Earth's Future

RESEARCH ARTICLE
10.1029/2022EF003059

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

Supporting Information:

Supporting Information may be found in the online version of this article.

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Citation:

Sanderson, D. R., Cox, D. T., Amini, M., & Barbosa, A. R. (2022). Coupled urban change and natural hazard consequence model for community resilience planning. *Earth's Future*, *10*, e2022EF003059. https://doi.org/10.1029/2022EF003059

Received 20 JUL 2022
Accepted 22 NOV 2022

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: (a) placing a cap on the number of vacation homes results in more visitors in damaged buildings, (b) that mandatory seismic retrofits do not reduce the number of people in damaged buildings when considering population growth, (c) polices diverge beyond year 10 in the model, indicating that many policies take time to realize their implications, and (d) 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 & 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., NIST, 2016a; OSSPAC, 2013; SPUR, 2009; UNDRR, 2015). 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-social environments, including climate change, and increased complexity of infrastructure systems themselves (Chester et al., 2021; Spies et al., 2014). Population growth, urban change, 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 (Bilskie et al., 2022; Cremen et al., 2022; Hemmati et al., 2020; Neumann et al., 2015). 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, potentially widening already existent inequities (Peek et al., 2020).

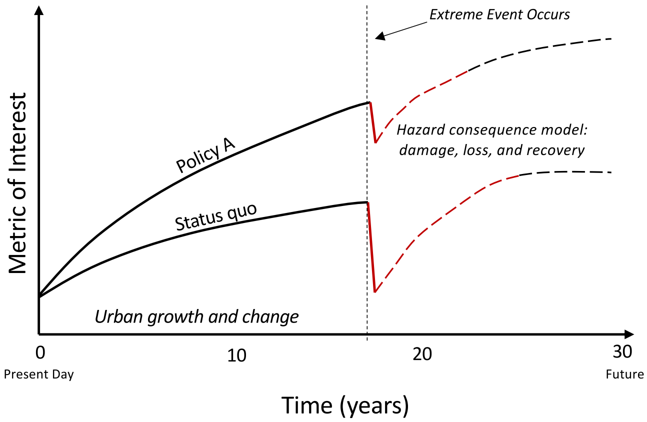

Figure 1. Situating infrastructure resilience within a larger temporal setting by coupling urban growth and change modeling with hazard consequence modeling.

Given these challenges and complexities, modeling and simulation have been identified as a means to inform disaster theory and understand emerging phenomena (Mostafavi & Ganapati, 2021). Subsequently, the use of simulation has proven effective to evaluate how natural hazard mitigation plans and policy can help improve community resilience (Nofal & van de Lindt, 2021; Talebiyan & Mahsuli, 2018; Wang et al., 2019). While many of these simulation efforts provide useful 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 toward considering disaster resilience under a more dynamic and future-oriented lens (Cremen et al., 2022; Galasso et al., 2021; Hemmati et al., 2020). 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 this type of modeling 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.

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: (a) urban growth and change models, (b) hazard consequence models, and (c) coupled urban change and hazard consequence models. It should be emphasized that the models and papers in Table 1 are not intended to be an exhaustive list as this convergence of disciplines is a rapidly growing field.

As shown in Table 1, modeling urban change can take on many forms ranging from cellular automata (Chaudhuri & Clarke, 2013; White & Engelen, 1993) to agent-based modeling (Huang et al., 2014; Parker & Filatova, 2008). The former, cellular automata is typically inductive and calibrated based on historic patterns, whereas the latter, agent-based modeling seeks to model real-world processes (Parker et al., 2012). Modeling land-cover, land-use change, and urban change dynamics has an extensive history (e.g., Miller et al., 2004; Parker & Filatova, 2008 for detailed reviews).

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., Deierlein et al., 2021; van de Lindt et al., 2018).

The coupling of urban change and hazard consequence 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. As indicated in Table 1, this convergence of disciplines is expanding rapidly, and the papers referenced herein are non-exhaustive.

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 modeling 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

Table 1
Review of: (a) Urban Growth/Change Models, (b) Hazard Consequence Models, and (c) 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
	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	

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Table 1
Continued

Model group	Paper	Urban change	Earthquake	Flood	Hurricane	Tornado	Tsunami	Model description/notes	Model name
	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	
	Sarica et al. (2020)	✓	✓					Apply SLEUTH model and consider buildings exposed to earthquake hazard	
	Calderón and Silva (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	

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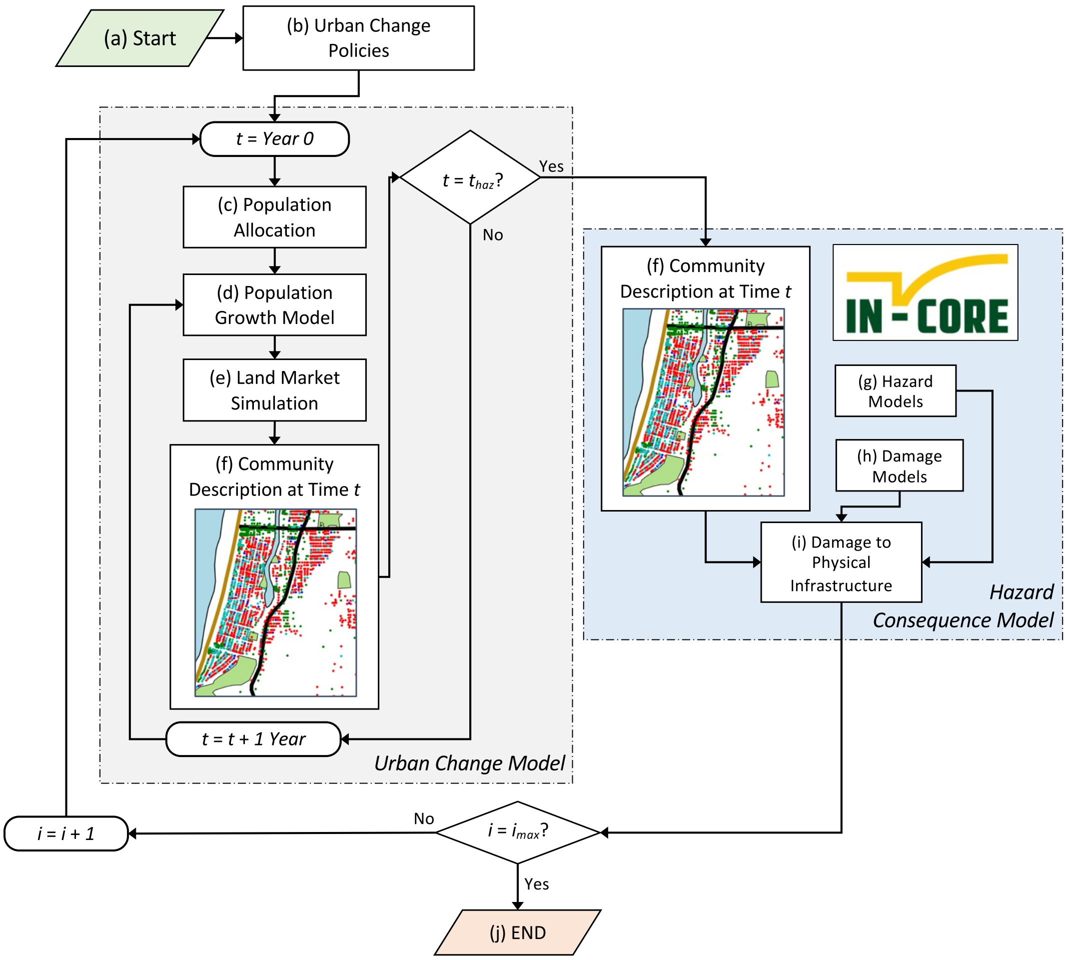

Figure 2. Flowchart of the coupled urban change (gray dash-dot box on left) and hazard consequence model (blue dash-dot box on right).

seismic-tsunami hazards associated with the Cascadia Subduction Zone (CSZ), yet is intended to be generalizable across different hazard types.

2. Coupled Urban Change and Hazard Consequence Model

Figure 2 shows a flowchart of the coupled urban change (gray dash-dot box) and hazard consequence model (blue dash-dot box). In its current form, the urban change component of the model focuses on the dynamics inside a community, rather than urban expansion. IN-CORE is used as the hazard consequence model and is selected due to its ability to model the impact of natural hazards at the parcel-level. IN-CORE is a comprehensive opensource ecosystem with a python package (pyIncore) available to interact with IN-CORE components and python libraries. Hazard consequences, including damage to buildings, lifelines, and social impacts, can be considered using IN-CORE. In this paper, we consider only building damage. Each time step in the model represents 1 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.

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 specifically 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.

Modifying the hazard includes implementing both gray and green engineered solutions to reduce the intensity of natural hazards (Feagin et al., 2015; Saleh & 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 planning measures that alter the buildings present within a community in some form. This can include planning measures such as zoning, acquisition of damaged buildings for repeating hazards, and managed retreat (Han et al., 2020; Hurlimann et al., 2021). Both acquisition of damaged buildings and managed retreat aim to remove buildings from hazardous areas, thus altering the building inventory. 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, van de, Lindt, Rosenheim, 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 (Alisjahbana et al., 2021; Costa et al., 2020; Dubbelboer et al., 2017). 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 other aspects of the built environment. For example, a community may recognize a need for their electric power or water supply networks to be more resilient, thus policies and resources could be focused on these aspects of the built environment.

2.2. Agent-Based Modeling of Urban Land Use Change

The gray 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 (Reilly 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 1 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—that is, 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 (a) full time resident and visitor populations, and (b) different types of development including single family homes, rental properties, and high occupancy development. Second, the model developed

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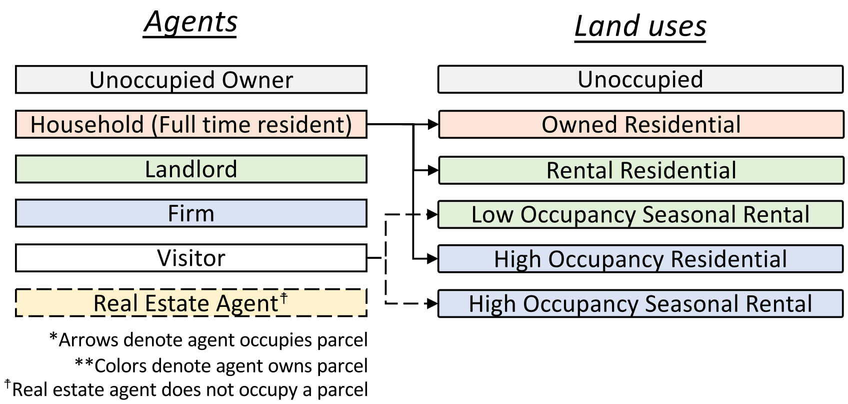

Figure 3. Agents and land uses in the urban growth and change model.

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 are responsible for retrofitting the building on their property if there are enforced building codes. 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.

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 new 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. The owned residential, rental residential, and low occupancy seasonal rental properties each have space for 1 occupying agent. These values are chosen based on the existing parcels in the testbed presented below, the total number of people, and an assumption that the model starts in equilibrium. An 80-year threshold is selected based on life expectancy in the US (Arias et al., 2022). Any values and distributions can be modified based on the study area and refined in future work with Supporting Information S1.

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. Thus, agents have heterogenous preferences. Proximity is computed using a scaled distance decay function, $P_{\text{dist}} = 100 \cdot e^{-\text{dk}}$, with d being distance to the feature and k being a tunable parameter. Market pressure is based on the number of buyers and sellers, $P_{\text{mkt}} = 100 \cdot (0.5 \cdot \epsilon + 0.5)$ where ϵ, as in the ALMA model, is computed as $\epsilon = (\text{NB} - \text{NS})/(\text{NB} + \text{NS})$, with NB number of buyers and NS number of sellers.

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

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

where Y is the agent budget sampled from a normal distribution—thus the agents have heterogenous economic statuses. U is the utility of the parcel as computed above, b represents costs of other goods and is a constant. 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 are mandatory. Here, ρ is a constant between 0 and 1 parameterized on the transition between structural-code levels, for example, $\rho = 0.6$ 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.

Agents have bounded rationality and are thus only aware of a user-defined number of parcels when evaluating available parcels in the land market. If more than one agent is bidding on a particular parcel, than the unoccupied owner agent associated with that parcel reviews the bids and selects the maximum if it exceeds their willingness to accept price. The willingness to accept price is dynamic and informed by the real estate agent at each time step. It should be noted that in other land market models, agents negotiate until a final price is determined (Parker & Filatova, 2008). We do not consider agent negotiations as the focus of this paper is on changing land uses for hazard implications, rather than the final selling price of parcels. Successful bids lead to new agents owning the parcels and thus changes in land use. A detailed flow chart of the agent processes that result in land use change is provided in Supporting Information S1 (Figure S2).

As an example, consider two agents—a household and landlord—bidding on a single parcel that is owned by an unoccupied owner agent. Both agents compute their utility gained from the parcel using Equation 1. This is

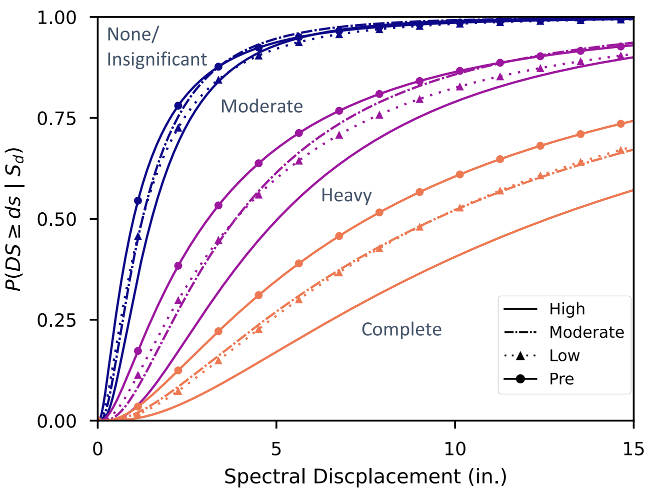

Figure 4. Example structural fragility curves for W1 structures (wood light frame) and four seismic-code levels (pre-, low-, moderate-, and high-code). Fragility curves are shown for moderate (blue), heavy (purple), and complete (yellow) damage. The probability of being in a discrete damage state given a hazard intensity is the difference between fragility curves.

based on the agents' unique preferences and properties of the parcel (distance to coast, distance to community assets, etc.). If the landlord bids more for the parcel and the bid price exceeds the unoccupied owner agent's willingness to accept price, then this successful bid leads to the landlord becoming the new owner of this parcel. The landlord, as they are associated with both rental residential properties and low occupancy seasonal rental properties, then chooses which land use the parcel will become. The landlord decides based on the utility gained from each land use, zoning restrictions, and any relevant policies in place that may impose limitations on development. Because the landlord agents own properties that provide places of residence for both households (rental residential) and visitors (low occupancy seasonal rental), this parcel may then be put on the market again for agents to bid on. That is, if it is a rental residential property, then in the next time step household agents can bid on this parcel to reside there without owning the property.

The urban change model simulates annual time steps with the land market updating the community description (f in Figure 2). The "community description" describes the built and social environments. This consists of attributes such as urban land use, structural properties, and the number of people in each parcel. Structural properties of each building are necessary for the damage modeling.

2.3. Damage and Loss Modeling

The urban change model runs 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. Depending on the hazard type, IN-CORE can either generate hazard information or use externally generated hazard layers in the form of raster files. 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, 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, 2021b). Using the fragility curves, the expected damage to a building can be determined (i in Figure 2). Additional examples of IN-CORE use applied to testbeds include: multi-hazard damages and losses across multiple infrastructure systems (Park et al., 2019; Sanderson, Cox, & Naraharisetty, 2021; Sanderson, Kameshwar, et al., 2021), chaining building and electric power network damages with economic models (Wang, van de, Lindt, Cutler, et al., 2021), and integrating detailed social science data with building damage and population dislocation models (Rosenheim et al., 2019).

3. Model Applied to a Testbed Community

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 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 1,700 and is estimated to have had a moment magnitude between 8.7 and 9.2. Some studies have estimated a 7%–11% chance that a full-margin rupture will occur between 2010 and

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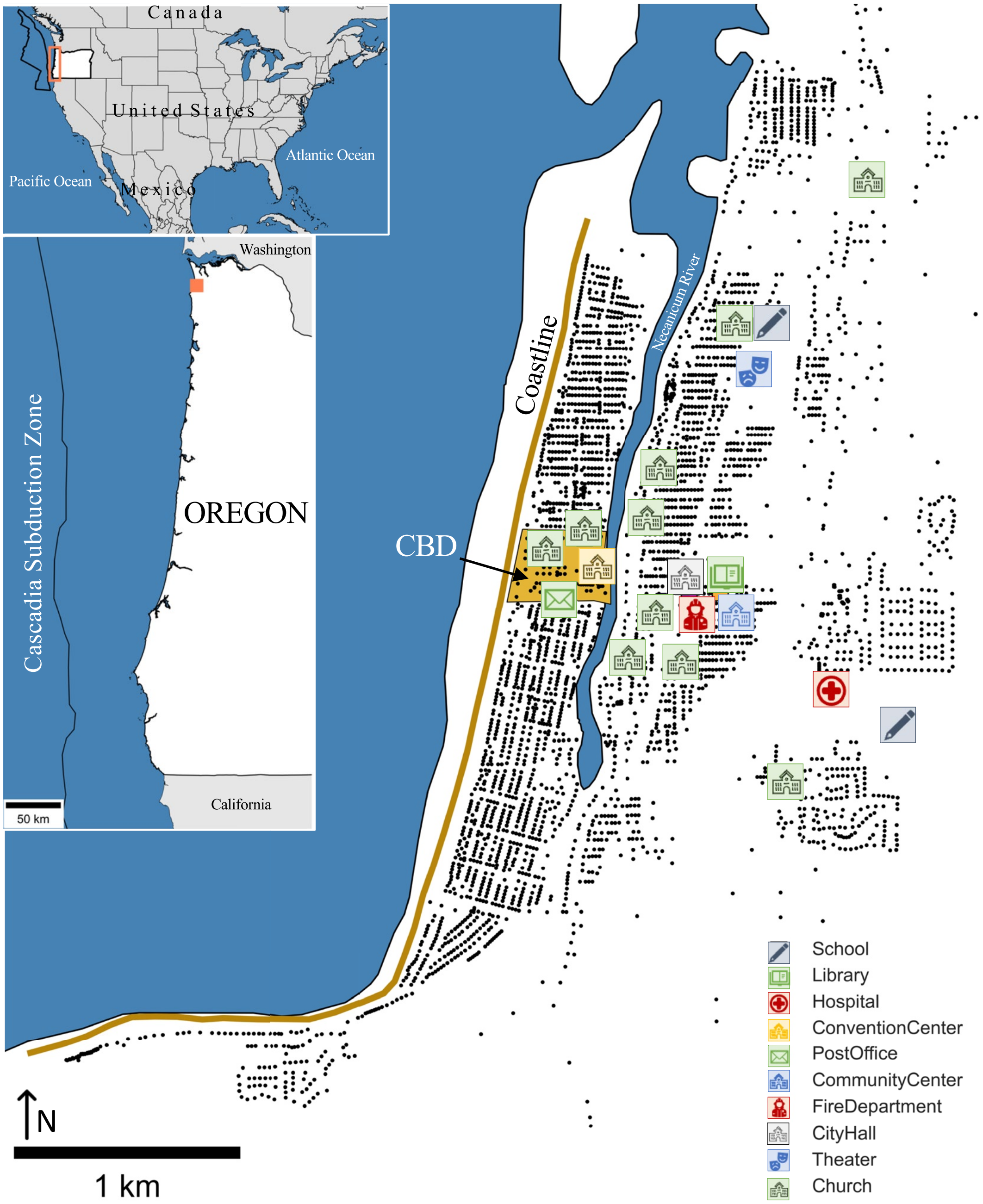

Figure 5. Testbed location of Seaside, Oregon showing parcels (black dots), community assets, and central business district (CBD; shaded central yellow region near the coast).

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 & Wang, 2017), making this an interesting testbed for other coastal towns with large tourist populations. It should be noted that the State of Oregon has urban growth boundaries, and for this work we focus on the dynamics inside the city, rather than urban expansion. 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, Cox, & Barbosa, 2017). Initial parcel population estimates are generated from a housing unit allocation algorithm that uses 2010 US Census data (Rosenheim et al., 2019). The earthquake and tsunami hazard layers used in this study are the result of a probabilistic seismic

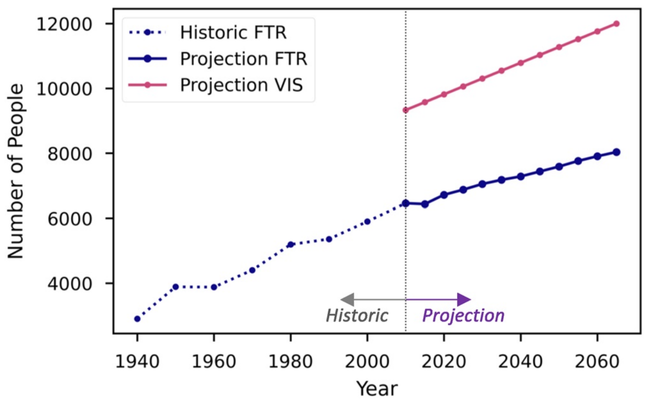

Figure 6. Historic population data and future population projections for Seaside for full-time residents and visitors.

and tsunami hazard analysis for Seaside and readers are directed here for detailed information on the hazard generation (PSTHA; Park, Cox, Alam, & Barbosa, 2017; Park et al., 2019). For the damage models, spectral displacement is used as the earthquake hazard intensity measure, whereas momentum flux is used as the tsunami hazard intensity measure. Seaside has been used as a testbed in previous studies to evaluate multi-hazard risks (Park et al., 2019; Sanderson, Kameshwar, et al., 2021), infrastructure resilience (Kameshwar et al., 2019; Sanderson, Cox, & Naraharisetty, 2021), and life-safety risks (Amini et al., 2022). 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. Example hazard layers (Figure S1 in Supporting Information S1), and input tables—including parameters of the distributions used in the model (Tables S1 and S2)—are provided in Supporting Information S1. Other hazard layers can be found in Park, Cox, Alam, and Barbosa (2017), for example,

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 2,065 is assumed in alignment with the full-time resident population growth.

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.

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

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

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

consider this to provide more housing for full-time residents (Vinogradov et al., 2020). This is modeled by not allowing any new low occupancy seasonal rental property into the community as long as the total number of these properties is above the cap. Thus, landlord agents must convert successful bids to rental residential properties. 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. Agent preferences to be near community assets are captured in Equation 1. As such, this scenario seeks to draw agents who prefer to live near community assets to these less hazardous areas. Scenario S1c restricts new high occupancy development for both high occupancy residential and seasonal rental properties. Similar to scenarios S1a, this is simulated by simply not allowing any new high occupancy development.

Scenario cluster S2 corresponds to building code requirements. Scenarios S2a, S2b, and S2c requires that any change of land use 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—thus drawing agents with preferences to be near community assets to less hazardous areas—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-year 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. Example animations are provided in Supporting Information (Movies S1 and S2). 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 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 FTR 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 FTR. The remainder of the visitor residents and full-time residents are in the other land uses.

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

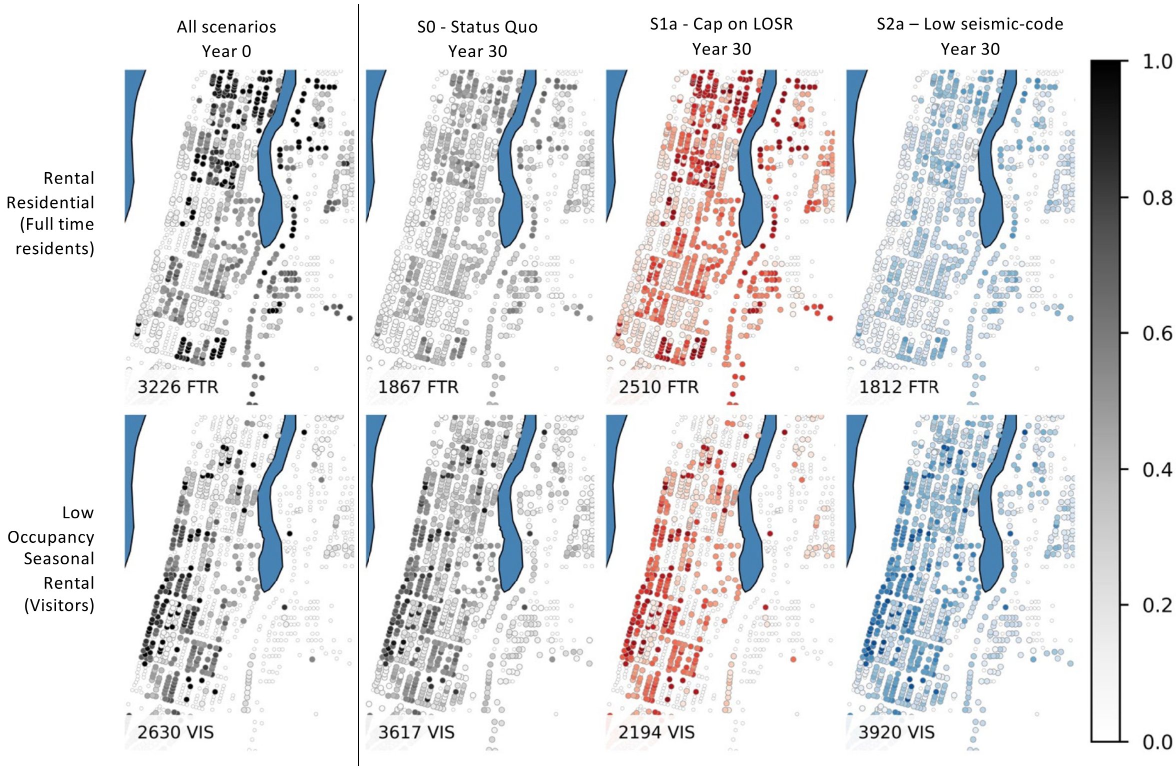

Figure 7. Probability of parcels having different land uses (rows) for the initial time step (first column) and at year 30 for S0 (second column), S1a (third column), and S2a (fourth column). The average number of full-time residents and visitors in the respective land use are shown in the lower left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

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).

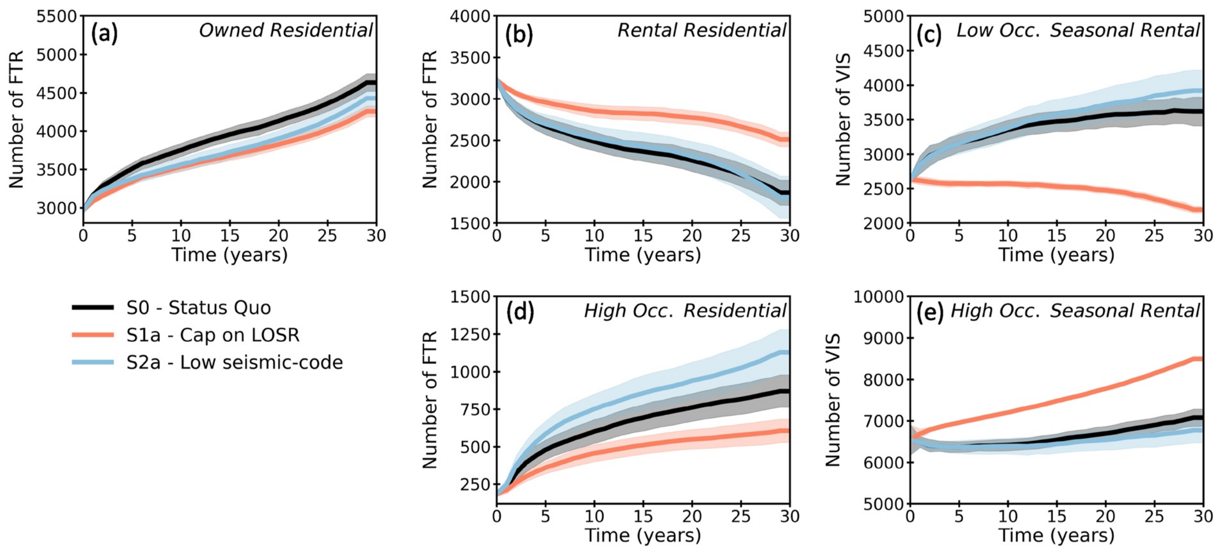

Figure 8. Average number of people (plus/minus one standard deviation) in each land use for: (a) owned residential, (b) rental residential, (c) low occupancy seasonal rental, (d) high occupancy residential, and (e) high occupancy seasonal rental.

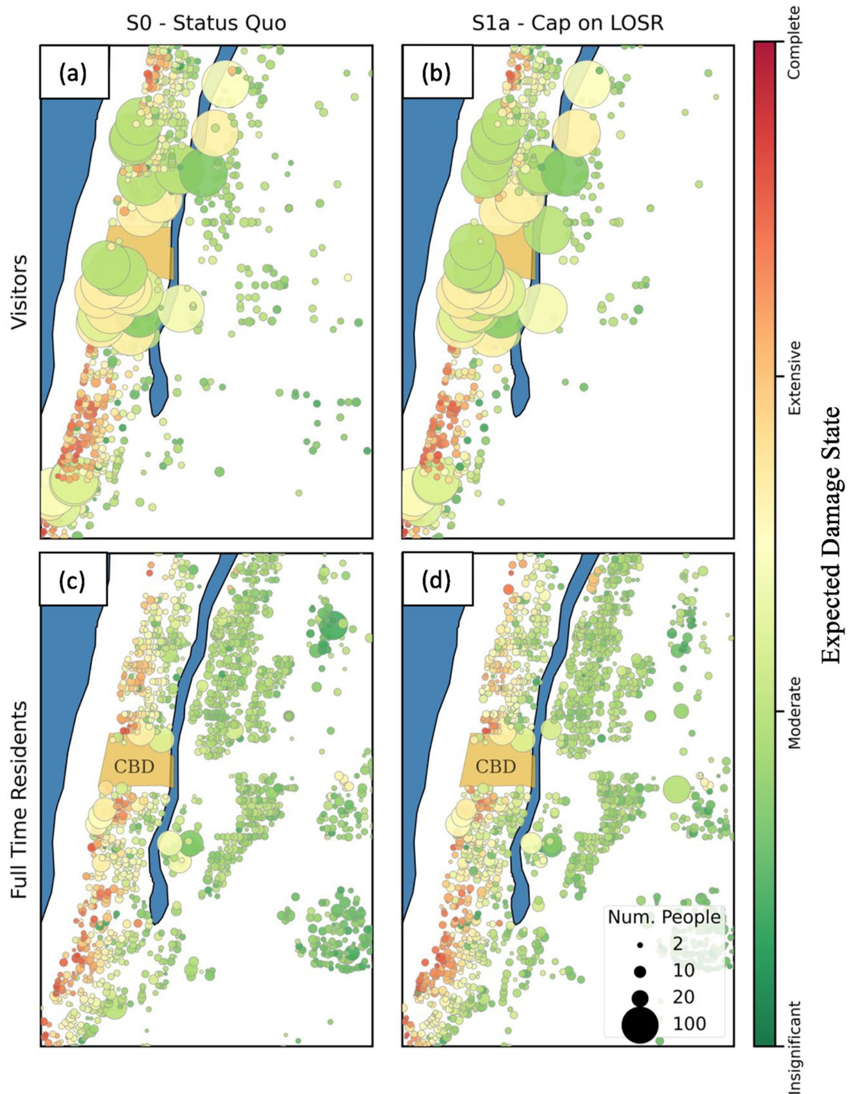

Figure 9. Single iteration showing expected damage due to 500-year Cascadia Subduction Zone and number of people in each parcel for: (a) scenario S0 and visitor population, (b) scenario S1a and visitor population, (c) scenario S0 and full-time resident population, and (d) scenario S1a and full-time resident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

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 FTR 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.

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-year 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

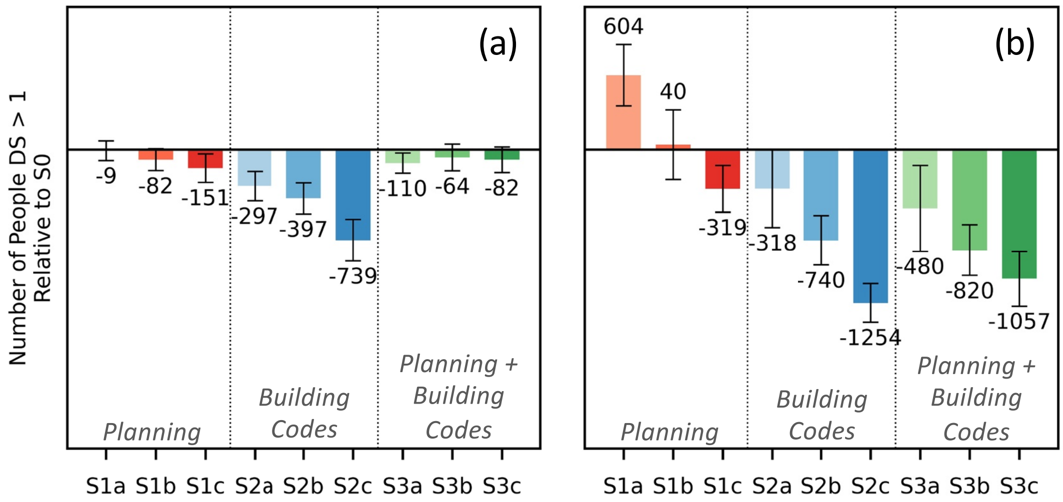

Figure 10. Average number of people in parcels with a damage state greater than moderate relative to status quo conditions for: (a) full time residents, and (b) visitors. Error bar shows plus/minus one standard deviation.

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 (Mostafizi et al., 2019; Wang et al., 2016).

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 modeling 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. This is reflected in Equation 2 as retrofitting costs for these scenarios reduce agent WTP calculations below the unoccupied owner agent willingness to accept price. The result is a significant number of unoccupied parcels at the end of the simulation run. In general, it has been identified that challenges of retrofitting existing buildings include costs and occupant disruptions (NIST, 2016b).

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.

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.

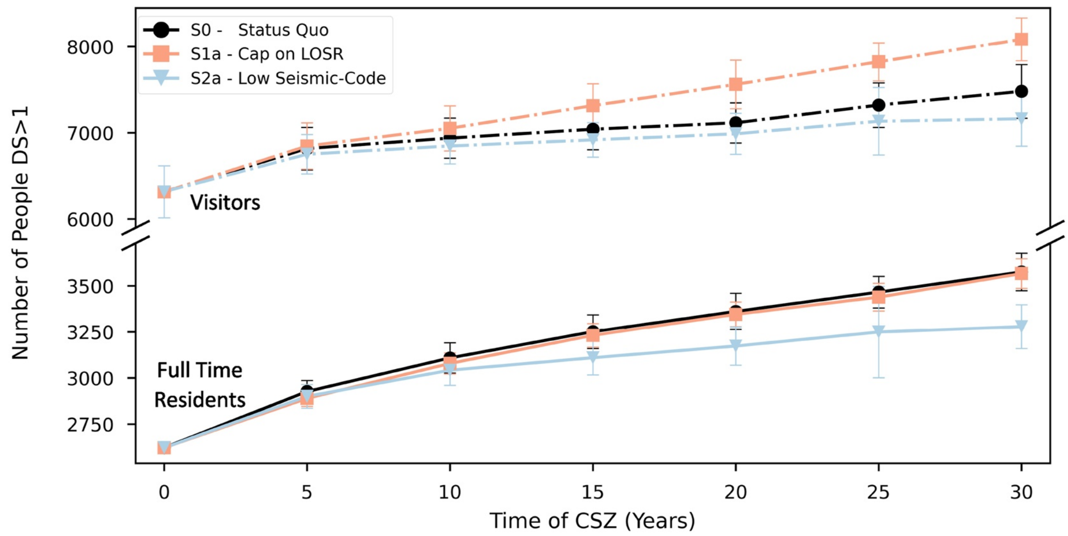

Figure 11. Number of full-time residents and visitors in parcels with a damage state greater than moderate if Cascadia Subduction Zone with 500-year recurrence interval were to occur at varying time steps in model.

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 & 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.

This type of modeling framework 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-social environments. While the agents and land uses presented herein were focused on a coastal community with a large transient seasonal population, additional agents and land uses can be considered to capture other relevant aspects of a community. For example, commercial properties, business districts, and historic centers could be included to evaluate post-disaster business interruptions. Additional infrastructure systems could also be included in this type of modeling framework to evaluate not only building damage, but also the number of people without access to electricity or water under alternative futures. Additional agent behaviors could be captured in the model such as having an awareness of hazards when bidding on parcels.

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.

Verification tests were performed to ensure that the model was implemented as conceptualized. These tests include degenerate tests, tracing agent behavior and parcel properties throughout the simulation, and setting up animations (Sargent, 2010). Validation has been based on both face validity and expert opinion. Calibration based on historic data can be performed and is beyond the scope of this paper (Ngo & See, 2012).

There are many 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 existing seismic-code levels (pre-, low-, moderate-, and high-code). 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 CSZ. 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 5-year intervals out to 30-year (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 toward planning for hazards in an uncertain future. Given urban change, 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.

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).

Acknowledgments

We acknowledge Peter Ruggiero, John Bolte, Jenna Tilt, and Steven Dundas of the Oregon Coastal Futures research group for their feedback on early model development, and Steven French at the Georgia Institute of Technology for his contributions to the natural hazard mitigation plans, identification of four classes of hazard planning, and face validation. We acknowledge funding in part through Oregon Sea Grant under award no. NA18OAR170072 (CDFA no. 11.417) from NOAA's National Sea Grant College Program, US Department of Commerce, and by appropriations made by the Oregon State Legislature; the cooperative agreement 70NANB15H044 between the National Institute of Standards and Technology (NIST) and Colorado State University through a subaward to Oregon State University; and the National Science Foundation through award NSF-2103713. The content expressed in this paper are the views of the authors and do not necessarily represent the opinions or views of the U.S Department of Commerce, NIST, or NSF.

References

Alisjahbana, I., Moura-Cook, A., Costa, R., & Kiremidjian, A. (2021). An agent-based financing model for post-earthquake housing recovery: Quantifying recovery inequities across income groups. *Earthquake Spectra*, *38*(2), 1254–1282. https://doi.org/10.1177/87552930211064319

American Society of Civil Engineers (ASCE). (2014). *Seismic evaluation and retrofit of existing buildings—ASCE standard ASCE/SEI 41-13*. American Society of Civil Engineers. https://doi.org/10.1061/9780784412855

Amini, M., Sanderson, D., Cox, D., Barbosa, A., & Rosenheim, N. (2022). Methodology to incorporate seismic damage and debris to evaluate strategies to reduce life safety risk for multi-hazard earthquake and tsunami. *Research Square*. https://doi.org/10.21203/rs.3.rs-1862973/v1

Arias, E., Tejada-Vera, B., Kochanek, K., & Ahmad, F. (2022). *Provisional life expectancy estimates for 2021* Report No. 23. NVSS Vital Statistics Rapid Release.

Berry, M., Hazen, B., MacIntyre, R., & Flamm, R. (1996). LUCAS: A system for modeling land-use change. *IEEE Computational Science and Engineering*, *3*(1), 24–35. https://doi.org/10.1109/99.486758

Bilskie, M., Angel, D., Yoskowitz, D., & Hagen, S. (2022). Future flood risk exacerbated by the dynamic impacts of sea level rise along the Northern Gulf of Mexico. *Earth's Future*, *10*(4). https://doi.org/10.1029/2021EF002414

Bolte, J., Hulse, D., Gregory, S., & Smith, C. (2007). Modeling biocomplexity—Actors, landscapes, and alternative futures. *Environmental Modelling & Software*, *22*(5), 570–579. https://doi.org/10.1016/j.envsoft.2005.12.033

Brown, D., & Robinson, D. (2006). Effects of heterogeneity in residential preferences on an agent-based model of urban sprawl. *Ecology and Society*, *11*(1), art46. https://doi.org/10.5751/es-01749-110146

Calderón, A., & Silva, V. (2021). Exposure forecasting for seismic risk estimation: Application to Costa Rica. *Earthquake Spectra*, *37*(3), 1806–1826. https://doi.org/10.1177/8755293021989333

Chang, S., Yip, J., & Tse, W. (2019). Effects of urban development on future multi-hazard risk: The case of Vancouver, Canada. *Natural Hazards*, *98*(1), 251–265. https://doi.org/10.1007/s11069-018-3510-x

Chaudhuri, G., & Clarke, K. (2013). The SLEUTH land use change model: A review. *The International Journal of Environmental Resources Research*, *1*(1), 88–104. https://doi.org/10.22069/ijerr.2013.1688

Chester, M., Underwood, S., Allenby, B., Garcia, M., Samaras, C., Markolf, S., et al. (2021). Infrastructure resilience to navigate increasingly uncertain and complex conditions in the Anthropocene. *NPJ Urban Sustainability*, *1*, 4. https://doi.org/10.1038/s42949-021-00016-y

Costa, R., Haukaas, T., & Chang, S. (2020). Agent-based model for post-earthquake housing recovery. *Earthquake Spectra*, *37*(1), 46–72. https://doi.org/10.1177/8755293020944175

Cox, D., Barbosa, A., Alam, M., Amini, M., Kameshwar, S., Park, H., & Sanderson, D. (2022). Seaside testbed data inventory for infrastructure, population, and earthquake-tsunami hazard [Dataset]. DesignSafe. https://doi.org/10.17603/ds2-sp99-xv89

Cremen, G., Galasso, C., & McCloskey, J. (2021). A simulation-based framework for earthquake risk-informed and people-centered decision making on future urban planning. *Earth's Future*, *10*(1). https://doi.org/10.1029/2021EF002388

Cremen, G., Galasso, C., & McCloskey, J. (2022). Modelling and quantifying tomorrow's risks from natural hazards. *Science of the Total Environment*, *817*, 152552. https://doi.org/10.1016/j.scitotenv.2021.152552

Datseris, G., Vahdati, A., & DuBois, T. (2022). Agents.jl: A performant and feature-full agent-based modeling software of minimal code complexity. *Simulation*, 00375497211068820. https://doi.org/10.1177/00375497211068820

Dean Runyan Associates. (2021). The economic impact of travel in Oregon [PowerPoint Slides]. Travel Oregon. Retrieved from https://industry.traveloregon.com/wp-content/uploads/2021/05/OR_2020_Final.pdf

Deierlein, G., Govindjee, S., & McKenna, F. (2021). Overview of SimCenter goals and computational tools. In G. Deierlein & A. Zsarnóczay (Eds.), *State of the art in computation simulation for natural hazard engineering* (2nd ed., pp. 1–9). Zenodo. https://doi.org/10.5281/zenodo.4558106

Dubbelboer, J., Nikolic, I., Jenkins, K., & Hall, J. (2017). An agent-based model of flood risk and insurance. *The Journal of Artificial Societies and Social Simulation*, *20*(1). https://doi.org/10.18564/jasss.3135

Feagin, R., Figlus, J., Zinnert, J., Sigren, J., Martínez, M., Silva, R., et al. (2015). Going with the flow or against the grain? The promise of vegetation for protecting beaches, dunes, and barrier islands from erosion. *Frontiers Ecological Environment*, *13*(4), 203–210. https://doi.org/10.1890/140218

Federal Emergency Management Agency (FEMA). (2020). *Hazus earthquake model technical manual: Hazus 4.2 service pack 3*. FEMA. Retrieved from https://www.fema.gov/sites/default/files/2020-10/fema_hazus_earthquake_technical_manual_4-2.pdf

Federal Emergency Management Agency (FEMA). (2021a). *Hazus inventory technical manual: Hazus 4.2 service pack 3*. Retrieved from https://www.fema.gov/sites/default/files/documents/fema_hazus-inventory-technical-manual-4.2.3.pdf

Federal Emergency Management Agency (FEMA). (2021b). *Hazus tsunami model technical manual: Hazus 4.2 service pack 3*. FEMA. Retrieved from https://www.fema.gov/sites/default/files/documents/fema_hazus-tsunami-technical-manual-4.2.3.pdf

Filatova, T. (2015). Empirical agent-based land market: Integrating adaptive economic behavior in urban land-use models. *Computers, Environment and Urban Systems*, *54*, 397–413. https://doi.org/10.1016/j.compenvurbsys.2014.06.007

Filatova, T., Parker, D., & van der Veen, A. (2009). Agent-based urban land markets: Agent's pricing behavior, land prices, and urban land use change. *The Journal of Artificial Societies and Social Simulation*, *12*(13). http://jasss.soc.surrey.ac.uk/12/1/3.html

Filatova, T., Voinov, A., & van der Veen, A. (2011). Land market mechanisms for preservation of space for coastal ecosystems: An agent-based analysis. *Environmental Modelling & Software*, *26*(2), 179–190. https://doi.org/10.1016/j.envsoft.2010.08.001

French, S. (2012). Modeling nonstructural damage for metropolitan building stocks. In *Proceedings of the 15th world conference on earthquake engineering*.

Galasso, C., McCloskey, J., Pelling, M., Hope, M., Bean, C., Cremen, G., et al. (2021). Risk-based, pro-poor urban design and planning for tomorrow's cities. *International Journal of Disaster Risk Reduction*, *58*, 102158. https://doi.org/10.1016/j.ijdrr.2021.102158

Goldfinger, C., Nelson, H., Morey, A., Johnson, J., Patton, J., Karabanov, E., et al. (2012). *Turbidite event history—Methods and implications for holocene Paleoseismicity of the Cascadia Subduction Zone*. US Geological Survey Professional *Paper* 1661-F. 170p Retrieved from https://pubs.er.usgs.gov/publication/pp1661F

Haer, T., Botzen, W., & Aerts, J. (2019). Advancing disaster policies by integrating dynamic adaptive behaviour in risk assessments using an agent-based modeling approach. *Environmental Research Letters*, *14*(4), 044022. https://doi.org/10.1088/1748-9326/ab0770

Haer, T., Husby, T., Botzen, W., & Aerts, J. (2020). The safe development paradox: An agent-based model for flood risk under climate change in the European Union. *Global Environmental Change*, *60*, 102009. https://doi.org/10.1016/j.gloenvcha.2019.102009

Han, Y., Ash, K., Mao, L., & Peng, Z. (2020). An agent-based model for community flood adaptation under uncertain sea-level rise. *Climatic Change*, *162*(4), 2257–2276. https://doi.org/10.1007/s10584-020-02802-6

Hemmati, M., Ellingwood, B., & Mahmoud, H. (2020). The role of urban growth in resilience of communities under flood risk. *Earth's Future*, *8*(3). https://doi.org/10.1029/2019EF001382

Hemmati, M., Mahmoud, H., Ellingwood, B., & Crooks, A. (2021a). Shaping urbanization to achieve communities resilient to floods. *Environmental Research Letters*, *16*(9), 094033. https://doi.org/10.1088/1748-9326/ac1e3c

Hemmati, M., Mahmoud, H., Ellingwood, B., & Crooks, A. (2021b). Unraveling the complexity of human behavior and urbanization on community vulnerability to floods. *Nature Scientific Reports*, *11*(1), 1–15. https://doi.org/10.1038/s41598-021-99587-0

Hino, M., Field, C., & Mach, K. (2017). Managed retreat as a response to natural hazard risk. *Nature Climate Change*, *7*(5), 364–371. https://doi.org/10.1038/NCLIMATE3252

Huang, Q., Parker, D., Filatova, T., & Sun, S. (2014). A review of urban residential choice models using agent-based modeling. *Environment and Planning B: Planning and Design*, *14*(4), 661–689. https://doi.org/10.1068/b120043p

Hunt, J., & Abraham, J. (2003). Design and application of the PECAS land use modelling system. In *8th international conference on computers in urban planning*. Retrieved from http://citeseerx.ist.psu.edu/viewdoc/summary?doi=10.1.1.197.8490

Hurlimann, A., Moosavi, S., & Browne, G. (2021). Urban planning policy must do more to integrate climate change adaptation and mitigation actions. *Land Use Policy*, *101*, 105188. https://doi.org/10.1016/j.landusepol.2020.105188

Jain, V., Davidson, R., & Rosowsky, D. (2005). Modeling changes in hurricane risk over time. *Natural Hazards Review*, *6*(2), 88–96. https://doi.org/10.1061/(ASCE)1527-6988(2005)6:2(88)

Jarosz, B. (2021). Poisson distribution: A model for estimating households by household size. *Population Research and Policy Review*, *40*(2), 149–162. https://doi.org/10.1007/s11113-020-09575-x

Jenkins, K., Surminski, S., Hall, J., & Crick, F. (2017). Assessing surface water flood risk and management strategies under future climate change: Insights from an Agent-Based Model. *Science of the Total Environment*, *595*, 159–168. https://doi.org/10.1016/j.scitotenv.2017.03.242

Kameshwar, S., Cox, D., Barbosa, A., Farokhnia, K., Park, H., Alam, M., & van de Lindt, J. (2019). Probabilistic decision-support framework for community resilience: Incorporating multi-hazards, infrastructure interdependencies, and resilience goals in a Bayesian network. *Reliability Engineering & System Safety*, *191*. https://doi.org/10.1016/j.ress.2019.106568

Koliou, M., van de Lindt, J., McAllister, T., Ellingwood, B., Dillard, M., & Cutler, H. (2018). State of the research in community resilience: Progress and challenges. *Sustainable and Resilient Infrastructure*, *5*(3), 131–151. https://doi.org/10.1080/23789689.2017.1418547

Magliocca, N., Safirova, E., McConnell, V., & Walls, M. (2011). An economic agent-based model of coupled housing and land markets (CHALMS). *Computers, Environment and Urban Systems*, *35*(3), 183–191. https://doi.org/10.1016/j.compenvurbsys.2011.01.002

McLaren, T., Myers, J., Lee, J., Tolbert, N., Hampton, S., & Navarro, C. (2008). MAEviz—An earthquake risk assessment system. In *Proceedings of the 16th ACE SIGSPATIAL international conference on advances in geographic information science*. https://doi.org/10.1145/1463434.1463534

Mesta, C., Cremen, G., & Galasso, C. (2022). Urban growth modelling and social vulnerability assessment for a hazardous Kathmandu Valley. *Nature Scientific Reports*, *12*(6152), 6152. https://doi.org/10.1038/s41598-022-09347-x

Mileti, D. (1999). *Disasters by design: A reassessment of natural hazards in the United States*. National Academies of Sciences, Joseph Henry Press. https://doi.org/10.17226/5782

Miller, E., Hunt, J., Abraham, J., & Salvini, P. (2004). Microsimulating urban systems. *Computers, Environment and Urban Systems*, *28*(1–2), 9–44. https://doi.org/10.1016/S0198-9715(02)00044-3

Mills, A., Bolte, J., Ruggiero, P., Serafin, K., Lipiec, E., Corcoran, P., et al. (2018). Exploring the impacts of climate and policy change on coastal community resilience: Simulating alternative future scenarios. *Environmental Modelling & Software*, *109*, 80–92. https://doi.org/10.1016/j.envsoft.2018.07.022

Moffatt, R. (1996). *Population history of western U.S. Cities & Towns, 1850-1990*. Scarecrow Press.

Mostafavi, A., & Ganapati, N. (2021). Toward convergence disaster research: Building integrative theories using simulation. *Risk Analysis*, *41*(7), 1078–1086. https://doi.org/10.1111/risa.13303

Mostafizi, A., Wang, H., Cox, D., & Dong, S. (2019). An agent-based vertical evacuation model for a near-field tsunami: Choice behavior, logical shelter locations, and life safety. *International Journal of Disaster Risk Reduction*, *34*, 467–470. https://doi.org/10.1016/j.ijdrr.2018.12.018

National Institute of Standards and Technology (NIST). (2016a). *Community resilience planning guide for buildings and infrastructure systems—Volume 1*. National Institute of Standards and Technology. https://doi.org/10.6028/NIST.SP.1190v1

National Institute of Standards and Technology (NIST). (2016b). *Community resilience planning guide for buildings and infrastructure systems—Volume II*. National Institute of Standards and Technology. https://doi.org/10.6028/NIST.SP.1190v1

Neumann, B., Vafeidis, A., Zimmermann, J., & Nicholls, R. (2015). Future coastal population growth and exposure to sea-level rise and coastal flooding—A global assessment. *PLoS One*, *10*(3), e0118571. https://doi.org/10.1371/journal.pone.0118571

Ngo, T., & See, L. (2012). Calibration and validation of agent-based models of land cover change. In A. Heppenstall, A. Crooks, L. See, & M. Batty (Eds.), *Agent-based models of geographical systems* (pp. 181–197). https://doi.org/10.1007/978-90-481-8927-4_10

Nofal, O., & van de Lindt, J. (2021). High-resolution flood risk approach to quantify the impact of policy change on flood losses at community-level. *International Journal of Disaster Risk Reduction*, *62*, 102429. https://doi.org/10.1016/j.ijdrr.2021.102429

Oregon Seismic Safety Policy Advisory Commission (OSSPAC). (2013). The Oregon resilience plan: Reducing risk and improving recovery for the next Cascadia subduction earthquake and tsunami. Retrieved from https://www.oregon.gov/oem/documents/oregon_resilience_plan_final.pdf

Park, H., Alam, M., Cox, D., Barbosa, A., & van de Lindt, J. (2019). Probabilistic seismic and tsunami damage analysis (PSTDA) of the Cascadia Subduction Zone applied to Seaside, Oregon. *International Journal of Disaster Risk Reduction*, *35*, 101076. https://doi.org/10.1016/j.ijdrr.2019.101076

Park, H., Cox, D., Alam, M., & Barbosa, A. (2017). Probabilistic seismic and tsunami hazard analysis conditioned on a megathrust rupture of the Cascadia Subduction Zone. *Frontiers in Built Environment*, *3*(32). https://doi.org/10.3389/fbuil.2017.00032
Park, H., Cox, D., & Barbosa, A. (2017). Comparison of inundation depth and momentum flux based fragilities for probabilistic tsunami damage assessment and uncertainty analysis. *Coastal Engineering*, *122*, 10–26. https://doi.org/10.1016/j.coastaleng.2017.01.008
Parker, D., Brown, D., Filatova, T., Riolo, R., Robinson, D., & Sun, S. (2012). Do land markets matter? A modeling ontology and experimental design to test the effects of land markets for an agent-based model of ex-urban residential land-use change. In A. Heppenstall, A. Crooks, L. See, & M. Batty (Eds.), *Agent-based models of geographical systems* (pp. 181–197). https://doi.org/10.1007/978-90-481-8927-4_26
Parker, D., & Filatova, T. (2008). A conceptual design for a bilateral agent-based land market with heterogeneous economic agents. *Computers, Environment and Urban Systems*, *32*(6), 454–463. https://doi.org/10.1016/j.compenvurbsys.2008.09.012
Peek, L., & Guikema, S. (2021). Interdisciplinary theory, methods, and approaches for hazards and disaster research: An introduction to the special issue. *Risk Analysis*, *41*(7), 1047–1058. https://doi.org/10.1111/risa.13777
Peek, L., Tobin, J., Adams, R., Wu, H., & Matthews, M. (2020). A framework for convergence research in the hazards and disaster field: The natural hazards engineering research infrastructure CONVERGE facility. *Frontiers in Built Environment*, *6*(110). https://doi.org/10.3389/fbuil.2020.00110
Portland State University Population Research Center. (2020). Coordinated population forecast for Clatsop county, its urban growth boundaries (UGB), and area outside of UGBs: 2020-2070. Retrieved from https://ondeck.pdx.edu/population-research/sites/g/files/znldhr3261/files/2020-07/Clatsop_Report_Final_2020.pdf
Raskin, J., & Wang, Y. (2017). Fifty-year resilience strategies for coastal communities at risk for tsunamis. *ASCE Natural Hazards Review*, *18*(1). https://doi.org/10.1061/(ASCE)NH.1527-6996.0000220
Reilly, A., Dillon, R., & Guikema, S. (2021). Agent-based models as an integrating boundary object for interdisciplinary research. *Risk Analysis*, *41*(7), 1087–1092. https://doi.org/10.1111/risa.13134
Rosenheim, N., Guidotti, R., Gardoni, P., & Peacock, W. (2019). Integration of detailed household and housing unit characteristic data with critical infrastructure for post-hazard resilience modeling. *Sustainable and Resilient Infrastructure*, *6*(6), 385–401. https://doi.org/10.1080/23789689.2019.1681821
Saleh, F., & Weinstein, M. (2016). The role of nature-based infrastructure (NBI) in coastal resiliency planning: A literature review. *Journal of Environmental Management*, *183*, 1088–1098. https://doi.org/10.1016/j.jenvman.2016.09.077
Sanderson, D. (2022). Coupled urban change and hazard consequence model (v0.3) [Software]. Zenodo. https://doi.org/10.5281/zenodo.6870341
Sanderson, D., Cox, D., & Naraharisetty, G. (2021). A spatially explicit decision support framework for parcel- and community-level risk and resilience assessment using Bayesian networks. *Sustainable and Resilient Infrastructure*, *7*(5), 531–551. https://doi.org/10.1080/23789689.2021.1966164
Sanderson, D., Kameshwar, S., Rosenheim, N., & Cox, D. (2021). Deaggregation of multi- hazard damages, losses, risks, and connectivity: An application to the joint seismic-tsunami hazard at Seaside, Oregon. *Natural Hazards*, *109*(2), 1821–1847. https://doi.org/10.1007/s11069-021-04900-9
San Francisco Planning & Urban Research Association (SPUR). (2009). The resilient city: Defining what San Francisco needs from its seismic mitigation policies. Retrieved from https://abag.ca.gov/sites/default/files/defining_what_san_francisco_needs_from_its_seismic_mitigation_policies.pdf
Sargent, R. (2010). Verification and validation of simulation models. In B. Johansson, S. Jain, J. Montoya-Torres, J. Hugan, & E. Yücesan (Eds.), *Proceedings of the 2010 winter simulation conference* (pp. 166–183). https://doi.org/10.1109/WSC.2010.5679166
Sarica, G., Zhu, T., & Pan, T. (2020). Spatio-temporal dynamics in seismic exposure of Asian megacities: Past, present and future. *Environmental Research Letters*, *15*(9), 094092. https://doi.org/10.1088/1748-9326/ababc7
Sleeter, B., Wood, N., Soulard, C., & Wilson, T. (2017). Projecting community changes in hazard exposure to support long-term risk reduction: A case study of tsunami hazards in the U.S. Pacific Northwest. *International Journal of Disaster Risk Reduction*, *22*, 10–22. https://doi.org/10.1016/j.ijdrr.2017.02.015
Spies, T., White, E., Kline, J., Fischer, A., Ager, A., Bailey, J., et al. (2014). Examining fire-prone forest landscapes as a coupled human and natural systems. *Ecology and Society*, *19*(3), art9. https://doi.org/10.5751/ES-06584-190309
Talebiyan, H., & Mahsuli, M. (2018). Risk-based prioritization of a building portfolio for retrofit. *ASCE Journal of Structural Engineering*, *144*(1). https://doi.org/10.1061/(ASCE)ST.1943-541X.0001927
United Nations Office for Disaster Risk Reduction (UNDRR). (2015). Sendai framework for disaster risk reduction 2015-2030. Retrieved from https://www.preventionweb.net/files/43291_sendaiframeworkfordrren.pdf
US Census Bureau. (2022). Table DP05: ACS demographic and housing estimates. Retrieved from https://data.census.gov/cedsci/
van de Lindt, J., Ellingwood, B., McAllister, T., Gardoni, P., Cox, D., Peacock, W., et al. (2018). Modeling community resilience: Update on the center for risk-based community resilience planning and the computational environment IN-CORE. In *17th United States-Japan-New Zealand workshop on the improvement of structural engineering and resilience (ATC-15-16)*. Retrieved from https://www.nist.gov/publications/modeling-community-resilience-update-center-risk-based-community-resilience-planning
Vinogradov, E., Leick, B., & Kivedal, B. (2020). An agent-based modelling approach to housing market regulations and Airbnb-induced tourism. *Tourism Management*, *77*, 104004. https://doi.org/10.1016/j.tourman.2019.104004
Waddell, P. (2002). UrbanSim: Modeling urban development for land use, transportation, and environmental planning. *Journal of the American Planning Association*, *68*(3), 297–314. https://doi.org/10.1080/01944360208976274
Wang, D., Davidson, R., Nozick, L., Trainor, J., & Kruse, J. (2019). Computational framework to support government policy-making for hurricane risk management. *ASCE Natural Hazards Review*, *21*(1). https://doi.org/10.1061/(ASCE)NH.1527-6996.0000348
Wang, H., Mostafizi, A., Cramer, L., Cox, D., & Park, H. (2016). An agent-based model of a multi-modal near-field tsunami evacuation: Decision-making and life safety. *Transportation Research Part C*, *64*, 86–100. https://doi.org/10.1016/j.trc.2015.11.010
Wang, W., van de Lindt, J., Cutler, H., Rosenheim, N., Koliou, M., Lee, J., & Calderon, D. (2021). Community resilience assessment of an EF-5 tornado using the IN-CORE modeling environment. In *Life-cycle civil engineering: Innovation, theory and practice* (pp. 394–398). CRC Press. https://doi.org/10.1201/9780429343292
Wang, W., van de Lindt, J., Rosenheim, N., Cutler, H., Hartman, B., Lee, J., & Calderon, D. (2021). Effect of residential building retrofits on social and economic community-level resilience metrics. *ASCE Journal of Infrastructure Systems*, *27*(4). https://doi.org/10.1061/(ASCE)IS.1943-555X.0000642
White, R., & Engelen, G. (1993). Cellular automata and fractal urban form: A cellular modelling approach to the evolution of urban land-use patterns. *Environment and Planning A*, *25*(8), 1175–1199. https://doi.org/10.1068/a251175
Williams, C., Davidson, R., Nozick, L., Trainor, J., Millea, M., & Kruse, J. (2022). Regional county-level housing inventory predictions and the effects on hurricane risk. *Natural Hazards and Earth System Sciences*, *22*(3), 1055–1072. https://doi.org/10.1007/s13753-021-00350-w