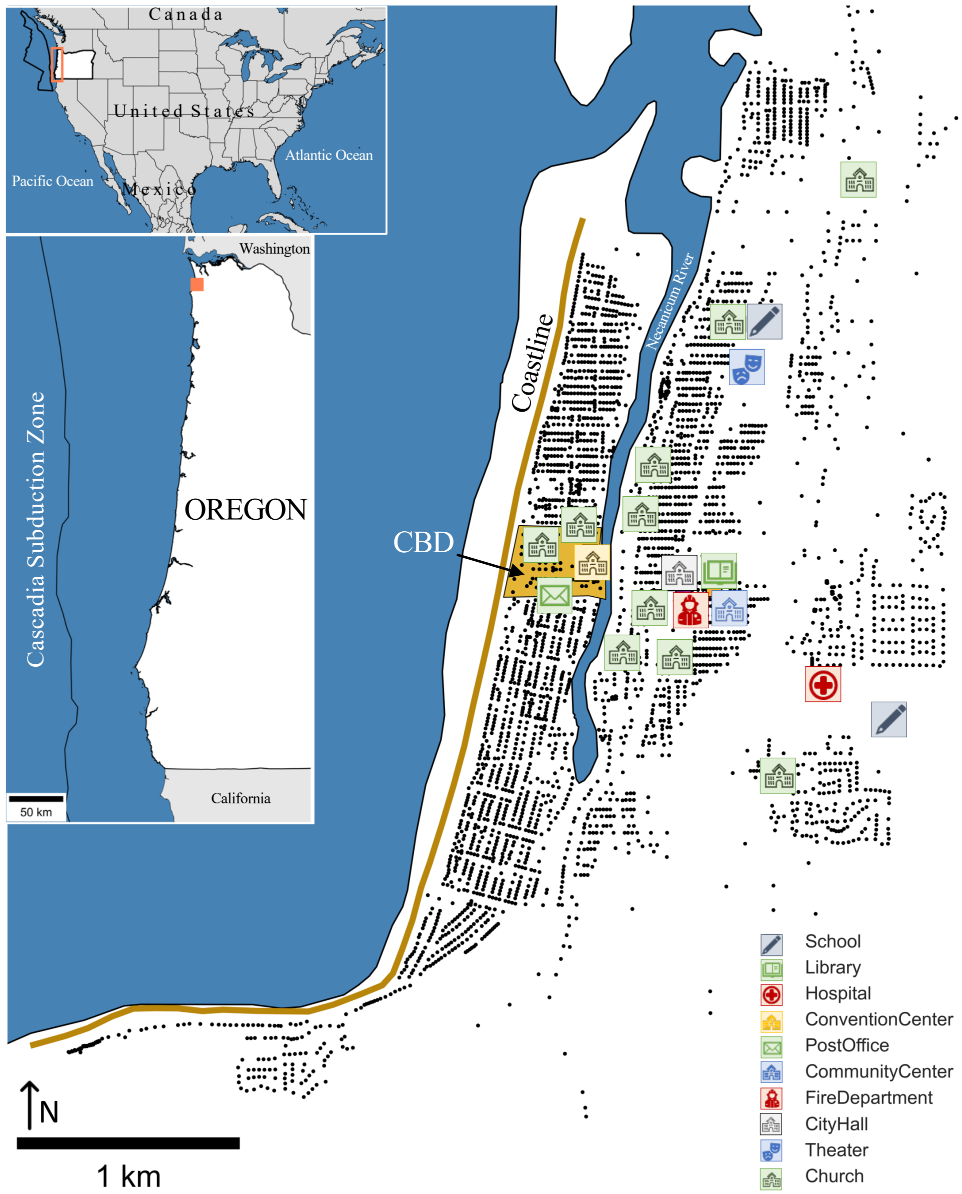

Figure 5: Case study location of Seaside, Oregon showing parcels (black dots), community assets, and central business district (shaded central yellow region near the coast)

The population projections for both full time residents (FTR) and visitors (VIS) are shown in Figure 6. The full-time resident population is shown as both historic (Moffatt, 1996) and future projections (Portland State University Population Research Center, 2020). We assume the model starts in 2010 as the building inventory is from 2012 and the housing unit allocation uses 2010 US Census data. No historic visitor population data was readily available; however, recent estimates were obtained from a combination of data from the Hatfield Marine Science Center, data from Oregon State Parks, and an Oregon visitor report (Dean Runyan Associates, 2021). It is assumed that the visitor population represents the peak summer nighttime population (*i.e.*, all visitors are located in either hotels or vacation homes). A linear growth in the visitor population to 12,000 by 2065 is assumed in alignment with the full-time resident population growth.

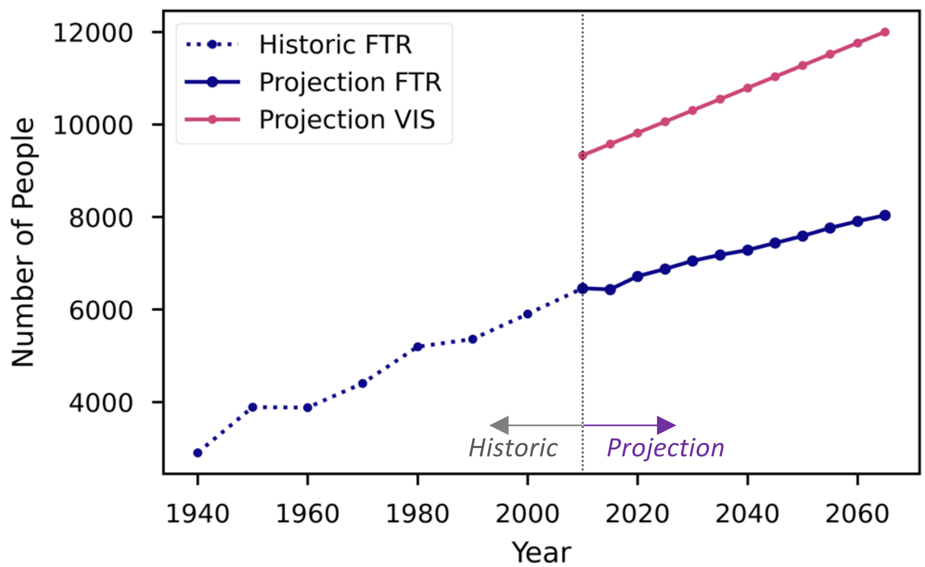

Figure 6: Historic population data and future population projections for Seaside for full-time residents (FTR) and visitors (VIS).

3.2 Planning and Building Code Scenarios

Ten scenarios, shown in Table 2, are considered as policy options, and are organized into four scenario clusters: (S0) status quo, (S1) planning, (S2) building codes, and (S3) a combination of planning and building codes. Scenario clusters S1-S3 each have three scenarios labeled a-c.

Table 2: Planning and building code scenarios

Scenario Cluster	Scenario Abbreviation	Cap on LOSR	Relocate Community Assets	No new high occupancy development	Owned Res.	Rental Res.	LOSR
Status Quo	S0	-	-	-	-	-	-
Planning	S1a	500	-	-	-	-	-
	S1b	-	East of Nec.	-	-	-	-
	S1c	-	-	HOR & HOSR	-	-	-
Building Codes	S2a	-	-	-	Low	Low	Low
	S2b	-	-	-	Moderate	Moderate	Moderate
	S2c	-	-	-	High	High	High
Planning & Building Codes	S3a	-	East of Nec.	-	-	-	High
	S3b	-	-	HOR & HOSR	-	Moderate	Moderate
	S3c			HOSR			High

LOSR: Low occupancy seasonal rental; **Nec**: Necanicum River; **HOR**: High occupancy residential; **HOSR**: high occupancy seasonal rental. Note all new high-occupancy development must be up to high-seismic code

Scenario cluster S1 corresponds to planning decisions. Scenario S1a places a cap on the number of low occupancy seasonal rental properties. While not a hazard mitigation plan, many communities with large visitor populations consider this to provide housing for full-time residents (Vinogradov *et al*., 2020). Scenario S1b relocates community assets that are west of the Necanicum River to the east side, further from the ocean and in areas with lower tsunami inundation. Scenario S1c restricts new high occupancy development for both high occupancy residential and seasonal rental properties.

Scenario cluster S2 corresponds to building code requirements. Scenarios S2a, S2b, and S2c requires any change of hands to be up to low-, moderate-, and high-seismic codes respectively. Seismic retrofit standards for existing buildings allow performance objectives to be less than that of new buildings (ASCE, 2014). Herein we assume that policies involving low and moderate-seismic code requirements (scenarios S2a and S2b) translate to these lower performance objectives, whereas the high-code requirement (scenario S2c) translates to the same performance objective as new buildings. All high occupancy buildings must conform to high-seismic code, and this does not differ across scenarios.

Scenario cluster S3 corresponds to both planning decisions and building code requirements. Scenarios considered here are intended to be complimentary. Scenario S3a consists of relocating community assets east of the Necanicum River in addition to enforcing any new low occupancy seasonal rental property conform to high-seismic code. S3b consists of no new high occupancy development while simultaneously enforcing that new rental residential and low occupancy seasonal rental properties conform to moderate-seismic code. Lastly, scenario S3c consists of no new high occupancy seasonal rental properties while enforcing that new low occupancy seasonal rental properties conform to high-seismic code.

3.3 Urban growth and change results

The model was run for the 10 scenarios in Table 2 with a 500-yr CSZ occurring at year 30. Each scenario was repeated 50 times with uncertainty propagated through the initial housing unit allocation, agent attributes, and ordering of agent scheduling. Figure 7 shows the evolution of the urban landscape for a portion of the city located on the coast and south of the CBD shown in Figure 5. The model considered all of Seaside; however, only a portion of the city is shown for clarity. The urban landscape at both the initial time step, assumed to be 2010, and at year 30 are shown in Figure 7 for both rental residential (top row) and low occupancy seasonal rental parcels (bottom row). The results of 3 scenarios from Table 2 are shown: (S0) status quo, (S1a) cap on low occupancy seasonal rental, and (S2a) all change of hands must conform to low seismic code. Rental residential and low occupancy seasonal rental land uses are shown here as they are both owned by landlord agents. The remaining land uses also evolve and are not shown for brevity. Each parcel is shaded according to the probability that the parcel is in the respective land use. The average number of full-time residents (FTR) and visitors (VIS) located in each land use for all of Seaside are shown in the bottom left corner of each panel in Figure 7.

Figure 7 shows the impact that policy has on both the urban landscape and number of people. For example, a cap on the number of low occupancy seasonal rental properties (S1a) naturally results in a significantly lower number of visitors in those parcels (2,194 VIS) compared to status quo (3,617 VIS). This also increases the availability of housing for full time residents in rental residential properties (2,510 FTR) compared to status quo (1,867 FTR).

The number of full-time residents in rental residential properties decreases for all scenarios at year 30 compared to at year 0. It is more advantageous for landlords to rent their properties as low occupancy seasonal rental units to visitor agents than it is to rent them to full time residents. The remainder of the visitor residents and full-time residents are in the other land uses.

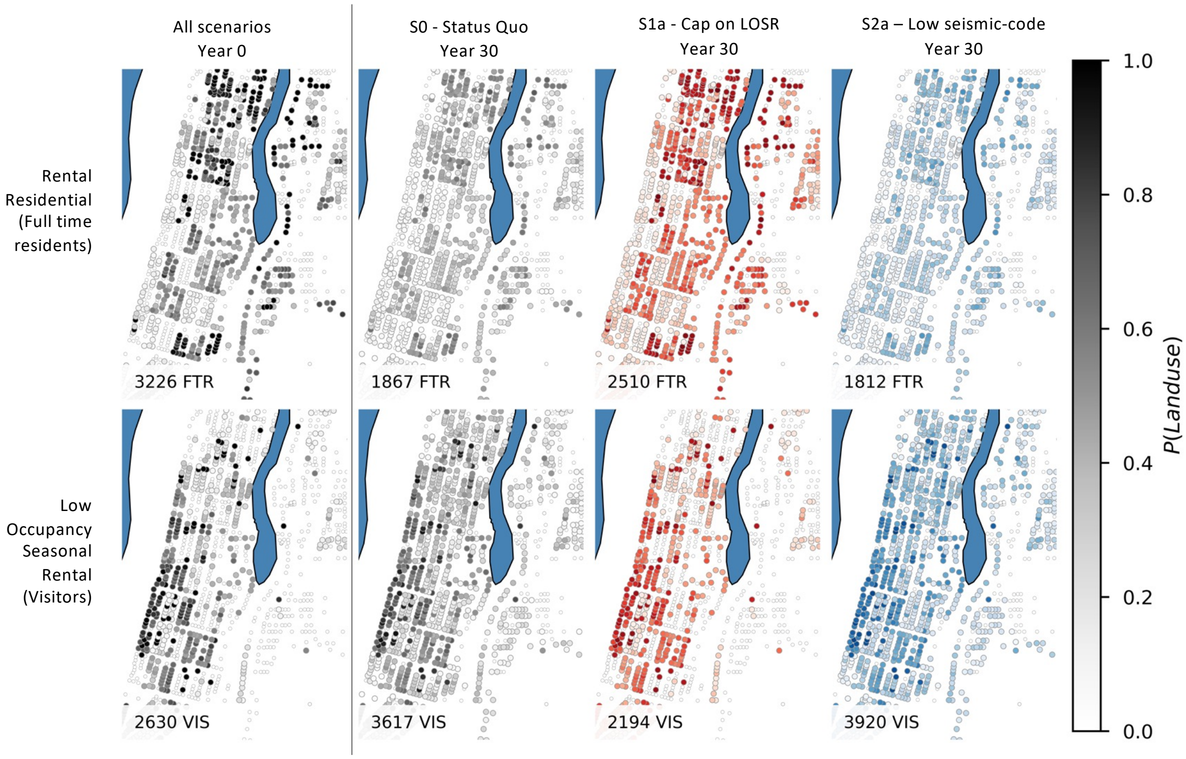

Figure 7: Probability of parcels having different land uses (rows) for the initial time step (first column) and at year 30 for S0 (second column), S1a (third column), and S2a (fourth column). The average number of full-time residents (FTR) and visitors (VIS) in the respective land use are shown in the lower left corner of each plot.

Figure 8 shows time series of the number of people in each land use under the same three scenarios (S0, S1a, S2a). Uncertainty in the model is shown via the shaded region as plus/minus one standard deviation. The implications of scenario S1a are clearly shown in Figure 8c by the decrease in number of visitors in low occupancy seasonal rental properties compared to the other scenarios. Interestingly, this policy simultaneously increases the number of visitors in high occupancy seasonal rental properties (Figure 8e) as there is a new unmet demand for visitors. As expected, this scenario frees up housing for full-time residents as the landlord agents transition to renting properties as rental residential (Figure 8b).

Scenario S2a results in more full-time residents in high occupancy residential properties compared to the other scenarios (Figure 8d). This is due to the cost of retrofitting, where full time residents are not able to afford as many single-family homes (Figure 8a). The firms then fill in this unmet demand for full time resident housing.

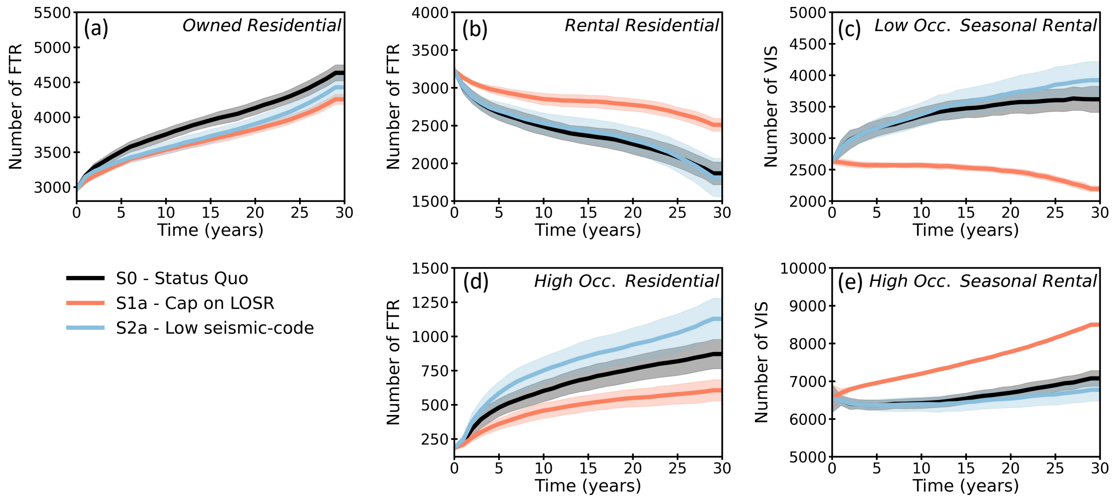

Figure 8: Average number of people (plus/minus one standard deviation) in each land use for: (a) owned residential, (b) rental residential, (c) low occupancy seasonal rental, (d) high occupancy residential, and (e) high occupancy seasonal rental.

3.4 Damage and loss results

To illustrate the urban change coupling with IN-CORE, Figure 9 spatially shows the damages to the built environment and number of people in each parcel. These results are for a 500-yr CSZ occurring at year 30. The parcels are color coded according to their expected damage state ranging between insignificant and complete. The size of each parcel corresponds to the number of people in that parcel for both visitors (top row) and full-time residents (bottom row). The two columns correspond to scenarios S0 and S1a. It assumed that this population represents the nighttime population in Seaside for summer months when the visitor population is high and when people are located in their places of residence. The larger circles in Figure 9 indicate high occupancy structures in which large concentrations of people are located. An emerging cluster of high occupancy seasonal rental properties can be seen to the north and on the waterfront in Figure 9b that is not present in 9a. As previously discussed, these high occupancy seasonal rental properties fill the unmet demand for visitors if a cap on low occupancy seasonal rentals is put in place. Not only is there a large concentration of visitors in concrete structures, but these are also located near to the coast and in the tsunami inundation zone. This would have implications for a potential increase in life safety risk depending on the type of evacuation actions taken by individuals (Wang *et al.*, 2016, Mostafizi *et al.*, 2019).

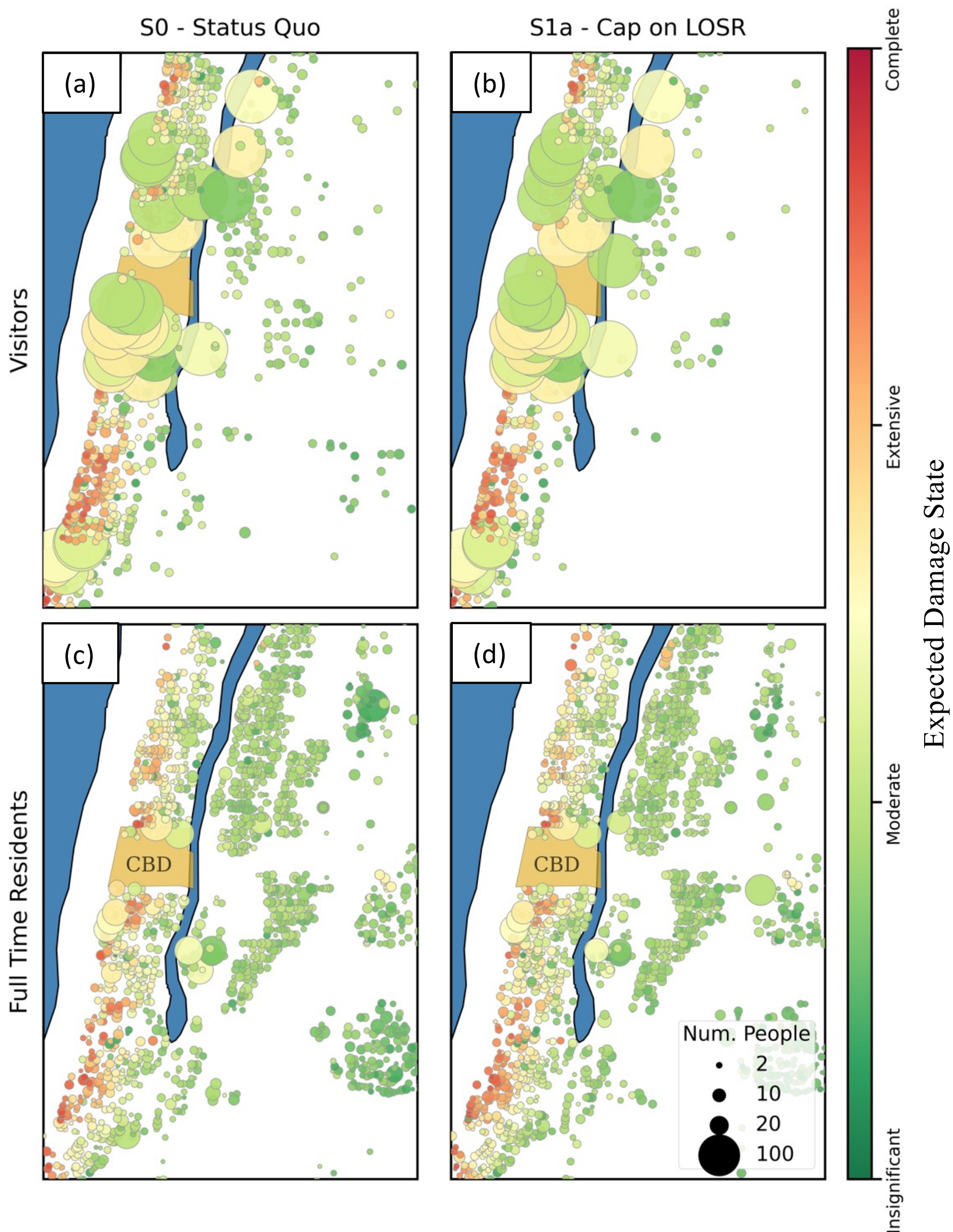

Figure 9: Single iteration showing expected damage due to 500-yr CSZ and number of people in each parcel for: (a) scenario S0 and visitor population, (b) scenario S1a and visitor population, (c) scenario S0 and full-time resident population, and (d) scenario S1a and full-time resident population. *CBD* is the Central Business District

Figure 10 shows the number of people relative to status quo in parcels with a damage state greater than moderate for all nine planning scenarios (S1a-S3c). This figure especially demonstrates how this modelling approach can be used to explore the emergent behavior of planning policies. Both the number of full-time residents (panel a) and visitors (panel b) are shown in Figure 10. The cap on the number of low occupancy seasonal rentals (S1a) results in significantly more visitors in damaged buildings relative to status quo. While S1a is not a hazard mitigation policy, it could have unintentional negative consequences if the CSZ were to occur during summer months when there are large visitor populations.

Scenarios S2b and S2c requires all change of hands to retrofit to moderate and high seismic codes respectively. These scenarios appear to reduce the number of people in damaged buildings more than any other policy. However, while not shown here, these scenarios also result in the largest number of unoccupied parcels indicating that the cost of retrofitting is prohibitive for many agents.

Scenarios in cluster S3 are a combination of planning and building code requirements. Figure 10b shows that these scenarios result in a significant decrease in the number of visitors in damaged buildings. While not shown, these scenarios also result in less unoccupied parcels than status quo conditions. This indicates that effective mitigation planning could consider some combination of policies.

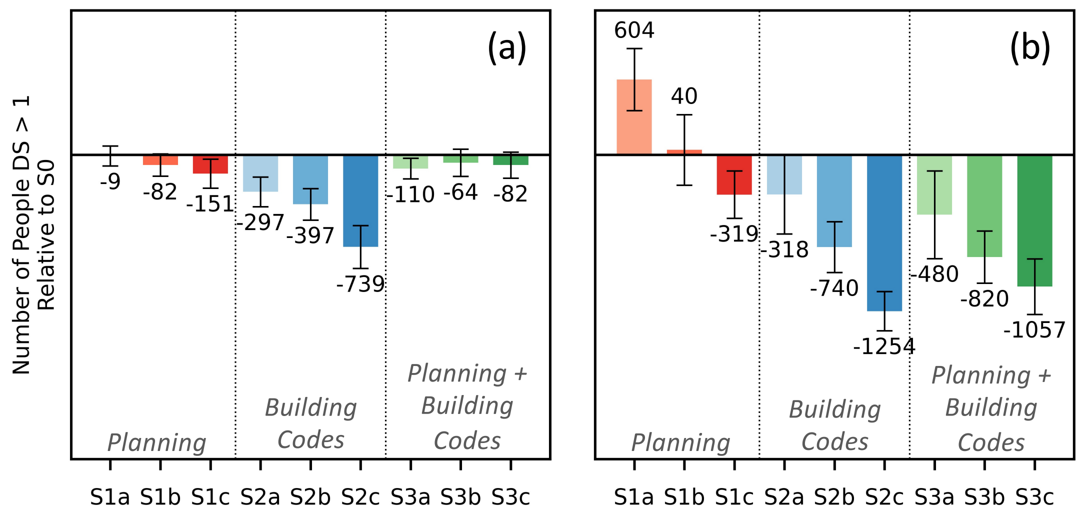

Figure 10: Average number of people in parcels with a damage state greater than moderate relative to status quo conditions for: (a) full time residents, and (b) visitors. Error bar shows plus/minus one standard deviation

To understand the temporal aspects of the CSZ occurring at any time, rather than only year 30 as assumed in the previous analysis, the model was rerun for three scenarios (S0, S1a, S2a) with the CSZ occurring at 5-year intervals, beginning in year 0 and ending at year 30. Figure 11 shows that the policies start to diverge beyond year 10 in the model, highlighting that the effects of many policies may take time to fully realize their implications. Further, as hazard mitigation policies aim to reduce the number of people impacted by disasters, Figure 11 highlights how this objective competes with population growth. While scenario S2a (low seismic code requirements) results in less people being in damaged parcels relative to scenario S0 (status quo), there are still more people in damaged parcels at year 30 than year 0. Uncertainty represented as plus/minus one standard deviation in Figure 11 does not overlap at the later time steps indicating that even with uncertainty there are significant deviations in policy implications.

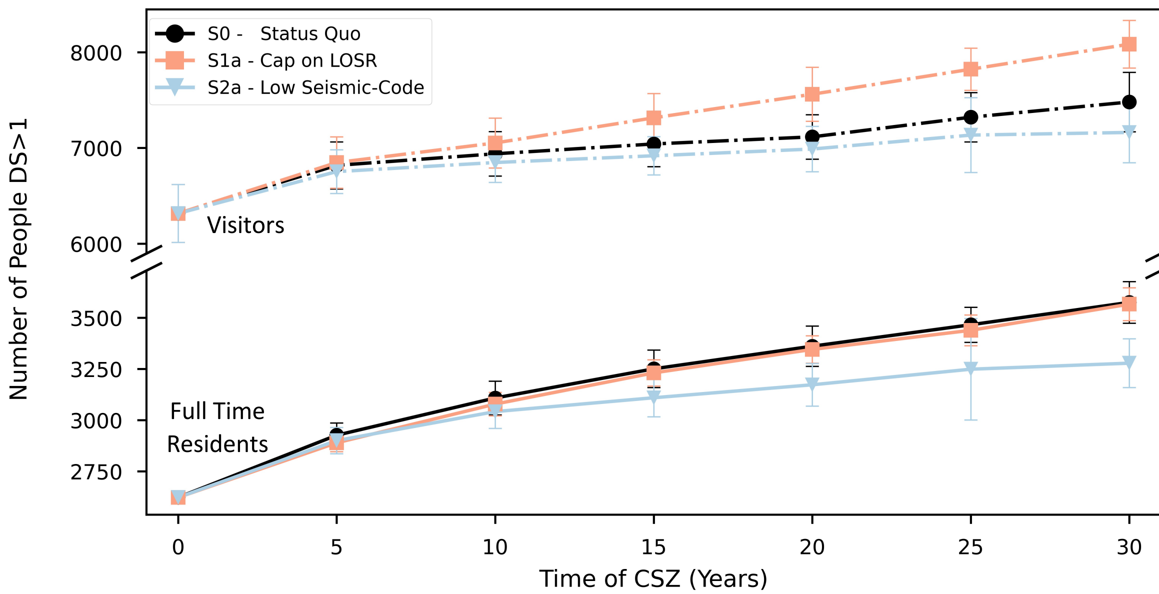

Figure 11: Number of full-time residents and visitors in parcels with a damage state greater than moderate if CSZ with 500-yr recurrence interval were to occur at varying time steps in model

4 Discussion

Community resilience planning for natural hazards involves many interacting entities as disasters occur at the interface of the built-natural-social environments (Mileti, 1999; Peek and Guikema, 2021). Many simulation efforts consider static representations of the built-natural-social environments despite their dynamic and complex nature. The model presented in this paper attempts to capture this dynamic interplay by considering population growth, a changing built environment, and policy choices. This model also situates the simulation of acute hazards within appropriate temporal settings given that these events do not occur immediately, as many simulation efforts assume, but at some point in the future.

The model can be extended and applied to other hazards, infrastructure systems, and communities. For example, many coastal communities are exposed to sea-level rise and hurricanes that also necessitate a future-oriented lens of the built-natural-human environments. Further, urbanization does not apply only to new buildings, but also to other infrastructure systems such as electric power, transportation, and water systems.

In addition to extending this model to other hazards and infrastructure systems, insights from the Seaside testbed can be applied to other communities. Many coastal communities have large tourist populations and this work showed that placing a cap on the number of vacation homes results in more visitors in damaged buildings compared to status quo scenarios. This was caused by high occupancy seasonal rental properties (*i.e.*, hotels) filling in a newly created unmet demand for visitors. These high occupancy structures are concrete and typically located in the inundation zone. This combination of factors could have negative implications for increases in life safety risk. In particular, this result highlights that coastal communities considering this policy and subject to rapid onset hazards - such as earthquakes and tsunamis – should have alternative plans in place for visitors. This could include well marked evacuation routes or vertical evacuation structures.

This work also highlighted that the most effective policies were those that considered elements of both urban planning and enforced building codes on new development. This indicates that there is no one-size-fits all solution to natural hazard mitigation planning, but rather policies should be tailored for specific communities and population groups. Through iterative processes, this type of modeling can be used to identify nuanced policies that may not be easy to initially imagine but do incorporate many different elements.

Given their complexities and many interacting entities, prediction of urban systems into the future is notoriously difficult. As such, the value of this modeling framework is not to predict the land use of individual parcels, but rather to provide insight into the collective behavior and emerging risks associated with planning policies. Similar efforts considering hazard exposure have involved stakeholder engagement (Mills *et al.*, 2018). This type of modeling with stakeholder engagement can seed rich discussions and be used to inform policy choices.

There are two interesting avenues for future work. First, this model could be coupled with a model of earthquake-tsunami life safety. As shown, some policies may put more visitors in damaged buildings that are located in the inundation zone. By coupling a life safety model, we could explore how policy choices impact life safety risk. This work could also include temporal fluctuations in visitor and full-time resident populations including day-night, weekday-weekend, and summer-winter. Second, this model uses existing fragility curves at various seismic-code levels. Advances in structural engineering may lead to buildings that are more resistant to hazard damages. Likewise, infrastructure ages and deteriorates over time, which was not accounted for here. Both of these could lead to temporal modifications in the fragility curves that are associated with buildings.

5 Conclusions

This paper presented a coupled urban change and hazard consequence model for evaluating community resilience under a future-oriented lens. Urban change was modeled via simulation of a land market whereas immediate post-disaster building damage was simulated using the opensource software IN-CORE. The coupled model was applied to Seaside, Oregon, located in the North American Pacific Northwest considering seismic-tsunami hazards associated with the Cascadia Subduction Zone. By applying the coupled urban change and hazard consequence model, the following conclusions can be made:

1. *Policies can result in unintended negative outcomes for different population groups:* It was shown that by placing a cap on the number of low occupancy seasonal rental properties in a community, more visitors were in damaged buildings compared to status quo conditions (Figure 10). As expected, this policy does free up more housing for full-time residents; however, this also highlights that additional hazard mitigation plans should be put in place if coastal communities pursue this option in areas that are subject to rapid onset disasters.
2. *Mandatory seismic retrofits do not reduce the number of people in damaged buildings when considering population growth*: Three scenarios were considered in which the CSZ was simulated at five-year intervals out to 30-years (status quo, a cap on vacation homes, and mandatory seismic retrofits). While the seismic retrofits can reduce the negative consequences of the CSZ relative to a status quo conditions, this scenario still resulted in an increase of total number of people impacted relative to present day conditions (Figure

11). This highlights the challenges of mitigation planning in areas with growing populations and that more transformative adaptation may be necessary.

3. *Policies take time to be fully realized*: By considering the CSZ occurring at 5-year intervals from year 0 to year 30, it was shown that the three policies diverge only after year 10 in the simulation (Figure 11). This indicates that many policies take time to fully realize their implications and highlights the urgency of mitigation planning in areas subject to disasters.

4. *The most effective policies were those that incorporated elements of both urban planning and mandatory building codes:* It was shown that only enforcing building codes may reduce the number of people in damage buildings; however, this also results in a significant number of unoccupied parcels at the end of the model run. This indicates that this is not attainable for many agents and could be cost prohibitive. More effective strategies that reduced the number of people in damaged buildings considered some combination of both enforced building codes and urban planning (Figure 10). Communities should tailor their resilience planning with no one-size-fits-all solution available.

Many resilience studies consider historic or static representations of the built-natural-social environments despite their dynamic and complex nature. The coupled urban change and hazard consequence model presented in this paper provides an avenue towards planning for hazards in an uncertain future. Given urbanization, population growth, policy choices, and a changing climate, more research should be conducted to account for the complexities that arise at the interface and future of the built-natural-social environments.

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Data Availability Statement

The model used in this paper was written in Julia and python. The model source code and additional documentation contained in a Jupyter Book are available at Sanderson (2022). The Seaside testbed data inventory is available on DesignSafe.org at Cox et al. (2022).

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