When Recovery Becomes Infeasible: A Markov Model of Housing Abandonment Risk in Flood-Prone Areas

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ABSTRACT

Floods can undermine long-term community viability by depressing housing markets and triggering property abandonment cycles. This study estimates the risk of housing abandonment by integrating traditional flood-risk frameworks with the concept of sub-replacement—a condition where the cost of repairing a house exceeds its market value. We propose a new risk metric that identifies whether a house enters a sub-replacement condition within a given time horizon.

Our stochastic model is a time-homogeneous, discrete-time Markov process that incorporates flood hazard, housing exposure, physical vulnerability, and housing market dynamics. We apply the model to two U.S. communities—Pascagoula, Mississippi, and McGregor, Florida. These two communities exhibit similar flood hazard, exposure, and building vulnerability, but markedly different housing market conditions. Despite comparable Average Annual Losses (AAL), the number of houses expected to experience sub-replacement within the next three decades is twenty five times larger in Pascagoula than in McGregor. We also find that the FEMA 50% rule—which mandates elevation when repair costs exceed 50% of a home's market value—reduces AAL by approximately 70%, but increases sub-replacement risk in areas with depressed housing markets. This risk is especially concerning in Pascagoula, where lower housing prices increase the number of houses expected to enter sub-replacement in the next three decades by a factor of eight. Our findings show that incorporating housing market conditions into flood risk analysis is important for anticipating long-term recovery trajectories and prevent downward spirals of disinvestment and population loss.

INTRODUCTION

When housing demand decreases in a specific location, the short-term housing supply remains stable because houses are durable goods. As a result, a decrease in housing demand causes prices to fall, but does not reduce the housing stock (at least in the short term), so the total population tends to remain stable (Glaeser and Gyourko 2005a). Over time, houses undergo natural physical degradation that requires investments in maintenance, such as roof replacement or structural retrofitting. If housing prices fall below replacement cost—the cost of rebuilding a house from scratch—investments in maintenance may no longer be economically viable. When maintenance becomes economically unviable, units requiring major repairs are more likely to remain unrepaired and be abandoned. Housing supply starts to shrink, inducing a progressive population loss (Glaeser and Gyourko 2005a).

To illustrate this mechanism, we assume that a house in good condition listed on the market has a price P_b (Figure 1). We refer to this value as the base price of the house. If the house requires repairs costing Δ, the price is reduced by Δ, resulting in a discounted selling price of $P_d = P_b - \Delta$. Since the selling price cannot be negative, we set $P_d = \max\{0, P_b - \Delta\}$. In other words, even if the house is completely destroyed and the land has no value, the owner might be willing to sell the property for free, but would not pay someone to take it. The maximum value that Δ can take is the total replacement cost of the house, C. If P_b is greater than C, P_d remains positive and repairs are always economically viable (Case 1 in Figure 1a). In fact, even if the house requires full reconstruction ($\Delta = C$), a buyer who acquires it at P_d and invests C in repairs sees the total investment fully reflected in the base price ($P_d + C = P_b$).

However, when P_b fall below C, Δ can exceed P_b, and the difference $P_b - \Delta$ can become negative (Case 2 in Figure 1b). This situation can happen, for example, when major maintenance is needed—such as a structural retrofitting—and its total cost exceeds the house's market value after the maintenance has been completed. In that case, even if a buyer acquires the house at no cost ($P_d = 0$), the base price of the house remains lower than the money invested to repair it ($P_b < \Delta$). In the absence of subsidies or risk-mitigation mechanisms (e.g., insurance), such an investment is not economically viable, so neither the current owner nor a potential buyer has an incentive to undertake the repairs. The house is therefore likely to remain unrepaired and eventually be abandoned. We define this process as the sub-replacement mechanism, and refer to a house with $\Delta > P_b$ as having entered the sub-replacement condition.

Under normal conditions, houses in low-price areas enter sub-replacement gradually due to natural physical deterioration, and the housing stock declines slowly over time (Glaeser and Gyourko 2005a). The occurrence of a destructive natural hazard can accelerate this process, causing sudden, widespread damage that could push many houses into sub-replacement at once (Cross 2014; Vigdor 2008). If homeowners lack the resources to repair, they may be forced to relocate. But since the property is in sub-replacement condition, it is unlikely to attract a buyer willing to invest in it, leading to the abandonment of the house and, consequently, a net loss of population for the community. Insurance or government subsidies may still enable repairs, even when costs exceed the home's base price, so entering sub-replacement does not necessarily lead to abandonment. However, even

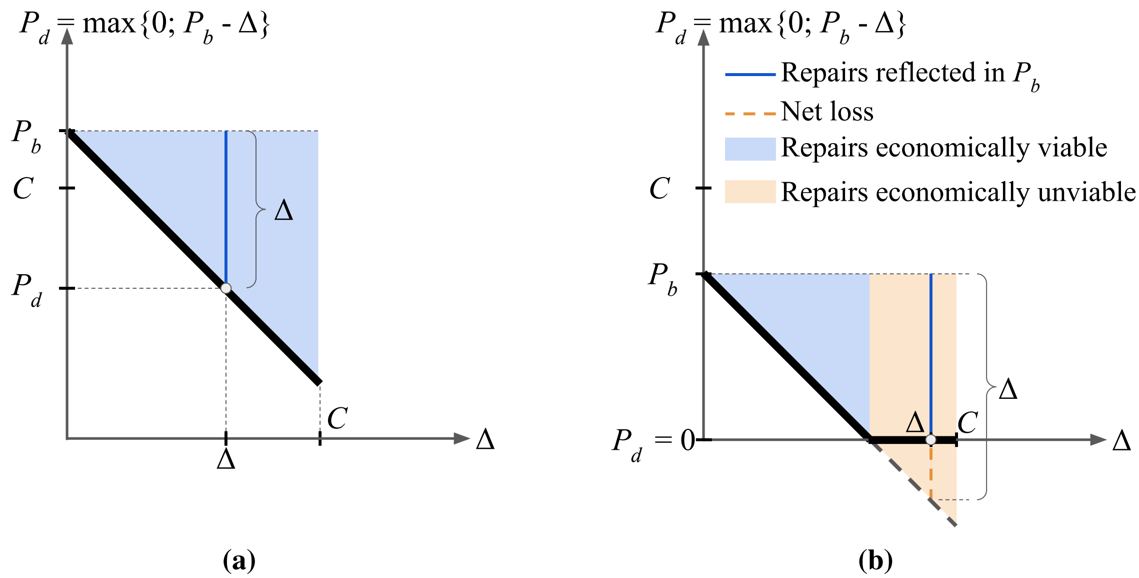


Fig. 1. Schematic illustration of the onset of the sub-replacement condition. (a) Case 1: $P_b > C$: any required repair cost Δ is always lower than P_b. In this case, an investment Δ in repairs can always be fully reflected in the post-repair market value of the house (P_b), making repairs economically viable. (b) Case 2: $P_b < C$: the repair cost Δ can exceed P_b. If $\Delta > P_b$, the owner would spend more on repairs than the resulting base price of the house, even if they had acquired the property for free ($P_d = 0$). The amount $\Delta - P_b$ would represent a net loss, making the investment economically unfeasible. This situation ($\Delta > P_b$) defines the sub-replacement condition.

when insurance is available, homeowners may find it more financially attractive to invest the payout in buying a property in a different location, where the full value of the investment is reflected in the house's base price. Therefore, although entering sub-replacement does not automatically imply population loss, it makes population loss more likely.

For communities affected by natural hazards, population loss poses an additional threat. As households leave, the property tax base shrinks, reducing funds for infrastructure and essential public services such as schools, hospitals, water supply, and transportation. Private services like grocery stores may also close if customer numbers decline, leading to fewer local services and job losses (Burchfield 2016). This reduction in services and jobs makes the community even less attractive and can, in extreme cases, trigger a self-reinforcing cycle of population loss.

It is therefore important to define a risk metric that indicates whether houses in a community will experience sub-replacement, based on their flood exposure, physical vulnerability, and housing market conditions. This metric can help identify communities at risk of irreversible decline and support effective mitigation and recovery efforts. In this paper, we introduce a stochastic model to estimate the probability that a house exposed to flood risk will reach sub-replacement condition in the future. Our model simulates how a home's market value and physical condition evolve over time, accounting for repeated flooding and recovery dynamics. It captures how flood events of different magnitudes cause physical damage and reduce property value, and how long it takes for damaged houses to be repaired. If, at any point, cumulative damage exceeds the post-repair market value, the house is considered to be in a sub-replacement condition, meaning repairs are no longer economically viable. The proposed risk metric enables the comparison of sub-replacement risk across communities with similar hazard, exposure, and physical vulnerability, but different housing price conditions.

Traditional risk analyses have focused on economic losses, infrastructure disruption, and the influence of socio-economic conditions on the recovery process (Cheng et al. 2024; Ceferino et al. 2018; Arora and Ceferino 2023; Negri et al. 2025; Houng et al. 2025; Xu and Noh 2021; Costa et al. 2024; Markhvida et al. 2020). Several studies have also modeled socio-economic and demographic changes following natural hazards. For example, Costa et al. (2022), Mongold et al. (2024), Burton et al. (2019), and Bhattacharya and Kato (2021) proposed models to estimate the probability that current residents will permanently out-relocate from communities impacted by a natural hazard. These models focus on how damage and prolonged recovery times for infrastructure and services can drive residents to leave their communities. However, they do not account for the financial viability of repairs, which can determine whether departing residents are replaced by new ones willing to invest in the community. As a result, while these models are useful for estimating the risk of community disruption, they cannot predict net population changes.

Other studies have integrated housing markets into flood risk models (Bakkensen and Barrage 2022; de Koning and Filatova 2020; McNamara et al. 2024; Tonn and Guikema 2018; Grinberger and Felsenstein 2016). These models focus on risk perception and behavioral economics, and do not explicitly account for physical flood damage or repair costs. An exception is the model proposed by (Karanci et al. 2018), which incorporates both flood damage and net population change. Their framework models housing demand as a function of population density (with higher density increasing demand), property taxes (with higher taxes reducing demand), and perceived flood risk (flood events heighten risk perception and decrease demand). However, their approach does not consider the sub-replacement mechanism. Our paper contributes to the existing literature by explicitly integrating the sub-replacement mechanism with probabilistic flood risk framework, providing a new risk metric to quantify the potential of long-term housing disinvestment and population decline.

The remainder of the paper is organized into the following four sections. In Section 2, we analyze housing prices and population trends across the US using Census data. This analysis supports the mechanism by which houses in low-price areas can fall into sub-replacement condition, as discussed by Glaeser and Gyourko (2005a) and Vigdor (2008). In Section 3, we present a novel stochastic model that integrates housing market dynamics into traditional flood risk frameworks that are based solely on AAL. In Section 4, we apply this model to two US communities with similar flood hazard, exposure, and physical vulnerability, but markedly different housing markets. We also extend the model to simulate the effects of the FEMA 50% rule, which requires homes undergoing substantial repair to be elevated above the 100-year flood level (Federal Emergency Management Agency (FEMA), U.S. Department of Homeland Security 2025). We show that this policy can reduce future flood losses, but it also increases the likelihood of sub-replacement, particularly in low-demand markets, thereby exacerbating the risk of long-term population decline. Lastly, in Section 5, we discuss the potential advantages of using our proposed metric to evaluate flood risk and the policy implications of our findings.

STATISTICAL RELATIONSHIP BETWEEN HOUSING PRICES AND POPULATION LOSSES

The sub-replacement mechanism is grounded in urban economic theory and supported by empirical evidence. For example, Glaeser and Gyourko (2005a) formalized it through a simple housing market model, showing how the durability of housing can slow population losses after negative demand shocks. They also supported this mechanism through data analysis. Using data from US cities over multiple decades, they found that cities with a higher share of homes priced below replacement cost were more likely to experience population decline.

Vigdor (2008) extended the sub-replacement mechanism proposed by Glaeser and Gyourko (2005a) to the case of damage caused by natural hazards. The author argued that sudden flood damage can have effects similar to slow physical deterioration, but with more immediate consequences. While gradual deterioration leads to slow population loss, a natural hazard can push many homes into sub-replacement condition simultaneously, accelerating the decline. Vigdor (2008) used this framework to predict the incomplete population recovery of New Orleans following Hurricane Katrina. The author's prediction, made just two years after the storm, proved accurate: despite substantial rebuilding resources, the city never fully regained its pre-disaster housing stock and population. Here, we provide further empirical support for the sub-replacement mechanism. We consider all US locations without distinguishing whether sub-replacement results from natural hazards or gradual physical deterioration.

Data and Method for the Logistic Regression

To assess whether low housing prices relative to replacement costs are associated with population decline, we conduct two logistic regression analyses at the Census tract level. In the first analysis, we examine the relationship between housing prices (measured relative to estimated replacement costs) and population changes. In the second, we stratify Census tracts by the age of their housing stock to test whether the relation between housing prices and population changes differs between areas with older versus newer homes.

Sample Selection

We select all US Census tracts that satisfy the following criteria:

1. **Geographic Stability:** tract boundaries remained unchanged between 2010 and 2020;
2. **Housing Composition:** more than 85% of housing units are single-family (SF) homes, and fewer than 20% are classified as seasonal or recreational use;

3. **No New Construction:** the total number of housing units did not increase between 2010 and 2020.

These restrictions help avoid confounding effects from boundary changes, presence of vacation-homes, and new development. We focus on single-family housing units for simplicity, as including multi-family buildings would introduce additional complexity due to differences in ownership structures, maintenance dynamics, and repair incentives. Moreover, we exclude tracts where the total number of housing units increased between 2010 and 2020. Our goal is to observe areas without new development, so that we can focus on how existing homes—and the population they support—evolve over time. New development may confound local housing dynamics; for example, if a new neighborhood is built within a Census tract and includes new amenities or infrastructure, both housing supply and demand may increase as a result. In such cases, population changes may reflect the effects of new investment rather than the economic viability of maintaining homes that are already existing.

Independent Variable: Housing Price to Replacement Cost Ratio

To estimate housing prices, we use the *Zillow Home Value Index (ZHVI)* (Zillow Group, Inc. 2025), which reports seasonally adjusted monthly average prices for single-family homes at the ZIP Code level. Since our analysis is conducted at the Census tract level, we map each tract to the ZIP Code with which it has the largest spatial overlap. We denote the estimated monthly price in each Census tract as $\hat{P}(t)$, where t indicates the month, from January 2010 to December 2019.

To estimate replacement costs, we use historical data from *RSMeans* (Gordian 2024), which provides annual average construction costs for typical single-family homes across major US cities. We estimate replacement costs for each tract using inverse-distance weighted averages from the three nearest cities with available construction cost data. We denote this value as $\hat{C}(t)$, where t indicates the corresponding year (from 2010 to 2019). Using these two sources, we define the variable $\psi(t)$ as the monthly ratio between estimated market price and replacement cost of a typical single-family home in each Census tract,

$$\psi(t) = \frac{\hat{P}(t)}{\hat{C}(t)} \tag{1}$$

A value of $\psi(t) < 1$ indicates that, in the considered Census tract, the market price of a home at month t is lower than the estimated cost to rebuild it. For each tract, we then compute the temporal average over the 2010–2019 period, denoted $\overline{\psi}$, which is used to define the binary indicator Ψ,

$$\Psi = \begin{cases} 1, & \text{if } \overline{\psi} < 1 \\ 0, & \text{otherwise} \end{cases} \tag{2}$$

The variable Ψ is a binary indicator that equals 1 if the average market-to-replacement cost ratio $\overline{\psi}$ over the 2010–2019 period is less than 1, and 0 otherwise. It identifies Census tracts where, on average over the decade, the market price of a typical single-family home was lower than its estimated replacement cost. Ψ serves as the main independent variable in our analysis.

Dependent Variable: Population Change

We obtain tract-level population estimates for 2010 and 2020 from the *U.S. Decennial Census* (U.S. Census Bureau 2011; U.S. Census Bureau 2021). We calculate the percentage change in population over the decade for each tract, and define a binary outcome variable, L, as follows:

$$L = \begin{cases} 1, & \text{if population declined between 2010 and 2020} \\ 0, & \text{otherwise} \end{cases} \tag{3}$$

We estimate two sets of logistic regressions. In the first regression, we test whether housing prices below replacement cost are associated with a higher likelihood of population decline, applying the following model:

$$P(\Psi) \ \equiv \ \Pr(L = 1 \mid \Psi) = \frac{\exp\big(\alpha_0 + \alpha_1 \cdot \Psi\big)}{1 + \exp\big(\alpha_0 + \alpha_1 \cdot \Psi\big)}. \tag{4}$$

where α_0 is the log-odds of population decline when $\Psi = 0$, and α_1 is the change in log-odds of population decline associated with $\Psi = 1$. We estimate Equation (4) using standard binary logistic regression by maximum likelihood, treating each Census tract as one observation.

In the second regression, we compute the share of housing units built before 1960, s, for each Census tract, using the *ACS 5-Year Estimates* (U.S. Census Bureau 2023). We then restrict the sample to tracts with s belonging to the top quartile (higher share of old houses, hence "older" stock) and bottom quartile (lower share of old houses, hence "newer" stock). On this restricted sample, we define the binary indicator W as

$$W = \begin{cases} 1, & \text{if } s \text{ belongs to the top quartile ("older" stock)} \\ 0, & \text{if } s \text{ belongs to the bottom quartile ("newer" stock)} \end{cases}$$

and use W in the interaction logit model described below.

$$P(\Psi, W) \equiv \Pr(L = 1 \mid \Psi, W) = \frac{\exp\big(\gamma_0 + \gamma_1 \cdot \Psi + \gamma_2 \cdot W + \gamma_3 \cdot \Psi \cdot W\big)}{1 + \exp\big(\gamma_0 + \gamma_1 \cdot \Psi + \gamma_2 \cdot W + \gamma_3 \cdot \Psi \cdot W\big)} \tag{5}$$

Here, γ_0 is the log-odds of population decline for tracts with newer housing stock ($W = 0$) and housing prices at or above replacement cost ($\Psi = 0$). γ_1 is the change in log-odds associated with housing prices below replacement cost ($\Psi = 1$) in newer housing areas ($W = 0$). γ_2 is the change in log-odds associated with older housing stock ($W = 1$) when housing prices are at or above replacement cost ($\Psi = 0$). And finally, γ_3 captures the interaction effect between Ψ and W, i.e., the additional change in log-odds when both $\Psi = 1$ and $W = 1$. This second regression allows us to assess whether the effect of Ψ is stronger in areas where homes are older and more likely to require maintenance. Also for Equation (5), we use standard binary logistic regression by maximum likelihood, treating each Census tract as one observation.

Empirical Support for the Sub-Replacement Mechanism

The results of the first regression, summarized in Table 1 and in Figure 2a, show a statistically significant association between Ψ and the probability of population decline (L). The estimated coefficient on Ψ in Equation (4) is $\alpha_1 = 1.30$ ($p < 0.001$), implying that tracts with housing prices below replacement cost have approximately 3.65 times higher odds of experiencing population decline compared to those where prices exceed replacement cost. In terms of predicted probabilities, the likelihood of population decline is about 71% when $\overline{\psi} \leq 1$, compared to 40% when $\overline{\psi} > 1$, an absolute difference of 31 percentage points. This pattern is consistent with the sub-replacement mechanism: when prices are low relative to replacement costs, reinvestment in deteriorating homes may become economically unjustifiable, leading to a reduction in housing stock and, consequently, population loss.

However, the model's McFadden pseudo-R^2 is only 0.057, suggesting that while Ψ is a significant predictor, it explains only a modest share of the variation in population outcomes. This result may reflect the influence of other drivers that affect population change independently of reinvestment incentives. For instance, if larger households are replaced by smaller ones (or vice versa), the size of the population may change even as the housing stock remains constant. Moreover, the sub-replacement mechanism implies that the housing stock shrinks as it ages, since physical degradation makes significant renovations necessary. In tracts where the housing stock is newer, the mechanism may not activate because newer houses typically do not require major renovations. For this reason, we use Equation (5) to test whether the effect of Ψ on L differs between tracts with newer and older housing stocks.

The results of the second regression (Equation (5)) are shown in Table 1 and Figure 2b. They show that the effect of Ψ on population decline depends on the age of the housing stock. In tracts with newer housing ($W = 0$), having housing prices below replacement cost ($\overline{\psi} \leq 1$) increases the probability of population loss modestly, from 46% to 55%. In contrast, in tracts with older housing ($W = 1$), the same condition has a markedly stronger effect, raising the probability of population loss from 25% to 65%. The interaction term between Ψ and W is large and highly significant ($\gamma_3 = 1.39$, $p < 0.001$), confirming that the relationship between price-to-cost ratios and population loss is significantly stronger in areas with older housing stock. These findings further support the sub-replacement mechanism: in areas with older housing stock, low price-to-cost ratios make reinvestment economically unviable, leading to the loss of deteriorating homes and, consequently, population decline. In contrast, in areas with newer housing, low price-to-cost ratios are less consequential, as these homes have not yet degraded and can continue to be inhabited without requiring substantial investments for maintenance. Our analysis shows a correlation between low housing prices and population loss, but it does not establish causation. As such, our results do not prove the sub-replacement mechanism, but they provide supporting evidence consistent with its predictions.

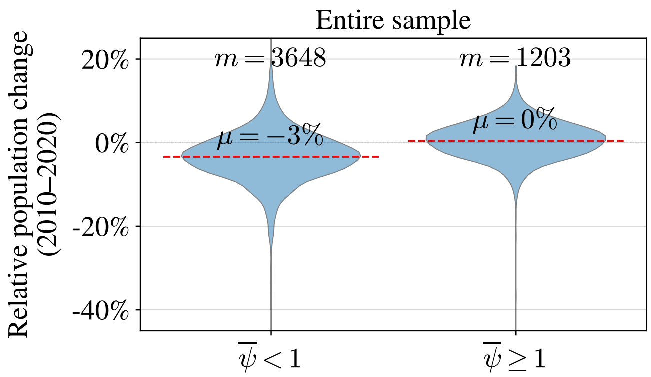
TABLE 1. Logistic regression results for two models predicting the probability of population decline in US census tracts. Model 1 uses a single predictor, Ψ, representing housing-price to replacement cost ratio < 1, across all tracts. Model 2 introduces an interaction between Ψ and W, an indicator for older housing stock (bottom vs. top quartile of housing age distribution) to test whether the effect of low price to cost ratios differs by housing stock age. Panel A reports logit coefficients with 95% confidence intervals; Panel B gives key odds ratios for Ψ in each considered sample, with 95% confidence intervals. The p-values are based on Wald tests of the null hypothesis that each coefficient is equal to zero.

	Model 1: Single predictor (all tracts)	**Model 2: Interaction (older tracts ($W = 1$) vs newer tracts ($W = 0$))**
Panel A: Logit coefficients (point estimate and 95% CI)		
Ψ	1.30^{**} [1.16, 1.43]	0.35^{*} [0.12, 0.57]
W	–	-0.98^{**} [−1.29, −0.66]
$\Psi \times W$	–	1.39^{**} [1.01, 1.76]
Sample size N	4,851	2,426
Pseudo-R^2 (McFadden)	0.057	0.048
Panel B: Key odds ratios (95% CI) for Ψ		
All tracts	3.66 [3.19, 4.19]	–
Newer tracts ($W = 0$)	–	1.41 [1.12, 1.77]
Older tracts ($W = 1$)	–	5.66 [4.21, 7.61]

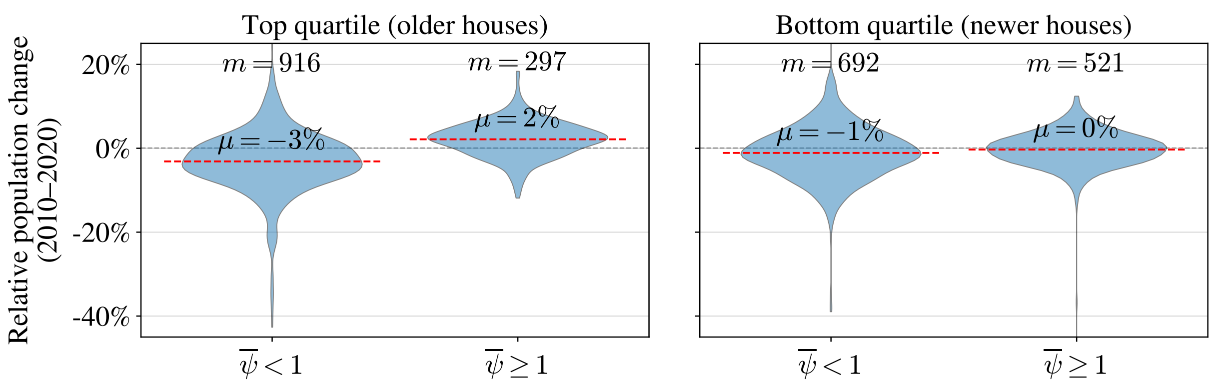
$^{*}p < 0.01$, $^{**}p < 0.001$. Square brackets report 95% confidence intervals.

INTEGRATING THE SUB-REPLACEMENT MECHANISM INTO FLOOD RISK ANALYSIS

Conventional flood risk models estimate risk based on flood intensity and frequency, physical



(a)



(b)

Fig. 2. Distribution of relative population change across US Census tracts between 2010 and 2020, stratified by whether average housing price-to-replacement-cost ratio $\overline{\psi}$ is above or below 1. Dashed red lines indicate group means (μ), while m denotes sample size. (a) Distribution across all eligible tracts. (b) Distribution restricted to tracts in the top and bottom quartiles by share of housing built before 1960, s (i.e., "older" vs. "newer" housing stock).

vulnerability, and exposure (Ceferino et al. 2018; Bowers et al. 2022; Arora and Ceferino 2023; Houng et al. 2025). We extend these models by integrating housing market dynamics, accounting for both flood-related damages and the evolution of a home's market value over time. Our goal is to estimate the probability that, within a given time frame, flood damages caused to a house exceed its base price, placing it in a sub-replacement condition.

Defining the Stochastic Model

We model the evolution of a house exposed to flooding as a time-homogeneous, discrete-time Markov process, where each time step represents one year. At step $n \in \mathbb{N}_0$, the state of the system is defined as

$$X^{(n)} = \left(\psi^{(n)}, \delta^{(n)}, \tau^{(n)}\right) \tag{6}$$

$\psi^{(n)}$ represents the normalized base price of the house at step n. Referring to Figure 1, $\psi^{(n)}$ is defined as the base price P_b (i.e., the market price the house would have if it were in perfect physical condition), divided by its replacement cost C. $\delta^{(n)}$ represents the normalized damage level of the house at step n. Also referring to Figure 1, $\delta^{(n)}$ is defined as the cost of repairs Δ associated with a given damage, divided by the full replacement cost C. $\tau^{(n)}$ is a clock variable that counts the number of years since the last time the flood level reached the ground elevation at the house location. Table 2 summarizes the transition rules and the associated probabilities for our Markov process.

Transition Probabilities

The transition probabilities reported in Table 2 depend on three main factors: the occurrence of flooding at the house location, the applied depth–damage function, and the probability that a damaged house is repaired in a year without flooding. First, regarding the occurrence of flooding at the house location, we define the yearly maximum flood level as H, with probability density function $f_H(h)$ (Figure 3). Each year, H can be either lower or greater than the ground elevation of the house, h_G. We refer to years with $H < h_G$ as dry years, associated with probability β_0, and to years with $H \geq h_G$ as wet years, associated with probability $1 - \beta_0$. Depending on the characteristics of the house, flooding may not cause damage immediately when H exceeds h_G. For example, elevated houses may withstand shallow flooding without incurring damage. We therefore define h_D as the flood level at which the house begins to incur physical damage. We denote as β_1 the probability that H reaches h_G but remains below h_D, causing no damage to the house (i.e., $\beta_1 = \mathbb{P}(h_G \leq H < h_D)$).

TABLE 2. One-step transition rules for the Markov process. The first three columns list the possible values of the three variables (ψ, δ, τ) at step $n + 1$. Rows 1–3 correspond to wet years ($H \geq h_G$), and rows 4–5 to dry years ($H < h_G$). σ is the fractional drop in the house's base price after a wet year. τ_0 is the number of consecutive dry years required for ψ to return to its initial value, ψ_0. r is the house's annual repair probability in dry years. $\beta_0 = \mathbb{P}(H < h_G)$ is the probability of a dry year. The function $f_\delta^*(d)$ is the mixed mass–density function for the normalized annual damage δ (Eq. (7)). $\beta_1 = \mathbb{P}(h_G \leq H < h_D)$ is the probability of a wet year with a flood level too low to damage the house. β_n is the probability of a flood level that is large enough to cause damage ($H \geq h_D$), but lower than the flood level associated with the current damage level $\delta^{(n)}$ (Eq. (8)). The sum of the wet-year probabilities (rows 1–3) equals $1 - \beta_0$, while the sum of the dry-year probabilities (rows 4–5) equals β_0.

$\boldsymbol{\psi}^{(n+1)}$	$\boldsymbol{\delta}^{(n+1)}$	$\boldsymbol{\tau}^{(n+1)}$	**Probability**	**Ref. in Figure 4**
$\psi^{(n)} \cdot (1 - \sigma)$	$\delta^{(n)}$	0	$\beta_1 + \beta_n$	WS
$\psi^{(n)} \cdot (1 - \sigma)$	$\delta^{(n)} < d < \delta_{\max}$	0	$f_\delta^*(d)\,\mathrm{d}d$	WI
$\psi^{(n)} \cdot (1 - \sigma)$	$\delta_{\max}$	0	$\beta_{\max}$	WM
$\psi^{(n)}$ (if $\tau^{(n)} < \tau_0 - 1$) ψ_0 (if $\tau^{(n)} \geq \tau_0 - 1$)	$\delta^{(n)}$	$\tau^{(n)} + 1$	$\beta_0 \cdot (1 - r)$	DN
$\psi^{(n)}$ (if $\tau^{(n)} < \tau_0 - 1$) ψ_0 (if $\tau^{(n)} \geq \tau_0 - 1$)	0	$\tau^{(n)} + 1$	$\beta_0 \cdot r$	DR

Second, transition probabilities depend on the applied depth–damage function (Figure 3). Depth–damage functions relate the flood level h to the resulting normalized damage δ. Several functions are available, depending on building characteristics such as age, materials, number of floors, and whether the structure is exposed to wave action. Given a specific depth–damage function, depending on the flood level occurring at the house location, δ can range from 0 (i.e., flood depth too low to cause any damage) up to a maximum value $\delta_{\max}$. The exact value of $\delta_{\max}$ depends on the utilized depth–damage function and is always less than or equal to 1. A value of $\delta = 1$ represents complete destruction. However, for certain types of buildings—such as a new, two-story concrete structure not exposed to wave action—even an extreme flood depth may not lead to total destruction, thus limiting $\delta_{\max}$ to a value below 1.

Let $\delta = g(h)$ be the depth–damage function for the house. As mentioned, $g(h)$ equals zero for $h < h_D$, and it saturates at $\delta_{\max}$ for $h \geq h_{\max}$. We define $\beta_{\max} = \mathbb{P}(H \geq h_{\max})$ as the probability that the yearly maximum flood level reaches or exceeds $h_{\max}$. Assuming that $g(h)$ is strictly increasing and differentiable over the interval $(h_D, h_{\max})$, we can define a mixed mass–density function $f^*_\delta(d)$ for $d \in [0, \delta_{\max}]$, representing the distribution of normalized annual damage δ:

$$f^*_\delta(d) = \begin{cases} \beta_0, & d = 0, \quad H < h_G \\ \beta_1, & d = 0, \quad h_G \leq H < h_D \\ \dfrac{f_H\big(g^{-1}(d)\big)}{g'\big(g^{-1}(d)\big)}, & 0 < d < \delta_{\max}, \quad h_D < H < h_{\max} \\ \beta_{\max}, & d = \delta_{\max}, \quad H \geq h_{\max} \\ 0, & \text{otherwise} \end{cases} \tag{7}$$

The function $f^*_\delta(d)$ includes a continuous component on $0 < d < \delta_{\max}$, obtained via change of variables from h to d, and point masses $(\beta_0 + \beta_1)$ at $d = 0$ and $\beta_{\max}$ at $d = \delta_{\max}$ (Figure 3). We explicitly separate the probability of $d = 0$ into two mutually exclusive cases: $H < h_g$ (dry year) and $H \geq h_g$ (wet year). This distinction is useful for defining β_n (Figure 3). By definition, $\beta_n = 0$ when the current damage state $\delta^{(n)}$ is zero. When $\delta^{(n)} > 0$, β_n is the probability that the flood level H exceeds the damage threshold h_D, but remains below the level associated with the current damage state, $h(\delta^{(n)})$:

$$\beta_n = \begin{cases} 0, & \delta^{(n)} = 0, \\ \mathbb{P}\Big(h_D < H \leq h(\delta^{(n)})\Big), & 0 < \delta^{(n)} \leq \delta_{\max} \end{cases} \tag{8}$$

When $\delta^{(n)} = \delta_{\max}$, we have $h(\delta^{(n)}) = h_{\max}$, and the probability of a wet year in which the damage level remains unchanged is $\beta_1 + \beta_n(\delta_{\max}) + \beta_{\max} = 1 - \beta_0$, which corresponds to the probability of a wet year.

Third, the parameter r represents the probability that a damaged house is repaired, given that the year is dry $(H < h_G)$. For simplicity, we assume r is constant. To estimate r, we analyzed building permit data from New York City following Hurricane Sandy (New York City Department of

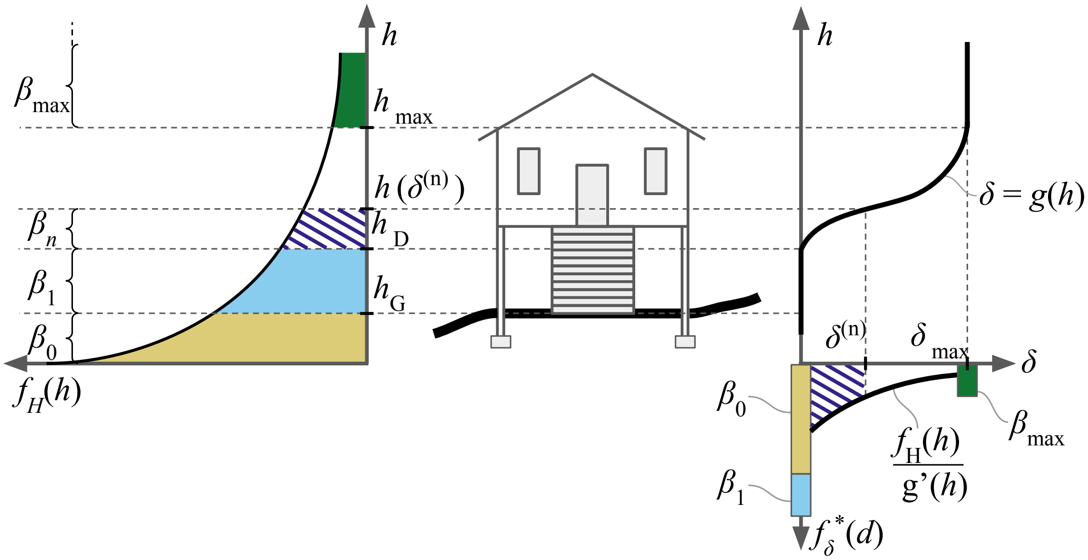


Fig. 3. The cumulative probabilities β_0, β_1, β_n, and $\beta_{\max}$, and the mixed mass–density function $f_\delta^*(d)$ are derived from the pdf of the yearly maximum flood elevation—$f_H(h)$—and the depth–damage curve $\delta = g(h)$. The total probability mass associated with $f_\delta^*(d)$ equals 1.

Buildings 2025a; New York City Department of Buildings 2025b) and found that the average repair time was approximately five years, corresponding to an annual repair probability of about 0.20. However, this estimate reflects the specific context of Hurricane Sandy and the institutional and socio-economic conditions in New York City. Repair timing can vary widely depending on factors such as flood severity, the availability of insurance or government aid, and local construction and permitting capacity. A broader, more generalizable estimate of r would require data from multiple regions and events, and should account for household characteristics, policy responses, and flood intensity. To address this uncertainty, we conducted sensitivity analyses (reported in the supplementary material), showing that our results are not highly sensitive to changes in r. Our main conclusions remain valid even when r varies across a wide range (from 0.10 to 1.00). Further details on the estimation of r are provided in the supplementary material.

Transition Rules

Our model is based on two simplifying assumptions: first, we assume that housing prices are only affected by flood events. Other factors that in reality influence housing prices, such as macroeconomic trends, zoning changes and new development, or varying crime rates, are not considered for simplicity. Second, we assume that housing prices and replacement costs inflate at the same rate over time. In reality, housing prices and replacement costs may diverge in the short term, but empirical evidence suggests that they share a similar long-run trend, making our assumption a reasonable simplification (Rosenthal 1999; Glaeser and Gyourko 2005b; Schulz and Werwatz 2008).

Based on these two assumptions, in the absence of flooding, the normalized base price ψ remains constant at a certain level ψ_0 (Figure 4b). When a wet year occurs (i.e., $H \geq h_G$, with probability $1 - \beta_0$), the base price of the house ψ decreases by a fixed fraction σ, such that $\psi^{(n+1)} = \psi^{(n)} \cdot (1 - \sigma)$ (Figure 4a). This mechanism reflects empirical findings from previous studies comparing the prices of similar houses located just inside and just outside flooded areas (Ortega and Taşpınar 2018). These studies report that homes in flooded zones tend to sell at a discount relative to nearby unaffected homes, even in the absence of physical damage. This price drop is generally attributed to reduced demand, as the event signals future risk and lowers buyers' willingness to pay for houses within the flooded area (Ortega and Taşpınar 2018). The value of σ is based on estimates from the literature, and typically ranges between 4 and 10 percent (Ortega and Taşpınar 2018; Bin and Kruse 2006).

Previous studies have shown that the drop in housing demand after a flood is temporary and typically fades after a few years (Bin and Landry 2013; Atreya et al. 2013). We account for this price recovery by introducing the clock variable $\tau^{(n)}$, which tracks the number of dry years since the latest wet year. We define τ_0 as the number of consecutive dry years required for housing prices to recover after a flooding event. When a wet year occurs—and ψ consequently drops by σ—the clock resets to zero ($\tau^{(n+1)} = 0$, Figure 4a). If the following years are dry, τ starts counting ($\tau^{(n+1)} = \tau^{(n)} + 1$) and ψ remains constant at its current value $\psi^{(n)}$ (Figure 4d). If another wet year occurs before τ reaches the value τ_0, the base price drops again by σ, and τ resets to zero (Figure 4c, 4e). If instead τ_0 consecutive dry years occur, then, in the τ_0^{th} year ψ rebounds to ψ_0 (Figure 4f), where it remains until the next wet year.

Based on the literature, we set $\tau_0 = 6$ years (Bin and Landry 2013; Atreya et al. 2013). As with the parameter r, assuming constant values for σ and τ_0 is a simplification. In reality, these parameters may vary with flood intensity and the socio-economic context. However, empirical data to support a more detailed specification are currently limited, and further empirical research is needed to better quantify how they vary across different contexts.

The damage variable δ transitions as follows. In dry years (Figure 4b, 4d, 4f), the house may either be repaired ($\delta^{(n+1)} = 0$) with probability $\beta_0 \cdot r$ or retain its current damage level ($\delta^{(n+1)} = \delta^{(n)}$) with probability $\beta_0 \cdot (1 - r)$. In wet years, δ follows the mixed mass–density function $f_\delta^*(d)$ (Figure 4a, 4c, 4e). In a wet year, the damage level may either increase or remain the same, but it cannot decrease. We assume that if a flood occurs but the associated damage realization d is lower than the current damage level $\delta^{(n)}$, the flood does not cause additional damage. This assumption represents a reasonable simplification: once key components (e.g., electrical systems, drywall, foundations) have been compromised by a previous event, a subsequent flood of lower intensity is unlikely to further damage those same components. The probability that a wet year occurs but causes less damage than the current damage level $\delta^{(n)}$ is $\beta_1 + \beta_n$ (Figure 3). In wet years, δ can also increase to a value d in the interval $(\delta^{(n)}, \delta_{\max}]$ according to the function $f_\delta^*(d)$, up to its maximum value $\delta_{\max}$, which occurs with probability $\beta_{\max}$.

Transition Kernel Function

Lastly, we define the time-homogeneous, one-step transition kernel. The state space of the system is given by $S = (0, \psi_0] \times [0, \delta_{\max}] \times \mathbb{N}_0$. For any region $B \subseteq S$, the one-step transition kernel K is defined as

$$K\big((\psi, \delta, \tau), B\big) \;:=\; \mathbb{P}\Big((\psi^{(n+1)}, \delta^{(n+1)}, \tau^{(n+1)}) \in B \,\Big|\, (\psi^{(n)}, \delta^{(n)}, \tau^{(n)}) = (\psi, \delta, \tau)\Big), \qquad (9)$$

The kernel K assigns, for any current state $(\psi^{(n)}, \delta^{(n)}, \tau^{(n)})$, the probability that the system will transition to a given subset B of the state space S in the following year. The transition probabilities and densities that determine K are those specified in Table (2).

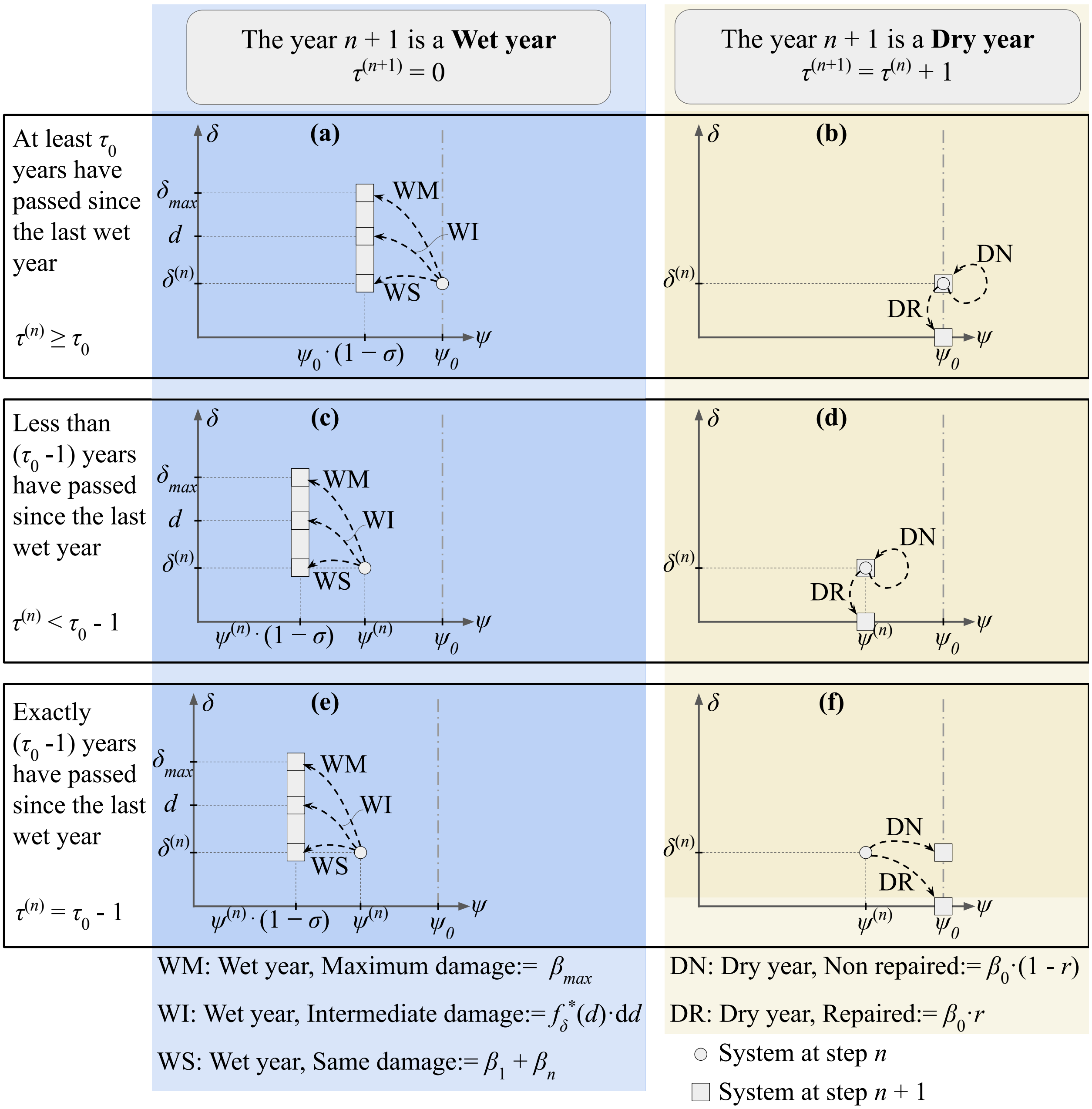


Fig. 4. Schematic representation of the transition rules of the Markov model, conditional on the system state at step n. The state space is defined by three variables (ψ, δ, τ); panels show transitions in the (ψ, δ) plane under different τ conditions. Rows correspond to: (a–b) $\tau^{(n)} \geq \tau_0$ (at least τ_0 consecutive dry years since the last wet year); (c–d) $\tau^{(n)} < \tau_0 - 1$; and (e–f) $\tau^{(n)} = \tau_0 - 1$. For each row, the transition probabilities (WS, WI, WM, DN, DR) sum to one. Left panels represent wet years, after which τ resets to zero ($\tau^{(n+1)} = 0$); right panels represent dry years, after which τ increases by one ($\tau^{(n+1)} = \tau^{(n)} + 1$). The wet-year probabilities (WS, WI, WM) sum to $1 - \beta_0$, and the dry-year probabilities (DN, DR) sum to β_0.

Estimating the Expected Number of Houses Entering Sub-Replacement and Annual Average Losses

Our goal is to estimate the probability that a given house experiences the sub-replacement condition at least once within a horizon of N years. The house starts undamaged ($\delta^{(0)} = 0$) and with full base price ($\psi^{(0)} = \psi_0$). Over time, flooding can cause physical damage that requires repair, and can reduce the house's base price. At the same time, damage may be repaired in dry years with conditional probability r, and the base price may rebound to its initial value after τ_0 consecutive dry years. The sub-replacement condition occurs if, at any time, the repair cost exceeds the base price, i.e., if $\delta^{(n)} > \psi^{(n)}$. We define the sub-replacement set as

$$A \; := \; \{(\psi, \delta, \tau) \, : \, \delta > \psi\}. \tag{10}$$

Starting from $(\psi^{(0)}, \delta^{(0)}, \tau^{(0)}) = (\psi_0, 0, \tau_0)$, we seek the probability that the system enters A at least once within N years. We call this probability the N-year sub-replacement probability and denote it by $\pi^{\text{sub}}(N)$. To compute $\pi^{\text{sub}}(N)$, we first define the survival probability at step N, denoted by $F_{\text{sub}}(N)$, i.e., the probability that the system has never entered A by year N:

$$F_{\text{sub}}(N) \; := \; \mathbb{P}\Big(X^{(n)} \notin A \text{ for all } n = 1, \ldots, N \,\Big|\, X^{(0)} = (\psi_0, 0, \tau_0)\Big). \tag{11}$$

The sub-replacement probability is then

$$\pi^{\text{sub}}(N) \; = \; 1 - F_{\text{sub}}(N) \tag{12}$$

Because of the structure of the kernel function K, defined by Table 2, Equation (12) does not admit a closed-form solution. We solve Equation (12) numerically by discretizing the state space and using the discrete version of the kernel K. Details of the numerical procedure are provided in the supplementary material.

Equation (12) applies to a single house. For a community of M houses—such as a neighborhood or town—we are interested in the number of houses that experience sub-replacement at least once within N years. Let this number be denoted by Z_N. Houses in the same community are exposed to the same flooding events and often share correlated recovery processes. As a result, their sub-replacement probabilities are not independent. However, we can still compute the expected number of affected houses using the linearity of expectation, which does not require independence. Let $\mathbb{E}[Z_N]$ denote the expected number of houses that experience sub-replacement at least once by year N. For house $i \in \{1, \ldots, M\}$, let $\pi_i^{\text{sub}}(N)$ be its N-year sub-replacement probability, defined by Equation (12) using its specific transition kernel K_i. Then $\mathbb{E}[Z_N]$ is given by

$$\mathbb{E}[Z_N] = \sum_{i=1}^{M} \pi_i^{\text{sub}}(N). \tag{13}$$

Lastly, we want to compare the number of houses expected to enter sub-replacement with the AAL, a standard measure of flood risk. We estimate AAL for a given house i as

$$\text{AAL}_i \;=\; C_i \cdot \int_{h_D}^{+\infty} d \cdot \, f^*_{\delta,i}(d) \;\cdot \mathrm{d}d \tag{14}$$

where C_i is the house's replacement cost in current-value USD, and $f^*_{\delta,i}(d)$ is the yearly distribution of δ (Equation (7)). The expected AAL for a community of M houses is

$$\text{AAL}_{\text{tot}} \;=\; \sum_{i=1}^{M} \text{AAL}_i. \tag{15}$$

APPLICATION OF OUR MODEL TO TWO CASE-STUDY AREAS

We apply our model to two US communities: McGregor, a census-designated place in Lee County, Florida, and the west side of Pascagoula, a city in Mississippi (Figure 5). These two locations share similar flood exposure but differ substantially in their housing markets, as summarized in Table 3. McGregor (Census tract 12-071-001801) is a small community in southwestern Florida, part of the Cape Coral–Fort Myers metropolitan area. It lies along tidal waters, with most of its properties exposed to flood risk. McGregor exhibits moderate-to-high housing values typical of

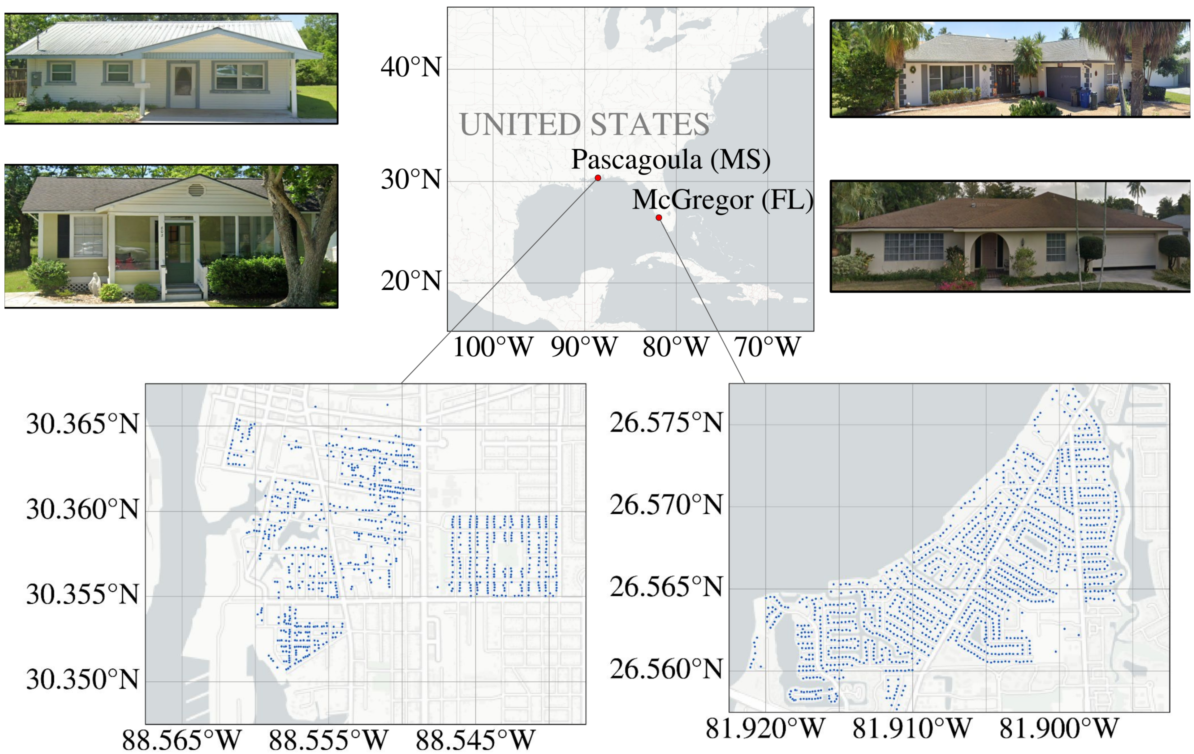


Fig. 5. Maps of the two case-study areas: Pascagoula (Census Tract 28-059-042900) and McGregor (Census Tract 12-071-001801). Blue dots indicate single-family homes in each community. The figure also highlights two representative houses per community.

Florida coastal communities: the median home value is approximately USD 360,000, according to recent Zillow data.

Pascagoula is located along the Gulf Coast of southern Mississippi. Its housing market is more modestly priced, with a median home value of about USD 140,000, based on Zillow data. The west residential side of Pascagoula (Census tract 28-059-042900), largely exposed to coastal flooding, is characterized by older, lower-value homes, often with lower rates of renovation and maintenance. Our goal is to show that, despite comparable expected economic losses, the risk of entering sub-replacement condition may differ significantly between the two communities, due to differences in housing prices. As our statistical analysis suggests (Figure 2), experiencing sub-replacement increases the likelihood of population losses, exposing affected communities to the risk of disinvestment and decline.

For both selected case-study regions, we used the following data sources to characterize our model. We obtained housing attributes from the National Structure Inventory (U.S. Army Corps of Engineers (USACE) 2022b; U.S. Army Corps of Engineers (USACE) 2022a), considering only single-family homes. For each house, we extracted ground elevation, structural material, total floor area, and number of stories. We verified the accuracy of ground elevation data using a USGS digital elevation model (U.S. Geological Survey 2025). Because accurate First-Floor Height Above Ground (FFHAG) for each house was not available, we assigned a uniform value of 45 cm to all houses, roughly equivalent to three stair steps. We also assumed that no house includes a basement. Our objective is to compare sub-replacement risk across communities with similar flood exposure but different housing markets. Therefore, even if the assumed FFHAG may not reflect actual conditions at every property, applying the same value across both locations supports a consistent comparison.

We then derived flood hazard information from the USACE Coastal Hazards System (CHS) South Atlantic Coastal Study (Yawn et al. 2024; U.S. Army Corps of Engineers (USACE) 2024; U.S. Army Corps of Engineers (USACE) 2022c). We used Annual Exceedance Probability (AEP) values at gridded points and applied linear spatial interpolation to estimate probability density functions of the yearly maximum flood level—$f_H(h)$—at each house location. To estimate physical damages, we used depth-damage functions from the USACE North Atlantic Coast Comprehensive Study Report (U.S. Army Corps of Engineers (USACE), North Atlantic Division 2015). We used curves for single-family houses with one or two stories and no basement, selecting the "Inundation Damage – Structure" category and using the maximum damage estimates.

For the normalized base price ψ_0, we combined information from real estate listings and construction cost data. We conducted a qualitative review of active and recently sold listings on Zillow to estimate base housing prices for homes in good physical condition. We estimated an average unit price of approximately 130 USD/ft^2 ($\approx$ 1,400 USD/m^2) in Pascagoula and 240 USD/ft^2 ($\approx$ 2,600 USD/m^2) in McGregor. For construction costs, we used RSMeans data (Gordian 2024), considering average-quality homes and accounting for variations by size, number of floors, and material. We also used RSMeans regional indexes to adjust construction costs for

TABLE 3. Key characteristics of the two case-study areas: McGregor (Lee County), Florida, and the west side of Pascagoula, Mississippi.

Row	Pascagoula	McGregor
Census tract	28-059-042900	12-071-001801
Number of SF houses (NSI)	895	1,231
% of houses within FEMA SFHA	93%	84%
Size of houses	126 ± 51 m^2	198 ± 95 m^2
Unit replacement cost (RSMeans)	1,570 ± 210 USD/m^2	1,397 ± 163 USD/m^2
Average replacement cost	187,743 ± 49,733 USD	264,911 ± 96,281 USD
Unit base price (Zillow)	1,399 USD/m^2	2,583 USD/m^2
ψ_0	0.91 ± 0.12	1.87 ± 0.21

Conversions used: 1 ft^2 = 0.093 m^2; 1 USD/ft^2 = 10.76 USD/m^2. Values rounded to the shown precision.

each location. We report more details about the the two case-study areas in the supplemental material.

Risk Analysis for Two US Communities

We first compare flood risk in the two case-study areas, as measured by AAL and by the expected number of houses experiencing sub-replacement conditions within the next 30 years. Figure 6a summarizes AAL statistics for Pascagoula and McGregor, including mean and maximum values. The average AAL in McGregor (1,128 USD) is about 43% higher than in Pascagoula (784 USD), though still within the same order of magnitude. In both communities, a typical home faces expected flood damages of around $1,000 per year—comparable to the national average flood insurance premium (Howley 2025). The distribution of AAL is similar across the two communities, with only 4% of houses in either location facing annual losses below 100 USD. The fact that AAL are slightly higher in McGregor is primarily due to larger home sizes in this location, which lead to higher replacement costs. However, when AAL is expressed relative to replacement cost, both communities exhibit the same average value of 0.36%. Therefore, by using AAL as flood-risk metric, Pascagoula and McGregor appear nearly equivalent in risk.

On the other hand, when we compare the expected number of houses that will experience sub-replacement in the next 30 years, the two communities differ substantially. As shown in Figure 6b, the expected number of houses entering sub-replacement in the next 30 years is approximately 25 times higher in Pascagoula than in McGregor. Furthermore, 13% of homes in Pascagoula face a sub-replacement probability greater than 0.01, compared to fewer than 0.4% in McGregor. This divergence is driven by differences in housing market conditions. In McGregor, base prices in the absence of flooding are roughly twice the replacement cost. As a result, even in the event of total damage, the probability that repair costs exceed the base price is low. In Pascagoula, by contrast, lower housing demand and depressed prices mean that a severe flood can more easily push a house into sub-replacement, where repair costs exceed the base price. In such cases, investment in repairs is not financially viable, since the difference between the repair cost and the house's base price would constitute a loss of money. Without insurance or public subsidies, houses in sub-replacement condition are more likely to remain abandoned and uninhabited. In summary, although Pascagoula and McGregor exhibit equivalent flood risk as measured by AAL, they differ markedly in their risk of losing housing stock and, consequently, losing population.

In our analysis, we assigned the same FFHAG to all houses in both Pascagoula and McGregor (45 cm, approximately three stair steps). This simplification supports comparisons between the two communities, but it does not reflect actual sub-replacement risk for individual houses. In fact, visual inspection using Google Street View shows that some homes appear elevated by an entire floor and therefore face lower flood risk than estimated. To provide more realistic estimates for the most vulnerable homes, we identified a small sample of non-elevated houses with high flood exposure in each community. Using manually estimated FFHAG values, we recalculated AAL and sub-replacement probabilities. The selected homes in Pascagoula show a 2–3.7% probability of entering sub-replacement within the next decade and a 5—12% probability within 30 years. In contrast, corresponding probabilities for homes in McGregor are nearly negligible (on the order of 10^{-4}). We also found that sub-replacement probabilities increase approximately linearly over time, over horizons of one to five decades. Full details of this analysis are provided in the supplementary material.

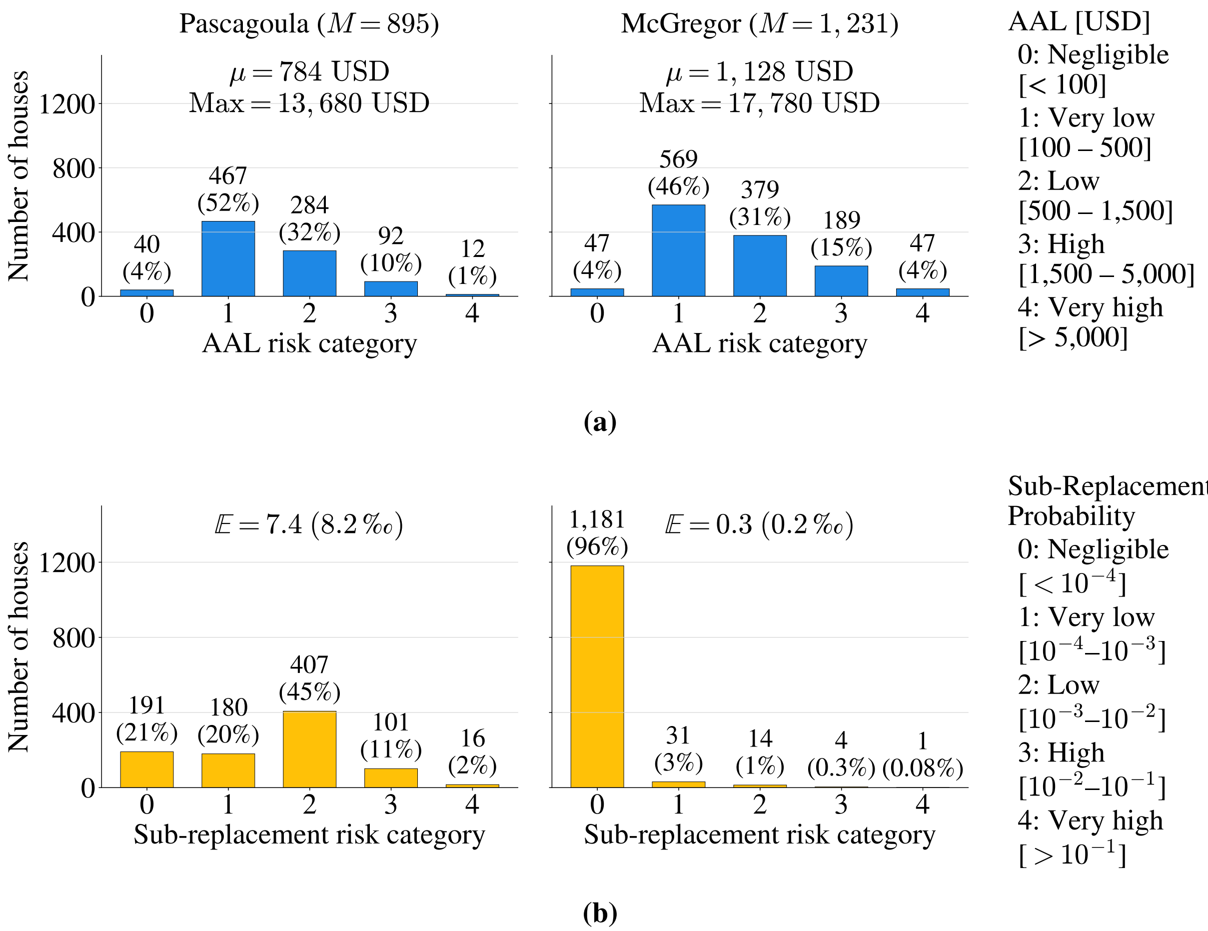


Fig. 6. Number of houses in different risk categories for Pascagoula and McGregor. Panel (a) shows flood risk measured by AAL; panel (b) shows risk measured by the probability of entering sub-replacement condition within the next 30 years. For each location, M denotes the total number of housing units. In panel (a), μ is the mean AAL. In panel (b), $\mathbb{E}$ indicates the expected number of houses entering sub-replacement within 30 years, shown both as an absolute count and as a fraction of the total housing stock.

Incorporating the FEMA 50% Rule in the Model

We then apply our model to study how the FEMA 50% rule (i.e., the NFIP's substantial improvement / substantial damage standard (Federal Emergency Management Agency (FEMA), U.S. Department of Homeland Security 2025)) affects both AAL and the risk of entering sub-replacement. The FEMA 50% rule states that when the cost to repair a structure equals or exceeds 50% of its pre-damage market value, the structure must be made fully compliant with local floodplain regulations. These regulations typically require that the elevation of the lowest habitable floor (FFE) meet or exceed the Base Flood Elevation (BFE, i.e., the 100-year flood level). Some jurisdictions enforce additional freeboard above the BFE, commonly 1 foot (approximately 30 cm). In our model, we define full compliance to the floodplain regulations as elevating the FFE to BFE plus 1 foot of freeboard (Xian et al. 2017). The cost of elevating a house can vary widely, depending on factors such as soil conditions, foundation type, house size and weight, the number of stories, and utility connection adjustments (Aerts 2018). For simplicity, we assume that the cost of elevating a house equals its full replacement cost. This assumption is a simplification, but it is reasonable because in many cases the cost of elevation can approach what it would cost to reconstruct the home (Aerts 2018). A second simplification concerns the structure's pre-improvement market value. Under FEMA regulations, this value should exclude the land component and reflect only the building's structural value. However, in the absence of detailed data, we assume the structure's pre-improvement market value equals the current base price at time step n, $\psi^{(n)}$, multiplied by the house's replacement cost C.

To incorporate the FEMA 50% rule into our model, we proceed as follows. For each house, we precompute two kernel functions: K_1, based on an assumed FFHAG of 45cm, and K_2, based on an FFHAG that sets the house's FFE to equal BFE plus 1 foot of freeboard. If an FFHAG of 45 cm already places the FFE at or above BFE plus freeboard, the process evolves entirely under K_1, and the model behaves as in the baseline case. Otherwise, we introduce a binary elevation flag $e \in \{0, 1\}$, initialized at $e^{(0)} = 0$. While $e^{(n)} = 0$, the process follows K_1. At the first step n for which $e^{(n)} = 0$ and the next-step damage would exceed half the base price, i.e., $\delta^{(n+1)} > 0.50 \cdot \psi^{(n)}$, the FEMA 50% trigger activates. We then set $e^{(n+1)} = 1$ and impose $\delta^{(n+1)} = 1$, which reflects the full cost of elevation. From step $n + 1$ onward, the system transitions according to K_2, and the elevation flag remains set to 1. The sub-replacement set remains $A = \{\delta > \psi\}$; therefore, if $\delta^{(n+1)} = 1$ implies $\delta > \psi$ at the trigger step, the house enters sub-replacement immediately; otherwise, it continues under K_2. To estimate AAL under the FEMA 50% rule, we first elevate each house's FFE to at least BFE plus one foot of freeboard, and then apply Equation **??**.

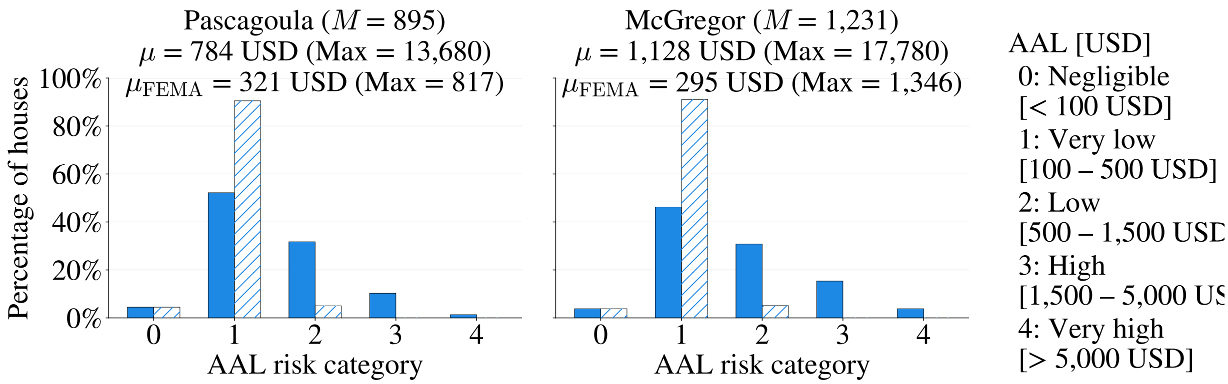
Figure 7a shows how AAL decreases when the FEMA 50% rule is applied. The average AAL across the entire community falls by nearly 60% in Pascagoula and by almost 75% in McGregor. Extreme values drop even more sharply: AAL for the most at-risk house is approximately 90% lower under the FEMA 50% policy in both communities. This result is expected, as the benefit of elevation is greatest for homes with higher flood exposure.

In contrast, Figure 7b shows how the FEMA 50% rule increases probabilities of entering sub-replacement. In this case, outcomes worsen when the policy is applied. For example, the number of houses expected to enter sub-replacement within 30 years increases by a factor of seven to eight in both communities. This occurs because, under the FEMA 50% rule, houses that suffer damage above the threshold are forced to pay the full cost of elevation. That cost, in turn, pushes the cumulative damage above the sub-replacement threshold more often. However, although sub-replacement probabilities increase in both communities, the increase is more concerning in Pascagoula. In McGregor, even after applying the FEMA 50% rule, the vast majority of houses (more than 90%) still face a negligible sub-replacement risk, with probabilities below 10^{-4}. In contrast, in Pascagoula, the share of houses facing high or very high sub-replacement risk increases sharply, from 11% to 40% and from 2% to 17%, respectively.

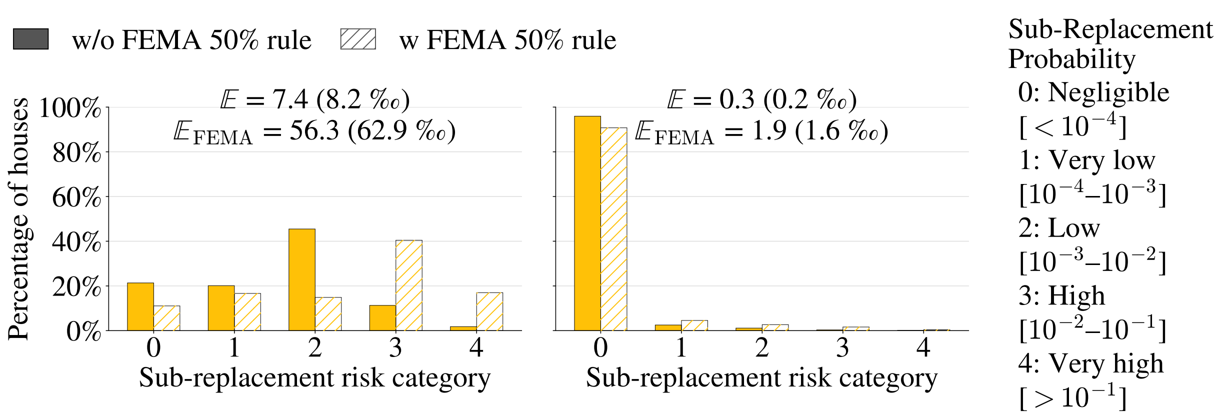
These results highlight an important tradeoff: while the FEMA 50% rule reduces physical flood losses, it can increase the likelihood of abandonment in low-value housing markets, where the cost of compliance may exceed a home's market value. This insight from our model aligns with recent reporting from Pascagoula, where residents and officials have raised concerns that FEMA requirements are weakening an already fragile housing market (DiNatale 2022). The article shows how elevation costs have made it more difficult for homeowners to sell or repair their properties, contributing to long-term disinvestment. Such anecdotal evidence corroborates our model's findings that well-intentioned mitigation policies may inadvertently accelerate decline in communities with depressed housing markets.

DISCUSSION AND CONCLUSIONS

Our analysis highlights why considering housing markets adds an important dimension to risk



(a)



(b)

Fig. 7. Percentage of houses in different risk categories for Pascagoula and McGregor, calculated with and without applying the FEMA 50% rule. Panel (a) shows flood risk measured by AAL; panel (b) shows risk measured by the probability of entering sub-replacement condition within the next 30 years. For each location, M denotes the total number of housing units. In panel (a), μ is the mean AAL. In panel (b), $\mathbb{E}$ indicates the expected number of houses entering sub-replacement within 30 years, shown both as an absolute count and as a fraction of the total housing stock.

analysis and suggests that locations with different market conditions require different mitigation strategies. In areas with a depressed housing market, risk-mitigation and protection policies should aim to prevent the negative effects of abandonment and population loss. First, for locations at high risk of losing population, policies should ensure that remaining residents retain access to essential services even as population density drops. In practice, such policies may include service-sharing agreements among nearby jurisdictions (e.g., shared schools, rotating clinics), and transit services to maintain accessibility at lower cost. Second, there should be policies to prevent long-term blight. The government could swiftly acquire abandoned properties—for example through land banks—and convert them into well-maintained open space and stormwater features. High-quality open space represents an amenity for residents and can partially offset the negative consequences associated with population loss.

Our analysis also shows that the FEMA 50% rule, while markedly reducing AAL, may exacerbate sub-replacement risk in communities with low housing prices. Implementation of the rule decreased AAL by 60 to 75% in Pascagoula and McGregor, respectively, but it also increased the expected number of houses entering sub-replacement by a factor of seven to eight. In McGregor, where housing prices are relatively high, this increase had modest effects, raising the number of houses expected to incur sub-replacement from 0 to 2. In contrast, in Pascagoula, where prices are lower, the expected number went from 7 to 56. This sharp increase poses a serious risk. A large number of unrepaired homes can initiate a feedback loop, where early signs of abandonment further depress housing values, pushing even more homes into sub-replacement and accelerating population loss. If unchecked, such dynamics could threaten the long-term viability of the community.

This side-effect of the FEMA 50% rule arises because, in low-price markets, a house that requires elevation may remain trapped in sub-replacement if the elevation cost exceeds the home's post-elevation market value. In these cases, owners may be unable to secure financing, as the home does not provide sufficient collateral to cover the loan. To address this problem, public agencies could offer a "gap" financing mechanism to cover the difference between elevation costs and the post-elevation market value. With such mechanism, owners who would otherwise be trapped in sub-replacement conditions could complete compliant repairs and gradually recover.

We conclude by reflecting on the model's constraints and highlighting promising directions for subsequent research. One important limitation is that we only consider the effects of flooding on housing prices. As discussed in the methods section, our model assumes that housing prices are influenced only by flood events. We do not account for other factors that can affect prices in reality, such as macroeconomic trends, new development, demographic shifts, or changes in crime levels.

Furthermore, we assume that both housing prices and replacement costs inflate at the same rate over time. These are two necessary simplifications, as it would be unrealistic to incorporate all potential factors influencing housing and construction markets into a single model. As a result, our findings are more reliable over shorter time horizons (two to three decades), during which the likelihood of external shocks to housing markets remains lower. Over longer periods, however, the probability that housing prices will be affected by factors unrelated to flooding increases, making our projections more uncertain.

A second limitation is that we use constant values for the model parameters across all houses. For example, the yearly repair rate (r) likely depends on household socio-economic conditions and should vary from house to house, and even more so across communities. Our analysis does not incorporate this variation. However, we found that varying the repair rate within plausible ranges did not significantly change the results, giving us confidence that the model's conclusions are robust with respect to this parameter. The situation is more complex for the price-discount parameter σ, to which our model is more sensitive (results of the sensitivity analysis are reported in the supplementary material). The empirical studies we used to estimate σ are based on single flood events. We lack data on how housing prices respond to repeated flood events that occur within short time intervals—specifically, intervals shorter than τ_0. Understanding how multiple events compound price discounts requires further research into housing market dynamics under repeated shocks. In general, while the parameters of our model are interpretable and can in principle be estimated from data, they remain uncertain. Further empirical research is needed to better quantify their values and how they interact with local conditions and external factors.

Lastly, our analysis is based on current climate conditions and flood hazard levels. In future work, our model could be applied under projected climate scenarios, including sea level rise and increasing frequency of extreme flooding. This extension would allow estimation of how sub-replacement risk may evolve under a changing climate.

DATA AVAILABILITY STATEMENT

A complete replication package for this study (including input datasets, and the code and model outputs used to produce the figures and tables) is archived on Zenodo (*version DOI:* https://doi.org/10.5281/zenodo.17970784.

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