Integrating Place Attachment into Housing Recovery Simulations to Estimate Population Losses

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Abstract: Following a disaster, residents of a community may be displaced from their damaged homes, leading to expensive and lengthy disruption, with many choosing to move away permanently. Population losses may hinder recovery and exacerbate inequalities across neighborhoods. This study considered household place attachment and identified groups with low place attachment along with expensive and slow postdisaster recovery. We developed a framework to integrate place attachment considerations into housing recovery simulations. We used data from the American Housing Survey to develop housing and neighborhood satisfaction models and identify the neighborhoods with the least-attached residents. A computational simulation framework was used to simulate postearthquake housing recovery for a community and assess expected costs and time frames. We used the triad of low place attachment, high cost, and slow recovery to identify households prone to permanently moving away from their communities. A case study of housing recovery after a hypothetical earthquake near San Francisco demonstrated the application of the methodology. We found that about 10% of the population in some neighborhoods are prone to moving away after a large earthquake. Households with low income, renters, and those in older buildings are most likely to have low place attachment and experience costly and slow recovery. Whereas existing approaches rely on heuristics, the approach and results in this paper provide quantitative means to assess potential population losses and inform efforts to reduce them. The framework to integrate place attachment into housing recovery simulations is versatile and employs publicly available information making it transferable to other communities. **DOI: 10.1061/(ASCE)NH.1527-6996.0000571.**

Introduction

The movement of individuals and households between homes is called residential mobility. Postdisaster residential mobility may result in population replacement and loss. The former occurs when long-term residents move away and are replaced with new residents. This process may accelerate gentrification if the postdisaster area is reconstructed to higher standards (van Holm and Wyczalkowski 2019), or may concentrate socioeconomically disadvantaged persons if the disaster deteriorates local property values and public infrastructures, thereby decreasing local resettlement by more-advantaged residents (Elliott and Pais 2010). Residential mobility also may lead to a permanent decrease in the population. Population losses are "one of the most destructive ills of postdisaster cities" (Lee and Otellini 2016, p. 87). Large-scale residential mobility reduces community cohesion and hinders recovery (Townshend et al. 2015; Cross 2014). Populations losses as low as 5% to 10% are accompanied by significant economic impacts such as the reduction of the taxpayer base and reduced demand from local businesses (SPUR 2012). Displaced persons experience higher unemployment rates (Zissimopoulos and Karoly 2010), limited participation in community recovery decisions (Bier 2017), and the "cultural trauma" of forcibly moving to a new community (Eyerman 2015). Thus, there are multiple benefits of mitigating postdisaster residential mobility. As communities continue work to understand and mitigate their disaster risks, computer simulations become a valuable tool to inform planning, for example, as in the HayWired Scenario study in the San Francisco Bay Area (Johnson et al. 2020). However, these are complex problems, and many models employed in these simulations still are being developed and refined by the engineers, planners, and social scientists leading these studies. Due to infancy of this field, the ability to simulate certain processes is limited.

Postdisaster residential mobility is one such process. The existing models often assume that residents will wait long periods to return home and repair if they can finance doing so (e.g., Costa et al. 2021; Sutley and Hamideh 2020), or that residents are perfectly rational decision makers who will maximize their monetary gains (e.g., Burton et al. 2018; Nejat and Damnjanovic 2012). However, scholars have demonstrated that economic concerns alone cannot explain postdisaster return decisions (Asad 2015; Morrice 2013). There are nonmaterial aspects of the decision to migrate (Adams 2016), such as the sense of loss associated with a change in the environment in which one lives, i.e., solastalgia (Albrecht et al. 2007; Tschakert and Tutu 2010). The aforementioned HayWired Scenario study acknowledged the effect of one's physical and social ties to a place, often called place attachment, on postdisaster decisions (e.g., Johnson et al. 2020, p. 11). Due to the lack of more-sophisticated models, Johnson et al. assumed that a portion of young, high-income renters have low place attachment and are the most likely to migrate out of the Bay Area after an earthquake. Although the assumption is justifiable, the insight that areas with a high concentration of young, high-income renters are the most prone to population losses is a direct consequence of the model assumptions. The challenges in the simulation of postdisaster decisions

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identified in the HayWired Scenario study provided the inspiration and practical foundation for this study.

The goal of this study was to develop a methodology to simulate the postdisaster decision of the residents with less strict assumptions. This was done in two steps. First, we reviewed the relevant literature on postdisaster decisions and place attachment to identify suitable ways to estimate the place attachment of the residents of a community. Then we used place attachment as the lens through which residents of single-family homes evaluate the benefits of staying and repairing against the option to move away. This approach bypassed the need to define a priori the demographic groups most prone to leave the community during recovery.

This study offers three contributions. First, we developed a methodology to assess the place attachment of households. The methodology employs publicly available data and is transferable to other metropolitan regions in the US. Second, we described a workflow to assess expected earthquake-induced losses and housing recovery time for urban communities. The workflow was applied to a case study of San Francisco, and impacts of moment magnitude (M_w) 6.5, 7.2, and 7.9 earthquakes were examined. Lastly, we contrasted the expected losses and recovery times for individual households with the results for place attachment. The goal was to identify the neighborhoods whose residents will jointly experience high losses, long times to regain a sense of normalcy, and low place attachment. We argue that the combined pressure from these three factors is a better predictor of population loss than are financial considerations alone. We identified the neighborhoods and socioeconomic groups with the highest potential for population losses. This information may help a city target neighborhoods and demographic groups that need help and foster a healthier postdisaster recovery.

Place Attachment and Disasters

Place attachment describes the deeply rooted bonds that individuals develop with their communities. Definitions of place attachment are vast and discipline-dependent (Lewicka 2011; Bonaiuto et al. 2016), often being intertwined with the definitions of place identity, place dependence, sense of place, and rootedness (Stedman 2002). Greer et al. (2020) provided a comprehensive and up-to-date review of the literature on place attachment. The popular Scannell and Gifford (2010) framework was adopted in this study. It defines place attachment as the tripartite combination of person (individually or collectively determined use and meanings), psychological process (affective, cognitive, and behavioral components), and place dimensions (symbolic aspects, whether social environment and social meanings, and physical environment, whether natural or built) (Bonaiuto et al. 2016).

This study focused on the place dimension of place attachment, which Scannell and Gifford (2010) argued is the most important. For brevity, we use the term place attachment to refer to its place dimension in this paper. Place attachment describes the qualities and specificity of the location to which one is attached, and it can be divided into social and physical place attachment (Scannell and Gifford 2013; Low and Altman 1992). Social place attachment has been defined as one's social ties and sense of belonging to a location, e.g., a neighborhood (Riger and Lavrakas 1981). Physical place attachment is related to one's dependence on the amenities or resources provided by a location to support one's goals. Thus, place attachment may be related to houses, streets, parks, and other outdoor settings. Place attachment has been shown to affect people's risk perception and disaster preparedness, and how they respond to disasters. Attached persons tend to minimize risks to which they are exposed, and therefore they are reluctant to change landscape change or move out of risky areas such as flood plains or wildland–urban interface zones (De Dominicis et al. 2015; Bonaiuto et al. 2016). Conversely, place attachment may influence disaster preparedness positively. It increases the likelihood that people will take action to prevent harm to the places to which they are attached (Anton and Lawrence 2016; Levac et al. 2012; Mishra et al. 2010). In postdisaster scenarios, persons forcibly separated from their usual living place may experience grief, similar to a situation in which people lose an important social relationship (Fried 2017). Residents with weak or no place attachment are more likely to move away in the face of environmental change such as a disaster (Dandy et al. 2019). Conversely, residents who perceive their neighborhood to be an excellent place to live have been shown to be 2 to 3 times more likely to stay (or return) after a disaster (Haney 2019). Scholars have demonstrated that place attachment is a better predictor of willingness to move away than is whether a resident was born and raised in the region (Jansen et al. 2017).

The influence of place attachment is stronger for homeowners, who tend to report a larger social and emotional place connection than renters (Windsong 2010). Hurricane Katrina has been investigated extensively from the perspective of disaster-induced outmigration. Cross-sectional studies of the recovery after Hurricane Katrina show that New Orleans' poorest permanently out-migrated (Dash et al. 2007; Elliott and Pais 2006; Frey and Singer 2006; Fothergill and Peek 2004). However, Asad (2015) argued that economic factors alone cannot explain the decisions of residents of New Orleans, because many displaced New Orleanians returned to the city even if that entailed paying an economic price. Li et al. (2010) found that among African American and Vietnamese communities, social capital and place attachment synergistically contributed to their decision to return. Among those who returned to the Ninth Ward after Hurricane Katrina, Chamlee-Wright and Storr (2009) found that they insisted that New Orleans provided a sense of place that cannot be found or replicated elsewhere.

Integrating Place Attachment into Housing Recovery Simulations

Postearthquake housing recovery models are varied in detail and scope and often tailored to specific applications. Fig. 1 illustrates some common features in such models. The output from ground motion simulations produces intensity maps of ground accelerations and displacements at the location of each building of interest. The next step is damage and loss assessment. For portfolios, due to lack of detailed data, damage and losses often are estimated as a function of the ground motions using fragility curves and estimates of the building replacement cost per square foot (FEMA 2015). More-sophisticated approaches may split the damage and loss assessments into multiple tasks. Important outputs from the damage and loss assessment step are estimates of repair time (i.e., worker-hours needed to repair the building) and repair costs for each building. The next step is to assess the homeowners' access to financing. Financing is tied to demographic characteristics, e.g., high-income persons may have easier access to private loans but may not qualify for public grants. The mismatch between repair costs and financing available can be used to estimate the indebtedness of each homeowner. If repairs would incur high debt, the homeowners may opt to sell the property. Homeowners who can finance repairs compete for the limited available recovery resources, such as construction workers. Because resources are scarce, some homeowners experience delays in their recovery processes. Thus, the recovery time for each building may substantially exceed the estimated repair time.

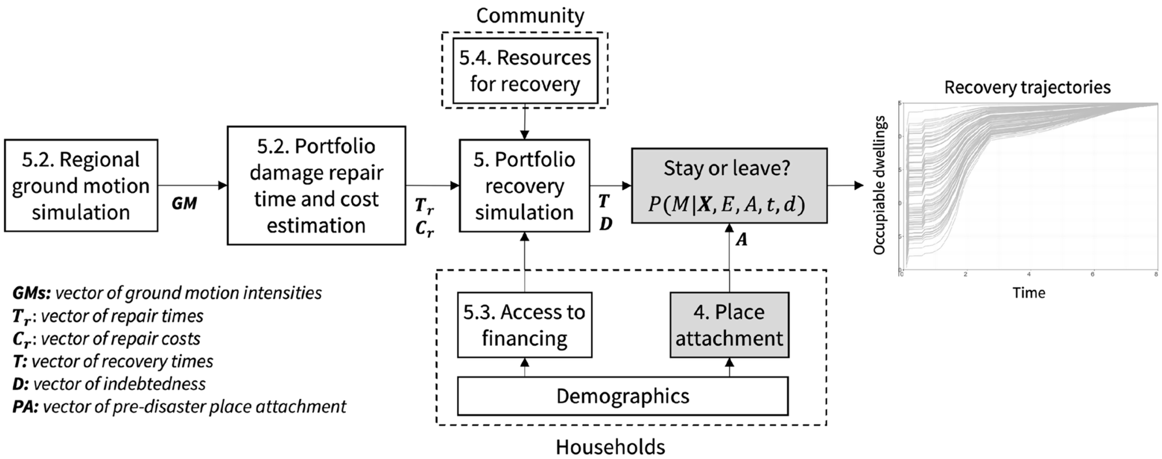

Fig. 1. Schematic representation of a housing recovery simulation model. The numbers in each box indicate the sequence in which the models are discussed. The shaded boxes indicate the contributions of this study.

The two shaded boxes in Fig. 1 indicate the contributions from this study. First, we use demographic data to estimate the strength of place attachment for each homeowner in our study. Second, we use the estimated indebtedness, recovery time, and place attachment to assess the likelihood of a homeowner engaging in repairs. Based on the literature discussed previously, we assume that households with low place attachment are less willing to take on debt and wait long periods to return home after a disaster. That is, homeowners in these conditions are prone to moving away. Thus, assessing the potential population losses involves two main tasks. The first is to assess place attachment for the population of interest. The second is to simulate housing recovery to predict household debt and displacement time of displacement. Thus we can assess, for each household, (1) the probability that its place attachment is low, $P(A = \text{low})$; (2) the probability that the debt incurred from the repair exceeds a given value, $P(D > d)$; and (3) the probability that the housing recovery time exceeds some threshold, $P(T > t)$. Some of these probabilities will change based on the demographics of the household ($\boldsymbol{X}$) and the impact of the earthquake (E). Thus, the probability of residential mobility after an earthquake for a household, $P(M|\boldsymbol{X}, E)$, is defined here as

$$P(M|\boldsymbol{X}, E, A, t, d) = P(A = \text{low}|\boldsymbol{X}) \times P(D > d|\boldsymbol{X}, E) \times P(T > t|\boldsymbol{X}, E) \quad (1)$$

Eq. (1) assumes the conditional statistical independence between place attachment, losses, and repair time, given demographics and impact. That is, A, D, and T are independent given $\boldsymbol{X}$ and E, but they are dependent overall because they all depend on $\boldsymbol{X}$ and E. This formulation allows us to build predictive models that maintain overall dependence among variables, while simplifying the treatment of model prediction residuals. The following sections introduce the models needed to assess the three terms on the right-hand side of Eq. (1).

Place Attachment and Satisfaction

Place attachment can be challenging to measure. However, place attachment consistently has been demonstrated to be correlated with place (housing and neighborhood) satisfaction—even if the nature of this correlation is a debated topic (Ramkissoon and Mavondo 2015). Housing satisfaction has been defined as the contentment felt when housing aspirations are met in the actual housing inhabited (Tan 2016; Mohit and Al-Khanbashi Raja 2014). Analogously, housing dissatisfaction has been suggested as a metric of the gap between housing aspirations and current housing conditions (Bruning et al. 2004). Neighborhood satisfaction is broader, encompassing one's social networks. Social bonds take time to build, and the longer people live in an area, the more friends they are likely to have, and the stronger is their place attachment (Clark et al. 2017; Speare 1974). Thus, a household may be dissatisfied with a high-quality, well-maintained home because the housing costs are too high, (e.g., affordability issue) or because the family is being expanded (e.g., suitability issue). An affluent neighborhood may not satisfy a household if the commute to work is too long, or if their relatives do not live in that neighborhood.

We used housing and neighborhood satisfaction as proxies of household place attachment. Measures of housing and neighborhood satisfaction are publicly available from the American Housing Survey (AHS) (United States Census Bureau 2019). To measure housing satisfaction, the AHS asked the respondents "[o]n a scale of 1 to 10, how would you rate your home as a place to live? (10 is best, 1 is worst)." An equivalent question was asked regarding neighborhood satisfaction. Previous studies used AHS data on place satisfaction to gain insight into social capital building (Li and Zhang 2021), demographic disparities (Ahn and Lee 2016; Boehm and Schlottmann 2008; Zhu and Shelton 1996), risk of housing problems (Crull 1994), and to evaluate the success of subsidized housing programs (James 2008).

In 2019, 1,883 occupants of single-family homes in San Francisco responded to the survey, answering both questions about place satisfaction and providing their demographic profiles. We limited our scope to single-family buildings due to limitations that arise when investigating the recovery of multifamily buildings, which are discussed subsequently. The responses from the 1,883 households are called samples herein. Table 1 presents an overview of the AHS data employed in this study. These demographics were chosen because they have been correlated with socioeconomic vulnerability in past studies (Cutter et al. 2010). We used these data to build a model to estimate the housing and neighborhood satisfaction of households, and use these as proxies for place attachment.

Fig. 2 presents the prevalence of the neighborhood scores across selected demographic groups. Few households had scores below 6, so values greater than or equal to 6 were grouped. There was a significant difference in the level of housing and neighborhood satisfaction reported by renters and owners. Recent-immigrant,

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Table 1. Demographic data available from American Housing Survey

Level of aggregation	Demographic	Categories
Housing Unit	Year built	Real number
	Building value	Real number
Householder	Immigrant	Yes, no
	Race	White, Black, Asian
	Hispanic	Yes, no
	Bachelor degree	Yes, no
	Gender	Female, male
Household	Tenure	Owner, renter
	Income bracket	High, moderate, low
	Income value	Real number
	Size	Integer number
	Year moved in	Integer number
	Has children	Yes, no
	Has elderly	Yes, no
	Has disable member	Yes, no
	Housing score[a]	Integer number (1,10)
	Neighborhood score[a]	Integer number (1,10)

[a]Independent variable.

non-White, and renter households were the least likely to report high housing and neighborhood satisfaction.

We assumed that a household has low place attachment when it has both low housing and neighborhood satisfaction, that is

$$P(A = \text{low}|\boldsymbol{X}, E) = P(HS < s_h(\boldsymbol{X})|\boldsymbol{X}, E) \times P(NS < s_n(\boldsymbol{X})|\boldsymbol{X}, E, HS) \tag{2}$$

where HS and NS = housing and neighborhood satisfaction, respectively; and $s_h(\boldsymbol{X})$ and $s_n(\boldsymbol{X})$ = thresholds of housing and neighborhood scores that characterize low satisfaction. The conditional dependence of NS on HS reflects a significant correlation between housing and neighborhood satisfaction that we identified while preparing the data for this study. Users define the thresholds $s_h(\boldsymbol{X})$ and $s_n(\boldsymbol{X})$. We assumed that all households have a consistent interpretation of satisfaction. However, the approach provides flexibility for the thresholds to be adjusted based on the household demographics. For example, disadvantaged households may indicate high satisfaction (e.g., 8) with a deteriorated home because the alternative is homelessness. In these cases, the user may opt to use $s_h(\text{Income} = \text{Low}) = 9$. We constructed the models for $P(HS < s_h|\boldsymbol{X}, E)$ and $P(NS < s_n|\boldsymbol{X}, E)$ from the AHS data. One challenge that arises when building a model for $P(HS < s_h|\boldsymbol{X}, E)$ is that if $s_h = 6$, for example, the majority of the samples have scores above the threshold. A model fitted to this imbalanced data is prone to be biased toward the majority class. To mitigate this bias when predicting households' housing and neighborhood scores, we employed an approach that combines minority oversampling with an ensemble classifier.

There are several techniques to reduce the class imbalance. Undersampling consists of using only a subset of the samples from the majority class so that balance is achieved. A common drawback of undersampling is the loss of information from discarding many samples in the majority class. Conversely, oversampling consists of increasing the number of samples in the minority class to match the majority class samples. Oversampling often is achieved by drawing replacements from the samples in the minority class. A potential problem of this approach is that oversampled sets may contain many copies of the same sample, leading to overfitting. Another group of techniques focuses on creating synthetic samples from the minority class. In this study, we used the synthetic minority oversample technique (SMOTE) (Chawla et al. 2002). The SMOTE creates synthetic samples of the minority class based on its nearest K minority neighbors. Estimators fit using the SMOTE are less prone to overfitting and do not incur a loss of information. After the class imbalance in the classification problem was adjusted, we uswed adaptive boosting (AdaBoost) to perform the model fitting (Freund et al. 1999). AdaBoost has three main concepts. First, it uses many weak learners rather than a single more-sophisticated learner. Weak learners are classification models that are intentionally simple and which do not have strong prediction capacity. In most applications, the weak learners employed in AdaBoost are decision trees with a single node, often called decision stumps. The predictions of each stump subsequently are combined to determine the most probable class for each sample. Second, classifications made by each stump

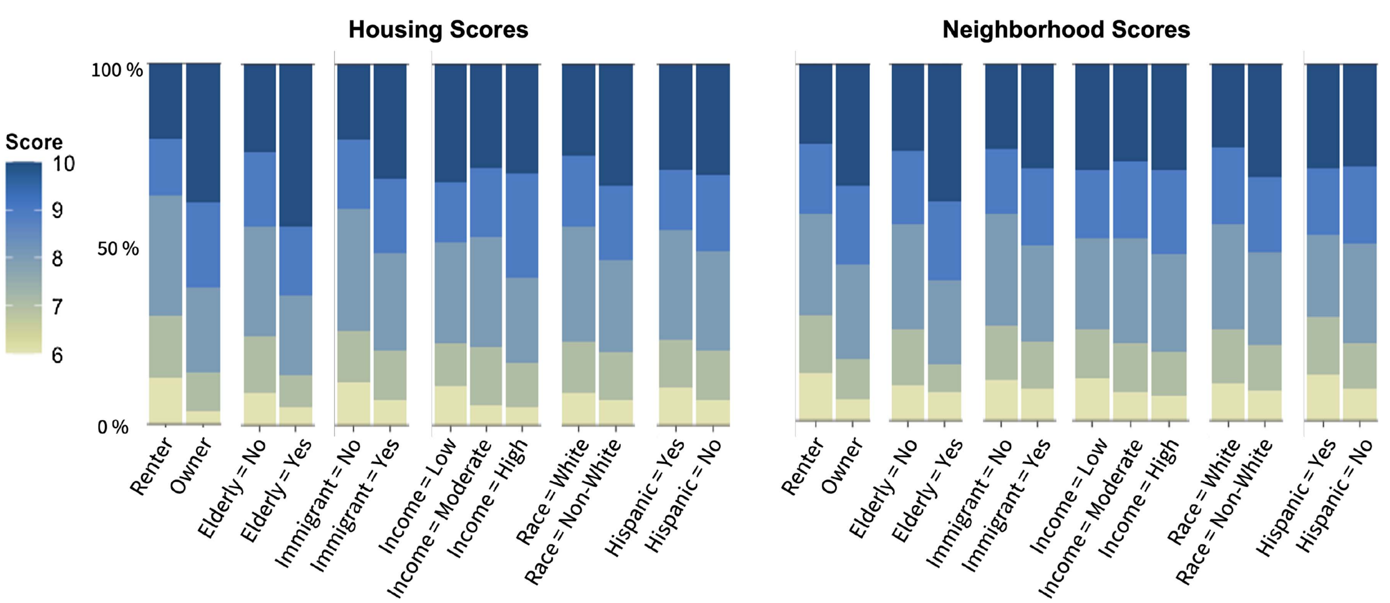

Fig. 2. Percentage of respondents indicating a given housing or neighborhood score for selected demographic groups. The vertical axis is normalized by the number of households in each group.

are weighted by the errors it makes. Thus, the more incorrect a stump's prediction, the less weight its vote has in the final classification. This property contrasts with the uniform weights used in a random forest, for example. Third, errors made by each stump are used to inform the creation of the next stump. This adaptive behavior once again contrasts with the independent trees in a random forest. Using these three concepts, an ensemble of weak learners trained via AdaBoost can make accurate predictions while being less susceptible to overfitting (Rätsch et al. 2001).

Combining the SMOTE and boosting algorithms is called SMOTEBoosting, and it improves prediction in imbalanced data sets (Chawla et al. 2003, pp. 107–119). The data in Table 1 were used to fit the models using SMOTEBoosting. The model for housing satisfaction uses the modified housing scores (i.e., scores below 6 were grouped) as the dependent variable. With the exception of the neighborhood scores, all other variables in Table 1 are used as independent variables. We used the housing satisfaction model to predict the housing scores for the 1,883 samples. The model for neighborhood satisfaction is fitted using the modified neighborhood scores (i.e., scores below 6 were grouped) as the dependent variable. The demographics in Table 1 and the predicted housing scores are used as independent variables in the neighborhood model. The predicted housing scores are used in place of the surveyed housing scores to simulate the behavior of the SMOTEBoosting classifier when applied to a new data set for which surveyed scores scores are not available.

To test the SMOTEBoost classifier, we first split the 1,883 samples in the AHS into a training set (1,318) and a testing set (565). The classifier was trained on the training set and used to predict the testing set. We tested the ability of the classifier to predict low satisfaction using different scores as the thresholds. That is, for each household in the testing set, we predicted wehether $HS < s_h$ and $NS < s_n$ for different s_h and s_n. To assess the quality of the classifier, Fig. 3 shows the receiver operating characteristic (ROC) curves for each threshold. ROC curves summarize the trade-off between the true-positive and false-positive rates for a predictive model using different probability thresholds. The ROC curve for a naive model that is correct 50% of the time is a straight line with a 45° slope. This line is shown in Fig. 3. The area under the curve (AUC) for this model is equal to 0.5. Models with AUC > 0.5 outperform the naive model, and AUCs closer to 1 are desirable. The models for neighborhood scores are slightly less accurate because they use the predicted housing scores as an independent variable. However, all models fitted for all thresholds had significant improvements over the naive model (Fig. 3). These results demonstrate the quality of the SMOTEBoost classifier and its suitability to assess the probability that a household has low place attachment as per Eq. (2).

Postearthquake Housing Recovery Simulations

This section describes the steps used to simulate postearthquake housing recovery and estimate repair cost and time for each household. The steps described in Fig. 1 were employed for this purpose.

Simulation of Buildings and Households

This study used the FEMA Hazus methodology (FEMA 2021) to build a portfolio of all single-family buildings in San Francisco from SimplyAnalytics (2019) projections based on the 2010 Census data. The methodology allowed us to estimate the structural type, code design level, and replacement cost for each considered single-family building. We associated one household (defined by the demographics in Table 1) with each single-family home in the portfolio. The demographics of the households were sampled from the distributions in each census tract, and correlations between demographics were not simulated directly. For example, if in census tract T 50% of the households have a Black householder, i.e., $P(\text{Race} = \text{Black}|T) = 0.5$, and 30% have a low income, i.e., $P(\text{Income} = \text{low}|T) = 0.3$, the probability that a household has a Black householder and low income is $P(\text{Race} = \text{Black}|T)$ $P(\text{Income} = \text{low}|T) = 0.5 \times 0.3 = 0.15$. San Francisco comprises 184 census tracts, and this approach partially captured the spatial correlation between demographics. For the preceding example, the Pearson correlation coefficient is $r(\text{Race}=\text{Black}, \text{Income}=\text{low}) = 0.55$.

Simulation of Ground Motion, Damage, and Losses

Shaking intensities are simulated at the centroid of each census block group. The ground-shaking simulations provide estimates of the peak-ground acceleration (PGA) and spectral acceleration

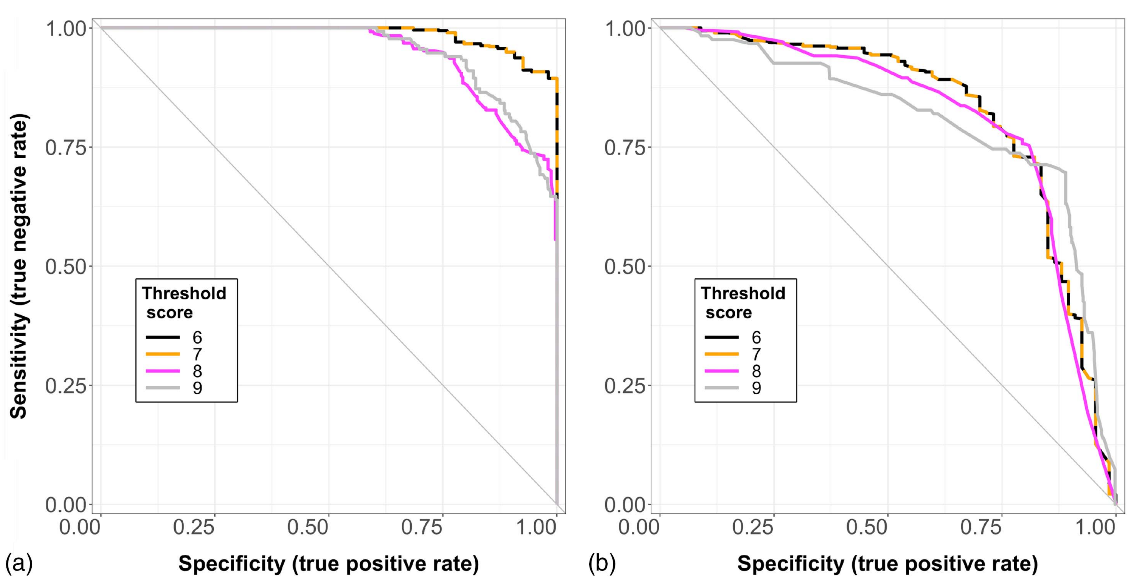

Fig. 3. Receiver operating characteristic curves considering different thresholds for the predicted: (a) housing scores; and (b) neighborhood scores.

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(SA). The Open-Source Seismic Hazard Analysis (OpenSHA version 1.5.2) event set simulator is used to predict median values of PGA and SA (Field et al. 2003). The distributions of ground shaking at each location, and the correlations between spectral acceleration values at multiple periods and multiple locations, are predicted using empirical models (Chiou and Youngs 2014; Baker and Jayaram 2008; Markhvida et al. 2018). Variability in predictions is captured by generating N realizations of ground-shaking intensities associated with the given rupture of interest. We consider buildings to potentially be on liquefiable soil, p_l, equal to the fraction of liquefiable soil within the census block group. For buildings on liquefiable soil, the probability of liquefaction is calculated as a function of the on-site PGA; the magnitude of the earthquake; the liquefaction susceptibility, which is assumed to be high; and a 1.5 m groundwater level, which is the default value for FEMA [2015, Eqs. (4)–(20)]. Using the probability of liquefaction and the on-site PGA, we calculate permanent ground deformation considering the expected lateral spreading and ground settlement (FEMA 2015, Section 4.2.2.1.4). The output from this assessment is a vector of permanent ground deformations. The estimated ground shaking and ground deformations are used to estimate damage using the methodology described in FEMA (2015) Sections 5.4–5.6.3. Vectors of structural and nonstructural damage states are output at this step, and then associated with vectors of repair costs ($\boldsymbol{C}_r$) and repair times ($\boldsymbol{T}_r$) for all buildings (FEMA 2015, Table 15.9).

Simulation of Housing Recovery Debt

We adopted the model of Alisjahbana et al. (2021), with modifications, to simulate recovery financing. This model was developed considering postearthquake housing recovery financing for a household in San Jose, California. Four funding sources are included: earthquake insurance, bank loans, Small Business Administration (SBA) loans, and Community Development Block Group for Disaster Recovery (CDBG-DR) grants. If the claims and applications are successful, insurance and loans are disbursed within weeks. The grants from CDBG-DR may take months to years to be disbursed because these funds have to be approved by Congress after each disaster. Funding from the FEMA Individuals and Households Program is not accounted for because these grants being relatively small compared with the expected losses (Alisjahbana et al. 2021). For each funding source, the model provides the probability of receiving funding, the expected amount received, and the time to receive the funding. The original model considers that homeowners who cannot obtain total financing cannot repair. Because we are interested in identifying the burden of repairing one's home, we assume that all homeowners will attempt to repair it. However, the gap between the financing needed to repair the home (R_c) and the financing that homeowners can obtain from insurance (F_i), bank loans (F_b), SBA loans (F_{sba}), and CDBG-DR grants (F_{cdbg}) is assessed, and it is defined as the indebtedness associated with the disaster, $D(\boldsymbol{X}, E)$

$$D(\boldsymbol{X}, E) = R_c(E) - (F_i(\boldsymbol{X}, E) + F_b(\boldsymbol{X}, E) + F_{\text{sba}}(\boldsymbol{X}, E) + F_{\text{cdbg}}(\boldsymbol{X}, E)) \tag{3}$$

where $\boldsymbol{X}$ and E = dependence on household demographics and losses associated with the earthquake being considered, respectively. We assume that homeowners will use their savings, sell nonliquid assets, or obtain high-interest loans to pay this debt. Thus, this amount is used to proxy the additional challenges households need to overcome to repair their homes. The probability that D exceeds a threshold d, $P(D > d|\boldsymbol{X})$, is needed for Eq. (1), and is given by

$$P_h(D > d|\boldsymbol{X}) = \frac{1}{N}\sum_{i=1}^{N} \mathbf{1}(D_i > d|\boldsymbol{X}, E) \tag{4}$$

where N = number of realizations of earthquake of interest; and $\mathbf{1}$ is an indicator function that returns 1 if $D_i > d$ and zero otherwise. Probability $P_h(D > d|\boldsymbol{X})$ is calculated only for owner households. Renters are not responsible for paying for repairs. Therefore, we do not consider debt as a factor influencing their decisions. The consequence of this assumption is that homeowners require one more adverse condition to be present for them to be susceptible to housing mobility. This assumption reflects findings from empirical studies that found that homeowners are less likely to move away in the aftermath of disasters.

Simulation of Recovery Times

We estimate an available construction workforce of 1,000 crews in San Francisco, based on data from ESRI (2021). The availability of other types of workers (e.g., inspectors or engineers) is not accounted for. The housing recovery of single-family homes often isbottlenecked by the availability of contractors (Costa and Haukaas 2021). We assumed that if the demand for contractor crews is higher than the local supply, workers come from nearby communities over time up to a limit. If the available supply exceeds this limit, workers leave the city over time. The limit used in this study was 80% of the current demand, which yields housing recovery rates similar to those observed in previous large disasters (Lee and Otellini 2016). Thus, during recovery, the number of construction crews in the community is at least 1,000, but it can increase to 80% of the total demand if the demand is higher than 1,000 crews. The recovery is simulated over discrete time steps. At each time step, households that have obtained funds (Section 5) request a contractor crew. If the number of contractor crews available exceeds the number of requests in the current time step, all households that requested a contractor can start repairs. The contractors stay allocated to the households for a time equal to the repair time of each building, T_r. After that, they become available for another household. When there are more requests than contractors, available contractors are allocated to the household that made the earliest request. This process produces the recovery trajectories in Fig. 1. The recovery simulation allowed us to estimate recovery time for each homeowner. The recovery time for a household with demographics $\boldsymbol{X}$ after earthquake E, $T(\boldsymbol{X}, E)$, is

$$T(\boldsymbol{X}, E) = T_f(\boldsymbol{X}, E) + T_c(\boldsymbol{X}, E) + T_r(E) \tag{5}$$

where T_r = repair time; T_f = time needed to obtain financing; and T_c = time needed for a contractor to become available to work on the building. That is, $T_c = 0$ if contractors are available immediately in the community. The recovery trajectories for each earthquake simulation provide the probability that a household's recovery time exceeds t given its demographics, $P_h(T > t|\boldsymbol{X}, E)$. This probability is the last factor needed to assess Eq. (1). For each household, this probability is

$$P_h(T > t|\boldsymbol{X}, E) = \frac{1}{N}\sum_{i=1}^{N} \mathbf{1}(T_i > t|\boldsymbol{X}, E) \tag{6}$$

where T_i = recovery time after each earthquake simulation $i = 1, \ldots, N$. Thus, $P(T > t|\boldsymbol{X})$ is the probability that the recovery time for a household will exceed t after an earthquake.

Assessing Potential Population Loss

To combine the models described previously and demonstrate the application of the proposed framework, we present a case study that investigated the impact of earthquakes on 124,563 single-family buildings in San Francisco. Three earthquakes occurring on the San Andreas fault with moment magnitudes of 6.5, 7.2, and 7.9 were selected. These earthquakes represent planning scenarios that the City of San Francisco has considered. One hundred simulations postearthquake housing recovery for each earthquake were conducted to capture uncertainty. In each simulation, random variables representing the ground motion, damage, losses, repair time, repair financing, and recovery speed of each household had different values. Conversely, household demographics and physical place attachment were simulated once before the first simulation was run. The case study included only the recovery of single-family homes for several reasons. Single-family homes are less varied in terms of their structural features than multifamily homes. The financing mechanisms available to repair single-family homes are more straightforward than those available to multifamily homes. More importantly, multifamily homes often are owned or managed by companies or strata, and the processes involved in deciding to rebuild are not trivial to simulate. Thus it is unclear if place attachment plays a pivotal role in the decision to repair multifamily buildings. Fig. 4 shows the spatial distribution of single-family homes in San Francisco. These are concentrated on the west side of the city, in wealthier neighborhoods, which are closer to the San Andreas Fault, the source of the earthquakes considered in the following analyses.

Place Attachment

The first step in using Eq. (1) to estimate potential population loss is to assess the number of households with low place attachment. After the demographics of each household are simulated from census data, the SMOTEBoost classifier is used to estimate their housing and neighborhood satisfaction. Households with housing and neighborhood scores below 7 are considered to have low place attachment. Fig. 5 shows the probability of low place attachment for households in each census tract. Lighter shades indicate areas whose residents are more prone to residential mobility. Unshaded areas contain fewer than 50 single-family residences (e.g., Golden Gate Park). The northeast and southeast parts of the city have the highest percentage of households with low predisaster place attachment. These areas have a significant number of households with low income and underrepresented minorities. The earthquakes considered in this study occurred on the San Andreas Fault to the west of the city. Thus, based on distance from the source, the neighborhoods with the lowest place attachment on average were exposed to lower ground motion intensities.

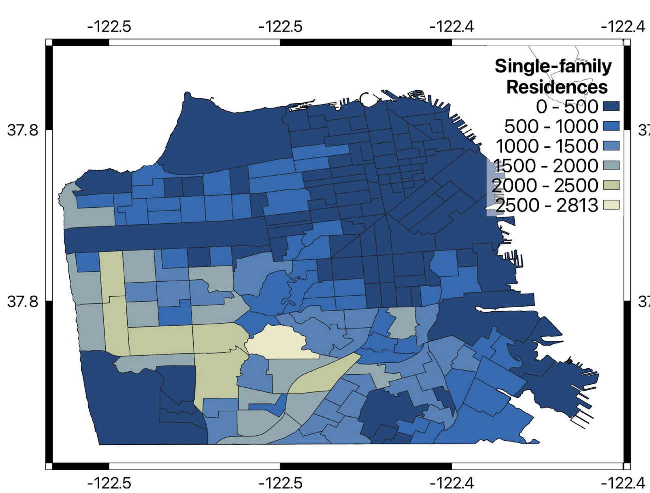

Fig. 4. Number of single-family residences per census tract in San Francisco.

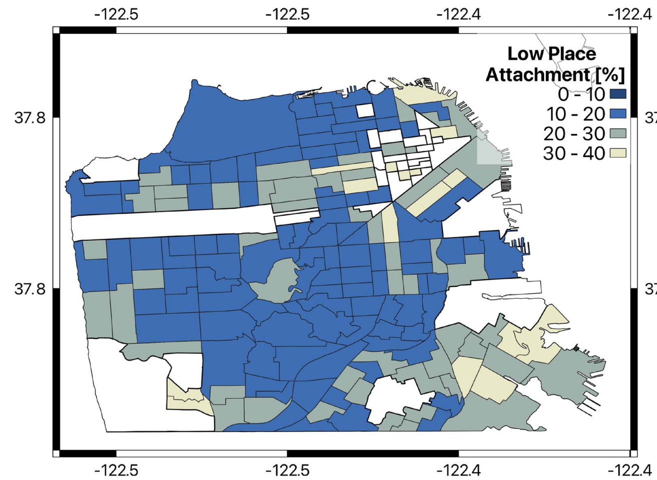

Fig. 5. Estimated percentage of households with low place attachment. Unshaded areas contain fewer than 50 single-family residences. Lighter shades indicate areas in which residents are more prone to residential mobility.

Housing Recovery Simulations

The impact of the three earthquakes on the housing stock in Fig. 4 is summarized in Table 2. Not surprisingly, the number of buildings with severe or complete damage, and the losses, increased with the earthquake magnitude. It was assumed that only buildings with severe or complete damage require major repairs (FEMA 2015). Repair time is a function of the damage state; hence it is constant. Repair delay measures the time from the day of the event to the moment when repairs start. Repair delay is bound by the ability of households to obtain financing and the competition for the skilled workforce in the community. There is significant variability in the repair delay (e.g., due to the funding sources available to each homeowner). The mean repair delay is slightly higher for completely damaged buildings, reflecting the longer period needed to finance the more expensive repairs to these buildings. The mean repair delays also increase slightly with earthquake magnitude, reflecting additional delays due to supply constraints when damage is more widespread.

Fig. 6 shows the spatial distribution of the impacts from the M_w 7.9 earthquake, the most damaging of the three. The results are aggregated by census tract. The maps show the average repair costs for the buildings in the tract considering 100 realizations of the earthquake, calculated as

$$L_t = \frac{1}{100 \cdot Nb} \sum_{j=1}^{100} \sum_{i=1}^{Nb} R_{c,i,j} \tag{7}$$

where Nb = number of buildings. Losses were affected by distance to the San Andreas Fault, building value, soil conditions, and the age of the buildings.

Recovery then was simulated over 8 years following the earthquake for each damage realization, using 14-day time steps.

Table 2. Expected impacts of three earthquakes on building portfolio

Earthquake magnitude (M_w)	Structural damage state	Number of buildings	Mean loss per building (USD)	Repair time (days)	Mean repair delay (days)
7.9	Severe	22,269	131,495	90	496
	Complete	16,584	217,541	180	526
7.2	Severe	11,488	92,565	90	499
	Complete	5,694	161,159	180	528
6.5	Severe	1,003	60,954	90	489
	Complete	443	125,958	180	498

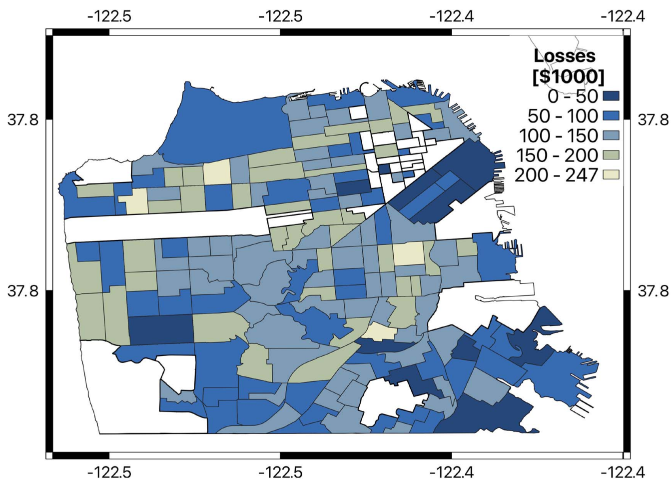

Fig. 6. Average repair cost per census tract per building expected after the M_w 7.9 earthquake. Unshaded areas contain fewer than 50 single-family homes.

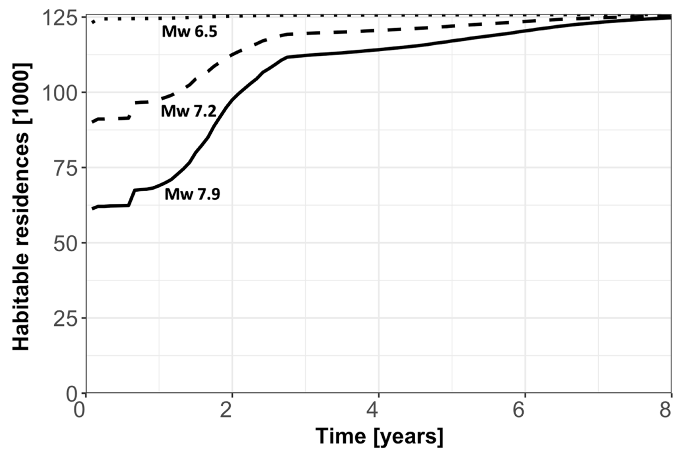

Fig. 7. Postearthquake housing recovery curves. The curves represent average results from the 100 simulations of each earthquake.

Each simulation took about 20 min to run on a high-performance computer and resulted in one recovery curve. The average recovery curve for each earthquake is presented in Fig. 7. Although not shown in the figure, there was significant variability in the immediate damage, i.e., the decrease in the number of habitable residences at time $t = 0$. The recovery progressed quickly until about 3 years after the earthquake. At this time, all households that are not dependent on public grants funding have repaired their homes. After this point, the constant slope of the recovery curves reflects the slow distribution of public grants funding over time.

The housing recovery simulations were used with Eqs. (4) and (6) to estimate the number of households experiencing long recovery time and high debt. The equations require the thresholds d and t to be defined. These thresholds can vary based on household demographics. For example, a young family with no children has fewer restrictions to moving away and may be less willing to wait long periods to repair their home. San Francisco also has a strong housing market, and the prospect of long-term gains may justify housing repair costs that would not be viable in other parts of the country. For exploratory studies, what-if scenarios can be used to determine lower and upper bounds. Here, we considered two combinations of t and d. The first represented a household with strict thresholds to decide to stay; namely, that recovery should cause a debt that is less than its annual income and should be finished within 1 year. The second combination represented a household willing to incur a debt equal to 2 times their annual income and wait up to 2 years to return home. We adopted $t = 2$ years as the upper bound because support for disaster-induced displaced persons typically lasts no longer 24 months (Mitchell et al. 2012).

The results from the two what-if scenarios are presented in Fig. 8. Lighter shades correspond to the stricter scenario. Two key insights are drawn from the figure. First, the choice of the thresholds t and d had a similar impact on the results as the choice of a different earthquake magnitude. These results highlight the need for community-specific quantitative research to assess the willingness of households to spend on and wait for recovery. Second, in the case study, there was a low probability (<3%) that a homeowner will not be able to afford repairs using funding from insurance, public and private loans, and grants after an earthquake. However, there was a nonnegligible probability (30% for the M_w 7.9 earthquake) that the recovery process will take longer than 2 years, i.e., the upper bound assumed for t. Our residential mobility results thus were controlled primarily by the recovery time rather than by costs.

Population Loss

The results from Figs. 8 and 5 allow us to use Eq. (1) to estimate the probability that a given household will move away after an earthquake, $P_h(M|X, E)$, which in turn allows us to estimate the potential population loss at different parts of the city as

$$L_c(E) = \frac{1}{H}\sum_{i=1}^{Nb} P_h(M|X_h, E) \tag{8}$$

where $L_c(E)$ = population loss in a census tract with Nb single-family homes. Eq. (8) can be applied to any combination of earthquake and thresholds t and d to gain insights into potential population losses. For brevity, Fig. 9 shows the results for the M_w 7.9 earthquake considering the strict scenario. The map is overlayed with the contour lines of the planning districts in the city. The Richmond and Outer Sunset districts are the most prone to losing population after any earthquake.

The socioeconomic characteristics of the at-risk households are as crucial as their locations. Fig. 10 presents the demographics of the households most likely to leave the city during recovery under the assumptions in the case study. The total heights of the bars represent the results for the M_w 7.9 earthquake, and the dashed lines are the results for the M_w 7.2 earthquake. Expected population losses after the M_w 6.5 were minimal and are not shown. Disparities were found across building and household characteristics. Low-income renters who occupy the more physically vulnerable buildings (i.e., low-code buildings) were the most prone to residential

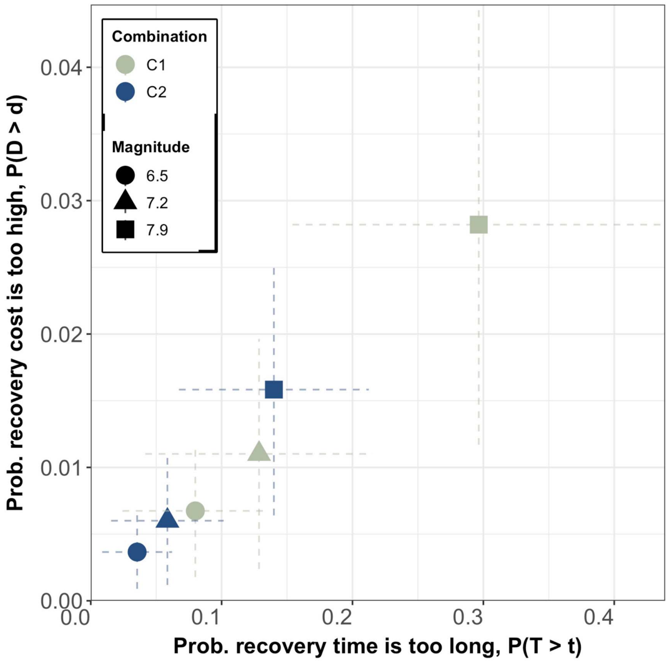

Fig. 8. Percentage of households experiencing high repair costs and recovery time after an earthquake on the San Andreas Fault. Symbols indicate the mean results. Dashed lines indicate the one standard deviation confidence intervals.

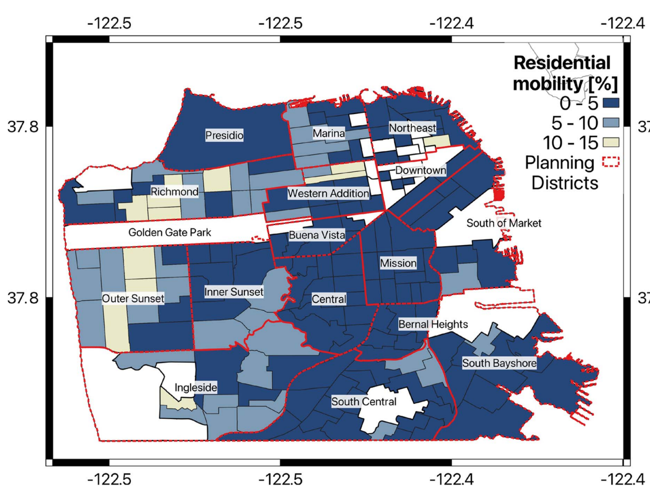

Fig. 9. Potential residential mobility as percentage of census tract population considering the strict scenario for the M_w 7.9 earthquake scenario.

mobility following an earthquake. Disparities across racial, ethnic, and immigrant groups were minor. The earthquake intensity was higher on the west side of the city, and we included only single-family buildings in the analysis. Non-White immigrant households are more prevalent on the east side of the city, and these households tend to occupy multifamily buildings. Lastly, the disparities between owners and renters were higher for the M_w 7.2 earthquake.

To conclude the analyses in this case study, we compared the results obtained from the proposed approach (Fig. 10) with those of two other approaches. In the first approach, denoted None, place attachment is not accounted for, e.g., the PA terms is not included in Eq. (1). In the second approach, denoted HayWired, only young, high-income renters are assumed to move out, which is similar to the assumption in the HayWired Scenario study. The results considering the M_w 7.9 earthquake are shown in Fig. 11. The probabilities of residential mobility across all demographics for each approach were $P_{\text{None}}(M|E) = 0.14$, $P_{\text{HayWired}}(M|E) = 0.033$, and $P_{\text{Proposed}}(M|E) = 0.034$. Thus, if the place attachment is disregarded, almost 5 times more households are considered to be prone to moving away. To gain insight into how each approach distributes $P(\cdot)$ across demographics, the results in Fig. 11 are normalized. That is, the ordinate axis shows $P(M|E, X_i)/P(M|E)$, and values above the horizontal line at $Y = 1$ indicate that a demographic is overrepresented among those expected to move away. The normalization eliminates the influence of the selection of thresholds in Eq. (1). The major disagreement between approaches lies in the influence of income on $P(M|E)$. If place attachment is not accounted for (i.e., the None approach), $P(M|E)$ is evenly distributed (i.e., all values are close to $Y = 1$). In the HayWired approach, high-income households are the only ones at risk of moving away permanently. In the proposed approach, lower-income residents are more prone to residential mobility. Thus, the proposed approach has similar data requirements; yields results similar to those from the HayWired Scenario approach, although using a less strict assumption; and is more consistent with empirical findings which show that socioeconomically disadvantaged persons are more likely to out-migrate (Schultz and Elliott 2013; Elliott and Pais 2010; Frey and Singer 2006; Dash et al. 2007; Fothergill and Peek 2004).

Discussion

The results in this case study indicated an overlap between the demographics of the households with low place attachment and those with difficulty promptly financing postearthquake housing repairs. We emphasize that these results do not directly predict population loss. Rather, they identify households that have to spend more (relative to their incomes), have to wait longer, and have fewer reasons to stay. San Francisco's long-term resilience plan includes measures to "increase neighborhood quality of life, overall physical conditions, and to build community capacity" (Lee and Otellini 2016, p. 109). These measures are expected to improve housing and neighborhood conditions and foster place attachment. The framework presented in this paper helps to assess the benefits of these actions.

Nonetheless, the problem addressed in this study is complex, and the framework has limitations. Per the Scannell and Gifford (2010) framework, we addressed only the place dimension of place attachment. The person and process dimensions were not accounted for, and our findings should be interpreted in light of this simplification. Furthermore, we used satisfaction as a proxy of place attachment. Although this has a basis in the literature, it is not a direct measure of place attachment. Moreover, the American Housing Survey satisfaction scale may not be interpreted consistently by all respondents.

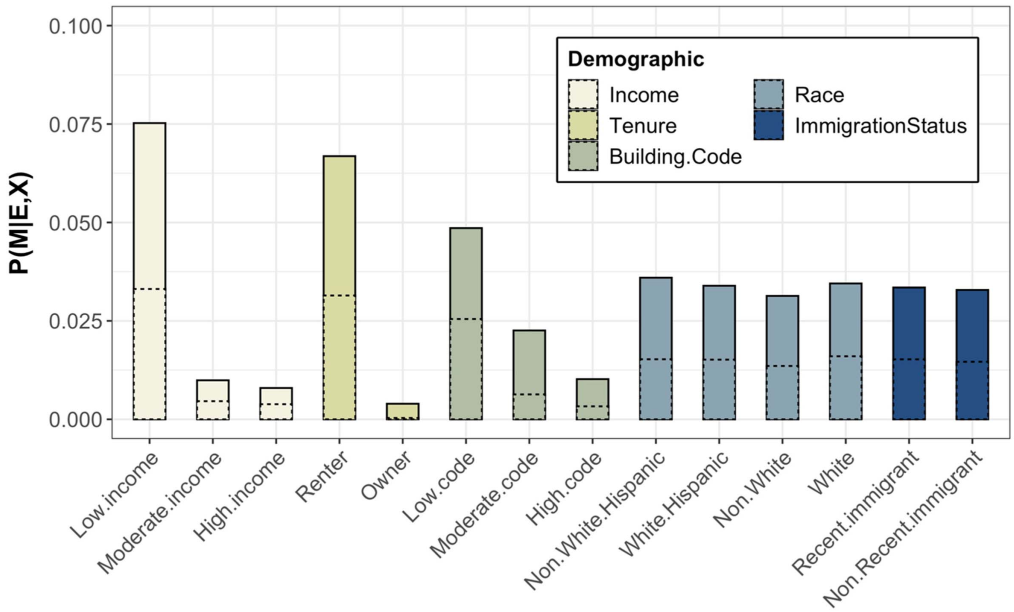

Fig. 10. Probability of out-migration for households in different socioeconomic groups. The heights of the bars indicate the results for the M_w 7.9 earthquake. The dashed lines indicate the results for the M_w 7.2 earthquake.

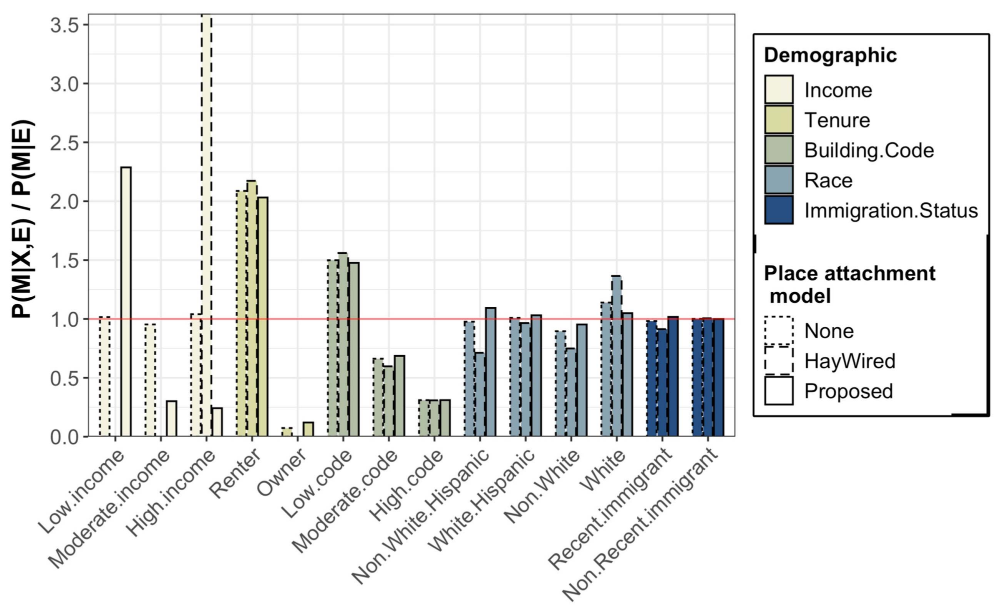

Fig. 11. Probability of out-migration for households in different socioeconomic groups using different approaches to simulate the effect of place attachment on the decision to stay. None considers that place attachment has no effect; HayWired considers that only young, high-income renters are prone to moving away; and Proposed is the approach described in this study. Values above the horizontal line indicate that a demographic group is overrepresented among those expected to move away.

We envision that these limitations can be overcome if questions related to place attachment are included in the American Housing Survey, (e.g., McNeil et al. 2015, p. 14). Those data could be employed in the proposed framework with minimal modifications.

Housing prices in San Francisco are much higher than the national average. Thus, the decision of homeowners to stay and repair or sell and leave may be affected significantly by their perception of the future monetary benefits of having a home in San Francisco. Moreover, we assumed that each homeowner has one home in San Francisco, and that homeowners wish to repair their homes as soon as possible. More-detailed data regarding homeowners with multiple homes would allow this assumption to be refined. Although our case study demonstrates the application of the proposed models, further investigation is needed to determine if the empirical findings regarding the role of place attachment on post-earthquake decisions observed in other communities are transferable to San Francisco.

Another limitation is with our model for financing the repair of rented housing. Owners of rented buildings do not have the same access to financing that is available for owner-occupied buildings.

Thus, their financing processes are unclear. We optimistically assumed that all landlords are high-income persons with sufficient insurance and private financing. With a more realistic model requiring longer waits for funding in some cases, a larger number of renter households would be prone to moving away. However, no such realistic models are available at present.

Lastly, the model assumes that buildings will be repaired to a predisaster state. Given San Francisco's competitive real state market, it is likely that some homeowners and landlords will improve damaged buildings or replace them with higher-density units. These limitations stem from the complexity of the problem and the challenges of anticipating human decisions. However, the proposed framework can be used in what-if studies, as long as assumptions are consistent across all scenarios. In that case, the impact of these limitations is minimized, and comparable results yield meaningful comparisons.

Conclusion

This study integrated place attachment considerations into housing recovery simulations. Place attachment was used as a surrogate for willingness to rebuild. We identified households with low place attachment and whose housing recovery process is expected to be the most challenging. Our premise is that households with low place attachment are less willing to take on debt and wait extended periods to restore their livelihoods. We introduced a classification algorithm that combines the synthetic minority oversampling technique and adaptive boosting (SMOTEBoost) to estimate household place attachment from data from the American Housing Survey. We used the place attachment estimates to study postearthquake decisions of households. We introduced a housing recovery simulation framework to estimate repair costs and housing recovery time for single-family buildings. We combined the place attachment, repair cost, and repair time results to estimate population losses. The place attachment assessment and the housing recovery simulations are decoupled. Thus, the place attachment assumptions can be revised without rerunning the computationally expensive housing recovery simulation. Although we focused on postearthquake decisions, the SMOTEBoost algorithm can be used to assess place attachment and investigate postdisaster decisions after other types of extreme events, such as hurricanes and floods.

The application of the framework was demonstrated in a case study of the potential population loss in San Francisco during the recovery from hypothetical earthquakes on the San Andreas Fault. The case study quantified housing repair costs (relative to household income), time to secure funding, and building repair time for 124,563 single-family households in San Francisco. The potential population loss was investigated under different scenarios. The results indicated that low-income renters occupying older buildings are the most prone to moving away after a disaster.

The framework presented in this study addresses the concern with the loss of populations with low place attachment which has emerged recently in studies of the regional impacts of earthquakes (Johnson et al. 2020, p. 11). Previous studies ignored the influence of place attachment or assumed a priori which demographic groups are most prone to moving away after a disaster. As a consequence, existing approaches provide limited insight into the demographic groups expected to struggle and perhaps move away during postearthquake recovery. The framework in this paper is based on a review of studies of previous disasters. It employs data from the American Housing Survey which are publicly available for multiple locations in the US. It is empirically based, can be employed in multiple regions, and is more nuanced in determining the demographic groups most prone to residential mobility. The framework can be incorporated in predisaster studies to estimate population losses using what-if scenarios (Johnson et al. 2020) and to evaluate the benefits of taking actions to improve neighborhood cohesion (Lee and Otellini 2016, p. 109). Some challenges remain in the application of the proposed framework, as highlighted in the "Discussion" section. Nonetheless, it offers a more robust procedure that can replace semiheuristic approaches and can help formalize the simulation of housing recovery.

Data Availability Statement

Some or all data, models, or code that support the findings of this study are available from the corresponding author upon reasonable request. These include the cleaned and recoded data and *R* scripts used to fit the models and create the figures.

Acknowledgments

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